Hidden Gender Gaps in Child Poverty

Jijeebisha Bhattarai[†] Rossella Calvi[‡] Ajinkya Keskar[†]

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ABSTRACT. While son preference in India is well documented, measuring gender differences in children's consumption remains challenging because consumption is typically observed only at the household level. We estimate gender-specific child consumption using a collective household model and data from rural India. We find substantial within-household inequality: boys consume systematically more household resources than girls. Translating these allocations into individual-level poverty, roughly 63.5 percent of girls are poor, compared to 56.3 percent of boys. These gaps account for age- and sex-specific needs, persist throughout childhood, and are largely invisible to standard household-level poverty measures. We further show that son-biased fertility stopping behavior contributes to the gender gap in child poverty by increasing girls' exposure to larger families with fewer resources per child, explaining about one-fifth of the overall gap. Finally, combining our model-based poverty estimates with administrative mortality data, we show that hidden gender gaps in child poverty can account for one in five Indian missing girls.

JEL codes: D13, I32, J13, J16

Keywords: child poverty, gender gap, fertility, intra-household allocation, missing women

[†]Department of Economics, Binghamton University, SUNY. Jijeebisha Bhattarai: jbhatta1@binghamton.edu. Ajinkya Keskar: akeskar@binghamton.edu.

[‡]Department of Economics, Rice University. Email: rossella.calvi@rice.edu.

1 Introduction

Son preference in India is well documented and economically consequential (Jayachandran, 2023). It shapes fertility decisions, survival, health investments, and human-capital accumulation, and underlies the phenomenon of *missing women* (Sen, 1990; Coale, 1991; Anderson and Ray, 2010). A large body of literature documents gender disparities in mortality, nutrition, and preventive health investments. For instance, girls have historically received fewer vaccinations than boys (Oster, 2009), are breastfed for shorter durations (Jayachandran and Kuziemko, 2011; Barcellos et al., 2014), receive less childcare time and vitamin supplementation (Barcellos et al., 2014), and experience differential survival and sex-selection risk (Bhalotra and Cochrane, 2010; Anukriti et al., 2022). Yet a basic question remains surprisingly difficult to answer: Does son preference translate into unequal everyday consumption within households? In particular, do boys receive a larger share of total household resources than girls?

Answering this question is challenging because most household surveys do not collect individual consumption data. Standard surveys record consumption at the household level, making it difficult to determine how resources are allocated among household members. As a result, while there is abundant evidence on specific inputs and outcomes, much less is known about children's overall command over consumption. Existing indicators such as nutrition, health, and educational attainment reflect the cumulative effects of many decisions and behaviors and therefore provide only indirect evidence on underlying consumption allocation.

Early empirical work attempted to infer gender bias in consumption from household demand patterns using Engel-curve tests (Deaton, 1989; Subramanian and Deaton, 1991; Case and Deaton, 2003). The intuition is that if households favor boys, the presence of sons should systematically affect expenditure shares on observable goods. While influential, these approaches cannot recover how resources are actually divided among children. As Deaton (1989) emphasized, the fundamental obstacle is the absence of individual consumption data. Without expenditures that can be directly assigned to boys and girls, household expenditure data alone cannot reveal how total resources are allocated within the family.

More recent work has addressed this limitation using collective household models (Chiappori, 1988, 1992). In these models, household allocations are Pareto efficient but need not be equal across members. A key methodological advance by Dunbar et al. (2013) shows that when privately consumed, assignable goods are observed—such as clothing—intrahousehold consumption allocations can be identified and estimated structurally from Engel curves under relatively mild restrictions on preferences. These methods have since been used to measure intrahousehold inequality and individual poverty among women, men and children in Malawi, Bangladesh, India, Mexico, and other settings.[1]

[1] See, e.g., Dunbar et al. (2013); Bargain et al. (2014); Calvi (2020); Penglase (2021); Brown et al. (2021); Sokullu and Valente (2022); Beltramo et al. (2023); Calvi et al. (2023); Lechene et al. (2022); Casco (2023); van der Merwe (2026). Of particular note is the recent contribution of Aminjonov et al. (2026), who estimate individual consumption and poverty rates for children, women, and men in 45 low- and middle-income countries using harmonized household survey data. By documenting the prevalence of hidden poverty on a global scale, their findings underscore the importance of moving beyond

However, evidence on gender gaps among children remains limited and context-dependent. One application to South Asian countries finds modest or no gender differences in child allocations (Brown et al. (2021) in Bangladesh), while others emphasize disparities among adults (such as Calvi (2020), Calvi and Keskar (2021), and Bandyopadhyay and Maity (2026) in India). For India specifically—where son preference remains particularly persistent and widespread—there is still no direct evidence quantifying total consumption allocation differences between boys and girls within households. Moreover, the broader welfare implications of such allocation differences remain largely unexplored. Even when unequal inputs and outcomes are documented, we know relatively little about how they translate into individual poverty and economic deprivation.

This paper overcomes the measurement barrier using disaggregated expenditure data and a collective household model. We use the 2006 Rural Economic and Demographic Survey (REDS), which records clothing and footwear expenditure separately for adult men, adult women, boys under 16, and girls under 16. These goods are privately consumed and assignable to specific member types. Following Dunbar et al. (2013) and Calvi (2020), we use the Engel curves of assignable clothing to recover *resource shares*—the fraction of total household expenditure allocated to each member— in nuclear and extended families, while explicitly distinguishing between boys and girls.

The intuition of the approach is straightforward. Consider two otherwise similar households that differ in total expenditure. If spending on boys' clothing rises more steeply with total household expenditure than spending on girls' clothing, this implies that additional resources are disproportionately allocated to boys. Under mild preference restrictions, the slope of boys' and girls' clothing Engel curves is proportional to their respective resource shares. Because resource shares across all household members must sum to one, comparing these slopes across family members allows us to recover how *total* resources are divided among men, women, boys, and girls. Importantly, identification comes from differences in Engel-curve slopes rather than from levels of clothing expenditure, which may reflect differences in tastes, prices, or norms rather than underlying resource allocation.

Our estimates reveal substantial within-household gender inequality among children. In the full sample (which includes both nuclear and extended families), boys receive a larger per-child share of total household resources than girls, with the gap widening in nuclear families. Adult allocations are also highly unequal: men receive substantially larger shares than women, consistent with the adult disparities documented in previous work (Calvi, 2020; Calvi and Keskar, 2021; Bandyopadhyay and Maity, 2026; Kapoor and Ravi, 2025).

To assess the welfare implications of unequal allocation, we translate the estimated resource shares into child-level consumption and poverty by gender. For each boy or girl, the level of consumption implied by the model equals the estimated resource share multiplied by total household expenditure. Unlike standard per-capita measures—which assign a common level of consumption and poverty status to all household members—this approach allows individual consumption and poverty status to differ within households (Dunbar et al., 2013; Brown et al., 2021, 2022). Conventional measures implicitly

household-level poverty measures.

assume equal sharing, so that either all members are poor or none are; by contrast, our framework allows some individuals to be poor even when their household is classified as non-poor, and vice versa.

Using a child-specific poverty line derived from standard equivalence-scale adjustments, we document substantial gender gaps in child poverty. We also construct an alternative poverty measure that allows needs to vary by age and sex, scaling the poverty line using age- and gender-specific caloric requirements. These adjustments recognize that children may need fewer resources than adults, and that children of different ages and sexes may face different needs. As a result, equal levels of consumption need not imply equal consumption adequacy.

Under both adjustments, we find evidence of gender disparities in child poverty. Under the calorie-based adjustment, roughly 63.5 percent of girls are poor, compared to about 56.3 percent of boys, with larger gaps in nuclear families. Under the equivalence-scale adjustment, 55.1 percent of girls and 42.9 percent of boys are poor. These disparities persist across ages and are largely invisible to standard household-level poverty measures. Among households classified as non-poor under the conventional per-capita approach—that is, households whose per-capita expenditure exceeds the poverty line—nearly 31.1 percent of girls and 28.5 percent of boys are nevertheless estimated to be poor. We refer to these findings as *hidden gender gaps in child poverty*: gender disparities in deprivation that arise within households above the poverty line and are obscured by the equal-sharing assumption embedded in household-level poverty measures.

We examine possible mechanisms generating these gaps. Son preference may affect child welfare not only through unequal treatment within households, but also through son-biased fertility behavior and household composition. A large literature shows that Indian households adjust fertility dynamically in response to the sex composition of existing children, continuing childbearing until a desired number of sons is achieved (Jensen, 2003; Barcellos et al., 2014; Anukriti et al., 2022). As a result, girls are disproportionately more likely to grow up in larger households and to face greater sibling competition for resources (Yamaguchi, 1989).

To isolate these two channels, we perform a Oaxaca-style decomposition based on the quasi-random variation in the sex of the firstborn child. The decomposition separates the overall gender gap in child poverty into a within-type component and a household-composition component. The latter captures differences in exposure to family environments associated with son-biased fertility-stopping behavior, whereby girls are more likely to reside in larger families with more children and fewer resources per child. The within-type component captures residual gender differences in poverty among children living in comparable family environments. We find that household composition explains one-fifth of the overall gender gap. Although girls are somewhat more likely to reside in households affected by son-biased fertility behavior, the majority of the disparity arises within household types, consistent with girls receiving systematically smaller shares of household resources than boys.

Our estimated poverty measures are strongly predictive of children's overall well-being. Even among children living in households with similar per-capita resources, those classified as individually poor exhibit significantly worse nutritional outcomes, receive lower educational investments, and perform worse on measures of advanced literacy. These results indicate that the hidden poverty documented in this paper is associated with tangible differences in children's health and human capital accumulation. More broadly, they suggest that intrahousehold allocation is important not only for measuring poverty accurately, but also for understanding disparities in children's long-run development.

Finally, we connect gender poverty gaps to the literature on missing women by combining our estimates of excess girl poverty by state and age with administrative mortality data from India's Sample Registration System (SRS). Following the framework of Anderson and Ray (2010, 2012), we construct measures of excess female death rates by comparing observed female mortality to benchmark mortality rates implied by male mortality and biologically plausible female survival advantages. We then ask whether states and ages with larger gender gaps in child poverty also exhibit larger excess female child mortality.

We find a strong positive relationship between excess poverty and excess mortality among girls, even when accounting for unobserved sources of heterogeneity across states and ages. A simple counterfactual exercise suggests that the hidden poverty gaps documented in our analysis could account for 20 to 40 percent of excess female deaths in childhood. While this exercise is intentionally simple, it highlights a plausible micro-level mechanism linking unequal intrahousehold allocation to broader demographic outcomes.

This paper makes three main contributions. First, we provide direct estimates of gender differences in child poverty in rural India by combining a collective household framework with detailed expenditure data that allow us to recover resource shares separately for boys and girls. Second, we show that the resulting measures of individual poverty are strongly associated with children's overall well-being: individually poor children exhibit worse nutritional outcomes, receive lower educational investments, and perform worse on measures of literacy, even after conditioning on household-level poverty status. Third, we connect the literatures on intrahousehold allocation, poverty, and missing women. Extending the insights of Calvi (2020) to childhood, we combine our poverty estimates with administrative mortality data and show that larger gender gaps in child poverty are strong predictors of higher excess female child mortality.[2]

Our findings have direct implications for the measurement and targeting of poverty. Policies that rely exclusively on household-level indicators implicitly assume that resources are shared equally among household members and therefore risk overlooking substantial deprivation among girls. In our data, many girls classified as non-poor under conventional household measures are individually poor once intrahousehold allocation is taken into account. Moreover, these differences are not merely statistical: individually poor children exhibit worse nutritional outcomes, receive lower educational investments, and perform worse on measures of literacy. As a result, household-level poverty measures may miss not only consumption-deprived children but also important inequalities in human capital formation. More broadly, our results suggest that intrahousehold consumption inequality is an important chan-

[2] Calvi (2020) shows that unequal resource allocation within households contributes to the phenomenon of missing women at post-reproductive ages in India.

nel through which son preference translates into disparities in health, education, and survival. While previous research has documented these disparities and often attributed them to differential treatment of boys and girls, direct evidence on the allocation of overall household resources has been lacking. By recovering individual consumption and poverty measures, our analysis makes this implicit channel explicit, and links it to both child well-being and excess female mortality in childhood.

The remainder of the paper is organized as follows. Section 2 presents the theoretical framework, describes the identification and estimation of resource shares, and outlines the construction of individual-level poverty measures. Section 3 reports the model estimates and documents hidden gender gaps in child poverty. Section 4 examines the role of son-biased fertility behavior. Section 5 examines whether the estimated poverty measures predict meaningful differences in children's health and human capital outcomes. Section 6 connects hidden gender gaps in child poverty to excess female child mortality and the missing-girls literature. Section 7 concludes.

2 Poverty Measurement with Intra-household Inequality

Poverty is fundamentally an individual-level concept, yet in practice it is almost always measured at the household level. Standard poverty measures classify households as poor or non-poor based on aggregate household resources and size, and then assign the same poverty status to all household members. This approach implicitly assumes that resources are shared equally within the household and therefore abstracts from the possibility that some members may systematically receive larger (or smaller) shares of household consumption than others. A large literature has documented that this assumption is often inconsistent with observed patterns of resource allocation (Haddad et al., 1997; Brown et al., 2021, 2022). Studies using individual food intake and nutritional data documented substantial variation in food allocation within households, implying that household-level measures may provide a misleading picture of individual living standards (Haddad and Kanbur, 1990; Behrman, 1988; Pitt et al., 1990; D'Souza and Tandon, 2019; Brown et al., 2021).

These considerations are particularly important when studying child poverty. If boys and girls receive different shares of household resources, household-level poverty measures may substantially misrepresent their living standards. Poor children may reside in households classified as non-poor, while children within the same household may experience markedly different levels of deprivation. As emphasized by Haddad and Kanbur (1990), the identification of vulnerable populations can change once intrahousehold inequality is taken into account.

Ideally, poverty would be measured using comprehensive information on individual consumption. In practice, however, collecting such data is exceptionally difficult. As a result, large-scale household surveys rarely collect the information required to construct complete individual consumption aggregates. The challenge of recovering individual living standards from household expenditure data has therefore been a central motivation for the development of models of household behavior that can deliver insights on intrahousehold consumption from household-level data.

In what follows, we adopt the approach developed by Dunbar et al. (2013), which uses information on assignable goods to identify resource shares for different groups within the household. Combining these estimated resource shares with observed household expenditure allows us to construct individual-level consumption measures and corresponding poverty rates. In this section, we outline the approach. Appendix A provides additional details on the model, identification, and estimation, as well as identification diagnostics.

2.1 Theoretical Framework

We model intrahousehold allocation using the collective household framework, in which household members have distinct preferences and allocations are Pareto efficient (Chiappori, 1988, 1992). The framework does not require that household members agree on how to spend income; rather, it assumes that the outcome of their bargaining is efficient—meaning that no reallocation could make one member better off without making another worse off. In this setting, household decisions can be represented through a two-step process: total household expenditure is first allocated across member types, and each type then chooses consumption subject to its shadow budget constraint (Browning et al., 2013).

Consider a household composed of adult men, adult women, boys under 16, and girls under 16, indexed by $j \in \{m, w, b, g\}$. Let n_j denote the number of members of type j, and let y denote total household expenditure. The household allocates resources across member types according to

$$\max_{\{c_j\}_{j\in\{m,w,b,g\}}} \sum_{j\in\{m,w,b,g\}} n_j \omega_j u_j(c_j) \quad \text{s.t.} \quad \sum_{j\in\{m,w,b,g\}} n_j c_j = y,$$

where $u_j(\cdot)$ denotes type-specific utility and ω_j captures the Pareto weight attached to members of type j. We summarize the resulting intrahousehold consumption allocation using per-capita resource shares η_j, defined by

$$c_j = \eta_j y, \qquad \sum_{j\in\{m,w,b,g\}} n_j \eta_j = 1.$$

Thus, η_j represents the fraction of total household expenditure allocated to each individual of type j, while $n_j\eta_j$ is the total share allocated to all members of that type. Under the collective model, resource shares provide a reduced-form summary of the household allocation outcome. As shown by Browning et al. (2013), for a given specification of preferences and consumption technology, there exists a one-to-one relationship between resource shares and the Pareto weights that govern intrahousehold decision-making.[3]

Our object of interest is the girl–boy gap in resource shares, $\eta_g - \eta_b$. A negative gap indicates that

[3]More generally, the collective framework can be extended to allow individual-specific preferences, Pareto weights, and resource shares. In principle, each household member may receive a distinct allocation. However, the expenditure data used here identify allocations only at the level of demographic groups. We therefore parameterize preferences and resource shares by member type—adult men, adult women, boys, and girls—and implicitly assume equal treatment of individuals within a given type. In estimation, the implied resource shares vary systematically with household composition and other observed household characteristics, allowing for substantial heterogeneity in allocations across households.

each girl receives a smaller per-child share of total household resources than each boy—that is, son preference is reflected not only in gaps in specific inputs and human capital outcomes, but also in the everyday allocation of consumption within the household. A gap of zero is consistent with equal per-child treatment, while a positive gap would indicate preferential allocation toward girls. We test whether $\eta_g - \eta_b < 0$ systematically across households and examine how the magnitude of the gap varies with household structure and characteristics. The resource share η_j captures the fraction of total household expenditure effectively commanded by a member of type j, encompassing both privately consumed goods and that member's implicit share of household public goods. As such, it reflects the outcome of intrahousehold bargaining and depends on preferences, bargaining power, and the institutional and social environment in which households operate.

To recover resource shares η_j, we exploit *private assignable goods*—goods that are privately consumed and for which expenditures can be observed separately by recipient type. Assignable goods play a crucial role in identification because they provide a direct link between individual consumption choices and the shadow budgets determined by the intrahousehold allocation rule. In the collective model, each individual allocates the resources available to them across goods according to their preferences. When spending on a good can be attributed to a specific individual or member type, variation in that spending reflects both the individual's preferences and the amount of resources allocated to them.[4] However, observing assignable goods alone is not sufficient to identify resource shares without additional structure. Intuitively, higher expenditure on an assignable good for a given individual could reflect either stronger preferences for that good or a larger share of household resources. As discussed below, to disentangle these two forces, we impose mild restrictions on preferences that discipline how demand responds to changes in total resources.

In line with the previous literature, we use clothing as the assignable good. Clothing is particularly well-suited for this purpose because it is largely privately consumed, and expenditures can typically be attributed to specific individuals within the household. Moreover, clothing purchases exhibit substantial variation across individuals and respond systematically to changes in total household resources. As emphasized by Bargain et al. (2018), these features make clothing expenditures especially useful for estimating individual Engel curves while minimizing concerns that the good is jointly consumed or difficult to assign to specific household members. The REDS 2006 survey reports clothing and footwear expenditures separately for adult men, adult women, boys under 16, and girls under 16, allowing us to estimate type-specific Engel curves and identify four separate resource shares.

2.2 Identification

Resource shares are identified from the Engel curves of assignable clothing and footwear (hereafter, clothing). An Engel curve describes the relationship between the budget share spent on a good—the fraction of total household expenditure devoted to it—and total household expenditure, holding prices

[4] Note that to recover children's resource shares, we need to model them as decision-makers, which is consistent with recent evidence from Bangladesh (Sözbir, 2025).

fixed. The key insight of Dunbar et al. (2013) is that, when an assignable good is observed separately for each member type, variation in how each type's clothing budget share responds to total household expenditure can reveal how the household's total resources are divided across members. Critically, *budget shares* and *resource shares* are distinct objects, and their relative magnitudes need not coincide. Observed clothing expenditures reflect both the resources allocated to a member and that member's preferences for clothing relative to other goods. For example, girls may spend a smaller fraction of their resources on clothing simply because their preferences differ from those of boys, even if their overall resource shares were identical. Conversely, equal clothing spending across children does not imply equal allocations of total resources.

The strength of the method is precisely that it disentangles these two forces. Differences in the levels of clothing budget shares capture heterogeneity in preferences across member types, while differences in how these shares change with total household expenditure capture differences in resource allocation. Under preference restrictions discussed below, if additional household resources lead to larger increases in clothing spending for boys than for girls, this indicates that boys receive a larger marginal share of the household budget.

Identification requires three conditions. First, at least one private assignable good must be observed for each member type. Second, resource shares must not vary with total expenditure, at least over some expenditure range.[5] Third, preferences over the assignable good must satisfy one of the semiparametric restrictions in Dunbar et al. (2013). In what follows, we impose that the slope of the individual-level clothing Engel curves is common across member types, so that differences in how household-level budget shares respond to total expenditure reflect differences in resource shares rather than differences in individual preferences. Note that this is a mild restriction, since it still allows for substantial heterogeneity in preferences across household members through the intercept terms and, importantly, only restricts preferences for one single good while leaving the others unconstrained. Appendix A discusses this assumption in more detail and provides empirical support of its validity in our study context.[6]

2.3 Estimation

We impose Piglog (price-independent generalized logarithmic) preferences, under which the Engel curves for assignable goods are linear in the logarithm of total household expenditure. Let W_j denote the budget share of assignable clothing for member type $j \in m, w, b, g$, n_j the number of household members of type j, η_j the corresponding per-capita resource share, and y total household expenditure.

[5] Resource shares may still depend on other household characteristics correlated with expenditure, such as demographic composition or wealth (Dunbar et al., 2013). Evidence from several settings supports this restriction: Menon et al. (2012) find little expenditure-dependence in children's resource shares for Italian households, and Bargain et al. (2018) obtain similar results using data from Bangladesh.

[6] Specifically, Appendix Table A1 re-estimates the model under an alternative identification restriction proposed by Dunbar et al. (2013), which allows the slopes of the individual-level Engel curves to differ across adult men, adult women, boys, and girls. This alternative specification yields estimates that are quantitatively consistent with our baseline. Importantly, we cannot reject our preferred restriction of equal slopes. Note that identification weakens when Engel curves are flat, or close to flat (Tommasi and Wolf, 2016). Appendix Table A2 shows that the slopes of the clothing Engel curves are negative and statistically different from zero for all four household member types in our sample.

Let α_j denote type-specific preference parameters and β the common Engel-curve slope parameter. The Engel curves for assignable clothing are

$$\begin{cases} W_m = n_m \eta_m \left(\alpha_m + \beta \ln \eta_m + \beta \ln y\right) + \varepsilon_m \\ W_w = n_w \eta_w \left(\alpha_w + \beta \ln \eta_w + \beta \ln y\right) + \varepsilon_w \\ W_b = n_b \eta_b \left(\alpha_b + \beta \ln \eta_b + \beta \ln y\right) + \varepsilon_b \\ W_g = n_g \eta_g \left(\alpha_g + \beta \ln \eta_g + \beta \ln y\right) + \varepsilon_g \end{cases} \tag{1}$$

where ε_j captures unobserved determinants of budget shares. Because expenditure decisions for different household members are jointly determined, the error terms may be correlated across equations. The slope of each Engel curve with respect to $\ln y$ equals $n_j \eta_j \beta$, which is proportional to the corresponding resource share. Together with the adding-up constraint $\sum_j n_j \eta_j = 1$, this relationship yields point identification of the resource shares $\eta_m, \eta_w, \eta_b, \eta_g$.

In households containing all four member types, the system consists of four Engel curves subject to the adding-up constraint. However, many households do not contain members of all types. For example, some households contain only boys or only girls. We retain these households in the estimation. In such cases, the corresponding equations are absent, and the model is estimated on the relevant subsystem. For instance, households with adult men, adult women, and boys but no girls contribute a system of three Engel curves, with the adding-up constraint adjusted accordingly.

We estimate the system jointly using nonlinear seemingly unrelated regression (NLSUR). Under the assumption that the disturbance vector $\boldsymbol{\varepsilon}$ is multivariate normal, iterated NLSUR corresponds to maximum likelihood estimation of the nonlinear Engel-curve system. The estimator is iterated until the estimated parameters and error covariance matrices settle. Joint estimation exploits cross-equation covariance in the disturbances while imposing the theoretical restrictions implied by the model, including the adding-up constraint on resource shares and the common Engel-curve slope parameter β.

To allow resource allocation and preferences to vary systematically across households, we parameterize all parameters (that is, α_j, β, and η_j) as functions of a wide set of observable household characteristics. Specifically, we allow the latent resource-share parameters to depend on demographic composition, age structure, education, caste, religion, geographic region, and family structure. As a result, the model permits heterogeneity in intrahousehold allocation and preferences while remaining fully consistent with the theoretical framework. Standard errors are clustered at the village level to account for within-village correlation in unobserved determinants of expenditure behavior.

2.4 Data and Measurement

REDS Sample and Descriptive Statistics. The Rural Economic and Demographic Survey (REDS) is a nationally representative panel survey of rural Indian households, first fielded in 1969 and subsequently followed in 1970, 1971, 1982, 1999, and 2006. We use the 2006 round because its consumption module reports clothing expenditures separately for adult men, adult women, boys under 16, and girls under

16.[7] This gender-disaggregated measurement of an assignable good is the key data requirement for separately identifying boys' and girls' resource shares within the collective household framework. Earlier REDS rounds and standard expenditure surveys in India—including the NSS Consumer Expenditure Survey used in Calvi (2020)—do not disaggregate children's clothing expenditures by gender, precluding analogous estimates.

We restrict the REDS 2006 sample to households that (i) include at least one adult man and one adult woman, (ii) have at least one child under 16, and (iii) do not employ live-in domestic workers. We further exclude mixed child-generation households, defined as households in which children under 16 include both the head's children and grandchildren. Grandchild-only households can remain in the all-families sample, but they do not enter subsequent analyses that require a clean parental fertility history. To remove composition outliers, we retain households with at most four adults of each gender and at most six children. Finally, we trim the top and bottom 1 percent of total expenditure and the top 1 percent of each clothing budget share. The resulting analysis sample includes 3,983 households; Appendix Figure A1 documents the sample restrictions and construction.

In our main analysis, we estimate the model separately over two samples: an *all-families* sample, which includes all qualifying households and therefore contains both nuclear and extended family structures (the latter include additional adult relatives, reflecting the prevalence of extended living arrangements in rural India (Calvi, 2020)) and a *nuclear-families* subsample, which restricts attention to households consisting of a married couple living only with their children (1,410 households). The results of model estimates over different samples are presented in the Appendix.

We construct budget shares for private assignable goods using households' reported annual expenditures on clothing for adult men, adult women, boys under 16, and girls under 16. Total household consumption expenditure is defined as the sum of food and non-durable non-food items (including clothing and footwear).

Table 1 reports selected descriptive statistics. The average household contains 5.6 members. Adult men and adult women account for 27.7 percent and 27.0 percent of household members, respectively, while among children under 16, boys represent 22.5 percent and girls 17.8 percent. Mean annual household expenditure is Rs. 38,495 (approximately $4,067 in 2011 PPP), corresponding to Rs. 7,188 per capita (approximately $759 in 2011 PPP).[8] Food accounts for 58.5 percent of total consumption expenditure. Average assignable clothing and footwear budget shares are 3.2 percent for adult women, 3.1 percent for adult men, 2.0 percent for boys, and 1.5 percent for girls, which is in line with previous studies. Women report 3.7 years of schooling on average compared to 6.5 years for men. The median age

[7] Although this survey is commonly referred to as the 2006 round, more than 85% of household interviews were conducted in 2008.

[8] PPP denotes purchasing power parity. We convert each household's nominal expenditure in interview year t to 2011 PPP US dollars by dividing Rupees by $13.173 \times (\text{CPI-AL}_t/\text{CPI-AL}_{2011})$. The factor 13.173 is the revised 2011 rural consumption PPP for India reported in Atamanov et al. (2020, Table A.2). Using the rural PPP follows the World Bank Poverty and Inequality Platform methodology, which computes separate rural and urban PPPs for India and converts household welfare across years using consumer price indices (World Bank, 2022). We use all-India Consumer Price Index for Agricultural Labourers (CPI-AL) values from India's Labour Bureau (Labour Bureau, Ministry of Labour and Employment, Government of India, 2012).

Table 1: Summary Statistics

	Mean	SD	Min	Max
Panel A: Household Composition				
Household size	5.56	1.75	3.00	14.00
Share adult men	0.28	0.11	0.08	0.67
Share adult women	0.27	0.10	0.09	0.67
Share boys under 16	0.22	0.15	0.00	0.71
Share girls under 16	0.18	0.15	0.00	0.75
Panel B: Expenditure ($/year, 2011 PPP)				
Total household expenditure	4,067	1,990	1,059	12,929
Per-capita expenditure	759	365	141	3,335
Panel C: Clothing and Footwear Budget Shares (%)				
Adult men	3.1	1.6	0.0	9.6
Adult women	3.2	1.6	0.0	9.6
Boys under 16	2.0	1.6	0.0	11.2
Girls under 16	1.5	1.5	0.0	8.6

Notes: Sample includes 3,983 households, including both nuclear and extended families. Expenditures are converted from Indian Rupees to 2011 purchasing power parity (PPP) US dollars.

is 33 for women and 35 for men, and the median number of children per household is 2. 89.3 percent of households identify as Hindu, and 74.6 percent belong to the Scheduled Castes/Scheduled Tribes/Other Backward Classes. Geographically, the sample is concentrated in North India (51.1 percent), followed by South (25.8 percent), West (14.2 percent), and East (8.9 percent).

Measurement and Outcomes. Using the estimated resource shares, we construct individual consumption levels and compute individual poverty rates. Our baseline poverty measure follows the World Bank's extreme poverty line of $1.90 per person per day (2011 PPP). Because REDS is a rural sample, we follow the World Bank's PIP methodology for rural India: we use the revised 2011 rural PPP conversion factor of Rs. 13.173 per international dollar and convert the line to the survey year using the CPI for Agricultural Labourers. For a 2006 REDS interview, this implies a poverty threshold of Rs. 15.46 per person per day; for a 2008 interview, the modal survey year in REDS 2006, the corresponding threshold is Rs. 18.25 per person per day.

To account for differences in consumption needs across demographic groups, we construct a poverty measure based on age- and sex-specific caloric requirements from the Indian Council of Medical Research and National Institute of Nutrition (2020). Specifically, we scale the $1.90/day poverty line by the ratio of recommended caloric requirements for each age-sex group relative to an adult reference individual. This adjustment recognizes that equal levels of consumption need not imply equal consumption adequacy across children of different ages and genders. For comparison, we also construct an OECD equivalence-scale-adjusted poverty measure commonly used in the poverty literature. Following Dunbar et al. (2013) and Calvi (2020), we assign children under age 15 a poverty line equal to 60 percent of the adult threshold. Unlike the calorie-adjusted measure, this approach does not distinguish between children under age 15 by age or gender. Finally, we report results using the Planning Commission of India's rural poverty line of Rs. 13 per person per day.

To assess whether the individual poverty measures recovered from the collective model capture meaningful differences in children's well-being, we also examine a range of child outcomes, including nutritional status, educational investments, and learning outcomes. The REDS survey contains anthropometric information for all household members as well as detailed data on children's schooling expenditures and literacy skills. We use these outcomes to evaluate whether children classified as individually poor exhibit systematically worse outcomes than otherwise similar children living in households with comparable overall resources.[9] If the estimated resource shares capture genuine differences in children's access to household resources, individual poverty should be associated with poorer nutritional status and also with lower educational investments and weaker learning outcomes, even after conditioning on conventional household poverty measures.

3 Individual Consumption and Poverty Among Children

We now present estimated resource shares and the implied rates of child poverty by gender. We then quantify the extent of hidden poverty generated by intra-household inequality. The next section decomposes the gender gap in child poverty into the contributions of differential resource allocation and son-biased fertility behavior.

3.1 Resource Share Estimates

Our estimates indicate large and systematic within-household gender disparities in consumption allocation among children. As shown in Table 2, boys receive a larger per-child share of household resources than girls in both samples, on average.[10] Because resource shares must sum to one, both the levels of the shares and the magnitude of the percentage-point gaps are mechanically affected by household composition: children account for a larger fraction of total household resources in smaller, nuclear households than in extended-family settings. Nevertheless, the estimates consistently indicate that boys receive

[9] The REDS 2006 survey collected height measurements for all household members, including children aged 0–15. However, these data contain some measurement error. Heights were recorded using a feet-and-inches format that appears to have been coded inconsistently across enumerators: some entries follow a feet-inches convention (e.g., 5.06 for 5 feet 6 inches), while others appear to record decimal feet (e.g., 5.50 for 5.5 feet). After converting these measures to centimeters and applying age-specific plausibility bounds, some observations fell outside expected biological ranges. For these reasons, we compute height-for-age z-scores using internal normalization—standardizing height within age-by-sex cells using the sample mean and standard deviation rather than external WHO growth standards.

[10] Recall that resource shares are parameterized as functions of household characteristics and jointly estimated within the nonlinear SUR system. Table A3 in the Appendix shows that estimated shares vary systematically with household demographic composition, particularly the number and age of boys and girls. Intuitively, additional boys significantly increase boys' resource shares while reducing girls' shares, and vice versa for additional girls. Older children also tend to receive larger shares within their own gender group. By contrast, parental education, caste, and religion exhibit relatively weak associations with estimated allocations once household composition is controlled for.

Table 2: Resource Share Estimates

	All Families			Nuclear Families		
	Mean	**Median**	**SD**	**Mean**	**Median**	**SD**
Men (η_m)	0.444	0.444	0.075	0.395	0.378	0.086
Women (η_w)	0.274	0.271	0.018	0.273	0.270	0.034
Boys (η_b)	0.205	0.202	0.045	0.253	0.251	0.047
Girls (η_g)	0.171	0.167	0.040	0.159	0.159	0.029
Girl-Boy Gap ($100 \times (\eta_g - \eta_b)$)		-3.4			-9.4	
p-value for gap $= 0$		0.091			0.001	
Observations		3,983			1,410	

Notes: Nonlinear SUR estimates. Resource-share rows report means, medians, and standard deviations. All families (N=3,983) include both nuclear and extended households. Nuclear families (N=1,410) include only parents and their children. Resource shares for boys are averaged over households with at least one boy; resource shares for girls are averaged over households with at least one girl. The reported gap is the average girls' share minus the average boys' share in percentage points, so negative values indicate that girls receive smaller resource shares than boys on average. The p-value tests H_0: average $\eta_g - \eta_b = 0$ using a delta-method linear combination of the nonlinear SUR coefficients and village-clustered variance-covariance matrix, treating the covariate distribution as fixed.

substantially more resources than girls across household structures. In nuclear families, the estimated resource share of boys is 25.3 percent, compared to 15.9 percent for girls, implying a gap of -9.4 percentage points ($p = 0.001$). In the all-families sample, the corresponding average shares are 20.5 percent for boys and 17.1 percent for girls, implying a smaller gap of -3.4 percentage points that is statistically significant at the 10 percent level ($p = 0.091$).

These gaps are economically meaningful. Because individual consumption is proportional to resource shares in our framework, a lower resource share for girls directly implies lower individual consumption relative to boys holding total household resources fixed. This within-household disparity, therefore, constitutes a direct channel through which gender differences in welfare can arise, even among children living in the same household.

Figure 1 shows that these differences are not driven by outliers or isolated segments of the distribution. The cumulative distribution function of girls' resource shares lies uniformly to the left of that of boys in both samples, implying that girls systematically receive lower predicted shares across the entire distribution. Equivalently, for any given level of resource share, girls are more likely than boys to fall below that threshold. A Kolmogorov–Smirnov test rejects equality of the two distributions in both samples ($p < 0.01$), consistent with first-order stochastic dominance of boys' allocations over girls' allocations (Table A6 in the Appendix). This pattern indicates that the gender gap in intra-household resource allocation is pervasive rather than concentrated among a small subset of households. At the same time, the distributions exhibit substantial dispersion, pointing to meaningful heterogeneity across households in the extent of intra-household inequality.

Appendix Figure A2 reports the estimated girl–boy resource-share gap across demographic and socioeconomic subgroups. The estimated gap is negative in every subgroup considered, although its magnitude varies. In particular, the disparity is largest among households with less educated mothers and among SC/ST/OBC households, suggesting that gender bias in intrahousehold allocation is widespread but not uniform across families.

For robustness, we estimate the system of Engel curves on a subsample of households containing at least one boy and one girl (Table A4 in the Appendix) and one of households containing exactly one boy and one girl (Table A5). Although the magnitude of the percentage-point gaps is mechanically influenced by household composition and the adding-up constraint on resource shares, the direction and economic significance of the gender disparity remain stable across specifications. For completeness, Appendix Table A12 examines the sensitivity of the estimated resource shares to alternative samples. We re-estimate system (1) under a range of restrictions on household composition, including narrower definitions based exclusively on the household head's children, samples requiring the presence of both parents, grandchild-only households, and broader kinship samples that relax relationship restrictions. Across samples, the estimated girl–boy resource-share gap remains negative and sizable, indicating that our findings are not driven by the particular sample used for our main estimates.

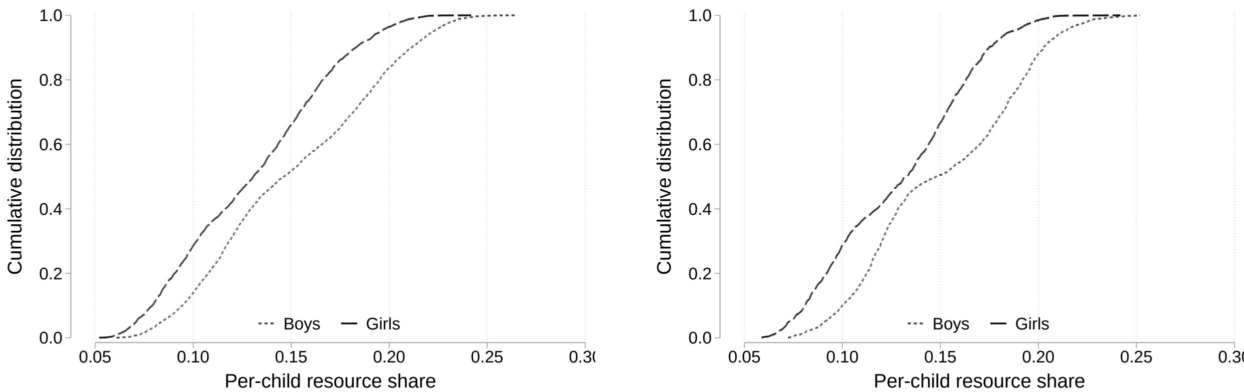
Table A7 in the Appendix provides a broader perspective on the estimated gender disparities by decomposing overall inequality in child consumption into between-household and within-household components using a generalized entropy measure (mean log deviation). As expected, the majority of inequality in children's consumption arises across households rather than within them. Nevertheless, intrahousehold differences account for a meaningful share of total inequality, ranging from 7.2 percent in the full sample to 11.9 percent among households containing both boys and girls.

These estimates should be interpreted as conservative lower bounds on the contribution of intrahousehold inequality. As previously discussed, our framework identifies consumption separately only for boys and girls and therefore assigns the same consumption level to children of the same gender within a household. As a result, the within-household component captures only gender-based differences in allocation and does not reflect inequality arising from birth-order effects, age-related disparities, or other forms of unequal treatment among siblings. The fact that the within-household component rises substantially in households containing both boys and girls is therefore particularly informative. In these households, where gender-based allocation differences can operate most directly, nearly one-eighth of total inequality in child consumption arises within rather than between families.

Adult allocations are also unequal. Men receive substantially larger resource shares than women—39.5 percent versus 27.3 percent in nuclear families and 44.4 percent versus 27.4 percent in the all-families sample—consistent with prior evidence on intra-household gender inequality in India (Calvi, 2020; Calvi and Keskar, 2021; Bandyopadhyay and Maity, 2026; Kapoor and Ravi, 2025).

Taken together, these results establish that unequal intra-household allocation is a central determinant of gender differences in individual consumption. However, unequal allocation is not the only potential source of gender differences in welfare. Even if boys and girls were treated equally within the household, differences in the types of households in which they reside could generate additional dis-

Figure 1: Distribution of Children's Resource Shares by Gender



A) All Families B) Nuclear Families

Notes: The panels plot empirical cumulative distribution functions of per-child resource shares for boys and girls in all families (N=3,983) and nuclear families (N=1,410). In both samples, the girls' CDF lies above the boys' CDF over most of the support, indicating systematically lower resource shares for girls. Kolmogorov-Smirnov tests reject equality of the two distributions in both samples (all families: $D = 0.211$; nuclear families: $D = 0.392$; $p < 0.01$ in both cases).

parities. In particular, if girls were disproportionately exposed to larger households—where resources are spread more thinly across children—then differences in household composition could generate aggregated patterns of gender inequality. The next subsection shows how these allocation differences translate into gender gaps in child poverty, before we return to this issue more formally.

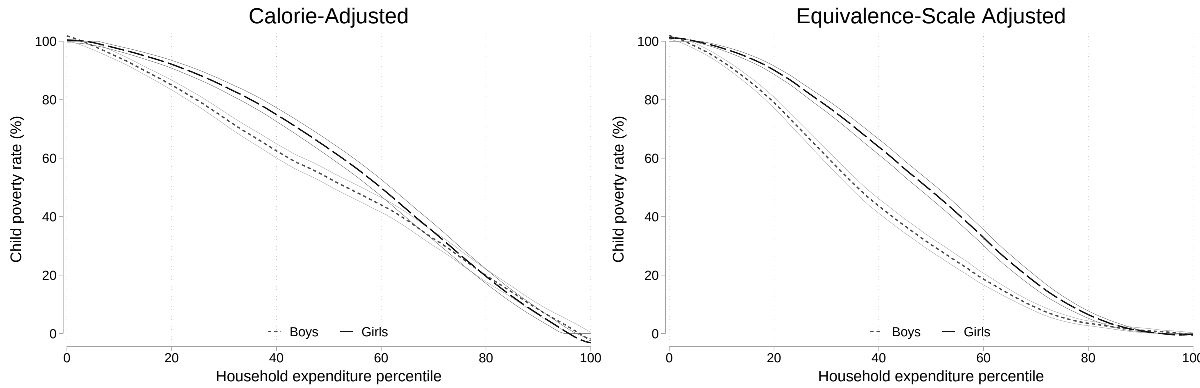
3.2 Hidden Gender Gaps in Child Poverty

Computing Child Poverty. Standard poverty measures assign a common poverty status to all members of a household based on per-capita expenditure, implicitly assuming equal sharing within the household (Dunbar et al., 2013; Bargain et al., 2014; Brown et al., 2021). As a result, they cannot capture inequality in resource allocation within families and may systematically obscure gender disparities in welfare.

To uncover these hidden gender gaps in child poverty, we map estimated resource shares into individual consumption. Specifically, model-implied individual consumption is computed as the product of each household member's estimated resource share and total household expenditure. Individuals are then classified as poor if their implied consumption falls below an age-adjusted poverty threshold.

Our preferred specification uses the World Bank extreme poverty line of $1.90 per person per day (2011 PPP), corresponding to an annual adult threshold of approximately Rs. 5,645 in 2006 REDS prices. Because material needs vary systematically by age and gender, however, applying a common poverty threshold to all household members may generate welfare-inconsistent comparisons. We therefore treat the World Bank poverty line as corresponding to the caloric requirements of a reference working-age adult and rescale individual poverty thresholds proportionally using age- and gender-specific caloric requirements. For comparability with earlier applications of the collective-household

Figure 2: Child Poverty by Household Per-capita Expenditure



Notes: Sample: children younger than 16 in both nuclear and extended families. Within each panel, boys and girls are shown separately, with shaded 95 percent confidence bands around the poverty curves. The calorie-adjusted panel scales the adult World Bank benchmark ($1.90/day) by Indian age-sex-specific calorific requirements from Indian Council of Medical Research and National Institute of Nutrition (2020). The equivalence-scale-adjusted panel assigns children under age 15 a poverty threshold equal to 60 percent of the adult World Bank benchmark. At a given expenditure percentile, a higher girls' curve indicates greater poverty among girls.

framework to poverty measurement, we also report results using the simpler equivalence-scale adjustment adopted by Dunbar et al. (2013) and Calvi (2020), which assigns children under age 15 a poverty threshold equal to 60 percent of the adult benchmark.

Gender Gaps in Child Poverty. Let $P_g = \Pr[\text{poor} \mid \text{girl}]$ and $P_b = \Pr[\text{poor} \mid \text{boy}]$ denote the poverty rates among girls and boys, respectively, and define the overall gender gap in child poverty as:

$$\Delta P = P_g - P_b.$$

In the full sample, 55.1 percent of girls are poor under the equivalence-scale adjustment, compared to 42.9 percent of boys, implying a gap of 12.1 percentage points. When poverty thresholds are adjusted for age- and gender-specific requirements, the estimated poverty rates increase for both groups, but substantial gender disparities remain: 63.5 percent of girls are poor compared to 56.3 percent of boys, implying a gap of 7.2 percentage points. The corresponding poverty gaps are even larger among nuclear families, consistent with the stronger disparities in resource shares documented above.

These differences are mechanically linked to unequal allocation in the model. Since individual consumption is proportional to resource shares, lower shares for girls imply lower consumption relative to boys facing the same household resource constraint. When household resources are sufficiently limited, these differences in implied consumption translate into systematically higher poverty rates for girls (as shown in Table A8 in the Appendix).

Figure 2 shows that gender gaps in poverty can persist across the household expenditure distribution, including among relatively well-off households. Figure A3 in the Appendix shows that these disparities emerge early in life and persist throughout childhood and early adolescence.

Hidden Poverty and Inequality. The *hidden* nature of these disparities becomes apparent when comparing individual poverty to standard household-level classifications. Under conventional approaches, households are classified as poor or non-poor based on per-capita consumption, and all members are assigned the same poverty status. By construction, this procedure ignores differences in resource allocation within families and can therefore generate two distinct forms of mismeasurement.

First, poverty may be hidden *within households*: some children may be individually poor even when their household is classified as non-poor. This phenomenon has been documented in several settings, including South Asia (Calvi, 2020; Brown et al., 2021). Second, poverty may be hidden *across genders*: because girls systematically receive smaller shares of household resources than boys, they are disproportionately likely to experience deprivation even when living in the same household.

Figure 3 reports individual poverty rates separately by child sex, household poverty status, and poverty-line adjustment. In every comparison, girls exhibit higher poverty rates than boys. Under the equivalence-scale adjustment, nearly 16.7 percent of girls living in households classified as non-poor are nevertheless individually poor, compared to 9.4 percent of boys. When poverty thresholds are adjusted for age- and gender-specific caloric requirements, the corresponding rates rise to 31.1 percent for girls and 28.5 percent for boys.

These findings imply that a substantial share of children—particularly girls—experience deprivation that is invisible to standard household-level poverty measures. Because anti-poverty programs are typically targeted using household rather than individual indicators, such children may be overlooked despite facing material deprivation.

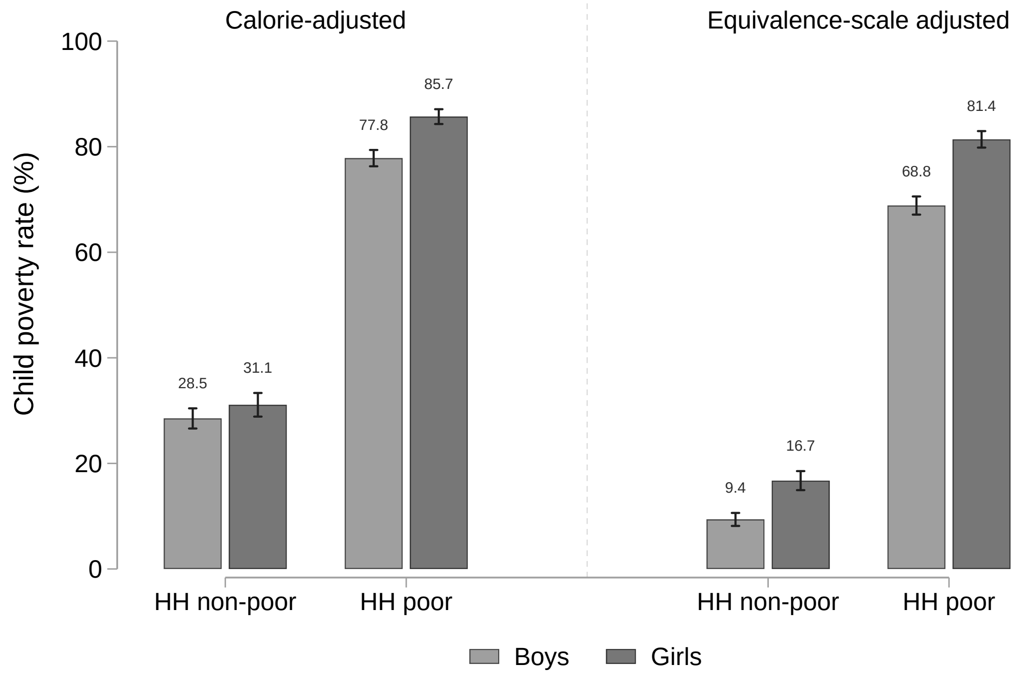
Note that child poverty rates are not necessarily equal to 100 percent even among households classified as poor. First, unequal intrahousehold allocation implies that some children receive larger shares of household resources than others. Second, children are evaluated against an age-adjusted poverty line that is generally lower than the unadjusted poverty line used to classify households. As a result, some children living in poor households may nevertheless have consumption levels above their individual poverty line.

Taken together, these results indicate that gender disparities in child poverty are both substantial and systematically understated by conventional household-based measures. They also motivate the next question: to what extent do these disparities reflect unequal allocation within households, as opposed to differences in the types of households in which girls and boys live? We address this question in the next section.

4 Son-Biased Fertility and Gender Poverty Gaps

The preceding results establish two central facts. First, girls experience higher rates of individual poverty than boys. Second, these disparities are largely invisible in standard household-level poverty measures

Figure 3: Child Poverty by Gender and Household Poverty Status



Notes: Sample: children younger than 16 in all families. Bars show actual individual poverty rates for boys and girls within each household-poverty stratum; whiskers show 95 percent confidence intervals. Household poverty status is computed using actual household per-capita expenditure and the adult World Bank benchmark ($1.90/day). The calorie-adjusted measure scales this benchmark by Indian age-sex-specific calorific requirements from Indian Council of Medical Research and National Institute of Nutrition (2020). The equivalence-scale-adjusted measure assigns children under age 15 a threshold equal to 60 percent of the adult benchmark.

because they arise within households rather than solely across households. A natural next question is, therefore, what mechanisms generate these gender gaps in child poverty?

Unequal allocation within households is one obvious candidate mechanism. Our estimates indicate that girls receive systematically smaller per-child resource shares than boys, implying lower individual consumption holding household resources fixed. However, differences in intrahousehold allocation are unlikely to be the only source of gender gaps in poverty. In settings characterized by strong son preference, fertility behavior may also shape the household environments in which girls and boys grow up.

A large literature documents that parents in India adjust fertility dynamically in response to the sex composition of existing children, continuing childbearing until a desired number of sons is achieved (e.g., Jensen, 2003; Barcellos et al., 2014; Jayachandran and Kuziemko, 2011; Anukriti et al., 2022). As a result, girls are disproportionately represented in larger families and therefore face greater competition for household resources. This mechanism can generate gender differences in poverty even in the absence of consumption discrimination within households.

To study the role of fertility-driven household composition, we classify households according to the sex of the firstborn child. In the cohorts represented in REDS 2006, firstborn sex is generally viewed as plausibly exogenous because sex-selective abortion at first birth remained relatively uncommon relative to later parities (Jayachandran, 2017; Anukriti et al., 2022). At the same time, firstborn sex has important downstream consequences for fertility behavior under son preference. Families whose first child is a girl are more likely to continue childbearing in pursuit of a son, leading to larger completed family size, higher parity, and different sibling composition. Table A10 provides direct evidence of these fertility responses in our sample. Families whose firstborn child is a girl have significantly more children than families whose firstborn child is a boy. Moreover, among firstborn-girl households, younger siblings are substantially more likely to be boys, consistent with continued fertility in pursuit of a son.

Defining household type using firstborn sex has two advantages. First, it captures fertility responses induced by son preference while remaining plausibly orthogonal to unobserved household characteristics. Second, it summarizes the cumulative consequences of dynamic fertility choices—including family size, birth order, and sibling composition—without conditioning directly on endogenous outcomes such as completed fertility or parity.[11]

We begin by documenting how gender gaps in consumption allocation within families vary across household composition. Figure A4 in the Appendix reports the girl–boy gap in per-child resource shares (that is, the difference between the average estimated resource shares for girls and boys) by firstborn sex, older-brother status, and the girls-to-boys ratio within the household. Several patterns emerge. First, the resource-share gap is substantially larger in households where the firstborn child is a girl than in households where the firstborn is a boy. This pattern is consistent with stronger son-biased fertility behavior in firstborn-girl households, which tend to be larger and more resource-constrained. Second, girls receive systematically smaller shares regardless of whether they have an older brother, indicating that unequal allocation is not driven solely by direct competition with older male siblings. Third, the gender gap in resource shares becomes substantially larger in households where girls outnumber boys. In households with more girls than boys, girls receive substantially smaller per-child allocations relative to boys, whereas the gap is close to zero in households where girls are relatively scarce.

Appendix Figures A5 and A6 show that these differences in allocation translate into substantial disparities in poverty. The gender gap in child poverty is considerably larger among households where the firstborn child is a girl, and increases sharply with the relative number of girls in the household. In households where girls outnumber boys, the poverty gap becomes particularly large, suggesting that the interaction between son-biased fertility stopping behavior and unequal intrahousehold allocation has major consequences for child deprivation.

To formally study the role of son-biased fertility, we perform a Oaxaca-style decomposition (Oaxaca, 1973; Blinder, 1973) of the overall gender gap in child poverty. The decomposition separates the gap into a within-type component and a household-composition component. Because the decomposition relies on fertility behavior and sibling composition, we restrict the analysis to nuclear families.[12] The

[11] For detailed evidence of the quasi-randomness of the sex of the firstborn, see Anukriti et al. (2022).

[12] The all-families estimation sample excludes households in which children under 16 include both the head's children and grandchildren, but grandchild-only households can remain in broader all-families analyses. In the nuclear sample used here,

household-composition component captures differences in exposure to family environments generated by son-biased fertility-stopping behavior, while the within-type component captures residual gender differences in poverty among children living in comparable family environments. Let $t \in \{0,1\}$ index household type, where $t = 1$ denotes households whose firstborn child is a girl and $t = 0$ denotes households whose firstborn child is a boy. For each child sex $s \in \{g, b\}$, define

$$\pi_{s,t} \equiv \Pr(T = t \mid S = s)$$

as the share of children of sex s who live in households of type t, and

$$P_{s,t} \equiv \Pr(\text{poor} = 1 \mid S = s, T = t)$$

as the poverty rates within that household type. The poverty rates among girls and boys can therefore be written as

$$P_s = \sum_{t \in \{0,1\}} \pi_{s,t} P_{s,t}.$$

We then construct a counterfactual poverty rate for girls:

$$P_g^{cf} = \sum_{t \in \{0,1\}} \pi_{b,t} P_{g,t},$$

which essentially captures what girls' poverty rate would be if girls faced the same distribution of household types as boys, while preserving the within-household poverty outcomes observed for girls.

Adding and subtracting P_g^{cf} yields the following decomposition of the gender gap in child poverty:

$$\Delta P = (P_g^{cf} - P_b) + (P_g - P_g^{cf}).$$

The first term captures the *within-type component*: differences in poverty between girls and boys holding constant household type. Because household type is defined by the sex of the firstborn child, this component reflects gender differences in poverty that arise within comparable family environments and is therefore most closely related to unequal intrahousehold allocation. The second term captures the *household composition component*: differences arising because girls and boys are differentially exposed to household types associated with son-biased fertility behavior. In particular, girls are more likely to reside in families whose firstborn child is a girl and which, due to son-biased stopping rules, tend to be larger and contain more children.

Table 3 reports the results. Note that child poverty rates are higher in nuclear families than in the full sample, particularly among girls, consistent with the lower resource shares estimated for girls in nuclear households (see Section 3). Overall, the vast majority of the gender gap in child poverty is explained by within-type differences rather than by differential household composition. Under the equivalence-scale-

under-16 children are the head's own children, so firstborn sex and sibling composition can be mapped cleanly to a parental fertility history.

Table 3: Decomposition of the Girl-Boy Child Poverty Gap

	Girls (%)	**Boys (%)**	**Total Gap (p.p.)**	**Within p.p. (%)**	**Composition p.p. (%)**
Calorie-adjusted	80.9	57.9	23.0	17.8 (77.3)	5.2 (22.7)
Equivalence-Scale Adjusted	74.1	43.6	30.4	25.6 (84.2)	4.8 (15.8)

Notes: The table decomposes the nuclear-family girl-boy poverty gap into within-household-type and household-composition components. Household type is indexed by the sex of the firstborn child. The within component is the gap that would remain if girls had the same distribution of firstborn-sex household types as boys. The composition component is the residual contribution from girls' and boys' differential exposure to firstborn-girl and firstborn-boy households. Values in parentheses report each component as a percentage of the total girl-boy gap.

adjusted calculations, approximately 84.2 percent of the total gender gap in child poverty is attributable to differences in poverty between girls and boys within the same firstborn-sex household type, while only 15.8 percent is explained by composition effects. When differences in needs by age and gender are taken into account, 77.3 percent of the gap is attributable to within-type differences, with the remaining 22.7 percent explained by differential exposure to different household types associated with son-biased fertility behavior.

These findings suggest that differences in household composition generated by son-biased fertility behavior explain only a modest share of the overall gender gap in child poverty. Although girls are somewhat more likely to reside in larger families with fewer resources available per child, most of the disparity remains among children living in similar household environments.

5 Child Poverty and Well-Being

An important question is whether the individual poverty measures recovered from the collective model capture meaningful differences in children's well-being beyond those reflected in conventional household poverty measures. If low consumption and poverty risk matter for children's well-being, then children classified as poor based on their own estimated individual consumption should exhibit worse outcomes even after accounting for overall household resources.

To investigate this question, Table 4 examines the relationship between child poverty and a range of child outcomes spanning health, educational investments, and learning. In each specification, we include both the child's individual poverty status and a conventional household per-capita poverty indicator. This allows us to assess whether the information contained in the estimated individual consumption has predictive power beyond that provided by standard household-level measures.

The first set of results considers height-for-age z-scores (HAZ), a widely used indicator of nutritional status. Under both poverty definitions, children classified as individually poor exhibit significantly lower height-for-age scores even after controlling for household poverty status. The relationship is particularly strong for boys. Under the calorie-adjusted measure, individually poor boys have height-for-age scores that are 0.14 standard deviations lower than those of non-poor boys living in households with similar poverty status, while household poverty itself has little explanatory power.

The second set of outcomes examines educational expenditures. Here, the associations are economically large. Under the calorie-adjusted measure, individually poor girls receive approximately 55 log points (about 42 percent) less educational spending than otherwise similar non-poor girls, while individually poor boys receive roughly 45 log points (about 36 percent) less. Comparable patterns emerge under the equivalence-scale-adjusted measure. Notably, the magnitude of the individual-poverty coefficient is often similar to, and sometimes larger than, that of household poverty.

The final set of outcomes considers advanced literacy skills, measured by the ability to read and write in English and the child's mother tongue. Individually poor children are substantially less likely to possess these skills. Under the calorie-adjusted measure, individual poverty is associated with reductions of approximately 10–11 percentage points in advanced reading and writing among girls and reductions of roughly 5–9 percentage points among boys. In several specifications, the estimated association between individual poverty and learning outcomes exceeds the corresponding association with household poverty, indicating that the consequences of unequal intrahousehold allocation extend beyond current consumption and are reflected in children's cognitive and educational development.

These findings provide strong evidence that the poverty measures recovered from the collective model capture meaningful differences in children's lived experiences. Children identified as poor on the basis of their own resource allocations exhibit worse nutritional outcomes, receive substantially lower educational investments, and achieve poorer learning outcomes, even when they reside in households with similar overall resources.

6 Gender Gaps in Child Poverty and Missing Girls

The previous sections document hidden gender disparities in child consumption and poverty. Girls receive systematically smaller resource shares than boys, experience significantly higher rates of individual poverty, and exhibit worse health and human capital outcomes conditional on household poverty. These findings naturally raise a broader question: can hidden inequalities in everyday consumption contribute to the large deficits in female survival documented in India?

Beginning with Sen (1990), a large literature has documented the phenomenon of *missing women*, defined as the shortfall in the number of surviving females relative to benchmark populations with similar demographic structures. Sex-selective abortion and differential investment in girls in infancy and early childhood have received substantial attention in this literature. A large body of evidence documents systematic gender disparities in health investments, nutrition, and medical care in India and other parts of South Asia (Das Gupta, 2005; Barcellos et al., 2014; Oster, 2009; Jayachandran and Kuziemko, 2011). More recent work has also emphasized the interaction between fertility decline, son preference, and prenatal sex selection (Jayachandran, 2017; Anukriti, 2018; Anukriti et al., 2022). At the same time, a growing body of work shows that excess female mortality cannot be explained solely by

Table 4: Individual Poverty and Child Human Capital Outcomes

	Girls				Boys			
	Health	Human Capital			Health	Human Capital		
	HAZ	Education Spending	Advanced Reading	Advanced Writing	HAZ	Education Spending	Advanced Reading	Advanced Writing
Panel A. Calorie-Adjusted Poverty Measure								
Individually Poor	-0.072^{*}	-0.552^{***}	-0.111^{***}	-0.100^{***}	-0.141^{***}	-0.453^{***}	-0.094^{***}	-0.045^{*}
	(0.040)	(0.059)	(0.028)	(0.028)	(0.035)	(0.049)	(0.024)	(0.024)
HH Per-Capita Poor	-0.076^{**}	-0.442^{***}	-0.029	-0.022	0.019	-0.520^{***}	-0.039^{*}	-0.079^{***}
	(0.036)	(0.052)	(0.026)	(0.025)	(0.031)	(0.043)	(0.022)	(0.022)
Observations	3,954	2,340	2,366	2,366	4,832	3,051	3,091	3,091
Panel B. Equivalence-Scale-Adjusted Poverty Measure								
Individually Poor	-0.088^{**}	-0.433^{***}	-0.047^{*}	-0.010	-0.062^{*}	-0.227^{***}	-0.086^{***}	-0.086^{***}
	(0.039)	(0.057)	(0.028)	(0.027)	(0.034)	(0.047)	(0.023)	(0.023)
HH Per-Capita Poor	-0.062^{*}	-0.472^{***}	-0.059^{**}	-0.069^{***}	-0.019	-0.632^{***}	-0.039^{*}	-0.053^{**}
	(0.037)	(0.054)	(0.026)	(0.026)	(0.033)	(0.045)	(0.022)	(0.022)
Observations	3,954	2,340	2,366	2,366	4,832	3,051	3,091	3,091

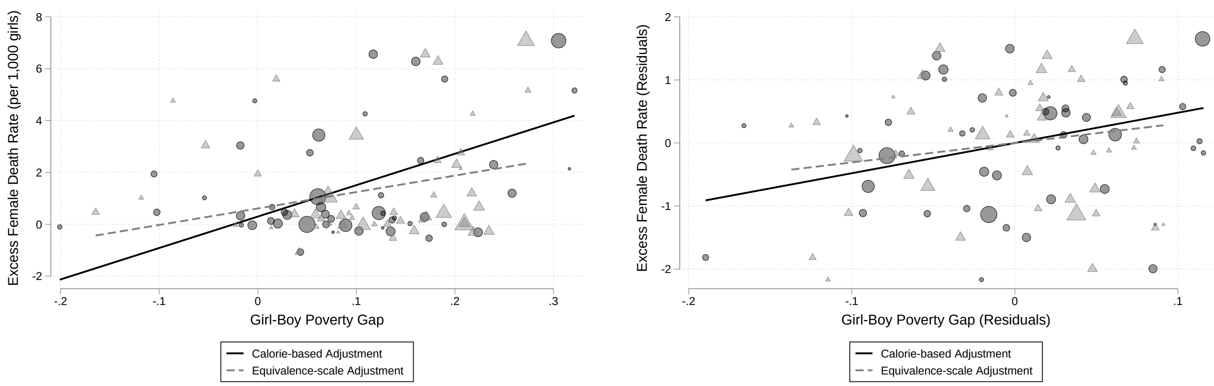
Notes: The table reports associations between individual poverty and child outcomes. Height-for-age z-scores (HAZ) are internally standardized by age and sex. Education Spending is measured as $\ln(1+\text{annual Rs.})$. Advanced Reading and Advanced Writing are indicators equal to one if the child can read or write in both English and their mother tongue. Panel A defines individual poverty using age- and sex-specific calorie-adjusted poverty thresholds. Panel B defines individual poverty using an equivalence-scale-adjusted poverty threshold, which assigns children under age 15 a poverty line equal to 60 percent of the adult World Bank benchmark. HH Per-Capita Poor is based on standard household per-capita expenditure. All specifications additionally control for child age and household composition (numbers of boys, girls, adult men, and adult women). Village-clustered standard errors are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

prenatal selection or discrimination at birth. Anderson and Ray (2010, 2012) demonstrate that excess female mortality in India is highly age-specific and extends well beyond birth.

Our poverty estimates above imply large gender asymmetries in individual deprivation even among children living in households that would appear non-poor according to conventional household-level measures. If unequal access to household resources translates into poorer nutrition, weaker health, and lower resilience among girls, then states and age groups with larger girl-boy poverty gaps should also exhibit larger excess female mortality. To test this hypothesis, we follow Anderson and Ray (2010, 2012), who provide an intuitive and tractable measure of missing women by comparing observed female mortality to a benchmark female mortality rate. We then conduct a simple counterfactual exercise in the spirit of Calvi (2020) relating excess female mortality to the gender gap in individual poverty estimated from the REDS data.[13] The exercise is intentionally simple, but it provides a quantitative benchmark for assessing whether the magnitudes of the hidden poverty gaps documented in this paper are large enough to plausibly account for differences in female child survival.

To measure excess female mortality, we combine state-age poverty gaps with age-specific mortality

[13] Calvi (2020)'s focus is on excess female mortality in adulthood, especially at post-reproductive ages. Here, instead, we focus on infancy, childhood, and early adolescence.



(a) Unconditional

(b) Residualized

Figure 4: Gender Gaps in Child Poverty and Missing Women

Notes: Each point represents a state-age cell formed by combining one of the 17 states that overlap between the REDS and SRS data with one of three child age groups (0–4, 5–9, and 10–14). The vertical axis reports the excess female death rate in rural areas per 1,000 girls. The horizontal axis reports the estimated girl-boy poverty gap. Circles and solid fitted lines correspond to the calorie-adjusted poverty measure, while triangles and dashed fitted lines correspond to the equivalence-scale-adjusted poverty measure. Panel A plots the unconditional relationship. Panel B residualizes both the excess female death rate and the poverty-gap measures with respect to state and age-group fixed effects. Observations and fitted lines are weighted by the rural female population in each state-age cell.

data from the 2011 Sample Registration System (SRS). Let d^g_{sa} and d^b_{sa} denote the observed death rates per 1,000 girls and boys in state s and age group $a \in \{0\text{–}4, 5\text{–}9, 10\text{–}14\}$, respectively, and let N^g_{sa} denote the female population in that state-age cell. Following Anderson and Ray (2010), let r_a denote the benchmark female-to-male mortality ratio, equal to 0.80, 0.76, and 0.67 for ages 0–4, 5–9, and 10–14, respectively. These benchmark ratios capture the biologically expected female survival advantage in low-discrimination mortality environments. The counterfactual female death rate implied by the benchmark is $\tilde{d}^g_{sa} = r_a d^b_{sa}$, and the excess female death rate in age group a and state s is defined as

$$EFDR_{sa} = d^g_{sa} - \tilde{d}^g_{sa} = d^g_{sa} - r_a d^b_{sa}.$$

Positive values indicate that girls die at higher rates than predicted by the benchmark female-male mortality relationship. Intuitively, $EFDR_{sa}$ measures the extent to which female mortality exceeds the level expected given observed male mortality in the same demographic environment.

For each state s and child age group a, let P^g_{sa} and P^b_{sa} denote the estimated poverty rates of girls and boys in the REDS sample, respectively, and define the girl–boy poverty gap as $\Delta P_{sa} = P^g_{sa} - P^b_{sa}$.

Figure 4 provides a graphical summary of the relationship between gender gaps in child poverty and excess female mortality. Each point represents a state-age cell formed by combining one of the 17 states that overlap between the REDS and SRS data with one of three child age groups (0–4, 5–9, and 10–14), weighted by the size of the female population in that cell. Under both poverty definitions, state-age cells with larger girl–boy poverty gaps tend to exhibit higher excess female mortality. The positive

Table 5: Gender Gaps in Child Poverty and Missing Girls

Measure	Marginal Effect	Counterfactual Missing Girls	Explained Share
Panel A. No Fixed Effects			
Calorie-Adjusted	12.07^{***} (2.95)	109,407	42.1%
Equivalence-Scale Adjusted	5.93 (3.59)	137,602	27.1%
Panel B. State and Age Fixed Effects			
Calorie-Adjusted	4.82^{*} (2.48)	150,081	20.5%
Equivalence-Scale Adjusted	2.74 (2.76)	160,924	14.8%

Notes: The dependent variable is the signed excess female death rate per 1,000 girls. REDS child poverty gaps are merged to 2011 rural SRS mortality rates and rural female populations for the child age bins 0–4, 5–9, and 10–14 across the 17 states common to both datasets. All specifications are weighted by the rural female population in each state-age cell. Panel A is pooled and includes no fixed effects. Panel B additionally includes state and age-group fixed effects. The final column reports the share of estimated missing girls statistically associated with the gender gap in child poverty. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

relationship remains visible after residualizing both variables with respect to state and age-group fixed effects, suggesting that the association is not driven solely by persistent differences across states or by the age profile of mortality.

Table 5 further quantifies this relationship. Across specifications, larger girl–boy poverty gaps are associated with higher excess female mortality, although the association is stronger when poverty is measured using age- and gender-specific caloric requirements. For the calorie-adjusted measure, a 10-percentage-point increase in the girl–boy poverty gap is associated with between 0.48 and 1.21 additional excess female deaths per 1,000 girls, depending on the specification. As expected, the relationship is strongest in the unconditional regressions. However, it remains positive and statistically significant at the 10 percent level after controlling for state and age-group fixed effects. This is noteworthy because identification in this specification comes entirely from within-state variation across age groups.

To assess the quantitative importance of these estimates, we conduct a simple counterfactual exercise. For each state-age cell, we predict the component of excess female mortality associated with the observed gender gap in child poverty and then consider a counterfactual in which $\Delta P_{sa} = 0$. The estimated coefficients imply a reduction in the excess female death rate of $\hat{\beta}\Delta P_{sa}$ deaths per 1,000 girls. Multiplying this predicted reduction by the corresponding female population yields the implied reduction in the number of excess female deaths in state s and age group a. We then aggregate these reductions across state-age cells and compare the result to the total number of estimated missing girls in our sample.

The results suggest that excess girl poverty may explain between 20.5 and 42.1 percent of missing girls in our sample. Repeating the exercise with the equivalence-scale-adjusted poverty measure yields somewhat smaller estimates, with implied explained shares ranging from 14.8 to 27.1 percent. Appendix Table A11 shows that the qualitative conclusions are robust to alternative specifications.

These estimates should be interpreted with caution. The poverty and mortality measures are drawn from different data sources, and female child mortality is influenced by many factors beyond material deprivation. At the same time, the specifications with fixed effects control for broad differences in mortality and poverty across states and stages of childhood, ensuring that the estimated relationships are not driven by persistent unobserved differences.

Even viewed as a descriptive benchmark, the results are striking. Hidden gender disparities in child poverty are systematically associated with excess female mortality, and the estimated relationship implies that unequal access to household resources and its implications for poverty may account for a substantial share of missing girls in childhood. More broadly, the findings suggest that intrahousehold allocation is an important channel through which son preference translates into disparities in child survival, helping to connect the literatures on intrahousehold allocation, poverty, and missing women.

7 Conclusion

This paper studies gender differences in child poverty in India through the lens of intrahousehold allocation. While a large literature has documented son preference through disparities in fertility behavior, health investments, education, and survival, much less is known about how household resources are allocated between boys and girls on a day-to-day basis. Using a collective household model and detailed expenditure data from rural India, we estimate individual consumption levels for children and construct poverty measures at the individual rather than household level.

We find substantial gender disparities in the allocation of household resources. Girls receive systematically smaller consumption shares than boys, resulting in significantly higher rates of individual poverty. These disparities persist across age groups and remain largely invisible to conventional household-level poverty measures. A substantial fraction of poor girls reside in households that would be classified as non-poor using standard per-capita consumption measures, implying that household-based poverty statistics substantially understate both the prevalence of child poverty and the extent of gender inequality among children.

The analysis further shows that most of the observed gender gap in child poverty arises within household types rather than through differential exposure to household environments generated by son-biased fertility behavior. Although girls are more likely to reside in larger families with fewer resources available per child, unequal allocation within families remains the dominant source of the gender poverty gap. Moreover, individually poor children exhibit worse nutritional outcomes, receive lower educational investments, and perform worse on measures of literacy even after conditioning on household poverty status.

Finally, this paper connects the literature on intrahousehold allocation and missing women. Combining our poverty estimates with state-by-age mortality data in rural India, we show that areas with larger excess girl poverty also exhibit higher excess girl mortality. A counterfactual exercise suggests that hidden gender gaps in child poverty can account for a substantial fraction of India's missing girls. Echoing results in Calvi (2020), this finding points to a potentially important link between intrahousehold consumption inequality, individual poverty, and excess female mortality in the Indian context. More generally, our results suggest that understanding gender disparities in child well-being requires looking beyond household averages and examining how resources are distributed among children within the household. Accounting for intrahousehold allocation is therefore important not only for measuring poverty accurately, but also for understanding how unequal treatment in childhood may shape longer-run inequalities in health, human capital, and survival.

An important question for future research is whether the patterns documented here persist in contemporary India. A growing body of evidence suggests that some manifestations of son preference have weakened over the past two decades, even as other dimensions of gender inequality remain persistent (Jayachandran, 2023). Yet little is known about whether these broader demographic changes have been accompanied by comparable shifts in the allocation of resources within households. Understanding whether hidden gaps in child poverty have narrowed remains an important direction for future work.

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Online Appendix

A Identification and Estimation: Details

This appendix provides formal details on the identification and estimation of intrahousehold resource shares in the collective model used in the paper. The theoretical framework and identification strategy follow Browning et al. (2013) and Dunbar et al. (2013), with the key difference that we identify separate resource shares for boys and girls. As in Calvi (2020), we consider a general framework that accommodates both nuclear and extended families.

A.1 Collective Framework and Resource Shares

Consider a household composed of adult men, adult women, boys under age 16, and girls under age 16, indexed by $j \in \{m, w, b, g\}$. Let n_j denote the number of household members of type j, and let y denote total household expenditure. Households differ in observable characteristics, including demographic composition, age structure, education, caste, religion, region, and family structure. These characteristics may affect both preferences and the allocation of resources within the household.

Let $h = (h^1, \dots, h^K)$ denote observed household purchases of K goods and let

$$x_j = (x_j^1, \dots, x_j^K)$$

denote the vector of private-good equivalents consumed by a representative member of type j. We allow for economies of scale in consumption through a Barten consumption technology. Specifically, there exists a $K \times K$ matrix A such that

$$h = A \sum_{j \in \{m,w,b,g\}} n_j x_j.$$

This technology transforms individual private-good equivalents into observed household purchases and permits goods to exhibit varying degrees of publicness within the household.

Members of each type derive utility from consumption according to $U_j(x_j)$, where $U_j(\cdot)$ is increasing, strictly quasi-concave, and continuously differentiable. The household is assumed to allocate resources efficiently. Consequently, observed allocations can be represented as the solution to a Pareto-weighted social welfare problem:

$$\max_{\{x_j\}} \sum_{j \in \{m,w,b,g\}} n_j \omega_j U_j(x_j)$$

subject to

$$h = A \sum_j n_j x_j, \qquad p'h = y,$$

where ω_j denotes the Pareto weight attached to members of type j.

Pareto weights summarize the influence of different household members in the allocation process and are often interpreted as measures of bargaining power. However, they are not directly observable and depend on the cardinalization of utility functions. Following Browning et al. (2013), we therefore focus on resource shares rather than Pareto weights.

Let η_j denote the per-capita resource share allocated to members of type j. Resource shares satisfy

$$\sum_{j\in\{m,w,b,g\}} n_j\eta_j = 1,$$

and imply that each member of type j controls resources equal to $\eta_j y$. Resource shares summarize the outcome of the household allocation process and are invariant to monotonic transformations of utility. Under the collective model, and for a given specification of preferences and consumption technology, there exists a one-to-one relationship between Pareto weights and resource shares (Browning et al., 2013).

A standard result from collective models is that the household problem can be decentralized into two stages. First, total household resources are allocated across member types through the resource shares η_j. Second, conditional on receiving resources $\eta_j y$, each member type chooses its preferred consumption bundle by solving

$$\max_{x_j} U_j(x_j)$$

subject to the shadow budget constraint

$$(A'p)'x_j \leq \eta_j y.$$

The resulting indirect utility functions can be substituted into the household optimization problem, yielding a reduced-form representation in which resource shares completely summarize intrahousehold allocation. Our objective is to estimate these resource shares.

A.2 Assignable Goods and Engel Curves

Standard expenditure surveys do not observe individual consumption directly. Identification instead exploits private assignable goods: goods that are privately consumed and recorded separately by recipient type (Dunbar et al., 2013). Let W_j denote the household budget share devoted to the assignable good for type j. In our application, the assignable good is clothing and footwear, which REDS 2006 records separately for adult men, adult women, boys, and girls.

For assignable goods, household demand admits the representation

$$W_j(y,p) = n_j\eta_j\, w_j(A'p, \eta_j y), \tag{A1}$$

where $w_j(\cdot)$ is the shadow-budget demand function for type j, and $A'p$ denotes shadow prices allowing for economies of scale (Browning et al., 2013).

A.3 Piglog Preferences

Under Piglog preferences, Engel curves linear in $\ln y$ and resource shares are by construction independent of y. The resulting assignable-good Engel curve system is:

$$W_m = n_m \eta_m \left(\alpha_m + \beta_m \ln \eta_m + \beta_m \ln y\right), \tag{A2}$$

$$W_w = n_w \eta_w \left(\alpha_w + \beta_w \ln \eta_w + \beta_w \ln y\right), \tag{A3}$$

$$W_b = n_b \eta_b \left(\alpha_b + \beta_b \ln \eta_b + \beta_b \ln y\right), \tag{A4}$$

$$W_g = n_g \eta_g \left(\alpha_g + \beta_g \ln \eta_g + \beta_g \ln y\right), \tag{A5}$$

where α_j and β_j are preference parameters for type j.

A.4 Identification

Identification follows Dunbar et al. (2013) and requires:

1. at least one assignable good observed for each household member type,
2. resource shares that do not vary with total expenditure,
3. a semiparametric restriction on preferences.

The first requirement is satisfied by the REDS expenditure module, which separately records clothing, footwear, and tailoring expenditures for adult men, adult women, boys, and girls. These goods are privately consumed and can therefore be assigned to specific household member types.

The second requirement assumes that, conditional on household characteristics, resource shares are independent of total expenditure. Intuitively, increases in household resources affect individual consumption through the Engel curves rather than through systematic changes in the allocation rule itself. This assumption is standard in the collective-demand literature and is necessary to distinguish resource allocation from preference heterogeneity (Menon et al., 2012; Bargain et al., 2018). This is also implied by construction by Piglog preferences.

For the third requirement, we impose the Similar Across People (SAP) restriction from Dunbar et al. (2013):

$$\beta_m = \beta_w = \beta_b = \beta_g \equiv \beta.$$

Under SAP, household members are allowed to differ in their overall demand for the assignable good through type-specific intercepts, but the slope of the Engel curve with respect to resources is assumed to be common across types. This restriction is substantially weaker than imposing identical preferences and is sufficient to separate preference parameters from resource shares. Under SAP, relative Engel-curve slopes identify relative resource shares, while the adding-up constraint determines their levels.

These identifying assumptions are transparent and testable with appropriate data. Previous work have tested SAP in similar settings with richer data (see Bargain et al. (2018) and Brown et al. (2021)

in Bangladesh), finding it to be a reasonable structure to be imposed to the data. Here, we assess its empirical relevance by estimating a more flexible Similar Across Types (SAT) specification in which the Engel-curve slope function is allowed to differ across adult men, adult women, boys, and girls. Specifically, we replace the common β function with type-specific β_j, which we parameterized using the same household characteristics as in the baseline specification minus the number of adult men, women, boys, and girls. We refer the reader to Dunbar et al. (2013) for a detailed proof about this alternative approach to identification.

Table A1 reports the results. Allowing for type-specific Engel-curve slopes has very little effect on the estimated resource shares. Under the preferred SAP specification, adult men, adult women, boys, and girls receive average resource shares of 0.444, 0.274, 0.205, and 0.171, respectively. The corresponding SAT estimates are 0.433, 0.285, 0.214, and 0.160. The implied girl–boy resource-share gap changes only modestly, from -3.4 to -5.3 percentage points. Moreover, a Wald test fails to reject the null hypothesis that the four βs are equal. Overall, these results suggest that the common-slope restriction imposed by SAP is broadly consistent with the data and that the estimated gender differences in resource allocation are not driven by this specific identifying assumption.

Finally, note that identification weakens when Engel curves are close to flat because resource shares become only weakly related to observed expenditure responses (Tommasi and Wolf, 2016). In our application, estimated Engel-curve slopes are statistically different from zero for all four member types, alleviating concerns about weak identification. Appendix Table A2 reports separate Engel-curve estimates for men, women, boys, and girls. The estimated slopes are all negative, statistically significant.

A.5 Estimation

We estimate the Engel-curve system using nonlinear SUR, imposing both the SAP restriction and the adding-up condition on resource shares. Estimation is conducted jointly across all household types, including households that do not contain members of all four demographic groups. For example, households containing only boys contribute a three-equation system, while households containing both boys and girls contribute the full four-equation system.

A key feature of the specification is that resource shares and preference parameters are allowed to vary systematically across households. Rather than estimating a single set of resource shares for the entire sample, we parameterize both preferences and allocations as functions of observed household characteristics:

$$\eta_j = \mathbf{x}'\boldsymbol{\delta}_j, \qquad \alpha_j = \mathbf{x}'\boldsymbol{\gamma}_j, \qquad \beta = \mathbf{x}'\boldsymbol{\phi},$$

where $\mathbf{x}$ includes household composition, demographic structure, education, caste, religion, and region indicators.

This parameterization allows intrahousehold allocations to differ across households with different demographic and socioeconomic characteristics. For example, the resource shares assigned to boys and girls may vary with the number of children in the household, the presence of adult men and women,

Table A1: Testing the SAP Restriction

	Men	**Women**	**Boys**	**Girls**	**Girl–Boy Gap**	**Wald Test for SAP**
SAP restriction	0.444	0.274	0.205	0.171	-3.4	–
SAT restriction	0.433	0.285	0.214	0.160	-5.3	$\chi^2(30) <$ 0.001, $p > 0.999$

Notes: The first row reports the preferred all-families resource shares estimates using the SAP restriction. The second row re-estimates the system after allowing the Engel-curve beta function to differ across adult men, adult women, boys, and girls. Beta functions under SAT include a constant, region, adult education, average age by type, caste, and religion, but exclude family-member counts. The SAT model is initialized at the estimated parameters with SAP. Adult shares are averaged over all households; boys' and girls' shares are averaged over households with at least one child of that sex. The gap is $100 \times (\eta_g - \eta_b)$, so negative values indicate smaller resource shares for girls. The Wald test is the joint test of equality of the four beta functions.

Table A2: Engel Curve Slope Estimates

	Men	**Women**	**Boys**	**Girls**
Log expenditure	-0.0074^{***}	-0.0073^{***}	-0.0057^{***}	-0.0037^{***}
	(0.0010)	(0.0012)	(0.0009)	(0.0008)
Observations	3,983	3,983	3,230	2,719
R^2	0.171	0.156	0.308	0.322

Notes: Sample: all families (N= 3,983). Dependent variable is budget share spent on assignable clothing (including footwear and tailoring) for each member type. Boys: households with at least one boy (N= 3,230). Girls: households with at least one girl (N= 2,719). Controls: region, education, ages, household composition, caste, religion. Village-clustered standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

children's and adults' ages, parental education, caste, religion, or geographic location. Similarly, preferences for assignable clothing expenditures are allowed to vary systematically across households through the α_j parameters. As a result, the model accommodates substantial heterogeneity in both preferences and allocations while maintaining the restrictions required for identification.

We impose the adding-up restriction by defining men's total share residually:

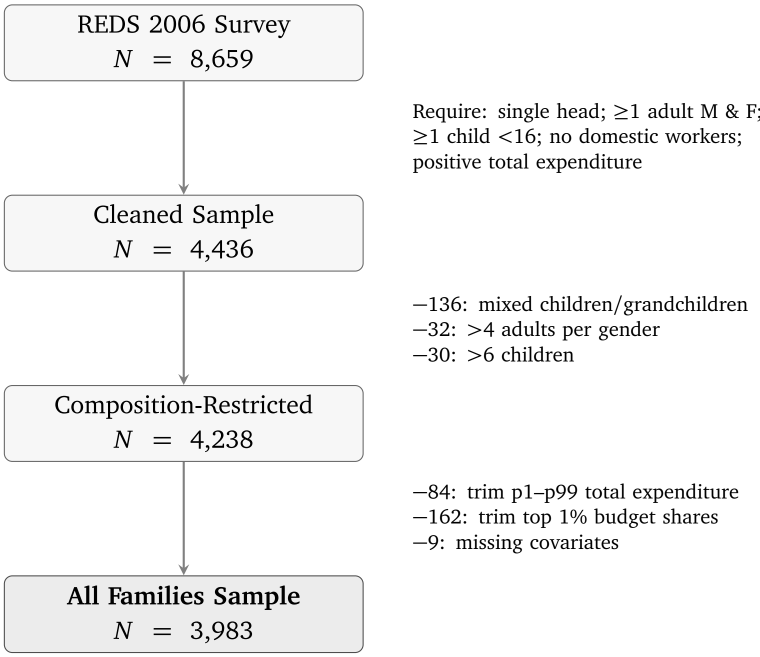
$$n_m \eta_m = 1 - n_w \eta_w - n_b \eta_b - n_g \eta_g.$$

This guarantees that the estimated resource shares satisfy

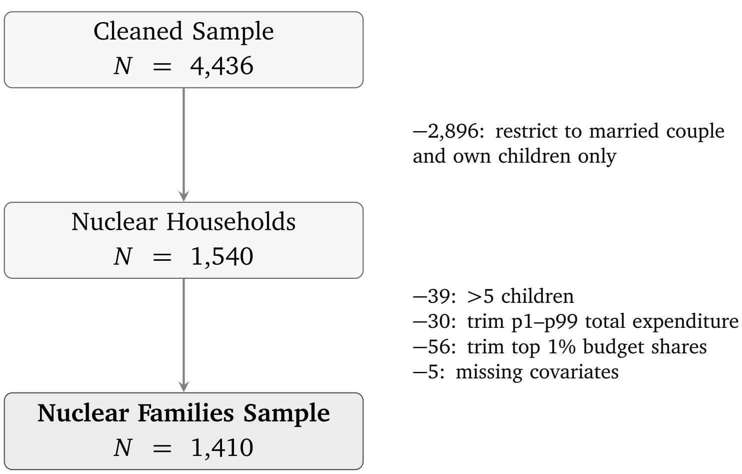
$$\sum_j n_j \eta_j = 1$$

for every household in the sample.

B Additional Figures



(a) All Families ($N = 3{,}983$)

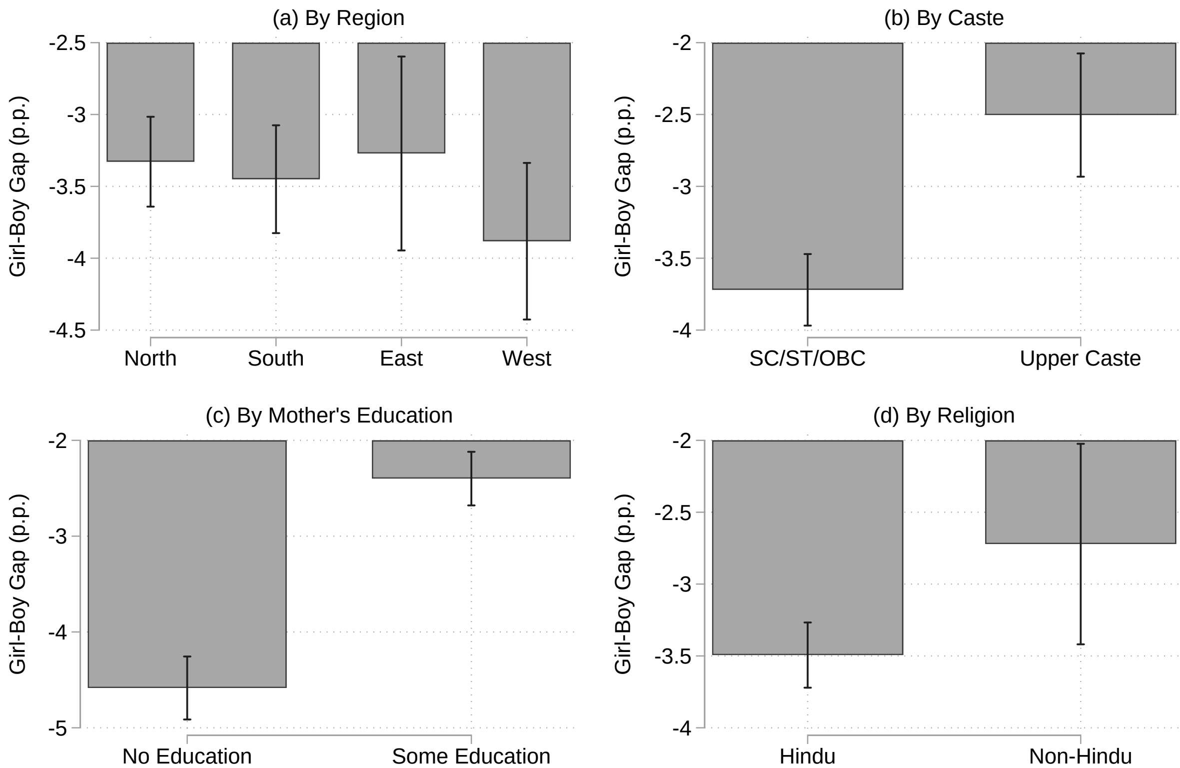


(b) Nuclear Families ($N = 1{,}410$)

Figure A1: Sample Construction

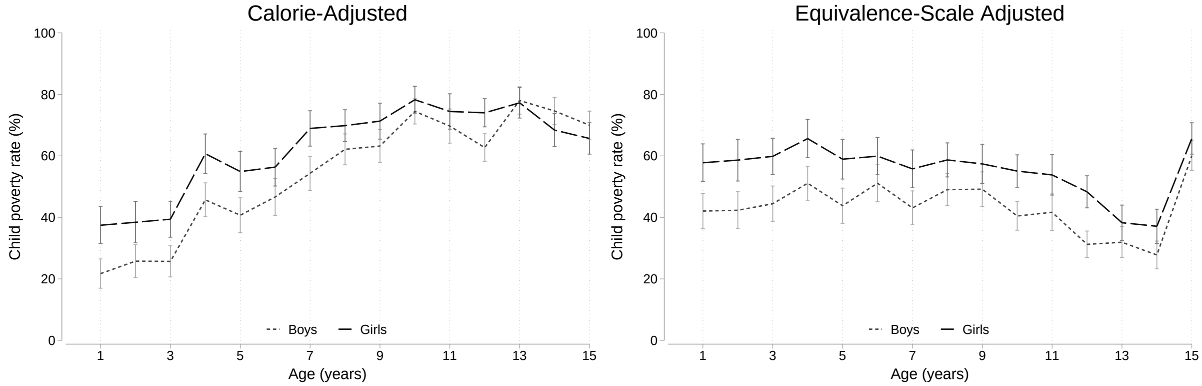
Notes: Panel (a) traces the construction of the all-families analysis sample from the full REDS 2006 survey. Panel (b) traces the construction of the nuclear-families subsample, starting from the cleaned sample in Panel (a). See Section 2.4 for details.

Figure A2: Heterogeneity in Girl-Boy Resource Share Gap by Household Characteristics



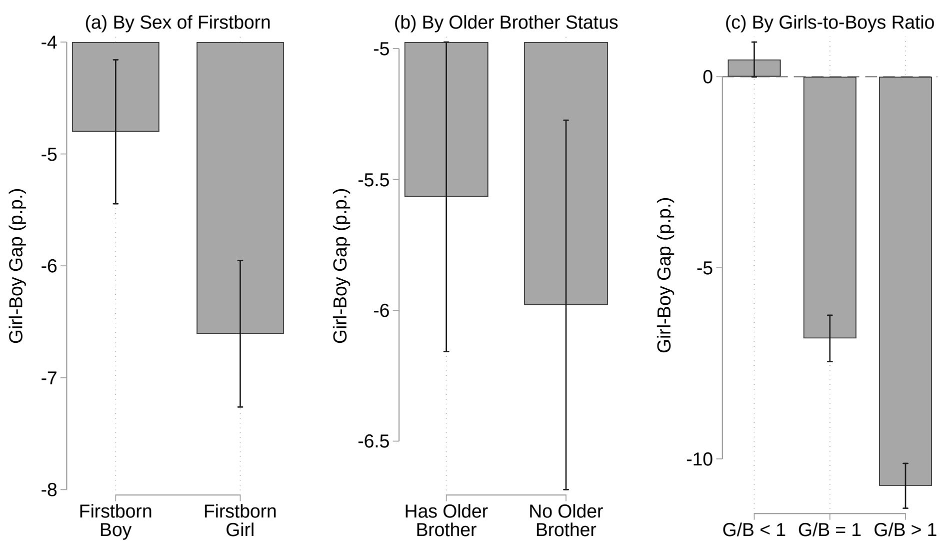
Notes: Bars show the girl–boy resource-share gap in percentage points, with 95% confidence intervals. Negative values indicate girls receive fewer resources. Sample: all families (N=3,983).

Figure A3: Child Poverty by Age



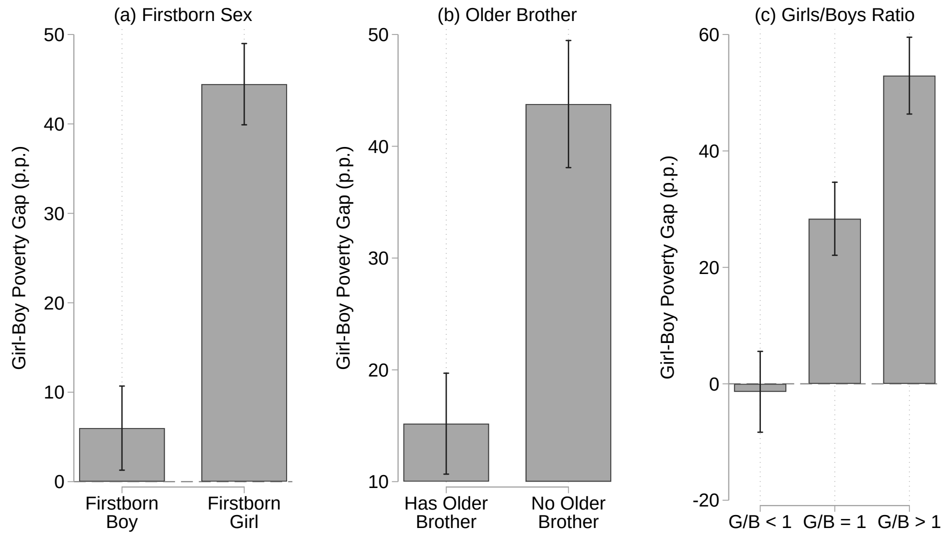
Notes: All families sample. The plotted age range is 1–15. In each panel, boys and girls are shown separately, with 95% confidence intervals at each age. The calorie-adjusted panels scale the adult World Bank benchmark ($1.90/day) by Indian age-sex-specific calorific requirements from Indian Council of Medical Research and National Institute of Nutrition (2020); the equivalence-scale-adjusted panels assign children under age 15 a poverty threshold equal to 60 percent of the adult World Bank benchmark.

Figure A4: Girl-Boy Per-Child Resource-Share Gap by Family Composition



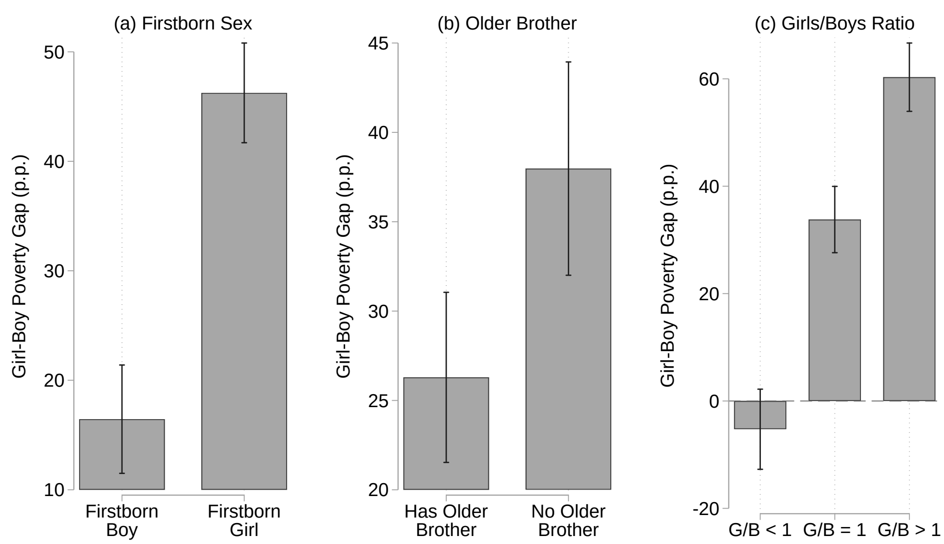
Notes: Sample: nuclear families with both boys and girls. Each bar shows the girl–boy gap in per-child resource shares, measured in percentage points, with 95% confidence intervals. Negative values indicate girls receive less per child. Between-group tests. The gap differs significantly by sex of firstborn ($p < 0.01$) and girls-to-boys ratio (all pairwise $p < 0.01$), but not by older brother status ($p = 0.31$).

Figure A5: Girl-Boy Calorie-Adjusted Poverty Gap by Family Composition



Notes: Sample: nuclear families. Each bar shows the girl–boy gap in individual poverty rates, measured in percentage points, with 95% confidence intervals under a calorie-adjusted poverty measure that scales the adult World Bank benchmark ($1.90/day) by Indian age-sex-specific calorific requirements from Indian Council of Medical Research and National Institute of Nutrition (2020). Positive values indicate higher poverty among girls. The gap is largest in firstborn-girl households and when girls outnumber boys.

Figure A6: Girl-Boy Equivalence-scale Adjusted Poverty Gap by Family Composition



Notes: Sample: nuclear families. Each bar shows the girl–boy gap in equivalence-scale-adjusted individual poverty rates, measured in percentage points, with 95% confidence intervals. The measure assigns children under age 15 a poverty threshold equal to 60 percent of the adult World Bank benchmark ($1.90/day). Positive values indicate higher poverty among girls. The gap is largest in firstborn-girl households and when girls outnumber boys.

C Additional Tables

Table A3: Covariates of Resource Shares

	Nuclear Families				All Families			
	Men	Women	Boys	Girls	Men	Women	Boys	Girls
Constant	0.4663***	0.1356**	0.2522***	0.1459**	0.4901***	0.2117**	0.1857***	0.1125**
	(0.1139)	(0.0676)	(0.0625)	(0.0702)	(0.1119)	(0.0895)	(0.0698)	(0.0532)
North	-0.0623**	0.0551*	0.0025	0.0047	-0.0262	0.0030	0.0083	0.0149
	(0.0306)	(0.0300)	(0.0217)	(0.0178)	(0.0299)	(0.0307)	(0.0198)	(0.0138)
Men's educ.	0.0008	-0.0019	0.0034	-0.0022	0.0005	-0.0008	0.0006	-0.0003
	(0.0029)	(0.0020)	(0.0024)	(0.0021)	(0.0028)	(0.0025)	(0.0023)	(0.0015)
Women's educ.	-0.0026	0.0026	-0.0003	0.0003	-0.0014	0.0003	-0.0009	0.0020
	(0.0033)	(0.0027)	(0.0027)	(0.0027)	(0.0041)	(0.0032)	(0.0026)	(0.0021)
Men's avg. age	0.0022	0.0014	-0.0042	0.0006	0.0003	0.0001	-0.0006	0.0002
	(0.0050)	(0.0020)	(0.0029)	(0.0035)	(0.0019)	(0.0016)	(0.0014)	(0.0009)
Women's avg. age	-0.0029	0.0016	0.0024	-0.0010	0.0004	0.0014	-0.0011	-0.0007
	(0.0052)	(0.0024)	(0.0032)	(0.0036)	(0.0019)	(0.0016)	(0.0013)	(0.0010)
Boys' avg. age	-0.0018	-0.0003	0.0004	0.0017	-0.0017	-0.0017	0.0052***	-0.0017
	(0.0032)	(0.0020)	(0.0026)	(0.0022)	(0.0027)	(0.0022)	(0.0019)	(0.0017)
Girls' avg. age	-0.0035	-0.0014	-0.0001	0.0050*	-0.0039	-0.0001	-0.0010	0.0050***
	(0.0033)	(0.0019)	(0.0022)	(0.0027)	(0.0025)	(0.0021)	(0.0017)	(0.0017)
No. adult men	–	–	–	–	0.0093	0.0006	-0.0072	-0.0027
					(0.0207)	(0.0177)	(0.0137)	(0.0096)
No. adult women	–	–	–	–	0.0072	0.0108	-0.0120	-0.0059
					(0.0195)	(0.0187)	(0.0125)	(0.0090)
No. boys	-0.0083	-0.0085	0.0419***	-0.0250**	-0.0245	-0.0059	0.0437***	-0.0133*
	(0.0184)	(0.0110)	(0.0154)	(0.0108)	(0.0156)	(0.0121)	(0.0130)	(0.0070)
No. girls	0.0089	0.0080	-0.0272***	0.0103	-0.0234	-0.0016	-0.0135	0.0384***
	(0.0167)	(0.0109)	(0.0100)	(0.0143)	(0.0145)	(0.0124)	(0.0084)	(0.0102)
SC/ST/OBC	-0.0292	0.0038	0.0132	0.0122	-0.0034	-0.0083	0.0086	0.0031
	(0.0288)	(0.0208)	(0.0198)	(0.0202)	(0.0323)	(0.0297)	(0.0182)	(0.0147)
Hindu	-0.0137	0.0221	0.0098	-0.0182	-0.0248	0.0250	0.0031	-0.0033
	(0.0423)	(0.0338)	(0.0237)	(0.0243)	(0.0448)	(0.0376)	(0.0250)	(0.0185)
Observations	1,410				3,983			

Notes: Nonlinear SUR estimates from the collective-demand model under the Similar Across People (SAP) restriction. Coefficients parameterize the type-specific resource-share functions and therefore describe how estimated allocations vary with observable household characteristics. Village-clustered standard errors are reported in parentheses. In nuclear families, the numbers of adult men and adult women are fixed at one, so the corresponding coefficients are not identified and are reported as dashes. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A4: Robustness: Resource Shares in Households with Both Boys and Girls

	All Families			**Nuclear Families**		
	Mean	**Median**	**SD**	**Mean**	**Median**	**SD**
Men (η_m)	0.377	0.369	0.122	0.317	0.315	0.069
Women (η_w)	0.242	0.257	0.067	0.348	0.353	0.061
Boys (η_b)	0.210	0.198	0.066	0.220	0.219	0.061
Girls (η_g)	0.171	0.163	0.062	0.116	0.107	0.038
Girl-Boy Gap ($100 \times (\eta_g - \eta_b)$)		-3.9			-10.4	
p-value for gap $= 0$		0.084			0.002	
Observations		1,947			822	

Notes: Sample restricted to households with at least one boy and one girl under 16. The table re-estimates the DLP/SAP nonlinear SUR system on this restricted sample, separately for all families and nuclear families. Resource-share rows report means, medians, and standard deviations. The reported gap is girls minus boys in percentage points, so negative values indicate girls receive less. The p-value tests H_0: average $\eta_g - \eta_b = 0$ using a delta-method linear combination of the nonlinear SUR coefficients and village-clustered variance-covariance matrix, treating the covariate distribution as fixed.

Table A5: Robustness: Resource Shares in Households with Exactly One Boy and One Girl

	All Families			**Nuclear Families**		
	Mean	**Median**	**SD**	**Mean**	**Median**	**SD**
Men (η_m)	0.402	0.399	0.029	0.349	0.349	0.038
Women (η_w)	0.271	0.268	0.015	0.263	0.258	0.031
Boys (η_b)	0.177	0.181	0.024	0.231	0.231	0.022
Girls (η_g)	0.150	0.151	0.021	0.157	0.155	0.027
Girl-Boy Gap ($100 \times (\eta_g - \eta_b)$)		-2.7			-7.3	
p-value for gap $= 0$		0.162			0.007	
Observations		798			317	

Notes: Sample restricted to households with exactly one boy and exactly one girl under 16. The DLP model is not re-estimated on this subsample; the table summarizes resource-share predictions from the DLP/SAP estimates used in Table 2. Resource-share rows report means, medians, and standard deviations. The reported gap is girls minus boys in percentage points, so negative values indicate girls receive less. The p-value tests H_0: average $\eta_g - \eta_b = 0$.

Table A6: Kolmogorov-Smirnov Tests: Boys' vs Girls' Resource Share Distributions

Sample	**D-statistic**	**p-value**	**N**
All Families	0.211	<0.001	3,983
Nuclear Families	0.392	<0.001	1,410

Notes: Two-sample K-S test of the null that boys' and girls' per-child resource shares are drawn from the same distribution. Row 1: all families (3,230 HH with boys, 2,719 HH with girls). Row 2: nuclear families (1,201 HH with boys, 1,041 HH with girls).

Table A7: GE(0) Decomposition of Inequality in Child Consumption

Sample	**Total GE(0)**	**Between-HH**	**Within-HH**	**Within Share**
All children	0.1387	0.1287	0.0100	7.2%
Nuclear families	0.1339	0.1224	0.0115	8.6%
Households with boys and girls	0.1276	0.1124	0.0152	11.9%

Notes: The table reports a decomposition of the generalized entropy measure GE(0) (mean log deviation) computed using estimated individual consumption levels for children. Total inequality is decomposed into a between-household component and a within-household component. Because the collective model identifies consumption separately only for boys and girls, the within-household component reflects gender differences in consumption within households and should be interpreted as a lower bound on total intrahousehold inequality among children.

Table A8: Individual Poverty Rates

	Calorie-Adjusted	**Equivalence-Scale**	**Planning Commission**
Men	31.2%	23.3%	25.5%
Women	45.1%	54.1%	56.5%
Boys	56.3%	42.9%	44.8%
Girls	63.5%	55.1%	57.3%
Girl-Boy Gap (p.p.)	7.1	12.1	12.5
Observations	3,983	3,983	3,983

Notes: Individual consumption equals estimated resource share multiplied by total household expenditure. The first column reports a calorie-adjusted poverty measure that scales the adult World Bank benchmark ($1.90/day) by age- and sex-specific calorific requirements from Indian Council of Medical Research and National Institute of Nutrition (2020). The second column reports an equivalence-scale-adjusted poverty measure that assigns children under age 15 a threshold equal to 60 percent of the adult benchmark. The third column uses the Planning Commission's rural poverty line of Rs. 13 per day in 1999 prices, inflated to the REDS interview year. The sample includes both nuclear and extended households. The reported gap is girls minus boys in percentage points, so positive values indicate higher poverty among girls.

Table A9: Calorie-Adjusted and Equivalence-Scale-Adjusted Hidden Poverty by Household Poverty Status

	Calorie-Adjusted			Equivalence-Scale Adjusted		
	Girls	**Boys**	**Girl-Boy Gap (p.p.)**	**Girls**	**Boys**	**Girl-Boy Gap (p.p.)**
All families (N=3,983; HH non-poor=1,923; HH poor=2,060)						
HH Non-Poor	31.1%	28.5%	2.6	16.7%	9.4%	7.4
HH Poor	85.7%	77.8%	7.9	81.4%	68.8%	12.5

Notes: Values are child poverty rates within each household-poverty stratum. Household poverty status is computed using household per-capita expenditure and the adult World Bank benchmark ($1.90/day). The left block reports a calorie-adjusted poverty measure that scales the adult benchmark by Indian age- and sex-specific calorific requirements from Indian Council of Medical Research and National Institute of Nutrition (2020); the right block reports an equivalence-scale-adjusted poverty measure that assigns children under age 15 a threshold equal to 60 percent of the adult benchmark. The reported gap is girls minus boys in percentage points, so positive values indicate higher poverty among girls.

Table A10: Evidence of Son-Biased Fertility Stopping Behavior

	Firstborn Boy	**Firstborn Girl**	**Difference**
Number of children	2.35	2.55	0.19***
			(0.06)
Fraction of younger siblings who are boys	0.516	0.632	0.115***
			(0.024)
Observations	770	638	

Notes: Sample: nuclear families (N=1,408). Two households with tied firstborn ages (mixed-gender oldest children) are excluded. Difference column reports the firstborn-girl mean minus the firstborn-boy mean, with standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A11: Missing-Girls Counterfactuals: Specification Robustness

Specification	Fixed effects used	β	p-value	Share explained
Panel A. Calorie-Adjusted Poverty Measure				
Pooled, unweighted	None	6.31	0.021	25.3%
State FE, unweighted	State	8.44	0.035	32.0%
State + age FE, unweighted	State + age group	1.73	0.447	8.3%
Pooled, population-weighted	None	12.07	< 0.001	42.1%
State FE, population-weighted	State	14.68	< 0.001	48.7%
State + age FE, population-weighted	State + age group	4.82	0.061	20.5%
Panel B. Equivalence-Scale-Adjusted Poverty Measure				
Pooled, unweighted	None	3.21	0.272	16.8%
State FE, unweighted	State	4.29	0.415	21.1%
State + age FE, unweighted	State + age group	1.33	0.591	7.6%
Pooled, population-weighted	None	5.93	0.105	27.1%
State FE, population-weighted	State	8.87	0.141	36.5%
State + age FE, population-weighted	State + age group	2.74	0.328	14.8%

Notes: The table reports the specification grid for the missing-girls counterfactual. All rows use rural SRS mortality rates and rural state-age female populations, matching the rural REDS sample. Panel A uses the calorie-adjusted REDS girl-boy poverty gap. Panel B uses the equivalence-scale-adjusted REDS girl-boy poverty gap, which assigns children under age 15 a threshold equal to 60 percent of the adult World Bank benchmark. Beta is the coefficient from a regression of the signed excess female death rate per 1,000 girls on the poverty gap. Population-weighted rows weight cells by the rural female population at risk. The explained share removes $\hat{\beta}\Delta P_{sa}$ from each state-age cell, truncates the adjusted excess female death rate at zero, and converts the adjusted rates back into missing-girl counts.

Table A12: Resource Shares under Alternative Household-Sample Restrictions

Sample	Children under 16	Adult structure	Observations	η_m	η_w	η_b	η_g	Gap	p-value
All families	**Children or grandchildren of head; mixed child-grandchild households excluded**	**Other currently allowed adults may remain**	**3,983**	**0.444**	**0.274**	**0.205**	**0.171**	**-3.4**	**0.078**
Nuclear families	**Head's children only**	**Head and spouse only; no other adults or elderly**	**1,410**	**0.395**	**0.273**	**0.253**	**0.159**	**-9.4**	**0.001**
Head and spouse present; head's children only	Head's children only; no under-16 grandchildren	Spouse of head present; other currently allowed adults may remain	2,717	0.424	0.278	0.217	0.174	-4.4	0.091
Head's children only; extended adults allowed	Head's children only; no under-16 grandchildren	No spouse requirement; other currently allowed adults may remain	2,782	0.422	0.282	0.216	0.173	-4.4	0.083
Grandchild-only households	Grandchildren of head only; no under-16 children of head	Other currently allowed adults may remain	1,203	0.473	0.305	0.162	0.141	-2.1	0.429
Broad kinship sample	Any resident kin under 16; explicit non-relatives excluded	Production relationship restrictions relaxed; adult siblings and other relatives may remain	4,829	0.444	0.272	0.202	0.174	-2.8	0.095

Notes: Each row re-estimates the DLP/SAP nonlinear SUR system on the stated household sample. Resource shares are means of predicted shares. Adult shares are averaged over all households in the sample; boys' and girls' shares are averaged over households with at least one boy or girl, respectively. The gap is $100 \times (\eta_g - \eta_b)$, so negative values indicate lower resource shares for girls. The p-value tests $H_0 : E[\eta_g] - E[\eta_b] = 0$. The phrase other currently allowed adults refers to the relationship-to-head categories retained by the production cleaning code: among ages 16–60, self, spouse, child, and daughter-in-law; above age 60, self, spouse, father, and mother. The broad kinship sample relaxes those relationship restrictions, while still excluding explicit non-relatives, live-in servants or laborers, second spouses, multiple-head households, and members older than 85.