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Intrahousehold Allocation of Public and Private Goods and Poverty Measurement: Evidence from Bangladesh

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Intrahousehold allocation of public and private goods: Evidence from Bangladesh

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Abstract

Understanding how households distribute resources is crucial for assessing individual well-being. Standard poverty and inequality metrics rely on total household consumption, assuming equal sharing among members, which does not account for within-household inequality. Using a unique survey experiment that collects fully individualized consumption data in Bangladesh, we validate collective models that infer resource shares from broad range of assignable goods. We found men's resource shares can be identified using a broad set of assignable goods, whereas women's and children's estimates are more sensitive to the choice of assignable goods. Clothing expenditures, typically collected in aggregated form in household surveys, provide the most reliable estimates for estimating resource shares and poverty measures across all groups when used as an assignable in collective models. The choice of assignable good has implications for measuring poverty headcount and other poverty indices.

Keywords: poverty, household surveys, intra-household allocation, Bangladesh

JEL classification: C81, D13, D31, I32, O12, O15

I. Introduction

Globally, children are more than twice as likely as adults to live in poor households (Newhouse, 2017), and women in their prime reproductive years are 23% more likely to experience poverty than men in the same age group (Boudet et al., 2021). While these figures highlight significant gender and age disparities in (monetary) poverty, they rely on traditional poverty measures that equate an individual's poverty status with that of their household, ignoring potential inequalities in resource allocation within households. Growing evidence suggests that such approaches can misrepresent the true extent of poverty when significant intrahousehold inequality exists (Brown et al., 2019; De Vreyer and Lambert, 2021; Brown et al., 2021; Bargain et al., 2022; Calvi et al., 2023). Moreover, accounting for intrahousehold allocation can alter poverty profiles, especially for children (Dunbar et al., 2013; De Vreyer and Lambert, 2021), which has direct implications for targeting and redistribution policies (Brown et al., 2019; Liang et al., 2024). High-quality consumption data at the individual level can serve as a benchmark for understanding how resources are shared within households. However, such data remains largely unavailable in most household surveys (World Bank, 2018). From a policy perspective, collecting individual-level consumption for the entire consumption basket on a large scale can be expensive. Existing evidence of such data comes mostly from high-income countries, such as the Netherlands (Cherchye et al., 2012), Japan (Lise and Yamada, 2019), and Italy (Menon et al., 2012), with a few exceptions from poorer countries, such as using highly disaggregated consumption data on Senegal (Lambert et al., 2021) or individualized consumption data on Bangladesh (Bargain et al., 2022). Additionally, certain consumption categories, such as housing, electricity, water, energy use, and transportation, are jointly consumed by multiple people, making it difficult to attribute their use to specific individuals.

Given the limited availability of individual-level consumption data, individual consumption can be inferred from household-level expenditure data using structural models of collective decision-making. The data requirements for implementing these methods are modest in the sense that they do not require detailed individual consumption information but instead rely on the consumption of a single “assignable good” that can be uniquely attributed to individual household members (or types of household members, such as men, women, and children). The “assignable good” refers to the fraction of total household resources allocated to a particular individual or group and can serve as an indicator of intrahousehold bargaining power. As long as household surveys collect information on some expenditure that can be assigned to specific household members, these methods can effectively identify how household resources are shared even when most consumption data are collected at the household level (Lewbel and Pendakur, 2008; Bargain and Donni, 2012; Dunbar et al., 2013). While collective models can improve poverty measurement over traditional household-based measures, the accuracy of model-based predictions across the entire consumption basket remains an open question. Private assignable goods play a key role in identifying individual resource shares, yet their inclusion is often limited in household surveys. Studies utilizing multiple assignable goods to identify sharing rules found estimated resource shares to be sensitive to the choice of assignable goods, which in turn affect individual poverty measures (Van Leeuwen et al., 2021; Bargain et al., 2022; Calvi et al., 2023). Thus, to accurately capture intra-household differences in consumption and poverty, it is necessary to improve the collection of individual-level consumption data and validate model-based estimates of individual resource shares. To date, the only study that uses individualized consumption data to evaluate the reliability of model-based estimates is Bargain et al. (2022), who validate both the Rothbarth method and the Dunbar, Lewbel, and Pendakur (2013) model using Bangladeshi data. Lechene, Pendakur, and Wolf (2022) evaluate their method indirectly by comparing predicted individual-level resource shares across two alternative private goods, clothing and food. To fill these knowledge gaps, we implemented an innovative experiment in Bangladesh that collects detailed consumption for each household member—a rare case in low-income countries where survey capacity is limited. The key feature of this data is that it measures individual consumption at an unprecedented level. The survey records each household member's consumption of private goods and their member-specific use of jointly consumed items. This approach offers a more detailed understanding of how private and public goods are shared, compared to the data used in previous studies.

We make several contributions to the literature. First, to our knowledge, this is the second study to validate the predictions of the widely used collective model by Dunbar, Lewbel, and Pendakur (2013) using highly individualized consumption data. Second, we evaluate the predictions generated from alternative assignable goods by comparing them directly with individualized consumption data. Existing validation studies, such as Bargain et al. (2022) and Lechene, Pendakur, and Wolf (2022), have focused on only a few assignable goods, including clothing, footwear, or food, overlooking the value of alternative categories for identifying individual resource shares. Third, to our knowledge, this is the first study to validate the linear estimation method proposed by Lechene, Pendakur, and Wolf (2022), which relaxes some of the restrictions of standard collective models and eliminates the computational complexity of nonlinear estimation, making it more attractive for implementation. Fourth, we also contribute to the literature on poverty and inequality by comparing predicted poverty measures with those derived from observed individual consumption, thereby extending prior studies that focus mainly on headcount poverty to the poverty gap and poverty gap squared. Finally, we highlight limitations of the DLP model by comparing predicted and observed shares both at the mean and across the entire distribution.

The results can be summarized as follows. First, we estimate resource shares for a range of assignable goods—including food subcategories, clothing, personal care, transportation, health, and adult goods—using a collective household model. In total, we employ eleven types of assignable expenditures to identify resource shares, and in most cases, find that men's allocations exceed women's, while children receive the smallest shares. These results are confirmed by existing studies on Bangladesh that consistently document the presence of gender and age inequality (e.g., Bargain et al., 2022; Brown et al., 2021; Lechene et al., 2022), as well as supported by studies on other low-income countries, such as Ghana (Aminjonov et al., 2025), Malawi (Aminjonov et al., 2025; Lechene et al., 2022), Argentina and South Africa (Bargain, 2024), Iraq (Lechene et al., 2022). Second, we validate model-based estimates by comparing actual resource shares derived from individualized consumption data with predicted resource shares, thereby identifying categories of "assignable goods" that most accurately approximate the allocation of household resources. We find that clothing expenditures, typically collected in aggregated form in household surveys, provide the most reliable estimates for estimating resource shares across all groups when used as an assignable in collective models. These results are consistent with the validation study of Bargain et al. (2022), who also find that structural models of intrahousehold allocation perform well when clothing is used as the assignable good. Although food expenditures are traditionally treated as strictly private, they yield reliable resource share estimates only for adults. At the same time, their use for children depends on data quality and the extent to which consumption can be clearly attributed to individual members. We also find heterogeneity across demographic groups in terms of the data requirements: men's resource shares can be identified using a broad set of assignable goods, whereas women's and children's estimates are more sensitive to the choice of assignable goods. Third, we assess the accuracy of these estimates in predicting different poverty measures, including the poverty headcount, poverty gap, and poverty gap squared. We found these poverty measures to be sensitive to the choice of assignable good, with clothing expenditures becoming a more reliable assignable good for poverty measurement, although for women, accurate results require individualized rather than aggregated clothing data. We also find significant gender- and age-based disparities in headcount poverty, depth, and severity in Bangladesh, with women and children being both more prevalent among the poor and deeper in poverty. Measuring the depth and severity of poverty is particularly important for Bangladesh, where recent World Bank projections suggest that economic slowdown could reverse decades of steady poverty reduction, with extreme poverty rising to 9.3 percent and an additional three million people falling deeper into poverty (World Bank, 2025). Finally, we find that weak assignability, limited identification, and restrictive preference assumptions in Dunbar, Lewbel, and Pendakur (2013) model can reduce the model's performance. These results provide policy-relevant implications for the use of collective models in household surveys that lack individualized data.

The paper is organized as follows: Section 2 describes the most important features of the data. Section 3 briefly discusses the identification of resource sharing using collective models and welfare indicators used in the analysis. Section 4 presents estimation results of resource shares and welfare analysis. Section 5 concludes.

II. Data

This paper draws on the World Bank's Bangladesh Individual Consumption Study (BICS) - a survey of approximately 1,000 households in Bangladesh collected during May and June 2024 across three divisions in rural and urban areas: Rangpur in the north, Khulna in the south, and Mymensingh in the central region. The survey targeted all adult members within sampled households; enumerators scheduled revisits to maximize self-reporting, and proxy responses were accepted only after repeated unsuccessful attempts. Households were eligible if they contained at least one married couple with both partners aged 18–66. The survey collected detailed information on household characteristics, demographics, education, and economic activities of all members, as well as food and non-food expenditures. Interviews were conducted in person, with household heads (typically men) providing demographic and socioeconomic information.

Food consumed at home was collected using three complementary approaches. A traditional 7-day recall collected detailed household-level data on a comprehensive list of food items prepared at home; for a subset of items, information was also gathered on which household members consumed them. In addition, individual dietary intake was measured through a single-day 24-hour recall combined with food weighing methods, in which the household member responsible for preparing and serving meals—typically the female spouse of the head—reported all foods consumed in the previous day. Enumerators recorded the source of food, ingredients, and raw and cooked weights, and then linked these meals to quantities consumed by household members for each food item. From this, individual food shares were calculated as each member's proportion of total cooked meal weights, excluding meals not taken due to illness, fasting, or guest participation. These shares were then applied to total household food expenditures from the 7-day recall and extrapolated to annual terms. The survey also collected information on food consumed away from home and captured meals consumed during the previous week that were not prepared by the household itself, including foods from restaurants, food stalls, takeaways, and meals provided in the homes of relatives or friends. For each reported item, respondents indicated the frequency of consumption, whether other household members joined, the sharing of payment responsibilities, and total expenditures (both individual and joint)[1].

Non-food non-durable consumption was measured using multiple recall periods. A 7-day recall administered to all adults recorded individual expenditures on frequently purchased goods and services, such as public transportation, mobile phone credit, betel nut, tobacco, personal care products, books, and entertainment. Respondents reported total spending, whether expenditures were for themselves or for other household or non-household members, and which household members used the items; additional questions captured individual usage of tobacco products regardless of who had paid. A 30-day recall collected household-level expenditures on regularly consumed goods and services, distinguishing between items typically shared among members (e.g., electricity, soap) and those used more individually (e.g., cosmetics, diapers). A 12-month recall covered infrequent or seasonal expenditures, including clothing, footwear, tailoring, furniture, housing repairs, education, health, insurance, and major ceremonies. To account for

[1] Meals offered by non-household members (e.g., relatives, colleagues) were also recorded. Food prepared by the household but consumed outside (e.g., carried meals) was explicitly excluded, as it was already captured in the home-prepared food module.

intra-household allocation, some items were treated as individually assigned (e.g., personal accessories), others as shared evenly across household members (e.g., cleaning utensils, donations, banking fees), and a subset as shared at the dwelling level (e.g., furnishings, housing repairs, property taxes). Clothing and footwear were collected through both the traditional household approach and a new individual allocation method. In the standard design, households reported total acquisitions of men's, women's, boys', and girls' clothing and shoes, including purchases, gifts, and items from own production. These categories were also linked to specific household members by recording who used the reported items and whether use was equal or unequal across them.

Household asset ownership was measured through a detailed list of durable goods, appliances, and transport equipment. For each asset, households reported whether they owned the item, the number owned, the year of most recent acquisition, purchase price, and the estimated resale value at the time of the interview. The survey recorded which household members used each asset and, for transport items, the frequency of use by individual members over the previous 30 days. Dwelling consumption was collected through a combination of household- and room-level reporting. Households provided information on tenure status (owned, rented, or free), actual rent payments and utilities, or imputed rental values if owned. For shared dwellings, the number of households sharing the unit was recorded to permit adjustment of housing costs. A roster of rooms was then created, and for each room, respondents identified which household members used it for sleeping, household or personal activities (such as studying or meal preparation), and business activities, as well as whether non-household members used the space. This design makes it possible to link room usage to individuals, thereby generating individual-level housing consumption values.

III. Empirical Strategy

Identification of Resource Sharing

Our empirical strategy builds on the collective household framework, which departs from the traditional unitary model that assumes households behave as if maximizing a single utility function and that decisions are Pareto efficient and are the result of the bargaining power of individual members (Bourguignon and Chiappori, 1994). Under this framework, household allocations are assumed to be Pareto efficient, and observed resource allocation can be interpreted through individual preference heterogeneity and distributional rules (Browning, Chiappori, and

Lewbel, 2013). Dunbar, Lewbel, and Pendakur (2013, hereafter DLP) develop a structural model that operationalizes this approach by identifying intrahousehold resource shares from observed consumption demand systems. Unlike earlier models, which required restrictive assumptions such as single and married individuals sharing the same preferences (Bargain and Donni, 2012; Lewbel and Pendakur, 2008), the DLP framework relaxes these constraints to identify both adult and child resource shares. This is achieved by exploiting variation in Engel curves for private assignable goods—goods that can be clearly attributed to specific household members, such as clothing.

The DLP model combines three key components. First, a resource share function specifies how total household resources are divided among members according to their relative bargaining power. Second, a consumption technology function maps household-level purchases into "private good equivalents" for each individual, allowing assignable expenditures to serve as instruments for identifying shares. Third, individual utility functions are assumed to be well-behaved to make sure that the model's demand system is consistent with rational preferences. Together, these components define shadow budget constraints for each household member, from which resource shares can be derived. By imposing restrictions on preferences and exploiting variation in assignable goods, the DLP framework provides an empirically implementable strategy for measuring intrahousehold allocation of resources.

Let individual j in household type be indexed by subscript s and η_{js} is the resource share allocated to individual j in household s. The individual budget share function is $w_j(y,p)$ and household-level observed budget share is $W_{js}(y,p)$ with p is a price vector that includes the prices of private assignable goods, the prices of private non-assignable goods, and the prices of shared goods. The indirect utility function for individual j is the following

$$V_j(p,y\,) = \, e^{F_j(p)}(lny - ln\alpha_j(p)) \tag{1}$$

where $F_j(p)$ is homogeneous of degree 0 and $\alpha_j(p)$ is homogeneous of degree 1. The individual budget share function for assignable good j is: $w_j(y,p) = \, \alpha_j(p) + \, \gamma_j(p)lny$ and the corresponding observed household-level budget share for assignable good is the following

$$W_{js}(y,p) = \, \sigma_j \eta_{js}(y,p) w_{js}\big(n_{js}(y,p)y, A_s'p\big) \tag{2}$$

Estimation of resource shares in the DLP model involves inverting the Engel curves under functional form assumptions (e.g., piglog) and restricting the shape parameters γ_{js} which can be interpreted as each individual's marginal propensity to consume the assignable good (Brown et. al., 2021).

While the DLP model provides an empirically implementable approach to identifying resource shares using assignable goods, it requires solving a nonlinear system and is computationally intensive. Building on this framework, Lechene, Pendakur, and Wolf (2022, hereafter LPW) propose a linear reformulation that preserves the theoretical foundations of the DLP model while greatly simplifying estimation. Their approach exploits the fact that type-specific Engel curves for assignable goods can be written with a common slope in log total expenditure across individuals. In this setup, each type's budget share for an assignable good is linear in logarithmic expenditure and covariates, with semi-elasticities constrained to be identical across types. Because the slope vector is proportional to the vector of resource shares, these shares can be recovered by estimating budget-share equations via OLS and applying a simple normalization that allows them to vary with demographics. Unlike the nonlinear likelihood methods required in DLP, the LPW approach yields regression estimates with straightforward inference, while remaining consistent with the collective household framework.

A linear version of the model involves linear projection of assignable-good budget shares on log total expenditure and household characteristics. The Engel curve specification is

$$c_{ij} = \alpha_j + \beta \ln(x) + \gamma_j Z + \varepsilon_{ij} \tag{3}$$

where c_{ij} is the budget share of the assignable good j for individual i, $\ln(x)$ is the log of total household expenditure, Z is a vector of control characteristics, the interaction of the log of total expenditure and the covariate, and ε_{ij} is an error term. The key restriction is that the slope on log expenditure, β, is common across individuals. OLS estimation of this equation allows for identifying relative resource shares by comparing coefficients across individuals.

Under the same identifying assumptions, the DLP and LPW approaches are observationally equivalent, in the sense that they recover the same intrahousehold resource shares. The key difference lies in estimation strategy: DLP estimates shares through constrained nonlinear likelihood, whereas LPW uses linear projections to obtain closed-form estimates and standard inference.

Assignable expenditures

Assignable expenditures (i.e., private expenses on men's, women's, and children's items) are key for the identification of resource shares, yet in practice, the choice is constrained by the limited set typically collected in household surveys. Traditional DLP models typically use food or clothing as assignable goods, as children's, men's, and women's expenditures can easily be distinguished. However, the method itself does not specify a category and allows flexibility in the choice of goods for estimating resource shares. In the LPW, any assignable good can, in principle, recover the same underlying shares, as noted by Lechene, Pendakur, and Wolf (2022).

Clothing is the most widely used private assignable good in the literature for estimating household members' resource shares[2] (Bourguignon, Browning, and Chiappori 2009; Dunbar, Lewbel, and Pendakur 2013; Calvi 2020; Lechene, Pendakur, and Wolf 2022; Calvi et al., 2023), since it is generally treated as individually consumed and is widely available in standard household survey data. Studies suggest that clothing has a relatively low degree of sharing (Browning et al., 1994; Logan, 2011). Dunbar et al. (2013), for instance, show that estimates based on clothing are consistent with those from footwear, which is even less likely to be shared. The use of clothing for resource share identification is also supported by validation studies (Bargain et al., 2022). At the same time, clothing is not entirely private, since in many households' items can be passed down between siblings, particularly among children, as explored by Calvi et al. (2023).

In the current analysis, we use several definitions of assignable clothing expenditures: (i) aggregated clothing expenditures only, (ii) aggregated clothing expenditures combined with footwear expenditures, and (iii) individualized expenditures on clothing, footwear, fabric, tailoring, and laundry. The first two definitions represent traditional methods of collecting clothing and footwear expenditures, where household surveys record total spending on men's, women's, and children's clothing and footwear at the household level. The last definition uses information

[2] See Table A.1 (Appendix A) with a review of studies in low and middle-income countries using DLP and LPW methods

on how consumption was distributed across household members to derive individualized consumption of clothing-related expenses for men, women, and children.

Food is less commonly used as an assignable good[3], with applications including Brown et al. (2021), Lechene, Pendakur, and Wolf (2022), Calvi et al. (2023). Using food as an assignable good has several advantages over clothing. It is considered more clearly attributed to individual household members, has less unobserved quality heterogeneity than clothing, and is consumed regularly, making it less durable and more sensitive to changes in resource allocation. Additionally, food budget shares are typically larger and display the expected downward slope with respect to total expenditure in estimating Engel curves. Lechene, Pendakur, and Wolf (2022) show that using food as an assignable good delivers resource share estimates that are close to the results with assignable clothing. In the current analysis, we use the following categories of assignable food expenditures: (i) total food consumed at home, (ii) cereals and grains, (iii) animal products, and (iv) food consumed outside the home.

Given the limitations related to using clothing and food as assignable in the models of collective decisions, we explore alternative solutions and use various consumption categories: cereals and grains, meat, eggs, dairy, clothing, clothing and footwear, personal care items, transportation costs, and adult goods. Each category offers distinct advantages. Cereals and grains are regularly purchased, easy to assign, and exhibit consistent spending patterns. Meat, eggs, and dairy are more nutrient-dense and may reflect differential allocation by gender or age. Clothing and footwear, while widely used in prior studies, may be less frequently purchased, but they remain valuable due to their availability in most household surveys. Personal care items are often gender-specific and can be highly assignable, as well as transportation costs and expenses associated with adult goods, which can reveal work-related or leisure activities. The complete list of assignable expenditures is presented in Table 1. Using this expanded set of assignable goods allows us to test the robustness of estimated resource shares and identify which categories most accurately capture intra-household allocation.

Poverty measures

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[3] See Table A.1 (Appendix A) with a review of studies in low and middle-income countries using DLP and LPW methods

The poverty indicators that we estimate belong to the Foster, Greer and Thorbecke (FGT) (1984) class. Consider N - a population of income-receiving units (persons or households), $i = 1, \dots N$, with income y_i and weight w_i. Let $N = \sum_{i=1}^{n} w_i$, when the data are unweighted $w_i = 1$ and $N = n$. The poverty line is z and the income gap up to the poverty line for person i is $max(0, z - y_i)$. The FGT class of poverty indices is given by

$$FGT(y;\alpha) = \sum_{i=1}^{N} \frac{w_i}{N} \left[\frac{(z-y_i)}{z}\right]^{\alpha} I_i \qquad (4)$$

where $I_i = 1$ if $y_i \leq z$ and $I_i = 0$ otherwise. α is a given parameter, whose first three non-negative integer values are most commonly used. In particular, $FGT(y;0)$ is the headcount poverty ratio and $FGT(y;1)$ is the (average normalized) poverty gap and $FGT(y;2)$ is the (average normalized) poverty gap squared. The larger α is, the greater the degree of poverty aversion is (i.e., more weights are placed on poorer individuals). In this paper, we focus on a specific class of FGT indices, called poverty headcount, poverty gap, and poverty gap squared.

IV. Descriptive statistics

Table 2 presents descriptive statistics for the sample used for the analysis. All the households in the analysis are couples with or without children. The average age of the men in the sample is about 42 years old, whereas the average age of the women is 38 years old. They have around 5 years of education, which is equivalent to an incomplete secondary school education. In terms of family composition, on average, households have 1.5 children, and the mean age of children is around 8 years old. The average number of adults (household members) equals 4.2. Table 3 reports household budget shares for assignable goods. Individualized consumption represents 42 percent of total household consumption. Food expenditure represents the highest portion of the total budget shares: 37 percent of the household budget is allocated to the food consumed at home, with 15 percent of the household budget devoted to men's food, 14 percent to women's food, and 10 percent to children's food. The next large food category is the consumption of cereal and grains, with a similar household budget devoted to men`s and women`s cereal consumption (about 6 percent), and around 4 percent to children`s cereal consumption. Expenditure on clothing and footwear represents a small portion of the household budget - about 4 percent. Finally, household health, transportation, and personal care budget shares are 10 percent, 7 percent, and 2 percent, respectively.

Table 2 also reports the percentage of zero expenditures in the budget shares. The rate of zero expenditures in food expenditures is minimal for adults, with no zeros for women, 0.4 percent for men, and about 4.5 percent for children. Cereal and clothing-related items show similarly low zero rate (≤ 5 percent). By contrast, more than 50 percent of observations are zeros for animal-source foods, and several other categories also show substantial zeros. These zero inflations are important for our validation: they weaken identification in the DLP model by compressing within-household variation. It inflates the variance of estimated shares and implied poverty rates.

V. Main Results

Estimation of Resource Shares

Using individualized data, we calculate the per-person share for each person type and find that the adult man consumes 29 percent of the household resources, the adult woman consumes 24 percent, and the child consumes 19 percent. These differences likely reflect cultural patterns of household consumption in Bangladesh, where men traditionally bear responsibility for market-related expenses and possess greater control over household resources. Even in the case of food, which all members consume, prevailing norms may allocate men larger portions of staple foods and higher-value items such as fish, meat, and eggs. Children's lower observed shares may reflect both the limited range of items that can be attributed to them and the irregular nature of child-specific expenses such as school-related costs, which vary by income group and between rural and urban households.

We estimate intrahousehold resource shares using the DLP collective household model and compare predicted resource shares with those directly observed in the data. Observed shares derived from individualized consumption data serve as a benchmark against model-based estimates of resource allocations. The variation in assignable expenditures is used to identify model-based resource shares, with standard errors obtained from nonlinear seemingly unrelated regressions. Predicted group-level shares are then converted into per-capita values by dividing the estimated allocation to each group by the number of individuals within that group. It provides predicted mean resource shares per woman, per man, and per child, which can be directly compared with observed shares. We first compare predicted and observed shares at the mean and then evaluate their fit across the entire distribution. Distributional analysis helps to uncover the differences beyond the mean, offering a stricter test of the DLP model's performance.

First, we compare observed intrahousehold allocations with shares predicted by the DLP model across several definitions of clothing: (i) aggregated clothing expenditures only, (ii) aggregated clothing expenditures combined with footwear expenditures, and (iii) individualized expenditures on clothing, footwear, fabric, tailoring, and laundry. (Figure 1). The DLP model produces estimates that are close to observed allocations for men and children when using aggregated assignable clothing. The predicted share for men and children (30 and 20 percent, respectively) is nearly the same as the observed benchmark (29 and 19 percent, respectively), while for women, the predicted share (21 percent) is lower than the observed share by 3 percentage points. Adding aggregated, assignable footwear to the model does not improve prediction accuracy for men or children and yields only a slight improvement for women. Exploiting individualized information about assignable clothing and footwear does not improve accuracy relative to the aggregated measures for any demographic group. However, despite variation in mean levels across clothing definitions, the observed resource shares for men, women, and children all lie within the 95 percent confidence intervals of the model-based predictions.

In addition to encouraging results for the mean levels, we also use kernel density plots of observed and predicted resource shares as a stricter test of the DLP model's ability to approximate the resource allocation. Using the aggregated data on assigned clothing and footwear (separately or combined) in the model produces estimates for men that are very close to the observed benchmark; however, the DLP model compresses variation relative to the benchmark data (Figure 2). The central tendency is reproduced with very high accuracy when individualized assignable clothing and footwear are used; however, the model predicts fewer households with men's high resource shares than are observed in the data. For women, aggregated assignable clothing makes the predicted distributions more compressed and understates variation in the upper tail, where women receive larger resource shares (Figure 3). Adding assignable footwear to the model improves distribution, yet the right tail remains underrepresented. Individualized, assignable clothing and footwear do not improve prediction accuracy relative to the traditional measures. Across all definitions of assignable clothing, the DLP model underrepresents households where men and women receive lower resource shares. Aggregated assignable clothing and footwear (separately or combined) underestimates the children`s higher resource shares, while individualized assignable clothing and footwear further compresses the distributions and underestimates the right tail (Figure 4).

Overall, the DLP model predicts men's distributions with high accuracy, is less accurate for women, and provides the least accurate approximation of individual resource shares for children. Aggregated assignable clothing and footwear (separately or combined) provide reliable information for identifying men's and women's resource shares. For children, however, these categories appear less reliable, likely because individual allocations can be less clearly reflected in household clothing irregular purchases.

Next, we compare observed and predicted resource shares using the following food categories as assignable goods: (i) food consumed at home, (ii) cereals and grains, (iii) animal products, and (iv) food consumed outside the home (Figure 5). For men, the highest accuracy is achieved when using assignable food expenditures and animal products (31 percent), with predicted shares close to the observed benchmark of 29 percent and observed values lying within the 95 percent confidence intervals. Similar to men, the highest accuracy for women and children is achieved when using assignable animal products, with the observed shares of 24 percent for women and 19 percent for children being very close to the estimated shares (23 and 14 percent, respectively) and lying within the 95 percent confidence intervals of the estimated values. The model overestimates women's allocations and underestimates children's allocations when using assignable food expenditures, as well as assignable cereal and grains, likely as a result of the weaker assignability of food consumption due to shared meals and collective preparation. Assignable animal products produce estimates whose confidence intervals overlap with the observed shares for men, women, and children; however, the high frequency of zero-reported expenditures in these categories, especially for women and children, may limit their reliability. Using food consumed outside in the model does not improve the estimates. However, it increases their variance across all demographic groups, with observed values remaining statistically insignificantly different from predictions due to the wide confidence intervals.

Similar to analysis with assignable clothing, we assess whether the model approximates not only mean allocations but also the entire distribution of resource shares when using assignable food categories. For the distributional analysis, we exclude estimates based on food consumed outside, as the high variability of these estimates limits the reliability of the estimates. Assignable food expenditures, as well as assignable cereals and grains, provide higher accuracy than animal products in reproducing the observed distributions of men`s resource shares (Figure 6). The differences appear only in the tails for the assignable food and cereals. In contrast, the predicted distribution is more skewed for animal products, overestimating households where men receive higher resource shares but also underrepresenting the households with very high shares. Using assignable food and cereals overestimates households where women receive higher shares but underrepresents households with very high shares (Figure 7). Accuracy is weaker when using assignable animal products, with the predicted density concentrated at lower shares and missing the wider tails of the observed distribution. Children's shares are predicted with the least accuracy across all food categories, with predicted shares below observed benchmarks and distributions centered at lower values (Figure 8). The bias between predicted and observed estimates is lower for assignable animal products; however, the estimated mean remains concentrated at lower values relative to the observed, and the model underestimates the thicker right tail of the observed distribution. In addition, the high incidence of zero-reported expenditures in animal products for children further compresses the estimated variance, contributing to a bigger bias between observed and estimated shares.

Overall, using assignable food expenditures, as well as assignable cereals and grain expenditures and grains in the estimation, can provide a reliable identification of men`s resource shares. In contrast, for women and children, average shares are recovered, but the distribution of allocations is not. Although food expenditures are often treated as a standard example of individualized consumption, their reliability in identifying women's and children's resource shares depends on whether consumption can be clearly attributed to specific household members. Shared preparation and joint consumption within households can make it difficult to treat food as a purely assignable good for these groups.

We next turn to other types of assignable goods, such as individualized expenditures on (i) personal care, (ii) health services, (iii) transportation, and (iv) adult goods (Figure 9). In contrast to the clearer patterns obtained for assignable clothing and food, the resource allocations predicted from other categories show higher variability in accuracy. For men, the model tends to overestimate resource allocations, particularly when comparing observed shares with model-based shares obtained using assignable transportation expenditures (36 percent) and health expenditures (32 percent). However, the observed resource shares lie within the 95 percent confidence intervals of the corresponding DLP estimates. Interestingly, using personal care as an assignable good provides a close approximation of men's resource shares (29 percent), but produces less accurate estimates for women (30 percent), overestimating their observed share by about six percentage points. However, the observed value still lies within the 95 percent confidence interval of the corresponding DLP estimate. For children, using assignable personal care and transport in the estimation produces resource share estimates that fall well below the observed mean levels, with the observed mean lying within the 95 percent confidence interval of the prediction only in the case of personal care. Interestingly, using individualized health expenditures as assignable goods produces estimates that overstate men's (32 percent) and children's (24 percent) mean shares while understating women's (16 percent), yet for all demographic groups, the observed mean levels still lie within the 95 percent confidence intervals of the model-based predictions. A similar pattern is observed when adult goods are used as assignable: mean shares are overestimated for men (42 percent) and underestimated for women (20 percent), yet in both cases the observed values lie within the 95 percent confidence intervals of the predictions. Overall, the DLP model approximates men's allocations more accurately than those of women or children, as the observed men's share lies within the 95 percent confidence interval of the predicted estimates across all assignable goods. At the same time, only the predicted confidence intervals for assignable personal care expenditures overlap with the observed mean shares for all demographic groups.

Distributional analysis shows that predicted men's resource shares closely approximate the observed distribution when personal care is used as the assignable in the DLP model. However, households at the lower and upper ends are underrepresented (Figure 11). Interestingly, for women, using assignable personal care in the DLP model yields a poorer approximation of the observed distribution than for men: the predicted distribution is skewed relative to the observed and overstates the probability of households with higher resource shares (Figure 12). Accuracy is weaker when transport expenditures are used in the estimation, though the observed distribution is approximated more closely for men than for women. The DLP model is least reliable when expenditures on health services and adult goods are used for identification, as it produces bimodal distributions that are not present in the data for both men and women. For children, the weakest results are observed across all types of individualized expenditures, with the DLP model producing more compressed distributions than those in the data (Figure 13).

Overall, the DLP model provides a reliable identification of individual resource shares for men using a wide range of assignable goods, including all definitions of clothing, food expenditures, personal care, and transport expenditures, yielding accurate estimates. For women, data used for identification of resource shares is more demanding in terms of the data: aggregated assignable clothing and footwear expenditures (together or separately) perform better than individualized data on clothing-related expenditures, while different categories of food expenditures approximate mean shares well, but not the entire distribution. For children, only the aggregated clothing expenditures and expenditures on animal products provide reliable predictions of resource shares. However, data on the consumption of animal products should be used cautiously due to the frequent occurrence of missing data for women and children. The weaker performance of services relative to clothing or food in the identification of resource shares is likely explained by structural features of the data. First, zero expenditures are far more common for categories such as personal care and health, which inflates variance and reduces the precision of DLP estimates. Second, the structural assumptions of the DLP model are more consistent with goods that are clearly assignable, such as clothing and food, than with services like health or transport, where consumption is often joint or lumpy and therefore less easily attributed to individuals.

From a policy perspective, the relative allocation of household resources shows important differences (Table 4). When clothing or food are used as assignable goods, men consistently receive larger shares than women, with gender ratios ranging from 1.0 to 1.5 for clothing and from 1.1 to 1.3 for food. These differences are even higher between men and children: men1s shares are about 1.5 to 1.9 times larger with assignable clothing and nearly twice as large with assignable food. These differences grow dramatically when other categories are used, such as transport or health, where male-to-child ratios can reach as high as 6.8.

We next estimate intrahousehold resource shares using the linearized version of the DLP collective household model proposed by Lechene et al. (2022) (LPW) and compare them with those directly observed in the data. Observed shares are constructed from individualized consumption and serve as the benchmark against which predicted allocations are evaluated. Predicted group-level shares are expressed on a per-capita basis by dividing the estimated allocation to each group by the number of individuals in that group. The LPW approach identifies assignable goods by estimating household-level Engel curves and testing whether their slopes are statistically different from zero, reporting the fraction of households with significant slopes. The model is considered identified only if a sufficiently large majority of households pass this test. We use 75 percent as the baseline cutoff in this paper.

Similar to the analysis made for the DLP model, we compare observed intrahousehold allocations with the shares predicted by the LPW model across several definitions of clothing expenditures (Figure 14). First, we confirm the model identification by the percentage of the sample in which the slope of Engel curves is statistically different from zero. According to Lechene et al. (2022), the model is identified when the sample percentage of Engel curve slopes statistically different from zero is above 75% of the whole sample. The LPW identification test is satisfied—82.9 percent for household-level clothing expenditures, 76.2 percent for household-level clothing expenditures combined with footwear expenditures, and 82.4 percent for individualized expenditures —all meeting or exceeding the 75 percent benchmark

Unlike the DLP model, the LPW model does not produce close estimates across any definition of assignable clothing expenditures (Figure A.1, Appendix A). The bias between predicted and observed shares ranges from 4 to 10 percentage points for men; from 3 to 15 percentage points for women; and from 12 to 18 percentage points for children. In some cases, however, the predicted estimates are not statistically different from the benchmark—for example, aggregated clothing and footwear (separately or combined) for men, and individualized clothing and footwear for women. For children, by contrast, observed resource shares lie outside the 95 percent confidence intervals of the model-based predictions under every definition. Overall, the LPW method assigns a larger share of resources to children than observed, as zeros in the data weaken slope information and the common-slope restriction misallocates responsiveness across goods, shifting shares from adults to children.

Next, we compare observed and predicted resource shares using similar assignable food categories as we used in the DLP model (Figure A.2, Appendix A). The LPW identification test is satisfied—95.6 percent for food consumed at home, 99 percent for cereal and grain expenditures, and 63.9% for animal products. For men, the highest accuracy is achieved with assignable food expenditures (30 percent), as predicted shares are close to the observed benchmark of 29 percent and lie within the 95 percent confidence intervals. For women and children, however, the LPW model performs poorly: women's allocations are overestimated by three percentage points, and children's are underestimated by five percentage points, with observed mean levels falling outside the 95 percent confidence intervals. When cereals are used in the estimation, the model overestimates men's and women's shares by three percentage points and underestimates children's by 7. A similar pattern appears for animal products, except that in this case the observed mean levels lie within the 95 percent confidence intervals for all groups, though the intervals for men and women are very wide. Overall, the LPW method reallocates resources from children to adults across all food categories, likely due to data features: food expenditures and cereals are widely consumed and fit better in the model, whereas animal products and children's food contain many zeros and irregular purchases that reduce the accuracy of the estimation. Compared to DLP model, the difference in the relative allocation of household resources is higher when using LPW model (Table 4). When clothing is used as the assignable good, gender ratios vary from 0.9 to 2.3, while food yields a narrower range of 1.1 to 1.8. Men`s shares are only 0.6-0.7 of children`s when clothing used but rise to 2.1-2.6 with assignable food.

Taken together, the LPW model provides less accurate estimates of the individual resource shares than the DLP model, since far fewer assignable categories can be used to obtain accurate estimates. Nevertheless, both models share common features: many assignable goods work well for men, while women's and children's shares are more demanding in terms of the definition of the assignable goods. Since the DLP model outperforms the LPW model, we proceed with the welfare analysis using the DLP framework.

Welfare Analysis

We derive the implications of the estimations in terms of individual poverty. Using DLP model estimates from the previous section, we calculate consumption-based poverty headcount, poverty gap, and poverty gap squared that incorporate unequal intrahousehold allocation of resources. Unlike standard poverty measures, which assume equal sharing within households, this approach assigns each household's total expenditure to men, women, and children in proportion to their estimated resource shares. This yields an implied consumption level for each group, which we compare to the World Bank's poverty line of US$2.15 per person per day in 2017 PPP (purchase power parity) for low-income countries. Groups whose allocated consumption falls below this line are classified as poor. We produce poverty rates for men, women, and children under different assignable goods. Observed individual poverty rates are constructed by comparing each household member's individualized consumption with the international poverty line and then averaging the resulting poverty indicator by demographic group (men, women, children). In addition to the FGT indexes, we also provide predicted estimates of the general distribution of individual consumption, which extends our estimation from focusing on the poorer part of the consumption distribution to the other parts of the distribution.

We find substantial intrahousehold inequality in poverty when measured at the individual level: male poverty is relatively low at 5 percent, female poverty is twice as high at 10 percent, and child poverty exceeds 25 percent—more than five times that of adult men. The corresponding poverty gaps are 0.97 percent for men, 2.03 percent for women, and 8.58 percent for children. These figures show that women are both more likely to be poor and further below the line than men, and children face the greatest disadvantage, being not only more prevalent among the poor but also much deeper in poverty.

We compare observed and estimated individual-level poverty rates using assignable clothing under alternative definitions (Figure 14). For men, most definitions of clothing produce estimates that differ from the benchmark by no more than two percentage points, and in all cases the observed means fall within the 95 percent confidence intervals of the corresponding predictions. Using aggregated assigned clothing or footwear (separately or combined) for women produces poverty rates more than twice the observed rates, with observed mean values falling outside the 95 percent confidence intervals of the predictions. By contrast, individualized assignable clothing and footwear improve accuracy: the difference between observed and predicted rates is reduced to about two percentage points, and the observed value falls within the confidence interval. These results are consistent with our earlier distributional analysis, where aggregated definitions of assignable clothing produced less accurate approximations of women's resource share distributions, while individualized data provide predictions that better approximate the observed distributions. For children, assignable clothing expenditures provide close estimates of the poverty rate (25 percent), with observed values lying within the 95 percent confidence intervals of the predictions. Adding footwear or using individualized clothing and footwear does not improve accuracy, although observed rates remain within confidence intervals. These results reflect the model's limited ability to estimate children's poverty rates when child-specific clothing is used as the assignable good, as joint purchases and frequent zeros complicate assignability. Overall, the DLP model predicts men's poverty with high accuracy across all clothing definitions. However, women's and children's poverty estimates are sensitive to the choice of assignable good, which is consistent with our earlier results on resource shares.

The poverty gap results are qualitatively similar to poverty rates but provide additional insight into the DLP model's ability to predict the depth of poverty across groups. For women, individualized assignable clothing and footwear provide the closest approximation (Figure 15). For men, all clothing definitions yield estimates that overlap with the observed values, though individualized data again produce the closest estimates to the benchmark. For children, accuracy improves when footwear is included in clothing expenditures or when individualized, assignable clothing and footwear are used. Overall, individualized data provide the most accurate approximation of the poverty gap across all demographic groups, with similar results obtained for the poverty gap squared (Figure A.3, Appendix A).

To further understand the poverty results, we compare the empirical distributions of individual expenditures with those predicted by the DLP model (in local currency units). For men, the estimated and observed distributions are closely matched across the entire distribution, with only minor deviations in the upper tail, which explains why the model reproduces men's poverty rates almost exactly across all clothing definitions (Figure 16). For women, the model systematically predicts lower consumption levels than observed, pushing more individuals below the poverty line and leading to overestimated poverty rates (Figure 17). This shows that although the DLP framework captures women's average resource allocation, small shifts near the threshold have important consequences for poverty estimation. For children, the model places more individuals just below the poverty line, which leads to overestimated poverty rates when either household-level or individual-level clothing and footwear data are used. However, the differences are smaller than for women, and the resulting poverty rates are closer to the observed benchmarks (Figure 18). Overall, these findings confirm that biases in predicted poverty relative to observed benchmarks are driven by localized differences between observed and predicted distributions around the poverty threshold.

We now apply the same exercise to food categories by comparing observed and predicted poverty headcount rates and poverty gaps. For men, predicted poverty headcount rates remain close to the benchmark, with assignable animal products producing the observed rate exactly, and predicted 95 percent confidence intervals overlapping with the benchmark. For women, assignable food consumption yields the closest poverty estimates. However, estimates based on assignable animal products are also not statistically different from the benchmark, as the wide 95 percent confidence intervals overlap with the observed rate. The differences in poverty headcount rates are larger for children than for other groups across all assignable categories, with observed rates lying within predicted 95 percent confidence intervals only when animal products are used as an assignable. These results are consistent with earlier findings for children's resource shares, which showed that the DLP model poorly replicates allocation distributions when clothing is used for identification. The poverty gap results are qualitatively similar to those for the poverty headcount, with greater accuracy for children when animal products are used for identification (Figure 17). The squared poverty gap results, in turn, mirror the patterns observed for the poverty gap (Figure A.4, Appendix A).

When we compare the empirical distributions of individual expenditures with those predicted by the DLP model for men, predicted consumption distributions are close to observed, with slight shifts near the poverty line that slightly underestimate men`s poverty (Figure 18). For women, using assignable animal products shifts the predicted distribution slightly above the observed value near the poverty line, leading to an understated poverty rate. In contrast, food and cereal consumption places greater weight just below the line, resulting in overstated poverty (Figure 19). For children, all assignable food categories shift the predicted distribution to the left of the observed distribution near the poverty line, adding more weight below the poverty threshold and systematically overstating poverty (Figure 20).

Overall, clothing stands out as the most reliable assignable good for measuring poverty, accurately reflecting men's poverty and providing accurate estimates for women and children under specific definitions. Food expenditures, especially food at home and cereals, produce reliable results for adults but overestimate child poverty. Together, the evidence shows that both food and clothing can be used for poverty analysis, although their reliability varies across demographic groups, with men's outcomes measured most robustly, women's estimates requiring individualized data, and children's poverty remaining the most difficult to capture accurately[4].

VI. Conclusion

Understanding how households distribute resources is crucial for assessing individual well-being. Typical poverty and inequality metrics often rely on total household consumption, assuming equal sharing among members, which overlooks variations in how resources are distributed within households. An increasing amount of research on intrahousehold inequality emphasizes that this assumption hides significant disparities within families. Intrahousehold inequalities not only change our view of who is poor, but also how poor they are. This is especially important for developing countries like Bangladesh, where small changes in resource distribution can significantly impact the poverty gap. We find substantial intrahousehold inequality in Bangladesh when consumption and poverty are measured at the individual level.

Using highly individualized data from World Bank's Bangladesh Individual Consumption Study (BICS), we find that men consume a larger share of the budget relative to women, who in turn consume relatively more than child. Based on the estimates from DLP model, men consistently receive larger shares than women when clothing or food categories used as an assignable goods, with gender ratios ranging from 1.0 to 1.5 for clothing categories and from 1.1 to 1.3 for food categories. These results are supported by other studies reporting systematic gender and age differences in the allocation of resources within Bangladesh households, with gender ratios varying between 1.1 (Aminjonov et al., 2025) and 1.3 (Bargain et al., 2022) with assignable clothing and 1.3 (Calvi et al., 2023) with assignable food. The difference is even higher between men and children: men`s shares are about 1.5 to 1.9 times larger with assignable clothing and nearly twice larger with assignable food. The corresponding ratios obtained for Bangladesh are 1.1 (Bargain et al., 2022) and 2.4 (Aminjonov et al., 2025) with assignable clothing and 1.4 (Calvi et

[4] Results using other categories, such as transportation, personal care, health, and adult goods, are not discussed in detail, as using these categories yields far less accurate predictions of headcount poverty rate than those obtained using assignable clothing or food. The DLP model approximates men's poverty rates well regardless of the type of assignable good used in the estimation, with the lowest differences observed when using assignable personal care and transport (Figure A.5, Appendix A). However, these assignable categories yield far less accurate predictions of poverty gap and squared poverty gap (Figure A.6, Appendix A). For women, assignable personal care and health expenditures do not yield poverty estimates that are close to the benchmark; however, the observed rate falls within their 95 percent confidence interval. For children, none of the assignable categories produce predicted poverty headcounts close to the benchmark, although for personal care and transport, the 95 percent confidence intervals overlap with the observed rate (Figure A.7, Appendix A).

al., 2023) with assignable food. We also find that clothing expenditures, typically collected in aggregated form in household surveys, provide the most reliable estimates for estimating resource shares across all groups when used as an assignable in collective models. These results are consistent with the validation study of Bargain et al. (2022), who also find that structural models of intrahousehold allocation perform well when clothing is used as the assignable good. Although food expenditures are traditionally treated as strictly private, they yield reliable resource share estimates only for adults. At the same time, their use for children depends on data quality and the extent to which consumption can be clearly attributed to individual members. We also find heterogeneity across demographic groups in terms of the data requirements: men's resource shares can be identified using a broad set of assignable goods, whereas women's and children's estimates are more sensitive to the choice of assignable goods.

We also find significant gender- and age-based disparities in headcount poverty, depth, and severity in Bangladesh, with women and children being both more prevalent among the poor and deeper in poverty. Recognizing hidden deprivation among women and children, by considering intrahousehold inequality, offers a more accurate and policy-relevant picture of poverty.

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Main Tables

Table 1. Assignable goods in BICS

Food	
Total food at home	All food items
Cereals and grains	Parboiled rice (coarse), Non-parboiled rice (coarse), Fine rice, Atta, Muri/Khoi (puffed rice), Cerelac, Other cereal (Rice flour, Suji (cream of wheat/barley), Wheat, Maida (wheat flour w/o bran), Semai/noodles, Chaatu, Chira (flattened rice), Barley, Sagu, Corn)
Animal products	Beef/buffalo, Mutton, Chicken, Duck, Pigeon, Pig, Stomach of beef/goat, Egg, Milk, Powdered Milk, Other meat (Fish egg), Other dairy
Total food outside	All meals consumed outside are included
Clothing	
Clothes for men	*aggregated*
Clothes for women	*aggregated*
Clothes for children	*aggregated (boys' and girls' clothing)*
Clothing and footwear for men	*aggregated*
Clothing and footwear for women	*aggregated*
Clothing and footwear for children	*aggregated (boys' and girls' shoes)*
Individualized clothing-related expenses	Clothes for boys, Clothes for girls, Clothes for men, Clothes for women, Boy's shoes, Girl's shoes, Men's shoes, Women's shoes, Fabric, Tailoring, School uniform
Other private services and goods	
Personal care	Skin care: snow cream, powder, perfume, cologne, etc, Hair products, Cosmetics, Feminine hygiene, Diapers, Haircut, shaving, Salon services
Transportation costs	Bus fare, Rickshaw fare, Taxi fare, Boat fare, Train fare, Education-related transportation costs
Health-related costs	Doctor`s appointments, medicine, vaccination, vitamins
Adult goods	Betel nuts, leaves, Cigarettes, tobacco, Lottery, raffles, gambling

Table 2. Descriptive Statistics, BICS

	Obs	Mean	Median	SD
Household expenditures				
Total household expenditure (LCU)	1000	339835.608	303055.250	185007.731
Budget share: Food at home	1000	0.368	0.365	0.130
Budget share: Cereal and grains	1000	0.155	0.144	0.085
Badget share: Animal products	1000	0.017	0.000	0.026
Budget share: Food outside	1000	0.001	0.000	0.002
Budget share: Men`s clothing	1000	0.009	0.007	0.007
Budget share: Women`s clothing	1000	0.006	0.004	0.007
Budget share: Children`s clothing	1000	0.008	0.006	0.009
Budget share: Men`s clothing and footwear	1000	0.010	0.008	0.007
Budget share: Women`s clothing and footwear	1000	0.007	0.005	0.008
Budget share: Children`s clothing and footwear	1000	0.012	0.009	0.011
Budget share: Individualized clothing-related expenses	1000	0.039	0.036	0.021
Budget share: Personal care expenses	1000	0.019	0.015	0.016
Budget share: Transportation	1000	0.070	0.048	0.078
Budget share: Health	1000	0.098	0.066	0.105
Budget share: Adult goods	1000	0.010	0.000	0.027
Household composition				
Number of household members	1000	4.228	4.000	1.414
Number of men in the household	1000	1.355	1.000	0.589
Number of women in the household	1000	1.419	1.000	0.611
Number of children in the household	1000	1.454	1.000	0.975
Number of non-relatives living in the household	1000	0.001	0.000	0.032
Household characteristics				
Mean age of men in household	1000	41.849	40.000	10.067
Mean age of women in household	1000	38.450	37.500	9.720
Mean age of children in household	822	8.285	8.000	4.380
Highest level of men`s education	1000	4.982	5.000	3.938
Highest level of women`s education	1000	5.002	5.000	3.604
Highest level of children`s education	822	0.500	1.054	0.000
Proportion of men engaged in paid or self-employment work	1000	0.730	1.000	0.408
Proportion of women engaged in paid or self-employment work	1000	0.211	0.000	0.377

Note: Individual education ranges from 0 (no schooling) to 16 (MA/MS and above).

Table 3. Household budget shares of the assignable goods, BICS

	Mean	Median	SD
Total food at home			
Budget share: men	14.650	13.539	7.714
	0.400	*0.000*	*6.315*
Budget share: women	13.666	12.897	6.427
	0.000	*0.000*	*0.000*
Budget share: children	10.271	9.409	6.817
	4.501	*0.000*	*20.746*
Budget share: total	36.758	36.495	13.018
	0.000	*0.000*	*0.000*
Cereals and grains			
Budget share: men	6.314	5.295	4.498
	2.200	*0.000*	*14.676*
Budget share: women	6.027	5.409	3.967
	1.700	*0.000*	*12.934*
Budget share: children	3.793	2.948	3.380
	6.569	*0.000*	*24.790*
Budget share: total	15.459	14.367	8.528
	1.700	*0.000*	*12.934*
Animal products			
Budget share: men	0.616	0.000	1.223
	58.800	*100.000*	*49.244*
Budget share: women	0.506	0.000	1.008
	60.700	*100.000*	*48.866*
Budget share: children	0.667	0.000	1.143
	54.501	*100.000*	*49.827*
Budget share: total	1.671	0.000	2.638
	52.200	*100.000*	*49.977*
Food outside the home			
Budget share: men	0.061	0.014	0.200
	39.500	*0.000*	*48.910*
Budget share: women	0.036	0.000	0.098
	64.200	*100.000*	*47.965*
Budget share: children	0.006	0.000	0.028
	90.146	*100.000*	*29.823*
Budget share: total	0.102	0.039	0.234
	29.000	*0.000*	*45.399*
Individualized clothing-related items			
Budget share: men	1.069	0.902	0.873
	4.500	*0.000*	*20.741*
Budget share: women	1.235	0.992	0.985
	1.100	*0.000*	*10.435*
Budget share: children	1.905	1.625	1.247
	0.608	*0.000*	*7.780*
Budget share: total	3.870	3.562	2.099
	0.200	*0.000*	*4.470*
Personal care			
Budget share: men	0.655	0.116	1.019
	42.000	*0.000*	*49.381*
Budget share: women	0.741	0.548	0.750
	6.400	*0.000*	*24.488*
Budget share: children	0.624	0.310	0.956
	31.144	*0.000*	*46.336*
Budget share: total	1.909	1.519	1.567
	3.500	*0.000*	*18.387*
Transportation			
Budget share: men	4.065	1.928	5.869
	33.000	*0.000*	*47.045*
Budget share: women	1.641	0.000	3.442
	53.100	*100.000*	*49.929*

Budget share: children	1.568 *67.640*	0.000 *100.000*	4.262 *46.813*
Budget share: total	6.995 *17.600*	4.846 *0.000*	7.790 *38.101*
Adult goods			
Budget share: men	0.601 *64.800*	0.000 *100.000*	2.170 *47.783*
Budget share: women	0.379 *72.800*	0.000 *100.000*	1.130 *44.521*
Budget share: children	0.008 *98.783*	0.000 *100.000*	0.109 *10.969*
Budget share: total	0.987 *54.600*	0.000 *100.000*	2.672 *49.813*
Health			
Budget share: men	3.416 *30.000*	0.825 *0.000*	6.126 *45.849*
Budget share: women	4.625 *24.500*	1.589 *0.000*	7.323 *43.030*
Budget share: children	2.163 *34.550*	0.594 *0.000*	4.285 *47.582*
Budget share: total	9.819 *4.500*	6.565 *0.000*	10.492 *20.741*
Total private goods			
Budget share: men	15.167 *0.000*	12.840 *0.000*	9.048 *0.000*
Budget share: women	12.245 *0.000*	10.721 *0.000*	6.717 *0.000*
Budget share: children	17.102 *0.000*	15.734 *0.000*	8.850 *0.000*
Budget share: total	41.470 0.000	40.714 0.000	12.458 0.000

Note: The numbers in italics are the proportion of zeros in household budget share. The sample size for women and men is 1,000 observations. The sample size for children is 822 observations.

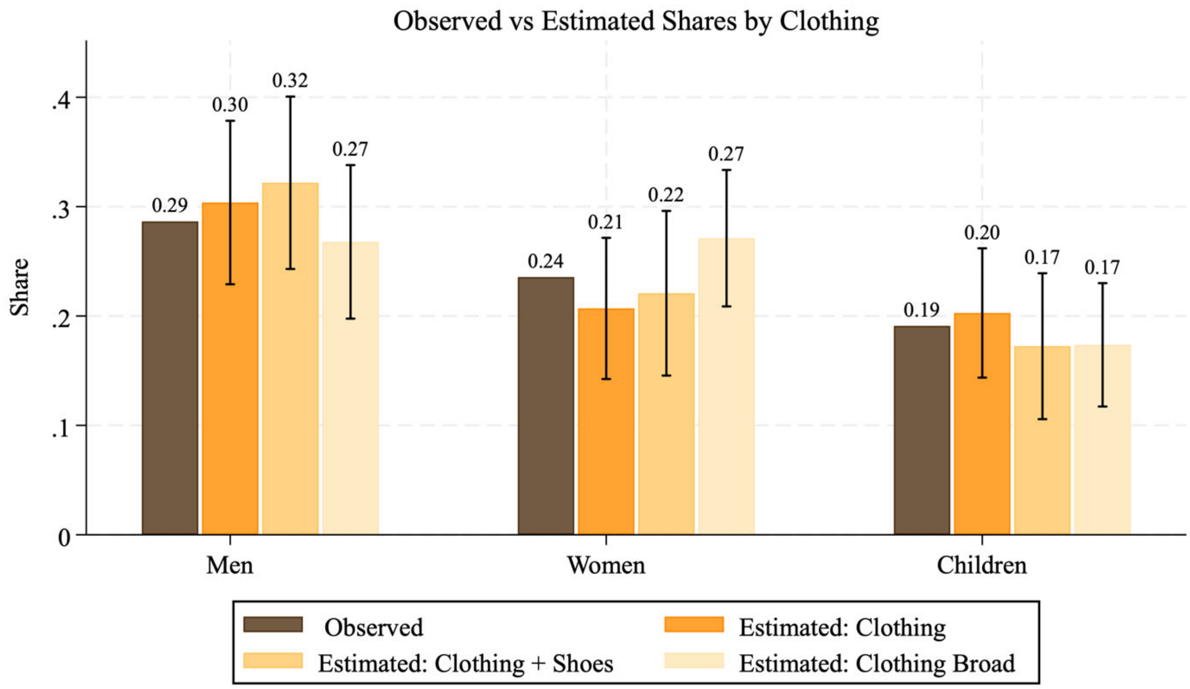
Table 4. Resource Share Estimations, BICS

Authors	Country Year(s)	Method	Households	Assignable good(s)	Men	Women	Child	Gender ratio	Male–child ratio	Validation	Household type
Palacios-Lopez et al. (2025)	Bangladesh 2024	DLP	1,000	Clothing	0.304	0.207	0.203	1.5	1.5	Yes	All household types
				Clothing + Shoes	0.322	0.221	0.172	1.5	1.9		
				Clothing (Broad)	0.268	0.271	0.174	1.0	1.5		
				Food	0.307	0.266	0.142	1.2	2.2		
				Animal Products	0.316	0.235	0.164	1.3	1.9		
				Cereal	0.302	0.269	0.144	1.1	2.1		
				Food outside	0.307	0.267	0.141	1.2	2.2		
				Personal care & hygiene	0.285	0.304	0.126	0.9	2.3		
				Transport	0.323	0.156	0.235	2.1	1.4		
				Adult goods	0.415	0.197	0.108	2.1	3.8		
				Health	0.358	0.304	0.057	1.2	6.3		
Palacios-Lopez et al. (2025)	Bangladesh 2024	LPW	1,000	Cloth	0.234	0.103	0.368	2.3	0.6	Yes	All household types
				Cloth+Shoes	0.246	0.094	0.366	2.6	0.7		
				Cloth (broad)	0.188	0.210	0.309	0.9	0.6		
				Food	0.301	0.271	0.141	1.1	2.1		
				Animal Products	0.354	0.202	0.150	1.8	2.4		
				Cereal	0.322	0.269	0.124	1.2	2.6		

Note: DLP = Dunbar, Lewbel, Pendakur (2013); LPW = Lechene, Pendakur, Wolf (2022). Gender ratio = Men/Women; Male–child ratio = Men/Child.

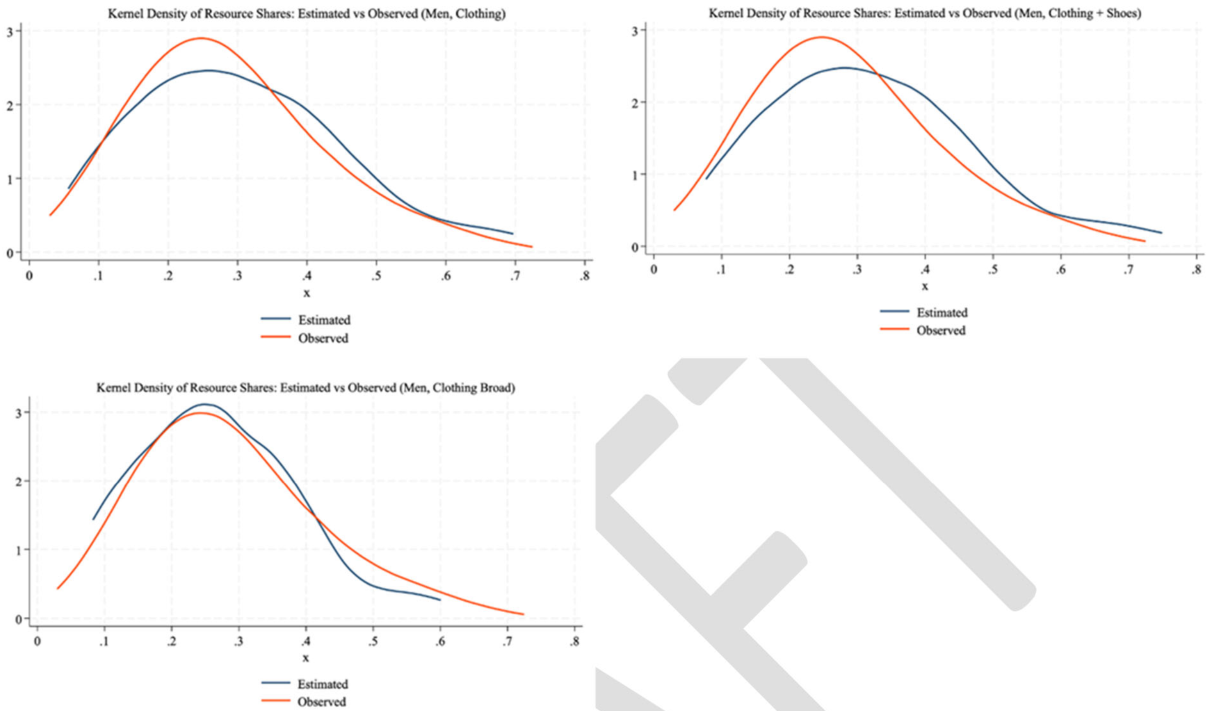
Main Figures

Figure 1. Observed vs Estimated Resource Shares Using Assignable Clothing, BICS



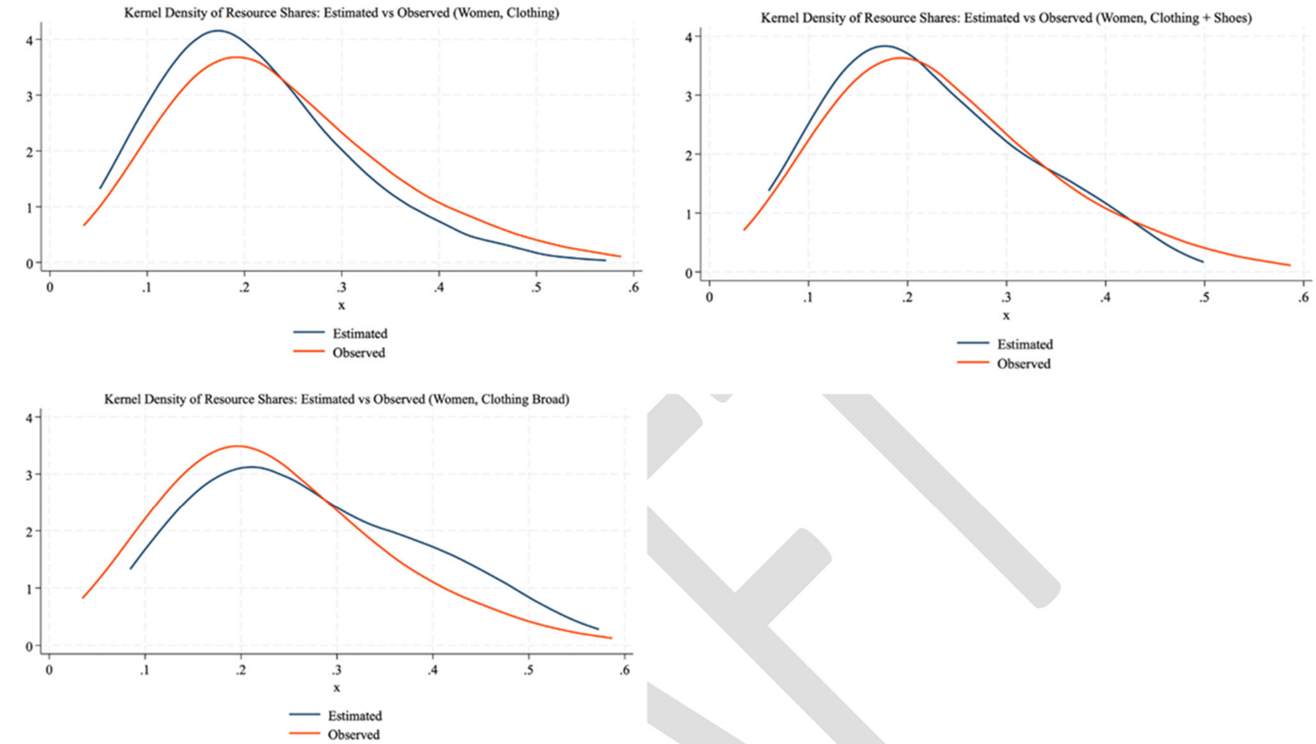
Notes: Bars show mean resource shares from the collective model (using clothing as the assignable good); whiskers are 95% confidence intervals. Observed shares come from fully individualized expenditure records.

Figure 2. Distribution of Observed vs Estimated Resource Shares Using Assignable Clothing, Men



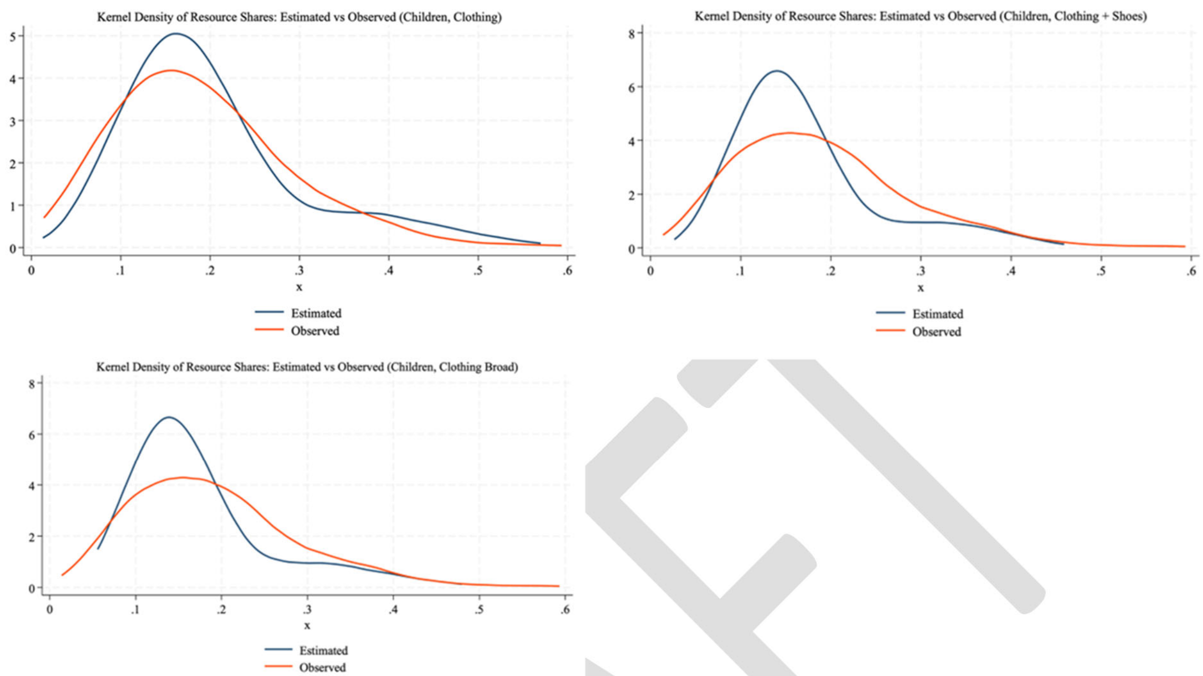
Note: Distribution of resource shares. The graphs illustrate the kernel density of predicted per-person resource shares.

Figure 3. Distribution of Observed vs Estimated Resource Shares Using Assignable Clothing, Women



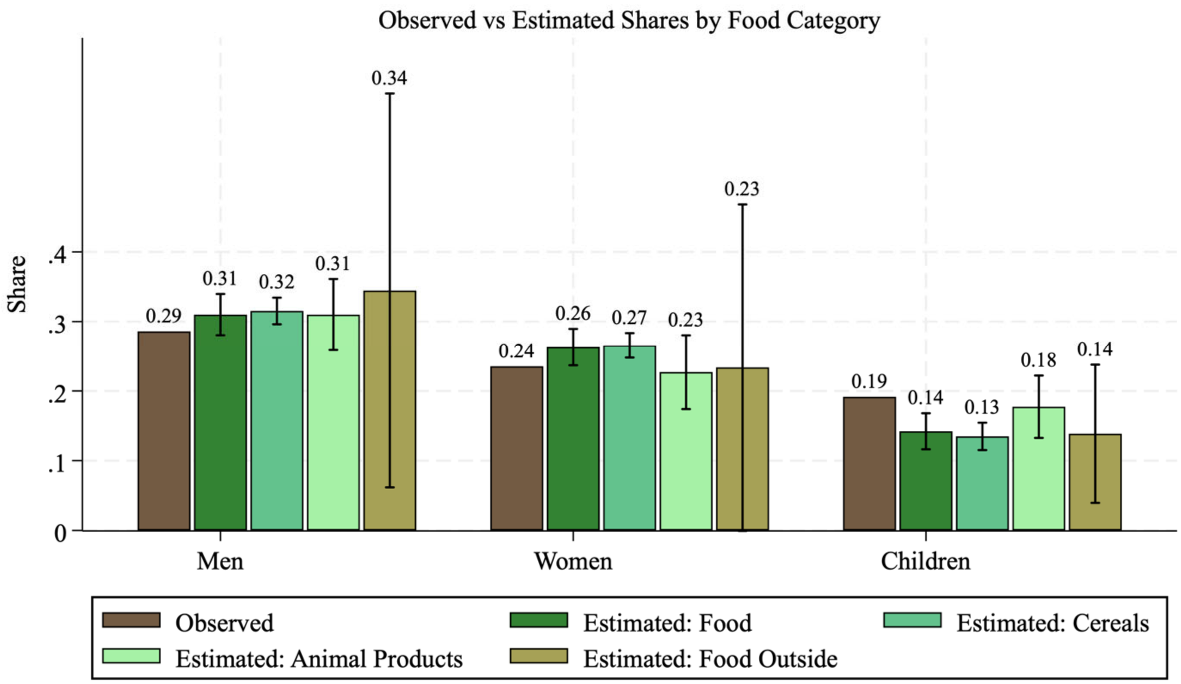
Note: Distribution of resource shares. The graphs illustrate the kernel density of predicted per-person resource shares.

Figure 4. Distribution of Observed vs Estimated Resource Shares Using Assignable Clothing, Children



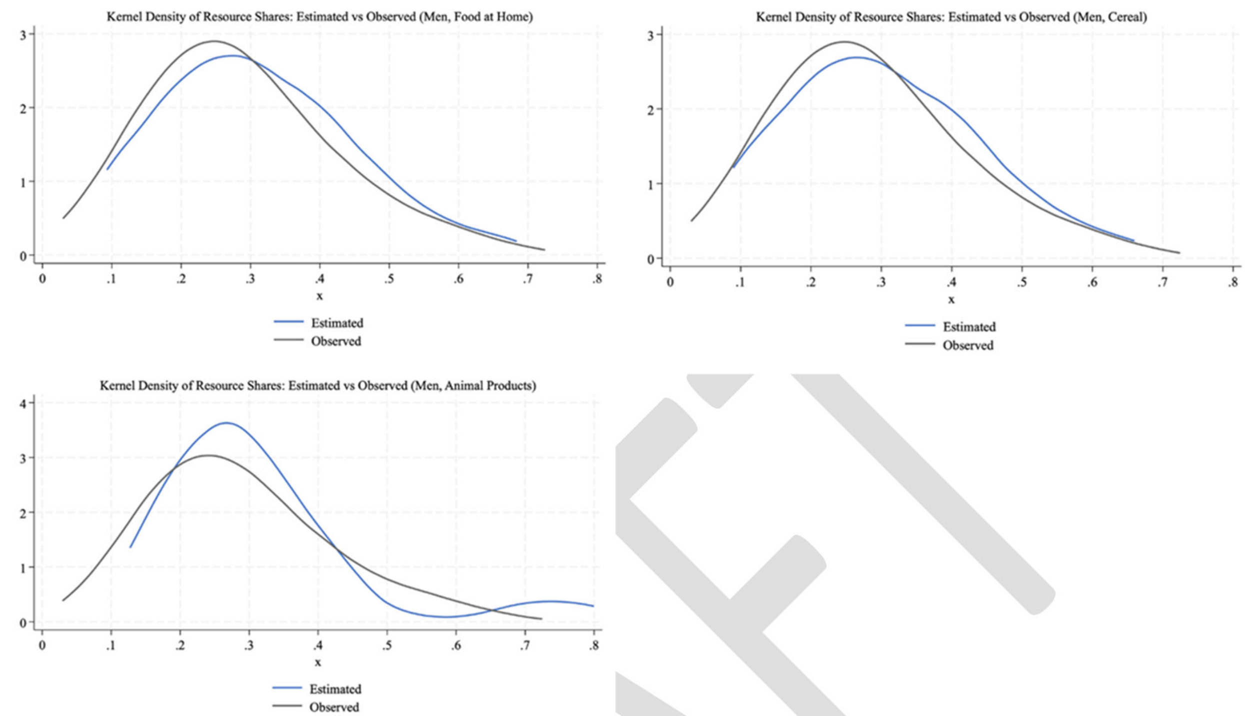
Note: Distribution of resource shares. The graphs illustrate the kernel density of predicted per-person resource shares.

Figure 5. Observed vs Estimated Resource Shares Using Assignable Food Categories



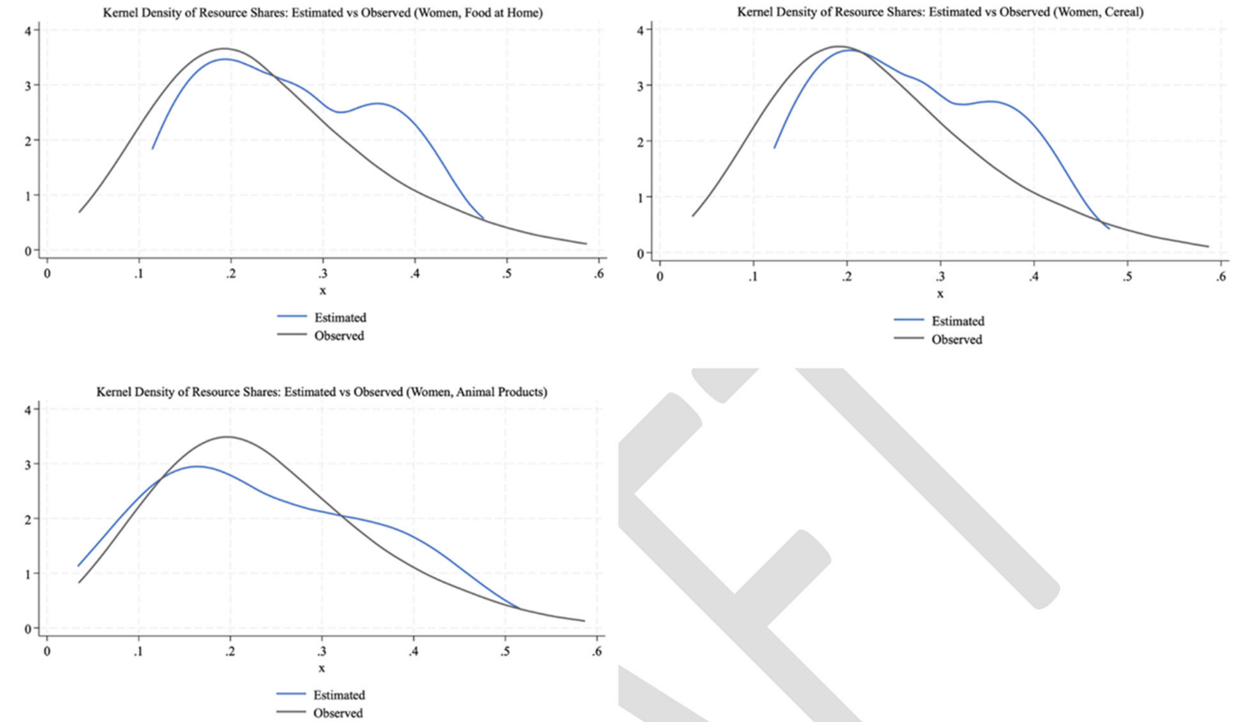
Notes: Bars show mean resource shares from the collective model (using food as the assignable good); whiskers are 95% confidence intervals. Observed shares come from fully individualized expenditure records..

Figure 6. Distribution of Observed vs Estimated Resource Shares Using Assignable Food, Men



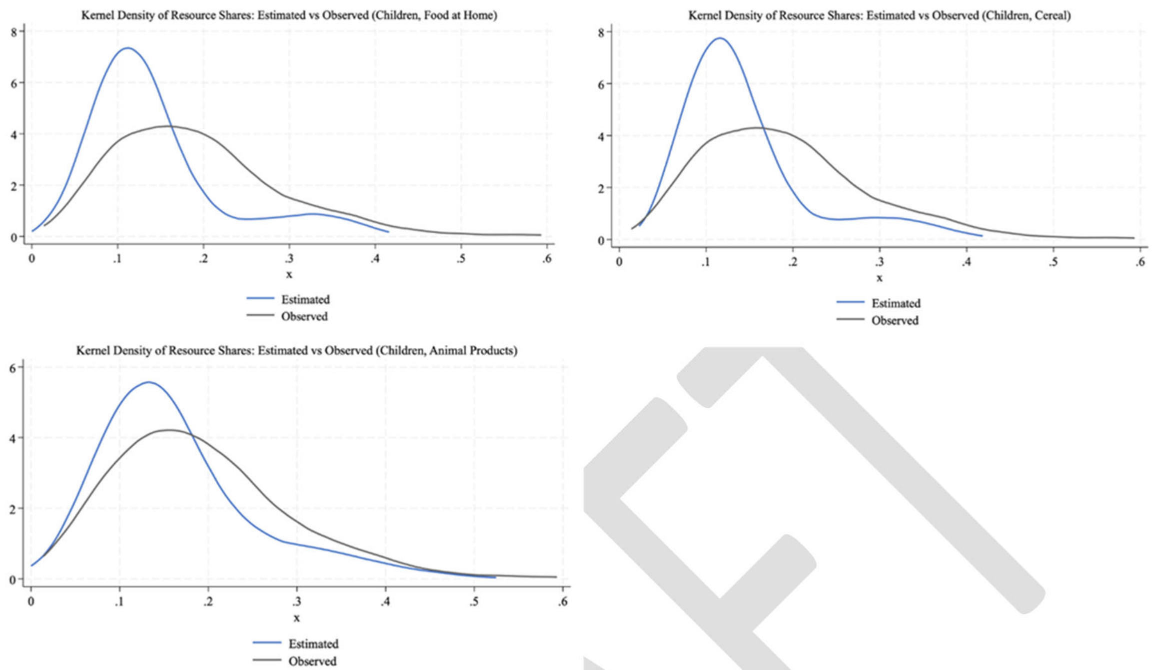
Note: Distribution of resource shares. The graphs illustrate the kernel density of predicted per-person resource shares.

Figure 7. Distribution of Observed vs Estimated Resource Shares Using Assignable Food, Women



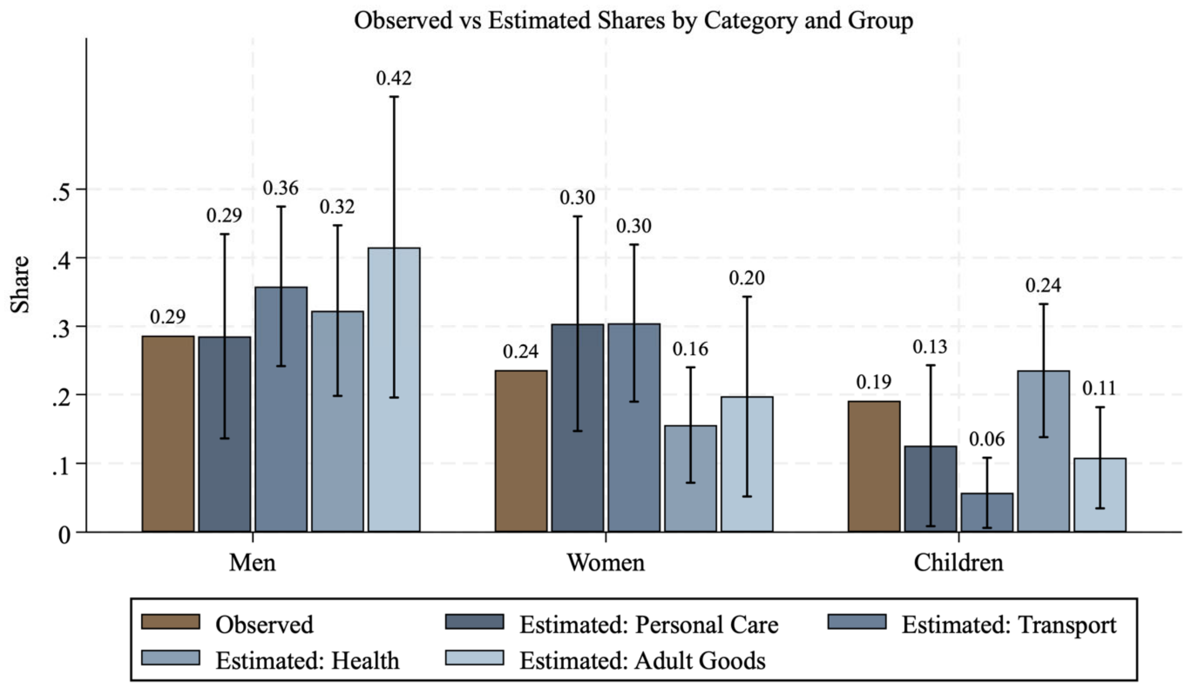
Note: Distribution of resource shares. The graphs illustrate the kernel density of predicted per-person resource shares.

Figure 8. Distribution of Observed vs Estimated Resource Shares Using Assignable Food, Children



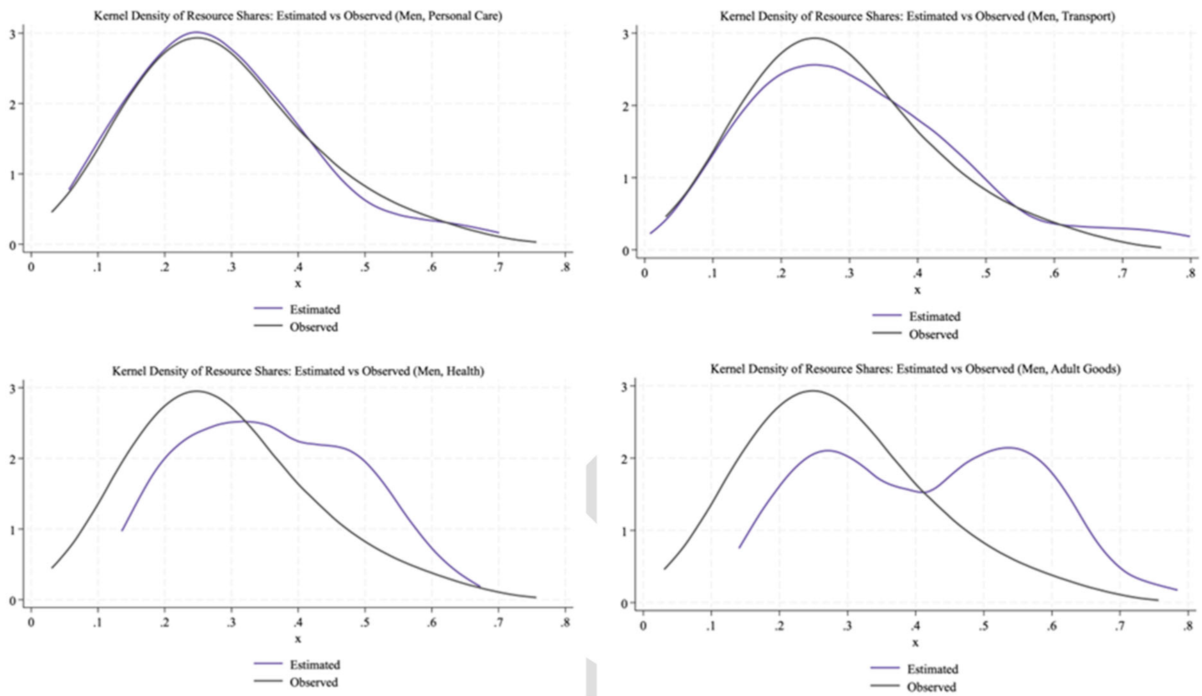
Note: Distribution of resource shares. The graphs illustrate the kernel density of predicted per-person resource shares.

Figure 9. Observed vs Estimated Resource Shares Using Other Expenditures



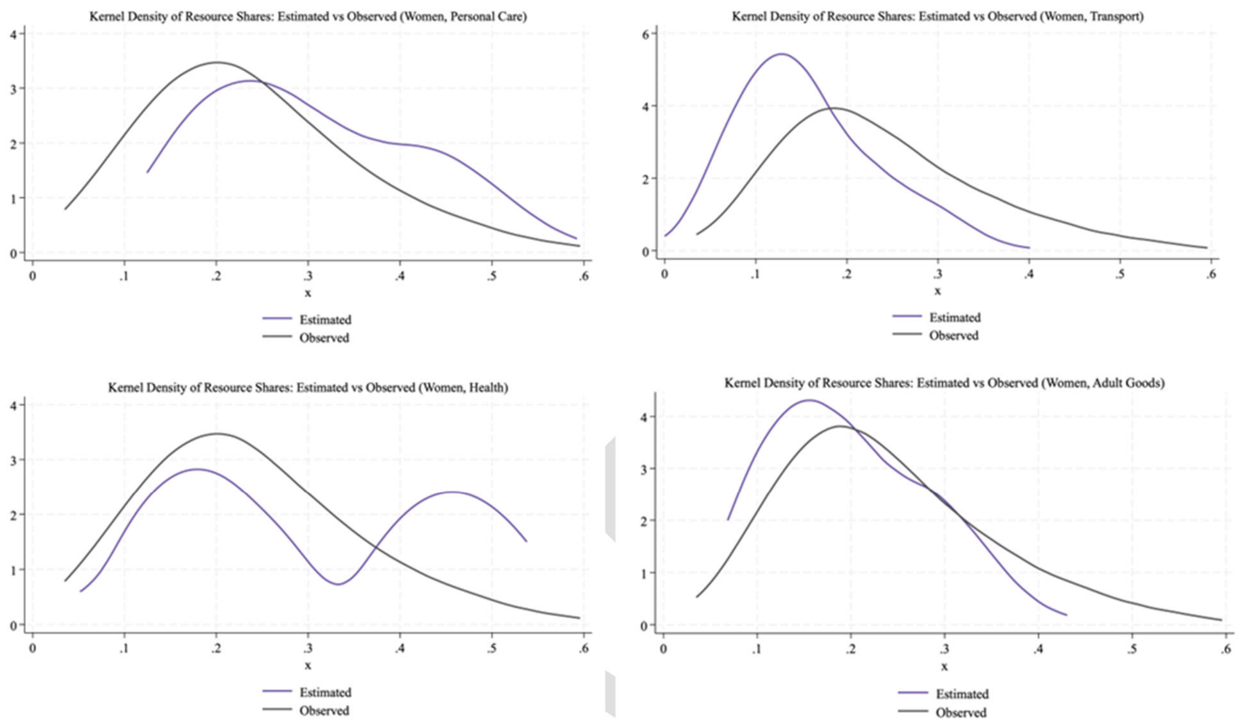
Notes: Bars show mean resource shares from the collective model (using other services as the assignable goods); whiskers are 95% confidence intervals. Observed shares come from fully individualized expenditure records.

Figure 10. Distribution of Observed vs Estimated Resource Shares Using Other Expenditures, Men



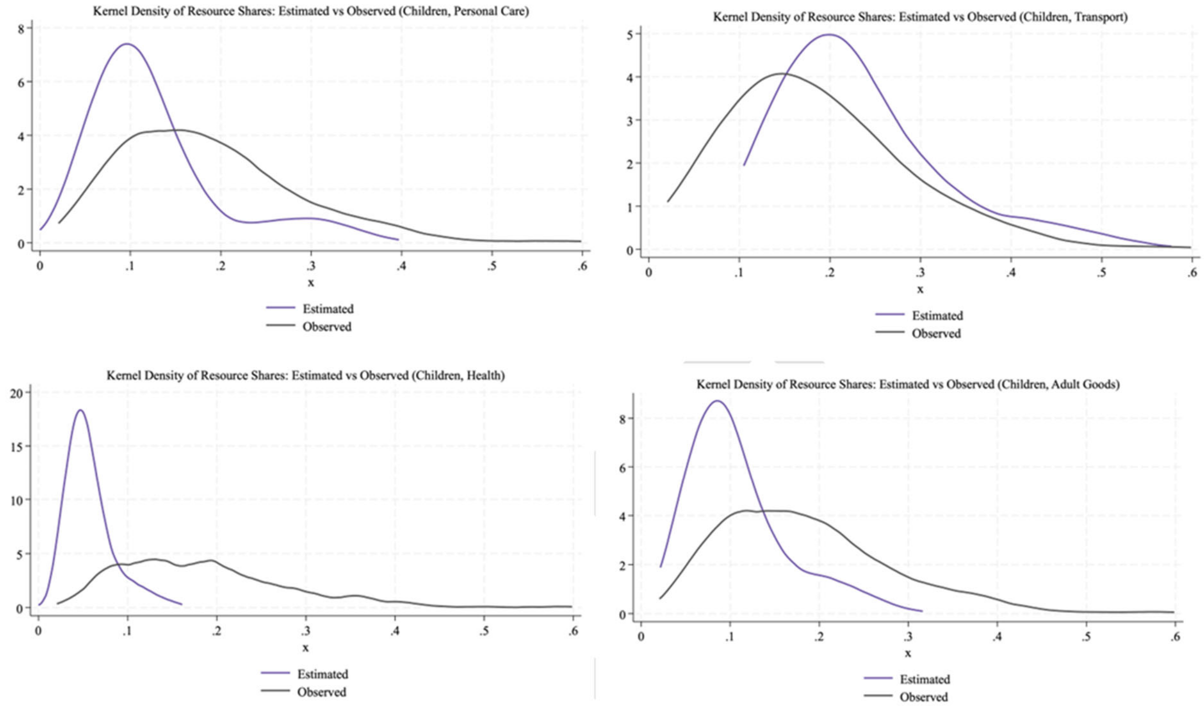
Note: Distribution of resource shares. The graphs illustrate the kernel density of predicted per-person resource shares.

Figure 11. Distribution of Observed vs Estimated Resource Shares Using Other Expenditures, Women



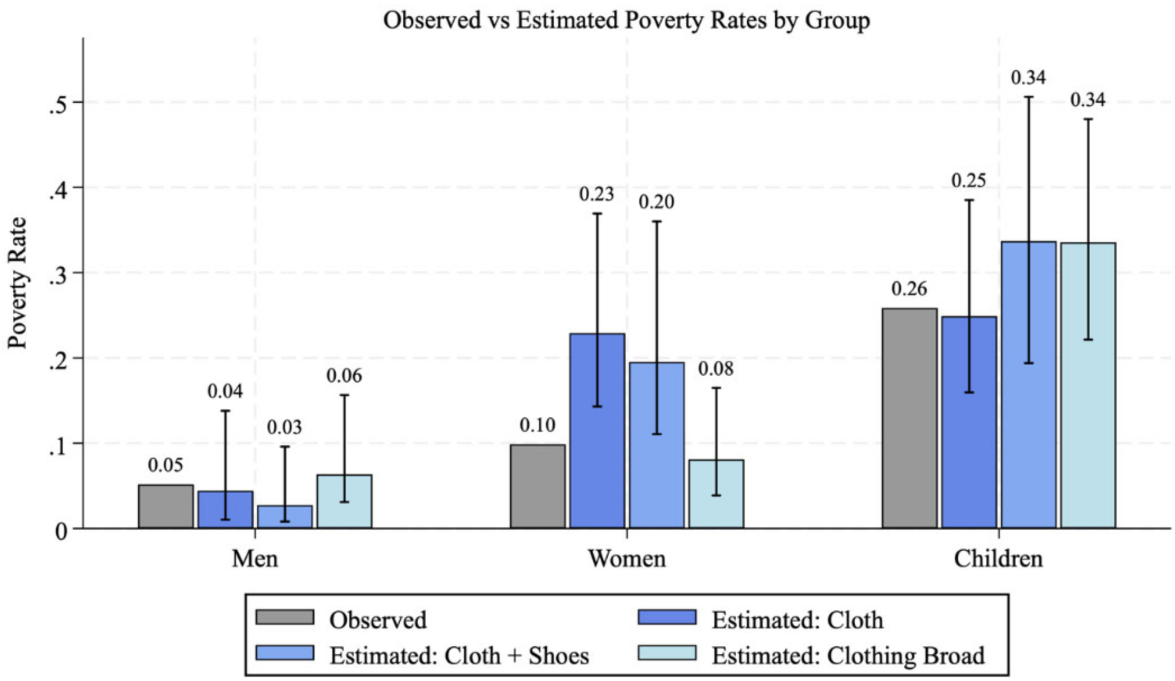
Note: Distribution of resource shares. The graphs illustrate the kernel density of predicted per-person resource shares.

Figure 12. Distribution of Observed vs Estimated Resource Shares Using Other Expenditures, Children



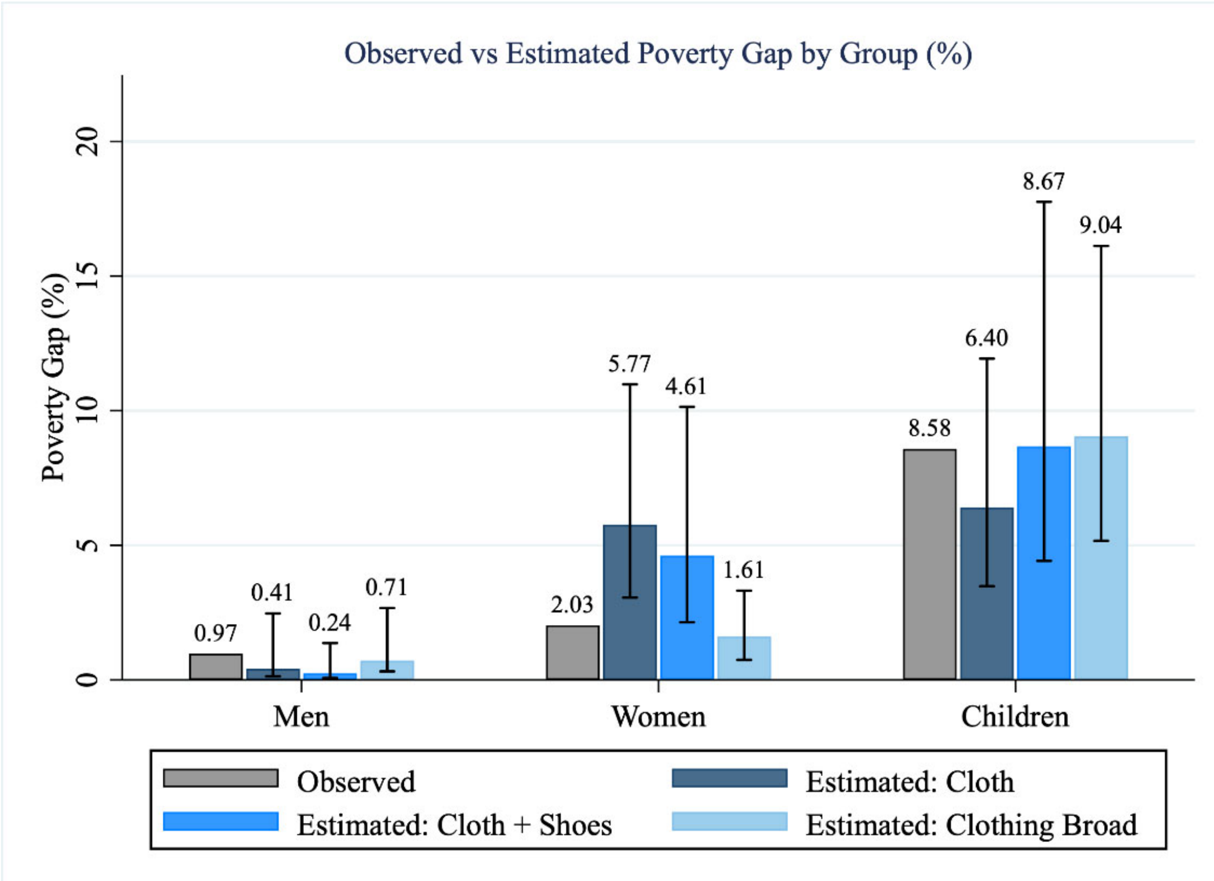
Note: Distribution of resource shares. The graphs illustrate the kernel density of predicted per-person resource shares.

Figure 13. Distribution of Observed vs Estimated Poverty Rates Using Assignable Clothing



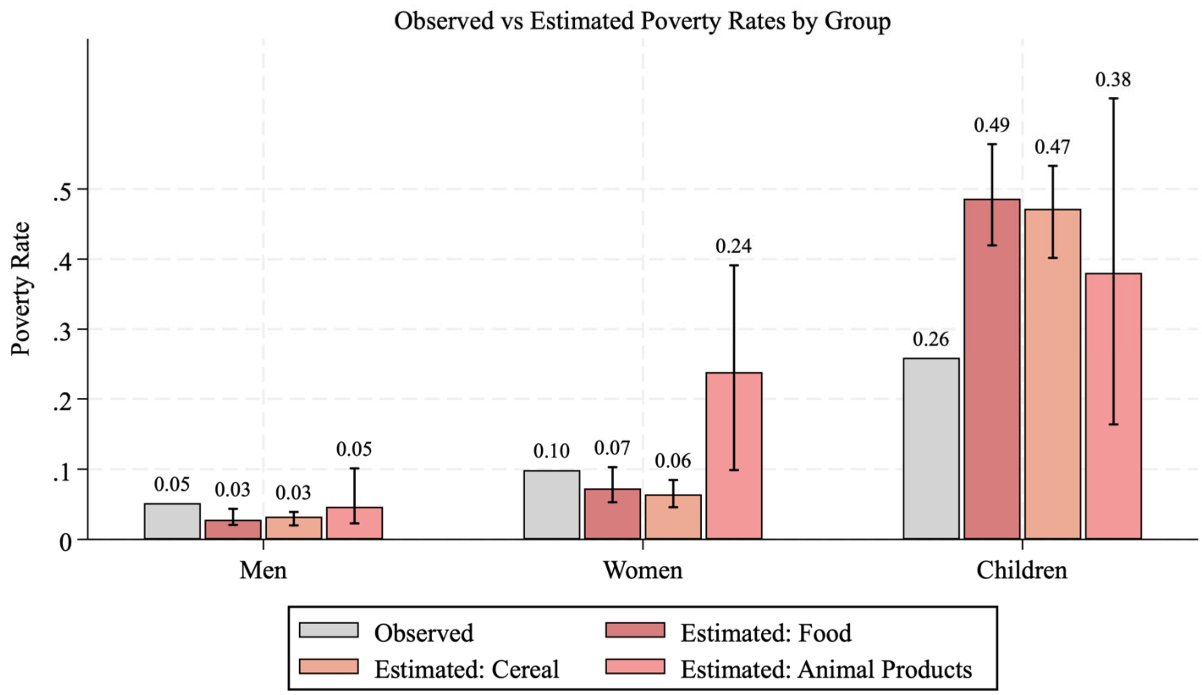
Note: Poverty lines correspond to 2.15$ (2017 US$ PPP per person per day) deflated to 2024. In per capita approach child needs are assumed equal to those of adults.

Figure 14. Distribution of Observed vs Estimated Poverty Gap Using Assignable Clothing



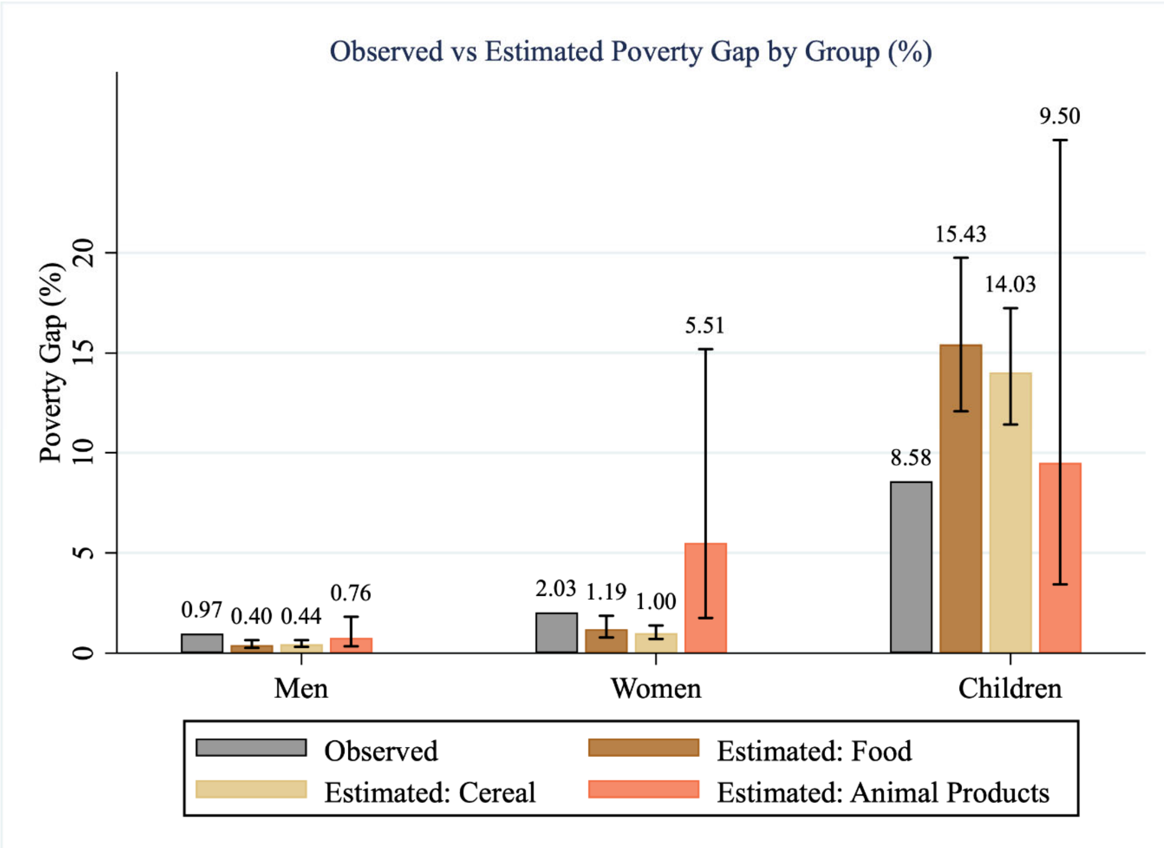
Note: Poverty lines correspond to 2.15$ (2017 US$ PPP per person per day) deflated to 2024. In per capita approach child needs are assumed equal to those of adults.

Figure 15. Distribution of Observed vs Estimated Poverty Rates Using Assignable Food



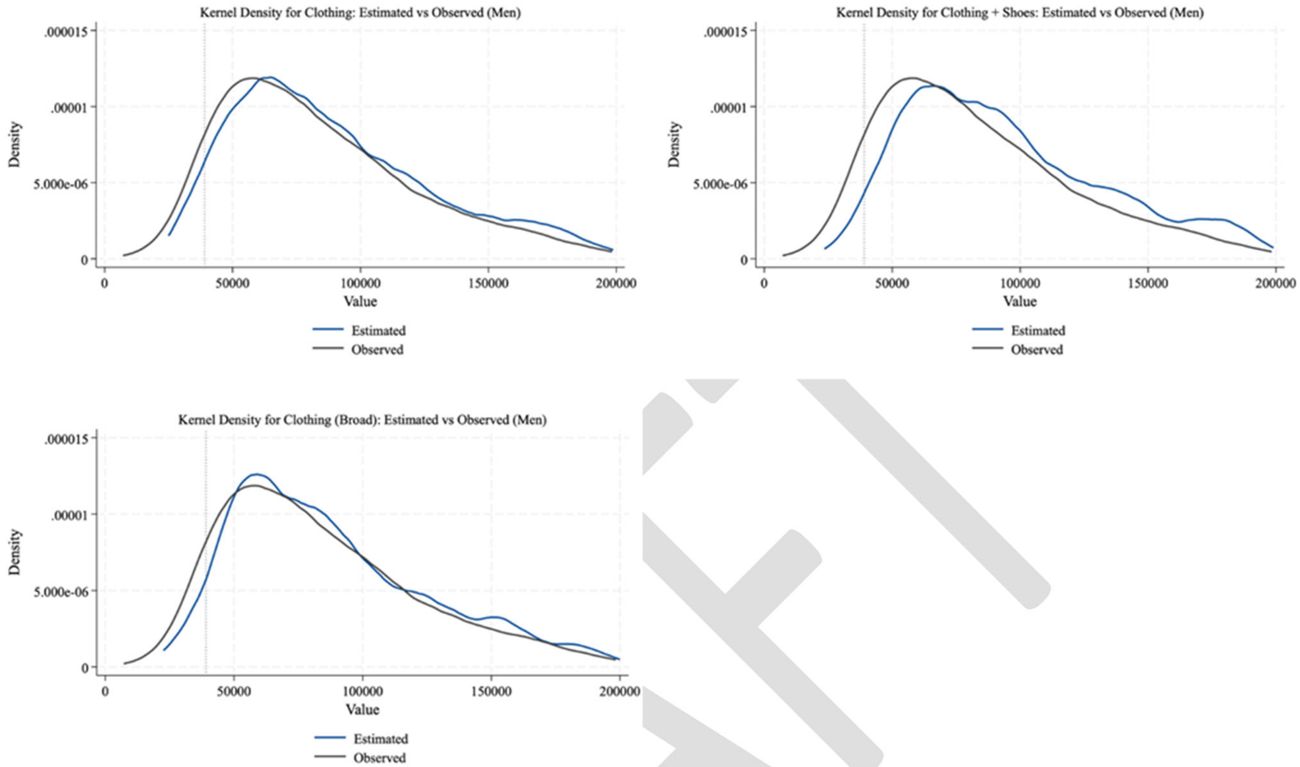
Note: Poverty lines correspond to 2.15$ (2017 US$ PPP per person per day) deflated to 2024. In per capita approach child needs are assumed equal to those of adults.

Figure 16. Distribution of Observed vs Estimated Poverty Gap Using Assignable Food



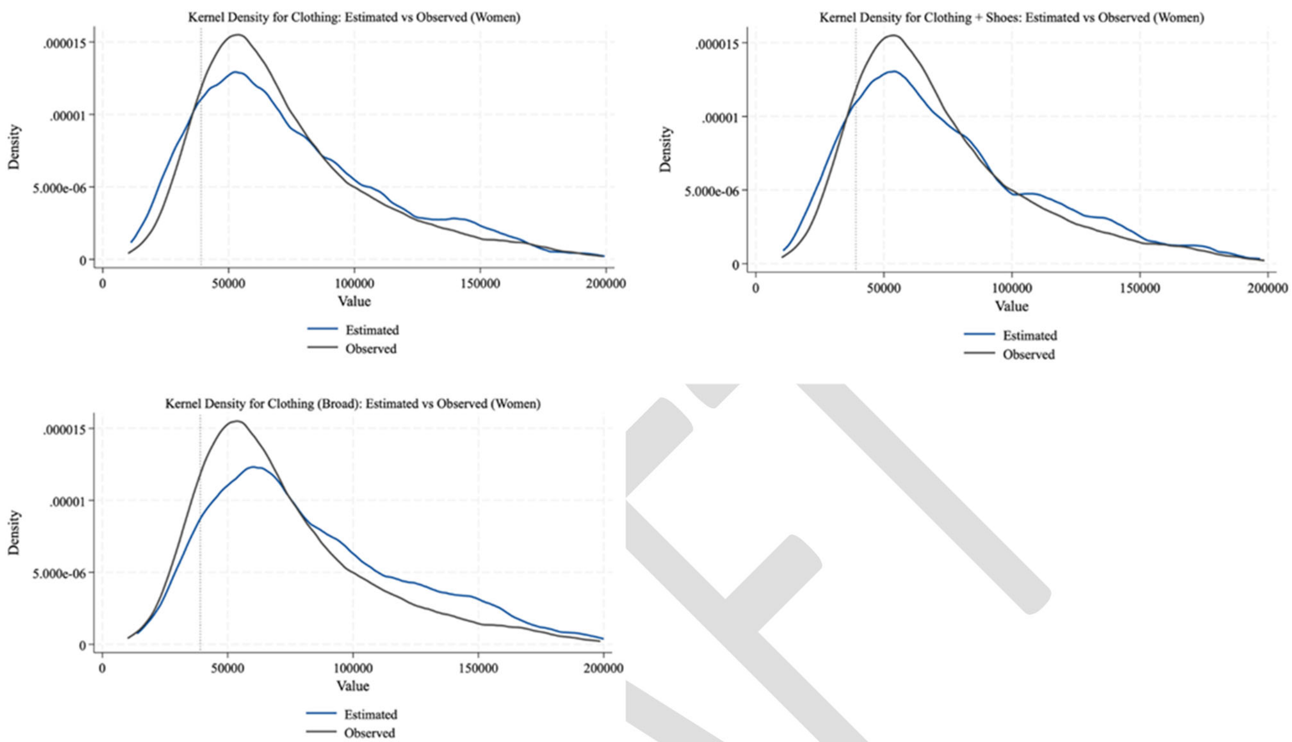
Note: Poverty lines correspond to 2.15$ (2017 US$ PPP per person per day) deflated to 2024. In per capita approach child needs are assumed equal to those of adults.

Figure 17. Distribution of Observed vs Estimated Consumption Using Assignable Clothing, Men



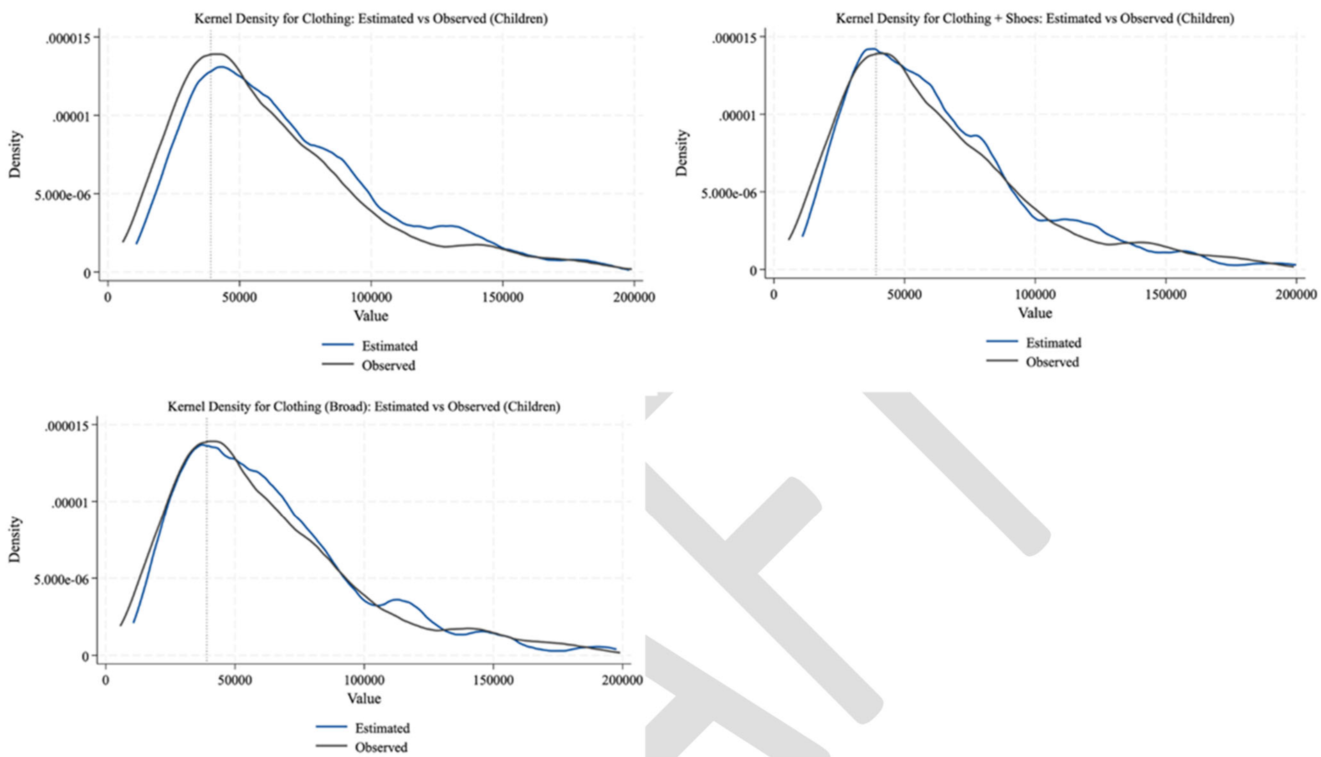
Note: Distribution of resource shares. The graphs illustrate the kernel density of predicted per-person resource shares.

Figure 18. Distribution of Observed vs Estimated Consumption Using Assignable Clothing, Women



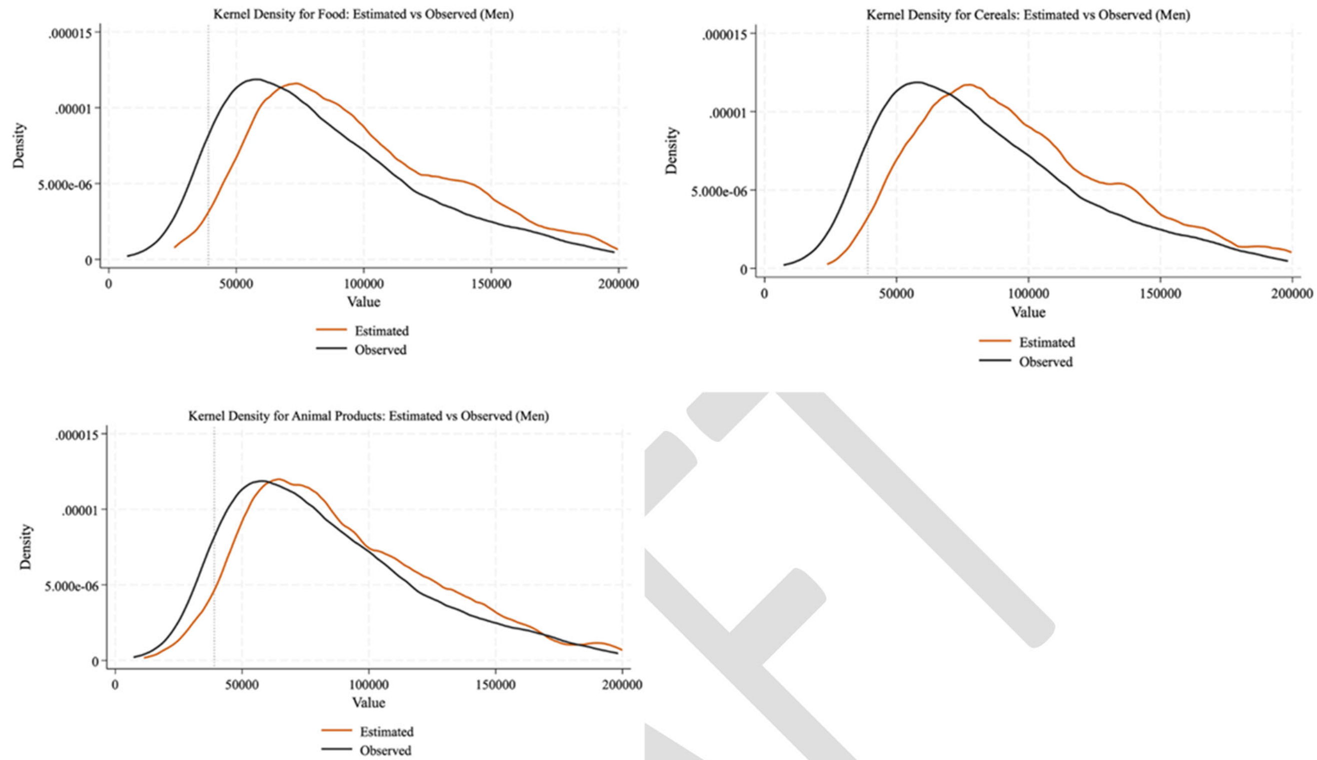
Note: Distribution of resource shares. The graphs illustrate the kernel density of predicted per-person resource shares.

Figure 19. Distribution of Observed vs Estimated Consumption Using Assignable Clothing, Children



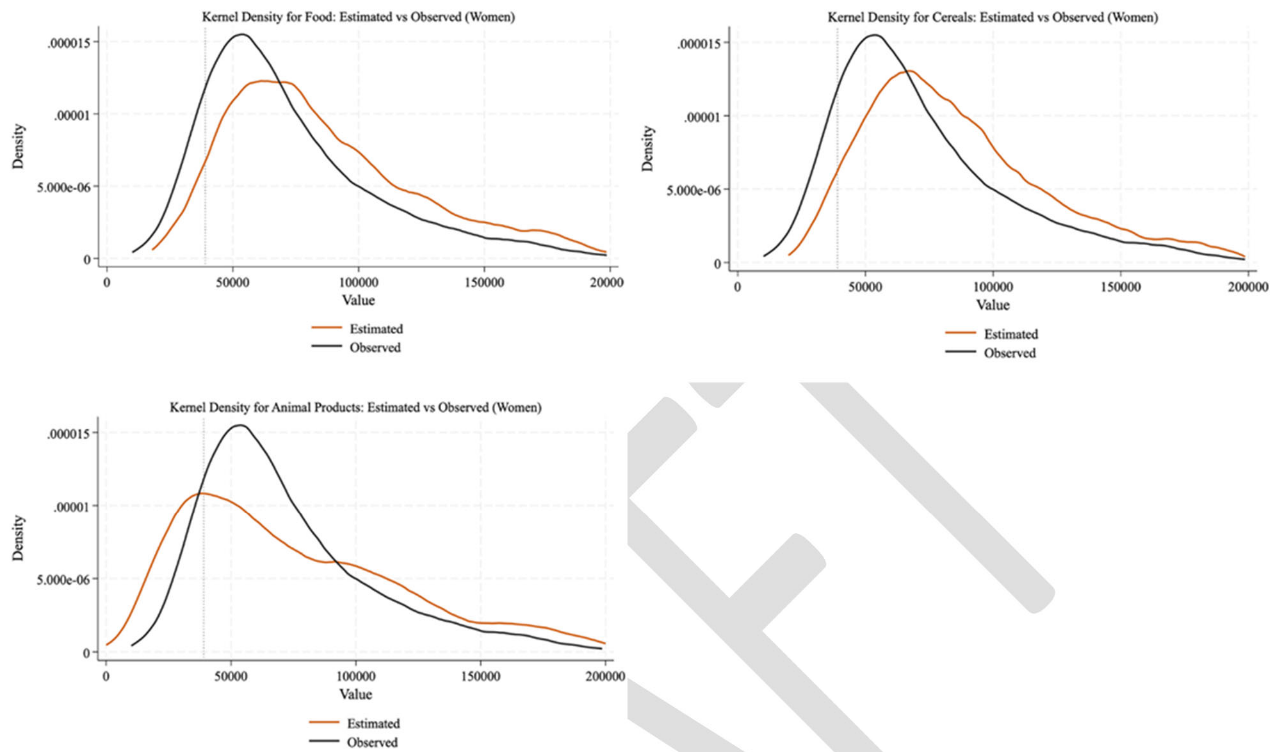
Note: Distribution of resource shares. The graphs illustrate the kernel density of predicted per-person resource shares.

Figure 20. Distribution of Observed vs Estimated Consumption Using Assignable Food, Men



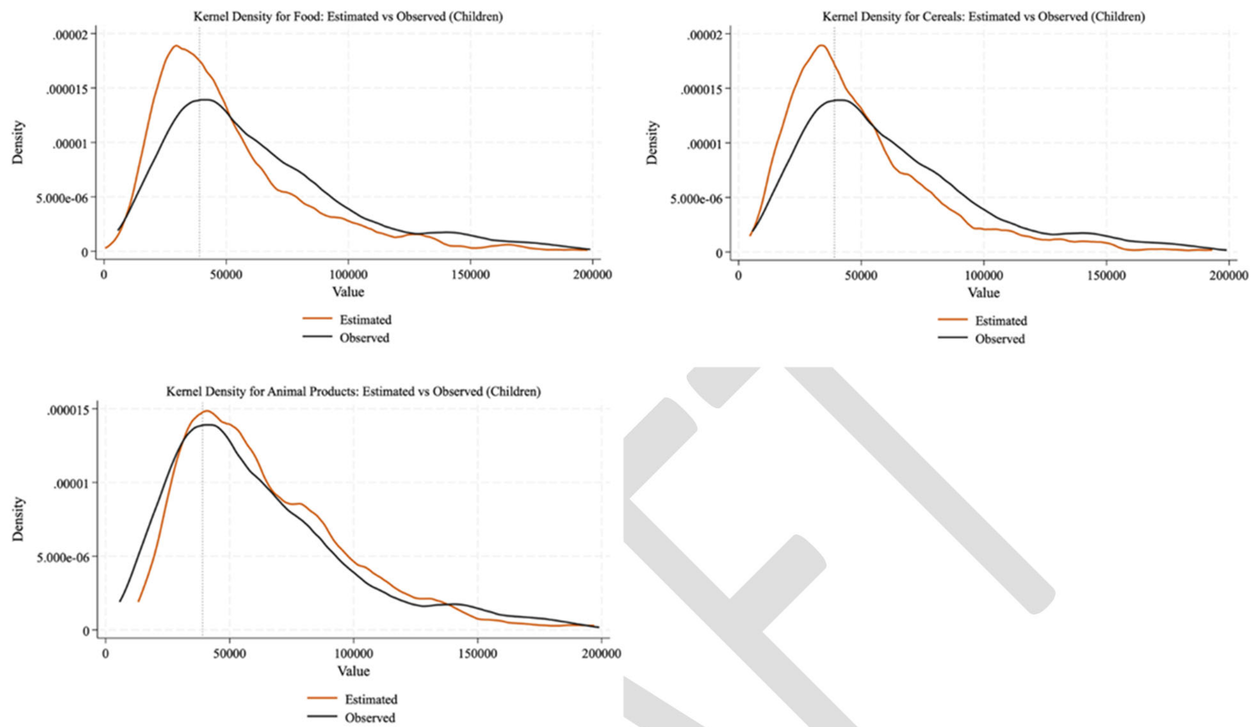
Note: Distribution of resource shares. The graphs illustrate the kernel density of predicted per-person resource shares.

Figure 21. Distribution of Observed vs Estimated Consumption Using Assignable Food, Women



Note: Distribution of resource shares. The graphs illustrate the kernel density of predicted per-person resource shares.

Figure 22. Distribution of Observed vs Estimated Consumption Using Assignable Food, Children



Note: Distribution of resource shares. The graphs illustrate the kernel density of predicted per-person resource shares.

Appendix A.

Table A.1. A Review of Country-Specific Resource Share Estimations

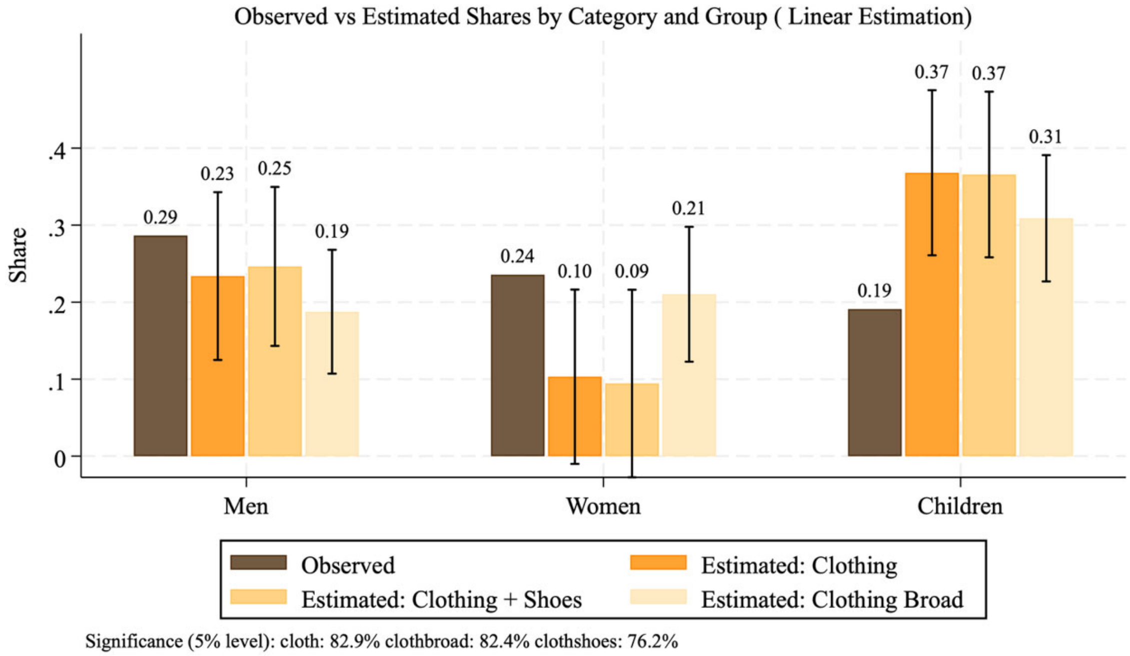
Authors	Country Year(s)	Method	Households	Assignable good(s)	Men	Women	Child	Gender ratio	Male–child ratio	Validation	Household type
Aminjonov et al. (2025)	Ghana 2016/17	DLP	7,756	Clothing	0.354	0.244	0.068	1.5	5.2	No	Couples with children
					0.425	0.315		1.3			Couples without children
	Malawi 2016/17	DLP	8,420	Clothing	0.299	0.287	0.149	1.0	2.0		Couples with children
					0.481	0.374		1.3			Couples without children
Bargain (2024)	Argentina 2017/18	DLP	14,670	Clothing	0.410	0.293	0.118	1.4	3.5	No	All couples
					0.373	0.255	0.140	1.5	2.7		Couples with 1 child
					0.366	0.266	0.097	1.4	3.8		Couples with 2 children
					0.312	0.229	0.068	1.4	4.6		Couples with 3 children
					0.446	0.323		1.4			Couples without children
	South Africa 2014/15	DLP	12,350	Clothing	0.319	0.287	0.175	1.1	1.8		All couples
					0.285	0.286	0.237	1.0	1.2		Couples with 1 child
					0.260	0.238	0.159	1.1	1.6		Couples with 2 children
					0.223	0.179	0.102	1.2	2.2		Couples with 3 children
					0.437	0.379		1.2			Couples without children
Bargain et al. (2022)*	Bangladesh 2004	DLP	701	Clothing	0.373	0.298	0.329	1.3	1.1	Yes	All household types
				Food							All household types
				Rice							All household types
				Protein							All household types
Calvi, Penglase, Tommasi & Wolf (2023)	Mexico 2018	DLP	35,056	Clothing	0.289	0.336	0.159	0.9	1.8	No	All household types
	Bangladesh 2011 & 2015	DLP	6,442	Food	0.335	0.258	0.247	1.3	1.4		All household types
Lechene, Pendakur & Wolf (2022)	Albania 2008	LPW	3,279	Clothing	0.282	0.247	0.134	1.1	2.1	No	All household types
	Bangladesh 2015	LPW	6,120	Clothing	0.312	0.286	0.120	1.1	2.6		All household types
	Bangladesh 2015	LPW	4,990	Food	0.309	0.256	0.174	1.2	1.8		All household types
	Bulgaria 2003	LPW	2,099	Clothing	0.304	0.372	0.188	0.8	1.6		All household types
	Iraq 2007	LPW	13,935	Clothing	0.249	0.210	0.045	1.2	5.5		All household types
	Malawi 2011	LPW	10,873	Clothing	0.312	0.274	0.124	1.1	2.5		All household types
Calvi (2020)	India 2011	DLP	84,380	Clothing	0.470	0.3161	0.214	1.5	2.2	No	All household types
Bandyopadhyay & Maity (2023)	India 2011	LPW	47,976	Clothing	0.522	0.324	0.153	1.6	3.4	No	Men, women, and children
		LPW	22,568	Clothing	0.641	0.357		1.8			Men and women
Iglesias & Coelho (2020)	Brazil 2008	DLP	9,771	Clothing	0.411	0.388	0.201	1.1	2.0	No	Couples with 1 child
					0.372	0.363	0.265	1.0	1.4		Couples with 2 children
					0.333	0.364	0.304	0.9	1.1		Couples with 3 children
					0.526	0.474		1.1			Couples without children
van der Merwe (2025)	Ethiopia 2019	LPW	5,250	Clothing	0.284	0.238	0.181	1.2	1.6	No	All household types
	Ghana 2016	LPW	9,736	Clothing	0.185	0.220	0.219	0.8	0.8		All household types
	Malawi 2019	LPW	10,092	Clothing	0.250	0.282	0.159	0.9	1.6		All household types
	Nigeria 2019	LPW	3,822	Clothing	0.104	0.249	0.209	0.4	0.5		All household types

Note: DLP = Dunbar, Lewbel, Pendakur (2013); LPW = Lechene, Pendakur, Wolf (2022). Gender ratio = Men/Women; Male–child ratio = Men/Child.

Authors	Country Year(s)	Method	Households	Assignable good(s)	Men	Women	Child	Gender ratio	Male–child ratio	Validation	Household type
Aminjonov, Bargain & Colacce (2025)	Albania 2005	DLP	2,603	Clothing	0.297	0.292	0.043	1.0	6.9	No	All household types
	Angola 2018	DLP	7,329	Clothing	0.346	0.267	0.101	1.3	3.4	No	All household types
	Argentina 2018	DLP	20,946	Clothing	0.240	0.226	0.150	1.1	1.6	No	All household types
	Bangladesh 2015	DLP	3,171	Clothing	0.293	0.263	0.122	1.1	2.4	No	All household types
	Benin 2018	DLP	3,893	Clothing	0.422	0.256	0.058	1.6	7.3	No	All household types
	Bolivia 2019	DLP	11,044	Clothing	0.346	0.250	0.087	1.4	4.0	No	All household types
	Brazil 2017	DLP	53,681	Clothing	0.349	0.237	0.127	1.5	2.7	No	All household types
	Bulgaria 2007	DLP	2,690	Clothing	0.314	0.335	0.055	0.9	5.7	No	All household types
	Burkina Faso 2014	DLP	7,090	Clothing	0.341	0.196	0.031	1.7	11.0	No	All household types
	Chile 2017	DLP	14,497	Clothing	0.209	0.225	0.228	0.9	0.9	No	All household types
	Colombia 2017	DLP	81,936	Clothing	0.351	0.237	0.059	1.5	5.9	No	All household types
	Costa Rica 2018	DLP	4,863	Clothing	0.233	0.276	0.148	0.8	1.6	No	All household types
	Cote d'Ivoire 2002	DLP	7,097	Clothing	0.298	0.210	0.053	1.4	5.6	No	All household types
	Ecuador 2011	DLP	37,059	Clothing	0.351	0.177	0.094	2.0	3.7	No	All household types
	Ethiopia 2015	DLP	4,052	Clothing	0.268	0.254	0.099	1.1	2.7	No	All household types
	Gambia 2015	DLP	11,130	Clothing	0.249	0.195	0.036	1.3	6.9	No	All household types
	Georgia 2019	DLP	9,769	Clothing	0.303	0.183	0.097	1.7	3.1	No	All household types
	Ghana 2017	DLP	6,204	Clothing	0.383	0.225	0.094	1.7	4.1	No	All household types
	Guinea-Bissau 2018	DLP	2,873	Clothing	0.256	0.189	0.036	1.4	7.1	No	All household types
	India 2011	DLP	72,189	Clothing	0.283	0.242	0.097	1.2	2.9	No	All household types
	Iraq 2012	DLP	11,346	Clothing	0.356	0.249	0.033	1.4	10.8	No	All household types
	Kenya 2015	DLP	16,817	Clothing	0.309	0.239	0.088	1.3	3.5	No	All household types
	Madagascar 2012	DLP	8,927	Clothing	0.315	0.288	0.111	1.1	2.8	No	All household types
	Malawi 2016	DLP	9,678	Clothing	0.304	0.268	0.120	1.1	2.5	No	All household types
	Mali 2014	DLP	1,353	Clothing	0.272	0.241	0.038	1.1	7.2	No	All household types
	Mexico 2018	DLP	63,195	Clothing	0.241	0.309	0.119	0.8	2.0	No	All household types
	Mongolia 2016	DLP	9,046	Clothing	0.461	0.294	0.043	1.6	10.7	No	All household types
	Morocco 2013	DLP	12,031	Clothing	0.294	0.283	0.033	1.0	8.9	No	All household types
	Namibia 2015	DLP	4,639	Clothing	0.346	0.311	0.044	1.1	7.9	No	All household types
	Niger 2014	DLP	1,733	Clothing	0.368	0.244	0.060	1.5	6.1	No	All household types
	Nigeria 2019	DLP	3,262	Clothing	0.329	0.264	0.050	1.2	6.6	No	All household types
	Pakistan 2015	DLP	17,412	Clothing	0.289	0.197	0.056	1.5	5.2	No	All household types
	Panama 2008	DLP	8,480	Clothing	0.203	0.266	0.124	0.8	1.6	No	All household types
	Paraguay 2011	DLP	5,274	Clothing	0.298	0.249	0.056	1.2	5.3	No	All household types
	Rwanda 2016	DLP	12,575	Clothing	0.324	0.279	0.085	1.2	3.8	No	All household types
	Senegal 2018	DLP	2,260	Clothing	0.276	0.191	0.059	1.4	4.7	No	All household types
	Serbia 2007	DLP	3,149	Clothing	0.283	0.281	0.053	1.0	5.3	No	All household types
	Sierra Leone 2011	DLP	6,109	Clothing	0.256	0.250	0.073	1.0	3.5	No	All household types
	South Africa 2014	DLP	8,838	Clothing	0.305	0.197	0.128	1.5	2.4	No	All household types
	Tajikistan 2009	DLP	974	Clothing	0.209	0.174	0.055	1.2	3.8	No	All household types
	Tanzania 2014	DLP	2,433	Clothing	0.406	0.249	0.044	1.6	9.2	No	All household types
	Timor-Leste 2007	DLP	2,492	Clothing	0.322	0.279	0.065	1.2	5.0	No	All household types
	Uganda 2015	DLP	2,432	Clothing	0.308	0.257	0.066	1.2	4.7	No	All household types
	Uruguay 2016	DLP	4,262	Clothing	0.265	0.210	0.221	1.3	1.2	No	All household types
	West Bank & Gaza 2016	DLP	2,212	Clothing	0.289	0.279	0.093	1.0	3.1	No	All household types

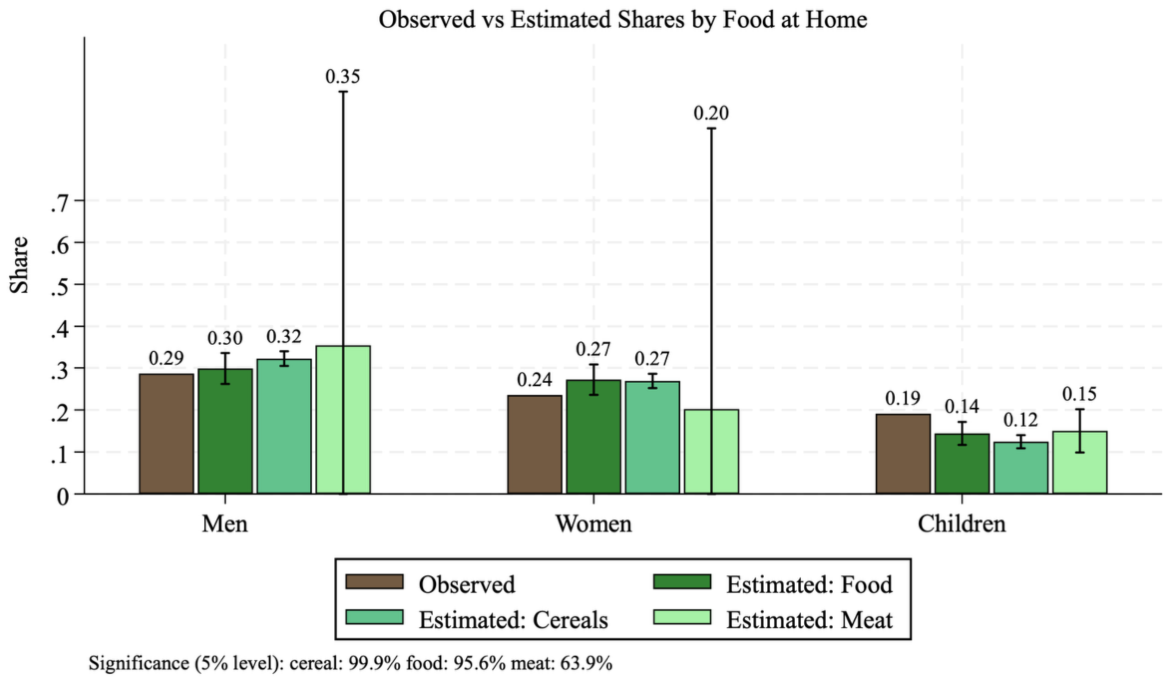
Note: DLP = Dunbar, Lewbel, Pendakur (2013); LPW = Lechene, Pendakur, Wolf (2022). Gender ratio = Men/Women; Male–child ratio = Men/Child.

Figure A.1. Observed vs Estimated Resource Shares Using Clothing Categories as an Assignable Good



Notes: Bars show mean resource shares from the collective model (using clothing as the assignable good); whiskers are 95% confidence intervals. Model predictions are evaluated at sample-mean covariates and then averaged across households. Observed shares come from fully individualized expenditure records.

Figure A.2. Observed vs Estimated Resource Shares Using Food Categories as Assignable



Notes: Bars show mean resource shares from the collective model (using clothing as the assignable good); whiskers are 95% confidence intervals. Model predictions are evaluated at sample-mean covariates and then averaged across households. Observed shares come from fully individualized expenditure records.

Figure A.3. Distribution of Observed vs Estimated Squared Poverty Gap Using Assignable Clothing

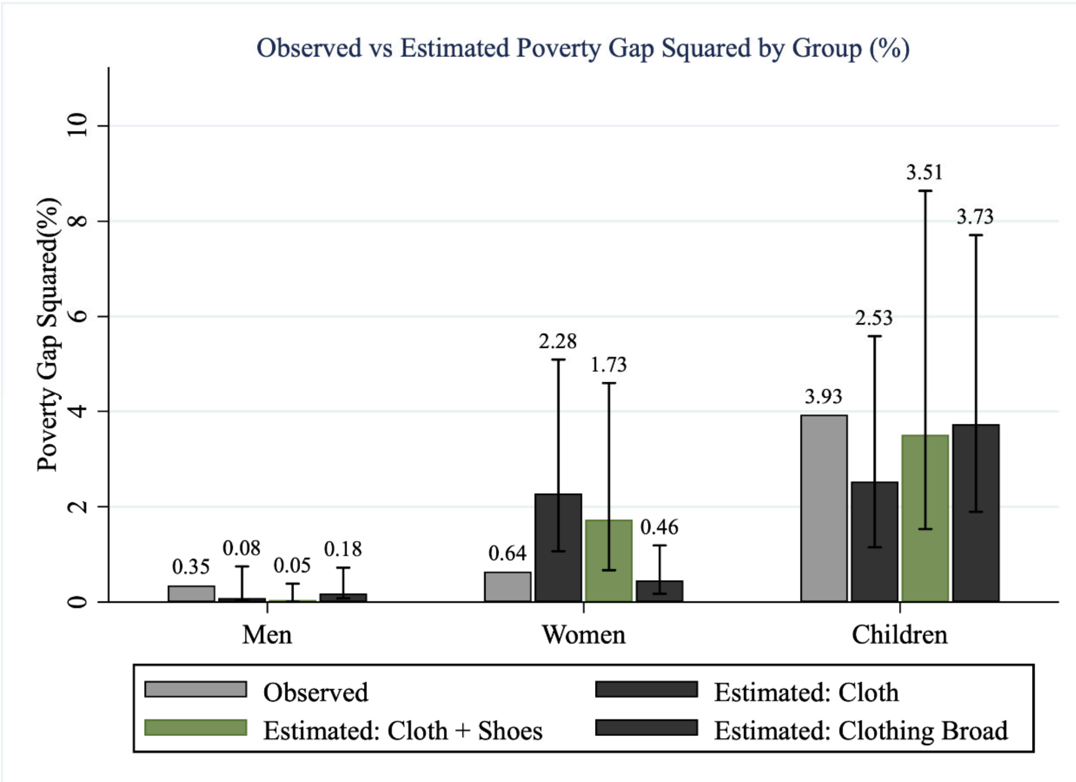


Figure A.4. Distribution of Observed vs Estimated Squared Poverty Gap Using Assignable Food

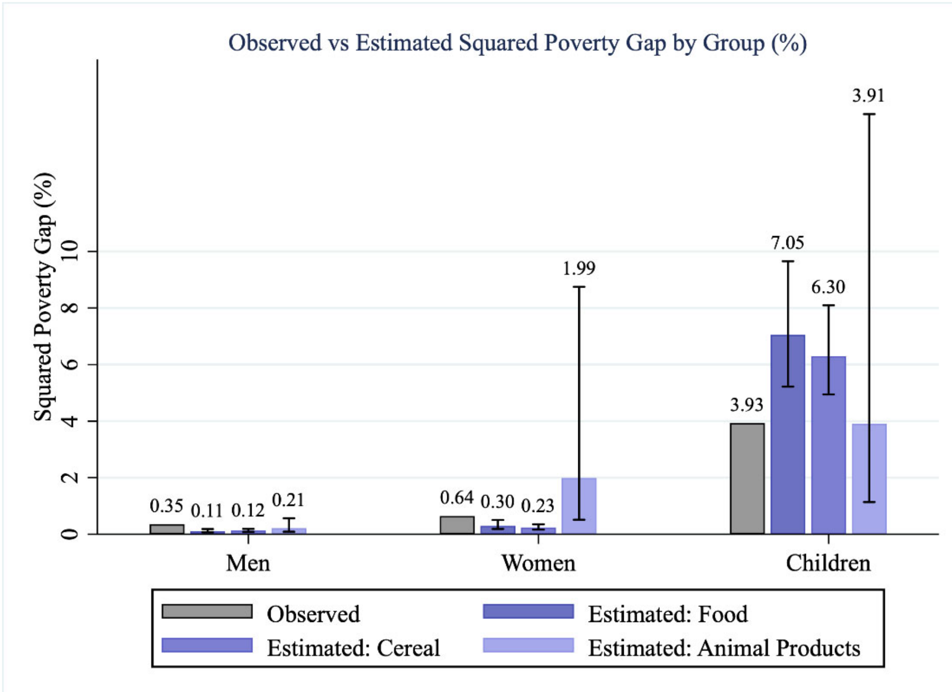


Figure A.5. Distribution of Observed vs Estimated Poverty Rates Using Assignable Services and Other Goods

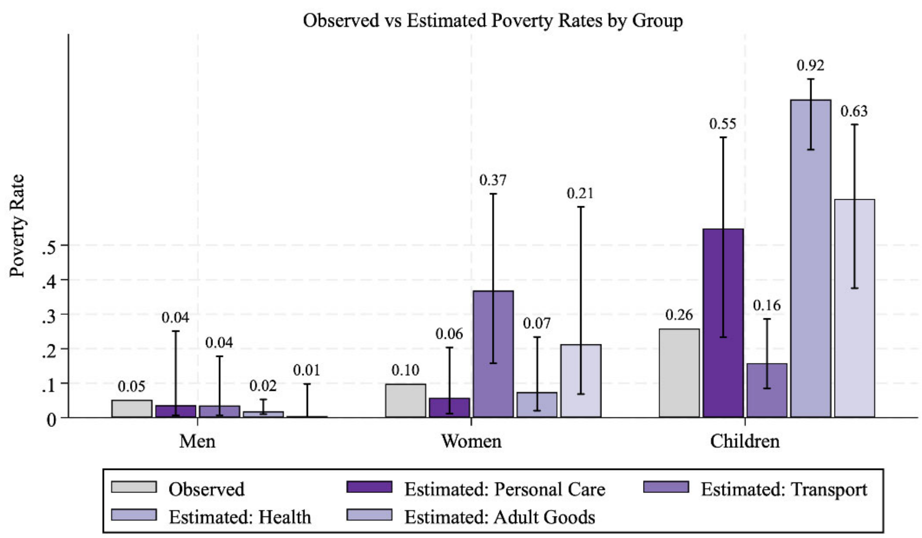


Figure A.6. Distribution of Observed vs Estimated Poverty Gap Using Assignable Services and Other Goods

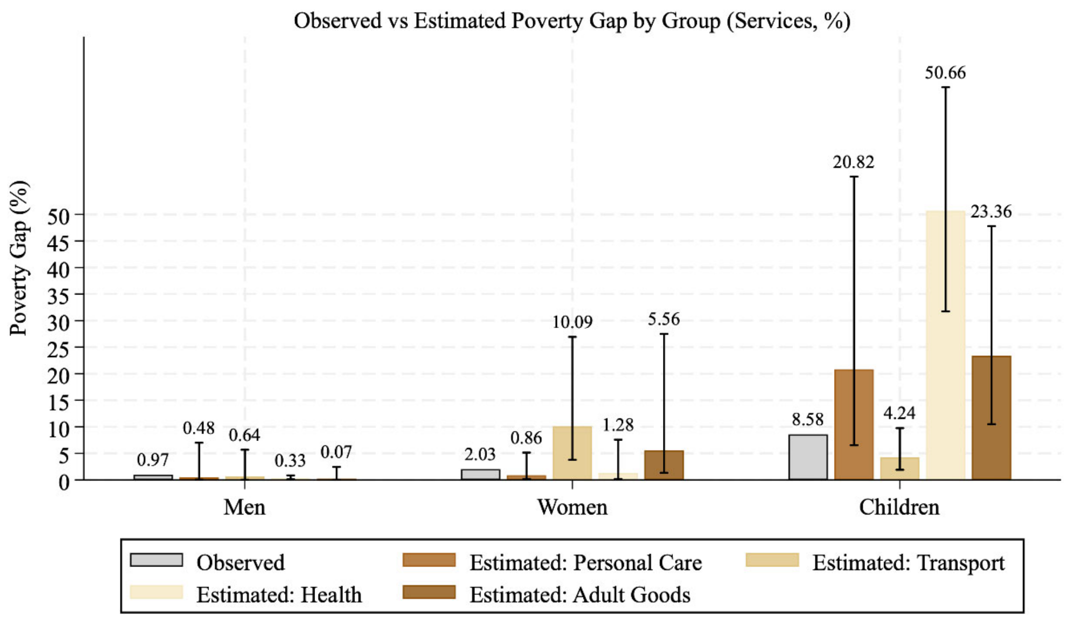


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Figure A.7. Distribution of Observed vs Estimated Squared Poverty Gap Using Assignable Services and Other Goods