



# Intrahousehold allocation of public and private goods: Evidence from Bangladesh

Presented by Amparo Palacios-Lopez

Joint work with Isis Gaddis, Josefina Durazo, Kseniya Abanokova, Rosella Calvi, Tanmay Devi

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# Motivation 1

- Traditionally poverty is measured at the individual level, however, household surveys record total household expenditure, not individual consumption (Newhouse, 2017; Boudet et al., 2021)
- Traditional measures ignore intrahousehold inequality, masking large gender and age gaps (Brown et al., 2019; De Vreyer and Lambert, 2021; Brown et al., 2021; Bargain et al., 2022; Calvi et al., 2023; Dunbar et al., 2013; De Vreyer and Lambert, 2021)
- Misrepresenting individual poverty can distort targeting and redistribution policies (Brown et al., 2019; Liang et al., 2024)
- Individual-level consumption data are costly and rare—mostly available in high-income countries, with only a few exceptions in low-income settings (e.g., Senegal (Lambert et al., 2021), Bangladesh (Bargain et al., 2022))



# Motivation 2

- In the absence of individual-level consumption data, structural collective models are used to infer intrahousehold resource allocation (Lewbel and Pendakur, 2008; Bargain and Donni, 2012; Dunbar et al., 2013)
- The accuracy of model-based predictions across the full consumption basket remains uncertain
- Private assignable goods are central for identifying resource shares, but their inclusion is limited in most household surveys
- Resource share estimates are sensitive to the choice of assignable goods (Van Leeuwen et al., 2021; Bargain et al., 2022; Calvi et al., 2023), yet only one prior study has validated model-based predictions with individualized consumption data (Bargain et al., 2022)

# Contribution

- We provide one of the few validation exercises of widely used collective models using highly individualized consumption data
- We evaluate predictions from a broad set of assignable goods, moving beyond the narrow focus on clothing, footwear, or food in previous literature
- We provide the first validation of the linear estimation method proposed by Lechene, Pendakur, and Wolf (2022), which simplifies computation relative to nonlinear collective models
- We assess model performance both at the mean and across the entire distribution, highlighting important limitations
- We compare predicted and observed poverty measures, extending analysis beyond headcount to poverty gap and squared poverty gap

# Results

- 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.
- 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.
  - clothing expenditures provide the most reliable estimates for estimating resource shares across all groups
  - food expenditures yield reliable resource share estimates only for adults. 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 find that predictions of headcount poverty, gap, and squared gap are sensitive to the choice of assignable good.
  - clothing emerges as the most reliable, though accurate estimates for women require individualized rather than aggregated clothing data

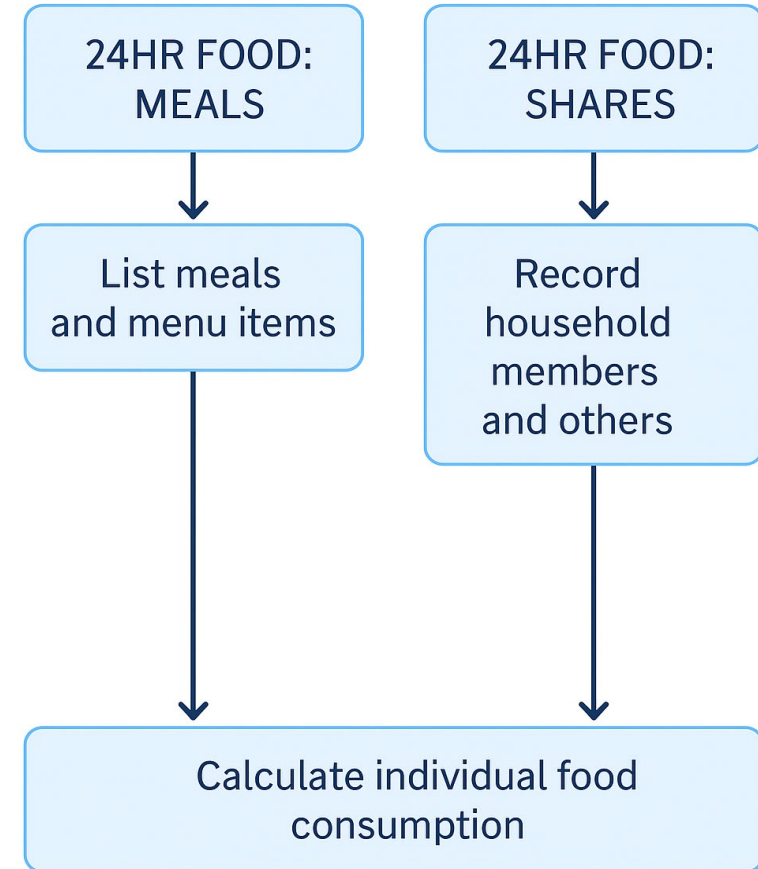
# Data

- World Bank's Bangladesh Individual Consumption Study (BICS)
- **Sample:** 1,000 households surveyed in May–June 2024 across three divisions (Rangpur, Khulna, Mymensingh), covering both rural and urban areas.
- **Eligibility:** Households included at least one married couple with both partners aged 18–66.
- **Respondents:** All adult members targeted for self-reporting; proxy responses accepted only after repeated unsuccessful attempts.
- Collected detailed information on demographics, education, economic activities, and food/non-food expenditures; household heads reported socioeconomic characteristics.



# Food consumption expenditures

- **At-home food:** Household-level 7-day recall of detailed food items, supplemented with member-specific consumption for selected items.
- **Individual intake:** Single-day 24-hour recall with food weighing, used to calculate individual food shares and allocate total household food expenditures.
- **Away-from-home food:** Weekly data on meals outside the household (restaurants, stalls, relatives/friends), including frequency, sharing arrangements, and expenditures.



# Non-food consumption expenditures

Frequent non-durables: 7-day recall of individual expenditures on items like transport, mobile credit, tobacco, personal care, and entertainment, including who paid and who used.

Regular and seasonal items: 30-day recall for shared and individual goods (e.g., electricity, soap, cosmetics) and 12-month recall for infrequent expenses (e.g., furniture, education, health, housing repairs, ceremonies).

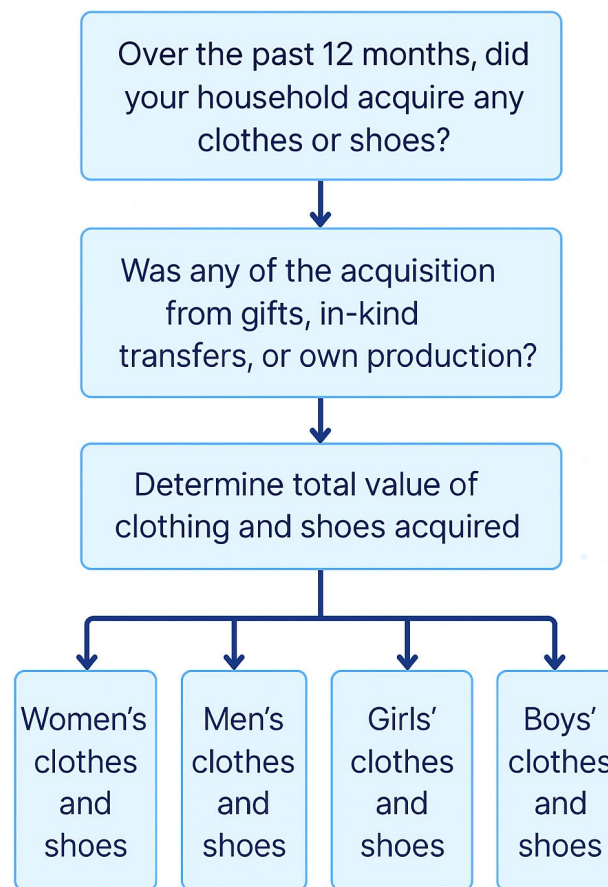
**Allocation rules: Items classified as individually assigned, equally shared among members, or shared at dwelling level.**

Assets and housing: Collected detailed information on asset ownership (durables, appliances, transport) and dwelling use, including ownership, value, and member-specific usage; room-level reporting enabled construction of individual-level housing consumption values.

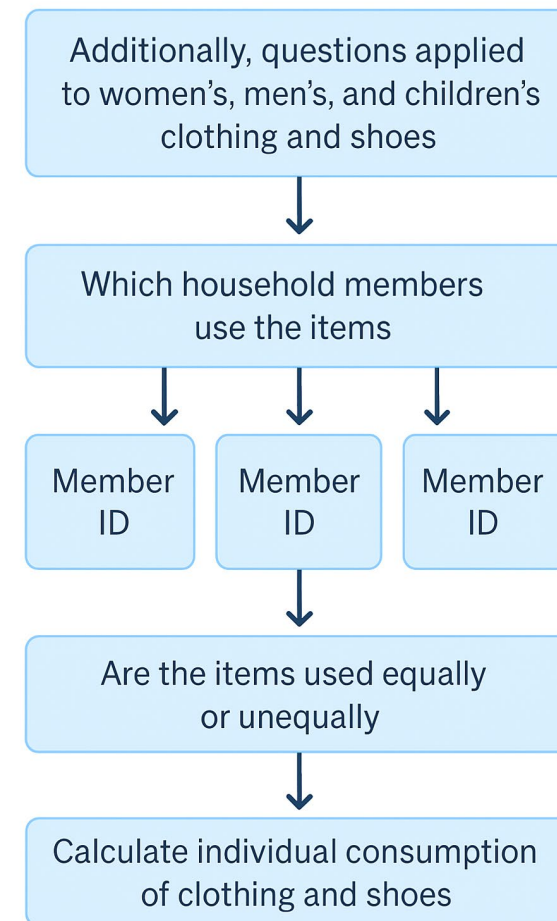
# Clothing consumption

- Collected through both household-level and individual allocation methods.
- Reported by gender/age categories (men, women, boys, girls), linked to specific users, and adjusted for equal vs. unequal use.

## Traditionally collected

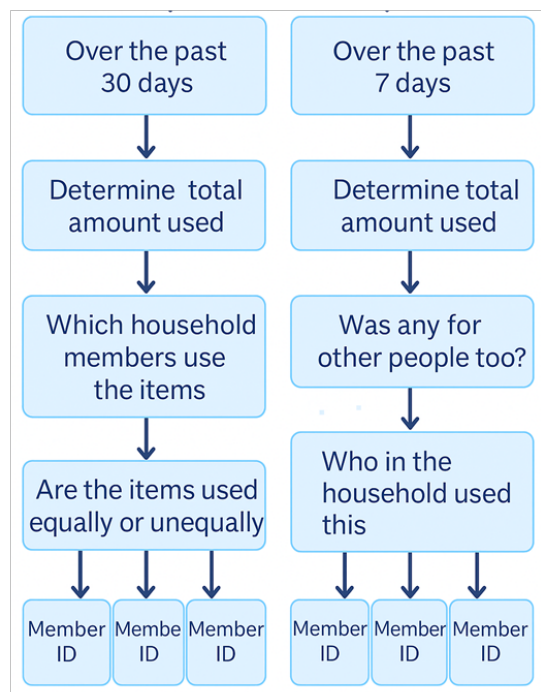


## Individually disaggregated

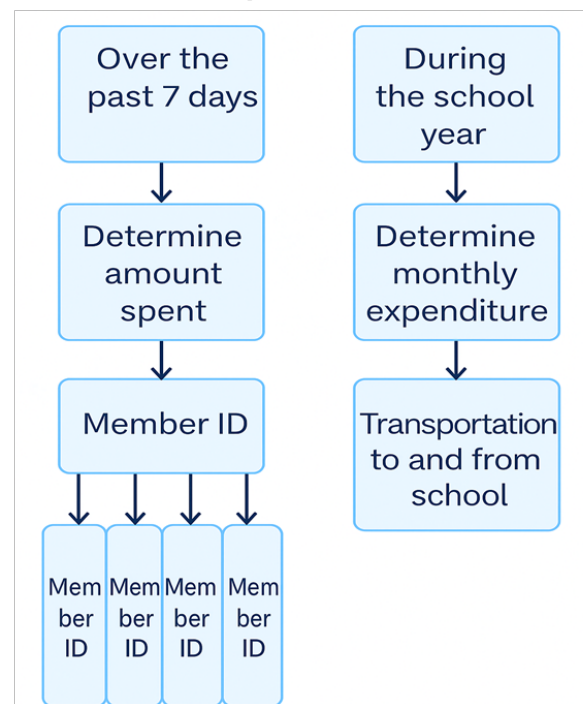


# Personal Care, Transportation and Adult Goods

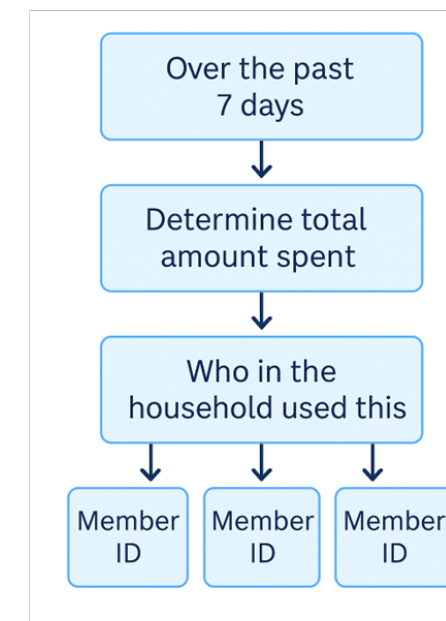
## Personal Care: skin/hair care, cosmetics, feminine prod, salon services



## Transportation: Bus/Rickshaw/Taxi fare, Boat/Train fare, school transportation



## Adult goods: Betel nuts, Cigarettes, Tobacco, Lottery, Gambling



# Empirical Strategy 1

## Identification of Resource Sharing DLP (Dunbar–Lewbel–Pendakur)

- 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
- Nonlinear Engel curves

$$w_j(y, p) = \alpha_j(p) + \gamma_j(p) \ln y$$

- Household-level observed share

$$W_{js}(y, p) = \sigma_j \eta_{js}(y, p) w_{js}(n_{js}(y, p)y, A'_s p)$$

- Resource shares  $\eta_{js}$  is recovered by inverting Engel curves under functional form restrictions (e.g., PIGLOG).
- Requires nonlinear likelihood estimation (computationally intensive).

# Empirical Strategy 2

## Identification of Resource Sharing LPW (Lechene–Pendakur–Wolf)

Linear Engel curve projection:

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

- Restriction: slope  $\beta$  common across individuals.
- Resource shares proportional to coefficients on demographics ( $\gamma_j$ ), recovered via OLS + normalization.
- Provides closed-form estimates with standard inference.
- Key point: Both frameworks yield observationally equivalent resource shares under the same assumptions; they differ in estimation strategy (nonlinear vs. linear).

# Empirical Strategy 3

## Assignable expenditures

- Assignable expenditures (private items for men, women, and children) are key for identifying resource shares in collective models.
- Traditional practice: Clothing and footwear are most widely used, as they are usually individually consumed and consistently available in household surveys
  - Applications: Bourguignon, Browning, and Chiappori (2009); Dunbar, Lewbel, and Pendakur (2013); Calvi (2020); Lechene, Pendakur, and Wolf (2022); Calvi et al., (2023).
- Food as assignable: Less commonly used, but offers advantages—regular consumption, lower quality heterogeneity, larger budget shares, and clear Engel curve patterns
  - Applications: Brown et al., (2021), Lechene, Pendakur, and Wolf (2022), Calvi et al. (2023).
- We test multiple definitions of clothing (aggregate vs. individualized) and food (total, cereals, animal products, outside food), alongside other categories (personal care items, transportation costs, and adult goods) to evaluate sensitivity of estimated resource shares.

# Empirical Strategy 4

## Poverty measures

The FGT class of poverty indices

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

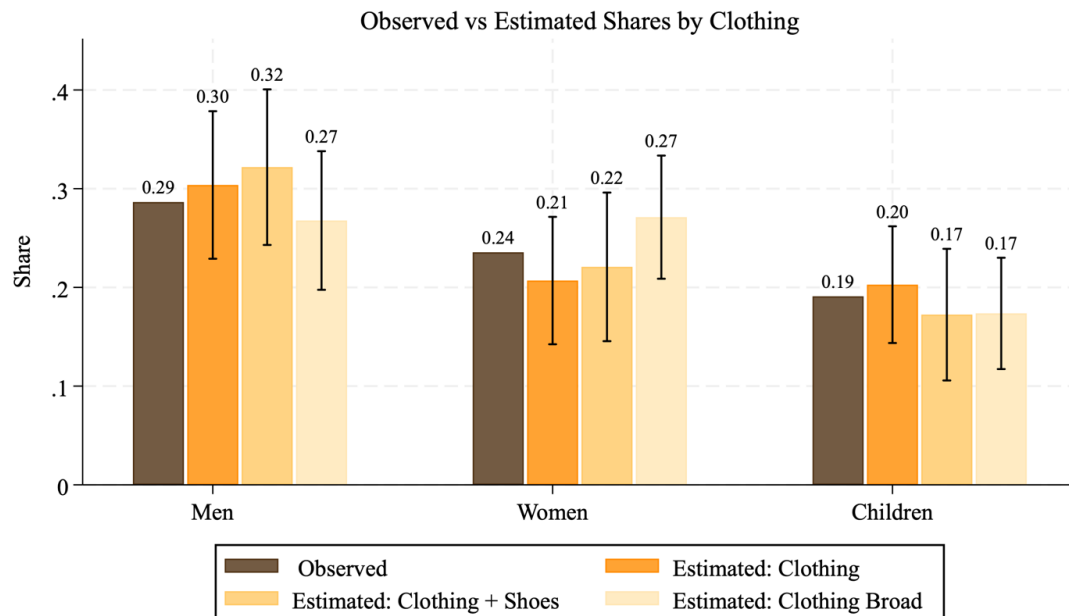
- where  $I_i = 1$  if  $y_i \leq z$  and  $I_i = 0$  otherwise.  $\alpha$  is a given parameter, whose first three non-negative integer values are most commonly used:
  - $FGT(y; 0)$  is the headcount poverty ratio
  - $FGT(y; 1)$  is the (average normalized) poverty gap
  - $FGT(y; 2)$  is the (average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

# Descriptive Statistics

- Household composition: All households are couples (with/without children); average of 4.2 adults and 1.5 children (mean child age  $\approx 8$ ).
- Respondent characteristics: Men average 42 years, women 38 years, both with  $\sim 5$  years of schooling (incomplete secondary).
- Budget shares:
  - Overall food (37%): Largest share of household budgets. Of this, 15% men's food, 14% women's food, 10% children's food.
  - Cereals & grains ( $\sim 16\%$  total): Roughly 6% for men, 6% for women, 4% for children.
  - Animal products: 1.7% ( $\approx 0.5\text{--}0.7\%$  each); proportion of zeros is very high ( $>50\%$ ).
  - Food outside home: 0.1% (near-zero for all members); zeros extremely high (29–90%)
  - Clothing & footwear (individualized): 3.9% (men 1.1%, women 1.2%, children 1.9%); zeros minimal ( $<5\%$ ).
  - Personal care: 1.9% (0.6–0.7% each); zeros substantial (6–42%).
  - Transportation: 7.0% (men 4.1%, women 1.6%, children 1.6%); zeros substantial (18–68%).
  - Health: 9.8% (men 3.4%, women 4.6%, children 2.2%); zeros moderate (25–35%).
  - Adult goods: 1.0% (men 0.6%, women 0.4%, children negligible); zeros very high (55–99%).

# Resource Share Estimations 1

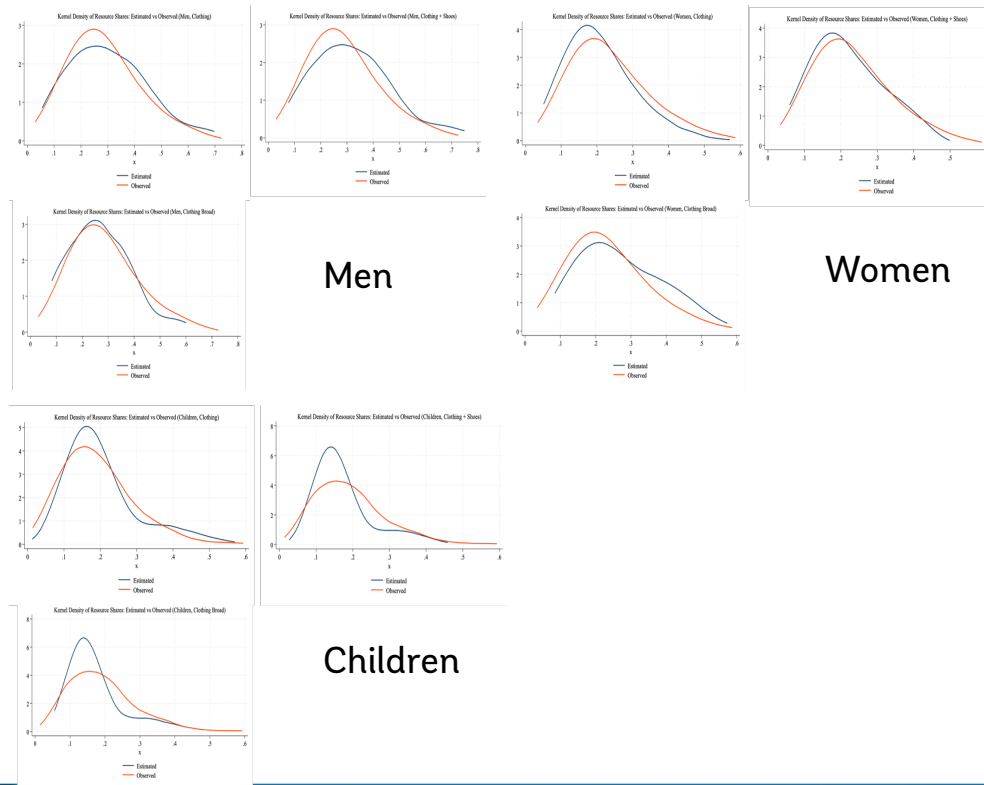
Observed vs Estimated Resource Shares Using Assignable Clothing, DLP



- Model-predicted shares (men 30%, children 20%) closely match observed benchmarks (29% and 19%); women's predicted share (21%) underestimates observed by 3 points.
- Adding aggregated footwear does not improve accuracy for men or children and only marginally helps for women.
- Using individualized rather than aggregated data does not yield better predictions.
- Observed shares for all groups fall within the 95% confidence intervals of model-based predictions.

# Resource Share Estimations 2

Distribution of Observed vs Estimated Resource Shares Using Assignable Clothing, DLP

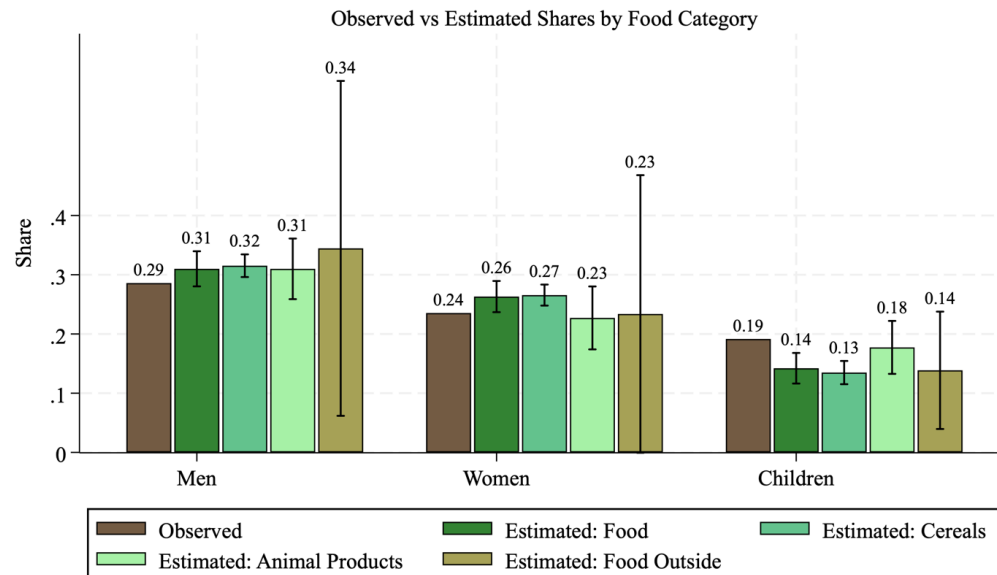


- Accuracy: DLP predicts men's shares well, less so for women, and least accurately for children.
- Assignable goods: Aggregated clothing/footwear reliably capture men's and women's shares, but are less reliable for children due to irregular purchases.

(red observed, blue estimated)

# Resource Share Estimations 3

## Observed vs Estimated Resource Shares Using Assignable Food Categories, DLP



- Men: Highest accuracy from assignable food and animal products (predicted 31% vs. observed 29%), with observed shares within 95% CIs.
- Women & children: Best fit with animal products (predicted 23% vs. observed 24% for women; 18% vs. 19% for children), also within 95% CIs.
- Food, cereals, and grains tend to overestimate women's shares and underestimate children's, reflecting weaker assignability from shared meals.
- Animal products & food outside: Animal products provide close estimates but are limited by high zero-expenditures; food consumed outside adds variance without improving accuracy.

# Resource Share Estimations, DLP

Assignable good

**Clothing (aggregated)**

**Clothing (individualized)**

**Footwear (aggregated)**

**Food (total, cereals, grains)**

**Animal products**

**Personal care**

**Transport**

**Health**

**Adult goods**

Men

● Reliable

● Reliable

● Reliable

● Reliable (means + distribution)

● Reliable

● Reliable

● Overestimates

● Overestimates

● Overestimates

Women

● Reliable

● Weaker fit

● Reliable

● Means only

● Partial (zeros)

● Overestimates

● Weak

● Underestimates

● Underestimates

Children

● Partial

● Weak

● Partial

● Weak

● Partial (zeros)

● Only means

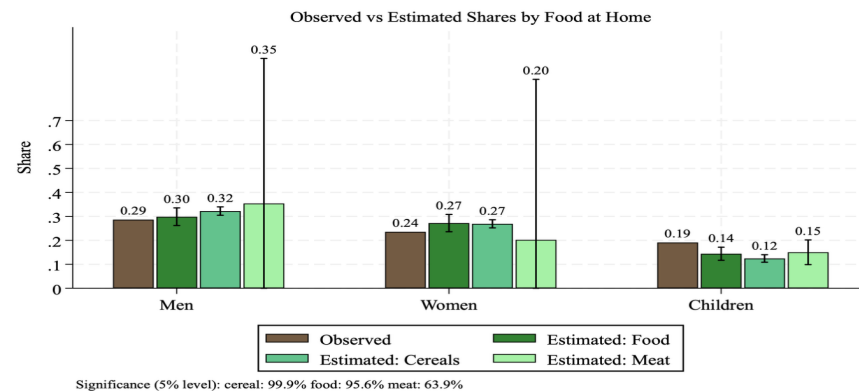
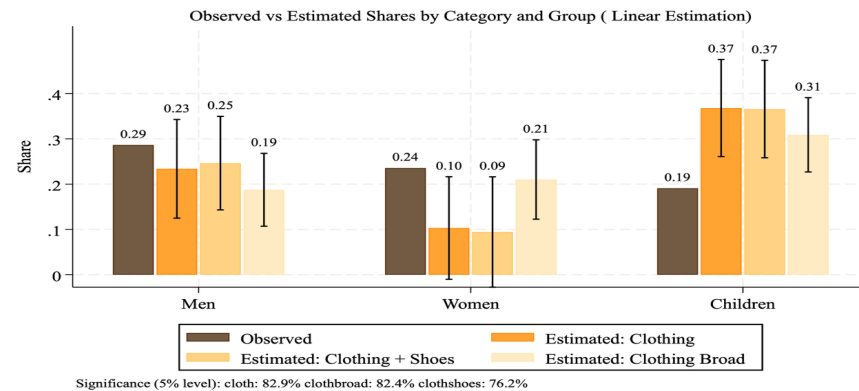
● Weak

● Overestimates

● Very weak

# Resource Share Estimations 7

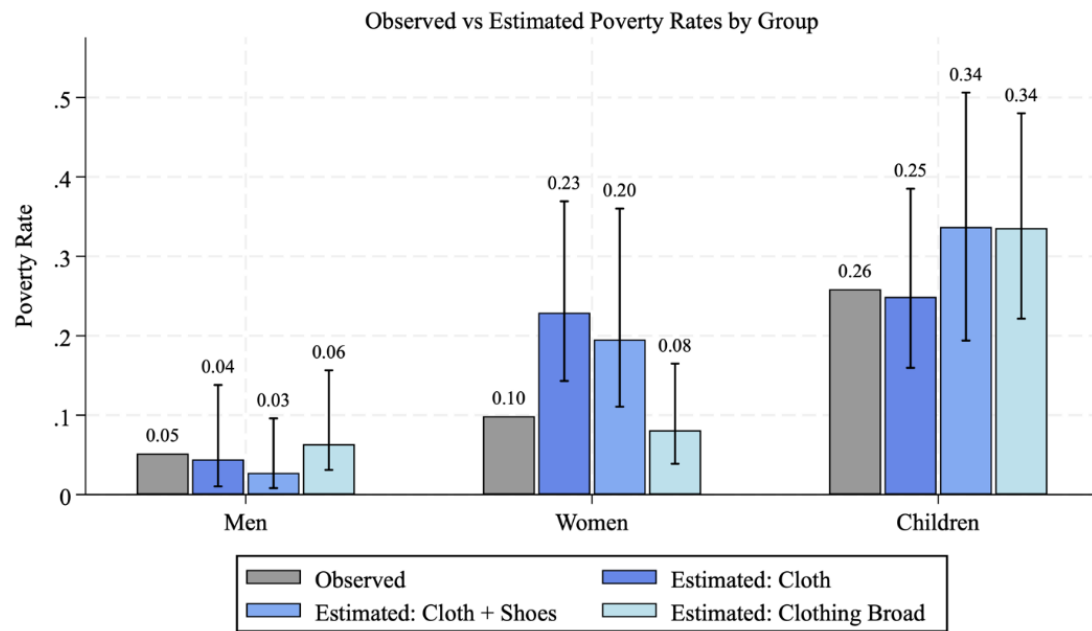
## Observed vs Estimated Resource Shares, LPW



- Clothing & footwear: LPW does not generate close estimates; bias ranges from 4–10pp for men, 3–15pp for women, and 12–18pp for children.
- Food & cereals: Men’s shares align well with food (30% vs. 29%, within 95% CI). For women, allocations are overestimated (~+3pp); for children, underestimated (~-5 to -7pp), with observed means outside 95% CIs.
- Animal products: Similar bias pattern (over for adults, under for children), but observed means lie within 95% CIs for all groups—though with wide confidence intervals for men and women.

# Welfare Analysis 1

## Distribution of Observed vs Estimated Poverty Rates Using Assignable Clothing



Overall per capita poverty rate = 6 %

Individual poverty rate = 13.6%

- Men: Clothing-based estimates are highly accurate; differences from benchmarks  $\leq 2$ pp, and observed means always within 95% CIs.

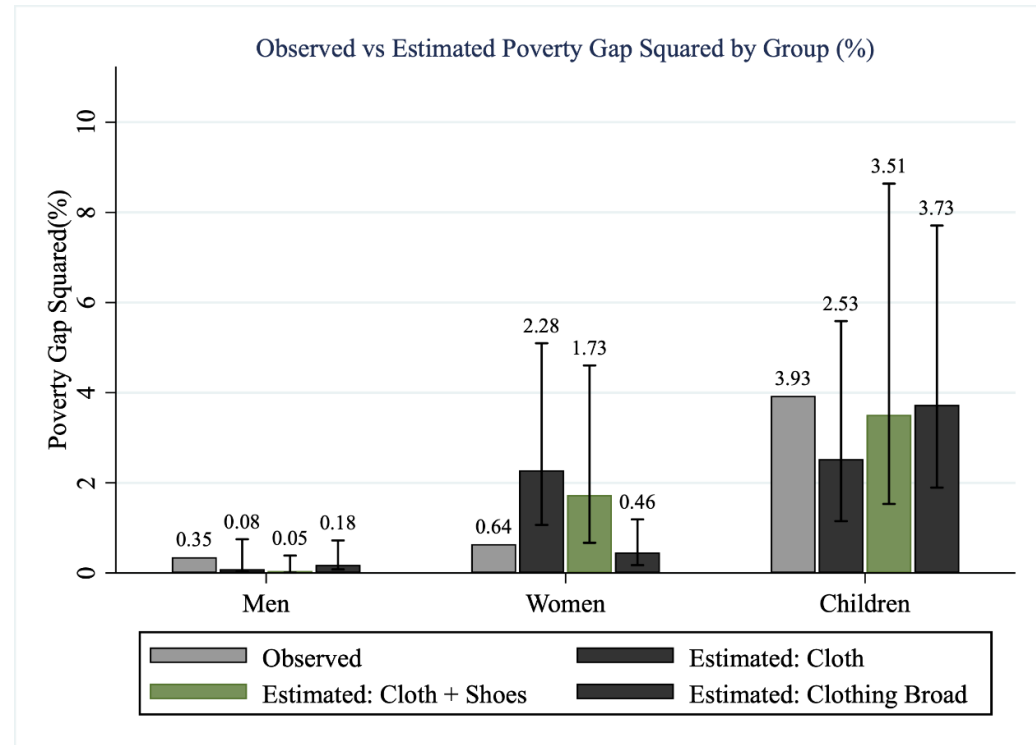
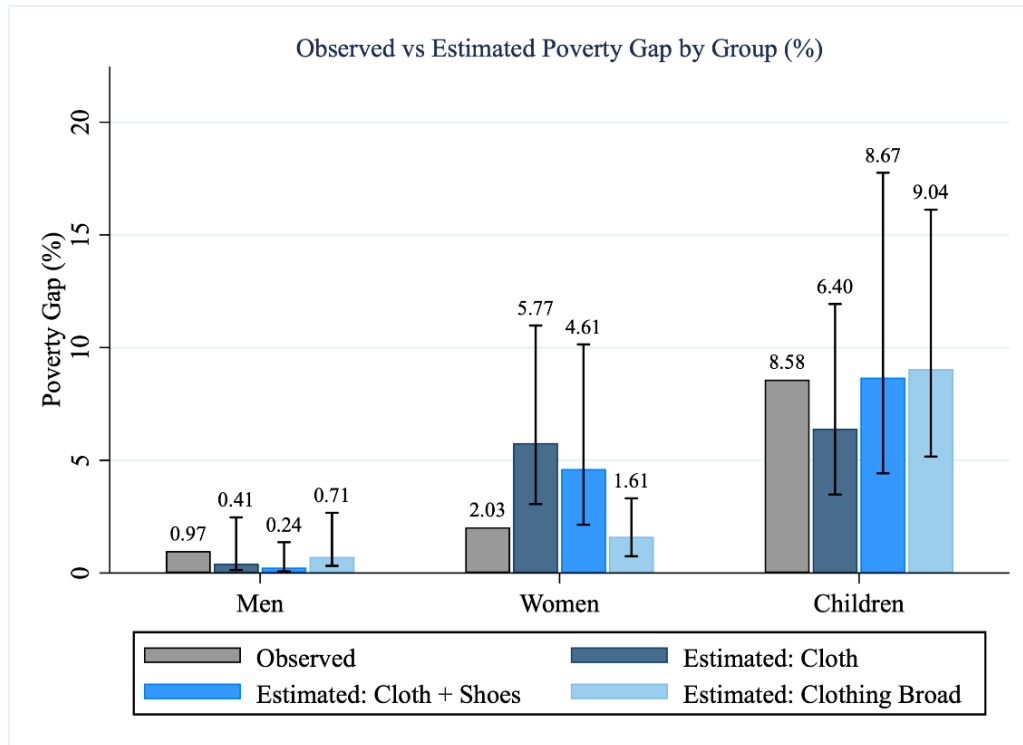
Women: Aggregated clothing/footwear overstate poverty (more than double observed), with means outside 95% CIs. Individualized clothing/footwear improves accuracy ( $\approx 2$ pp difference, within CI).

Children: Clothing-based estimates approximate observed poverty ( $\approx 25\%$ ) within 95% CIs, but adding footwear or using individualized data does not improve accuracy; assignability is weakened by joint purchases and frequent zeros.

Overall: DLP predicts men's poverty robustly, but estimates for women and children remain sensitive to the choice of assignable goods—consistent with earlier results on resource shares

# Welfare Analysis 2

## Distribution of Observed vs Estimated Poverty Gap and Gap Squared Using Assignable Clothing



# Conclusion

- **Overall accuracy:** The DLP model predicts men's resource shares and poverty outcomes with high accuracy, but performs less well for women and is least reliable for children.
- **Assignable goods:** Clothing (especially aggregated) and food provide the most reliable identification of adult shares; alternative categories (personal care, transport, health, adult goods) are inconsistent.
- **Women:** Estimates depend heavily on the assignable used—aggregated clothing performs better than individualized, while food captures mean shares but misrepresents distributions near the poverty threshold.
- **Children:** Predictions are the weakest; only aggregated clothing and animal products approximate observed outcomes.
- **Poverty Implications:** 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

# References

- Browning, M., Bourguignon, F., Chiappori, P.A. and Lechene, V., 1994. Income and outcomes: A structural model of intrahousehold allocation. *Journal of political Economy*, 102(6), pp.1067-1096.
- Dunbar, G.R., Lewbel, A. and Pendakur, K., 2013. Children's resources in collective households: identification, estimation, and an application to child poverty in Malawi. *American Economic Review*, 103(1), pp.438-471.
- Sokullu, S. and Valente, C., 2022. Individual consumption in collective households: Identification using repeated observations with an application to progresa. *Journal of Applied Econometrics*, 37(2), pp.286-304.
- Mercier, M. and Verwimp, P., 2017. Are we counting all the poor?: Accounting for the intra-household allocation of consumption in burundi. *Journal of Demographic Economics*, 83(3), pp.307-327.

# Assignable goods in BICS

<b>Food</b>	
<b>Total food at home</b>	All food items
<b>Cereals and grains</b>	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)
<b>Animal products</b>	Beef/buffalo, Mutton, Chicken, Duck, Pigeon, Pig, Stomach of beef/goat, Egg, Milk, Powdered Milk, Other meat (Fish egg), Other dairy
<b>Total food outside</b>	All meals consumed outside are included
<b>Clothing</b>	
<b>Clothes for men</b>	aggregated
<b>Clothes for women</b>	aggregated
<b>Clothes for children</b>	aggregated (boys' and girls' clothing)
<b>Clothing and footwear for men</b>	aggregated
<b>Clothing and footwear for women</b>	aggregated
<b>Clothing and footwear for children</b>	aggregated (boys' and girls' shoes)
<b>Individualized clothing-related expenses</b>	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
<b>Other private services and goods</b>	
<b>Personal care</b>	Skin care: snow cream, powder, perfume, cologne, etc, Hair products, Cosmetics, Feminine hygiene, Diapers, Haircut, shaving, Salon services
<b>Transportation costs</b>	Bus fare, Rickshaw fare, Taxi fare, Boat fare, Train fare, Education-related transportation costs
<b>Health-related costs</b>	Doctor`s appointments, medicine, vaccination, vitamins
<b>Adult goods</b>	Betel nuts, leaves, Cigarettes, tobacco, Lottery, raffles, gambling



# Descriptive Statistics, BICS

Household expenditures	Obs	Mean	Median	SD
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
Budget 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	1.410	1.000	0.611



# LSMS

Living Standards Measurement Study



The LSMS website