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Validating the Collective Model of Household Consumption Using Direct Evidence on Sharing

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Abstract

Recent advances in the collective model literature suggest ways to estimate the complete allocation of resources within households, using assignable goods and assuming adult preference similarity across demographic groups (or across spouses). While it makes welfare analysis at the individual level possible, the predictive power of the model is unknown. We propose the first validation of this approach, exploiting a unique dataset from Bangladesh in which the detailed expenditure on private goods by each family member is collected. Individualized expenditure allows us to test the identifying assumptions and to derive 'observed' resource sharing within families, which can be compared to the resource allocation predicted by the model. Sharing between parents and children is well predicted on average while the model detects key aspects like the extent of pro-boy discrimination. Results overall depend on the identifying good: clothing provides the best fit compared to other goods as it best validates the preference-similarity assumption. The model leads to accurate measures of child and adult poverty, indicating the size and direction of the mistakes made when using the traditional approach based on per adult equivalent expenditure (i.e. ignoring within-household inequality). This assessment of existing approaches to measure individual inequality and poverty is crucial for both academic and policy circles and militates in favor of a systematic use of collective models for welfare analyses.

JEL Classification: D11, D12, D36, I31, J12
Keywords: Collective Model, Engel Curves, Rothbarth Method, Sharing rule.

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1 Introduction

Welfare and distributional analyses should ultimately concern the well-being of individuals. Yet, surveys almost always contain information about *household* expenditure. Specific surveys focusing on 'who gets what' in the household are scarce and costly. In the absence of direct observations on the intra-household allocation of resources, one may rely on applied economic theory. Collective models of household decision-making have been designed precisely for this purpose, i.e. to conduct welfare analysis at the individual level. Since the seminal contribution of Chiappori (1988), the bulk of the literature has focused on tests of the efficiency assumption at the core of the collective approach.[1] The literature has also suggested identification results (e.g. Browning et al., 1994), but most of them focus on the marginal sharing rule – i.e. how an extra dollar is allocated between family members – and not on the complete distribution across family members. Only recently, it has become possible to operationalize the model for individual welfare analysis, following the work of Browning et al. (2013). Under some assumptions about the stability of preferences across demographic groups, these authors propose the identification of the complete allocation process in a collective model of consumption.[2] Several studies have suggested useful simplifications (Lewbel and Pendakur, 2008), relevant applications (Cherchye et al. 2012a) and the extension to couples with children (Bargain and Donni, 2012; Dunbar et al., 2013; Bargain et al., 2015). All these contributions have in common the intuition behind the Rothbarth method (initially designed to elicit the resources accruing to children) and the use of exclusive goods, i.e. goods consumed by certain type of individual in the household (e.g. adult women's clothing).

In principle, this approach makes it possible to base welfare and distributional analyses on individual resources. Yet, the predictive performances of the model – how well resource sharing is predicted – are unknown. We propose a validation of this approach, exploiting an exceptional dataset in which the detailed expenditure on private goods consumed by each family member is collected. The question is central in both academia and policy circles because the traditional approach broadly ignores intra-household inequality. In the context of developing countries, inequalities are potentially high within the family. Using anthropometric information for the Philippines, Haddad and Kanbur (1990) show that $30-40\%$ of inter-individual inequality is explained by inequality among household members. Recent applications of the collective model to Malawi (Dunbar et al, 2013) and

[1] See Bourguignon et al. (2012) for a review of relevant tests and Cherchye et al. (2007) for nonparametric tests. Useful surveys of this literature have been suggested by Vermeulen (2002), Browning et al. (2013) and Chiappori and Donni (2011).

[2] Resource sharing is the first step towards a proper characterization of money-metric utility at the individual level (see Chiappori and Meghir, 2015).

Côte d'Ivoire (Bargain et al., 2015) point to the underestimation of child poverty when inequality within families is ignored. Intra-household inequities may also be nontrivial in the case of rich countries.[3] Generalizing the use of collective models would allow analysts to characterize the extent of inequality within households – and to measure poverty at the individual level – more broadly. However, there has been not attempt, as yet, to validate the predictions of models in the vein of Browning et al. (2013) or Dunbar et al. (2013). It is crucial to check if collective models can reliably predict the extent of intra-family inequalities, the degree of error committed by the standard approach based on per capita expenditure, or even the nature of inequalities (e.g. the degree of pro-boy discrimination in developing countries).

In this paper, we suggest the first validation exercise of that sort. We exploit a dataset from Bangladesh that comprises the detailed expenditure of each individual in the household – a relatively unique feature in the context of poor countries. Focusing on private consumption – which is essentially nutrition in this context – we can use the fully individualized expenditure to compute individual shares of total household resources. We compare them to the shares derived from the estimation of a collective model of consumption. We distinguish the complete collective approach, with sharing between women, men and children, and the Rothbarth version, focusing only on the allocation between 'unitary' parents and their children. In both cases, we provide straightfoward identification results assuming (i) the existence of adult goods and (ii) the similarity in adult preference across demographic groups (which is close to the 'Similar Across Type' (SAT) assumption of Dunbar et al., 2013). A particularly interesting aspect is the sensitivity of the fit to the choice of the identifying good. We opt for clothing, i.e. a good commonly used for identification in the literature because it is available in most expenditure surveys in a form that is assignable to specific household members (e.g. adult women's clothing). We suggest alternative composite goods whose consumption is usually not assignable in standard surveys (other nonfood private goods, protein products and rice). Individualized expenditure data are used to estimate the individual Engel curves of men and women in different demographic groups and, for each identifying good, to test the SAT assumption.

Our main results go as follows. First, to check how well the model predicts the determinants of the sharing rule, we compare the estimated coefficients with those obtained from direct estimations of the observed shares on the same set of covariates. The model predicts well the effect of family size and composition, and most importantly, the magnitude of the pro-boy discrimination in resource allocation – a key finding with respect to the policy implications of collective models. The model based on clothing seems to

[3]Collective model estimates from Lise and Seitz (2011) indicate that within-couple inequality contributes to $10-20\%$ of total inequality across individuals in the UK.

perform best, which reflects the fact that this good best validates the preference stability assumption (SAT is not rejected in the case of clothing, except for women in large families, but broadly rejected with alternative identifying goods). We continue the validation exercise with a comparison of observed versus estimated resource shares, on average and for demographic subgroups. The model performs well in predicting the allocation between parents and children, which suggests the robustness of the identification based on adult exclusive goods (as originating from the Rothbarth intuition).[4] Predicted sharing among adults is less accurate as the model rests on more structure and assumptions in this case. We go beyond mean comparisons and confront the *distributions* of estimated and observed shares. As could be expected, predictions are not very good at the tails of the distribution. Nonetheless, formal tests of similarity between the distributions of observed and estimated child shares are rarely rejected – except in the case of large families, which is consistent with the rejection of SAT for women in this case.[5]

Finally, we undertake an illustrative distributional analysis, using clothing as the identifying good. The high rank correlation between estimated and observed shares leads to relatively accurate measures of individual inequality, using both the standard deviation and the Theil indices. The model also performs well in showing that $40 - 50\%$ of total individual inequality in the Bangladeshee sample is due to within-household inequality. Turning to a poverty analysis based on individual resources, we do not only require good predictions of the distribution of shares but also of their levels – which is the case for children versus parents. Consistently, our results point to correct measures of child versus adult poverty (but overstate women's poverty and understate male's). A poverty analysis based on predicted shares provides an assessment of 'true' individual poverty that departs quite strongly from poverty rates based on per adult equivalent expenditure. The latter – a traditional approach ignoring the extent of within-household inequality – leads to an underestimation of children's and/or mother's poverty rates (depending on the assumption made on children's weight relative to adults). This set of result motivates the use of collective models of consumption for welfare analyses, both in academia and international organizations, especially in the context of poor countries where (i) within-household inequality is potentially large and (ii) the poverty of (discrimination against)

[4]Engel curves on goods assignable to specific household members (e.g. adult goods in the Rothbarth approach) allow inferring how much is allocated to other members (children) from the comparison of budget shares on these goods between different demographic groups (say, childless couple and couples with one child). A natural assumption close to SAT was already used in applications like Gronau (1988, 1991), i.e. the fact that adults' preferences regarding adult goods do not change across these groups.

[5]Another important result is that there is little reranking: even if resource allocation *levels* are not always well predicted, individual *ranks* are relatively well established captured, which is what matters for individual inequality analyses.

specific household members prevails.

2 Models and Estimation Method

2.1 Overview and Main Assumption

Relevant Literature. The fundamental assumption in our approach is the efficiency of household decision, and more specifically the efficiency of consumption choices. Efficiency is the core assumption of the whole literature on collective models since Chiappori (1988). This explains why this literature has strongly focused on testing this assumption (see Chiappori and Donni, 2011). Compared to other types of less frequent decisions that potentially lead to strategic behavior (e.g. Iyigun and Walsh, 2007, Lundberg and Pollak, 2003), consumption decisions correspond to repeated choices for which the assumption of efficiency is plausible (Browning et al., 2013).[6] Many studies also suggest identification strategies to retrieve the *marginal* sharing rule (Browning et al., 1994, Bourguignon et al., 2012). Only recently, Browning et al. (2013) have suggested a way to identify of the complete sharing rule between childless spouses. They exploit data on couple and single-person households simultaneously. They also model economies of scale for each composite good using Barten scales and price variation. Lewbel and Pendakur (2008) suggest a simpler but more tractable model that can be estimated on cross-section data, whereby the economies from joint consumption are modeled as a single function (an Engel scale).

Separability and Preference-Similarity Assumptions. In both studies, a fundamental assumption is the separability between the identifying goods and other determinants of the individual utility function, and the fact that individual preferences regarding these identifying goods are stable across marital statuses.[7] In what follows, we make use of a slightly milder assumption regarding adult-specific goods, namely that the preferences of adults in a childless couple can be used to represent the preferences of adults in a family with up to three children. This assumption relates to the Rothbarth-Gronau approach (Rothbarth, 1943, Gronau, 1988, 1991). Taking for granted that adult-specific consumption is observed, the latter approach consists in measuring by how much adult

[6] In the context of poor countries, some studies have rejected the efficiency hypothesis, but mainly when it comes to household production decisions (Udry, 1996). Daily consumption decisions probably have less of a strategic content (see a modern statement in Baland and Ziparo, 2017).

[7] The idea of combining data on people living alone and in couples to retrieve the complete resource sharing rule was already applied in the context of labor supply by Laisney et al. (2003), Couprie (2007) and Lise and Seitz (2011). As explained in the introduction, the intuition of combining demographic variation and individual-specific goods originates from the Rothbarth approach, which addressed resource sharing between adults and children.

expenditure is depressed in couples with $X + 1$ children compared to couples with X children. This is again an assumption of separability (this time with respect to fertility choices, i.e. family size) and of stability of adult preferences across families of different size. In this simplest version of the collective model, referred to as the *Rothbarth-Gronau model* hereafter, parents will be treated as a 'unitary' sub-group and so is the group of children – i.e. we focus on sharing between adults and children taken as two entities. While we do not retrieve sharing among children, we can still include variables like the proportion of boys in order to check for potential discrimination in consumption against girls. In the complete version, referred to as the *collective model* hereafter, we assume efficient bargaining between spouses and explicitly posit individual utilities for the father and the mother. To identify this model, we shall rely on wife- or husband-specific expenditure and, again, on the assumption that their individual preferences do not depend on the number of children. This is very close to the 'Similar Across Type' (SAT) assumption made in Dunbar et al. (2013). Most importantly, we will be able to directly test this assumption using the observed Engel curves of men and women in couple.

Two Additional Separability Assumptions. To formalize the way we are going to organize the consumption data, we make explicit two other separability assumptions. The first one concerns public consumption. For simplicity, we shall ignore the publicness or jointness of consumption while focusing on the comparison of observed versus estimated allocations of *private* expenditure. Focusing on private goods can be seen as a reasonable approximation in our context, since private consumption represents the large majority of total expenditure in a very poor country like Bangladesh (nutrition alone represents 60% of total expenditure on average). Many studies assume the separability of public good in individual utility functions. It allows positing a multi-stage representation of the household allocation process, the initial stage corresponding to the decision upon public consumption (see for instance Browning et al., 1994, Blundell et al., 1999, or Cherchye et al., 2012b). In other words, the sharing rule upon private expenditure will be decided conditionally on an agreed level of public consumption.

Another type of separability in the household decision process – more specific to our context – concerns other household members beyond the basic couple and its children. An option is to select only nuclear households (e.g. Bargain et al., 2015). This is very restrictive since in poor countries especially, nuclear families typically live with other relatives. This would also reduce sample size much, which may be an issue given the small initial size of surveys containing individualized expenditure – such as ours. To accommodate the inclusion of non-nuclear households, we assume that the multi-stage decision process includes a preliminary step where virtual transfers between the nucleus and other intra-family units are made. We can remain agnostic about this first stage,[8] while focusing on the sharing process within nuclear families. Using individualized expenditure for all the household members allows extracting the expenditure of the nuclear family and conditioning on the consumption of other members.

2.2 Models and Identification

Set-up and Notations. We start with the presentation of the more general collective model, taking childless couples as the reference group. The following notations apply to the nuclear family. As stated above, this general set-up will allow modeling sharing between father, mother and children. Note that children are taken as a whole: we do not model sharing among siblings, but we shall control for their demographic composition (children's gender and age). Denote by x the log expenditure of the (nuclear) household, $\boldsymbol{z}$ the vector of household characterisics and $\boldsymbol{p}$ the vector of log prices. We examine household consumption decisions for four types of households indexed by $n = 0$ for childless couples and $n = 1, 2, 3$ for couples with 1 to 3 children. Goods are indexed by superscript $k = 1, ..., K$. Individual types are indexed by subscript i, with $i = f$ indicating women, $i = m$ men and $i = c$ the children. Efficient decisions can be represented as a two-stage budgeting process (after an initial stage setting the level of public consumption and transfers within the extended family, as explained above). In a first stage, household resources are supposed to be allocated between f and m in $n = 0$, or between f, m and c in $n > 0$, according to a sharing rule, i.e., the outcome of an unspecified decision process. Individual i in family of type n receives a share $\eta_{i,n}(\boldsymbol{p}, \boldsymbol{z})$ of total expenditure $\exp(x)$, which depends on prices and household characteristics. In a second stage, 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). Individual log resources can be written $x_{i,n} = x + \log \eta_{i,n}(\boldsymbol{p}, \boldsymbol{z})$. The (well-behaved) indirect utility of adult individuals $i = f, m$ living in a family of type n is written $v_i(x_{i,n}, \boldsymbol{p}, \boldsymbol{z})$ and depends on own resources, prices and household characteristics. Roy's identity applied to adult indirect utility gives an expression for an adult budget share on good k, i.e. the fraction of her budget $x_{i,n}$ spent on this good in the second stage of the decentralized process:

$$\omega_{i,n}^k(x, \boldsymbol{p}, \boldsymbol{z}) = w_i^k \left(x + \log \eta_{i,n}(\boldsymbol{p}, \boldsymbol{z}), \boldsymbol{z} \right), \; i = f, m. \tag{1}$$

[8] A theoretical justification is that households are more likely to be Pareto efficient within the nuclear cell. So parents and their children may be Pareto efficient, but including a father/mother in law may lead to Pareto inefficient allocations between the parent-in-law and the nuclear family (see Gupta et al., 2017).

We assume that there is no spatial price variation and focus on cross-sectional data in our application. Thus, we can take out prices and rewrite the adult budget shares for good k:

$$\omega_{i,n}^{k}(x, \boldsymbol{z}) = w_i^k \left(x + \log \eta_{i,n}(\boldsymbol{z}), \boldsymbol{z}\right), \; i = f, m. \tag{2}$$

The n-type family budget share on good k is then written:

$$W_n^k(x, \boldsymbol{z}) = \sum\nolimits_i \eta_{i,n}(\boldsymbol{z}) \cdot \omega_{i,n}^{k}(x, \boldsymbol{z}). \tag{3}$$

Identification of the Complete Collective Model. Identification relies on the existence of assignable adult goods k_i, $i = f, m$, i.e. goods that are specifically consumed by adult women and men. In general, the choice set for such goods is very limited. Typically, clothing is used as an assignable expenditure since one can distinguish adult male and female clothing in standard expenditure data (see Browning et al, 1994). In the present case, basically any private expenditure can be used since we observe fully individualized private consumption. Hence, we will be able to check the sensitivity of our results to the nature of the identifying good (see Deaton, 1997). Previous studies have used information on single individuals to identify individual 'basic' budget share functions $w_i^{k_i}$ (Browning et al., 2013, Lewbel and Pendakur, 2008, Bargain and Donni, 2012, Bargain et al., 2015). Instead, we choose childless couples ($n = 0$) as our reference group. For them, the family budget share on good k_i is written:

$$W_0^{k_i}(x, \boldsymbol{z}) = w_i^{k_i}\left(x_{i,0}, \boldsymbol{z}\right), \; i = f, m, \tag{4}$$

which allows us to identify basic budget shares $w_i^{k_i}(\cdot)$ provided we know individual budgets $x_{i,0} = x + \log \eta_{i,0}(\boldsymbol{z})$. While it is possible to make some assumption on the degree of sharing between childless spouses, we can also directly use *observed shares* $\eta_{w,0}^{obs}(\boldsymbol{z})$ and $\eta_{m,0}^{obs}(\boldsymbol{z}) = 1 - \eta_{w,0}(\boldsymbol{z})$, i.e. those derived from our detailed individualized expenditure data. Of course, this could not be done with standard surveys – but remember that we simply aim to test the performance of the collective model. Next, total budget shares on adult goods in families of type $n > 0$ are written:

$$W_n^{k_i}(x, \boldsymbol{z}) = \eta_{i,n}(\boldsymbol{z}) \cdot w_i^{k_i}\left(x + \log \eta_{i,n}(\boldsymbol{z}), \boldsymbol{z}\right) \tag{5}$$

which directly identify $\eta_{i,n}(\boldsymbol{z})$ for $i = f, m$. Indeed, the left hand side is observed while $w_i^{k_i}(\cdot, \boldsymbol{z}_i)$ is known from the estimation on $n = 0$, thanks to the preference-similarity assumption. Again, this assumption states that the individual Engel curves of adults $i = f, m$ are similar across couples of different size. This assumption is close to Dunbar et al. (2013)'s "Similar Across Type" (SAT) assumption.[9] This is a nonparametric *generic*

[9] The difference is that they use one-child (rather than childless) couples as the reference group. For the rest, both studies avoid the assumption of preference similarity with single individuals as in aforementioned studies since Browning et al. (2013). Thus preference-similarity is weaker here, since it avoids the issue of selection in marriage. It is also practical, since few people live alone in poor countries.

identification, i.e. each observation $(x, \boldsymbol{z})$ provides an equation in the only unknown $\eta_{i,n}$ (see Browning et al., 2013, for a discussion). Children's share is just the complement to 1, i.e. $\eta_{c,n}(\boldsymbol{z}) = 1 - \eta_{w,n}(\boldsymbol{z}) - \eta_{m,n}(\boldsymbol{z})$. Dunbar et al. (2013) require that only part of the adult preferences are similar across demographic groups – the slope of the Engel curve – in a semi-parametric identification (they impose linearity in the log expenditure).[10]

Identification of the Rothbarth-Gronau Version. Using standard surveys, we would not observe $\eta_{m,0}(\boldsymbol{z})$ and $\eta_{w,0}(\boldsymbol{z})$, and hence could not complete identification. We can nonetheless identify the allocation to children without further assumption about sharing within childless couples. In other words, our second model, the 'Rothbarth-Gronau' version of the collective model, will focus on intergenerational sharing between a "unitary" couple and its children. This model is also less demanding in terms of identifying goods, i.e. we do not need gender-specific adult goods but just adult goods (ex: adult clothing). Simply replacing subscript i (f and m) by a (for "adults") in the model above, we can estimate total budget shares $W_n^{k_a}(x, \boldsymbol{z})$ for adult good k_a :

$$\begin{aligned} W_0^{k_a}(x, \boldsymbol{z}) &= w_a^{k_a}(x, \boldsymbol{z}) \\ W_{n>0}^{k_a}(x, \boldsymbol{z}) &= \eta_{a,n}(\boldsymbol{z}) \cdot w_a^k\left(x + \log \eta_{a,n}(\boldsymbol{z}), \boldsymbol{z}\right), \end{aligned} \tag{6}$$

which generically identify $\eta_{a,n}(\boldsymbol{z})$ and the children's share $\eta_{c,n}(\boldsymbol{z}) = 1 - \eta_{a,n}(\boldsymbol{z})$. A variant of the Rothbarth-Gronau model is the alternative assumption in Dunbar et al. (2013), namely the "Similar Across People" (SAP). As for the SAT assumption, it simply imposes preference similarity on the slope of individual Engel curves, here between men and women.

2.3 Functional Forms and Estimation Method

We turn to the empirical specification of the model and introduce an index h for households observed in the data. We first specify the household budget share equations. For identification, we only need adult goods. Yet, for couples with children, we will reinforce identification by adding child goods. That is, the empirical version of the collective model for couples with children will comprise $K = 4$ budget shares, i.e. one for the female adult good k_f, one for the male adult good k_m, one for the child good k_c and one for the composite good representing all the other private expenditure. The latter does not need to be specified in the estimation since the four shares sum up to one. For childless

[10] It is easily show that this simpler version of preference-similarity is all that is needed here as well. In principle, our setting can accommodate more flexible functional forms – we will rely on quadratic Engel curves – but the main identification relies on preference-similarity regarding the first derivative of the Engel curve.

couples, the empirical model will comprise $K = 3$ goods, i.e. the same as above except the child budget share. For the particular case of the Rothbarth-Gronau model, the same principle applies but male and female expenditure are merged into one adult good k_a, so the empirical model comprises $K = 2$ budget shares for $n = 0$ and $K = 3$ for $n > 0$. To summarize, we estimate jointly the system of family budget share equations for assignable goods:

$$\begin{aligned} \widetilde{W}_{n,h}^{k_i} &= \eta_{i,n,h}(\boldsymbol{z}_h).w_i^{k_i}\left(x_h + \log \eta_{i,n,h}(\boldsymbol{z}_h), \boldsymbol{z}_h\right) + \varepsilon_{n,h}^{k_i} \\ \text{for } i &= f, m, c \text{ (Collective model) or } i = a, c \text{ (Rothbarth-Gronau).} \end{aligned} \tag{7}$$

This system is estimated by the iterated SURE method. To account for the likely correlation between the error terms $\varepsilon_{n,h}^{k}$ in each budget share function and the log total expenditure, each budget share equation is augmented with the 'Wu-Hausman' residuals (Banks et al., 1997; Blundell and Robin, 1999). These are obtained from reduced-form estimations of x on all exogenous variables used in the model plus some excluded instruments (a third order polynomial in household disposable income). The error terms are supposed to be uncorrelated across households but correlated across goods within households. They are also assumed to be homoskedastic for each family type (see Bargain and Donni, 2012, for more details).

We now specify the two structural components of the model. The first one, which appears in the specification of the different demographic groups, is the individual budget share equation. We assume that individual preferences are consistent with a generalization of the Piglog indirect utility functions (Banks et al., 1997), so we can adopt the following quadratic specification:

$$\begin{aligned} w_i^{k_i} &= a_i^{k_i} + b_i^{k_i}\boldsymbol{z}_{i,h} + c_i^{k_i} \cdot x_{i,n,h} + d_i^{k_i} \cdot (x_{i,n,h})^2 \\ \text{for } i &= f, m, c \text{ or } i = a, c, \end{aligned} \tag{8}$$

where $x_{i,n,h} = x_h + \log \eta_{i,n,h}$ represents the log resources for individual i in household h of type n; $a_i^{k_i}$, $b_i^{k_i}$, $c_i^{k_i}$ and $d_i^{k_i}$ are parameters; $\boldsymbol{z}_{i,h}$ is a set of socio-demographic variables comprising the number of children, the average age and education level of the parents, a urban dummy and a 'nuclear family' dummy. The latter variable accounts for potential differences in the sharing rule of the nuclear family when other relatives are present in the household. This could be due to a different consumption technology or to selection. For children, the budget share includes the same variables plus the average age of children.

Then, the resource sharing functions are written as follows:

$$\begin{aligned} \text{Collective model:} \qquad & \eta_{i,n,h}(\boldsymbol{z}_h^{share}) = \frac{\exp(\alpha_i + \gamma_i \boldsymbol{z}_h^{share})}{1 + \sum_{j \in \phi} \exp(\alpha_j + \gamma_j \boldsymbol{z}_h^{share})} \qquad (9) \\ \text{for } i \;&=\; f, \text{ with } \phi = (f), \text{ for } n = 0, \\ \text{and } i \;&=\; f, c, \text{ with } \phi = (f, c), \text{ for } n > 0 \\ \text{Rothbarth-Gronau:} \qquad & \eta_{c,n,h}(\boldsymbol{z}_h^{share}) = \frac{\exp(\alpha_c + \gamma_c \boldsymbol{z}_h^{share})}{1 + \exp(\alpha_c + \gamma_c \boldsymbol{z}_h^{share})}, \text{ for } n > 0 \end{aligned}$$

where α and γ are parameters. The specification above implicitly defines husbands' share (adults' share) as the complement to one for the Collective model (Rothbarth-Gronau model). Socio-demographic variables $\boldsymbol{z}_h^{share}$ determining the sharing rules include the number of children, their average age, the proportion of boys, the 'nuclear' and urban dummies.

3 Data

3.1 Data and Selection

A Brief Review on Studies Recording Fully Assignable Consumption. There are very few surveys containing detailed information about who consumes what in the household. They usually focus on rich countries: Denmark (Bonke and Browning, 2009, 2011), the Netherlands (Cherchye et al., 2012b), Japan (Lise and Yamada, 2014) and Italy (Menon et al., 2012). As far as we know, there are hardly any data of this type for poor countries. Related surveys consider nutritional status (rather than expenditure allocation), as those used in Brown et al. (2017) or Haddad and Kanbur (1990). Recent research on Senegal, Lambert et al. (2017), has made use of a survey in which resource allocation is recorded at cell levels (mothers and their children in polygamous families). Most of these datasets are relatively small. This is not an impediment for what we try to achieve.[11] Indeed, we do not attempt to produce a representative distributional analysis for Bangladesh but rather to conduct a comparison of observed versus estimated resource allocation – and its implication for poverty measurement – on a group of households with different demographic compositions.

Dataset. Our sample draws from the Household Income and Expenditure Survey (HIES) for the year 2004 and a special component collected in the framework of the research project "Capturing Intra-household Distribution and Poverty Incidence: A Study on

[11] These surveys could be used in the same way as we do – with an appropriate treatment of public consumption in the context of richer countries.

Bangladesh". This project was conducted by the Bureau of Economic Research (BER, 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 intra-household resource allocation behavior. That particular survey module comprises information on $1,039$ households, randomly drawn from 33 districts (704 from rural areas). Data on a wide variety of subjects were collected, including household characteristics, demography, educational attainment and economic activities of household members, as well as expenditure on food and non-food items. Most originally, individual dietary intake was recorded by specially trained enumerators. This team has observed all meals prepared and consumed within households over three full days, weighting food items while being cooked and the amount consumed by each individual. Information on food consumption outside the home was gathered by interviewing the relevant persons and consolidated with expenditure on meals at home (see the detailed explanations of the procedure in Razzaque et al, 2011). Market prices were used to compute the value of the quantity daily consumed of each food item. The survey also collected information on most non-food consumption by each individual household member, using the recall method or interviewing the household head or the person who took the decision on specific expenditures including health, education, household essentials, clothing, footwear, cosmetics and toiletries, personal items, utilities and other durables. The respondents could specify the expenses incurred for a particular individual and, based on such information, private non-food consumption was measured.[12]

Sample Selection. Given the small size of the sample – $1,039$ households – our selection cannot be too restrictive. In particular, we cannot focus solely on nuclear family, which represent 44.5% of the original sample. As explained above, we rather opt for the largest possible sample and assume separability of private consumption between the nucleus and other family members. We use detailed individual expenditure so as to isolate the budget of the nuclear family. We select childless couples and couples with up to three children (larger families are too few to be a relevant inclusion). We drop polygamous households (6), singles and single parent households (117), couples with older children (i.e. above 17 years old) only (104), and those with missings for the key variables (9). We are left with 803 households, described in Table 1. Empirically, the Rothbarth-Gronau model (the complete collective model) is based on one (two) exclusive good(s) for adults and one for unitary children, so that our selected sample comprises $1,606$ $(2,308)$ individual observations.

[12] The data is described and used for intra-household welfare analysis in Cockburn et al. (2009) and Toufique and Razzaque (2007).

3.2 A First Insight in the Data

We focus on the private expenditure of the nuclear household (we retain food and non-food expenditure that can be individually allocated). Overall it represents between 63% (childless couples) and 73% (couples with three children) of total expenditure. The fact that private consumption increases with family size is mainly due to the rise in food expenditure – which is essentially private – in larger families.[13] It is well-known that in poor countries, food consumption can take up the majority of the household budget, sometimes more than three-quarters of it (Deaton, 1997). In our sample from Bangladesh, nutrition represents between 50% (childless couples) and 65% (couples with three kids) of total expenditure. Note that most of it is private (exactly 90% of it is individually attributed in our data). The only exception is spice (10% of food expenditure), the use of which could not be individually recorded. Regarding nonfood goods, between 38% and 43% of it is private. Items that could not be assigned mainly concerned housing and durables. We consider two broad categories of private nonfood items: clothing and "others".

Table 1 provides more insight in consumption patterns. The upper panel focuses on the privately assigned expenditure (nuclear family), excluding public consumption of the only non-private food item (spice) and of public nonfood expenditure. We report both the family budget shares on the main groups of food and nonfood goods and the percentage of zero expenditure (in square brackets). In particular, we show detailed expenditure on the four groups of goods used as alternative identifying composite goods, namely (i) clothing, (ii) rice, (iii) dairy and protein (fish/meat/eggs) and (iv) other private nonfood goods (health/treatment related expenditure, education cost and personal things like ornaments). For them, we report the individual budget shares for the husband, the wife and the children. Reassuringly, the rate of zeros is very small for these identifying goods,[14] with the exception of the "other nonfood" composite good.[15]

[13] As pointed out by Deaton (1997), the fact that children's food consumption is disproportionately higher makes that the cost of children is usually overestimated when calculated on the basis of variations in food expenditure across household types (the Engel approach). The Rothbarth approach based on adult goods avoids this critique.

[14] There might be a concern that in Bangladesh, a significant percentage of individuals were sick and skipped meals for this reason – or were just absent during the meals. For absents, information on what they ate outside has been collected and consolidated with expenditure on meals at home. For those who were present but report zero total food consumption, we ignore if it is due to sickness or breastfeeding for young children. This concerns 7 men, 3 women, 13 first child, 19 second child, 12 third child. We have rerun our estimations while (i) ignoring these households, (ii) controling for a dummy ("one member skips meal"), and found no substantial differences with the baseline results presented hereafter.

[15] Note that our statistics are relatively comparable with those reported in Table 5.1 of the report Del Ninno (2001, ed.) that is based on a nationally representative sample. In particular,

Table 1: Descriptive Statistics of the Selected Sample

Family Type		Childless couple		Couple + 1 child		Couple + 2 children		Couple + 3 children	
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]
Rice	Total	0.217	[0.010]	0.249	[0.005]	0.261	[0.000]	0.293	[0.000]
	Father	0.117	[0.010]	0.106	[0.019]	0.092	[0.009]	0.083	[0.041]
	Mother	0.100	[0.010]	0.092	[0.005]	0.079	[0.006]	0.072	[0.006]
	Children	-	-	0.051	[0.108]	0.090	[0.000]	0.137	[0.041]
Fish, meat, eggs, dairy	Total	0.210	[0.010]	0.205	[0.028]	0.207	[0.019]	0.196	[0.036]
	Father	0.120	[0.010]	0.083	[0.042]	0.067	[0.034]	0.054	[0.095]
	Mother	0.090	[0.010]	0.068	[0.042]	0.052	[0.041]	0.039	[0.053]
	Children	-	-	0.055	[0.117]	0.088	[0.031]	0.103	[0.083]
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]
Other private non food	Total	0.116	[0.079]	0.101	[0.085]	0.109	[0.038]	0.099	[0.030]
	Father	0.045	[0.178]	0.028	[0.296]	0.019	[0.306]	0.013	[0.249]
	Mother	0.071	[0.149]	0.031	[0.300]	0.041	[0.266]	0.034	[0.219]
	Children	-	-	0.042	[0.194]	0.049	[0.097]	0.051	[0.104]
Total 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	
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	
Heads with lower education (%)		0.762		0.732		0.688		0.456	
Working women (%)		0.139		0.188		0.144		0.225	
Urban (%)		0.406		0.329		0.381		0.278	
# households		101		213		320		169	
# adults + "unitary" children		202		639		960		507	

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

Note: Figures refer to the main nuclear family of the household (parents and children). We show family budget shares and percentages of zeros (in square brackets) of all private expenditures, with detailed individual expenditure for father, mother and children on (i) clothing, (ii) other private nonfood goods, (iii) fish/meat/eggs/dairy and (iv) rice, i.e. the four alternative groups of identifying goods used to estimate the collective model. The lower panel reports total annual expenditure, characteristics of the nuclear families (or their head) and the number of individual observations.

An important observation pertains to the shifts in consumption patterns when family composition changes. As expected, the share of primary food expenditure, like rice, increases with the presence (and the number) of children. This pattern is less marked for other types of food products. The share of protein/dairy products is relatively stable across demographic groups, although absolute amounts of these goods do increase with family size (and with total expenditure). Total budget shares on clothing tend to decrease with the second and third child (but the absolute expenditure level also increases). If we look at individual budget shares, we find, as expected, that the presence of children reduces the budget shares devoted to parents' consumption. For instance, while couples without children allocate 6.5% (6.1%) of their budget to men's (women's) clothing, this drops to 5.3% (4.7%) in couples with one child and to 3.8% (3.5%) in couples with two. The pattern uncovered here is in line with the widely accepted notion that children impose economic costs on their parents – the income effect associated with the cost of children in the Rothbarth-Gronau intuition.

The lower part of Table 1 presents household characteristics. Since identification relies on the comparison between the different demographic groups, it is reassuring to see that they are not completely different with respect to basic characteristics as used in the model. They tend to differ on average for some of them, such as education levels. The important point is that adults in the different demographic groups show at least some 'common support' with respect to these characteristics. In the Appendix, Figure A.1 reports the distribution of household head's age and years of schooling. Childless couples are defined as household where "no children are currently living". Hence, they are mechanically older (some of them are older parents whose children have left the home). Still, there is a relative large overlap in the age distributions of the different family types. For education, the difference at the mean is mainly driven by a concentration of large families (childless couples) at very low (higher) education levels. Nonetheless, there is a relatively large overlap across the four groups.

3.3 Testing Adult Preference Similarity

Originally, we can verify the assumptions of preference similarity used in the literature. We essentially focus on adult preference stability – regarding identifying goods – across demographic types. Our data allows calculating individual resources and, hence, how adults' basic budget shares $w_i^{k_i}$ vary with individualized expenditure x_i for $i = f, m$ (or $i = a$) and for the different adults goods. These individual Engel curves are typically

zero-consumption shares in all our categories are highly comparable with their reported figures. See https://www.alnap.org/system/files/content/resource/files/main/rr122.pdf.

unobserved in standard data. A visual inspection of $w_{i,n}^{k_i}(x_i)$, for $i = f, m, a$ separately, is carried out for clothing in the Appendix Figure A.2. It shows the fit of individual Engel curves estimated using a quadratic form in log expenditure, which is consistent with our specification, and the corresponding confidence intervals. We observe little differences in individual Engel curves – for both men and women – between childless couples (our benchmark) and couples with one or two children. Some discrepancies appear for women in three-child households.

To test the assumption of preference-similarity across demographic groups more formally, we now estimate adults' Engel curves for each identifying good (clothing, other nonfood goods, rice, fish/meat/egg/dairy). In several cases, the coefficients on the squared log expenditure are significant so that we prefer to retain the quadratic form – as specified in the model – rather than the specification in Dunbar et al. (linear in log expenditure). We test the null hypothesis that the slope is identical between individuals in childless couples and those in other household types, for $i = f, m, a$ respectively. P-values of the tests are reported in the upper panel of Table 2. A key result is that clothing provides the best results. We cannot reject the stability of preferences, except for women's clothing in $n = 3$ households, which is consistent with the visual inspections above. Things are less satisfying with the other goods, and especially with the other non-food private goods (women's Engel curves significantly change with the arrival of children). These results allow anticipating some of our validation outputs: because clothing respects the basic identifying assumption, it is expected to provide the best fit when comparing observed and predicted resource shares. This is reassuring given the fact that this good has been extensively used for identification in the collective model literature (at least since Browning et al., 1994).

Finally, we can also test whether men's and women's Engel curves are similar to each other within each demographic group. This assumption is used as an alternative to SAT in Dunbar et al. (2013), i.e. a 'Similar across People' (SAP) assumption. The lower panel of Table 2 shows that it is clearly rejected in the case of two-child couples when using clothing. This is true with a quadratic form in log expenditure, but also with the linear form as used by Dunbar et al. (2013). Since couples with two children represent the largest group in our sample (40% of all couples), it would make the identifying strategy based on SAP relatively fragile in the present context. We also find that it is rejected in a majority of cases when using the other identifying goods. These results do not preclude that SAP could work well in other settings. However, based on the above results and to simplify our demonstration, we solely rely on SAT as the central identifying assumption. A final remark: the Rothbarth-Gronau approach does not imply SAP. It only requires SAT for 'unitary' adults' preferences (adult Engel curves are pooled across spouses in this case).

Table 2: Tests of Adult Engel Curve Stability across Demographic Types

	Clothing			Non-food private			Rice			Protein/dairy		
Similar Across Types	Individual Engel curves are quadratic in log expenditure:											
	Women	Men	Adults	Women	Men	Adults	Women	Men	Adults	Women	Men	Adults
Couples with 1 child	0.220	0.569	0.540	0.001	0.457	0.002	0.814	0.175	0.341	0.056	0.545	0.141
Couples with 2 children	0.794	0.345	0.577	0.050	0.546	0.020	0.076	0.004	0.008	0.000	0.078	0.002
Couples with 3 children	0.000	0.351	0.075	0.025	0.575	0.028	0.057	0.035	0.027	0.029	0.063	0.031
Similar Across People	Individual Engel curves are either linear or quadratic in log expenditure:											
	Linear	Quad.		Linear	Quad.		Linear	Quad.		Linear	Quad.	
Couples with 1 child	0.183	0.357		0.969	0.994		0.131	0.085		0.014	0.014	
Couples with 2 children	0.000	0.000		0.000	0.000		0.000	0.000		0.564	0.031	
Couples with 3 children	0.453	0.271		0.007	0.014		0.021	0.011		0.305	0.088	

We estimate women's, men's and adults' individual Engel curves for each identifying adult good. We test the null hypothesis that the slopes of the Engel curves are identical between individuals in childless couples and individual in couples with 1, 2 or 3 children ('Similar Across Types'), using the specification that is quadratic in log expenditure (similar results are obtained with linear form in log expenditure). We also test identical slopes for men and women within each demographic group ('Similar Across People'), using either linear or quadratic forms in log expenditure. Figures represent the p-value of these tests.

4 Results

Results are presented in three steps. First, we examine the ability of the structural model to correctly predict the sign and magnitude of the determinants of the sharing rule. Then, we assess how predicted resource shares replicate observed ones, on average (overall and for different demographic subgroups) and distribution-wide. Finally, we focus on 'individual' inequality and poverty measures, i.e. measures originally based on the resources accruing to the different family members. In particular, child poverty rate will not be defined as the proportion of children living in poor households (according to household equivalized expenditure) but as the proportion of poor children (according to their own individual resources). This is important given the recognition that households are often composed of both poor and nonpoor individuals (Brown et al., 2017) – something that is missed by the traditional approach based on per capita (or per adult equivalent) expenditure.

4.1 Sharing Rule Estimations

Table 3 first presents the estimated coefficients γ_i of the children's resource share ($i = c$). The upper panel focuses on the Rothbarth-Gronau model and the middle one on the complete collective model. The lower panel presents the estimates of the women's share ($i = f$) in the latter model. The first four columns correspond to the estimates of these models for the different identifying goods. To elicit the 'true' determinants of the sharing rule, we also estimate the actual resource shares – derived from individual expenditure data – on the same set of covariates $\boldsymbol{z}_h^{share}$ as in the structural model. The estimation is conducted by maximum likelihood using a logistic form to model individual shares. For instance, in the case of the Rothbarth model, we estimate

$$\eta_{c,n,h}^{obs} = \frac{\exp(a_c + g_c \boldsymbol{z}_h^{share})}{1 + \exp(a_i + g_i \boldsymbol{z}_h^{share})} + u_{n,h}. \tag{10}$$

The last column of Table 3 reports the coefficients g_c.

The first observation is that model estimates show some variability across the identifying goods. Yet, the effects of family size and children's average age on the share of children is consistently positive in almost all models. A crucial point is that observed shares (last column) flag a significant pro-boy discrimination, which is well identified in the Rothbarth/Collective model estimations based on individual clothing (first column) or rice consumption (third column). More generally, the model based on clothing seems to perform particularly well regarding children age and gender. Observed child shares appear to be significantly higher in households comprising the nuclear family only and in urban households. These effects are not rendered well by structural estimations. As expected, there is a broad similarity between the Rothbarth-Gronau approach and the complete collective model when it comes to child shares. It reflects the fact that child costs are essentially identified on adult good variation across family types (the Rothbarth intuition). Nonetheless, it also tells us that the way budget shares of men and women vary across these types are not too contrasted.

Regarding women's shares, the set of child characteristics explain little of the household variation. The exception is the effect of living in a nuclear family, which increases mothers' shares. A possible interpretation goes as follows: Living with others means that older household members can enforce gender norms, so that women in extended household may have less power, as confirmed for India by Debnath (2015). Again, models based on clothing or rice match observed shares with a positive and significant effect of living in a nuclear household. Overall, these identifying goods tend to fit actual observed heterogeneity in household allocation best. Note that we have experimented alternative specifications, notably a model accounting for x (the log expenditure) in the sharing rule. This term was never significant – for instance the coefficient in the child share of the Rothbarth model was .0822 (.1523). This is an interesting observation. Indeed, our identification does not require the independence from total expenditure, in contrast with Browning et al. (2013), Dunbar et al. (2013) or Bargain et al (2014). Hence we can freely test its effect – and reject the dependence. It confirms another test of independence in Menon et al. (2012). We also find that accounting for log expenditure when calculating child and

Table 3: Sharing Rule Coefficients

	Model Estimates of Resource Shares using Identifying Good:				Logistic Estimation on Observed Shares:
	Clothing	Non-food private	Rice	Protein/dairy	
Rothbarth-Gronau Model: estimates of the children's share					
# children	0.646 ***	0.159 *	0.793 ***	0.582 ***	0.463 ***
	(0.084)	(0.085)	(0.093)	(0.100)	(0.024)
mean child age	0.062 ***	0.087 ***	0.249 ***	0.040 ***	0.063 ***
	(0.013)	(0.017)	(0.023)	(0.013)	(0.004)
proportion of boys	0.088 *	0.057	0.242 *	0.021	0.098 **
	(0.047)	(0.059)	(0.125)	(0.058)	(0.044)
nuclear household	-0.107	-0.753 ***	0.230 **	0.247 *	0.071 **
	(0.099)	(0.200)	(0.115)	(0.131)	(0.035)
urban	0.065	-0.032	-0.267 *	0.135	0.056 *
	(0.095)	(0.120)	(0.153)	(0.096)	(0.034)
constant	-2.438 ***	-1.900 ***	-4.826 ***	-1.553 ***	-2.195 ***
	(0.328)	(0.361)	(0.473)	(0.481)	(0.069)
Collective Model: estimates of the children's share					
# children	0.527 ***	0.407 ***	0.710 ***	0.450 ***	0.447 ***
	(0.121)	(0.130)	(0.114)	(0.091)	(0.028)
mean child age	0.082 ***	0.089 ***	0.260 ***	0.034 ***	0.065 ***
	(0.014)	(0.019)	(0.026)	(0.009)	(0.004)
proportion of boys	0.092	0.051	0.410 ***	0.029	0.109 **
	(0.057)	(0.078)	(0.158)	(0.067)	(0.051)
nuclear household	0.012	-0.516 ***	0.360 **	0.250 **	0.128 ***
	(0.129)	(0.195)	(0.163)	(0.099)	(0.040)
urban	0.120	-0.601 ***	-0.270	0.210 **	0.034
	(0.267)	(0.196)	(0.198)	(0.096)	(0.039)
constant	-2.264 ***	-1.399 ***	-4.100 ***	-0.340	-1.631 ***
	(0.339)	(0.360)	(0.535)	(0.293)	(0.076)
Collective Model: estimates of the mother's share					
# children	-0.300 **	0.208 *	-0.140	-0.410 ***	-0.031
	(0.132)	(0.121)	(0.122)	(0.116)	(0.029)
mean child age	0.010 *	0.048 ***	0.030	-0.001	0.003
	(0.006)	(0.014)	(0.021)	(0.006)	(0.005)
proportion of boys	-0.018	-0.035	0.310 *	0.089	0.025
	(0.055)	(0.097)	(0.172)	(0.060)	(0.042)
nuclear household	0.206 **	0.084	0.360 *	0.130	0.127 ***
	(0.093)	(0.141)	(0.224)	(0.082)	(0.038)
urban	0.204 ***	-2.974 **	0.006	0.047	-0.050
	(0.075)	(1.306)	(0.300)	(0.074)	(0.039)
constant	-0.500 ***	-1.415 ***	-0.280	-0.900 ***	-0.282 ***
	(0.101)	(0.246)	(0.449)	(0.315)	(0.070)

Notes: sharing rule estimates from expenditure data in columns 1-4 and from observed shares (logistic estimation) in column 5. *, **, *** indicate 1%, 5% and 10% significance levels. Standard errors in parenthesis.

adult shares does not change the conclusion of our comparisons between estimated and observed shares hereafter.

We have also replicating our estimations while adding 'bargaing factors' and interesting heterogeneity in the sharing rule. The literature has focused on distribution factors that may affect the balance of power in the household (e.g. Bourguignon et al., 2013). We test three of these factors: the women's contribution to household income, the woman's participation to the labor market and the level of dowry and gifts by the women's family. We also add a measure of household wealth. Given the correlation between women's labor supply and her contribution to household income, we add these variables one at a time. In the Appendix, Table A.1 reports the coefficients for these additional sharing rule determinants when using clothing. The other determinants are barely affected by this inclusion. Results point again to a very good prediction of the effect of women's financial power (and labor market participation) on hers and her children's resource shares (yet insignificant for the latter). The effect of wealth is also accurately and precisely estimated. We do not focus more on these variables due to the fact that the causal effect of distribution factors is not at all guaranteed: omitted variables (e.g. the degree of exposure to traditional norms) may influence both women's income/labor supply and the intra-household distribution.

4.2 Resource Share Comparison on Average and by Subgroups

Average Shares. We move to the direct comparison of estimated shares $\widetilde{\eta}_{i,n}$ (equations 9) and observed shares $\eta_{i,n}^{obs}$ (equation 10) for $n = 1, 2, 3$. The complete set of results is provided in Appendix Table A.2 for the Rothbarth model and Tables A.3-A.4 for the collective model. A visual illustration of the main findings is suggested in a series of graphs. We start with children's shares ($i = c$) with the Rothbarth approach in Figure 1. The upper graph reports average shares per child across the different family types, first comparing the estimated shares (using clothing) and the observed shares. The model predicts a share of 23.2% for the first child, which compares well with the observed share of 23.8%. This performance is also found in larger households. The model reproduces well the fact that (i) child shares increase with family size but (ii) do not increase proportionally. The fact that per-child shares decrease with family size is consistently found in the estimation of collective models for other poor countries, notably Dunbar et al. (2013) and Bargain et al. (2015). Importantly here, this result tends to be validated by direct comparison with the observed resource allocation. Figure 1 also indicates that the estimated share of the first child is similar to what is found in the aforementioned studies on Malawi and Côte d'Ivoire respectively. The Figure also shows the concentrated share, which is simply the prediction of the observed share $\widetilde{\eta}_{c,n}^{obs}$ (from equation 10): it is again very similar to the estimated and observed shares.

Sensitivity to Identifying Goods. The lower graph of Figure 1 inspects the sensitivity of our results to the use of alternative identifying goods. Resource shares obtained using rice expenditure are relatively correct while those estimated on the basis of other identifying goods are off the mark. The fact that child costs vary considerably with the choice of the identifying good is not unusual. When several adult goods are available, they usually give different estimates of the Rothbarth approach, as shown by Deaton (1989) on Thailand. The key fact is that we now have a benchmark to evaluate them, namely the observed shares. Protein/dairy goods tend to considerably overstate child resources, probably because parents do divert the consumption of such goods – important for child growth – towards their children. Inversely, a clear underestimation of child shares for families with two or three children is found when using the "other" nonfood composite good. From Table 1, we infer that the most obvious difference with the other goods is its much larger rate of zeros, which may limit its validity as an identifying good. These results confirm that clothing is our best choice. This is good news for two reasons: (a) clothing is one of the rare assignable expenditure commonly provided in standard surveys and (b) it has been used systematically – for that reason – in the collective model identification based on exclusive goods (at least since Browning et al., 1994). Overall, it is likely that clothing is the least subject to the pitfalls attached to the Rothbarth-Gronau approach (see Deaton, 1997), namely (i) substitution effects (between own consumption and family size), (ii) the necessity that the relative price of the adult goods does not change across demographic types;[16] (iii) the requirement for adult goods not to be inelastic to total expenditure (some of the food items are relatively inelastic). Point (i) is crucial – and we have shown that clothing performs best when testing the assumption of preference stability across demographic types (SAT).

Results with the Complete Collective Model. In Figure 2, we show the results of our comparison exercise for the collective model, focusing on clothing and rice goods. The upper graph reports estimated and observed shares for children. Conclusions are very similar to the above discussion based on the Rothbarth approach. The only difference is a slight underestimation of child shares, of around $3-4$ points of percentage, in families with one and two children. The lower graph shows the comparison of women's share. As expected from the sharing rule estimates, results are not as good. Clothing underestimates women's share by at least 5 percentage points in all family types. Rice overestimates it by a similar margin in families with one or two children. These results confirm that

[16] Here, the implicit price of food may change if the returns to scale in food production are not constant.

Figure 1: Average Resource Shares: Rothbarth-Gronau Model

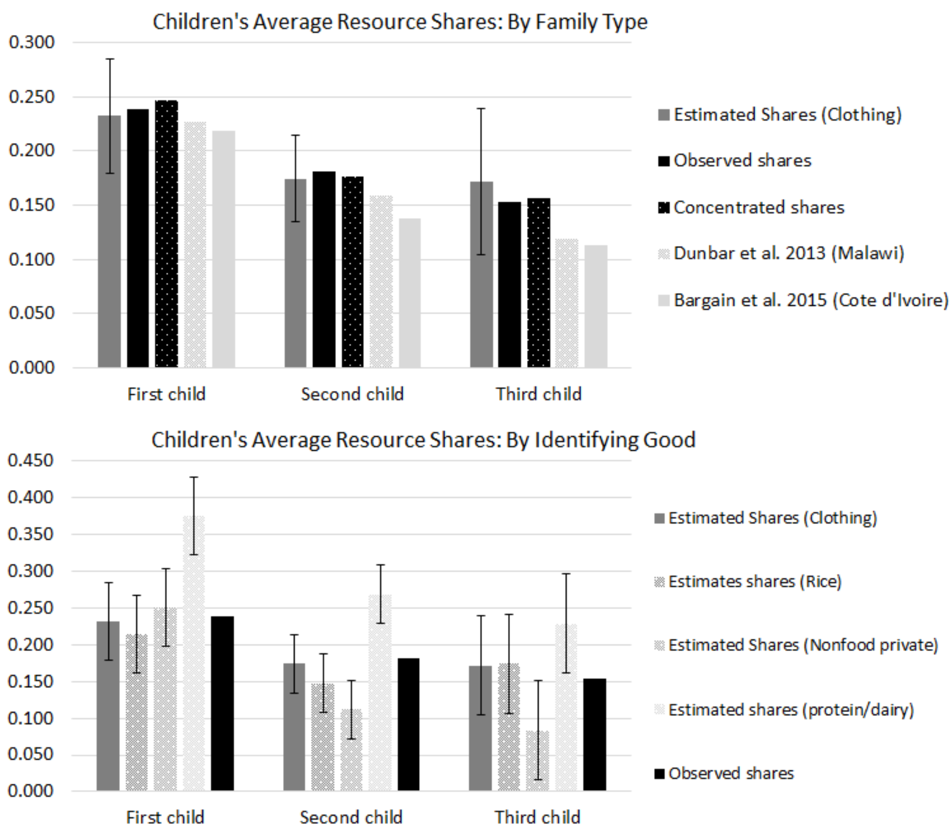
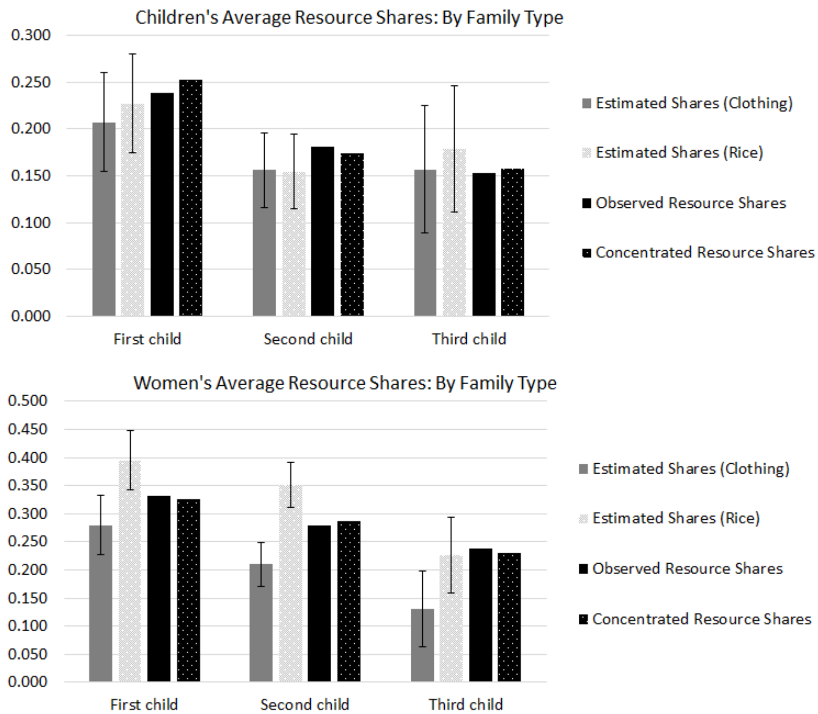


Figure 2: Average Resource Shares: Collective Model



the identification of sharing within couples is not as strong as for children because (i) it relies on more observations (goods assignable to men versus women) and (ii) the relative preferences of adults is more difficult to assess since there is no variation in that respect.[17] In contrast, the identification of child shares benefits from demographic variation – a varying number of children – that reveals how resources are directed towards additional children.

Average Shares for different Subgroups. Next, we compare mean shares for different subgroups, using clothing and rice. Figure 3 focuses on children's shares using both models and the comparison with observed shares. Subgroups correspond to demographic variation along two margins: size and gender composition (upper graphs) or size and rural/urban (lower graphs). The four graphs confirm the good performance of the models regarding demographic effects. Importantly, both models yield the same predictions, which are also very close to observed shares. For a given number of children, the decrease in the proportion of boys leads to a substantial decline of the per child share. This pro-boy discrimination, previously reported in the estimates of the sharing rule, is quantified here

[17]It may be the case that information on single individuals – as used in previous studies, and despite stronger preference-stability assumptions – improve identification.

Figure 3: Average Children Shares by Size and Gender (Rothbarth and Collective Models)

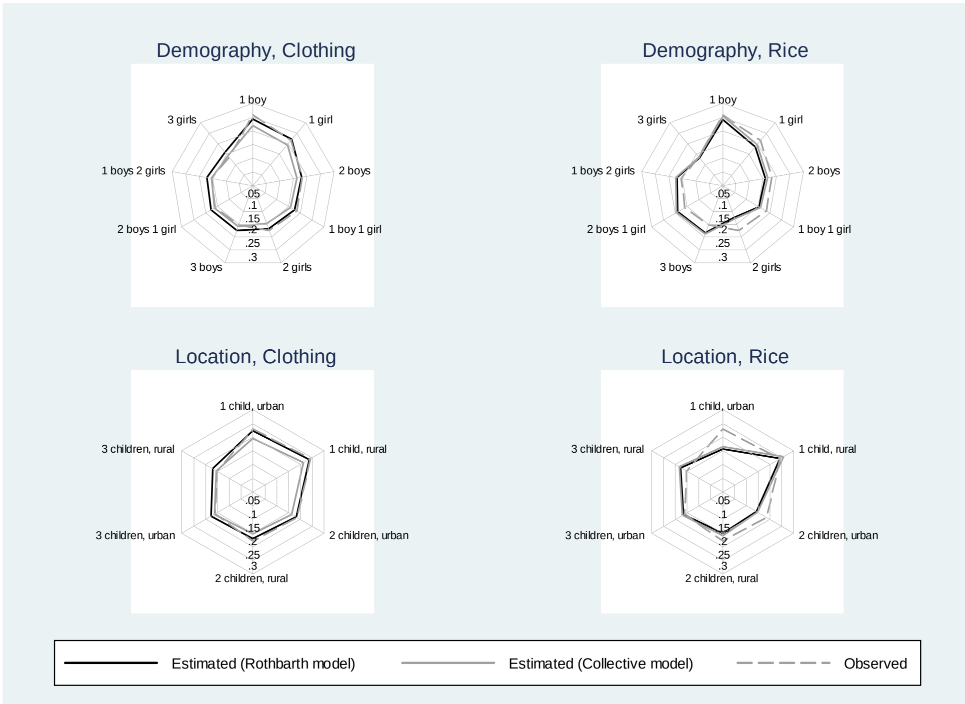
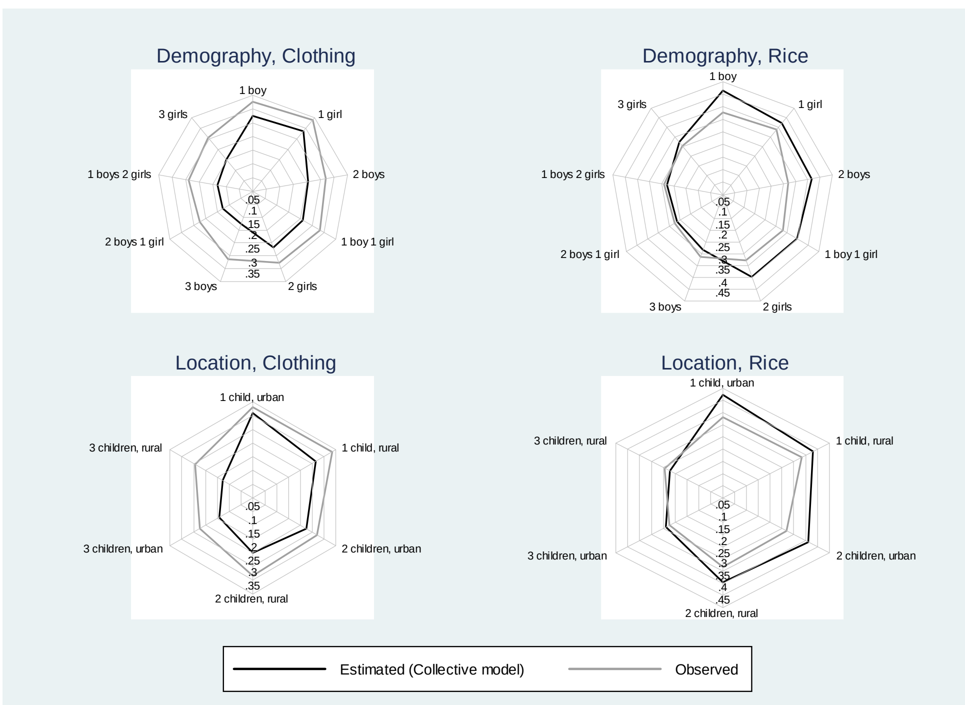


Figure 4: Average Women's Shares by Size and Location (Collective Model)



and seems well predicted by the model with clothing. For instance, a boy in a one-child family receives 25.8% in reality (24.3% according to the model with clothing) while a girl gets 21.6% (22.0% according to the model). As before, there is some overestimation for very large families: the share per boy in a family of three boys is 15.2% (the model predicts 17.3%) while the share of girls in a family of three girls is 13.7% (15.9%). Our results – both observed and predicted differences in shares between gender – are in line with past evidence of gender discrimination in Bangladesh (see Quisumbing and Maluccio, 2000, 2003, Murdoch and Stern, 1997) and India (for instance Rose, 1999, and Zimmermann, 2012).[18] Finally, Figure 4 displays observed versus estimated shares of women in the collective model: as before, clothing (rice) leads to an underestimation (overestimation) of female shares, which is equally pronounced in most of the demographic subgroups.

Andrews Tests. To assess the overall quality of the Rothbarth-Gronau/Collective model, we use the chi-square goodness of fit test introduced by Andrews (1988). This test is based on partitioning the dependent and explanatory variables into cells, and then comparing the observed frequencies with those implied by the model. The main benefit of the proposed test is its ability to reject the structural model if misspecification is such that the data generated by the model leads to biased conclusions regarding the distribution of shares. Under the null hypothesis that the model is correctly specified, the sample distribution of shares and the distribution generated by the model should be similar. In the context of our model, we contrast the predicted shares $\widetilde{\eta}_{k,n}$ to the observed shares $\eta_{k,n}^{obs}$, for $k = c, f$, using either the Rothbarth-Gronau model or the collective model.[19] We thus partition the resource shares into cells of equal size (4, 6 or 8 cells, for sensitivity analysis), and contrast the number of right and wrong cell predictions.[20] The test is a chi-square statistics and can easily be computed by performing an auxiliary OLS regression (see Andrews, 1988, for more details). Table 4 reports the p-value of the test overall and for different demographic groups. We cannot reject the test overall: p-value are high

[18]There is a considerable amount of empirical evidence, much of it from the Indian subcontinent, that documents discrimination against females (e.g. Sen, 1984 and the survey by Behrman, 1987). Yet, much of the evidence is concerned with measurements of nutritional outcomes, mortality, and health status rather than with the direct good allocation by gender. Also, there is more mixed evidence in other poor regions. In particular in an African context, pro-boy discrimination is found by Dunbar et al. (2013) for Malawi while there is no boy-girl difference in resource shares in Côte d'Ivoire (Deaton, 1989; Bargain et al., 2015).

[19]A more demanding test for the collective model would confront the estimated joint distribution of mother's and child shares $(\widetilde{\eta}_{f,n}, \widetilde{\eta}_{c,n})$ to the observed one $(\eta_{f,n}^{obs}, \eta_{c,n}^{obs})$. Given the sample size, it is unfortunately not feasible to partition the data into a meaningful number of cells for mothers and children.

[20]It is unknown what is the best way to choose these cells. We have used various cell partitioning methods as proposed by Andrews (1988). It turns out our results are relatively robust to cell partitioning.

so that the null hypothesis – observed and estimated shares are identical – cannot be rejected at standard levels.

Arguably, performances are a bit more contrasted when considering different groups. The prediction of the models tends to be rejected in the case of two children (and with three children, for Rothbarth-Gronau). However, with other sources of household heterogeneity (urban/rural and household head above/under 40 years old), the model is rarely rejected. We do not report the test results for women's share (or men's share, which is just the complement to one of child and women's shares) with the collective model: it is systematically rejected by the data. This is consistent with the fact that mothers' shares tend to be underestimated when using clothing, especially in large households, as discussed above. Note that the Andrew's test is more demanding than a simple test of equality between observed and predicted mean shares. What is most interesting is that the performance of the collective model regarding children's shares (and hence 'unitary' adults' shares) is similar to that of the Rothbarth-Gronau model. This is not surprising given that both rely on similar identifying assumptions. As previously discussed, the collective model is more ambitious as it makes additional assumptions in order to predict each spouse's share.

Table 4: Andrews Test: Estimated versus Observed Child Resource Shares

		Rothbarth-Gronau Model			Collective Model		
		Andrews Test # of sample partitions:			Andrews Test # of sample partitions:		
Household type	# obs.	4	6	8	4	6	8
		P-value	P-value	P-value	P-value	P-value	P-value
All	702	0.1046	0.6882	0.9403	0.0018	0.0849	0.5147
1 child	213	0.4130	0.2114	0.1314	0.1076	0.4950	0.8837
2 children	320	0.0003	0.0122	0.0182	0.0000	0.0025	0.1477
3 children	169	0.0000	0.0000	0.0000	0.3721	0.7930	0.9128
Urban	239	0.7344	0.9396	0.9939	0.9699	0.9943	0.9994
Rural	463	0.0882	0.5628	0.9084	0.0001	0.0363	0.3157
Head under 40	413	0.2010	0.2692	0.4888	0.0001	0.0313	0.3092
Head above 40	289	0.5253	0.9501	0.9809	0.4950	0.9476	0.9988

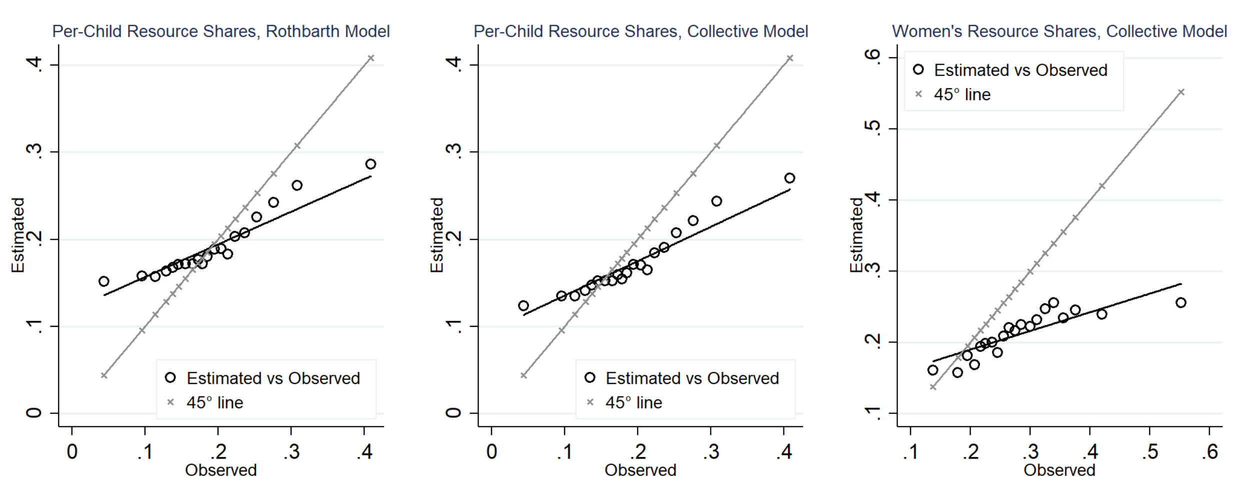
The table reports the p-value of an Andrews' test of the distributional difference between observed and estimated child resource shares, for different sample partitioning of the shares (4, 6 or 8 partitions).

4.3 Resource Share Comparison: Distributional Analysis

The final step of our analysis must confront the distribution of observed versus estimated shares. We first check their correlation at various degrees of disaggregation. Then, we perform distributional analyses originally based on individual resources and compared to the traditional approach.

Correlation between Estimated and Observed Shares. We compare the dispersion of individual resource shares as predicted by the models (based on clothing) with the actual dispersion in observed shares. We start with a semi-disaggregated approach. We calculate the average estimated and observed shares by equal-sized bins of the distribution of observed shares. We use 20 bins, 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 displayed in Figure 5 show two aspects of the same picture. On the negative side, estimated shares understate the variance of observed shares. This is an expected result: predicted outcomes typically tend to show more concentration (and mispredictions) in the tails of the distribution. The optimistic view is that there is very little reranking: especially in the case of child shares, estimated shares monotonically increase with observed share. This is certainly important for the robustness of distributional analyses based on ranks – i.e. inequality and relative poverty analyses – when conducted on the basis of individual resources.

Figure 5: Observed vs. Estimated Resource Shares: Binned Scatterplots



Dots represent the mean observed and estimated shares of each vintile of the observed share distribution (same-sized bins)

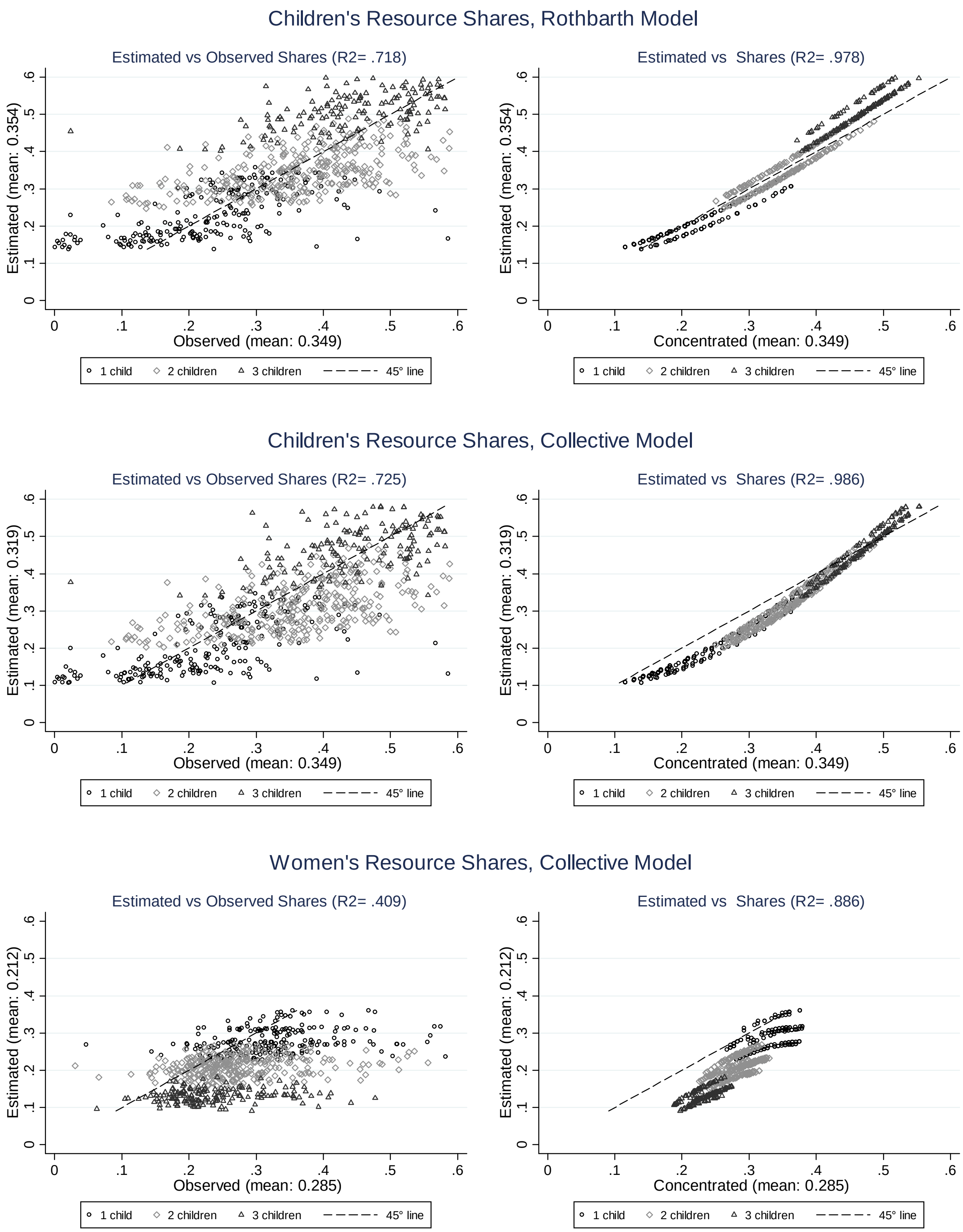
We now move to the most disaggregated level. On the left hand side of Figure 6, we show the complete dispersions of estimated/observed shares, distinguishing between family types. There is obviously more noise than in binned scatterplots. Yet, the correlation is relatively high for child shares (around .71 with both Rothbarth and collective models) but smaller for female shares (.41). There is much variation within each demographic group, which is partly due to the fact that we have used a limited set of explanatory variables. Nonetheless, the prior analysis of sharing rule estimates has shown the relevance of the collective model in explaining key determinants. The graphs on the right hand side actually plot estimated shares against 'concentrated' shares, i.e. the observed shares purged from the unexplained component $\widetilde{u}_{n,h}$. These concentrated shares extract the variation in actual shares explained by the set of covariates used in the model. The very high correlation obtained in this case confirms that the model performs well in terms of the role attributed to the different determinants of sharing. Most of the dispersion that is seen on the left hand side – and most of the potential bias in individual welfare analysis – is therefore due to the unobserved heterogeneity in the sharing rule.

Inequality and Poverty Analyses. We finally check the performances of the model when conducting distributional analyses. Previous findings have conveyed that the model may be well suited for inequality analyses at the individual level. We use resource shares – observed or predicted – together with family expenditure to evaluate individual resources $x_i = \eta_{i,n}(x, \boldsymbol{z}). \exp(x)$.[21] Few papers have actually operationalized the collective model to estimate the contribution of intra-household inequality to total consumption inequality: Lise and Seitz (2011) for the UK, Dunbar et al. (2013) for Malawi, Bargain et al. (2015) for Côte d'Ivoire. In particular, both studies on African data focus on families with children to assess how intra-household inequality alters the measure of individual poverty.

We start with individual inequality, measured using two decomposable indices: the standard deviation and the Theil index. These indices are calculated over personal resources x_i for all the individuals in our sampled population of nuclear couples with children. In the case of the Rothbarth model, we assume that each adult avails of half of total adult resources x_a. Results are reported in Table 5. The equal split for unitary adults is assumed for the estimated but also observed adult expenditure, hence different inequality levels in the first and third column. First rows (for each index) show that both Rothbarth and collective models predict well the extent of individual inequality. Both indices are decomposable: second and third rows show the contribution of between- and within-household

[21] For adults, individual resources are consistent with the concept of indifference scales and represent money metric utility, possibly with a specific interpretation of the reference price (cf. Chiappori and Meghir, 2015).

Figure 6: Correlation of Observed Estimated Resource Shares



Note: 'Concentrated' refers to observed shares predicted on the same covariates as in the structural model, i.e. purged from unexplained variation.
Identifying Good: Clothing.

inequality to total individual inequality. 'Between' inequality is simply the standard per capita measure of inequality. We show that the latter (the traditional approach) ignores $40 - 50\%$ of total individual inequality in our Bangladeshee sample, i.e. the extent of inequality explained by within-household inequality. It is remarkable to see that both models predict the 'within' contribution relatively well.

Table 5: Individual Inequality Analysis using Observed vs Estimated Resource Sharing

	Rothbarth-Gronau Model		Collective Model	
	Observed	Estimated (Clothing)	Observed	Estimated (Clothing)
Std. Dev.				
Overall	0.915	0.871	0.819	0.840
Within households	0.631	0.554	0.578	0.607
Between households	0.668	0.676	0.594	0.594
% variance due to "within"	0.476	0.405	0.498	0.522
Theil				
Overall	0.212	0.193	0.207	0.232
Within households	0.097	0.077	0.089	0.113
Between households	0.115	0.116	0.119	0.118
% inequality due to "within"	0.458	0.399	0.430	0.487

Inequality measures and their decompositions are based on individual resources (observed vs estimated). With Rothbarth, we assign to each adult half of the total adult resources. Note that the Theil index is chosen as it belongs to the group of additively decomposable inequality measures (Generalized Entropy Class).

For poverty, we use an absolute line as commonly suggested for developing countries. We adopt the adult poverty line of $1.25 per day recommended by the World Bank for the year 2004. Results may be sensitive to the weights put on children. We start with a weight of 1 for all children, i.e. using the same line as for adults. This is nothing else than the 'per capita' analysis frequently used in development studies. Results are reported in the upper part of Table 6. The first column gives the poverty rate for different members according to the observed resources they receive in the household: children (80%), mothers (62%) and a lower poverty of adults in general (50%) that reflects the lower poverty of fathers (38%). If we now compare these rates to poverty headcounts predicted by the collective models, individual child poverty is remarkably well predicted – around 81% with the Rothbarth-Gronau model and 85% with the complete model – and so is adult poverty when ignoring sharing among spouses (51%). Since we underpredict mothers's share, we also overpredict the incidence of poverty in their case (78%). Nonetheless, the collective model correctly indicates larger poverty rates in this group compared to adults in general. Table 6 indicates a small degree of mismatch in poverty status when using estimated versus observed shares. For instance, 4% (5%) of the children are deemed poor according to observed (estimated) shares but not according to estimated (observed) shares.

Table 6: Individual Poverty Analysis using Observed vs Estimated Resource Sharing

	Individual Poverty : Based on Individual Resource Shares			Per Adult Equivalent Poverty (ignoring unequal sharing in the family)
	Observed Shares	Estimated Shares with the Rothbarth-Gronau Model	Estimated Shares with the Collective Model	
Child weight = 1 x the weight of an adult (per capita approach)				
Child poverty rate	0.80	0.81	0.85	0.65
% poor according to observed shares only (a)		0.04	0.03	
% poor according to estimated shares only (b)		0.05	0.07	
Adult poverty rate	0.50	0.51		0.65
% poor according to observed shares only (a)		0.04		
% poor according to estimated shares only (b)		0.04		
Mothers' poverty rate	0.62		0.78	0.65
% poor according to observed shares only (a)			0.02	
% poor according to estimated shares only (b)			0.18	
Child weight = .8 the weight of an adult on average (age-specific weights)				
Child poverty rate	0.69	0.68	0.74	0.57
Adult poverty rate	0.50	0.51		0.57
Mothers' poverty rate	0.62		0.78	0.57
Child weight = .6 the weight of an adult				
Child poverty rate	0.50	0.50	0.58	0.37
Adult poverty rate	0.50	0.51		0.37
Mothers' poverty rate	0.62		0.78	0.37

Note: we use three alternative scaling factor for child's weight: 1 (per capita approach); weights reflecting differences in calorie requirements per age relative to an adult's, as suggested in FAO/WHO/UNU (1985) (the average child weight is .8); the same weight of .6 for all children. Poverty measures are: Per adult equivalent poverty based on equivalized expenditure using the aformentioned weights. Individual poverty rates based on individual resources : observed versus estimated (Rothbarth-Gronau model or complete collective model). Adult poverty line at \$1.25/day (2005 PPP) and child poverty line as a fraction of the adult's line using aforementioned weights. Mismatch measures: (a) proportion of persons deemed poor according to the observed resources shares but not according to the estimated ones, (b) proportion of persons deemed poor according to the estimated resources shares but not according to the observed ones.

The last column of Table 6 shows individual poverty rates based on per capita expenditure. It highlights how much of individual poverty is missed by the traditional approach. Indeed, ignoring within-household inequality leads to the conclusion that 65% of the children and 65% of the mothers are poor in our Bangladeshee sample. This rate understates child poverty by a large margin. This analysis depends on arbitrary dimensions compared to the inequality analysis – notably the choice of child weights. Yet our conclusions point to the rejection of the traditional approach in any case. For instance, let us retain lower child weights. We take weights that are proportional to the calorie requirements of children at every age, relative to adults (we rely on the age-specific scale suggested in FAO/WHO/UNU, 1985). This gives an average child weight of .8 (rather than 1). Child poverty mechanically decreases, as can be seen in the middle panel of Table 6, but remains larger than the per capita measure. Let us decrease child weight a little more and opt for an equal weight of .6 for all children, as in Dunbar et al. (2013). Child poverty is still far above the (new) per adult equivalent measure of poverty and, in addition, the traditional approach now underestimates mothers' poverty.[22] The main lesson from this exercise is twofold: whatever the true level of child nutritional requirement, (i) structural models point to relatively accurate levels of child and adult poverty, (ii) the traditional approach broadly ignore the potentially large extent of child and/or mothers' poverty.

5 Conclusion

This paper suggests the first direct validation of the collective model of consumption for individual welfare analysis. We exploit a unique dataset from Bangladesh, which provides the individual consumption of each family member (private consumption represents the vast majority of all goods consumed). Observed individual resource shares are compared to the shares estimated from the Rothbarth version of the collective model (sharing between parents and children) or from the more complete collective model (sharing between mothers, fathers and children). Identification of the complete resource allocation is based on assignable goods (adult goods or adult male/female goods) and a preference-similarity assumption that can be tested. The various specifications of the model provide very encouraging results regarding its ability to perform individual welfare analysis, especially for (i) the determination of pro-boy discrimination, (ii) the prediction of sharing between parents and children, (iii) the measure of between versus within-household inequality and (iv) the measure of child versus adult poverty based on predicted individual resources. We show some sensitivity to the type of identifying good at use. In particular, we highlight

[22] With lower child weights (.6), the per adult equivalent poverty decreases (37%). Adult poverty based on individual resources remains unchanged since the adult poverty line is fixed.

the fact that clothing expenditure provides the best fit. This is good news because this is one of the rare goods assignable to specific family members in standard data; also because clothing has been used extensively – for this reason – as an identifying good in the child cost literature (e.g. Gronau, 1988, 1991) and the collective model literature (at least since Browning et al., 1994).

The important message is that collective models should be systematically used in distributional and policy analyses. The identification technology proves sufficiently strong – at least for child versus adult sharing – to fare better than the traditional approach based on per capita (or equivalized) expenditure. The latter approach broadly ignores the (large) extent of within-family inequality in poor countries like Bangladesh and, hence, greatly understates the poverty of specific family members. Beyond this key conclusion, more can be done to improve or validate model estimations. Our study was a first attempt to check collective model predictions for distributional analyses at the individual level. However, many additional aspects could be addressed. First, while the data at use is unique in its ability to inform about individual resource shares in a poor region, larger samples should be collected for more precise estimations. Second, price variation could also be introduced along the lines of Browning et al. (2013) in order to capture joint consumption through Barten scales for certain goods (economies of scale in food preparation/consumption, re-use of clothing among siblings, etc.). Finally, further work should also augment the model to account for the quality of goods, in particular the calory/protein content of food expenditure. In this way, more could be said about intra-household inequality in terms of malnutrition – and not only in terms of under-nutrition (see D'Souza and Tandon, 2018, and Brown et al., 2018, for recent developments along these lines).

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A Appendix

A.1 Data and Statistics

Figure A.1: Density of Age and Education of the Household Head by Family Type

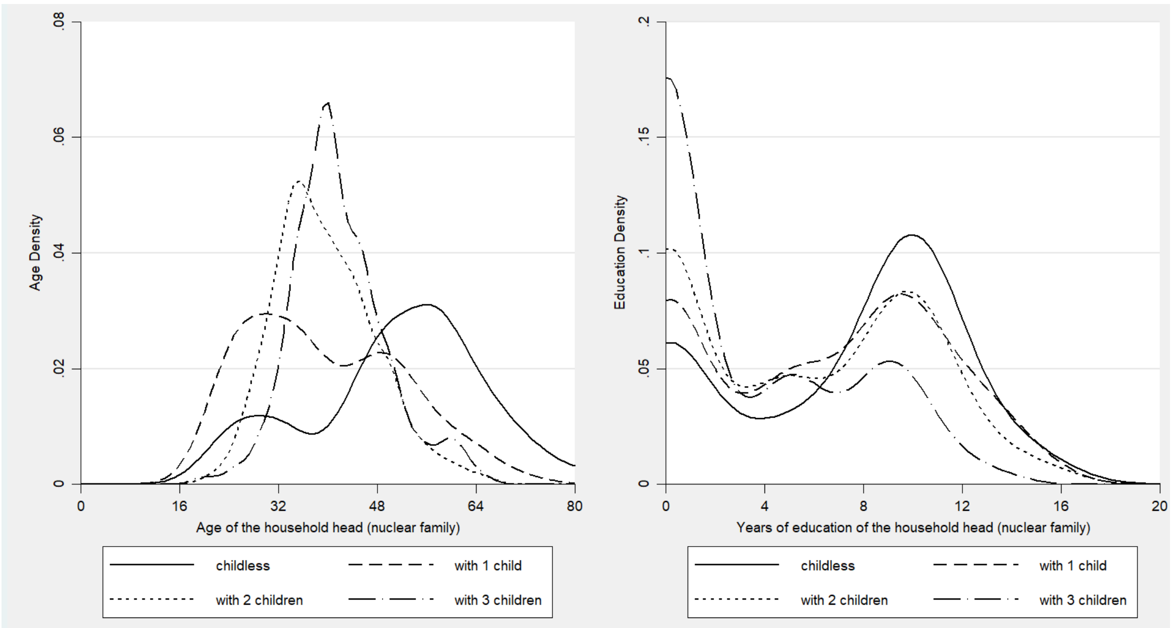
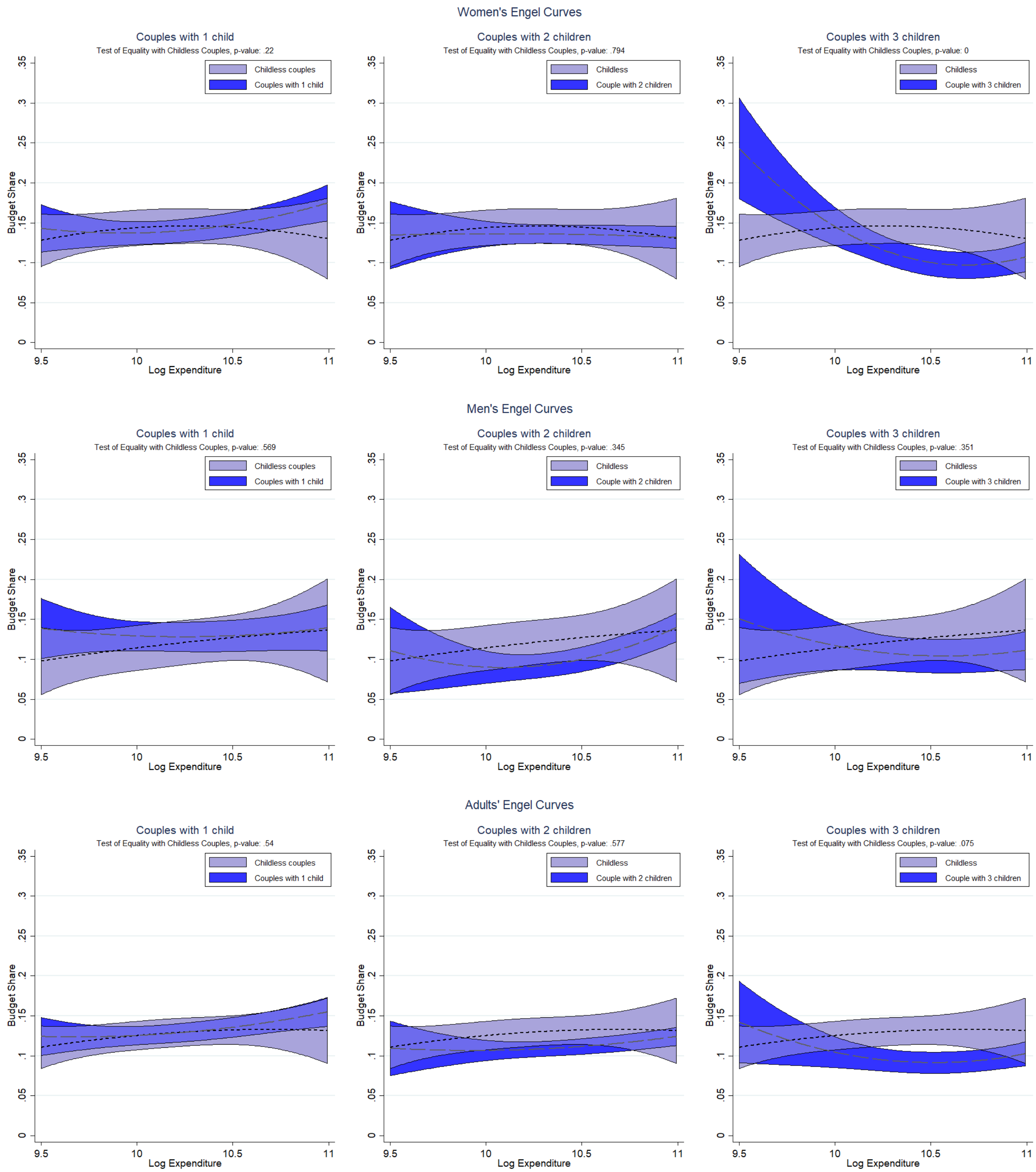


Figure A.2: Individual Engel Curves for Adult Identifying Goods: Clothing



Note: Individual Engel curves estimated from observed individualized expenditure (quadratic form in log expenditure), with 95% confidence intervals.

A.2 Additional Results

Table A.1: Additional Heterogeneity in the Sharing Rule: Distribution Factors and Wealth

	Children's share		Children's share		Women's share	
	Rothbarth model	Observed	Collective model	Observed	Collective model	Observed
Woman's share of household income	0.190 *	0.208 *	0.272 *	0.374 ***	0.141	0.364 ***
	(0.118)	(0.120)	(0.159)	(0.123)	(0.192)	(0.116)
Woman in work	0.019	0.042	0.064	0.081 *	0.104	0.087 *
	(0.046)	(0.042)	(0.059)	(0.049)	(0.067)	(0.047)
Dowry	0.012 ***	0.005	0.009 **	0.005	-0.013 *	-0.0004
	(0.003)	(0.005)	(0.004)	(0.006)	(0.007)	(0.006)
Household wealth	0.009 ***	0.008 *	0.014 ***	0.013 ***	0.015 ***	0.010 ***
	(0.002)	(0.004)	(0.003)	(0.005)	(0.004)	(0.003)

Notes: sharing rule estimates from expenditure data or from observed shares. *, **, *** indicate 1%, 5% and 10% significance levels. Standard errors in parenthesis. "Dowry": value of assets brought to marriage from the spouse's parents as dowry or as gift. Each coefficient stems from a separate estimation (we introduce distribution factors one at a time). Results are very similar when adding all of them except 'woman in work', which is highly correlated with the women's share of household income.

Table A.2: Children's Average Resource Shares: Rothbarth-Gronau Model

	Estimated Resource Shares				Observed Resource Shares	Concentrated Resource Shares
Identifying good:	Clothing	Other non-food private	Rice	Protein/dairy		
First child	0.232	0.251	0.214	0.375	0.238	0.246
Second child	0.175	0.112	0.147	0.269	0.182	0.176
Third child	0.172	0.084	0.174	0.229	0.154	0.157
1 child, urban	0.224	0.220	0.156	0.388	0.229	0.238
2 children, urban	0.363	0.225	0.283	0.562	0.372	0.365
3 children, urban	0.532	0.254	0.497	0.711	0.479	0.484
1 kid, rural	0.236	0.267	0.243	0.368	0.243	0.250
2 kids, rural	0.341	0.222	0.302	0.523	0.358	0.345
3 kids, rural	0.510	0.249	0.532	0.678	0.454	0.466
1 kid, nuclear	0.204	0.140	0.169	0.407	0.225	0.238
2 kids, nuclear	0.333	0.166	0.286	0.557	0.357	0.351
3 kids, nuclear	0.505	0.206	0.523	0.700	0.466	0.471
1 kid, no nuclear	0.242	0.289	0.229	0.363	0.242	0.249
2 kids, no nuclear	0.375	0.317	0.309	0.507	0.374	0.355
3 kids, no nuclear	0.546	0.371	0.522	0.654	0.446	0.472
1 child, boy	0.243	0.258	0.240	0.382	0.258	0.263
1 child, girl	0.220	0.244	0.185	0.366	0.216	0.228
2 child, 2 boys	0.361	0.231	0.318	0.541	0.366	0.365
2 children, 2 girls	0.332	0.212	0.246	0.530	0.346	0.334
2 children, 1 boy 1 girl	0.351	0.225	0.306	0.540	0.370	0.355
3 children, 3 boys	0.521	0.249	0.550	0.687	0.457	0.479
3 children, 3 girls	0.479	0.196	0.392	0.688	0.410	0.442
3 children, 2 boys 1 girl	0.531	0.263	0.568	0.694	0.478	0.484
3 children, 1 boys 2 girl	0.510	0.255	0.505	0.680	0.459	0.463

Table A.3: Children's Average Resource Shares: Collective Model

	Estimated Resource Shares				Observed Resource Shares	Concentrated Resource Shares
Identifying good:	Clothing	Other non-food private	Rice	Protein/dairy		
First child	0.207	0.319	0.227	0.569	0.238	0.246
Second child	0.156	0.173	0.155	0.355	0.182	0.176
Third child	0.157	0.144	0.179	0.270	0.154	0.157
1 child, urban	0.196	0.259	0.165	0.596	0.229	0.238
2 children, urban	0.326	0.328	0.296	0.737	0.372	0.365
3 children, urban	0.489	0.427	0.510	0.833	0.479	0.484
1 kid, rural	0.213	0.348	0.257	0.557	0.243	0.250
2 kids, rural	0.304	0.356	0.317	0.693	0.358	0.345
3 kids, rural	0.464	0.435	0.547	0.800	0.454	0.466
1 kid, nuclear	0.182	0.214	0.175	0.602	0.225	0.238
2 kids, nuclear	0.300	0.291	0.297	0.725	0.357	0.351
3 kids, nuclear	0.464	0.392	0.534	0.818	0.466	0.471
1 kid, no nuclear	0.216	0.354	0.245	0.558	0.242	0.249
2 kids, no nuclear	0.332	0.433	0.329	0.685	0.374	0.355
3 kids, no nuclear	0.491	0.542	0.543	0.786	0.446	0.472
1 child, boy	0.219	0.329	0.254	0.574	0.258	0.263
1 child, girl	0.194	0.307	0.197	0.564	0.216	0.228
2 child, 2 boys	0.325	0.355	0.334	0.712	0.366	0.365
2 children, 2 girls	0.293	0.331	0.259	0.705	0.346	0.334
2 children, 1 boy 1 girl	0.315	0.347	0.321	0.711	0.370	0.355
3 children, 3 boys	0.477	0.434	0.565	0.807	0.457	0.479
3 children, 3 girls	0.429	0.367	0.403	0.814	0.410	0.442
3 children, 2 boys 1 girl	0.488	0.449	0.582	0.813	0.478	0.484
3 children, 1 boys 2 girl	0.463	0.435	0.519	0.804	0.459	0.463

Table A.4: Women's Average Resource Shares: Collective Model

	Estimated Resource Shares				Observed Resource Shares	Concentrated Resource Shares
Identifying good:	Clothing	Other non-food private	Rice	Protein/dairy		
First child	0.280	0.141	0.395	0.098	0.332	0.328
Second child	0.210	0.150	0.352	0.049	0.279	0.284
Third child	0.131	0.178	0.227	0.023	0.238	0.232
1 child, urban	0.310	0.016	0.423	0.095	0.331	0.326
2 children, urban	0.225	0.019	0.361	0.046	0.270	0.274
3 children, urban	0.142	0.021	0.240	0.021	0.224	0.221
1 kid, rural	0.265	0.202	0.381	0.100	0.333	0.329
2 kids, rural	0.201	0.230	0.346	0.052	0.284	0.291
3 kids, rural	0.127	0.238	0.222	0.024	0.243	0.237
1 kid, nuclear	0.318	0.143	0.475	0.099	0.357	0.345
2 kids, nuclear	0.225	0.163	0.380	0.049	0.286	0.292
3 kids, nuclear	0.138	0.192	0.238	0.023	0.242	0.238
1 kid, no nuclear	0.266	0.140	0.368	0.098	0.324	0.322
2 kids, no nuclear	0.187	0.128	0.307	0.050	0.266	0.271
3 kids, no nuclear	0.113	0.140	0.197	0.024	0.226	0.218
1 child, boy	0.275	0.146	0.414	0.100	0.327	0.324
1 child, girl	0.285	0.134	0.373	0.096	0.338	0.332
2 child, 2 boys	0.205	0.140	0.365	0.051	0.270	0.281
2 children, 2 girls	0.217	0.148	0.347	0.048	0.278	0.289
2 children, 1 boy 1 girl	0.209	0.155	0.348	0.049	0.283	0.284
3 children, 3 boys	0.127	0.210	0.233	0.024	0.263	0.234
3 children, 3 girls	0.150	0.127	0.274	0.022	0.254	0.243
3 children, 2 boys 1 girl	0.127	0.174	0.212	0.023	0.225	0.228
3 children, 1 boys 2 girl	0.131	0.190	0.227	0.023	0.240	0.234