CHILDREN'S RESOURCES, WELL-BEING AND SOCIAL PROTECTION: EVIDENCE FROM ETHIOPIA

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Summary

The bargaining power of children has long been neglected in the literature since children have been considered as public or private goods for their parents. Given that they do not enter households by choice and generally bring little to household resources, children could be the most vulnerable to intrahousehold inequality although they may benefit from parental altruism. Recent collective household consumption models help recover the sharing rules of children using observation of some exclusive, privately-assigned expenditure and distribution factors. The sharing rules of children can then be used to analyze their monetary poverty. As well-being is multidimensional, it is also imperative to look at deprivations in other dimensions including health, nutrition, education and living standards. From a policy perspective as well, the role of social protection in affecting children's decisions and well-being is worth researching since understanding the responses to a program in terms of those outcomes provides comprehensive impacts on deprivations in needs and capabilities. The Dissertation in general looks at these issues in its three essays (papers).

In the first essay, "**Children's Resources and Poverty in Single-mother and Male-headed Households**", we estimate a collective complete demand system model to recover children's resource shares and analyze their poverty. Identification of the sharing rule between children and adults relies on private assignable goods and distribution factors. Resource shares are used to compute poverty measures of incidence, depth and severity. These intrahousehold inequality-robust rates are also compared with those based on equal resource sharing (household level). Based on Ethiopian LSMS-ISA data for two sub-samples of families with children (married male-headed and single female-headed), it finds inequalities in intrahousehold resource allocation and welfare. In particular, we find that children command less household resources and are poorer than adults which worsen with the number of children. Resource allocation is affected by parental differences in education and age, child education, proportions of female children and women, and number of non-biological children. Single-mothers not only are more altruistic to their children, they also avoid higher child poverty than married male heads although this seems to disappear when the number of children increases. Unlike the general belief that poor children live only with poor adults and households, our estimates show that non-poor families also host poor children. Further, traditional poverty measures, which ignore intrahousehold resource allocation, are found to understate child (and adult) poverty. Lastly, regional and rural-urban disparities exist. Findings have implications for fertility, gender, targeting and spatial redistribution issues.

The second essay, "**Children's Multidimensional Deprivation, Monetary Poverty and Undernutrition**", analyzes children's well-being in terms of multidimensional de-

privation, monetary poverty and undernutrition. After identifying children as poor using their resource shares, it also extends a version of the traditional multidimensional child deprivation index to include a monetary dimension. We also look at the overlaps between the three alternative measures of child well-being: monetary, undernutrition and multidimensional. For instance, we ask: Are all monetarily non-poor children also not undernourished? Do non-poor households host stunted children? What portion of children identified monetarily-poor is also multidimensionally-deprived? Using the 2013/14 Ethiopian LSMS data, we find that multidimensional child deprivation is high and differs with demography and geography. The probability of falling into multidimensional deprivation and the average intensity of it almost monotonically increase with the number of children. Indices for urban children jump in values when a monetary indicator is included. Although stunted and multidimensionally-deprived children concentrate more at the lower household/child income levels, there is also evidence that the monetarily non-poor still host deprived children. Depending on the type of poverty measure, 10 percent to a quarter of monetarily non-poor children are deprived multidimensionally. We find no evidence suggesting that children's nutrition is related to either child- or household-level expenditure. In particular, about 60 percent of expenditure-poor under-7 children and 46 percent living in expenditure-poor households are not found to be nutrition-deprived. And about two-thirds of stunted children are not found in the poorest 20% or 40% of children/households. Evidences question the use of only monetary information in targeting children.

Lastly, in "**Impacts of Social Protection Programs on Children's Resources and Well-being**", we evaluate the separate and joint impacts of Ethiopia's Productive Safety Net Program (PSNP) and allied transfers on children's bargaining power and well-being. PSNP is Africa's second largest social protection program with public works (PW) and direct support (DS) components. While estimated resources and shares from a collective demand system proxy bargaining power, we measure child well-being by resource-based monetary poverty, undernutrition and multidimensional deprivation. Inverse-probability-weighted regression adjustment, which also controls for other correlates of outcome variables including previous participation, provides the average treatment effect on the treated with alternative specifications, disaggregations and traditional propensity score matching methods used for checking robustness. Using LSMS-ISA data from Ethiopia Socioeconomic Survey 2013/14, we find that PSNP and joint PNSP-allied transfers slightly reduce relative resource shares of children. Allied programs, in contrast, increase resource shares of boys. Impacts on child monetary poverty are mixed and directly follow from effects on sharing rules: when a program positively affects child resource shares, it decreases child poverty and vice versa. Accordingly, child poverty is worse with PSNP and its joint with allied transfers, but better with allied transfers alone. Household-level poverty is not affected except by DS which reduces it only after a previous participation is controlled. PW (only for under-seven children) and allied programs desirably impact child multidimensional deprivation. We also find that stunting among under-seven children is worse with PW (especially for boys). In lending support to previous evidence that when women receive exogenous transfers, child outcomes improve, we find that children in single-mother families participating in PW program better of in terms of resources, poverty and nutrition compared to those in in male-headed families. The undesirable impacts may require revising these on-going social protection schemes to a "cash plus" form such as by incorporating parental awareness on child nutrition and education.

1. Children's Resources and Poverty in Single-mother and Male-headed Households*

1.1. Introduction

Considering the household as a black box, the unitary model assumes that choices of all household members, including children, are proxied by a single preference of the household head. This, besides violating the microeconomics teachings of individual consumer theory, hides a member's welfare loss or gain due to any inequality in intrahousehold resource allocation. However, there is substantial evidence that rejects this model and underlines the role of intrahousehold resource allocation since the early 90's (e.g., Thomas, 1990; Schultz, 1990; Bourguignon et al., 1993; Browning et al., 1994). Very importantly, ignoring this intrahousehold resource allocation leads to a considerable understatement of the level of poverty in developing countries (Haddad and Kanbur, 1990; Dunbar et al., 2013; Bargain et al., 2014).

Unlike the neoclassical model, the collective household model argues that household choices are grounded on individual member preferences. In seminal contributions, Chiappori (1988, 1992) contends that the key to unlock the black box is the sharing rule with which the family allocates available resources across its members. When such a rule exists, efficiency of the collective decision process is implied and exogenous bargaining process within the household is captured. One can thus consider intrahousehold inequality in resource allocation and make individual welfare analyses.

Consequently, there has been an increased interest, both in academic and global policy fronts, to measure resource shares and welfare of household members including

*With Federico Perali and Martina Menon

children. Academia continues documenting inequality in intrahousehold resource allocation (Bourguignon et al., 1993; Browning et al., 1994; Lise and Seitz, 2011; Dunbar et al., 2013; Bargain et al., 2014; Mangiavacchi et al., 2018). Globally, Commission on Global Poverty recently recommended the World Bank to compute poverty rates at women, children and young adults levels. However, until the seminal article of Bourguignon (1999), children had no bargaining power and were considered as public or private goods for their parents. As they do not enter households by choice and generally bring little to household resources, children could be the most vulnerable to intrahousehold inequality (Dunbar et al., 2013). On the other hand, they may benefit from parental altruism (Bhalotra, 2004) especially from mothers.

Yet, only few empirical evidence is available from developing countries on resource shares and welfare of children allowing them to bargain with adults in a collective framework. And the existing scant evidence is mixed. Dunbar et al. (2013) and Bargain et al. (2014) apply almost similar collective consumption models, though with different identification strategies, on data from Malawi and Cote d'Ivoire respectively. Very recently, the methodologies in these studies are applied using data from two more sub-African countries: Bose-duker (2018) in Ghana and Bargain et al. (2018) in South Africa. All, except Bose-duker (2018), find that child resource shares are lower than adults and vary by family size and structure, and that conventional poverty measures understate the incidence of child poverty. In contrast, Mangiavacchi et al. (2013), fitting a complete collective demand system model, document children enjoying higher resource shares than adult females but traditional poverty indices slightly overstating child poverty in Albania. This goes in line with the findings of Bose-duker (2018) for Ghana.[1] The current study aims to contribute to this debate by estimating the sharing rule of children from a complete collective demand system and analyzing their poverty status using data from Ethiopia.

One source of debate in the collective consumption model literature is identification of the sharing rule. As almost all surveys collect consumption data at household level, the issue is on how one can recover from household level consumption data information about individual members. While some of the recommended structural models are highly restrictive (e.g., consumption of purely private and private goods)

[1] In fact, the issue of overstatement or understatement of child poverty across authors and methods needs to be examined cautiously since that depends on the assumption made on children's needs. Child poverty line is lower with lower needs so that poverty is lower. Thank you Olivier Bargain for raising this issue.

and easy to estimate resource shares such as Chiappori (1992), others are liberal but difficult such as Browning et al. (2006). Yet, others propose models at the middle that are only a little restrictive and easy to estimate from Engel curves (Lewbel and Pendakur, 2008; Dunbar et al., 2013). A crucial identifying restriction, for example, is that resource shares are independent of total household expenditure which Menon et al. (2012) and Bargain et al. (2018) empirically validate it.

In this study, we use a similar restriction but follow the estimation procedures of a collective Almost Ideal Demand System model as in Menon et al. (2017) and Mangiavacchi et al. (2013, 2018) to recover the resource sharing rules of children and adults. The demand system consists of four commodity groups: food and beverages, clothing, utilities and energy, and other non-durable goods. The sharing rule is allowed to depend on individual observed assignable expenditures and distribution factors where the former are scaled by a function that captures the within-household resource transfer. Private assignable expenditures are found from assignable clothing and footwear, education, certain personal care items, and other adult goods (alcohol, tobacco, chat/Khat). In addition to the traditional distribution factors in the literature (parental differences in education and age), we use as distribution factors other variables pertinent to children (if all children attend school, proportions female children and women, and number of non-biological children).

Our empirical exercise uses data from the 2013/14 wave of the Ethiopia Socioeconomic Survey (ESS), conducted as part of the LSMS-ISA project by the World Bank and Ethiopia's Central Statistical Agency (CSA). Missing prices are also obtained from prices surveys of the CSA. We choose a sample of families with children, composed of two sub-samples (two-parent male-headed and single-parent female-headed families). Ethiopia is an interesting case study for our issue it is one of the poorest countries in the world with a sizable child population, over 52% according the latest census. Official adult-equivalent-based child poverty incidence (32.4%) is higher than that at the household level (29.6%) (MoFED, 2012; CSA et al., 2015). Multidimensional poverty incidence is also among the highest in the world (87%) and human development index remains one of the least (0.396). These are despite the government pursuing various anti-poverty and 'transformation' strategies over the past couple of decades and the economy growing fast, for instance at 8% in per-capita terms over the period 2004–2014 (World Bank, 2016). Moreover, the ESS provides many household and individual consumption and other details which we exploit for implementing our theoretical framework.

Once children's resource shares are estimated and analyzed, we use them to compute poverty measures of incidence, depth and severity. These intrahousehold inequality-robust rates are then compared with those based on equal resource sharing (household level). A needs-based national poverty line is preferred to dollar/day thresholds. We also test the hypotheses by Haddad and Kanbur (1990) that poverty depth and severity measures which ignore intrahousehold resource allocation understate the level of poverty and that the fate of the headcount ratio is an empirical matter. In addition, we aim to provide some evidence on the gender and family structure aspects of intrahousehold resource allocation as we estimate child resource shares and poverty indices for married male-headed and single female-headed families. As a further benefit of the new method to child poverty estimation using resource shares, we look at the overlap between the poverty of children, adults and the household. What proportion of poor children live with non-poor adults? What portion of poor children live in non-poor households? Do these differ when the head is a female? We also provide some evidence on the overlap between child undernutrition and monetary poverty at child, adult and household levels. We lastly answer the question of how our estimates vary with the number of children and over space.

Our results generally confirm inequalities in intrahousehold resource allocation and poverty which vary with number of children, family structure and space. The allocation is significantly affected by parental differences in education and age, child education, proportions of female children and women and number of non-biological children. In particular, older mothers assign more resources to children. Children's expenditure shares are also higher if they are all in school and when there are more girls relative to boys. We find that children have lower expenditure shares (16% or 30%) than adults (23% or 32%) depending on family type (male-headed or single-mother). Monetarily, these correspond to monthly non-durable per-child outlays of ETB 339 or 433 and per-adult outlays of ETB 491 or 457 in male-headed or single-mother families respectively. Consistent with Bargain et al. (2014), results show that single-mothers are more altruistic to children than male-heads.

Using resource shares to estimate poverty incidence, depth and severity measures, we find that children are poorer than adults which also vary with family type and space. In a sample of families with children, prevalence of child poverty increases from 65% when there is only one child to 93% when families host more than four children. Single-mothers, besides being more altruistic to their children, host less poorer children than male-heads. Inline with previous literature and hypotheses by Haddad and Kanbur (1990), traditional poverty measures, which by construction ignore intrahousehold resource allocation, are found to understate child (and adult) poverty compared to those based on resource shares.

Our estimates also show that up to a fifth of non-poor households and adults host poor children, unlike the general belief that poor children live only with poor adults and households. Changing the poverty measure to undernourished children also provides similar conclusion, in particular and consistent with Brown et al. (2017), that up to a tenth of monetarily non-poor adults or households host stunted children. Moreover, less portion of poor children live with non-poor adults in female-headed families than in male-headed ones, in line with our previous evidence that single mothers in general are more equal to their children than adults in male-headed families. These overlaps question the effectiveness of using household information to target children's welfare. Finally, we observe regional and rural-urban disparities in resource shares and poverty. The remaining part of the first essay is organized as follows. In the next section, we discuss the theoretical framework as well as empirical and post-estimation issues. After describing the data in the third section, we present and discuss the results in the fourth section. The last section provides concluding remarks.

1.2. Theoretical Framework and Estimation Issues

In this section, we provide the theoretical framework with the underlying assumptions and identification strategies of the sharing rule. This is followed by brief discussion of empirical issues pertinent to estimation of a collective Almost Ideal Demand System. Post-estimation matters related to recovering of resource shares and poverty measurement are also highlighted.

1.2.1. The Collective Household Consumption Model

Consider a household consisting of adults and children, indexed by $k = 1, 2$ respectively.[2] Private goods could either be assigned to each member, e.g., clothing, or non-assigned, e.g., food. Represent adults' assignable consumption by c^1 and children's by c^2 and aggregate non-assignable consumption by q so that total household consumption becomes[3] $C = c^1 + c^2 + q$.

In a centralized setting, the budget constraint of the collective household is $p_{c^1}c^1 + p_{c^2}c^2 + p_q q = e$, where p_h , $h = c^1, c^2, q$, are associated prices of assignable and non-assignable goods and e is total household expenditure. Unlike assignable goods, one cannot observe individual quantities and prices of non-assignable goods $(q^1, q^2, p_{q^1}, p_{q^2})$. Only $q(= q^1 + q^2)$ and p_q are observable.

Preferences of each household member are assumed to be caring type in which the utility of one member depends on the sub-utility of the other; i.e. for each $k = 1, 2$ we consider $U^k(c^1, c^2, q^1, q^2; \boldsymbol{d}) = U^k[u^1(c^1, q^1; \boldsymbol{d}), u^2(c^2, q^2; \boldsymbol{d})]$ where $\boldsymbol{d}$ represents a vector of demographic variables[4] that affect preferences of the members directly so that observed heterogeneity is captured. Note that $\boldsymbol{d} = (d_1, d_2, d_{12})$ where d_1 and d_2 are characteristics specific to adults and children respectively while d_{12} are household-level characteristics. We also assume that utilities u^k are continuously differentiable as a consequence of which demand functions of each member will ultimately be smooth.

We assume that household decisions are Pareto-efficient (Chiappori, 1988, 1992). This alternatively means that family decisions are made in a decentralized fashion in two stages: (i) Members decide on how to share the total household expenditure e so that each member receives a sharing rule ϕ_k with $\phi_k > 0$ and $e = \phi_1 + \phi_2$. (ii) Given the sharing rule ϕ_k, each member maximizes her own utility function $u^k(c^k, q^k; \boldsymbol{d})$

[2] The very scant literature that estimates a collective consumption model with public goods makes a strong assumption that people in different marital status have similar preferences, as done for singles and married ones by Browning et al. (2013). However, such an assumption fails to identify the model when children are considered as decision makers, as we do in this paper, and it is difficult to observe children living alone. Moreover, in our empirical application, the vast majority of goods are private, for e.g. food and beverages, clothing, and other goods categories constitute a total share of over 92%.

[3] Note that if index $k = 1, 2$ is superscript, it indicates an endogenous variable and if it is subscript, it is associated with an exogenous variable. Also note that i and j index goods.

[4] They are also termed "preference factors" (Bourguignon et al., 2009).

subject to her individual budget constraint $p'_{c^k}c^k + p'_c q^k = \phi_k$ thereby choosing her optimal (Marshallian) consumptions of assignable goods $\widehat{c}^k = c^k(p_{c^k}, p_q, \phi_k, \boldsymbol{d})$ and non-assignable goods $\widehat{q}^k = q^k(p_{c^k}, p_q, \phi_k, \boldsymbol{d})$.

Household-level (aggregate) Marshallian demand systems of assignable and non-assignable goods are obtained as

$$\widehat{c}(p_{c^1}, p_{c^2}, p_q, e, \boldsymbol{d}) = c^1(p_{c^1}, p_q, \phi_1, \boldsymbol{d}) + c^2(p_{c^2}, p_q, \phi_2, \boldsymbol{d})$$

and

$$\widehat{q}(p_{c^1}, p_{c^2}, p_q, e, \boldsymbol{d}) = q^1(p_{c^1}, p_q, \phi_1, \boldsymbol{d}) + q^2(p_{c^2}, p_q, \phi_2, \boldsymbol{d}).$$

Note that individual-level optimal Marshallian demands are observed as functions of prices, the sharing rule and demographic attributes. Optimal consumption levels of the non-assignable goods are only observed at the household level.

1.2.1.1. The Collective Complete Demand System

The demand system model we specify follows from Menon et al. (2017) and Mangiavacchi et al. (2013, 2018) who extend the QUAIDS of Banks et al. (1997) to the collective framework and hence named the Collective Quadratic Almost Ideal Demand System (CQUAIDS). The model begins with a specification of an individual expenditure function in terms of price aggregators and a demographically-translating household technology to ultimately get individual Hicksian and Marshallian budget share demands. The sharing rule is specified as a function of observed individual expenditure and a vector of distribution factors. Individual expenditures are also scaled (Chavas et al., 2017) in a way that guarantees independence of the sharing rule and total expenditure (Menon et al., 2012). However, we fit a linear version of the model to our data. For a detailed derivation of the model, see Appendix A.1.

Given continuous and concave price p aggregators taking up the usual functional forms, $lnA_k(\boldsymbol{p}) = \frac{1}{2}\left(\alpha_0 + \sum_i \alpha_i lnp_i + \frac{1}{2}\sum_i\sum_j \gamma_{ij} lnp_i lnp_j\right)$; $B_k(\boldsymbol{p}) = \beta_0 \mathit{\Pi}_i p_i^{\beta_i^k}$, and $\lambda_k(\boldsymbol{p}) = \sum_i \lambda_i^k p_i$, additionally assumed to be a differentiable, homogeneous function of degree zero of prices.

The demographically-modified demand for good i in terms of budget share w_i is aggregated from member demands w_i^k as

$$w_i = \alpha_i + t_i(\boldsymbol{d}) + \sum_j \gamma_{ij} lnp_j + \beta_i^1 [lne_1^* - lnA_1(\boldsymbol{p})] + \lambda_i^1 \frac{[lne_1^* - lnA_1(\boldsymbol{p})]^2}{B_1(\boldsymbol{p})}$$

$$+\beta_i^2 [lne_2^* - lnA_2(\boldsymbol{p})] + \lambda_i^2 \frac{[lne_2^* - lnA_2(\boldsymbol{p})]^2}{B_2(\boldsymbol{p})} \tag{1.1}$$

where lne_1^* and lne_2^* are modified logarithmic individual total expenditures from observed ones (lne_k) given by a translating household technology:

$$lne_k^* = lne_k - \sum_i t_i(\boldsymbol{d}) lnp_i. \tag{1.2}$$

Demographic augmenting of the demand system helps capture observed heterogeneity among households and is done by introducing a translating technology $t_i(\boldsymbol{d})$ so that demographic attributes $\boldsymbol{d}$ enter additively with expenditures (Lewbel, 1985; Perali, 2003). They are defined for simplicity as $t_i(\boldsymbol{d}) = \sum_r \tau_{ir} d_r$ for $r = 1, ...R$. Note that we can estimate, for each good i, income parameters (β_i^1, β_i^2, λ_i^1 and λ_i^2) at the individual level while the rest at the household level (i.e. intercepts α_i, price parameters γ_{ij} and demographic scaling effects $t_i(\boldsymbol{d})$).

1.2.1.2. The Sharing Rule

Until now, we have made an implicit assumption that individual total expenditures e_k are observed. Such information, nonetheless, is barely collected, as is the case in many household surveys and in the survey we use in this study. As a solution to this issue, one can exploit expenditures on exclusive or assignable goods $\boldsymbol{p_c' c^k}$ to learn about how much each member receives from total household resources and then correct for the resulting measurement error (Caiumi and Perali, 2015; Menon et al., 2017; Mangiavacchi and Piccoli, 2017). Obviously, the lower the proportion of non-assignable expenditures $\frac{\boldsymbol{p_q' q}}{e_k}$, the lower will be the measurement error. We will get back to this correction issue in a moment.

In our case, we have exploited all available expenditure information in the survey if some goods are consumed exclusively by adults or children. Expenditures on clothing, which are collected at male, female, girl and boy levels, as well as on education, which are collected at each individual level, are clearly assignable expenditures. Moreover, we make an assumption to regard consumption of the following items exclusively by adults: alcoholic drinks, stimulants (specifically, chat and cigarettes) and certain personal care items. Once assignable individual expenditures are taken into account, non-assignable expenditures are assumed to be shared equally by adults and children.[5] Hence, one can consider $e_k = \frac{\boldsymbol{p}_c' \boldsymbol{c}^k}{h_k} + \frac{\boldsymbol{p}_q' \boldsymbol{q}}{h}$ where h_k is the number of persons in adult and children groups and h is household size (Chavas et al., 2017). Consequently, observed resource shares become $\sigma_k = \frac{e_k}{\sum\limits_k e_k}$ where $\sigma_1 + \sigma_2 = 1$, so that we can write

$$lne_k = \sigma_k lne. \tag{1.3}$$

Returning to the awaiting correction issue of e_k, a modifying function $m(\boldsymbol{z}) \in \left(0, \frac{e}{e_k}\right)$ is used to correct any measurement error related to e_k which leads to specification of the sharing rule. The arguments of this function are distribution factors $\boldsymbol{z}$ which affect the intrahousehold bargaining between adults and children but not their preferences.[6] The m-function can optionally be thought to capture the magnitude and direction of transfer of resources from adults to children or vice versa (Menon et al., 2017): if $m < 1$, the expenditure transfer goes from member 1 (adult) to member 2 (child) and the direction is reversed if $m > 1$.

This enables to define the sharing rule, which explains a shadow intrahousehold resource allocation, as a function of individual expenditures and distribution factors, i.e. for member 1 (adult), we have $\phi_1(e_1, \boldsymbol{z}) = e_1 \cdot m(\boldsymbol{z})$ which in log becomes linear as[7]

$$ln\phi_1(e_1, \boldsymbol{z}) = lne_1 + lnm(\boldsymbol{z}) = \sigma_1 lne + lnm(z). \tag{1.4}$$

[5] Chavas et al. (2017) test the innocence of such an assumption; they show that assuming a fair distribution of non-assignable goods among family members does not affect parameter estimates of the sharing rule (see their Proposition 5 and Appendix B).

[6] Note that the scaling function does not depend on expenditures, a separability property in line with the theoretical properties of independence of income of the sharing rule by Dunbar et al. (2013) and Chavas et al. (2017) and the empirical validation by ?.

[7] Since ϕ_k should not exhaust all household total expenditures e, i.e. $\phi_k < e$, the m-function is restricted to stay between 0 and $\frac{e}{e_k}$.

Since by definition $lne = ln\phi_1 + ln\phi_2 = lne_1 + lne_2$, we have the sharing rule for member 2 (child) equal to

$$ln\phi_2(e_2, \boldsymbol{z}) = lne - ln\phi_1 = \sigma_2 lne - lnm(\boldsymbol{z}). \tag{1.5}$$

The functional form of the scaling function $m(\boldsymbol{z})$ is assumed to be of Cobb-Douglas type for empirical purposes so that in log form, it becomes linear as:

$$lnm(\boldsymbol{z}) = \sum_{l=1}^{L} \phi_{z_l} lnz_l \tag{1.6}$$

where L is the dimension of distribution factors vector $\boldsymbol{z}$.

The introduction of the expenditure-scaling function $m(\boldsymbol{z})$, and consequently the sharing rule, has the effect of modifying the system specified in 1.1 into

$$w_i = \alpha_i + t_i(\boldsymbol{d}) + \sum_j \gamma_{ij} lnp_j + \beta_i^1[ln\phi_1^* - lnA_1(\boldsymbol{p})] + \lambda_i^1 \frac{[ln\phi_1^* - lnA_1(\boldsymbol{p})]^2}{B_1(\boldsymbol{p})}$$

$$+\beta_i^2[ln\phi_2^* - lnA_2(\boldsymbol{p})] + \lambda_i^2 \frac{[ln\phi_2^* - lnA_2(\boldsymbol{p})]^2}{B_2(\boldsymbol{p})} \tag{1.7}$$

where, from (1.2), (1.4) and (1.5), $ln\phi_1^*$ and $ln\phi_2^*$ are given by $ln\phi_1^* = \sigma_1 lne + lnm(\boldsymbol{z}) - \sum_i t_i(\boldsymbol{d}) lnp_i$ and $ln\phi_2^* = \sigma_2 lne - lnm(z) - \sum_i t_i(\boldsymbol{d}) lnp_i$. In our empirical application, we fit to our data the linear version the above model where the quadratic terms λ_i^1 and λ_i^2 are not estimated.

1.2.2. Empirical Estimation and Post-estimation Issues

Endogeneity of Total Expenditure

We address endogeneity of total expenditure primarily due to measurement errors by instrumenting total expenditure using wealth indicators as an instrument.[8] However,

[8] We also note that prices too may potentially be endogenous due, for example, to common unobserved shifts in preferences affecting both prices and quantities. However, lack of plausible instruments for a host of prices leads us to assume that they are exogenous. In fact, we are

wealth may still be mismeasured as a result, for example, of omission or incorrect valuation of its components. As far as these mismeasurements are independent of consumption recall errors and if wealth is correlated with true total expenditures, our proposed instrument remains valid (Dunbar et al., 2013). A control function procedure is used, which uses as regressors the residuals of an auxiliary regression of total expenditure on a set of socio-demographic variables and our instrument into the demand system model (Dauphin et al., 2011; Mukasa, 2015; Mangiavacchi et al., 2018). The procedure is executed in two steps: the log of total expenditure lne is first estimated using OLS on a vector η of socio-demographic variables and the instrument as $lne = \eta.\delta + \upsilon$ and then the residual $\widehat{\upsilon} = lne - \eta.\delta$ enters in the estimation of the demand system.

This gives the CAIDS model in budget shares as

$$w_i = \alpha_i + t_i(\boldsymbol{d}) + \sum_j \gamma_{ij} lnp_j + \beta_i^1 [ln\phi_1^* - lnA_1(\boldsymbol{p})]$$

$$+\beta_i^2 [ln\phi_2^* - lnA_2(\boldsymbol{p})] + \rho_i \widehat{\upsilon} + \xi_i \tag{1.8}$$

where ρ_i captures any endogeneity of total expenditure and ξ_i is the error term.

The system is finally estimated using feasible generalized nonlinear least squares method and imposing the QUAIDS standard regulatory conditions: adding-up ($\sum_i \alpha_i = 1$), homogeneity ($\sum_i \gamma_{ij} = \sum_j \gamma_{ij} = 0$, $\sum_i \tau_{ir} = 0$ and $\sum_i \beta_i^k = 0$ for each $k = 1, 2$) and symmetry ($\gamma_{ij} = \gamma_{ji}, \forall i \neq j$).

In our empirical exercise, we estimate the model for two sub-samples of families with children: married male-headed and single female-headed families. The basic motivation behind our choice of the two sub-samples is that our assumption that children may be treated differently in the two family structures and hence their bargaining power and welfare may vary.[9]

not alone in this respect (see, for instance, Dauphin et al. (2011) and Mangiavacchi and Piccoli (2017) for recent ones who only consider endogeneity of total expenditure but assume exogeneity of prices).

[9] Estimating a single model merging married male-headed and married female-headed together suffers from very low sample sizes for the latter. For drawing better gender-based comparisons, we exclude married female-headed and single male-headed households, both of which are

Post-estimation Issues

Once the estimated resources of adults ϕ_1^* and children ϕ_2^* are recovered, aggregate resource shares S_k are given by

$$S_k = \frac{\phi_k^*}{e}, \quad k = 1, 2$$

where e is total household expenditure. Per-child and per-adult resources r_k and resource shares s_k are given by

$$r_k = \frac{\phi_k^*}{h_k} \ \ and \ \ s_k = \frac{S_k}{h_k}$$

where h_k is the number of adults or children.

The identification of resource shares allows us the measurement of poverty and inequality at individual level. Unlike the traditional method, which relies on counting of families with children living below the poverty line to identify children as poor, this new method provides the "true" poverty of children. It also provides better estimation of the depth and severity of poverty. In the empirical estimation, we consider the national poverty line that is based on the Cost of Basic Needs and takes into account both food and non-food needs. Two types of poverty estimates are computed for each index: one group based on estimated resources r_k for children and adults, which take into account the intrahousehold resource allocation, and another based on equal-sharing expenditures y at the household level (adult-equivalents in our case). Haddad and Kanbur (1990) show that poverty measures which ignore intrahousehold allocation understate the level of poverty.

Consider two expenditure gap functions, $g(r_k, z)$ convex in estimated individual resources r_k and $g(y, z)$ convex in household level expenditures y, defined as

$$g(r_k, z) = \begin{cases} \left(\frac{z - r_k}{z}\right)^\alpha, & r_k \leq z \\ 0, & r_k > z \end{cases} \quad and \quad g(y, z) = \begin{cases} \left(\frac{z - y}{z}\right)^\alpha, & y \leq z \\ 0, & y > z \end{cases}$$

where z is poverty line. α is a measure of poverty aversion. When $\alpha = 0$, the

very negligible. Hence, we separately estimate for married male-headed and for single-mother families with children. This is also due to the fact that some of our distribution factors account for parental (wife-husband) differences in age and education which cannot be defined for single-mothers. Bargain et al. (2014) do similarly in their alternative estimations.

function g measures headcount. $\alpha = 1$ implies depth, and $\alpha = 2$ indicates severity of poverty. Note also that it is only when $\alpha \geq 1$ that $g(r_k, z)$ and $g(y, z)$ become convex in r_k and y respectively. Hence, the FGT (Foster et al., 1984) poverty indices based on individual resources r_k and adult-equivalent household level expenditure y are given by

$$P_{\alpha k}(r_k, z) = \frac{1}{N}\sum_{n=1}^{N} g(r_k, z) \quad \textit{and} \quad P_{\alpha}(y, z) = \frac{1}{N}\sum_{n=1}^{N} g(y, z)$$

where $n = 1, 2, ..., N$ is the number of households with children. For convex $g(r_k, z)$ and $g(y, z)$ (i.e. $\alpha = 1, 2$), Haddad and Kanbur (1990) show that $P_{1k}(r_k, z) > P_1(y, z)$ and $P_{2k}(r_k, z) > P_2(y, z)$. These say that both poverty depth and severity measures that ignore intrahousehold resource allocation understate the level of poverty. Nonetheless, where convexity fails (i.e. $\alpha = 0$), Haddad and Kanbur (1990) argue that $P_{0k}(r_k, z) \gtreqless P_0(y, z)$, implying a headcount ratio with no account of intrahousehold resource allocation can overstate or understate poverty and is an empirical matter. Later, we will verify these hypotheses using data from Ethiopia.

1.3. Ethiopian Expenditure Data

Data for the study come from the 2013/14 wave of Ethiopia Socioeconomic Survey (ESS) collected jointly by the World Bank and the Central Statistical Agency of Ethiopia (CSA) as part of the Living Standard Measurement Study-Integrated Surveys of Agriculture (LSMS-ISA). ESS is a panel survey with three waves to date (2011/12, 2013/14 and 2015/16). While the sample design of the first wave provides representative estimates for rural-area and small-town households, subsequent waves include medium and large towns and cities so that they have become nationally-representative. It uses a stratified, two-stage design where regions of Ethiopia serve as the strata. The first stage involves the selection of primary sampling units (or enumeration areas) using simple random sampling. The second stage of sampling entails the selection of households. Data came from 3969, 5262 and 4954 households in the three waves. ESS contains household-level data on a range of modules including expenditure, assets, shocks, non-farm enterprises, credit and farm production. Individual data on demographics, education, health, some expenditure items and time use are also collected. Moreover, community-level data as well as data on prices from local markets are available. However, in addition to being a rural-only survey, the 2011/12 wave lacks expenditure data on education, health, housing and food away from home. Lack of price data for assignable clothing and other goods such as education and personal care also forced us to exclude the 2015/16 wave.

This study, therefore, employs the 2013/14 wave. All of the waves of ESS do not collect expenditures on durable goods except on home furniture. Only information on the number of ownership of more than 35 assets is gathered. A wealth index from these assets is used to instrument total household expenditure. Individual-level labor incomes and household-level income from various non-labor sources, transfers and non-farm enterprises are aggregated with farm income which is extracted from the production, sales, home consumption and associated costs of various crops, livestock and their by-products. The wealth index aggregate of ESS by FAO's Rural Income Generating Activities (RIGA) project are used in this study.

We aggregate the various non-durable expenditure items into four expenditure groups: food at home and alcohol, clothing, household utilities and energy, and other goods. The details are available in Table A.1 in the Appendix. The food and alcohol expenditure group is aggregated from 26 food items and a sub-group of alcoholic drinks. The second group in our expenditure aggregation is clothing. It is composed of non-assignable linen as well as assignable clothes, shoes and fabric for men, women, boys and girls. The third expenditure group consists of household utilities and energy.[10] All other non-durable expenditures are aggregated in the fourth group: other goods, composed of spending on education, food away from home, cigarettes, laundry and other personal care, and transport.

Prices data come in various forms. For food at home items, we calculate unit values from expenditure and quantity information. For the majority of non-food items, local market prices collected in ESS price questionnaire are employed. For alcoholic drinks, food away from home and for non-food items whose prices are missing in ESS (namely, water, electricity, communication, education, personal care items, matches, and assignable and non-assignable clothing), we resort to the 2013/14 CSA's average

[10] We exclude housing rents because only 13% of households with children reported rents and no housing prices are available. Given that over 70% of our sample are of rural households and over 92% have their own home so that they do not pay rents, this assumption of equal treatment of rents will not pose a serious problem. The associated welfare differences could be captured by differences in spending on various household utilities and energy items.

retail prices. We first aggregate them up to the *zone* (provincial) level and then match them to the ESS data.

From a total of 5262 households, we select 3196 families with children composed of two sub-samples: two-parent male-headed (2467 households) and single-parent female-headed (729 households). Exclusive/assignable consumption is based on a host of non-durable expenditure items. Clothing and footwear expenditures, collected at male, female, girl and boy levels as well as education expenditures, collected at individual level, are clearly assignable. Further, we assign expenditures on alcoholic drinks, stimulants (*chat/khat* and cigarettes) and some personal care items to adults.

Table 1.1 presents the descriptive statistics of key variables by family structure and for the whole sample. As expected, the vast majority of household resources (about 70 percent in male-headed and 65 percent in single-mother households) are spent on food at home and alcohol. However, compared to the male-headed, single-mother families spend a little higher share on non-necessities (household utilities and energy and other goods). Moreover, t-test results for mean differences in observed resource and shares of each child and adult exhibit statistical differences in the two family types.

We consider 15 demographic variables referring to the household in general and its members (head and children) in particular. If the head sick and Christian (Muslim and other religions being the reference category) capture the head's characteristics. The number of children who fell sick and, to account for the age factor, the number of older children (aged between 15 and 17) are incorporated to control for children's attributes. Two household level characteristics are used to control for economic status: female employment ratio (working females over household total labor of 14-60 years) and if the household has safe water source. Presence of other adults than parents is also controlled. Whether seasonal differences matter is captured by a dummy if the household was interviewed in February. Exposures to price shock and natural shocks are also accounted for. Finally, spatial differences in demand are controlled by incorporating dummies for rural areas as well as five regions (Amhara, Oromia, SNNP, Tigray and Other regions), with living in the capital, Addis Ababa, being the reference category.

In total, 71% of our sample households live in rural areas, 75% for the traditional

Table 1.1.: Descriptive statistics of key variables: ESS 2013/14

Variable	Male-headed HHs (N = 2467)					Single-mother HHs (N = 729)					Whole sample (N = 3196)			
	Zero%	Mean	S.d.	Min.	Max.	Zero%	Mean	S.d.	Min.	Max.	Mean	S.d.	Min.	Max.
Expenditures, shares and prices														
Food***	0.08%	0.69	0.15	0.07	0.98	0.28%	0.66	0.17	0.07	0.97	0.68	0.16	0.0678	0.979
Clothing***	3.66%[b]	0.11	0.04	0.02	0.68	9.66%[c]	0.09	0.04	0.02	0.24	0.10	0.04	0.0152	0.681
Utilities***	0.91%	0.07	0.07	0.00	0.69	1.99%	0.10	0.09	0.00	0.55	0.08	0.08	0.0002	0.688
Other goods***	0.54%	0.13	0.12	0.00	0.82	1.00%	0.16	0.14	0.00	0.88	0.14	0.13	0.0006	0.884
Log of food prices***		2.56	0.67	-5.30	4.70		2.41	0.71	-4.25	4.28	2.52	0.68	-5.2983	4.697
Log of clothing prices***		5.25	0.13	4.92	5.79		5.21	0.14	4.93	5.77	5.24	0.13	4.9166	5.787
Log of utilities prices**		2.35	1.73	-4.80	6.77		2.13	1.79	-4.00	6.36	2.30	1.74	-4.8007	6.771
Log of other goods prices***		3.28	0.56	-0.29	6.11		3.44	0.58	0.69	5.17	3.31	0.57	-0.2877	6.106
Log of total expenditure***		7.51	0.70	4.18	9.63		7.22	0.73	4.52	9.39	7.44	0.72	4.1805	9.634
Share of assignables***		0.16	0.09	0.02	0.79		0.13	0.07	0.02	0.55	0.16	0.09	0.0175	0.786
Observed share: children		0.50	0.14	0.11	0.85		0.50	0.16	0.14	0.86	0.50	0.15	0.1083	0.856
Each child's share***		0.18	0.07	0.04	0.49		0.29	0.12	0.08	0.67	0.21	0.10	0.0393	0.667
Observed share: adults		0.50	0.14	0.15	0.89		0.50	0.16	0.14	0.86	0.50	0.15	0.1439	0.892
Each adult's share***		0.21	0.07	0.07	0.72		0.31	0.13	0.09	0.76	0.24	0.10	0.0728	0.757
Demographic variables														
Head is Christian***		0.65	0.48	0	1		0.74	0.44	0	1	0.67	0.47	0	1
Head sick***		0.20	0.40	0	1		0.38	0.49	0	1	0.24	0.43	0	1
# of sick children***		0.50	0.91	0	8		0.28	0.61	0	6	0.45	0.85	0	8
A stunted child in household***		0.31	0.46	0	1		0.12	0.32	0	1	0.26	0.44	0	1
# of children aged 15-17y**		0.39	0.59	0	3		0.47	0.59	0	3	0.41	0.59	0	3
Female employment ratio***		0.51	0.16	0	1		0.65	0.34	0	1	0.54	0.22	0	1
Other adult in household**		0.32	0.47	0	1		0.37	0.48	0	1	0.33	0.47	0	1
HH has safe water source***		0.67	0.47	0	1		0.79	0.41	0	1	0.70	0.46	0	1
HH interviewed in February*		0.90	0.30	0	1		0.87	0.33	0	1	0.89	0.31	0	1
HH faced price shock***		0.18	0.39	0	1		0.23	0.42	0	1	0.19	0.39	0	1
HH faced natural disaster shock		0.15	0.36	0	1		0.13	0.33	0	1	0.14	0.35	0	1
HH lives in rural area***		0.75	0.43	0	1		0.55	0.50	0	1	0.71	0.46	0	1
HH lives in Addis Ababa***		0.03	0.17	0	1		0.07	0.26	0	1	0.04	0.20	0	1
HH lives in Amhara region*		0.19	0.39	0	1		0.22	0.42	0	1	0.20	0.40	0	1
HH lives in Oromia region**		0.21	0.41	0	1		0.16	0.37	0	1	0.20	0.40	0	1
HH lives in SNNP region***		0.26	0.44	0	1		0.19	0.39	0	1	0.24	0.43	0	1
HH lives in Tigray region***		0.10	0.30	0	1		0.19	0.39	0	1	0.12	0.33	0	1
HH lives in other regions***		0.21	0.41	0	1		0.16	0.37	0	1	0.20	0.40	0	1
Distribution factors														
Education diff. of parents (w - h)[a]		-1.29	3.19	-15	10		-	-	-	-	-	-	-	-
Age diff. of parents (w - h)[a]		-8.48	6.48	-40	25		-	-	-	-	-	-	-	-
All children in school***		0.61	0.49	0	1		0.70	0.46	0	1	0.63	0.48	0	1
Proportion of female children		0.51	0.33	0	1		0.52	0.41	0	1	0.52	0.35	0	1
Proportion of women***		0.49	0.10	0	1		0.84	0.23	0	1	0.57	0.21	0	1
Number of non-biological children***		0.19	0.48	0	4		0.82	1.11	0	8	0.33	0.73	0	8
Household size***		5.78	1.97	2	15		3.96	1.76	2	11	5.36	2.07	2	15
# of children***		3.28	1.71	1	10		2.05	1.27	1	8	3.00	1.70	1	10
Wealth index*		1.17	3.27	-4.42	28.37		0.93	3.73	-3.22	28.09	1.12	3.38	-4.4182	28.37

Notes: [a] Not used in model estimation in single-mother sub-sample. [b] Clothing zero values are before Tobit regressions were run to correct for them. *, ** & *** show significance in mean difference of variables in the two samples at 10%, 5% & 1% levels respectively. For region dummies, the left-out category in regressions is living in the capital, Addis Ababa. SNNP=Southern Nations, Nationalities and Peoples.

male-headed and 55% for single-mother ones. Moreover, a fifth of them are drawn from each of Amhara region, Oromia region and other smaller regions, a quarter from SNNP region, a tenth from Tigray and the rest from Addis Ababa. Both family types statistically differ in almost all of the demographic variables considered. Notably, average household size in married male-headed families is 5.8, of whom 3.3 (57%) are children, while these figures are 4.0 and 2.1 (53%) in single-mother families. For the total sample, children account for 56% of the 5.4 family size. The latest available census shows that children constitute over 52% of the population in Ethiopia.

We use six distribution factors to partly capture the rule governing bargaining between children and their parents: education and age differences between wife and husband (only for the male-headed sub-sample), if all children are in school, proportion of female children, proportion of women, and number of non-biological children. Distribution factors, by definition, do not affect preferences but do influence bargaining power. As that feature of not affecting preferences is difficult to verify, we prefer motivating the choice of the majority of the distribution factors from the literature. Education and age differences or ratios of couples are quite popular determinants of intrahousehold resource allocation (Dercon and Krishnan, 2000; Menon et al., 2017; Chavas et al., 2017). To capture the role played by gender in intrahousehold resource allocation, we use two ratios - proportions of female children and female adults, the first of which is also employed by Mangiavacchi and Piccoli (2017). Lastly, we consider as exogenous the number of extended or non-biological children which may also affect bargaining power in the household without affecting consumption choices.

Note that, as demonstrated in Table 1.1, the various budget shares significantly differ in the two family types implies that it is wrong to analyze intrahousehold bargaining of children with adults merging the two sub-samples and using single-motherhood as a distribution factor. For married male-headed households, the husband on average has 1.3 more years of education than his wife, which could reach up to 15 years. There is also a substantial age gap between couples, the wife being 8.5 years younger on average, and ranging between 40 years younger and 25 years older.[11] In over 70 percent of single-mother households, school-age children attend school which is significantly higher than in male-headed households (60 percent). While

[11] This is not in fact surprising as women in Sub-Saharan Africa typically marry older men, with median difference of 7 years (UN Population Division, 2001, World Marriage Patterns, New York). Bargain et al. (2014) also find for Cote d'Ivoire that mean difference ranges between 8.2 to 8.7 depending on the number of children.

the proportion of girls and boys is almost balanced in both family structures, single-mother families have obviously more adult women. Moreover, not all children live with their biological parents: as many as four and eight children in male-headed and single-mother households are non-biological (extended) respectively. These distribution factors are proposed to play a role in the resource allocation between children and their parents.

1.4. Results and Discussion

This section presents the results of our estimations and discussions are also made where deemed necessary. After briefly presenting our intermediate results from the demand system estimations, we present and discuss our estimates on child resource shares and poverty. Analyses are also made disaggregating the estimates by number of children, region and rural/urban residence.

1.4.1. Demand System Estimation Results

We estimate two collective AIDS models: a quadratic version for married male-headed households and a linear version for single female-headed households. These specifications are dictated by the Engel curves in shown in Figure A.1 and estimation results are summarized in Table A.3 in the Appendix. In addition to having the expected sign, the majority of price- and expenditure-related parameters are significantly different from zero at conventional levels. Control parameters ρ_i capturing endogeneity of total expenditure are significant in three-fourths of both sub-sample regressions indicating that the log of total expenditure would have been endogenous had it not been instrumented. Results of the regression of log of total expenditure on the wealth index instrument and other variables, whose residuals enter in the demand systems regressions for our controlling exercise, are summarized in Table A.2 in the Appendix.

Some significant non-spatial demographic effects on non-durable consumption are observed. For example, religion plays a role where families headed by a Christian male, relative to Muslims and other believers, have lower spending on food and alcohol but higher on household utilities and energy. While the sickness of the head increases food spending and reduces clothing, more number of sick children does the opposite. And as expected, both family types with more older children (15 to 17 years) as well as other adults have higher clothing demands. Households hit by price shocks adjust by reducing consumption of food alcohol and increasing that of other goods. These correlations reverse direction when shocks are natural disasters.

Regarding spatial effects, there exist significant differences in demand across regions. As expected, compared to living in the capital city, living in less urbanized regions of Amhara, Oromia, SNNP and other smaller regions is associated with higher food expenditure shares and lower demands for utilities and energy and other goods categories.

The associated income and prices elasticities are also estimated and they are summarized, along with their standard errors, in Table A.4 of the Appendix. The signs are in line with theory. Both children and adults reveal almost similar income elasticity patterns: inelastic for food and clothing, almost unitary for utilities and elastic for other goods. Magnitude wise, adults are a little more elastic than children for clothing and utilities. Consistent with consumption theory, all own-price elasticities (uncompensated and compensated) are also negative. In particular, own-price effects indicate that except the other goods category, which is elastic, all categories are inelastic. The compensated cross-price elasticities generally suggest substitutability: food and alcohol category is a significant substitute for clothing category and other goods category, and the latter are substitutes for food, clothing and utilities categories in traditional families.

The estimated coefficients of the sharing function are presented in Table 1.2. Five out of six distribution factors in married male-headed and and two out of four in single female-headed families significantly affect the bargaining power between children and adults. The years of schooling difference between parents (wife minus husband) positively and significantly affects adults' sharing rule, against the expectation that educated mothers, relative to fathers, are more altruistic towards their children. In contrast, Dunbar et al. (2013) find that higher mother's education is associated with higher bargaining power (resource shares) for both children and women in Malawi. The negative coefficient of the difference in age between the wife and the husband also implies that older mothers tend to keep more resources to children.

Table 1.2.: Coefficients of the sharing rule's expenditure scaling m-function: bargaining

Variable	**Male-headed**		**Single-mother**	
	Coeff.		**Coeff.**	
Educ. diff. (wife-husb.)	0.187***	(0.037)	-	
Age diff. (wife-husb.)	-0.069***	(0.015)	-	
All children in school	-0.324*	(0.166)	1.200**	(0.504)
% of female children	-0.409*	(0.228)	-0.181	(0.327)
% of women	1.188	(0.862)	3.178***	(2 .940)
# of non-biol children	0.291**	(0.145)	0.120	(0 .122)

Notes: *, ** & *** show significance at 10%, 5% & 1% levels respectively. Standard errors, corrected for clustering and sampling weights, are in parentheses.

When all children are in school, their relative resource sharing rules are higher in traditional families where the male is the head though this effect is reversed in single-mother families. On the other hand, parents with more female children keep less resources to themselves, as shown by the negative coefficient attached to the proportion of female children, also suggesting a boy-girl discrimination as documented elsewhere (Deaton, 1989; Gibson and Rozelle, 2004; Dunbar et al., 2013). This distribution factor nonetheless is not significant in single-parent families. Also as expected, the proportion of women reduces children's sharing rule. Lastly, the number of non-biological (extended) children is also another distribution factor and it reduces the resource share of children in both family types though it is not statistically significant in single-mother households. This is in line with discrimination by adults against children who are not their own biological daughters or sons. These findings have important policy implications such as in income transfer programmes targeted at child poverty since their effectiveness is largely conditional on parental altruism (Bhalotra, 2004).

1.4.2. Estimated Children's Resources and Poverty

1.4.2.1. Children's Resources

Based on observed individual expenditures and estimated expenditure-scaling function coefficients, which are demographically-augmented, we compute the sharing

Table 1.3.: Means of estimated resources and shares by family type

	Male-headed		Single-mother		Whole sample	
Total expenditure (ETB) (e)	2221	(53.04)	1664	(87.82)	2115	(46.33)
Resources in ETB:						
Children's resources (ϕ_2)	1033***	(28.02)	804***	(56.76)	989	(25.18)
Each child	339***	(8.87)	433***	(20.00)	357	(8.37)
Adults' resources (ϕ_1)	1188***	(35.38)	860***	(44.23)	1126	(30.01)
Each adult	491	(14.82)	457	(19.70)	485	(12.57)
Resource shares:						
Children's resource share ($S_2 = \phi_2/e$)	0.47*	(0.005)	0.49*	(0.008)	0.48	(0.005)
Each child ($r_2 = S_2/h_2$)	0.16***	(0.002)	0.30***	(0.007)	0.19	(0.002)
Adults' resource share ($S_1 = \phi_1/e$)	0.53*	(0.005)	0.51*	(0.008)	0.52	(0.005)
Each adult ($r_1 = S_1/h_2$)	0.23***	(0.003)	0.32***	(0.007)	0.24	(0.003)

Notes: ** & *** show significance of mean difference in male-headed and single-mother sub-samples at 5% & 1% levels respectively. ETB = Ethiopian Birr; 1 ETB = 0.0524 US$ (2013/14 Avg.) (NBE). All observations are weighted to make estimates nationally representative. Standard errors, corrected for clustering and sampling weights, are in parentheses.

rule or the shadow resource allocation between children and adults. The average estimates for both family structures and the whole sample, along with observed shares for comparison, are presented in Table 1.3.

Our estimates generally reveal significant inequalities in intrahousehold resource allocation. In aggregate terms, children command slightly less resources (48% of total expenditure in the whole sample, 47% in male-headed and 49% in single-mother families). These are not of course surprising, given that children constitute 55%, 56%, 53% in the total sample, male-headed and single-mother households respectively. Recall that the observed aggregate shares indicate equal allocations between children and adults in all family structures.

The distributions of children's and adults' resource shares in the space of total expenditure are depicted in Figure A.2 in the Appendix. For the whole of the expenditure distribution, the trends in the shares remain generally similar. The finding of almost horizontal curves is very important as it goes inline with our identification restriction that the sharing rule is not affected by total household expenditure.

Aggregate child and adult resource shares are affected by the number of children and adults and hence are less informative. As a result, we need to consider the average per-child resource shares in households of different sizes. Intrahousehold inequalities between children and adults widen when one considers average per-member shares. In the whole sample, while each child claims less than a fifth of household resources, each adult gets about a quarter. Not only a child in single-mother families (30%) commands more resources than that in male-headed families (16%) but also the gap between children and adults is lower in the former than in the latter. This finding is in line with that elsewhere in Africa. Bargain et al. (2014) find, for instance in Cote d'Ivoire, that in single-mother families, children claim higher share of household resources (31%) than in two-parent families (23%) which are likely to be male-headed. As expected, families headed by unmarried females have lower total household expenditure (1664 ETB) than those headed by married males (2221 ETB). However, single-mothers spend more for each child (433 ETB per month) than male-headed couples (339 ETB per month) suggesting that female heads are more altruistic to their children than male heads.

1.4.2.2. Child Poverty

While resource shares provide information on who gets what from the household's cake, they do not tell whether the allocated cake to each member is enough to satisfy their needs. A step computing member's welfare and any intrahousehold disparity therein is needed. For instance, in addition to analyzing poverty among children, one can assess any existing inequality between child and adult poverty.

Accordingly, we use the estimated per-member resources to compute FGT rates of poverty incidence, gap and severity among children and adults for both family types and the whole sample of households with children. For comparison, rates are also computed based on adult-equivalent (equivalent scale) expenditures where resources are assumed to be shared equally among members. The poverty threshold considered is the (official) national poverty line computed using the Cost of Basic Needs approach.[12] Results are presented in Table 1.4. Note that the new approach of employing estimated resources in poverty measurement provides us with more

[12] We use the national poverty line (MoFED, 2012) since it is used to target the poor in the country and is based on their needs. In 2010/11, the poverty line was 315 ETB/person/month (3781 ETB/person/year) and after adjusted for inflation, it becomes 501 ETB/person/month in 2013/14.

Table 1.4.: Poverty measures based on new method and traditional approaches (%)

	Male-headed families		Single-mother families		Whole sample	
	New Method	Household level	New Method	Household level	New Method	Household level
	(1)	(2)	(3)	(4)	(5)	(6)
Child poverty headcount P_0	83.8***	66.5^u	72.9***	61.2^u	81.7	65.5^u
Adult poverty headcount P_0	70.2		69.7		70.1	
Child poverty gap rate P_1	45.9***	27.8^u	33.0***	22.7^u	43.4	26.8^u
Adult poverty gap rate P_1	32.3***		28.2***		31.5	
Child poverty severity P_2	29.6***	14.6^u	18.8***	11.2^u	27.6	14.0^u
Adult poverty severity P_2	18.4***		14.4***		17.6	

Notes: *, ** & *** show significance of mean difference of poverty rates (based on estimated resources) between male-headed and single-mother sub-samples at 10%, 5% & 1% levels respectively. ^{u}shows household level or equal sharing-based poverty rates are less (or understate poverty) than estimated resources-based rates at 1%. MoFED (2012)'s 2010/11 CBN-based national poverty line, adjusted for inflation, is considered. All observations are weighted to make estimates nationally representative.

disaggregations in the indices compared to the traditional approach (shown here by an extra row per family member group and poverty index).[13]

Some immediate results are worth noting. Firstly, it is comforting to notice from columns 1, 3 and 5 that indicators of poverty incidence, gap and severity are higher for children than for adults. In the whole sample, about 84% of children live below the national poverty line, lower at 70% among adults.[14] Such gaps between child and adult poverty incidence also exist in both family types though the one in single-mothers is lower. This finding strengthens the previous evidence of intrahousehold inequality in resource allocation. Secondly, the incidence, depth and severity of poverty among children in male-headed families are significantly higher than those in female-headed families.

Thirdly, in all cases, our estimated resources count more poor children (and adults) than what household level or equal-sharing methods do; and the same is true for

[13] We do not need to make a fixed adjustment to the poverty line to consider the lower needs of children such as the OECD scale. Our estimation of the intrahousehold resource allocation is such that a fair distribution of goods not assigned to members is corrected by our expenditure-scaling function (Menon and Perali, 2012) whose estimates were presented in the previous section. Note also that Bargain et al. (2014) question the relevance of the OECD scale to adjusting child poverty lines.

[14] Care must, however, be exercised in taking these figures. The 2013/14 round of the ESS considers a select of consumer goods, missing certain food aggregates. The poverty estimates here primarily aim to show use of resources share as an alternative method to the traditional ones, and hence cannot easily be compared with other estimates such as those in MoFED (2012).

higher child poverty measures (compare estimates in columns 1, 3 and 5 correspondingly with those in columns 2, 4 and 6). All the differences are statistically significant at the 1% level. This shows that the traditional approach of measuring poverty based on equal resource sharing, which by default ignores intrahousehold distribution among members, understates poverty situation. We thus verify the hypotheses of Haddad and Kanbur (1990). Recent collective consumption model studies also document similar conclusions from other sub-Saharan Africa countries although their analyses are restricted only to poverty headcount ratio. Dunbar et al. (2013) on Malawi and Bargain et al. (2014) on Cote d'Ivoire find that standard poverty indices understate the incidence of child poverty.

Child poverty estimates discussed so far do not tell any existing disparity in poverty status with a change in family size. One may also be interested to see what sacrifices parents and/or children have to pay when more children join the family. Table 1.5 summarizes poverty headcount estimates by number of children.[15]

As expected, child poverty increases with the number of children in the household. In the whole sample of families with children, incidence of child poverty increases from 65% when there is only one child to 93% when families host more than four children. Dunbar et al. (2013) also find similar positive relationship between child poverty and number of children. Similar trends are observed in the two family structures. However, the previous finding that children in single-mother families are less likely to be poor than those in male-headed couples no more stays when disaggregated by the number of children. No difference in child poverty incidence rates is statistically significant except the overall rate. On the other hand, like in the overall case, poverty among children consistently remains worse than that among adults though the gap falls with an increase in the number of children. If intrahousehold resource allocation was ignored, poverty would be understated with any number of children, once again confirming the Haddad and Kanbur (1990) hypotheses.

[15] We are aware that modeling multi-children and multi-adults households is challenged by economies of scale. For instance, children may share clothing, books, etc. thereby underestimating child resource shares and overestimating poverty among larger families. Our current estimations cannot consider this and it remains a limitation of the paper. In fact, this issue of joint consumption by children is a limitation of collective consumption models to date (Bargain et al., 2014; Mangiavacchi et al., 2018) and forms a future research agenda. Some prefer to use a very restrictive sample such as households with just one child (?) or separate estimations by size (Bargain et al., 2014). While we provide results for families with one child as well as with two, three, four and over four children, the estimates should be taken with caution.

Table 1.5.: Child poverty headcount rates (%) by number of children

	One child	Two children	Three children	Four children	Over four children	Overall
Male-headed households:						
Poverty rate: child	65.5	78.8	87.2	87.5	92.9	83.8***
Poverty rate: adult	47.4***	61.5**	71.0	78.8	84.1	70.2
Pov. rate: household level	41.1**	57.5**	68.3	72.2	83.4	66.5***
Single-mother households:						
Poverty rate: child	64.1	76.7	78.1	86.5	92.7	72.9***
Poverty rate: adult	62.5***	71.7**	76.5	81.1	86.5	69.7
Pov. rate: household level	53.2**	67.3**	63.6	66.4	79.1	61.2***
Whole sample:						
Poverty rate: child	64.9	78.3	86.2	87.4	92.9	81.7
Poverty rate: adult	53.9	64.1	71.6	79.0	84.2	70.1
Pov. rate: household level	46.3	60.0	67.7	71.6	83.2	65.5

Notes: *, ** & *** show significance of poverty difference between male-headed and single-mother sub-samples at 10%, 5% & 1% levels respectively. All observations are weighted to make estimates nationally representative.

1.4.2.3. Child Poverty, Household Poverty and Undernutrition Overlap

A further benefit of the new method to child poverty estimation using resource shares is that it helps to look at the existing overlap between the poverty of children, adults and other members. What proportion of poor children live with non-poor adults? What portion of poor children live in non-poor households? Do these differ when the head is a female? We also provide some evidence on the overlap between child undernutrition and monetary poverty at child, adult and household levels.

Table 1.6 summarizes estimates of the overlap between child-, adult- and household-level poverty by family structure. Two-thirds of poor children live with poor adults or households in general, irrespective of family structure. However, the proportion of poor children living with non-poor adults is non-negligible: 15 percent in the whole sample. Far less portion of poor children live with non-poor adults in female-headed families (8 percent) than in male-headed ones (17 percent), supporting our previous evidence that single mothers in general are more equal to their children than male-heads. Note that these estimates only slightly change when child poverty is allowed to overlap with household poverty. Our estimates also show that the match in poverty status of children and either of adults or households in general ranges between 80 to 87 percent depending on the family type and comparison group

Table 1.6.: Overlap between child, adult and household poverty by family structure

		Male-headed families				Single-mother families				Whole sample			
		Adult is poor		HH is poor		Adult is poor		HH is poor		Adult is poor		HH is poor	
		Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Child is poor	Yes	0.67	0.17	0.66	0.18	0.65	0.08	0.60	0.13	0.67	0.15	0.67	0.17
		(0.013)	(0.011)	(0.013)	(0.011)	(0.024)	(0.014)	(0.025)	(0.017)	(0.011)	(0.009)	(0.011)	(0.009)
	No	0.03	0.13	0.00	0.16	0.05	0.22	0.01	0.26	0.04	0.15	0.01	0.18
		(0.005)	(0.008)	(0.002)	(0.009)	(0.009)	(0.020)	(0.004)	(0.021)	(0.004)	(0.008)	(0.002)	(0.009)
Status match*		0.80		0.82		0.87		0.86		0.82		0.83	
Poor in ALL three		**0.63** (0.013)				**0.59** (0.025)				**0.62** (0.012)			

Notes: *Status match implies the proportion of children with similar status in two measures. All estimates are weighted to make them representative of the corresponding population. Standard errors in parentheses.

Table 1.7.: Overlap between child undernutrition and poverty of children, adults and the household

		Child poverty		Adult poverty		Household poverty	
		Poor	Non-poor	Poor	Non-poor	Poor	Non-poor
		(1)	(2)	(3)	(4)	(5)	(6)
Child stunting	Any stunted	0.24 (0.010)	0.03 (0.004)	0.21 (0.010)	0.06 (0.005)	0.19 (0.009)	0.09 (0.006)
	No stunted	0.58 (0.012)	0.15 (0.008)	0.50 (0.012)	0.24 (0.010)	0.47 (0.012)	0.26 (0.010)
Status match*		0.39		0.45		0.45	

Notes: *Status match implies the proportion of children with similar status in two measures. All estimates are weighted to make them representative of the corresponding population. Standard errors in parentheses.

considered. Moreover, only about 60 percent of poor children reside with a poor adult and in a poor household which is slightly higher in male-headed households.

Table 1.7 provides further evidence on other overlaps for the whole sample, this time the overlap of child stunting with child poverty, adult poverty and household poverty where stunting here refers to prevalence of any under-7 child who is stunted. Two interesting results stand out. First, undernourished children still exist in monetarily non-poor households which is also consistent with recent findings across Africa (Brown et al., 2017). Second, the prevalence of undernourished children decreases from 9%, 6% and 3% as one changes the child stunting overlap with household-, adult- and child-level poverty estimates respectively.

These evidences lend support to the burgeoning literature on the role of inequality in intrahousehold resource allocation on household member's welfare (Haddad and Kanbur, 1990; Dunbar et al., 2013; Bargain et al., 2014). In particular, it adds to

Table 1.8.: Spatial distribution of resource shares and poverty headcount rate (%)

	Regions						Rural/urban		
	Addis Ababa	Amh-ara	Oro-mia	SNNP	Tig-ray	Other regions	Rural	Small towns	Medium & large
Male-headed:									
Per-child resource share	0.21***	0.16***	0.16***	0.15***	0.15***	0.16***	0.16***	0.17***	0.17***
Per-adult resource share	0.26	0.24***	0.22***	0.22***	0.23***	0.24***	0.22***	0.24***	0.28***
Poverty headcount: child	50.9*	85.2**	84.0	87.2	78.5***	80.7***	87.5**	74.2	58.7
Poverty headcount: adult	26.9**	73.2	69.5	77.7*	61.1	59.0	76.1	56.2*	29.6***
Poverty headcount: household	16.5	72.1	64.6	72.8	59.2**	57.0	73.2	47.1	21.7***
Single-mother:									
Per-child resource share	0.26***	0.33***	0.27***	0.30***	0.30***	0.29***	0.29***	0.32***	0.32***
Per-adult resource share	0.24	0.35***	0.30***	0.33***	0.31***	0.32***	0.32***	0.32***	0.32***
Poverty headcount: child	35.6*	76.1**	76.4	86.3	66.9***	63.7***	80.6**	63.7	54.9
Poverty headcount: adult	46.0**	73.8	69.4	85.2*	58.6	54.0	76.2	68.7*	52.2***
Poverty headcount: household	27.2	65.0	65.1	73.4	46.7**	52.1	69.7	52.3	40.9***
Whole sample:									
Per-child resource share	0.23	0.20	0.17	0.17	0.20	0.18	0.18	0.21	0.22
Per-adult resource share	0.25	0.26	0.23	0.23	0.20	0.25	0.23	0.26	0.29
Poverty headcount: child	44.7	83.1	82.9	87.1	73.0	77.8	86.4	71.3	57.4
Poverty headcount: adult	34.5	73.3	69.5	78.8	60.3	58.1	76.1	59.3	37.4
Poverty headcount: household	20.9	70.5	64.7	72.9	55.1	56.2	72.7	48.5	28.5

Notes: *, ** & *** show significance of mean difference in male-headed and single-mother sub-samples at 10%, 5% & 1% levels respectively. All observations are weighted to make estimates representative.

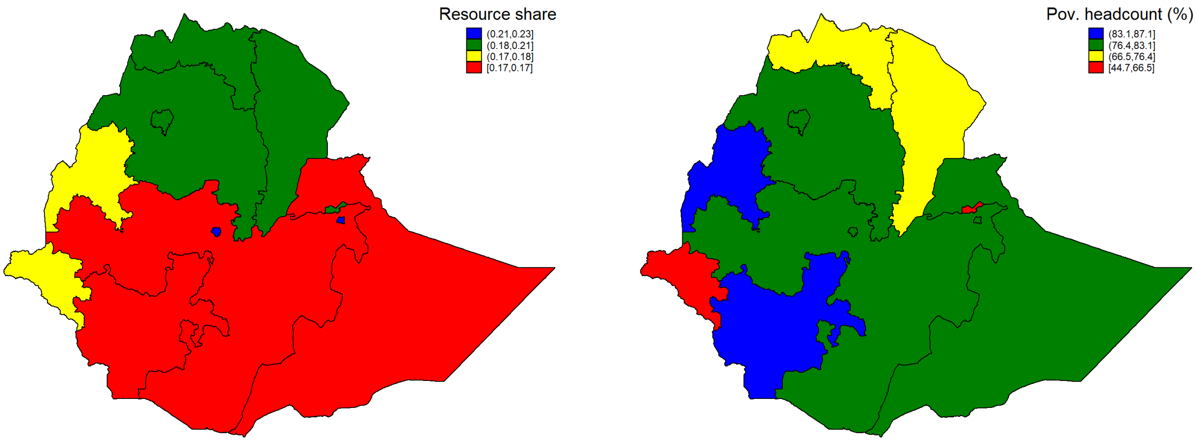
the rejection of the widely held view that poor children live with/ in poor adults/ households (Brown et al., 2017, 2018).. From a policy perspective, it questions the effectiveness of targeting poor households for a social protection aiming at improving child welfare.

1.4.3. Spatial Distribution of Child Resource Shares and Poverty

Answering the question of where on the map children make the most/least decisions on home resources and locating poor children aid policymakers interested on the issue. Hence, average resource share and poverty estimates are disaggregated by region and place of residence (rural, small towns, and medium and large towns).[16]

[16]Based on the 2007 Population Census, the ESS defines a small-sized town as one with population of less than 10,000; medium-sized between 10,000 and 100,000 and big-sized greater than

Figure 1.1.: Regional distribution of child resource shares and poverty headcount rates (%)



Note: Estimates are representative only to regions of Addis Ababa, Amhara, Oromia, SNNP and Tigray.

Table 1.8 summarizes the results.

Looking at the average resource share estimates, three findings stand out. Firstly, in line with our previous finding, a child has less resource share than an adult across regions and rural/urban residence. Secondly, a child's resource share shows no systematic relation with urbanization. For a map of regional disparities in child resource shares for the whole sample, see the left panel of Figure 1.1. Average per-adult expenditure shares vary across regions between 20% and 26% in the whole sample. Thirdly, across all regions and residence types, single-mothers significantly allocate more resources children compared with married males.

Regarding poverty incidence, disaggregated estimates in Table 1.8 similarly disclose presence of large spatial disparities. For instance, the chance of children falling in poverty in male-headed (resp. single-mother) families ranges between 88% (81%) in rural areas to 59% (55%) in medium and large towns, and falling as low as 51% (46%) in the nation's largest city and capital, Addis Ababa. There is significant difference in child poverty incidence between male-headed and single-mother households in the majority of the regions and rural areas. On the other hand, if intrahousehold resource allocation was ignored, poverty would once again be understated and we would notice no significant poverty prevalence difference between the two family structures in all regions (except Tigray) and rural/urban areas (except medium and

100,000.

large towns). Figure 1.1 (right panel) visually maps the disparities in child poverty across regions for the whole sample of families with children.

1.5. Concluding Remarks

Children have long been sidelined in the literature as decision makers in household resources. While they could be a victim of the widely-evidenced intrahousehold inequality, parental altruism may benefit them. The scant collective model evidence on children's shares of household resources and poverty in developing countries that are sizably populated by children is inconclusive. We estimate a complete collective demand model to recover children's resource shares and analyze poverty in married male-headed and single female-headed families in Ethiopia. Identification strategy of the sharing rule relies on use of private exclusive goods and distribution factors.

Results generally confirm disparities in intrahousehold resource allocation and poverty which vary with the number of children, family type and space. The allocation is significantly affected by parental differences in education and age, child education, proportions of female children and women as well as number of non-biological children. Children command less household resources than adults and children in single-mother families have higher resource shares than those in male-headed families.

After using resource shares for computing incidence, depth and severity of poverty, we also find that children are poorer than adults. Single-mothers not only are more altruistic to their children, they also avoid higher child poverty than married male heads although this seems to disappear when the number of children increases. We find that traditional poverty measures, which by construction ignore intrahousehold allocation, understate child (and adult) poverty compared to those based on our resource shares. Our estimates also show that non-poor families also host poor children, unlike the general belief that poor children live only with poor adults and households. We also find that monetarily non-poor adults and households host stunted children. Finally, regional and rural-urban disparities exist in both child resource shares and poverty.

Our results are important for few intervention issues. Firstly, by disclosing intra-household inequalities in resource allocation and poverty that children do better only at low family size, the results lend support to fertility interventions. Ignoring this inequality means a misleading picture of the incidence, depth and severity of poverty. Secondly, gender of the household head matters to children as mothers found to be more pro-child. Thirdly, the overlaps between child poverty, adult poverty, household poverty and child stunting question the effectiveness of targeting just poor households for a social protection aiming at improving child welfare. Lastly, pro-rural spatial redistributive efforts are implied to reduce disparity.

The study contributes to the methodological and evidence gap in system-wide estimation of resource shares and use of them in poverty estimation and analysis. Yet, given that child well-being is multidimensional, the overlap between the new monetary child poverty and multidimensional poverty as well as impact of social protection on children's resource shares and well-being remain as future research agenda which the remaining two essays investigate.

2. Children's Multidimensional Deprivation, Monetary Poverty and Undernutrition

2.1. Introduction

Child well-being is multidimensional. This is clearly reflected when the world commits itself via the 1989 Convention on the Rights of the Child (CRC) to meet children's rights and well-being such as being able to be healthy, learn, develop and play. The Sustainable Development Goals (SDGs) also place a lot of emphasis on multidimensional deprivation. Yet, 689 million children in developing countries live in multidimensional poverty (Alkire et al., 2017) which only slightly decreased from over one billion deprived in one or more dimensions (Gordon et al., 2003).Children, compared with adults, are over-represented in poverty, whether measured using monetary or multidimensional methods (Newhouse et al., 2016; Alkire et al., 2017).

Most of the literature on multidimensional deprivation analysis uses Demographic and Health Surveys (DHSs). However, DHSs lack expenditure data and little effort has been made to use data from the Living Standard Measurement Studies (LSMS) surveys for such analyses (Klasen, 2000). In addition, there is only scant evidence linking together monetary and non-monetary dimensions and the majority of these are at the household level (Klasen, 2000; Bruck and Kebede, 2013). Only few recent efforts bring in intrahousehold resource allocation to the focus and analyze the links between children's undernutrition and child/ household monetary poverty (Brown et al., 2017, 2018).

This study fills the aforementioned evidence gap by bringing in the collective household consumption model's resource sharing rule to monetary poverty and multidimensional deprivation measurement. Unlike the majority of the available literature on multidimensional poverty, which is based on household level data and assumes equal access to services or equal resource distribution among all family members, one of our indices includes a monetary indicator that capture children's bargaining power. Moreover, the study considers a nutrition-based definition of child well-being and looks at its overlap with monetary poverty besides the latter's overlap with multidimensional deprivation. In particular, we ask: Are all monetarily non-poor children also not undernourished? Do non-poor households host stunted children? What portion of children identified monetarily-poor is also multidimensionally-deprived? Lastly, we look at if estimates differ with various demographic and geographic classifications.

The study adopts a holistic definition of children's well-being, focusing on their capabilities as well as access to various goods and services crucial for their survival and development. Beginning with a dashboard approach (Ravallion, 2011a) where child deprivations in each of the well-being indicators are reported, we end up aggregating into an index. In the baseline multidimensional child deprivation index, we include 11 non-monetary indicators grouped under the three traditional dimensions (education, health and living standards) as in Alkire and Santos (2010) but they are child-specific except some in living standards. The extended index incorporates a monetary child poverty indicator. The assumption is that non-monetary dimensions can be used to proxy capabilities of children that are actually achieved, the monetary dimension captures both present and future capabilities. It is derived from a collective almost ideal demand system (CAIDS) model estimation (Menon et al., 2017). Based on observation of expenditures on private assignable goods, distribution factors breaking the intrahousehold resource allocation between children and adults and adjusting the arising measurement error, we recover the sharing rule of children. These are ultimately used to identify whether the average child is expenditure-poor. Deprivations indices are computed following the procedures of Alkire and Foster (2009, 2011). We use the child as the unit of analyses.

We use Ethiopia Socioeconomic Survey (ESS) 2014 for the empirical exercise. The ESS is conducted as part of the LSMS-ISA project by the World Bank and Ethiopia's Central Statistical Agency (CSA). It contains various child, household and community level details that we exploit for meeting the objectives. Besides data issues, Ethiopia is a good setting for our purpose as it is one of the poorest countries in the world with a sizable child population, over 52 percent according to the latest census. Equivalence scale-based (monetary) child poverty rate at 32.4 percent (CSA et al., 2015) and multidimensional child deprivation rate at 94 percent (Plavgo et al., 2013) are higher than monetary and multidimensional rates at the household level, 29.6 percent (MoFED, 2012) and 87 percent (UNDP, 2013) respectively.

We find that multidimensional child deprivation is high and varies with children's gender, their number, family structure and location. The probability of falling into multidimensional deprivation and the average intensity of it almost monotonically increase with the number of children. Deprivation indices for urban children jump in a high magnitude when a monetary indicator is included. Although multidimensionally-deprived children concentrate more at the lower household/ child income levels, there is evidence that the monetarily non-poor still host deprived children. For instance, depending on the type of monetary poverty measure considered, 10 percent to a quarter of monetarily non-poor children are deprived multidimensionally. Regression results, besides confirming the decreasing role of income, indicate that boys as well as children living in rural areas, single-mother families and large families are highly likely to be multidimensionally-deprived.

Findings also show that about 60 percent of expenditure-poor under-7 children and 46 percent living in expenditure-poor households are not found to be nutrition-deprived. About two-thirds of stunted children are not found in the poorest 20% or 40% of children/households. After controlling for child-, head-, household- and community-level effects, including shocks and common health effects, we find no evidence suggesting that children's nutrition is related to either child- or household-level expenditure. We also find that children living in households with more informational assets as well as those in educated heads and single-mothers are less stunted.

Evidences raise questions on the use of only monetary information to targeting child poverty. It may be incorrect to design antipoverty policies with the assumption that targeting poor households suffices in reaching poor or deprived children. The remainder of the current essay is organized as follows. In the second section, we discuss the methods. After describing the data in the third section, results are presented and discussed in section four. The last section concludes.

2.2. Methods

2.2.1. Dimensions, Indicators, Weights and Deprivation Thresholds

We use indicators that are specific to children and those that are common to all household members but yet having implications to children's well-being. Table 2.1 provides the chosen dimensions, indicators, weights and deprivation thresholds for constructing child-level multidimensional deprivation index.

The baseline index contains three dimensions that are traditional in the literature: education, health/nutrition and living standards. In the extended index, we add monetary poverty as a fourth dimension. Indicators of the living standards dimension (access to safe water, sanitation, electricity, cooking, housing and asset) are common to children of all age groups. The health and nutrition dimension contains common and individual indicators.[1] Indicators of the education dimension (current attendance and formal schooling) refer only to school-age children of 7 to 17 years.

Whether a child is deprived in a certain indicator is decided based primarily on national and international standards such as national poverty lines for monetary poverty and WHO standards for nutrition deprivation. Below, we briefly describe the dimensions and their corresponding indicators.

Education

Education is an important indicator of future capability of children. Two indicators - compulsory child enrollment and years of schooling - form the education dimension. Deprivation in child enrollment is measured by presence of any school-age child not in school. Indicator of school enrollment for children of compulsory school-age, which is 7 to 17 years in Ethiopia, is widely used in the literature (Alkire and Santos, 2010) and goes in line with national and UNESCO's standards and SDG targets. If any school-age child has no formal education captures deprivation in child years

[1] Nutrition data in the ESS are collected for children of ages between 6 and 83 months (under-seven years and over 6 months). We thus assume that children of other ages are not deprived in nutrition.

Table 2.1.: Dimensions, indicators, weights and deprivation thresholds of child multidimensional deprivation

Dimension (weight)	Indicator (weight)	Deprived if
D1. Child education (1/3)*	**D11**. Child enrollment (1/6)	A school-age child is not currently attending school.
	D12. Child formal education (1/6)	A school-age child has no formal education.
D2. Child health and nutrition (1/3)	**D21**. Child mortality (1/9)	Any child died over the past 2 years.
	D22. Child sickness (1/9)	A child faced serious illness since two months.
	D23. Child stunting (1/9)	A 6-83-months-old child (under 7-old) is stunted (height-for-age z-score < -2) (WHO).
D3. Living standards (1/3)		*...child lives in a household with...*
	D31. Safe water (1/18)	Unsafe source of drinking water (WHO).
	D32. Sanitation (1/18)	Unimproved toilet facility (WHO).
	D33. Electricity (1/18)	No access to electricity.
	D34. Cooking fuel (1/18)	No improved cooking fuel (dung, wood or charcoal).
	D35. Floor (1/18)	Floor made of natural, non-permanent material.
	D36. Information (1/18)	No TV/ radio/ mobile phone/ fixed phone.
***D4**. Child monetary poverty (1/4**)	**D41**. Child is poor (1/4**)	Estimated resource share-based per-child expenditure is below the national poverty line.

Notes: *For the under-7 children sample, the education dimension is represented by an indicator that a child's biological mother is illiterate. **When child monetary poverty is added as a (fourth) dimension, the weight of each dimension becomes 1/4 and the corresponding indicators are weighted as multiples of 1/4. Two types of child monetary poverty are used, one adjusting for children's requirement using age and another without. The adjusted one modifies the national poverty line (NPL) for children as 0.6*NPL if their age is less than 14.

of schooling. For children under the age of seven, we proxy education by mother's education.

Health and nutrition

This dimension constitutes three indicators capturing human capital functionings: any child mortality in the household in the past two years, if a 6-83-month-old child (hereafter under-7 child) is stunted and if the child faced serious illness. The first two are traditional in the literature while the third incorporates the health situation of living and older children. Where we are faced with a household with no 6-83-month-old child, we assume they are not deprived in this indicator.

Standards of living

Seven indicators are included in the standards of living dimension. While the above dimensions contain a significant component of intrahousehold inequality, indicators in this dimension are similar for all members and capture the household public good component of well-being. In particular, the living standards indicators measure deprivations in safe drinking water, electricity, cooking fuel, toilet, housing and information. The choice of informational assets over all other assets is motivated by the literature (e.g. Plavgo et al. (2013)), the CRC (Art. 17)) and other international targets such as in the MDG and SDG.

Monetary child poverty based on resource shares

A version of our child multidimensional deprivation index contains child monetary poverty as one of the dimensions. While the above non-monetary dimensions can be used to proxy capabilities of children that are actually achieved, the monetary dimension may be considered as capturing both present and future capabilities. Child poverty is computed from the expenditure share of children in the total household expenditure after estimating a collective complete Almost Ideal Demand System (CAIDS) using the identification strategy developed by Chavas et al. (2017) and implemented by Menon et al. (2017). Based on observation of consumption of private assignable goods (clothing, education and adult goods), distribution factors breaking the intrahousehold resource allocation between children and adults as well as a function adjusting the arising measurement error, we recover the sharing rule of children. These are ultimately used to identify whether the average child is poor. The national poverty line aids the identification of children as poor. For a technical detail of this estimation, see Appendix A.2.

Weight of dimensions and indicators

An important step in multidimensional deprivation analysis is weighting of dimensions and indicators. We opt to provide equal weight to all dimensions and each indicator in a dimension is similarly equally weighted. This is in fact the tradition in the majority of the literature (Alkire and Santos, 2010; Apablaza and Yalonetzky, 2012; Roche, 2013; Trani et al., 2013; Singh and Sarkar, 2015). However, subjective weights could also be assigned (Decancq and Fleurbaey, 2014) but we could not find the required information in the survey we use to implement such weights.

2.2.2. Multidimensional Deprivation Identification and Aggregation

We adapt the procedures of Alkire and Foster (2009, 2011) for identifying children as multidimensionally-deprived as for computing relevant indices as well as undertaking sub-group decomposition. Besides the raw (unweighted) deprivation headcount ratios for each indicator (h_j), we compute weighted deprivation count (C), censored multidimensional deprivation headcount ratio (H), average intensity of deprivations (A) and the adjusted multidimensional deprivation index ($M = H * A$). The contributions of indicators, dimensions and population sub-groups such as rural/urban areas are also calculated. The details on these computations are available in Appendix A.3.

Multidimensional deprivation (dual) cut-off

A final note on multidimensional identification is worth highlighting. In the Alkire-Foster framework, someone is identified as multidimensionally-deprived if she is deprived in several indicators at the same time. This identification of the poor is done in two cut-offs: deprivation cut-off that shows whether someone is deprived in a certain indicator or not, and a deprivation cut-off (equivalent to the poverty line in the monetary approach) that helps identify those deprived multidimensionally.

In general, three identification criteria are available in the literature: the union, the intersection and intermediate (dual cut-off) approaches. According to the union approach, someone is said to be multidimensionally-deprived if there is at least one dimension in which the person is deprived. However, this approach has the weakness that when the number of dimensions is large, it often identifies most of the population as being poor. For instance, deprivation in a single dimension may imply something else other than poverty and hence the approach is not appropriate in all circumstances (Alkire and Foster, 2011). On the other extreme, the intersection approach identifies someone as multidimensionally-deprived only if she is deprived in all dimensions. This approach, however, certainly misses people who experience extensive, but not universal, deprivation like those with insufficiency in every other dimension who happen to be healthy (Alkire and Foster, 2009).

An alternative and more reasonable approach is to base identification on a cut-off lying somewhere between those extremes - the intermediate or dual cut-off approach which is used in the AF framework. Accordingly, an individual is identified as multidimensionally-deprived if the weighted count (or number) of dimensions in which the person is deprived is at least above some minimum cut-off number of dimensions (k). The dual cut-off approach is more inclusive than the extremes union and intersection approaches. In short, if all dimensions d are equally weighted, the value of k varies from 1 to d. When $k = 1$, the identification refers to the union approach; when $k = d$, it is the intersection approach. In the dual cut-off approach, other k values lying between the extremes ($1 < k < d$) can be chosen.

2.3. The Data and Descriptive Statistics

Data for the study come from Ethiopia Socioeconomic Survey (ESS) collected jointly by the World Bank and the Central Statistical Agency of Ethiopia (CSA) as part of the Living Standard Measurement Study-Integrated Surveys of Agriculture (LSMS-ISA). ESS is a panel survey with three waves to date (2011/12, 2013/14 and 2015/16). While the sample design of the first wave provides representative estimates for rural-area and small-town households, subsequent waves include medium and large towns and cities so that they have become nationally-representative. It uses a stratified, two-stage design where regions of Ethiopia serve as the strata. The first stage involves the selection of primary sampling units (or enumeration areas) using simple random sampling. The second stage of sampling entails the selection of households.

ESS contains household-level data on a range of modules including expenditure, assets, shocks, non-farm enterprises, credit and farm production. Individual data on demographics, education, health, some expenditure items, and time use are also collected. Moreover, community-level data as well as data on prices from local markets are available. However, in addition to being a rural-only survey, the 2011/12 wave lacks expenditure data on education, health, housing and food away from home. Lack of price data for assignable clothing and other goods such as education and personal care also forced us to exclude the 2015/16 wave. This study, therefore, employs the 2013/14 wave. A total of 23,785 individuals, of whom 11,343 are children under 18, living in 5,262 households were interviewed. The chosen sample for this study is 9,345 children who live with married male-headed (two-parent) and single female-headed (single-mother) households. These two sub-samples are considered to make a comparative analysis of child well-being over parental gender and family structure. In fact, the left out categories (married female-headed and single-father) are very negligible.

In the demand system estimation used for recovering children's expenditure shares and hence monetary poverty, we aggregate the various non-durable expenditure items into four expenditure groups: food at home and alcohol, clothing, household utilities and energy, and other goods. Exclusive/assignable consumption is based on a host of non-durable expenditure items. Clothing and footwear expenditures, collected at male, female, girl and boy levels as well as education expenditures, collected at individual level, are clearly assignable. Further, we assign expenditures on alcoholic drinks, stimulants (*chat/khat* and cigarettes) and some personal care items to adults. Prices data come in various forms including unit values for food items, local market prices for the majority of non-food items and CSA's average retail prices for others.

Data on non-monetary deprivations are obtained from the various other modules of the ESS. Indicators of the child education dimension are retrieved from the education section which collected information at each individual level. For the child health and nutrition dimension, information from the health section of the survey is used which once again collects data at individual level although anthropometric measures are obtained for children between 6 and 59 months (under 7 years). Living standards indicators at the household level are gathered from the housing and assets sections of ESS.

Table 2.2 presents the descriptive statistics of our sub-sample in selected variables at child, household and community levels. While half of the children are girls, a little more than that engage in some form of labor activity. Three-quarters pf children live with working parents while a quarter have a single-mother. Over half of their parents are illiterate and only 10 percent make it to high school or above. Roughly equally a fifth of the children fall in each of the five relative poverty quintiles of

Table 2.2.: Descriptive statistics of selected variables: ESS 2013/14 (N = 9345)

Variable	Type	Mean	Std. Dev.	Min	Max
Child is a girl	I	0.50	0.500	0	1
Child works	I	0.56	0.496	0	1
Head works	HH	0.73	0.443	0	1
Head is single mother	HH	0.16	0.366	0	1
Head was ill	HH	0.23	0.419	0	1
Household size	HH	6.40	2.130	2	15
Number of children					
One	HH	0.07	0.258	0	1
Two	HH	0.16	0.371	0	1
Three	HH	0.19	0.394	0	1
Four	HH	0.20	0.404	0	1
Over four	HH	0.37	0.482	0	1
Head's education					
Illiterate	HH	0.56	0.497	0	1
Elementary	HH	0.34	0.475	0	1
High school	HH	0.06	0.231	0	1
Above high school	HH	0.04	0.204	0	1
Relative child poverty: quintiles					
Poorest	I	0.19	0.396	0	1
Poor	I	0.19	0.390	0	1
Middle	I	0.19	0.393	0	1
Rich	I	0.21	0.409	0	1
Richest	I	0.22	0.411	0	1
Shocks: price changes	HH	0.20	0.400	0	1
Shocks: natural	HH	0.16	0.371	0	1
Distance to health>5km	HH	0.74	0.436	0	1
Community faced epidemic disease		0.07	0.252	0	1
Location: rural/urban					
Rural	HH	0.77	0.419	0	1
Small town	HH	0.08	0.264	0	1
Medium & large town	HH	0.15	0.359	0	1
Location: region					
Addis Ababa	HH	0.03	0.159	0	1
Amhara	HH	0.17	0.380	0	1
Oromia	HH	0.21	0.407	0	1
SNNP	HH	0.26	0.438	0	1
Tigray	HH	0.11	0.316	0	1
Others	HH	0.22	0.413	0	1

Note: Data type: HH = household level; I = individual (child) level. SNNP = Southern Nations, Nationalities and Peoples region.

estimated child expenditures. One child in five live in households reporting to have faced economic shocks in terms of either rise or fall of food prices and 7 percent in communities who faced an epidemic disease. Location-wise, the majority (77 percent) live in rural areas while about a fifth come from each of Amhara, Oromia and other small regions except Addis Ababa (3 percent), SNNP (a quarter) and Tigray (11 percent).

2.4. Results

In this section, we first present results on the types of children's monetary and non-monetary deprivations. Once deprivations are weighted, counted and poverty cut-offs are decided, the multidimensional deprivation situation of children with and without intrahousehold resource allocation is analyzed. The link between children's monetary, nutrition and multidimensional deprivation is then dealt with. Concentration curves and regression models support the analyses.

2.4.1. Children's Monetary and Non-monetary Raw Deprivations

Table 2.3 provides average raw (unweighted) child deprivation rates in selected indicators for the whole sample and by gender, family structure and location. The upper panel summarizes deprivation rates in child-specific, non-monetary indicators (education, health and nutrition). We find substantial deprivation of children's future development in education, health and nutrition. There also exist significant gaps in deprivations when disaggregated by children's sex (except in health and education), family type and residence where girls and children living with single-mother families and in urban areas are better off compared to boys and those living with male-headed families and in rural areas. In particular, 7 percent of school-age children are not attending school and 14 percent have no formal education. However, children seem to be less deprived of formal education when living in single-mother families and urban areas. Although lower rates of child mortality are reported generally within two years, rates are higher among single-mothers and rural dwellers. Non-negligible rates of child sickness two months from survey (14 percent) and any stunted child (11 percent) are also reported.

Table 2.3.: Average raw (unweighted) child deprivation rates (N = 9345)

Deprivation variable	Whole sample	Sex		Family type		Rural/urban	
		Girls	Boys	Single-mother	Male-headed	Rural	Urban
Non-monetary: child-specific							
Child not enrolled	0.07	0.06**	0.08	0.10***	0.06	0.07	0.06
Child has no formal education	0.14	0.14	0.15	0.15	0.14	0.16***	0.05
Child mortality	0.03	0.03	0.03	0.08***	0.02	0.03***	0.01
Child sickness	0.14	0.14	0.14	0.12*	0.14	0.14	0.16
Child stunting	0.11	0.11	0.12	0.06***	0.12	0.12***	0.07
Non-monetary: household-level							
No safe water	0.35	0.33***	0.37	0.26***	0.36	0.40***	0.04
Poor sanitation	0.95	0.95	0.95	0.94	0.95	0.97***	0.83
No electricity	0.78	0.76***	0.80	0.63***	0.80	0.89***	0.13
Poor cooking fuel	0.98	0.98**	0.98	0.95***	0.98	1.00***	0.86
Poor floor	0.92	0.91***	0.93	0.90*	0.92	0.97***	0.63
No information source	0.43	0.43	0.43	0.49*	0.42	0.49***	0.10
Monetary poverty							
Child poverty rate	0.86	0.83***	0.89	0.78***	0.88	0.90***	0.67
Adjusted child poverty rate	0.68	0.63**	0.73	0.57***	0.69	0.72***	0.45
Household poverty rate	0.72	0.71	0.73	0.65**	0.73	0.77***	0.40

Notes: *, ** and *** imply mean difference (boy - girl, single-mother - male-headed and rural - urban) is statistically significant at 10%, 5% and 1% levels respectively. The monetary poverty line used is the national poverty line (NPL) provided by the Ministry of Finance and Economic Development (MoFED, 2012) modified to take into account inflation. The adjusted child monetary poverty modifies the NPL for children as 0.6*NPL for those aged less than 14 years. All estimates are weighted to make them representative of the corresponding population.

Children also live in households that are highly deprived of basic living standards as reported at the middle panel of Table 2.3. In fact, the largest rates of children's deprivations are associated with living standards. These range from 35 percent of not having access to safe water to 98 percent of use of health-threatening cooking items; and all deprivations are worse in rural than urban areas. Others include deprivations in sanitation facilities (95 percent), housing in terms of floor (92 percent), access to electricity (78 percent) and access to information sources (43 percent).

The bottom three rows of Table 2.3 provide monetary poverty rates. The poverty line used is the (official) national poverty line (NPL) provided by Ethiopia's Ministry of Finance and Economic Development (MoFED, 2012) and modified to take into account inflation. The adjusted child monetary poverty modifies this poverty line for children as 0.6*NPL for those aged less than 14 years. In addition to the poverty rates from our new approach of using estimated sharing rules, the one based on the traditional approach of adult-equivalents (household level) is reported for comparison. We find high monetary child poverty rates. For the whole sample, child poverty headcount rate stands at 86 percent. Boys are poorer than girls, as are children in male-headed families and rural areas relative to their counterparts in single-mother and urban areas. If intrahousehold resource allocation was not considered, poverty rate would be lower at 72 percent. This is in line with the collective household model's empirical evidence elsewhere in Africa that the unitary model understates poverty (Dunbar et al., 2013; Bargain et al., 2014, 2018). As expected, adjusting the poverty line for children under the age of 14 lowers the poverty situation.

The estimates above are not weighted and simply show the prevalence of child deprivations in their corresponding sectors. A policymaker interested in these separate issues may make use of them in the design of anti-poverty or anti-deprivation interventions. This is what is known in the literature as the dashboard approach (Ravallion, 2011b). If interest lies in the overall status of child deprivation, one needs to compute the (weighted) multidimensional measure and shares of each of the previous deprivations in the aggregate measure can also be analyzed.

2.4.2. Multidimensional Child Deprivation and Intrahousehold Resource Allocation

Traditional measures of multidimensional deprivation do not usually contain a monetary component. Here, in addition to the widely-used index, we estimate two more indices which include a monetary dimension and consider intrahousehold resource allocation. After counting the number of deprivations encountered by children, we aggregate into multidimensional deprivation incidence and intensity. To look more into where the deprivation is concentrated, contributions to the total multidimensional child deprivation of indicators and dimensions as well as select locations and demographic groups are also presented.

2.4.2.1. Weighted Count of Children's Deprivations

Table 2.4 summarizes weighted count of deprivations of children in three cases for the whole sample and various sub-groups. When a monetary dimension does not

Table 2.4.: Weighted count of children's deprivations by gender, family type and location

Deprivation count	Whole sample	Children's gender		Family type		Rural/urban	
		Girls	Boys	Single-mother	Male-headed	Rural	Urban
Without monetary dimension	0.31	0.31***	0.32	0.28***	0.32	0.33***	0.20
	(0.004)	(0.005)	(0.005)	(0.007)	(0.005)	(0.004)	(0.008)
With monetary dimension:							
(a) With child poverty	0.45	0.44***	0.46	0.41***	0.46	0.47***	0.31
	(0.005)	(0.005)	(0.005)	(0.009)	(0.005)	(0.004)	(0.010)
(b) With adjusted child poverty	0.40	0.39***	0.42	0.36***	0.41	0.43***	0.26
	(0.006)	(0.007)	(0.007)	(0.009)	(0.007)	(0.007)	(0.012)

Notes: *, ** and *** imply the mean difference (boy - girl, single-mother - male-headed and rural - urban) is statistically significant at 10%, 5% and 1% levels respectively. Standard errors are in parentheses. The adjusted monetary child poverty modifies the national poverty line (NPL) for children as 0.6*NPL if age is less than 14. All estimates are weighted to make them representative of the corresponding population.

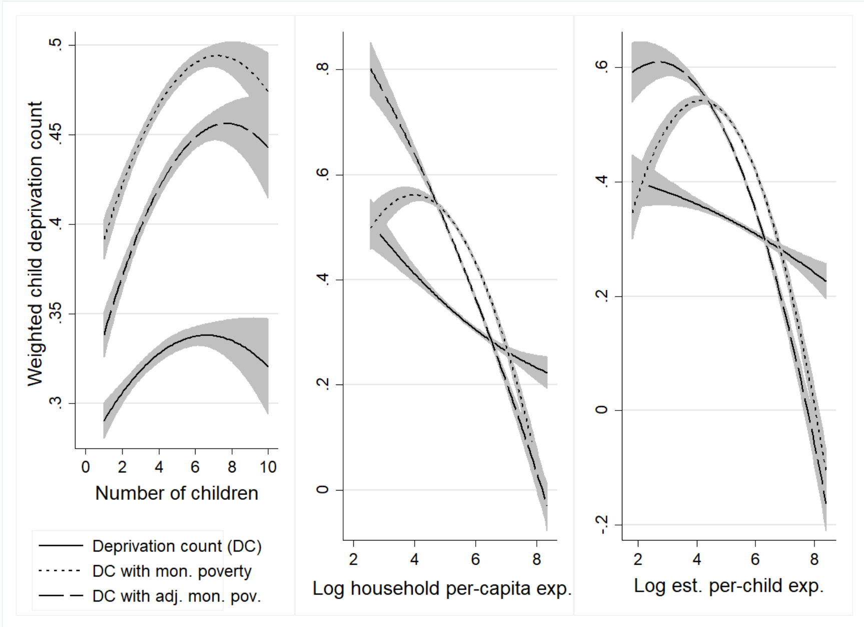
enter the index, the average weighted child deprivation count is computed as 0.31 for the whole sample. The figure is slightly higher for boys and children in male-headed parents (0.32 in each) as well as those in rural areas (0.33). What happens if one adds a dimension that measures child monetary poverty? In one case, this dimension refers to whether the average child is poor monetarily with no adjustment in the poverty line while in the other case the poverty line is adjusted to the needs of children using their age. Recall that we make use of the national poverty line (NPL) provided by the Ministry of Finance and Economic Development (MoFED, 2012) modified to take into account inflation so that our adjusted child monetary poverty modifies NPL for children as 0.6*NPL for those aged less than 14 years.[2]

However, the addition of a monetary poverty dimension worsens the situation of children's multiple deprivations. For the whole sample, for example, the average weighted count of deprivations rises to 0.45 and to 0.40 in the adjusted case. Once again, girls and children living with single-mothers and in urban areas are less likely to be poor.

How does children's multiple deprivation count change with family size and income at household and child levels? Figure 2.1 depicts weighted child deprivation counts

[2]The reason for reporting the one with no adjustment of the poverty line to children is in part due to the fact that children's expenditures here are estimated with consideration of intrahousehold resource allocation using a function capturing child-adult differences. Recall that the monetary child poverty dimension is added means an equal weight of 0.25 for the four dimensions and their corresponding indicators are equally-weighted.

Figure 2.1.: Weighted child deprivation counts over the number of children and expenditure



Note: 95% confidence intervals are shaded. The adjusted monetary child poverty modifies the national poverty line (NPL) for children as 0.6*NPL if age is less than 14.

over the number of children, household per-capita expenditure (adult-equivalent) and per-child expenditure. As expected, we generally count more children deprived in multiple indicators with an increase in the number of children with a slight fall at higher sizes. On the other hand, multiple deprivations generally decrease with expenditures. However, trends in these relationships slightly vary depending on the inclusion of a monetary poverty dimension/indicator in the deprivations.

2.4.2.2. Multidimensional Child Deprivation

We now add the second cut-off to the indicator-specific cut-offs in order to identify a child as multiply-deprived. This, in our case, refers to in how many weighted indicators a child should be deprived to be deemed multidimensionally-deprived. The two extreme cut-offs, $k \cong 0$ or the union approach and $k \cong 1$ or the intersection approach, identify almost all and no children as multidimensionally-deprived respectively. In order to see the sensitivity of multidimensional deprivation to the choice of a poverty line, we opt to report six intermediate cut-offs representing deprivations in at least 10%, 25%, 33%, 50% and 67% of weighted count of indicators. Table 2.5

provides the summary of multidimensional deprivation indices computed based on each of these.

Multidimensional deprivation headcount ratio (H) measures the proportion of children deprived in at least a given count (k) of weighted dimensions. In the baseline index, which excludes a monetary dimension, our estimates show H reaches as high as 98 percent when $k = 0.10$ and only 7 percent when $k = 0.50$ while no child is multidimensionally-deprived at $k = 0.67$. At the widely-used intermediate line of $k = 0.33$, multidimensional deprivation headcount rate stands at 47 percent. This contrasts with the monetary headcount rate of 86 percent and 68 percent when the official poverty line is adjusted for children. The average intensity of simultaneous deprivations suffered by poor children (A) is estimated as 0.32 at a 0.10 cut-off and 0.79 at the 0.67 line. Adjusting H by A gives the adjusted multidimensional deprivation index (M) which ranges between 31 percent and 0 percent with those two cut-offs respectively. At the popular line of $k = 0.33$, average intensity is 0.41 and adjusted multidimensional index is 20 percent.

How do the results using the baseline index change with an inclusion of a monetary dimension (an indicator of intrahousehold resource allocation)? The monetary dimension refers to whether a child is poor as computed from children's estimated sharing rule and compared to an official poverty line. Two more indices are then computed: one using the official adult-equivalent poverty line and the other using an adjusted one to children's needs. To begin with, no differences in H among the three indices are seen at the lowest and highest multidimensional cut-offs considered above. The differences in A and M at these cut-offs are moderate. However, at low and middle cut-offs, the effects of the inclusion of a child monetary poverty indicator in the index seem to be large. For instance at $k = 0.33$, H almost doubles to 87 percent with the unadjusted case and becomes 72 percent with the adjusted one. This, coupled with a slight jump in A, makes M to more than double to 43 percent in the unadjusted and to 35 percent in the adjusted case.

We also decompose the multidimensional deprivation measures by children's gender, family type, number of children and residence (see Table 2.6). Although boys (49 percent) are likely to be more multidimensionally-deprived (H) than girls (45 percent), this difference seems to vanish when the intensity of deprivation is accounted for (M) (19 versus 20 percent). On the other hand, boy-girl gap in multidimensional deprivation remains when indices include a monetary dimension. Children living in

Table 2.5.: Estimates of multidimensional child poverty with intrahousehold resource allocation

Poverty measure	$k = 0.10$	$k = 0.25$	$\boldsymbol{k = 0.33}$	$k = 0.50$	$k = 0.67$
	Without monetary poverty (3 dimensions)				
H	0.98	0.69	**0.47**	0.07	0.00
	(0.004)	(0.018)	(0.016)	(0.008)	(0.000)
A	0.32	0.37	**0.41**	0.53	0.79
	(0.004)	(0.002)	(0.002)	(0.003)	(0.008)
M	0.31	0.25	**0.20**	0.04	0.00
	(0.004)	(0.007)	(0.007)	(0.004)	(0.000)
	With monetary child poverty (4 dimensions)				
H	0.98	0.91	**0.87**	0.39	0.01
	(0.003)	(0.008)	(0.010)	(0.016)	(0.001)
A	0.46	0.48	**0.49**	0.57	0.72
	(0.004)	(0.003)	(0.003)	(0.002)	(0.005)
M	0.45	0.44	**0.43**	0.22	0.00
	(0.005)	(0.006)	(0.006)	(0.009)	(0.001)
	With adjusted monetary child poverty (4 dimensions)				
H	0.97	0.79	**0.72**	0.32	0.01
	(0.005)	(0.005)	(0.010)	(0.005)	(0.001)
A	0.42	0.47	**0.49**	0.57	0.72
	(0.006)	(0.008)	(0.003)	(0.004)	(0.004)
M	0.40	0.37	**0.35**	0.18	0.00
	(0.007)	(0.008)	(0.009)	(0.010)	(0.001)

Notes: k = poverty cut-off. H = multidimensional headcount ratio. A = average intensity of deprivation among the poor. M = multidimensional deprivation index. Standard errors in parentheses. The adjusted monetary child poverty modifies the national poverty line (NPL) for children as 0.6*NPL if age is less than 14. All estimates are weighted to make them representative of the corresponding population.

families with a male head are also found to have higher chance of being multiply-poor despite the measure being adjusted for intensity or including a monetary dimension. As expected, the probability of falling into multidimensional deprivation and the average intensity of it almost monotonically increase when the number of children increases. For example in the baseline index excluding monetary dimension, a child living in a large family (over four children) is more probable to fall in multidimensional deprivation by 19 percentage points compared to that in a one-child family. In the other two indices, this gap only slightly falls to 15 and 13 percentage points.

The spatial inequality is also high. A very large disparity is noticeable between children living in rural areas and their urban counterparts. Very importantly, in urban areas the estimates show a large jump from the baseline index to those indices that include monetary poverty. This signals that a multidimensional deprivation

Table 2.6.: Decomposition of multidimensional child deprivation by gender, family type, number of children and location

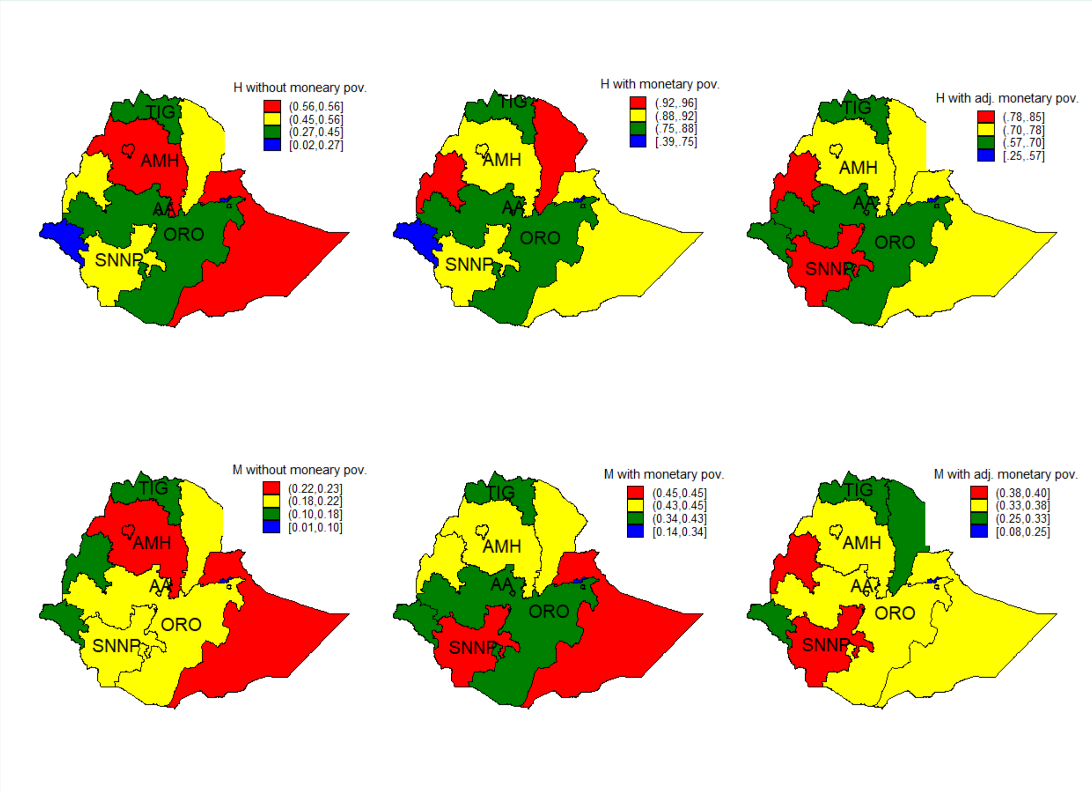
	Without monetary pov.			With monetary pov.			With adj. monetary pov.		
	H	*A*	*M*	*H*	*A*	*M*	*H*	*A*	*M*
Girls	0.45	0.42	0.19	0.87	0.47	0.41	0.68	0.49	0.33
Boys	0.49	0.41	0.20	0.90	0.48	0.44	0.77	0.49	0.38
Single-mother	0.43	0.42	0.18	0.79	0.49	0.39	0.64	0.48	0.31
Male-headed	0.48	0.42	0.20	0.88	0.49	0.43	0.89	0.40	0.36
One child	0.40	0.40	0.16	0.68	0.47	0.32	0.58	0.47	0.27
Two children	0.40	0.43	0.17	0.78	0.49	0.38	0.60	0.47	0.28
Three children	0.48	0.42	0.20	0.86	0.50	0.43	0.71	0.48	0.34
Four children	0.49	0.45	0.22	0.88	0.49	0.43	0.72	0.49	0.35
> Four children	0.50	0.74	0.37	0.94	0.50	0.47	0.81	0.49	0.40
Rural	0.53	0.42	0.22	0.92	0.50	0.46	0.77	0.49	0.38
Small town	0.21	0.43	0.09	0.76	0.43	0.33	0.54	0.44	0.24
Medium & large town	0.10	0.40	0.04	0.54	0.41	0.22	0.36	0.42	0.15
Addis Ababa	0.02	0.50	0.01	0.36	0.39	0.14	0.21	0.38	0.08
Amhara	0.55	0.42	0.23	0.88	0.50	0.44	0.76	0.50	0.38
Oromia	0.45	0.42	0.19	0.88	0.49	0.43	0.70	0.49	0.34
SNNP	0.48	0.42	0.20	0.93	0.48	0.45	0.80	0.49	0.39
Tigray	0.41	0.39	0.16	0.81	0.48	0.39	0.62	0.47	0.29
Other regions	0.49	0.41	0.20	0.88	0.49	0.43	0.72	0.47	0.34
Overall	**0.47**	**0.41**	**0.20**	**0.87**	**0.49**	**0.43**	**0.72**	**0.49**	**0.34**

Notes: H = multidimensional headcount ratio. A = average intensity of deprivation by the poor. M = multidimensional deprivation index. The estimates here are based on a poverty cut-off $k = 0.33$. The adjusted monetary child poverty modifies the national poverty line (NPL) for children as 0.6*NPL when their age is less than 14. All estimates are weighted to make them representative of the corresponding population.

measure of the Alkire and Santos (2010) family excluding monetary variables is less useful for identification and hence targeting the urban poor in developing countries.

To further disentangle the spatial inequality in multidimensional child poverty in Ethiopia, we disaggregate estimates by region and map them (see Figure 2.2). Inline with the rural-urban divide, the capital city, Addis Ababa, has the smallest incidence even after adjusting for average intensity and adding a monetary dimension to the index. Children in Tigray region follow those in Addis Ababa at a distant second. On the other worst extreme, children in Amhara region are the most likely to be multidimensionally-deprived when excluding the monetary dimension, followed by those in SNNP. These regions switch positions in indices that include a monetary child resource-sharing dimension.

Figure 2.2.: Decomposition of multidimensional child deprivation by region



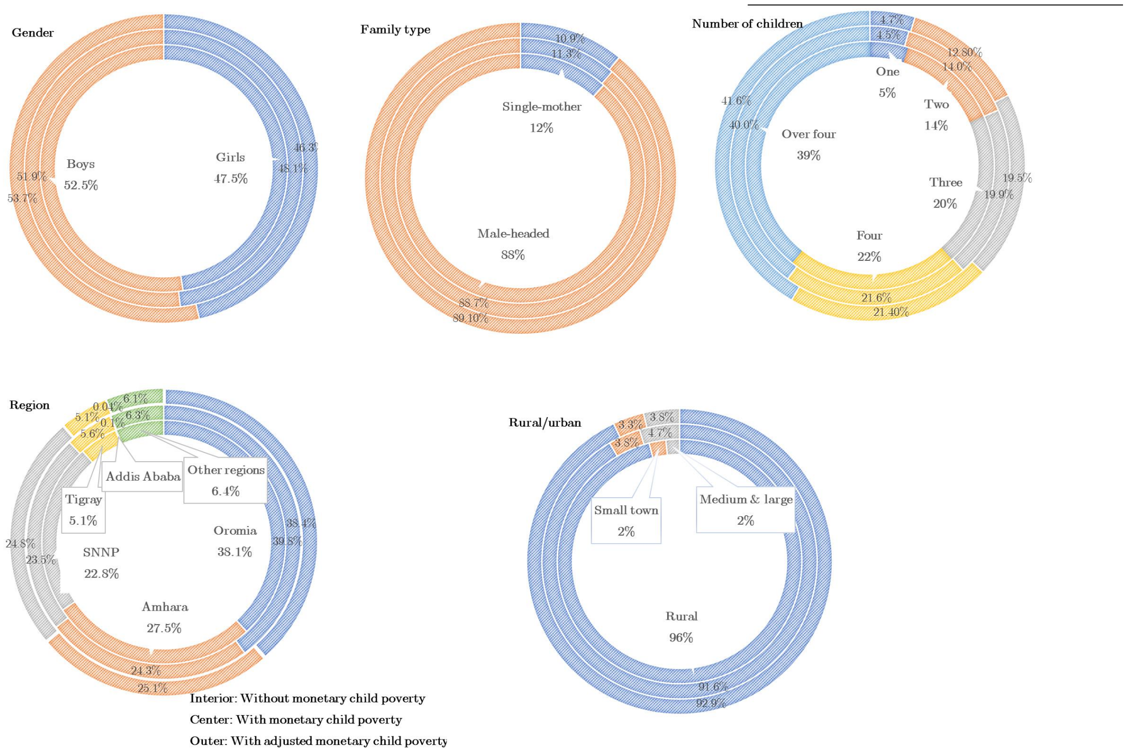
Notes: H = multidimensional headcount ratio. M = multidimensional deprivation index. Standard errors in parentheses. The adjusted monetary child poverty modifies the national poverty line (NPL) for children as 0.6*NPL if age is less than 14. All estimates are weighted to make them representative of the corresponding population. Estimates are representative only for Addis Ababa, Amhara, Oromia, SNNP and Tigray.

2.4.2.3. Concentration of Multidimensional Child Deprivation

An important step in multidimensional deprivation analysis is to compute the contribution to poverty of a certain population sub-group and an indicator/dimension. This has the obvious advantage of aiding policies that aim at its reduction.

The upper panel of Figure 2.3 summarizes the contribution to the overall multidimensional child deprivation of certain demographic sub-groups. Despite an equal representation in the sample, the contribution of boys (52.5 percent) is slightly higher than that of girls (47.5 percent) with slight variations when monetary indicators are taken into account. And due to their dominant population, children living in male-headed families have a share of about 90 percent in all indices. Children in large families have obviously a large burden in bad circumstances and the clockwise increment in the contribution of children to poverty in one-child to over-four-child

Figure 2.3.: Spatial contribution to the overall multidimensional child deprivation index (M)

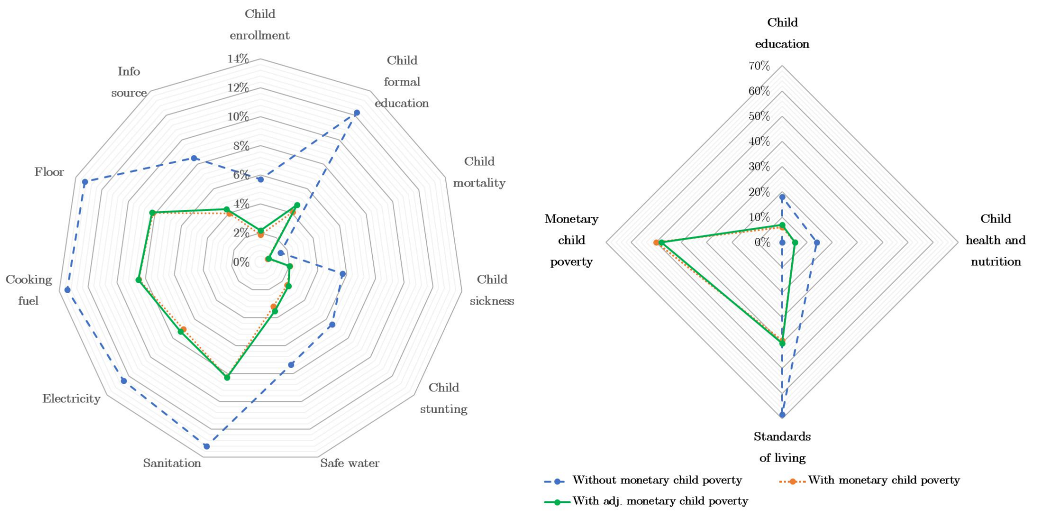


Notes: The adjusted monetary child poverty modifies the national poverty line (NPL) for children as 0.6*NPL if age is less than 14. All estimates are weighted to make them representative of the corresponding population.

families confirms this fact. The lower panel of Figure 2.3 provides evidence on spatial disparity. Multidimensional child deprivation is a rural problem with a share of 96 percent, the remaining being of urban children. In fact, this share slightly drops to 92 percent when a monetary child poverty enters. The three most populous regions of the country, Oromia, Amhara and SNNP, jointly contribute almost 90 percent, with 40 percent and 25 percent coming from Oromia and Amhara. As expected children in Addis Ababa have the smallest share. Adding an indicator of a monetary intrahousehold resource allocation does not seem to bring a difference in this regard.

Figure 2.4 depicts the contribution of indicators (left panel) and dimensions (right panel) to the overall (adjusted) multidimensional child deprivation index in the three cases. When a monetary dimension is not included, the main sources of deprivation seem to be household living standards deprivations contributing almost 70 percent to the aggregate index. This is constituted to a large extent by deprivations in

Figure 2.4.: Contribution to multidimensional child deprivation of indicators and dimensions



Notes: The monetary dimension's indicator is omitted from the left panel for scale reasons and, more importantly, to show the effect of its inclusion on other indicators. The adjusted monetary child poverty modifies the national poverty line (NPL) for children as 0.6*NPL if age is less than 14. All estimates are weighted to make them representative of the corresponding population.

sanitation, electricity, cooking fuel and housing (floor). Child level deprivations in receiving formal education and nutritious food also hold important shares.

When the multidimensional deprivation index accommodates a monetary child poverty dimension, the share of the above non-monetary dimensions significantly shrinks. Monetary poverty, when included, contributes about half of the multiple deprivations faced by children irrespective of the poverty line being adjusted. This is followed by a 40 percent share by household living standards and about 5 percent by each of child education and health dimensions. The finding of such higher contributions to multiple child deprivation is consistent with previous evidence in Ethiopia (Plavgo et al., 2013).

2.4.3. Overlaps between Children's Monetary Poverty, Undernutrition and Multidimensional Deprivation

Use of child anthropometric information is one of the ways to gauge child welfare. However, the overlap between monetary poverty and undernutrition is still among the unsettled research agenda (Brown et al., 2017, 2018). Are undernourished children also monetarily-poor? Are all monetarily non-poor children also not undernourished? Yet, another important issue is the link between being multidimensionally-deprived and being monetarily-poor. What portion of children identified monetarily-poor is also multidimensionally-deprived? This section adds to this line of empirical evidence for under-7-years-old children.[3] For that purpose, we use simple overlap tabulations, expenditure quintile-based disaggregations, concentration curves and regressions.

Overall, among children whose nutritional information is available, a fifth to a quarter are found to be disadvantaged simultaneously in all those three measures of child well-being: monetarily poor (themselves or their households), undernourished and deprived multidimensionally (see Table 2.7).

Undernutrition - monetary poverty overlap

Let us first see the monetary poverty-undernutrition nexus among under-7 children. Columns 1 and 2 of Table 2.7 summarize the overlap between children's status in terms of monetary poverty and stunting. Two child expenditure- and one household expenditure-based monetary poverty measures are used. Estimates show that depending on the type of monetary poverty measure used, in only about 20 to 30 percent of the cases an under-7 stunted child is also poor monetarily. The match in poverty status (poor/deprived in both or non-poor/non-deprived in both) is less than 50 percent. More importantly, children are stunted although they non-poor monetarily (3 percent, rising to 10 percent when using child-adjusted poverty line) and in 9 percent of non-poor households there are stunted children. On the flip side, unlike the expectation, about 60 percent of expenditure-poor under-7 children are not found to be nutrition-deprived. And in 46 percent of expenditure-poor households, a child is not nutrition-deprived.

We further disentangle this issue using relative monetary poverty measures (expenditure quintiles) and disaggregating by population sub-groups (see columns 1 through 5 of Table 2.8). For the whole sample, about two-thirds of stunted children are not found in the poorest 20% or 40% of children/households. The findings contrast with

[3] As we cannot expect all under-7 children to be in school in Ethiopia, the education dimension in the multidimensional deprivation indicator is proxied by if the child's mother is illiterate.

Table 2.7.: Overlap between children's monetary poverty, undernutrition and multidimensional deprivation

		Child stunting		Multidimensional child deprivation	
		Deprived (1)	Not deprived (2)	Deprived (3)	Not deprived (4)
Monetary child poverty	Poor	0.29 (0.011)	0.59 (0.011)	0.70 (0.010)	0.17 (0.009)
	Non-poor	0.03 (0.004)	0.09 (0.006)	0.08 (0.006)	0.05 (0.004)
	Match in status*	0.38		0.75	
	Poor in the three	**0.27** (0.010)			
Adj. monetary child poverty	Poor	0.21 (0.009)	0.44 (0.011)	0.54 (0.012)	0.12 (0.007)
	Non-poor	0.10 (0.007)	0.24 (0.010)	0.24 (0.010)	0.11 (0.007)
	Match in status*	0.45		0.65	
	Poor in the three	**0.20** (0.009)			
Monetary household poverty	Poor	0.23 (0.010)	0.46 (0.012)	0.58 (0.012)	0.10 (0.007)
	Non-poor	0.09 (0.006)	0.23 (0.010)	0.19 (0.009)	0.12 (0.007)
	Match in status*	0.46		0.70	
	Poor in the three	**0.22** (0.010)			

Notes: Multidimensional deprivation status here is based on non-monetary dimensions and a cut-off $k = 0.33$. *Match in status implies the proportion of children with similar status in two measures (poor & deprived or non-poor/non-deprived). The adjusted monetary child poverty modifies the national poverty line (NPL) as 0.6*NPL since all children here are under-7s. All estimates are weighted to make them representative of the corresponding population. Standard errors in parentheses.

a very recent finding for Africa by Brown et al. (2017) who do not find three-quarters and half of undernourished children in the poorest 20% and 40% of households respectively. While boys and girls do not differ, rural children are found to be more undernourished than their urban counterparts; nonetheless, only few rural-urban child stunting disparities over the income distributions are statistically significant. One can also notice that there is only a slight difference in the prevalence of stunting at the bottom (poorest) 20% and the top (richest) 20% although the concentration seems more to be seen at the bottom.

The concentration information is visually observed from the concentration curves of child stunting in Figure 2.5 which plot the cumulative share of stunted children against expenditure percentiles (of children on the left and of the household on the right) ranked from the poorest up. The greater the degree of concavity, or the further away the concentration curve from the 45-degree line, the more stunted children tend to concentrate in the poorer strata of child/household expenditure. The concentration curves do not seem to provide much information on the at this level. But, comparing the left and right curves for stunting, we notice that the

Table 2.8.: Overlap between children's monetary poverty, undernutrition and multidimensional deprivation over expenditure quintiles and by their gender and residence type

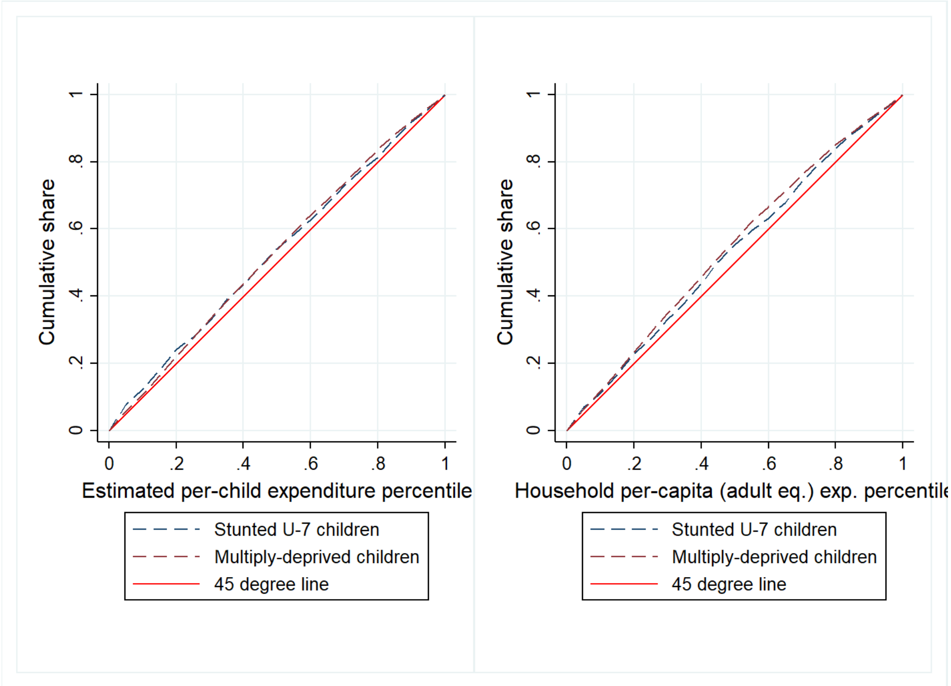
	Child is stunted					Child is multidimensionally-deprived				
	All	Girls	Boys	Rural	Urban	All	Girls	Boys	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quintiles based on estimated per-child expenditure										
Poorest	0.36	0.34	0.37	0.37**	0.19	0.86	0.91**	0.83	0.91***	0.40
Poor	0.33	0.30	0.36	0.34	0.26	0.83	0.84	0.82	0.86***	0.49
Middle	0.30	0.32	0.28	0.30	0.28	0.78	0.79	0.77	0.83***	0.37
Rich	0.31	0.33	0.30	0.33**	0.20	0.76	0.73	0.79	0.83***	0.35
Richest	0.27	0.27	0.27	0.29*	0.21	0.62	0.59*	0.67	0.78***	0.21
Quintiles based on household expenditure (adult-equivalent)										
Poorest	0.36	0.32	0.40	0.37	0.26	0.91	0.91	0.87	0.92***	0.59
Poor	0.32	0.31	0.33	0.33	0.25	0.87	0.87	0.88	0.88**	0.70
Middle	0.35	0.37	0.33	0.36*	0.23	0.86	0.86	0.86	0.89***	0.48
Rich	0.30	0.31	0.30	0.32**	0.20	0.70	0.67	0.71	0.79***	0.24
Richest	0.26	0.25	0.26	0.27	0.22	0.60	0.57	0.62	0.76***	0.24
Overall	**0.32**	**0.31**	**0.32**	**0.33*****	**0.22**	**0.78**	**0.77**	**0.79**	**0.85*****	**0.33**

Notes: *, ** and *** imply mean difference (boy-girl and rural-urban) is statistically significant at 10%, 5% and 1% levels respectively. Multidimensional deprivation status here is based on non-monetary dimensions and a cut-off $k = 0.33$. All estimates are weighted to make them representative of the corresponding population. All estimates are weighted to make them representative of the corresponding population.

concentration of under-7 children at the lower income levels is visible only when child-level expenditures are used. As also shown in Figure A.3 of the Appendix, the concentration of stunting varies with gender, family type and location across the income distributions. For example, more stunted boys than girls concentrate in the lower income tiers.

We finally run two augmented regressions of child stunting, each on child-level and household-level expenditure quintile dummies and other covariates. We control for child-, head-, household- and community-level effects including economic and natural shocks, common health effects and spatial differences which may influence children's nutritional outcomes. Results are summarized in Table A.5 of the Appendix (columns 3 and 4). We find no evidence suggesting that children's nutrition is related to either child- or household-level expenditure. This finding in fact is not uncommon. In particular, we share similar conclusion with Brown et al. (2017) who conclude that it is wrong to design antipoverty policies with the assumption that targeting poor households suffices in reaching poor individuals such as children.

Figure 2.5.: Concentration curves for stunted and multidimensionally-deprived children over child- and household-level expenditures



Note: Multidimensional deprivation status here is based on non-monetary dimensions and a cut-off at $k = 0.33$. All estimates are weighted to make them representative of the corresponding population. All curves consider 95% confidence intervals (not shown).

Our results also lend support to studies which find no impact of Ethiopia's Productive Safety Net Program on children's nutritional outcomes and suggest 'cash plus' programs where the plus may include packages on proving child nutrition information to parents (Berhane et al., 2017). This is also verified by the significance of the variable measuring informational assets where children in households lacking such assets have higher probabilities of being stunted. Moreover, children living with educated heads as well as single-mothers are less stunted.

Multidimensional deprivation - monetary poverty overlap

Let us now shift attention to the monetary poverty-multidimensional deprivation nexus. Columns 3 and 4 of Table 2.7 summarize this overlap (this time multidimensional index does not include a monetary dimension and child education is proxied by mother's education). Generally, there is a 75 percent match in status in which 70 percent of expenditure-poor children are also multidimensionally-deprived, falling to

54 percent with adjusted monetary poverty and 58 percent with household level monetary poverty. Bruck and Kebede (2013) find that 30 percent of households in rural Ethiopia were both consumption-poor and multidimensionally-deprived in 2009. We also find that depending on the type of monetary poverty measure considered, 10 percent to a quarter of monetarily non-poor children are deprived multidimensionally, once again questioning the use of only monetary information to targeting child well-being.

Columns 6 through 10 of Table 2.8 provide further evidence on the monetary poverty-multidimensional deprivation link expenditure quintiles and give disaggregated results by child gender and location. An immediate finding is that the incidence of multidimensional child poverty falls with both child- and household-level expenditure, from 90 percent to 60 percent. However, although only few (10 to 15 percent) of the bottom 20% not found to be multidimensionally-deprived, 40 percent of the top 20% are deprived. Bruck and Kebede (2013) estimate the the bottom level as 40 percent at household level for rural Ethiopia in 2009. Children in rural area tend to significantly have higher multidimensional deprivation probabilities over the income distributions.

Looking at the concave concentration curves for multiply-deprived children ranked by child- and household-level expenditures also supports the above evidence that lower income tiers are homes to child deprivations (see Figure 2.5). Results also hold when we use an augmented regression to control for other factors influencing multidimensional child deprivation (see columns 5 to 8 of Table A.5 in the Appendix). Besides income variables, children living in urban areas, single-mother families as well as in educated household heads are found to be less deprived multidimensionally. We also confirm that girls are less probable to be multidimensionally-deprived than boys but only if a monetary dimension is included. And as expected, multidimensional child deprivation increases with the number of children.

2.5. Conclusions

Child well-being is multidimensional but the overlap between monetary and non-monetary components is far from being obvious. We analyze children's well-being in terms of multidimensional deprivation, monetary poverty and undernutrition. After identifying children as poor using their resource shares, we compute an alternative version of the traditional multidimensional child deprivation index by including a monetary dimension. We also look at the overlaps between the three alternative measures of child well-being: Are all monetarily non-poor children also not undernourished? Do non-poor households host stunted children? What portion of children identified monetarily-poor is also multidimensionally-deprived? The empirical exercise uses the 2013/14 Ethiopian LSMS data.

We find that multidimensional child deprivation is high and varies with children's gender and number as well as family structure and location they live in. The probability of falling into multidimensional deprivation and the average intensity of it almost monotonically increase with the number of children. Deprivation indices for urban children jump in values when a monetary indicator is included. Although multidimensionally-deprived children concentrate more at the lower household/ child income levels, there is also evidence that the monetarily non-poor still host deprived children. For instance, depending on the type of monetary poverty measure considered, 10 percent to a quarter of monetarily non-poor children are deprived multidimensionally. Regression results indicate that, besides confirming the role of income, boys as well as children living in rural areas, single-mother families and large families are highly likely to be multidimensionally-deprived.

We also estimate that about 60 percent of expenditure-poor under-7 children and 46 percent living in expenditure-poor households are not found to be nutrition-deprived. And about two-thirds of stunted children are not found in the poorest 20% or 40% of children/households. After controlling for child-, head-, household- and community-level effects, including shocks and common health effects, we find no evidence suggesting that children's nutrition is related to either child- or household-level expenditure. We also find that children living in households with more informational assets as well as those living with educated heads and single-mothers are less stunted.

Our findings question the use of only monetary information to targeting and formulating welfare policies. It may be incorrect to design antipoverty interventions with the assumption that targeting poor households suffices in reaching poor or deprived children. Non-monetary dimensions of welfare also need to be considered. The stunting of children in non-poor families seems to be an issue of lack of awareness. Children in rural areas require the most intervention. However, the issue of whether existing social protection programs have any impact on children's well-being remains as an important research agenda which we investigate in the upcoming essay.

3. Impacts of Social Protection Programs on Children's Resources and Well-being

3.1. Introduction

Putting in place proper measurement and evaluation techniques is a crucial component of social protection programs. This has both theoretical and global policy backs. Theory-wise, while gauging the full effect of an intervention on child poverty, for example, use of unitary or household level measures may hide the impact since ignoring the inequality in intrahousehold resource allocation leads to considerable understatement of the poverty level (Haddad and Kanbur, 1990; Dunbar et al., 2013; Bargain et al., 2014). Children may be severely affected by such an inequality. As an income source, transfers from social protection programs accrue to different household members with varying preferences thereby making unitary poverty indicators inappropriate. In a global policy front, poverty of children, women and men is emphasized in the Sustainable Development Goals (SDGs) and the importance of measuring poverty at those disaggregated levels is also recommended to the World Bank by the Commission on Global Poverty (CGP) (World Bank, 2017). Moreover, the multidimensionality of well-being is recognized by the Report by the Commission (Stiglitz et al., 2009), UN's Human Development reports, and also echoed very recently by the SDGs and the CGP.

Use of estimated household resource shares from a collective consumption model (Chiappori, 1988, 1992) has been pursued as the latest approach to measuring child poverty and applied to data from sub-Saharan Africa countries (Dunbar et al., 2013; Bargain et al., 2014). However, the impact of social protection programs on children's resource-based bargaining power and poverty within such a collective framework is least researched and far from being obvious. Besides the monetary dimensions of child well-being, understanding the responses to a program in terms of children's non-monetary outcomes such as nutrition, education, health, and family-wide living standards may show comprehensive and long-term impacts. In so doing, one can assess a program's effect on deprivations in needs and capabilities. While one can expect a positive effect of social transfer programs, they may still have no or negative impact by reducing individual's incentive to work (Farrington and Slater, 2006) or crowding out private transfers (Jensen, 2004). Moreover, the effects on children's nutritional and educational deprivations as well as aggregate multidimensional deprivations may be undesirable when a social program has a parental labor requirement.

The Productive Safety Net Program (PSNP) of Ethiopia is Africa's largest social protection scheme outside of South Africa. Designed to tackle chronic food insecurity and asset depletion in rural populations through transfers, it has covered 8 million beneficiaries since its inception in 2005. PSNP has two modalities: public work (PW) transfers for working in labor-intensive community projects, and unconditioned direct support (DS) transfers, in cash or in-kind, primarily to those with limited labor capacity such as the disabled and elderly. There are also other smaller, allied social protection programs like food-for-work, cash-for-work, free food and household asset building on which the survey we use collects data. PSNP and allied programs may benefit children directly (e.g. through food consumption) and/or indirectly through intrahousehold transfers from adults. In contrast, the positive income effect could be outweighed. For instance, the public work requirement of PSNP may force children to work on the family farm and/or domestic chores at the expense of their school/studying time and health. Separate and joint impacts of the programs on various forms of children's well-being and bargaining power is an empirical matter which this study shall investigate.

There is a fairly large body work evaluating the impact of Ethiopia's PSNP. However, this literature limits itself to household level outcomes. For example, significant positive impacts are found on food security and asset holding (Gilligan et al., 2009; Berhane, 2014); credit for productive purposes and engagement in own non-farm businesses (Gilligan et al., 2009); and agricultural technology adoption, productivity and investment (Hoddinott et al., 2012). Hoddinott et al. (2012) also examine the joint impact of the PSNP and Other Food Security Program/Household Asset Building Program transfers on agricultural productivity. Very recently, few papers also document impacts on child-level outcomes such as on child nutrition (Porter and Goyal, 2016; Berhane et al., 2017) and child education (Favara et al., 2016). However, there is no ample evidence on how PSNP and allied transfers affect intrahousehold resource allocation and child well-being.

This study, therefore, primarily aims to fill this lacuna by evaluating the separate and joint impacts of those social protection programs (PSNP's PW, DS and allied assistances) on child resources and shares as well as on monetary poverty, undernutrition and multidimensional deprivation. LSMS-ISA data for the study come from Ethiopia Socioeconomic Survey 2013/14.

Impacts in the form of average treatment effect on the treated (ATET) are identified by the inverse-probability-weighted regression adjustment (IPWRA) which also controls for other correlates of outcomes besides treatment including previous participation. Alternative specifications, disaggregations and traditional propensity score matching (PSM) methods are used for checking robustness. For outcome variables observed in 2013/14 and program participation throughout the past year, we match participant and non-participant households using variables observed in 2011/12. These include demographic, economic and geographic correlates. PSNP participation is reviewed every year with possible graduation from the program by the no-more-eligibles and inclusion of new ones.

We find that PSNP separately and jointly with allied joint transfers reduce relative resource shares of children. These range from 0.7 percent to 3 percent depending on the type of program. In contrast, allied transfers increase resource shares of boys. Impacts on child monetary poverty are generally mixed and directly follow from effects on sharing rules: when a program positively affects child resource shares, it decreases child poverty and vice versa. We find that PSNPs and a joint with allied transfers increase child poverty, allied transfers alone decrease it. In contrast, household-level poverty is generally not affected except a reduction effect by direct supports only after a previous participation is controlled. Public works (only for under-sevens) and allied programs desirably impact child multidimensional deprivation. We also find that under-seven children, specifically boys, living in public works families are more stunted than their counterparts in non-PW families. Other transfers are found to have no impact on child stunting. Results are checked for being robust using PSM estimators.

Our results also lend support to previous evidence that when women receive exogenous transfers, child outcomes improve (Duflo, 2000). For example, we find that PW program significantly reduces children's resources in male-headed families while their monthly resources in levels are higher when the single-mother head is in PW. This also matters to child and household poverty. Estimates, for instance, show that when the head is male, child and household poverty slightly increase with PW transfers. In contrast, when the head receiving the PW transfers is a single-mother, both child and household poverty slightly decrease. Comparing the two family types regarding impacts on child nutritional outcomes, we find that only children in male-headed families in PW are significantly stunted while the impact in single-mother families is, as expected, negative though insignificant in a statistical sense.

The findings that children's poverty, undernutrition and multidimensional deprivations are worse or not better for participants of a social protection program are quite unwelcome. The nonimpact and undesirable impacts of PSNP need attention such as through incorporating awareness on child nutrition and education. Restricting receipts of transfers to females may also help. Although designed at the household level, with the implicit assumption that targeting poor households suffices in reaching poor or deprived children, improving on these considerations is crucial. The remainder of the current (second) essay is organized as follows. The second section discusses the methods while the third section describes the social protection programs, the data and empirical strategy. After presenting the results in the fourth section, we lastly conclude.

3.2. Methods

3.2.1. Outcome Variables of Interest: Children's Resources and Well-being

In order to look into the household black box, we pursue the collective model of Chiappori (1988, 1992) which assumes that household decisions are Pareto-efficient.

This implies that family decisions are made in a decentralized fashion in two stages: (i) Members decide on how to share the total household expenditure so that each member receives a sharing rule; (ii) Given the sharing rule, each member maximizes her own utility subject to her individual budget constraint, finally choosing optimal consumption of assignable and non-assignable goods. A collective Almost Ideal Demand System (CAIDS) is estimated to recover children's shares from household resources following Menon et al. (2017) and Mangiavacchi et al. (2018). The sharing rule is specified as a function of observed individual expenditure and a vector of distribution factors, variables which affect intrahousehold bargaining but not preferences. For a detailed description of the estimation of children's resource shares, see Appendix A.2.

After recovering children's expenditure shares, one can use them to identify whether a child is monetarily-poor. This new approach is superior to the traditional approach of using adult-equivalence scales or per-capita expenditure which do not consider intrahousehold inequality in resource allocation. For comparison, we also consider household poverty as one of the outcomes. Besides monetary indicators of child well-being, we also use the available child anthropometric information to recover the nutritional status of under-seven children. In particular, the standards of the World Health Organization (WHO) are used to identify whether a child is stunted (height-for-age z-score is less than two standard deviations). As child well-being is multidimensional, we lastly incorporate a range of non-monetary dimensions (child education, health, nutrition and living standards) into a child multidimensional deprivation index. Procedures of the counting approach (Alkire and Foster, 2011) are used to identify whether a child is multidimensionally-deprived.

In a nutshell, the study aims to find if PSNP and allied social transfers, separately and jointly, have any impacts on the following outcome variables: child bargaining (proxied by child resource shares and monetary values) and child well-being (monetary poverty, undernutrition and multidimensional deprivation) as well as household monetary poverty. Matching methods coupled with regression discussed below help identify the impacts where available.

3.2.2. Estimation of Impacts Using Matching and Regression Methods

We use matching methods to estimate the various impacts of the programs on our proposed outcome variables. But before resorting to matching, we explored other impact estimator options. In fact, the design of the PSNP makes it difficult to effectively apply other methods. Gilligan et al. (2009); Hoddinott et al. (2012); Porter and Goyal (2016); Favara et al. (2016); Berhane et al. (2017) are some of other studies using matching methods for the similar program. In what follows, we shortly discuss why this study and those researchers evaluating PSNP end up in matching procedures.

The basic problems of any impact evaluation exercise - the counterfactual and selection bias - can generally be addressed by the following methods: randomized evaluation design, regression discontinuity design (RDD), instrumental variables (IV) or matching estimators. However, a randomized design evaluation of the PSNP was impossible, due to Ethiopian government's refusal at the outset (Berhane et al., 2017). RDD was not feasible either since there was no cut-off or threshold applied by local authorities in selecting beneficiaries. The next option is use of IV which needs identifying an instrument affecting the treatment variable directly without affecting the outcome variable unless via the treatment. However, our search for strong instruments was not successful. In view of all these, we are forced to resort to matching methods.

There is ample evidence that matching estimators help reduce selection bias due to systematic differences between treated and comparison units (Dehejia and Wahba, 1999; Smith and Todd, 2005). We use an extended version of matching where regression can be used to control for other correlates of the outcome variable: Inverse-probability-weighted regression adjustment (IPWRA). For checking robustness of the estimates, we also use the traditional propensity score matching (PSM) methods where impacts are estimated in non-parametric procedures.

Let Y_{1i} represents a program's outcome if unit i is in a treatment state and Y_{0i} if in a control state. If the program is random, its effect on unit i is

$$\Delta_i = Y_{1i} - Y_{0i}$$

which is not directly observable because only one of the two counterfactual treatment situations is observed. The average treatment effect is

$$ATE = E[\Delta_i] = E[Y_{1i} - Y_{0i}].$$

The average treatment effect on the treated population (ATET), which is the primary treatment effect of interest in non-experimental settings (Dehejia and Wahba, 1999) such as ours, is given by

$$ATET = E[\Delta_i|T_i = 1] = E[(Y_{1i} - Y_{0i})|T_i = 1] = E[Y_{1i}|T_i = 1] - E[Y_{0i}|T_i = 1]$$

where $T_i = 1$ if unit i is in treatment and $T_i = 0$ if in control. The ATET answers the question "how much did persons participating in the program benefit compared to what they would have experienced without participating in the program?" (Heckman et al., 1997). The challenge is that $E[Y_{0i}|T_i = 1]$ cannot be observed and using $E[Y_{0i}|T_i = 0]$ instead provides a potentially biased estimator of $ATET$, unless the program is random, where the size of the bias is $B = E[Y_{0i}|T_i = 1] - E[Y_{0i}|T_i = 0]$. Randomization, hence, implies

$$(Y_{0i}, Y_{1i}) \perp\!\!\!\perp T_i \Rightarrow E[Y_{0i}|T_i = 1] = E[Y_{0i}|T_i = 0] = E[Y_i|T_i = 0]$$

where $Y_i = T_i \cdot Y_{1i} + (1 - T_i) \cdot Y_{0i}$ is the observed value of the outcome variable so that $B = 0$. In other words, no systematic difference exists between the treated and control groups, making the conditioning on T_i in the expectation unnecessary (Dehejia and Wahba, 1999) so that $ATE = ATET$ with randomization.

Propensity Score Matching (PSM)

In the absence of randomization and experiments, evaluation methods pursuing matching based on observable characteristics may offer a way to estimate average treatment effects. However, these methods require the assumption of "unconfoundedness" or conditional independence introduced by Rosenbaum and Rubin (1983).

In particular, the unconfoundedness assumption states that

$$(Y_{0i}, Y_{1i}) \perp\!\!\!\perp T_i | X_i$$

which says that beyond the observed covariates X_i there are no (unobserved) characteristics of the unit associated both with the potential outcomes and the treatment[1] and implies that $E[Y_i|T_i, X_i] = E[Y_i|X_i]$.

To reduce the dimensionality problem arising from using multiple obervables, Rosenbaum and Rubin (1983) propose use of the propensity score $p(X_i)$ which measures the probability of unit i receiving treatment conditional on obervables. In this case, the unconfoundedness assumption can be equivalently expressed as

$$Pr(D_i = 1|Y_{1i}, Y_{0i}, X_i) = Pr(D_i = 1|X_i) = E(D_i|X_i) \equiv p(X_i)$$

which excludes the dependence between potential outcomes and the probability of selection into treatment. This is a condition at the center of the econometrics of self-selection.

In PSM methods, once the propensity score $p(X_i)$ is estimated and a matching method is decided, it is used to match units who receive the treatment to those who do not (comparison group). The sample counterpart of the $ATET$ is estimated as (Dehejia and Wahba, 1999)

$$\widehat{ATET} = \hat{\Delta}|_{T=1} = \frac{1}{N^T}\sum_{i \epsilon T}\left(Y_i^T - \frac{1}{N^C}\sum_{j \epsilon C_i} Y_j^C\right)$$

where N^T is the number of units in the treatment group and N^C is the number of units in the comparison group (C_i) matched to unit i.

We employ matching methods of kernel-based and radius in the empirical exercise. In kernel-based matching, the control unit outcome matched to a treated observation is obtained as kernel-weighted average of control unit outcomes. In radius matching,

[1]Pure randomization $(Y_{0i}, Y_{1i}) \perp\!\!\!\perp T_i$ is a particularly strong version of unconfoundedness in which treatment assignment is unconfounded independently of pre-treatment variables.

a control matched to a treated observation lies within a certain radius and where multiple best controls are available, the average outcome of those controls is used.

Inverse-probability-weighted regression adjustment (IPWRA)

IPWRA estimator uses the propensity scores as weights to obtain outcome-regression parameters that account for the counterfactual problem. These adjusted outcome-regression parameters are then used to compute averages of treatment-level predicted outcomes. The contrasts of these averages provide estimates of the treatment effects.

Technically, once the treatment model is run and the propensity scores $p(X_i)$ are predicted, IPWRA runs two more basic steps. It first runs two outcome variable models, one for each of the treatment ($T = 1$) and comparison ($T = 0$) groups. Suppose $\boldsymbol{Z}$ is a vector of covariates of the potential outcome variable Y, then

$$Y_{1i} = \frac{1}{p(X_i)}[\alpha_1 + \boldsymbol{Z}'\boldsymbol{\beta_1} + \varepsilon_{1i}]$$

$$Y_{0i} = \frac{1}{p(X_i)}[\alpha_0 + \boldsymbol{Z}'\boldsymbol{\beta_0} + \varepsilon_{0i}]$$

where $\alpha's$ and $\boldsymbol{\beta}'s$ are parameters and $\varepsilon's$ are error terms. Note that the regressions are weighted by the inverse-propensity scores $\frac{1}{p(X_i)}$. These then help estimate treatment-specific predicted outcomes for each unit.

IPWRA finally computes and compares the means of the treatment-specific predicted outcomes where restricting average calculations to the treated units estimates the ATET. The estimates are consistent as long as the treatment is independent of the potential outcomes after conditioning on the covariates X. Further, the assumption of the common support (overlap) ensures that predicted inverse-probability weights $\frac{1}{p(X_i)}$ are not too large. In fact, the two assumptions must also hold for PSM.

However, if the treatment model is miss-specified, PSM will provide inconsistent estimates. This is highly unlikely with IPWRA estimators since they have the double-robust property. Combining regression and weighting, IPWRA removes the correlation between the omitted covariates and reduce the correlation between the omitted and included variables (Imbens and Wooldridge, 2008). Put differently, if the treatment model is miss-specified, estimates of the treatment effect will still be consistent so long as the outcome model is not also miss-specified and the reverse is also true (Berhane et al., 2017).

Besides guaranteeing double-robustness, IPWRA also improves on PSM in terms of efficiency. Berhane et al. (2017) discuss these gains in detail. By fully-specifying an outcome outcome, IPWRA provides more efficiency by including control variables and this precision gain is similar to the one we get by including additional covariates in the evaluation of a randomized control trial. Ensuring balance across the baseline covariates that appear in the treatment model used to estimate the propensity scores is not required. IPWRA further increases statistical precision as it includes more observations in the model that compares a treatment unit to its hypothetical counterfactual.

3.3. The Productive Safety Net Program and the Data

Ethiopia's Productive Safety Net Program (PSNP) and Allied Programs

The Productive Safety Net Program (PSNP) of Ethiopia is Africa's largest social protection scheme outside of South Africa. Designed to provide transfers to chronically food insecure and asset-poor rural populations, it has covered about 8 million beneficiaries since its inception in 2005. It reaches to beneficiaries in two modalities. The first and the largest is the public works (PW) program in which beneficiaries, who should be adult able-bodied people, receive payments after participating in labor-intensive community projects. Major PW sub-projects include soil and water conservation, water harvesting and supply schemes, afforestation, infrastructure development and construction of social services. The second, which primarily covers those with limited labor capacity such as the disabled and elderly, is the unconditioned direct support (DS). Transfers could be made either in cash or in kind, usually grain. PW and DS participants receive the same rate of transfer. Households leave the programs through graduation when they are able to accumulate assets. There are also other smaller, allied social protection programs (hereafter allied programs) like food-for-work, cash-for-work, free food and household asset building on which the survey we use collects data.

There are no scientifically-designed eligibility criteria for joining the PSNP and the majority of the allied programs. It rather uses administrative and community level targeting approaches. The administrative targeting determines the number of PNSP beneficiaries in a specific location (woreda and kebele). The community-based approach involves identification of potential beneficiaries by the community Food Security Task Force (FSTF) and verification of the beneficiaries in a public meeting in which the entire PSNP beneficiary list is read out and discussed. FSTF is made up of government officials, local elders and representatives of local associations (such as of youth and women).

Usually, the kebele FSTF makes some assessment of the asset holdings of each household and ranks them. It then takes the list to the community gatherings to match with the 'quota' allocated by the woreda to the kebele (Tafere and Woldehanna, 2012). Eligibility cut-offs vary. Tafere and Woldehanna (2012), for example, document the following: "In Tach-Meret and Zeytuni, having two oxen automatically excluded households, whereas in Leki, in addition to possession of an ox, the size of irrigable land was taken into account and in Buna the number of coffee seedlings and sometimes enset (false banana) were considered. In Buna, as people cultivate the land by hand using a hoe, having oxen is less important, and in Leki having irrigable land was significant as it could be rented out for good amount of money."

PSNP and allied programs may benefit children directly (e.g. through food consumption) and/or indirectly through intrahousehold transfers from adults. In contrast, the positive income effect could be outweighed. For instance, the public work requirement of PSNP may force children to work on the family farm and/or domestic chores at the expense of their school/studying time and health.

The Data: Ethiopia Socioeconomic Survey (ESS)

Data for the study come from Ethiopia Socioeconomic Survey (ESS), collected jointly by the World Bank and the Central Statistical Agency of Ethiopia (CSA) as part of the LSMS-ISA project. ESS is a panel survey with three waves to date (2011/12, 2013/14 and 2015/16). However, the 2011/12 wave lacks certain expenditure data including on education, health, housing and food away from home. Lack of price data for some goods also forced us to exclude the 2015/16 wave. Hence, this study primarily employs the 2013/14 wave. ESS contains individual, household and community level data on a range of modules. Data on missing prices are obtained from CSA's retail price surveys which are first aggregated as 2013/14 averages to a *zone* (province) level and then matched with the ESS.

To estimate children's (and adults') resource shares, we aggregate expenditure items into four commodity groups: food and alcohol, clothing, household utilities and energy, and other goods. These estimates are used to define the monetary dimension of child well-being. Non-monetary dimensions of well-being are obtained from the health, education, food security, housing and assets modules of ESS. Data on the public work (PW) component of PSNP come from the time-use section of ESS while its direct support (DW) component and other allied transfers are available in the survey's assistance section. In order to match program participants with the non-participants at baseline, we also import data from the 2011/12 round of ESS.

Empirical Strategy

To implement IPWRA (and PSM), we define treatment as participation in PSNP public work, PSNP direct support, allied programs and joint PSNP-allied programs. The program participation model is specified as a function of observed variables from 2011/12. The 2013/14 survey asks if a household had its member participating in PSNP over the last year. Given that PSNP activities and payments are usually active from February, this question should collect information from 2012/13. We thus consider household characteristics from the previous wave of the survey (2011/12) as baseline information and use them to match program participants and non-participants thereby ultimately estimating impacts in 2013/14.[2] The following

[2]Berhane et al. (2017) also use a previous-year household livestock holdings as one correlate of participation in PSNP's public work while estimating its impact on child nutrition.

variables are used to specify treatment models in the various programs: gender and age of the household head, number of adults of ages 18 to 60, land size, total livestock unit, receiving any income from nonfarm activities, and regional dummies. The treatment models, which ultimately predict the propensity scores of program participation, are estimated using a probit.

Besides the treatment model, IPWRA also needs to specify an outcome model. For the four well-being-related outcome variables (child monetary poverty, undernutrition, multidimensional deprivation and household monetary poverty), we employ common covariates. These socio-demographic current-year (2013/14) outcome controls are: gender and age of the child, age and education status of the household head, if head is a single-mother, number of adults of ages 18 to 60, number of children under 18, distances from main road and health facility, access to safe drinking water, if the community faced any epidemic disease recently and regional dummies. In a separate specification, we also control if the household participated in a program during the previous survey year (2011/12). And for resource allocation outcome variables, namely, child resource shares and monetary resources, distribution factors affecting the resource sharing between children and adults are controlled besides the above common socio-demographic covariates. Distribution factors include whether all school-age children are attending school, proportions of female children and women, and number of extended or non-biological children. The outcome models for continuous variables (child resource shares and values) are considered as linear whereas binary outcome models are estimated using a probit.

3.4. Results and Discussion

3.4.1. Descriptive Statistics

Table 3.1 summarizes the descriptive statistics of some variables during the year of interest (2013/14) and other variables from 2011/12 that are used for matching. Our sample of children is a gender-balanced one with the average age of the child being about 9 years. 3 percent of children live in households with a child mortality record since two years while 14 percent of them experienced some form of illness over the two months before surveyed. All school-age children are not in school: 7 percent

Table 3.1.: Descriptive statistics of some variables: ESS 2013/14 and 2011/12

Variable	2013/14 wave (N=7,928)		2011/12 wave (N=7,381)	
	Mean	Std. dev.	Mean	Std. dev.
Child is a girl	0.49	0.500		
Age of child	8.78	4.556		
Any child mortality in HH in 2 years	0.03	0.179		
Child ill in past 2 months	0.14	0.346		
School-age child not attending school	0.07	0.257		
School-age child has no formal education	0.16	0.363		
Child's mother is illiterate	0.76	0.426		
HH has no access to clean drinking water	0.38	0.486		
HH has poor sanitation	0.97	0.172		
HH has no electrcity	0.85	0.354		
HH has poor cooking facility	1.00	0.063		
HH has poor housing floor	0.96	0.200		
HH has no informational assets	0.47	0.499		
Distance to major road	33.26	39.367		
Distance to health>5km	0.71	0.455		
Community faced epidemic disease	0.05	0.224		
Head is female			0.10	0.304
Head's age			42.75	11.996
Number of adults aged 18-60y			2.21	0.859
Number of children (<18y)			3.98	1.849
Land size (hectare)			0.98	1.086
TLU (total livestock unit)			2.71	2.527
Agricultural wealth index			0.26	0.441
Received income from nonfarm enterprise			0.01	0.896
Faced shock: drought or flood			0.25	0.436
Living in Amhara region			0.24	0.427
Living in Oromia region			0.42	0.493
Living in SNNP region			0.23	0.419
Living in Tigray region			0.06	0.234
Living in other regions			0.06	0.238

Note: HH = Household. SNNP = Southern Nations, Nationalities and Peoples. Estimates are weighted to represent the population. The 2011/12 data are used only for matching purposes.

Table 3.2.: PSNP and allied programs participation and amount received: ESS 2013/14 & 2011/12

	Public Work		Direct Support		Allied programs	
	2013/14	2011/12	2013/14	2011/12	2013/14	2011/12
Household participates in a program	0.07	0.10	0.02	0.02	0.08	0.11
	(0.263)	(0.302)	(0.141)	(0.146)	(0.265)	(0.307)
Mean income from a program among participants (birr)	137.22	127.24	1718.76	1649.86	1451.93	1041.77
	(115.543)	(93.570)	(2022.286)	(4773.961)	(1978.955)	(2391.023)

Note: Standard deviations in parentheses. Estimates are weighted to represent the population.

are not currently attending and 16 percent have no formal years of education. This adds to the fact that 76 percent of children have an illiterate biological mother. A considerable portion of children also live in poor housing conditions. This ranges from 38 percent of them having no access to clean drinking water to 100 percent living in households that use unimproved cooking materials such as wood and dung. Only about half have access to information-providing assets such as radio.

The last two columns of Table 3.1 also describe the sample's characteristics in 2011/12 which we use to specify program participation to ultimately estimate the propensity scores for matching participants with non-participants in 2013/14. For instance, back in 2011/12, only 10 percent was headed by a female. Less number of adults who can work than children was reported. Land size was less than a hectare and about a fifth faced natural shocks of either drought or flood.

How are the extents of coverage of PSNP and allied programs and how much do participants receive? Table 3.2 provides the summaries. The public work (PW) component of the PSNP covers 7 percent of the sample of children whose family member participated in 2013/14. In the previous wave of the survey (2011/12), this was higher at 10 percent. On the other hand, only 2 percent of children have a household member covered in PSNP's direct support and this figure remained unchanged since the previous wave. 8 percent have their families reporting to have received any other non-PSNP, allied assistance (in terms of cash-for-work, inputs-for-work, etc.). Regarding the amount of money received from each of those programs, one can easily observe that PSNP's public works program provides relatively lesser amounts and the receipts in all programs increase over the years of the survey.

Table 3.3 describes outcome variables by various programs as well as for the full sample of children and under-seven-olds. In general, we observe slight differences among

Table 3.3.: Mean of outcome variables by child sample program participation: ESS 2013/14

Outcome variable	Public Work sample	Direct Support sample	Allied sample	Full sample
All children sample:	(N=918)	(N=297)	(N=774)	(N=7928)
Child's share in HH resources	0.14 (0.064)	0.19 (0.110)	0.16 (0.083)	0.15 (0.072)
Log of child's HH resources	5.46 (0.799)	5.41 (0.637)	5.46 (0.774)	5.43 (0.742)
Child is monetarily-poor	0.91 (0.289)	0.94 (0.238)	0.86 (0.351)	0.89 (0.314)
HH is monetarily-poor	0.79 (0.408)	0.69 (0.463)	0.79 (0.411)	0.76 (0.426)
Child is multidimensionally-deprived	0.51 (0.510)	0.65 (0.477)	0.53 (0.499)	0.51 (0.500)
Under-seven children sample:	(N=336)	(N=100)	(N=300)	(N=2901)
Child is multidimensionally-deprived	0.82 (0.338)	0.91 (0.294)	0.90 (0.256)	0.83 (0.375)
Child is stunted	0.44 (0.498)	0.40 (0.492)	0.31 (0.462)	0.33 (0.469)

Note: Standard deviations in parentheses. Estimates are weighted to represent the population.

children in the three programs in terms of monetary and non-monetary outcomes. For instance, a child of a family participating in public works program commands 14 percent of the family's expenditure whereas a child in direct support program has a higher share at 19 percent. These compare with the 15 percent share for the whole sample of children. Consequently, poverty among children as well as household poverty with DS is slightly lower than those with PW. Multidimensional deprivation and child stunting rates are also slightly lower among under-seven children in DS than in PW although multidimensional deprivation rate goes in the opposite direction for all children. The question that we ask at this point is the following: does participation in these programs have any impact on children's resources and welfare? The next sub-sections provide answers.

3.4.2. Correlates of Participation in PSNP and Allied Programs

Recall that participations in PSNP and allied programs in 2012/13 are specified as functions of observed variables from the previous wave of the survey (2011/12) to ultimately measure impacts on outcomes in 2013/14. Previous survey round variables used as covariates of treatment include characteristics of the head, household labor, economic status, and regional dummies.

Table 3.4 summarizes probit regression results (marginal effects) of participation

Table 3.4.: Correlates of participation in PSNP and allied programs (marginal effects from probit): ESS 2013/14

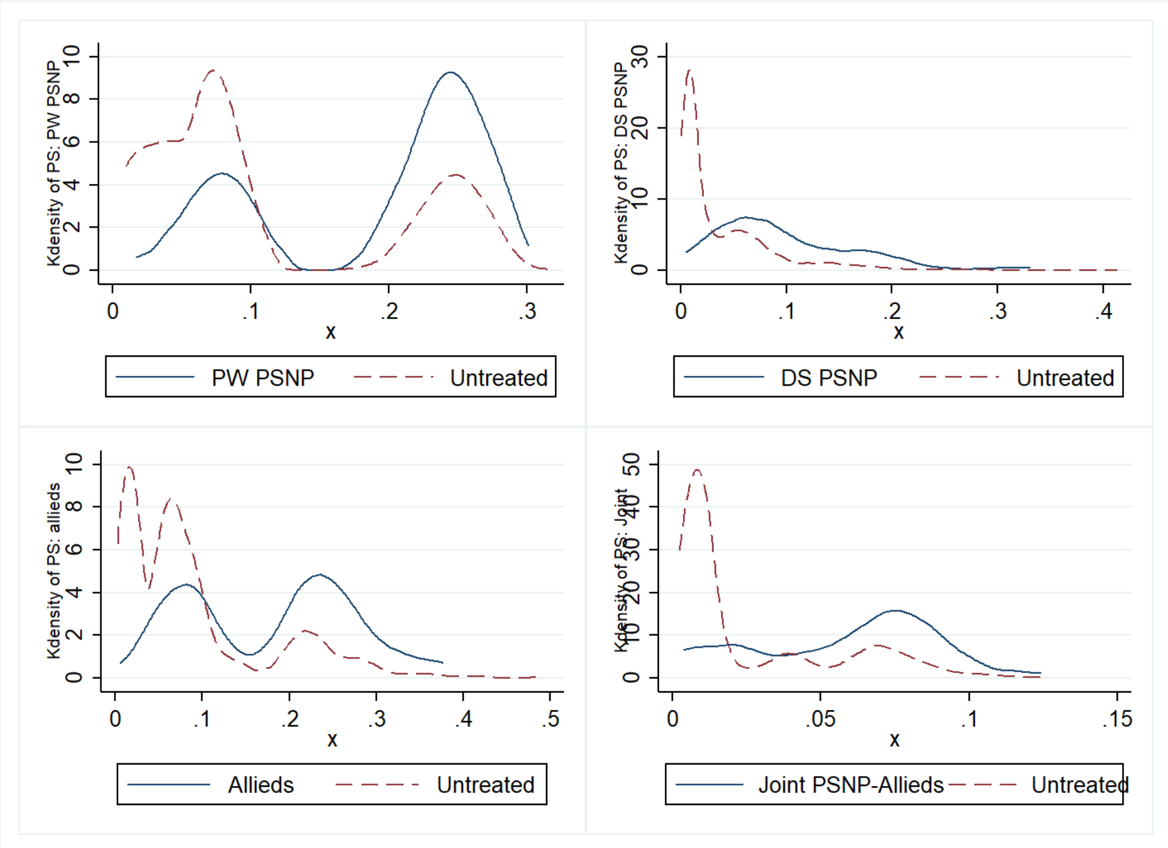
Variable	PSNP Public work (1)	PSNP Direct support (2)	Allied programs (3)	Joint PSNP-Allied (4)
Head is female	0.031** (0.014)	0.018*** (0.005)	0.008 (0.012)	-0.003 (0.006)
Head's age	-0.0008*** (0.0003)	0.0005*** (0.0001)	-0.001** (0.0003)	-0.0001 (0.0001)
Number of adults aged 18-60y	-0.0005 (0.004)	-0.004** (0.002)	-0.017*** (0.005)	-0.006*** (0.002)
Land size (ha)	-0.005 (0.004)	-0.012*** (0.003)	0.019*** (0.004)	0.003* (0.002)
Livestock holdings (TLU)	-0.009*** (0.002)	-0.0003 (0.001)	-0.001 (0.002)	-0.001** (0.001)
Received income from nonfarm enterprise	-0.033*** (0.010)	-0.006 (0.005)	-0.019** (0.009)	-0.005 (0.004)
Living in Amhara region	-0.096*** (0.011)	-0.015*** (0.005)	-0.118*** (0.010)	-0.037*** (0.005)
Living in Oromia region	-0.141*** (0.011)	-0.032*** (0.006)	-0.115*** (0.008)	-0.042*** (0.005)
Living in SNNP region	-0.058*** (0.010)	-0.017*** (0.005)	-0.229*** (0.014)	-0.049*** (0.006)
Living in Tigray region	0.022*** (0.010)	0.018*** (0.005)	-0.092*** (0.012)	-0.022*** (0.005)
N	7381	7372	7381	7381
Wald Ch2	581.45	404.39	627.96	310.62
Psuedo-R2	0.14	0.21	0.18	0.15

Notes: *, ** and *** imply statistical significance at 10%, 5% and 1% levels respectively. All explanatory variables are from 2011/12. Standard errors in parentheses. PSNP=Productive Safety Net Program. TLU=Total livestock unit. SNNP=Southern Nations, Nationalities and Peoples.

in the three programs (public work, direct support and allied programs) as well as the joint of PSNP (either PW or DS) with allied programs. In general, every variable is statistically significant in at least two of the four regressions. In particular, female-headed households are found to have higher chance of participation in both of PSNP's PW and DS programs. As expected, head's age is correlated negatively with participation in PW and allied programs but positively with that of DS. As a corollary to this, households with more labor force (proxied here by the number of adults aged 18 to 60 years) are found to have less probability of receiving DS. Recall that DS is designed primarily for those with limited labor such as the elderly and disabled. Labor-rich households are also less likely to be part of allied programs as well as a joint of these with PSNP's PW or DS.

Besides those demographic factors, almost all economic variables have also the expected correlations with participation in PSNP and allied programs. For example, those with large land holdings are less likely to engage in just PSNP programs unless they are in joint with allied programs of input-for-work or cash-for-work. Expectedly as well, higher livestock holdings and income from non-farm activities have the effects of consistently reducing participation in all programs. Berhane et al. (2017) document similar results when they find PW participation likelihoods fall for land- and livestock-wealthier households.

Figure 3.1.: Kernel densities of the propensity scores for common support: ESS 2013/14



From the highly-significant regional dummies, we lastly notice presence of large spatial variations in participation likelihood. Compared with other small regions altogether, households in the regions of Amhara, Oromia and SNNP are generally less likely to involve in the social protection programs. An exception is Tigray where higher participation in both PSNP programs is observed.

Before directly proceeding to presenting the impact estimates, let us see how close are the non-participants that are matched with participants. This is a requirement in impact estimation methods based on (inverse) propensity scores and can be checked by existence of a common support which implies that the probability of being a participant (non-participant) is both non-zero and less than 1. Figure 3.1 depicts kernel densities of the propensity scores for both groups and show that their distributions overlap in all programs thereby confirming presence of a common support.

We also use formal balancing tests to check how similar are the correlates of program participation between treated and control groups. We follow the standardized bias approach of Rosenbaum and Rubin (1983) to check the power of the matching approach in balancing the relevant covariates of these two groups. The results for public works program are presented in Table A.7 of the Appendix. The overall average bias before matching was 18% significantly falling to 4.4% after matching implying improvement in the balancing characteristics of the treatment and the matched comparison groups. Moreover, none of the mean differences of each covariate between the treatment group and the matched comparison group is statistically significant.

3.4.3. Impacts of PSNP and Allied Programs on Children's Resources and Well-being

Once a probit treatment model is estimated and propensity scores are predicted, participant and non-participants are matched. We primarily choose the inverse-probability-weighted regression adjustment (IPWRA) since its parametric feature helps to control for other covariates of the outcome variable including previous program participation. Results from two non-parametric PSM-based methods (kernel and radius matching) are also reported in the Appendix. In addition to previous program involvement, our IPWRA outcome regression models control for various socio-demographic and economic variables which include characteristics of children, the household head, the household and community at large.

Below, we present and discuss the effects of PSNP's public work (PW), direct support (DS) and other allied social protection transfers on children's relative resource shares, absolute resource receipts and their well-being in terms of monetary poverty, undernutrition and multidimensional deprivation. We also present the effects of simultaneous participation in PSNPs and allied transfers. The various outcome variables are analyzed in three categories: resource allocation, monetary poverty and non-monetary deprivation.

3.4.3.1. Impacts of PSNP's Public Work

Table 3.5 summarizes IPWRA impact estimates of PSNP's public work (PW) on children's relative resource and well-being. We find that PW participation reduces

Table 3.5.: Impacts of PSNP's public work on children's resources and well-being: IPWRA method

Outcome variable	Full sample	Boys	Girls	Male-headed	Single-mother	2012 PW participation controlled		
						Full sample	Boys	Girls
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Child's share in household resources	-0.007***	-0.007**	-0.006	-0.006**	-0.007	-0.007***	-0.009***	-0.003
	(0.003)	(0.003)	(0.004)	(0.003)	(0.007)	(0.002)	(0.003)	(0.004)
Log of child's household resources	0.050	-0.012	0.133**	-0.034	0.389**	-0.003	-0.005	0.063
	(0.039)	(0.048)	(0.063)	(0.040)	(0.152)	(0.044)	(0.054)	(0.071)
Child is monetarily-poor	0.025*	0.017	0.029	0.034**	-0.033	0.027	0.016	0.038
	(0.014)	(0.014)	(0.027)	(0.011)	(0.084)	(0.018)	(0.019)	(0.032)
Household is monetarily-poor	0.014	0.038	-0.020	0.069***	-0.215**	0.049*	0.052	0.042
	(0.020)	(0.024)	(0.034)	(0.018)	(0.097)	(0.027)	(0.032)	(0.044)
Child is multidimensionally-deprived	0.033	0.059*	0.004	0.038	0.024	0.017	0.058	-0.030
	(0.025)	(0.035)	(0.035)	(0.027)	(0.062)	(0.032)	(0.046)	(0.045)
Child engaged in non-domestic work	0.073***	0.067**	0.083**	0.067**	0.131**	0.016	0.033	0.008
	(0.021)	(0.029)	(0.032)	(0.022)	(0.050)	(0.028)	(0.039)	(0.040)
A school-age child not enrolled	0.005	0.019	-0.014	0.006	-0.020	-0.003	0.014	-0.029
	(0.012)	(0.017)	(0.015)	(0.012)	(0.045)	(0.015)	(0.023)	(0.020)
U-7 child is multidimensionally-deprived	-0.064*	-0.015	-0.119**	-0.043	-0.133	-0.100***	-0.053	-0.152***
	(0.034)	(0.042)	(0.052)	(0.038)	(0.163)	(0.037)	(0.047)	(0.052)
U-7 child is stunted	0.092*	0.131*	0.063	0.115**	-0.066	0.133**	0.187**	0.093
	(0.048)	(0.072)	(0.063)	(0.050)	(0.166)	(0.061)	(0.091)	(0.081)

Notes: *, ** and *** imply statistical significance at 10%, 5% and 1% levels respectively. Standard errors in parentheses.U-7=Under-7-year-old. PW=Public work. IPWRA=Inverse-probability-weighted regression adjustment. Estimates are weighted to represent the population.

the child's average share of household resources and the effect remains unchanged after controlling for a previous participation. However, the magnitude of the impact is very small. Specifically, a household's engagement in PW has the effect of decreasing children's share of total household expenditure by 0.7 percent. The overall negative impact of public work transfers on children's relative resource allocations is also robust to alternative matching methods although of larger magnitude. Non-parametric PSM estimators (kernel and radius matching) provide a significant and negative impact of 1.4 percent (see panel (a) of Table A.8 at the Appendix).

Disaggregating the IPWRA estimates by children's gender indicates that all the significant impact is related to boys; resource shares of girls do not seem to be adversely affected by their family's participation in PW. On the other hand, PW transfers have no significant effect on children's resources in levels in general but raise girls' monthly resources only slightly by 1.14 Ethiopian Birr (ETB).

Although it is difficult to provide a direct explanation to the negative effect of PW transfers on children's relative home resource allocations, the program's labor requirement may give some hint. ESS data show that participation in PW by male adults of ages 18 to 65 is as almost twice as that of female adults which may pave ways for consumption of adult goods like alcohol and food away from home by men at the expense of (or no change to) children's goods. Children may even drop from school since engagement of adults in PW may force them to work on household chores or the farm thereby reducing their monetary shares. We attempt to see if the public works force children to engage in any non-domestic work, including substituting their parents in the PW project works, and find that it does. The result on the education issue is not the expected one. Same results are confirmed by PSM techniques (reported in Table A.8 of the Appendix).

Yet another explanation could be found from the type of family structure: male-headed or single mother. This partly captures who in the household gets the PW transfers. We find that PW program significantly reduces children's resources in male-headed families (see column (4) of Table 3.5). In contrast, the average child's monthly resources in levels are higher by 1.48 ETB when the single-mother head is in PW. This adds to the evidence elsewhere in Africa that when women receive exogenous transfers, child outcomes improve (Duflo, 2000). Mangiavacchi et al. (2018) analyze the effect of remittances by a migrating household adult member on children's resource shares and find a positive impact in Albania. This is partly because migration of an adult frees resources to children and the majority of remitting members are males which may allow children to enjoy maternal altruism.

The impact of PW program participation on the incidence of children's monetary poverty and its explanations descend from PW's impact on children's resource allocations despite the fact that the poverty line also matters. After using a child's estimated resource shares and age-adjusted poverty line to judge a child monetarily-poor, we find that PW slightly increases poverty incidence. In particular, compared with those in non-participant families, children in PW families are 2.5 percent poorer although the figure is only marginally significant. However, the effect disappears when disaggregated by gender and the outcome regression controls for recent past PW program participation. Motivated to loosely evaluate if PW has differential effects on the poverty of children and of the household in general, we find that there is no such an impact unless a 2011/12 participation is controlled for where PW households are poorer by 5 percent, again marginally, relative to non-participants. Gilligan et al. (2009) also find no significant effect of PW on per capita consumption expenditure as well as household assets.

Another interesting finding is that it matters to child and household poverty who receives the transfer as proxied by the type of family structure. Estimates show that when the head is male, child and household poverty slightly but significantly increase with PW transfers. In contrast, when the head receiving the PW transfers is a single-mother, both child and household poverty slightly decrease though the fall in child poverty is not statistically significant.

Besides the monetary dimension, we also look at how public works program affects the non-monetary dimensions of child well-being. We aggregate into a weighted multidimensional deprivation incidence measure of over 10 indicators of three dimensions (child schooling, health and living standards). IPWRA estimates generally show that there is no impact except a marginally-significant deprivation-worsening effect of 6 percent among boys in PW participating households. One explanation for this could be children are absent from school due to work. Data from the ESS show that a third of children missing classes for over a week mention working as their main reason (not reported).

We lastly investigate the effect of the public works wing of PSNP on the well-being of children under the age of seven years and over 6 months whose nutritional information is collected. IPWRA estimator, which also controls health-related variables such as access to clean drinking water and common health shocks, shows that PW participation by parents worsens undernutrition (stunting) among under-7 children which is significant only for under-7 boys. The size of the impact, 9 percent (13 percent among boys), is more pronounced when a previous PW engagement is taken into account, rising to 13 percent (19 percent among boys). Comparing the two family types, we find that only children in male-headed families are significantly undernourished while the impact in single-mother families is, as expected, negative though insignificant in statistical sense. Multidimensional deprivation among under-7s, which also includes stunting among other dimensions, is nonetheless found to be better in PW families, this time significantly in favor of under-7 female children and irrespective of accounting for previous participation.

Despite the expectation that children in households participating in a social protection program experience improved nutrition (less stunting in our case), undesirable impacts (or nonimpact) cannot be ruled out for programs that have an adult labor requirement such as the public works program of PSNP. One explanation is that increased household income due to the program may not translate into improved child nutrition (Porter and Goyal, 2016). As mentioned earlier, which type of household member, male or female, participates and gets the transfers also matters. To look more into this issue, we disaggregate results by family structure and find that under-7 child stunting due to PW is only worse in male-headed households and the coefficient is negative though insignificant for those in single-mother families (not reported). Moreover, due to the labor requirement of PW, children receive less parental time for cooking and helping calories burned. Previous evidence in the literature on the impact of PW on child nutrition is inconclusive. For example, while Porter and Goyal (2016) estimate a nutrition-improving impact, Berhane et al. (2017) find no impact and argue that parental lack of information about child nutrition is to blame for the nonimpact. Gilligan et al. (2009) do not find a significant effect of PW on the daily number of child meals that is related to their nutritional outcomes.

3.4.3.2. Impacts of PSNP's Direct Support

Table 3.6 provides impacts of participation in the direct support (DS) component of PSNP on children's relative resource and well-being. Similar to the case in PW, we find that DS transfers have a small, negative and significant impact on per-child share of household resources. This effect on the full child sample is robust to a specification that controls for past participation and alternative impact estimators (see panel (b) of Table A.8 at the Appendix for PSM estimates). Also like PW, the negative effect is only significant for male children and those living in male-headed households. Estimates range from less shares by 2 percent for all children to 2 percent for male children, relative to non-DS children. However, IPWRA estimates do not provide any significant effect of DS participation on the monetary values of children's resources except when the household head is a male where the average child's monthly expenditures fall by 1.2 birr due to PW. In single-mothers, effects on child resources are not statistically different from zero.

In spite of the expected finding that DS in general reduces household monetary poverty, the impact on child poverty is undesirable and significant throughout. These results are also robust to alternative estimations with inclusion of a previous participation and disaggregated data by gender, family structure. Moreover, impacts on

Table 3.6.: Impacts of PSNP's direct support on children's resources and well-being: IPWRA method

Outcome variable	Full sample	Boys	Girls	Male-headed	Single-mother	2012 PW participation controlled		
						Full sample	Boys	Girls
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Child's share in household resources	-0.016***	-0.031***	-0.009	-0.012*	-0.014	-0.018***	-0.030***	-0.012
	(0.006)	(0.008)	(0.009)	(0.008)	(0.009)	(0.006)	(0.008)	(0.010)
Log of child's household resources	-0.039	-0.070	-0.051	-0.175**	-0.118	-0.010	-0.062	-0.021
	(0.052)	(0.071)	(0.073)	(0.064)	(0.093)	(0.061)	(0.075)	(0.108)
Child is monetarily-poor	0.071***	0.076***	0.090***	0.071***	0.099*	0.064***	0.067***	0.080*
	(0.020)	(0.021)	(0.039)	(0.015)	(0.053)	(0.021)	(0.020)	(0.044)
Household is monetarily-poor	-0.075	-0.144**	0.020	0.007	-0.128	-0.081*	-0.150**	0.004
	(0.047)	(0.064)	(0.061)	(0.047)	(0.090)	(0.048)	(0.064)	(0.064)
Child is multidimensionally-deprived	0.128***	0.126**	0.132***	0.127**	0.071	0.120***	0.122**	0.118**
	(0.036)	(0.054)	(0.051)	(0.046)	(0.057)	(0.037)	(0.055)	(0.058)
Child engaged in non-domestic work	0.025	0.111*	-0.066	0.052	-0.082	-0.005	-0.070	-0.091
	(0.050)	(0.064)	(0.077)	(0.059)	(0.080)	(0.048)	(0.064)	(0.068)
A school-age child not enrolled	-0.016	-0.041**	0.014	-0.021	-0.058	-0.017	-0.057**	-0.027
	(0.021)	(0.019)	(0.039)	(0.018)	(0.044)	(0.019)	(0.019)	(0.033)
U-7 child is multidimensionally-deprived	0.028					0.054		
	(0.043)					(0.048)		
U-7 child is stunted	0.113					0.089		
	(0.082)					(0.089)		

Notes: *, ** and *** imply statistical significance at 10%, 5% and 1% levels respectively. Standard errors in parentheses. U-7=Under-7-year-old. DS=Direct support. IPWRA=Inverse-probability-weighted regression adjustment. Estimates are weighted to represent the population.

poverty incidences are also supported by kernel and radius matching estimators of PSM (Table A.8). There are few significant household poverty-reducing impacts of direct support transfers that make it different from PW. It should be noted, however, that DS has effects on household poverty only when the outcome regression controls for a 2011/12 participation and in households with boys (in both specifications).

In contrast, children in families covered by direct supports have more multiple deprivations compared with those in families not covered by the program. The impacts in both specifications and disaggregations are higher and highly significant, reaching 13 percent, and are confirmed by PSM estimators in Table A.8. But, for the under-seven child sample, the effect on multidimensional deprivations vanishes. Moreover, we find no effect of participation in DS on under-seven child stunting despite controlling for a previous same program participation. The low number of DS participants with under-seven children did not allow us to run disaggregations by gender.

The nonimpacts as well as worsening impacts of direct support transfers on child monetary poverty and multidimensional deprivation could be explained on grounds of intrahousehold resource allocation and the size of transfers themselves. The finding that children relatively command on less resources in families receiving the transfers automatically implies that they are more poorer and deprived than those in non-recipient families. Moreover, the size of the transfer may not be large enough to lift beneficiaries out of poverty and deprivation or help accumulate assets. It seems noting this that Gilligan et al. (2009) specify the per-member benefits from PSNP to 90 birr although they still find no effects on total household expenditure, meals and assets. Tafere and Woldehanna (2012) also qualitatively find that the amount of transfer is so small to help some households achieve the programs objective of food security.

3.4.3.3. Impacts of Allied Transfers

Transfers which we refer to 'allied' are those social protection programs that have almost similar objectives as the PSNP but may not necessarily be delivered by the government as non-governmental organizations also offer them. ESS collects data if households participate in these transfer programs in the form of cash-for-work, input-for-work, etc. We aim to see if such programs do have any impact on children's well-being in beneficiary households and if those impacts, if any, differ from PNSP's.

In Table 3.7, we summarize the impacts of allied transfers on children's relative resource and well-being. Unlike PSNP's PW and DS, which have negative effects, allied transfers generally have no impact on children's resource shares even after similar previous engagements are taken into account by the IPWRA output regression. The effect is only robust to a kernel estimator of the PSM results, reported at panel (c) of Table A.8 in the Appendix). However, a unique finding here is that boys in allied transfer families command on more household resources, though higher only by 1 percent, than those in non-recipient families. On the other hand, estimates reveal no significant effects of allied transfers on the monetary resources allotted to children.

Moving to impacts on monetary poverty, recall that we find both PSNPs generally worsen child poverty, with the popular public works wing having a marginally-significant impact for all children while the direct support component affecting highly significantly in all specifications. On the contrary, we now estimate that allied

Table 3.7.: Impacts of allied transfers on children's resources and well-being: IP-WRA method

Outcome variable	Full sample	Boys	Girls	Male-headed	Single-mother	2012 PW participation controlled		
						Full sample	Boys	Girls
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Child's share in household resources	0.004	0.010**	-0.002	0.002	-0.004	0.004	0.010**	-0.002
	(0.003)	(0.004)	(0.004)	(0.003)	(0.008)	(0.003)	(0.004)	(0.004)
Log of child's household resources	-0.038	-0.027	-0.056	-0.047	-0.133	-0.029	-0.026	-0.038
	(0.045)	(0.067)	(0.060)	(0.048)	(0.100)	(0.047)	(0.070)	(0.061)
Child is monetarily-poor	-0.036*	-0.058**	-0.014	-0.033	-0.072	-0.037*	-0.056*	-0.022
	(0.021)	(0.029)	(0.030)	(0.023)	(0.029)	(0.021)	(0.030)	(0.030)
Household is monetarily-poor	0.043*	0.036	0.052*	0.059**	0.068	0.014	0.020	-0.0001
	(0.022)	(0.032)	(0.032)	(0.024)	(0.080)	(0.023)	(0.034)	(0.032)
Child is multidimensionally-deprived	-0.049*	-0.078**	-0.041	-0.049	0.099	-0.050*	-0.091**	-0.010
	(0.028)	(0.039)	(0.038)	(0.031)	(0.063)	(0.029)	(0.041)	(0.041)
U-7 child is multidimensionally-deprived	0.005					-0.001		
	(0.027)					(0.026)		
U-7 child is stunted	-0.023					-0.031		
	(0.044)					(0.046)		

Notes: *, ** and *** imply statistical significance at 10%, 5% and 1% levels respectively. Standard errors in parentheses. U-7=Under-7-year-old. IPWRA=Inverse-probability-weighted regression adjustment. Estimates are weighted to represent the population.

transfers have generally a child poverty-reducing effect where poverty incidence is lesser by about 4 percent. Although the same impact sustains with controlling past program participation, it disappears for female children while boys in such allied programs are 6 percent less poor relative to non-recipients. On the other hand, allied transfers are also found to increase poverty at the household level in the full sample, households with girls and those headed by male.

The other notable difference between PSNP transfers and allied transfers in terms of impact is that the latter reduce children's multiple deprivations. In particular, children bound to non-PSNP (allied) supports are less likely to be multidimensionally-deprived by 5 percent which is higher for boys (9 percent) although impact is nonexistent for girls. In contrast, we earlier find that PW has generally no such an impact, unless data is restricted to under-seven children where impact is favorably negative, and DS has the undesirable effect of worsening children's multiple deprivation. Our data fall short of providing impacts of allied supports on the undernutrition and multiple deprivation of children under the age of seven which is similar to DS in this regard.

Table 3.8.: Joint impacts of PSNP & allied transfers on children's resources & well-being: IPWRA method

Outcome variable	Full sample	Boys	Girls	Male-headed	Single-mother	2012 PW participation controlled		
						Full sample	Boys	Girls
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Child's share in household resources	-0.011**	-0.007	-0.015*	-0.007*	0.004	-0.011***	-0.007	-0.015*
	(0.005)	(0.005)	(0.008)	(0.004)	(0.024)	(0.005)	(0.005)	(0.008)
Log of child's household resources	0.050	0.130*	-0.021	0.029	0.188	0.027	0.101	-0.035
	(0.043)	(0.071)	(0.050)	(0.051)	(0.133)	(0.042)	(0.069)	(0.051)
Child is monetarily-poor	0.034	-0.058	0.126***	0.007	0.108	0.038	-0.053	0.128***
	(0.025)	(0.040)	(0.027)	(0.025)	(0.070)	(0.025)	(0.039)	(0.027)
Household is monetarily-poor	0.012	-0.007	0.044	0.071**	-0.232	0.015	-0.010	0.047
	(0.040)	(0.049)	(0.067)	(0.032)	(0.179)	(0.039)	(0.049)	(0.067)
Child is multidimensionally-deprived	0.059	0.027	0.102	0.100	0.220*	0.057	0.028	0.097
	(0.052)	(0.075)	(0.067)	(0.053)	(0.121)	(0.051)	(0.075)	(0.068)

Notes: *, ** and *** imply statistical significance at 10%, 5% and 1% levels respectively. Standard errors in parentheses. IPWRA=Inverse-probability-weighted regression adjustment. Estimates are weighted to represent the population.

3.4.3.4. Joint Impacts of PSNP and Allied Transfers

What happens to children's resource-related bargaining power and well-being if their families participate simultaneously in PSNP and allied social protection schemes? In this study, despite unable to provide results for under-seven children as not so many such households participate in both programs, we present impact estimates for the full sample of children, also disaggregated by family structure and gender. Results are summarized in Table 3.8.

Estimates show that full sample joint impacts on children's resource shares are similar to the separate impacts of PW and DS. Children living in households who receive any of PW or DS transfers coupled with other allied transfers, compared with children of families who do not receive such benefits, see their shares in household expenditures falling by 1 percent. This impact is also robust to consideration of the 2011/12 joint receipt of the transfers and to alternative matching methods whose results are available in panel (d) of Appendix Table A.8. The negative impact is also visible on children in male-headed families. However, unlike the separate impacts of PW, DS and allied transfers, joint participation reduces resource shares of girls, despite being marginally significant. On the other hand, joint transfers are generally found to have no significant impact on children's resources in levels. But when disaggregated by gender, they raise boys' monthly expenditures only slightly by 1.14 ETB.

Regarding monetary poverty, we find no impacts of the joint transfers with the full child sample. Neither do they impact household level monetary poverty except in male-headed families where effect is unfavorable. However, girls in joint transfers are found to be poorer than those in non-recipient families. The data also fall short to provide further effect on children's multidimensional deprivation except on children in single-mother families where it is undesirable.

Looking at joint impact of PSNP and related programs is not new although none evaluates effects on child outcomes. For example, Hoddinott et al. (2012) examine the joint impact of the PSNP and Other Food Security Program/Household Asset Building Program (OFSP/HABP) transfers on agricultural productivity. Using a dose-response method, they find that access to the PSNP plus OFSP/HABP transfers improve use of fertilizer and enhanced agricultural investments. They also find participation in the PSNP alone has no effect on agricultural input use or productivity and limited impact on agricultural investments.

3.5. Conclusions

Ethiopia's Productive Safety Net Program (PSNP) is Africa's second largest social protection program with public works (PW) and direct support (DS) components. There are also other allied transfer programs to the PSNP in the form of cash-for-work, inputs-for-work, free food and asset building programs. The study evaluates the separate and joint impacts of PSNP and allied transfer programs on children's resource-related bargaining power and well-being. Estimated resources and shares from a collective demand system proxy bargaining power and child well-being is measured by resource-based monetary poverty, undernutrition and multidimensional deprivation. Impacts in the form of average treatment effect on the treated (ATET) are estimated by the inverse-probability-weighted regression adjustment (IPWRA) which also controls for other correlates of outcome variables. Alternative specifications, disaggregations and traditional propensity score matching (PSM) methods are used for checking robustness. For outcome variables observed in 2013/14 and program participation throughout the past year, we match participant and non-participant households using variables observed in 2011/12. LSMS-ISA data from Ethiopia Socioeconomic Survey 2013/14 are used.

We find that almost all of demographic, economic and geographic variables have generally the expected correlations with participation in PSNP and allied programs. In particular, female-headed households are found to have higher chance of participation in both of PSNP's PW and DS programs. In line with the design of DS for those with limited labor such as the elderly and disabled, we find head's age and household labor force being inversely correlated with participation in DS. Moreover, those with large land holdings are less likely to engage in just PSNP programs unless they are in joint with allied transfers. Higher livestock holdings and income from non-farm activities have all the effect of consistently reducing participation in all programs.

We estimate that PSNP programs separately, and jointly with allied transfers, have the impact of slightly reducing children's relative resource shares. Allied transfers, in contrast, increase resource shares of boys. Impacts on child monetary poverty are quite mixed and directly follow from effects on sharing rules: when a program positively affects child resource shares, it decreases child poverty and vice versa. Accordingly, we find that while PSNPs and a joint with allied transfers increase child poverty, allied transfers alone decrease it. In contrast, household-level poverty is generally not affected except a reduction effect by direct supports only after a previous participation is controlled. Public works (only for under-sevens) and allied programs desirably impact child multidimensional deprivation. We also find that under-seven children, specifically boys, living in public works families are more stunted than their counterparts in non-PW families. Other transfers are found to have no impact on child stunting. Results are checked for being robust using PSM estimators.

Results particularly lend support to previous evidence that when women receive exogenous transfers, child outcomes improve. For example, we find that PW program significantly reduces children's resources in male-headed families while their monthly resources in levels are higher when the single-mother head is in PW. It also matters to child and household poverty who is engaged in the transfer programs as proxied by the type of family structure. Our estimates, for instance, show that when the head is male, child and household poverty slightly increase with PW transfers. In contrast, when the head receiving the PW transfers is a single-mother, both child and household poverty slightly decrease. Comparing the two family types regarding impacts on child nutritional outcomes, we find that only children in male-headed families in PW are significantly stunted while the impact in single-mother families is, as expected, negative though insignificant in a statistical sense.

The findings that children's undernutrition and/or multidimensional deprivations are worse or not better for participants of a social protection program are raise questions. These may require revising the on-going social protection schemes to a "cash plus" form such as by incorporating parental awareness on child nutrition and education. Restricting receipts of transfers to females may also help.

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A. APPENDIX

A.1. Derivation of the Collective Demand System Model

The derivation is based on Menon et al. (2017) and Mangiavacchi et al. (2013, 2018). Consider an extended PIGLOG individual expenditure function:

$$lne_k(u_k, \boldsymbol{p}) = lnA_k(\boldsymbol{p}) + \frac{\varphi(u_k)B_k(\boldsymbol{p})}{1 - \varphi(u_k\lambda_k(\boldsymbol{p})} = lnA_k(\boldsymbol{p}) + \frac{B_k(\boldsymbol{p})}{\Psi(u_k) - \lambda_k(\boldsymbol{p})}$$

where $\Psi(u_k) = \varphi(u_k)^{-1}$ is decreasing in utility $\varphi(u_k)$; $\boldsymbol{p} = \{p_{c^1}, p_{c^2}, p_q\}$; and the continuous and concave price aggregators take up the usual functional forms: $lnA_k(\boldsymbol{p}) = \frac{1}{2}\left(\alpha_0 + \sum_i \alpha_i lnp_i + \frac{1}{2}\sum_i\sum_j \gamma_{ij} lnp_i lnp_j\right)$, $B_k(\boldsymbol{p}) = \beta_0 \mathit{\Pi}_i p_i^{\beta_i^k}$ and $\lambda_k(\boldsymbol{p}) = \sum_i \lambda_i^k p_i$, assumed to be a differentiable, homogeneous function of degree zero of prices. $\alpha_i, \gamma_{ij}, \beta_i^k$ and λ_i^k are parameters to be estimated. One can interpret the price aggregator $A(\boldsymbol{p})$ as that level of subsistence expenditure [or poverty expenditure (Deaton and Muellbauer, 1980)] of member k when her utility $u_k = 0$. The remaining two price aggregators, $B_k(\boldsymbol{p})$ and $\lambda_k(\boldsymbol{p})$, are associated with expenditure levels of each household member whose variations allow identification of the corresponding parameters β_i^k and λ_i^k.

Shephard's lemma gives individual Hicksian demand of good i as budget share:

$$w_i^k = \frac{\partial lne_k(u_k, \boldsymbol{p})}{\partial lnp_i} = \frac{\partial lnA_k(\boldsymbol{p})}{\partial lnp_i} + \frac{\frac{\partial B_k(\boldsymbol{p})}{\partial lnp_i}[\Psi(u_k) - \lambda_k(\boldsymbol{p})] + B_k(\boldsymbol{p})\frac{\partial \lambda_k(\boldsymbol{p})}{\partial lnp_i}}{[\Psi(u_k) - \lambda_k(\boldsymbol{p})]^2}.$$

Inverting this individual expenditure function gives indirect utility function:

$$\Psi(u_k) - \lambda_k(\boldsymbol{p}) = \frac{B_k(\boldsymbol{p})}{lne_k(u_k, \boldsymbol{p}) - lnA_k(\boldsymbol{p})}.$$

Substituting this gives the individual budget share of good i

$$w_i^k = \frac{\partial lnA_k(\boldsymbol{p})}{\partial lnp_i} + \frac{\frac{\partial B_k(\boldsymbol{p})}{\partial lnp_i}[\frac{B_k(\boldsymbol{p})}{lne_k(u_k,\boldsymbol{p}) - lnA_k(\boldsymbol{p})}] + B_k(\boldsymbol{p})\frac{\partial \lambda_k(\boldsymbol{p})}{\partial lnp_i}}{[\frac{B_k(\boldsymbol{p})}{lne_k(u_k,\boldsymbol{p}) - lnA_k(\boldsymbol{p})}]^2}$$

which could be expressed as:

$$w_i^k = \frac{\partial lnA_k(\boldsymbol{p})}{\partial lnp_i} + \beta_i^k[lne_k - lnA_k(\boldsymbol{p})] + \lambda_i^k\frac{[lne_k - lnA_k(\boldsymbol{p})]^2}{B_k(\boldsymbol{p})}.$$

Given the aforementioned informational constraint that quantities and prices of non-assignable goods are not observed, the above decentralized budget shares are aggregated at the household level for good i as follows:

$$w_i = \alpha_i + \sum_j \gamma_{ij} lnp_j + \beta_i^1[lne_1 - lnA_1(\boldsymbol{p})] + \lambda_i^1\frac{[lne_1 - lnA_1(\boldsymbol{p})]^2}{B_1(\boldsymbol{p})}$$

$$+\beta_i^2[lne_2 - lnA_2(\boldsymbol{p})] + \lambda_i^2\frac{[lne_2 - lnA_2(\boldsymbol{p})]^2}{B_2(\boldsymbol{p})}.$$

Following Lewbel (1985) and Perali (2003), the demand system is augmented to capture observed heterogeneity among households by introducing a translating technology $t_i(\boldsymbol{d})$ so that demographic attributes $\boldsymbol{d}$ enter additively with expenditures. This provides the demographically-modified demand system as follows:

$$w_i = \alpha_i + t_i(\boldsymbol{d}) + \sum_j \gamma_{ij} lnp_j + \beta_i^1[lne_1^* - lnA_1(\boldsymbol{p})] + \lambda_i^1\frac{[lne_1^* - lnA_1(\boldsymbol{p})]^2}{B_1(\boldsymbol{p})}$$

$$+\beta_i^2[lne_2^* - lnA_2(\boldsymbol{p})] + \lambda_i^2\frac{[lne_2^* - lnA_2(\boldsymbol{p})]^2}{B_2(\boldsymbol{p})}$$

where lne_1^* and lne_2^* are modified logarithmic individual total expenditures given by the translating household technology $lne_k^* = lne_k - \sum_i t_i(\boldsymbol{d}) lnp_i$. The demographic functions are simply defined as $t_i(\boldsymbol{d}) = \sum_r \tau_{ir} d_r$ for $r = 1, ...R$. Note that from the above demand system, we can estimate, for each good i, income parameters (β_i^1, β_i^2, λ_i^1 and λ_i^2) at individual level while the rest at household level (i.e. the intercepts α_i, price parameters γ_{ij} and demographic scaling effects $t_i(\boldsymbol{d})$). While price elasticities remain the same as in the unitary setting, income elasticities capturing Engle effects for $x_i = c_i, q_i$ and for each household member $k = 1, 2$ are given in the decentralized CQUAIDS by:

$$\epsilon_i^{e_k} = \frac{\partial ln x_i}{\partial ln e_k} = 1 + \frac{\beta_i^k}{w_i} + \frac{2\lambda_i^k}{B_k(\boldsymbol{p})} \frac{1}{w_i} (ln e_k - ln A_k(\boldsymbol{p})).$$

Table A.1.: Aggregation of consumption expenditure items: ESS 2013/14

Expenditure group/sub-group and item			**Recall***	**Price type**
I. FOOD AT HOME AND ALCOHOL				
1. Teff	10. Lentils	19. Milk		
2. Wheat	11. Haricot beans	20. Cheese		
3. Barley	12. Niger seed	21. Eggs		Unit values
4. Maize	13. Linseed	22. Sugar	All monthly	(For alcoholic
5. Sorghum	14. Onion	23. Salt		drinks: CSA
6. Millet	15. Banana	24. Coffee		retail prices)
7. Horse beans	16. Potato	25. Bula		
8. Chick pea	17. Kocho	26. Chat/Kat		
9. Field pea	18. Meat	27. Alcoholic drinks		
II. CLOTHING				
2.1. Adult clothing				
1. Clothes/shoes/fabric for men				
2. Clothes/shoes/fabric for women			All annually	CSA retail
2.2. Child clothing				prices
1. Clothes/shoes/fabric for boys				
2. Clothes/shoes/fabric for girls				
2.3. Non-assignable clothing (Linen: sheets, towels, blankets)				
III. HOUSEHOLD UTILITIES AND ENERGY				ESS local
3.1. Utilities: water, electricity & cell phone/landline use			Monthly	prices and
3.2. Household energy		5. Firewood	Monthly	CSA retail
1. Matches	3. Batteries	6. Kerosene	(Annually	prices
2. Candles (tua'f), incense	4. Charcoal	7. Lamp/torch	for lamp)	
IV. OTHER GOODS				
4.1. Education: fees, books, uniforms, stationery, assistance, etc.			Monthly	
4.2. Food away from home and cigarettes			Weekly	
1. Full meals: breakfast, lunch, dinner				CSA retail
2. Snacks (kolo, bread, biscuits, cakes, etc.)				prices (For
3. Dairy products (milk, yoghurt, etc.)				transport: ESS
4. Vegetables and roasted/boiled items				local prices)
5. Non-alcoholic drinks (coffee, tea, fruit juice, soda, etc.)				
6. Cigarettes, tobacco, suret and gaya				
4.2. Laundry and personal care			Annually	
4.3. Transport			Monthly	

Notes: *Recall periods here are as available in the ESS; all are finally converted to monthly values.

Figure A.1.: Engel curves of commodity groups by family type

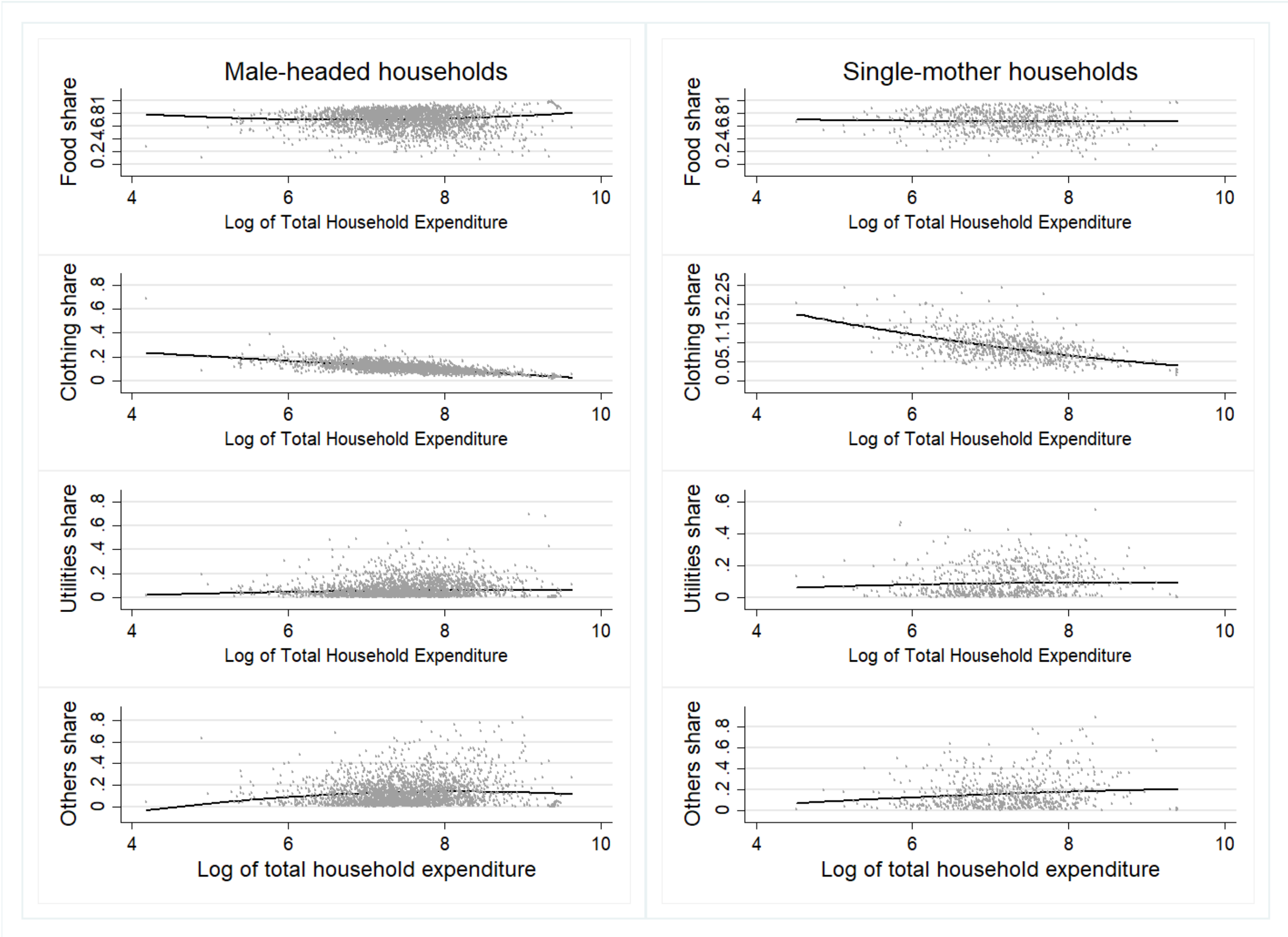


Table A.2.: Regression of total household expenditure: First stage

Variable	Male-headed HHs			Single-mother HHs		
Log of food prices	0.398	***	(0.034)	0.371	***	(0.061)
Log of clothing prices	-0.073		(0.166)	0.342		(0.215)
Log of utilities prices	0.029	***	(0.010)	0.008		(0.018)
Log of other goods prices	-0.128	***	(0.034)	-0.092	*	(0.053)
Head is Christian	-0.122	*	(0.072)	-0.117		(0.086)
Head sick	-0.039		(0.037)	0.024		(0.063)
# of sick children	0.024		(0.017)	0.055		(0.040)
# of children aged 15-17y	0.081	***	(0.021)	0.155	***	(0.048)
Female employment ratio	-0.098		(0.091)	0.187	*	(0.108)
Other adult in household	0.140	***	(0.032)	0.197	***	(0.063)
HH has safe water source	0.096	**	(0.048)	0.055		(0.081)
HH interviewed in February	-0.075		(0.059)	-0.060		(0.093)
HH faced price shock	-0.115	**	(0.049)	0.059		(0.075)
HH faced natural disaster shock	0.127	**	(0.061)	0.238	**	(0.107)
HH lives in Amhara region	0.186	**	(0.092)	0.161		(0.128)
HH lives in Oromia region	0.243	***	(0.075)	0.302	***	(0.113)
HH lives in SNNP region	0.098		(0.085)	0.139		(0.125)
HH lives in Tigray region	0.322	***	(0.089)	0.318	***	(0.115)
HH lives in other regions	0.217	**	(0.094)	0.321	**	(0.123)
Education diff. of parents (w - h)	-0.015	***	(0.005)	-	-	-
Age diff. of parents (w - h)	-0.003	*	(0.002)	-	-	-
All children in school	0.042		(0.037)	-0.026		(0.077)
Proportion of female children	0.077	*	(0.042)	0.001		(0.079)
Proportion of women	0.065		(0.153)	-0.572	***	(0.163)
Number of non-biological children	0.042	*	(0.023)	-0.020		(0.024)
Wealth index	0.066	***	(0.007)	0.061	***	(0.009)
Constant	6.840	***	(0.936)	4.822	***	(1.154)

Notes: Dependent variable is log of household total expenditure. *, ** & *** show significance at 10%, 5% & 1% levels respectively. Standard errors, corrected for clustering and sampling weights, are in parentheses. SNNP=Southern Nations, Nationalities and Peoples.

Table A.3.: Collective AIDS regression results

Variable	Male-headed households (N = 2367)				Single-mother households (N = 729)			
	Food	Clothing	Utilities	Other goods	Food	Clothing	Utilities	Other goods
Intercepts α_i	1.175 *** (0.061)	0.177 *** (0.013)	0.027 (0.025)	-0.379 ** (0.053)	1.162 *** (0.116)	0.116 *** (0.023)	0.040 (0.047)	-0.319 *** (0.111)
Price effects γ_{ij}	-0.055 *** (0.016)	-0.056 *** (0.004)	0.003 (0.004)	0.107 *** (0.015)	-0.032 (0.027)	-0.040 *** (0.005)	-0.004 (0.007)	0.076 *** (0.026)
		0.028 *** (0.002)	0.006 *** (0.001)	0.022 *** (0.003)		0.023 *** (0.004)	0.004 *** (0.002)	0.013 *** (0.005)
			0.004 *** (0.002)	-0.013 (0.004)			0.003 (0.003)	-0.004 (0.005)
				-0.116 *** (0.015)				-0.085 *** (0.027)
Adults' income effects β_i^1	-0.107 *** (0.012)	-0.046 *** (0.004)	0.020 *** (0.005)	0.133 *** (0.011)	-0.098 *** (0.023)	-0.031 *** (0.006)	0.022 ** (0.010)	0.106 *** (0.023)
Children's income effects β_i^2	-0.110 *** (0.012)	-0.038 *** (0.004)	0.020 *** (0.005)	0.128 *** (0.011)	-0.070 *** (0.024)	-0.024 *** (0.006)	0.011 (0.010)	0.084 *** (0.023)
Head is Christian	-0.046 *** (0.012)	-0.001 (0.002)	-0.001 (0.004)	0.048 *** (0.011)	-0.035 (0.028)	0.002 (0.003)	-0.002 (0.011)	0.036 (0.028)
Head sick	0.017 ** (0.008)	-0.002 * (0.001)	-0.005 ** (0.003)	-0.010 (0.007)	0.006 (0.018)	-0.008 *** (0.002)	-0.015 *** (0.006)	0.017 (0.016)
# of sick children	-0.013 *** (0.004)	0.002 *** (0.001)	0.001 (0.002)	0.010 ** (0.004)	0.016 (0.011)	0.004 ** (0.002)	-0.006 (0.005)	-0.014 (0.010)
# of children aged 15-17y	-0.009 * (0.005)	0.007 *** (0.001)	-0.002 (0.002)	0.004 (0.005)	0.003 (0.018)	0.008 *** (0.002)	-0.002 (0.006)	-0.009 (0.016)
Female employment ratio	0.021 (0.021)	-0.005 (0.004)	0.004 (0.006)	-0.021 (0.020)	-0.021 (0.028)	0.017 *** (0.004)	0.019 * (0.011)	-0.015 (0.027)
Other adult in household	0.004 (0.008)	0.014 *** (0.001)	0.000 (0.002)	-0.019 ** (0.008)	0.044 ** (0.019)	0.014 *** (0.003)	-0.008 (0.008)	-0.049 *** (0.019)
HH has safe water source	0.002 (0.010)	0.000 (0.001)	0.020 *** (0.003)	-0.022 ** (0.010)	-0.048 ** (0.022)	0.001 (0.003)	0.046 *** (0.009)	0.001 (0.022)
HH interviewed in February	0.004 (0.015)	0.003 * (0.002)	-0.003 (0.006)	-0.004 (0.013)	0.014 (0.029)	0.004 (0.003)	-0.014 (0.014)	-0.004 (0.025)
HH faced price shock	-0.031 *** (0.011)	-0.002 (0.002)	0.010 ** (0.005)	0.022 ** (0.010)	-0.001 (0.025)	-0.004 * (0.002)	0.000 (0.010)	0.005 (0.026)
HH faced natural disaster shock	0.037 *** (0.012)	0.000 (0.002)	-0.018 *** (0.003)	-0.020 * (0.012)	0.033 (0.030)	-0.004 (0.003)	-0.030 *** (0.009)	0.001 (0.032)
HH lives in Amhara region	0.118 ** (0.025)	0.021 *** (0.002)	-0.083 *** (0.010)	-0.055 *** (0.020)	0.036 (0.039)	0.013 *** (0.004)	-0.104 *** (0.018)	0.055 (0.038)
HH lives in Oromia region	0.124 *** (0.026)	0.036 *** (0.002)	-0.080 *** (0.010)	-0.081 *** (0.020)	0.084 ** (0.036)	0.021 *** (0.004)	-0.098 *** (0.018)	-0.006 (0.036)
HH lives in SNNP region	0.117 *** (0.026)	0.021 *** (0.002)	-0.072 *** (0.010)	-0.066 *** (0.021)	0.080 ** (0.036)	0.005 (0.004)	-0.108 *** (0.016)	0.024 (0.036)
HH lives in Tigray region	0.092 *** (0.027)	0.047 *** (0.003)	-0.073 *** (0.011)	-0.066 * (0.022)	0.025 (0.037)	0.036 *** (0.005)	-0.086 *** (0.018)	0.026 (0.038)
HH lives in other regions	0.087 *** (0.028)	0.033 *** (0.003)	-0.055 *** (0.012)	-0.066 *** (0.023)	0.023 (0.040)	0.024 *** (0.005)	-0.050 ** (0.023)	0.003 (0.037)
Endog. of total expenditure	0.155 *** (0.014)	-0.002 (0.004)	-0.031 *** (0.006)	-0.122 * (0.012)	0.110 *** (0.029)	-0.007 (0.006)	-0.035 *** (0.010)	-0.067 ** (0.029)

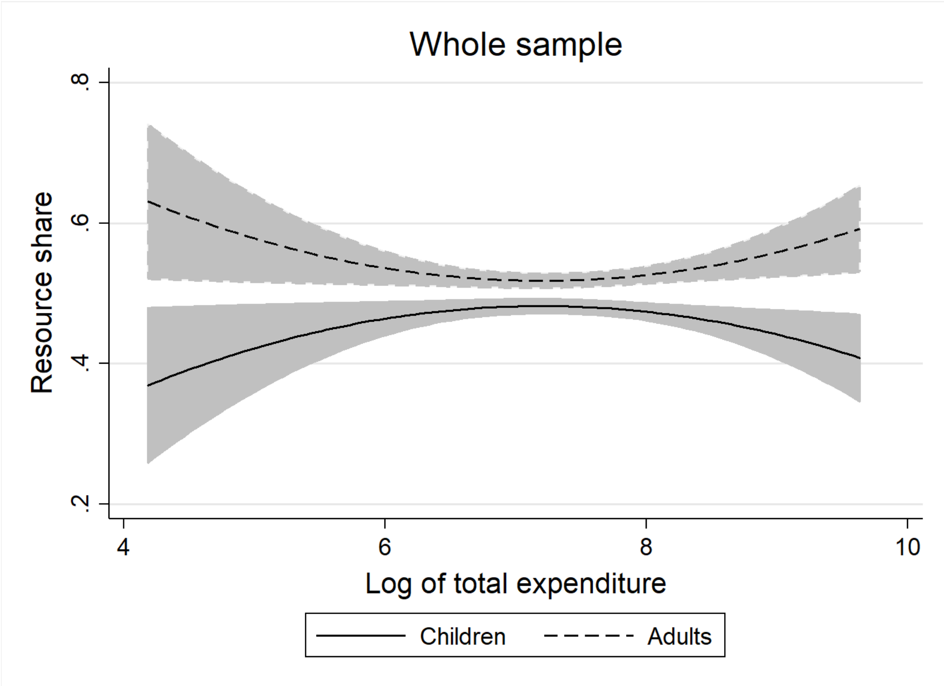
Notes: *, ** & *** show significance at 10%, 5% & 1% levels respectively. Standard errors, corrected for clustering and sampling weights, are in parentheses. 'Other regions' includes the small regions of Afar, Benishangul-Gumuz, Dire Dawa, Gambella, Harari and Somali; the left-out category is the capital, Addis Ababa. SNNP=Southern Nations, Nationalities and Peoples.

Table A.4.: Income and price elasticity estimates

	Male-headed households				Single-mother households			
	Food	Clothing	Utilities	Others	Food	Clothing	Utilities	Others
Income elasticities								
Adults	0.92***	0.65**	1.03***	1.67***	0.92***	0.70***	1.11***	1.52***
	(0.032)	(0.274)	(0.310)	(0.470)	(0.013)	(0.143)	(0.130)	(0.551)
Children	0.93***	0.63***	0.98***	1.65***	0.92***	0.59***	1.093***	1.59***
	(0.008)	(0.213)	(0.184)	(0.386)	(0.013)	(0.198)	(0.114)	(0.625)
Uncompensated price elasticities								
Food	-0.94***	-0.03***	-0.02***	0.06***	-0.95***	-0.03***	-0.02**	0.08***
	(0.012)	(0.005)	(0.005)	(0.012)	(0.009)	(0.005)	(0.007)	(0.021)
Clothing	-0.07	-0.58	0.04	0.03	-0.13	-0.41	0.02	-0.02
	(0.106)	(1.968)	(0.070)	(0.379)	(0.914)	(4.097)	(0.211)	(0.279)
Utilities	-0.30	0.07	-0.82	0.05	-0.30	0.01	-0.91***	0.08
	(0.746)	(0.172)	(0.448)	(0.104)	(0.626)	(0.030)	(0.204)	(0.176)
Other goods	-0.25	-0.06	0.03	-1.37***	-0.13	-0.09	0.05	-1.40***
	(0.263)	(0.059)	(0.063)	(0.175)	(0.267)	(0.092)	(0.128)	(0.368)
Compensated price elasticities								
Food	-0.28***	0.04*	0.05	0.19***	-0.34***	0.04*	0.08	0.22***
	(0.792)	(0.022)	(0.045)	(0.052)	(0.104)	(0.023)	(0.059)	(0.073)
Clothing	0.33	-0.53	0.08	0.11	0.23	-0.36	0.08	0.05
	(0.075)	(1.964)	(0.083)	(0.073)	(0.171)	(4.094)	(0.217)	(0.626)
Utilities	0.41	0.15	-0.75*	0.19*	0.45	0.10***	-0.80***	0.2609
	(0.692)	(0.171)	(0.437)	(0.106)	(0.436)	(0.035)	(0.187)	(0.229)
Other goods	0.94***	0.07**	0.13***	-1.15***	0.94***	-0.02	0.21	-1.17***
	(0.178)	(0.032)	(0.050)	(0.206)	(0.314)	(0.044)	(0.132)	(0.404)

Notes: *, ** & *** show significance at 10%, 5% & 1% levels respectively. Bootrapped standard errors in parentheses.

Figure A.2.: Sharing rules of children and adults over the income distribution



Notes: Shaded areas are 95% confidence intervals. Observations are weighted to make estimates nationally representative.

A.2. Estimation of children resource shares from a collective complete demand system

The demand system model we specify follows from Menon et al. (2017) and Mangiavacchi et al. (2013, 2018) who extend the QUAIDS of Banks et al. (1997) to the collective framework and hence named the Collective Quadratic Almost Ideal Demand System (CQUAIDS).

Consider an extended PIGLOG individual expenditure function:

$$lne_k(u_k, \boldsymbol{p}) = lnA_k(\boldsymbol{p}) + \frac{\varphi(u_k)B_k(\boldsymbol{p})}{1 - \varphi(u_k\lambda_k(\boldsymbol{p})} = lnA_k(\boldsymbol{p}) + \frac{B_k(\boldsymbol{p})}{\Psi(u_k) - \lambda_k(\boldsymbol{p})}$$

where $\Psi(u_k) = \varphi(u_k)^{-1}$ is decreasing in utility $\varphi(u_k)$; $\boldsymbol{p} = \{p_{c^1}, p_{c^2}, p_q\}$; and the continuous and concave price aggregators take up the usual functional forms: $lnA_k(\boldsymbol{p}) = \frac{1}{2}\left(\alpha_0 + \sum_i \alpha_i lnp_i + \frac{1}{2}\sum_i\sum_j \gamma_{ij} lnp_i lnp_j\right)$, $B_k(\boldsymbol{p}) = \beta_0 \Pi_i p_i^{\beta_i^k}$ and $\lambda_k(\boldsymbol{p}) =$

$\sum_i \lambda_i^k p_i$, assumed to be a differentiable, homogeneous function of degree zero of prices. $\alpha_i, \gamma_{ij}, \beta_i^k$ and λ_i^k are parameters to be estimated.

Shephard's lemma gives individual Hicksian demand of good i as budget share:

$$w_i^k = \frac{\partial lne_k(u_k, \boldsymbol{p})}{\partial lnp_i} = \frac{\partial lnA_k(\boldsymbol{p})}{\partial lnp_i} + \frac{\frac{\partial B_k(\boldsymbol{p})}{\partial lnp_i}[\Psi(u_k) - \lambda_k(\boldsymbol{p})] + B_k(\boldsymbol{p})\frac{\partial \lambda_k(\boldsymbol{p})}{\partial lnp_i}}{[\Psi(u_k) - \lambda_k(\boldsymbol{p})]^2}.$$

Inverting this individual expenditure function gives indirect utility function as

$$\Psi(u_k) - \lambda_k(\boldsymbol{p}) = \frac{B_k(\boldsymbol{p})}{lne_k(u_k, \boldsymbol{p}) - lnA_k(\boldsymbol{p})}.$$

Substituting this gives the individual budget share of good i

$$w_i^k = \frac{\partial lnA_k(\boldsymbol{p})}{\partial lnp_i} + \frac{\frac{\partial B_k(\boldsymbol{p})}{\partial lnp_i}[\frac{B_k(\boldsymbol{p})}{lne_k(u_k,\boldsymbol{p}) - lnA_k(\boldsymbol{p})}] + B_k(\boldsymbol{p})\frac{\partial \lambda_k(\boldsymbol{p})}{\partial lnp_i}}{[\frac{B_k(\boldsymbol{p})}{lne_k(u_k,\boldsymbol{p}) - lnA_k(\boldsymbol{p})}]^2}$$

which could be expressed as

$$w_i^k = \frac{\partial lnA_k(\boldsymbol{p})}{\partial lnp_i} + \beta_i^k[lne_k - lnA_k(\boldsymbol{p})] + \lambda_i^k \frac{[lne_k - lnA_k(\boldsymbol{p})]^2}{B_k(\boldsymbol{p})}.$$

Given the aforementioned informational constraint that quantities and prices of non-assignable goods are not observed, the above decentralized budget shares are aggregated at the household level for good i. After capturing observed heterogeneity among households by introducing a translating technology $t_i(\boldsymbol{d})$ so that demographic attributes $\boldsymbol{d}$ enter additively with expenditures, we have the demographically-modified demand system as

$$w_i = \alpha_i + t_i(\boldsymbol{d}) + \sum_j \gamma_{ij} lnp_j + \beta_i^1[lne_1^* - lnA_1(\boldsymbol{p})] + \lambda_i^1 \frac{[lne_1^* - lnA_1(\boldsymbol{p})]^2}{B_1(\boldsymbol{p})}$$

$$+\beta_i^2[lne_2^* - lnA_2(\boldsymbol{p})] + \lambda_i^2 \frac{[lne_2^* - lnA_2(\boldsymbol{p})]^2}{B_2(\boldsymbol{p})}$$

where lne_1^* and lne_2^* are modified logarithmic individual total expenditures given by the translating household technology $lne_k^* = lne_k - \sum_i t_i(\boldsymbol{d}) lnp_i$.

Until now, we have made an implicit assumption that individual total expenditures

e_k are observed. Such information, nonetheless, is barely collected, as is the case in many household surveys and in the survey we use in this study. As a solution to this issue, one can exploit expenditures on exclusive or assignable goods to learn about how much each member receives from total household resources and then correct for the resulting measurement error (Caiumi and Perali, 2015; Menon et al., 2017; Mangiavacchi and Piccoli, 2017).

Once assignable individual expenditures are taken into account, non-assignable expenditures are assumed to be shared equally by adults and children.[1] Hence, observed resource shares become $\sigma_k = \frac{e_k}{\sum\limits_k e_k}$ where $\sigma_1 + \sigma_2 = 1$, so that we can write$lne_k = \sigma_k lne$.

Returning to the awaiting correction issue of e_k, a modifying function $m(\boldsymbol{z}) \in \left(0, \frac{e}{e_k}\right)$ is used to correct any measurement error related to e_k which leads to specification of the sharing rule. The arguments of this function are distribution factors $\boldsymbol{z}$ which affect the intrahousehold bargaining between adults and children but not their preferences[2].

This enables to define the sharing rule, which explains a shadow intrahousehold resource allocation, as a function of individual expenditures and distribution factors, i.e. for member 1 (adult), we have $\phi_1(e_1, \boldsymbol{z}) = e_1 \cdot m(\boldsymbol{z})$ which in log becomes linear as[3]

$$ln\phi_1(e_1, \boldsymbol{z}) = lne_1 + lnm(\boldsymbol{z}) = \sigma_1 lne + lnm(z).$$

Since by definition $lne = ln\phi_1 + ln\phi_2 = lne_1 + lne_2$, we have the sharing rule for member 2 (child) equal to

$$ln\phi_2(e_2, \boldsymbol{z}) = lne - ln\phi_1 = \sigma_2 lne - lnm(\boldsymbol{z}).$$

The functional form of the scaling function $m(\boldsymbol{z})$ is assumed to be of Cobb-Douglas

[1] Chavas et al. (2017) test the innocence of such an assumption; they show that assuming a fair distribution of non-assignable goods among family members does not affect parameter estimates of the sharing rule (see their Proposition 5 and Appendix B).

[2] Note that the scaling function does not depend on expenditures, a separability property in line with the theoretical properties of independence of income of the sharing rule by Dunbar et al. (2013) and Chavas et al. (2017) and the empirical validation by **?**.

[3] Since ϕ_k should not exhaust all household total expenditures e, i.e. $\phi_k < e$, the m-function is restricted to stay between 0 and $\frac{e}{e_k}$.

type for empirical purposes.

To take into account the endogeneity of total expenditure, we employ a control function procedure which uses as regressors the residuals of an auxiliary regression of total expenditure on a set of socio-demographic variables and our instruments into the demand system model (Dauphin et al., 2011; Mukasa, 2015; Mangiavacchi et al., 2018). The procedure is executed in two steps: the log of total expenditure lne is first estimated using OLS on a vector η of socio-demographic variables and instruments as $lne = \eta.\delta + \upsilon$ and then the residual $\widehat{\upsilon} = lne - \eta.\delta$ enters the demand system estimation. This gives the final CQUAIDS model in budget shares to be estimated as

$$w_i = \alpha_i + t_i(\boldsymbol{d}) + \sum_j \gamma_{ij} lnp_j + \beta_i^1[ln\phi_1^* - lnA_1(\boldsymbol{p})] + \lambda_i^1 \frac{[ln\phi_1^* - lnA_1(\boldsymbol{p})]^2}{B_1(\boldsymbol{p})}$$

$$+\beta_i^2[ln\phi_2^* - lnA_2(\boldsymbol{p})] + \lambda_i^2 \frac{[ln\phi_2^* - lnA_2(\boldsymbol{p})]^2}{B_2(\boldsymbol{p})} + \rho_i\widehat{\upsilon} + \xi_i$$

where $ln\phi_1^* = \sigma_1 lne + lnm(\boldsymbol{z}) - \sum_i t_i(\boldsymbol{d}) lnp_i$ and $ln\phi_2^* = \sigma_2 lne - lnm(z) - \sum_i t_i(\boldsymbol{d}) lnp_i$. Note that ρ_i captures any endogeneity of total expenditure. ξ_i is the error term.

The system is estimated using feasible generalized nonlinear least squares method and imposing the QUAIDS standard regulatory conditions: adding-up ($\sum_i \alpha_i = 1$), homogeneity ($\sum_i \gamma_{ij} = \sum_j \gamma_{ij} = 0$, $\sum_i \tau_{ir} = 0$ and $\sum_i \beta_i^k = \sum_i \lambda_i^k = 0$ for each $k = 1, 2$) and symmetry ($\gamma_{ij} = \gamma_{ji}, \forall i \neq j$). However, based on the evidence that Engel curves are linear in income, we use a linear version of the model so that the two quadratic parameters, λ_i^1 and λ_i^2, are not estimated.

A.3. Aggregation of multidimensional deprivation indices and decomposition

We adopt the procedures of Alkire and Foster (2009, 2011) for computing relevant poverty indices and undertaking sub-group decomposition. These are shown below.

Deprivation headcount ratios (h_j)

The single raw deprivation rates or headcount ratios (h_j) in each indicator j are computed as

$$h_j = \frac{1}{N}\sum_{i=1}^{N} I_{(0,1)}(y_{ji} \leq z_j)$$

where $\frac{1}{N}\sum_{i=1}^{N} I_{(0,1)}(y_{ji} \leq z_j)$ is an indicator function taking 1 if the expression in parenthesis is satisfied and 0 otherwise, y_{ji} is child attainment living in household i in indicator j, z_j is the cut-off in indicator j, also called indicator-specific poverty line, and N is the number of children. Note that these raw deprivations provide the proportion of children who are poor in a specific indicator only, regardless of whether they are deemed multidimensionally-deprived, i.e., they are not censored by multidimensional deprivation status (Apablaza and Yalonetzky, 2012).

Weighted deprivation count (C)

The sum of weighted deprivations (C) for each child i, also called deprivation count, is

$$C = \sum_{j=1}^{D} w_j I_{(0,1)}(y_{ji} \leq z_j)$$

where w_j is the weight given to indicator j, and D is the total number of indicators.

Multidimensional deprivation headcount rate (H)

Now, censoring at a given number of C_i (taking into account multiple deprivations) helps find the multidimensional deprivation headcount ratio (H) as

$$H = \frac{1}{N}\sum_{i=1}^{N} I_{(0,1)}(C_i \geq k)$$

where k is the multidimensional deprivation cut-off or poverty line.

Average intensity of deprivations among the poor (A)

Also important is the average intensity of deprivations (A) (number of deprivations as a proportion of the maximum number of possible deprivations) suffered by the multidimensionally-deprived children, defined as

$$A = \frac{1}{N \cdot D \cdot h_j} \sum_{i=1}^{N} I_{(0,1)}(C_i \geq k) \cdot C_i.$$

Adjusted multidimensional deprivation index (M)

The adjusted multidimensional deprivation index (M) is simply given by the product

$$M = H \cdot A.$$

Decomposition of M by dimensions and population sub-groups

The percentage contribution (Q_j) of indicator j to the overall multidimensional deprivation index (M) is calculated using

$$Q_j = \frac{1}{N \cdot D \cdot M} \sum_{i=1}^{N} I_{(0,1)}(y_{ji} \leq z_j) \cdot I_{(0,1)}(C_i \geq k)$$

where the terms on the right hand side are as defined previously. Lastly, the contribution of a population sub-group s (e.g. rural) to the overall child multidimensional deprivation index is extracted from the identity

$$\frac{M_1(\frac{N_1}{N})}{M} + \frac{M_2(\frac{N_2}{N})}{M} + ... + \frac{M_s(\frac{N_s}{N})}{M} = 1$$

where N_s is the number of households with children in each sub-group $s = 1, 2, \ldots, S$. Each element at the left hand side of the equation is, therefore, the contribution of a specific sub-group.

A.4. Dimensions, indicators and aggregation of child multidimensional deprivation

Dimensions and indicators

Identification and aggregation

We adopt the procedures of Alkire and Foster (2009, 2011) to identify a child as multidimensional deprived and to aggregate into an index. The sum of weighted deprivations (C) for each child i, also called deprivation count, is

$$C = \sum_{j=1}^{D} w_j I_{(0,1)}(y_{ji} \leq z_j)$$

where w_j is the weight given to indicator j, and D is the total number of indicators.

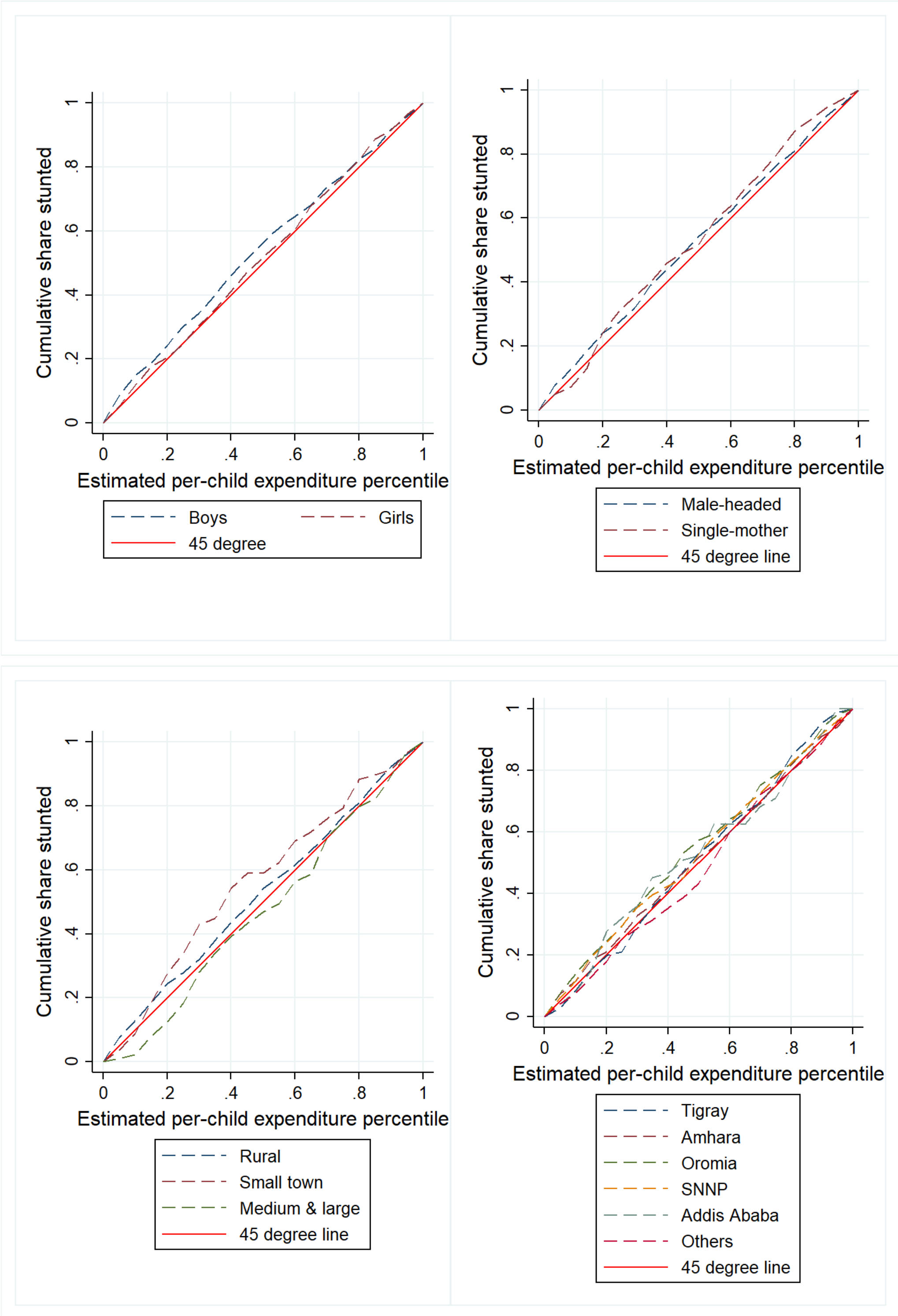
We then identify a child as multidimensionally-deprived if she is deprived in at least 33% of the weighted deprivations, i.e., $C_i \geq 0.33$.

For aggregation, censoring at a given number of C_i (taking into account multiple deprivations) helps find the multidimensional deprivation headcount ratio (H) as

$$H = \frac{1}{N}\sum_{i=1}^{N} I_{(0,1)}(C_i \geq k)$$

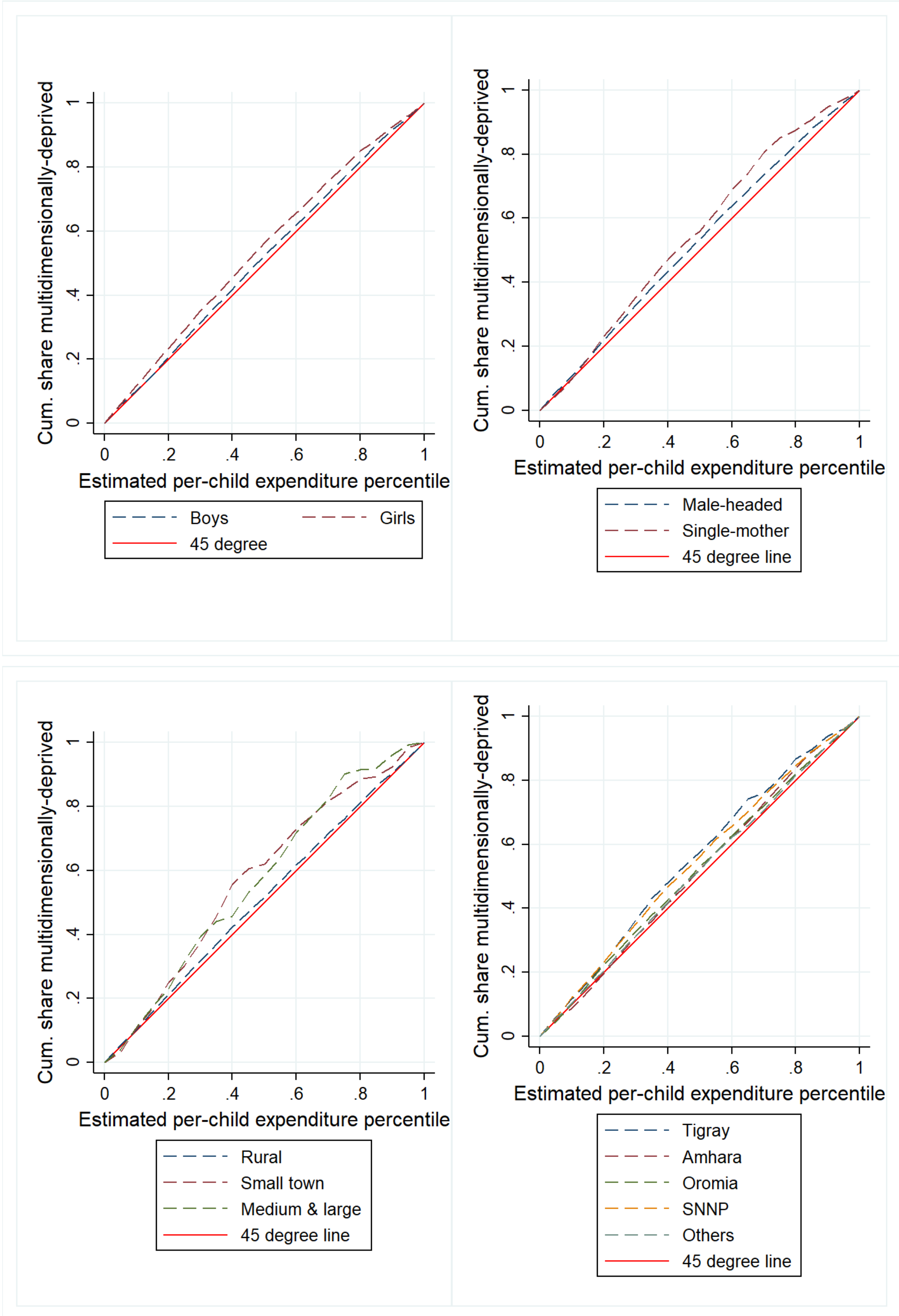
where k is the multidimensional deprivation cut-off, 0.33 in our case.

Figure A.3.: Concentration curves for child stunting ranked by child expenditure



Note: All estimates are weighted to make them representative of the corresponding population. All curves consider 95% confidence intervals (not shown).

Figure A.4.: Concentration curves for child multidimensional deprivation ranked by child expenditure



Note: Multidimensional deprivations status here is based on non-monetary dimensions and a cut-off at $k = 0.33$. All estimates are weighted to make them representative of the corresponding population. All curves consider 95% confidence intervals (not shown).

Table A.5.: Correlates of children's monetary poverty, stunting and multidimensional deprivation

	Monetary child poverty		Child is stunted		Multidimensional child dep.: without		Multidimensional child deprivation	
	Child poverty	Adjusted child poverty	Model 1	Model 2	Model 1	Model 2	With child mon. poverty	With adj. child mon. poverty
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Quintile based on children's est. exp. (Omitted: Poorest)								
Poor			-0.010		-0.051			
Middle			-0.013		-0.067*			
Rich			0.033		-0.063*			
Richest			0.006		-0.087**			
Quintile based on household exp. (Omitted: Poorest)								
Poor				-0.020		-0.018		
Middle				0.043		-0.013		
Rich				0.017		-0.120***		
Richest				0.007		-0.097**		
Child is stunted	0.009	-0.041	-	-	-	-	-	-
Child is a girl	-0.073***	-0.122***	-0.015	-0.014	-0.009	-0.015	-0.047***	-0.075***
Child is working	-0.033	-0.090*	-0.047	-0.043	0.025	0.022	-0.004	-0.040
Child was ill	0.004	0.037	0.052	0.053	0.128***	0.132***	0.024	0.031
Children consume < 3 times/day	-0.049	-0.049	-0.049	-0.044	-0.012	-0.006	0.000	-0.011
Number of children (Omitted: One)								
Two	0.061	-0.034	-0.003	-0.019	-0.033	-0.039	0.040	-0.057
Three	0.106*	0.032	0.015	0.015	0.074	0.064	0.072*	0.027
Four	0.124**	0.025	0.000	-0.015	0.110**	0.091*	0.092**	0.058
Over four	0.172***	0.133*	0.017	0.039	0.127**	0.101*	0.118***	0.121**
Number of adults	0.022*	0.052**	-0.003	-0.007	-0.018	-0.018	-0.002	0.015
Head is single mother	0.014	-0.114*	-0.084*	-0.082*	-0.075*	-0.070	-0.004	-0.093**
Head is working	0.024	-0.039	-0.001	0.000	-0.016	-0.012	-0.028**	-0.040*
Head was ill	0.008	0.022	0.027	0.025	0.021	0.016	0.000	0.018
Head is christian	0.020	-0.017	-0.003	-0.002	-0.012	-0.013	0.031*	-0.009
Head's education (Omitted: Illiterate)								
Elementary	0.008	-0.039	-0.077*	-0.076*	-0.156***	-0.151***	-0.008	-0.082***
High school	-0.004	-0.003	-0.104*	-0.110*	-0.358***	-0.347***	-0.142**	-0.248***
Above high school	-0.124*	-0.098	-0.190***	-0.191***	-0.477***	-0.465***	-0.289***	-0.331***
Water source is not safe	-0.007	0.066	0.025	0.026				
Toilet facility is not imroved	0.019	-0.030	0.000	-0.002				
Source of light is not improved	0.038	0.056	0.009	0.007				
Cooking fuel is not improved	0.080	0.182*	0.063	0.053				
Floor is made of mud/dung	0.186***	0.092	0.018	0.017				
No information source assets	0.041	0.134***	0.108***	0.111***				
Household faced food price shocks	0.055*	0.101*	0.05	0.048	0.043	0.036	0.025	0.057**
Household faced natural shocks	-0.010	-0.041	-0.055	-0.055	0.009	0.011	0.009	0.002
Health facility is over 5 kms	0.006	0.087	0.006	0.005	-0.026	-0.032	0.001	0.040
Community faced epidemic disease	-0.060	-0.072	-0.019	-0.023	0.023	0.02	0.035	0.031
Rural-urban (Omitted: rural)								
Small towns	0.020	-0.048	-0.022	-0.019	-0.230***	-0.227***	-0.052	-0.183***
Medium and arge towns	-0.029	-0.057	-0.007	-0.004	-0.370***	-0.358***	-0.182***	-0.254***
Region (Omitted: Addis Ababa)								
Amhara	0.041	0.067	-0.009	-0.007	0.111	0.108	0.241**	0.257**
Oromia	0.053	0.032	-0.147**	-0.143**	0.079	0.078	0.262**	0.225**
SNNP	0.084	0.171	-0.039	-0.034	0.087	0.081	0.255**	0.257**
Tigray	0.023	-0.022	0.000	0.000	0.096	0.102	0.201*	0.192*
Other regions	0.057	-0.028	-0.155*	-0.151*	0.13	0.139	0.271**	0.224**
Constant	0.350**	0.177	0.017	0.013	0.840***	0.860***	0.660***	0.680***
N	3400	3400	3400	3400	3400	3400	3400	3400

Notes: *, ** and *** imply statistical significance at 10%, 5% and 1% levels respectively. Model 1 uses as regressors quintiles based on household-level (adult-equivalent) expenditure while Model 2 is based on estimated child-level expenditure. SNNP = Southern Nations, Nationalities and Peoples region. Multidimensional poverty status here is based on non-monetary dimensions and a cut-off k=0.33. The adjusted monetary child poverty modifies the national poverty line (NPL) for u-7 children as 0.6*NPL. All estimates are weighted to make them representative of the corresponding population.

Table A.6.: Dimensions, indicators, weights and deprivation thresholds of child multidimensional deprivation

Dimension (weight)	Indicator (weight)*	Deprived if
D1. Child education (1/3)*	**D11**. Child enrollment (1/6)	A school-age child is not currently attending school.
	D12. Child formal education (1/6)	A school-age child has no formal education.
D2. Child health and nutrition (1/3)	**D21**. Child mortality (1/9)	Any child died over the past 2 years.
	D22. Child sickness (1/9)	Child faced serious illness since two months.
	D23. Child stunting (1/9)	Child (under 7-old) is stunted (height-for-age z-score $<$ -2) (WHO).
D3. Living standards (1/3)		*...child lives in a household with...*
	D31. Safe water (1/18)	Unsafe source of drinking water (WHO).
	D32. Sanitation (1/18)	Unimproved toilet facility (WHO).
	D33. Electricity (1/18)	No access to electricity.
	D34. Cooking fuel (1/18)	No improved cooking fuel (dung, wood or charcoal).
	D35. Floor (1/18)	Floor made of natural, non-permanent material.
	D36. Information (1/18)	No TV/ radio/ mobile phone/ fixed phone.

Notes: *For the under-7 children sample, the two indicators of the child education dimension is proxied by an indicator that a child's biological mother is illiterate.

Table A.7.: Balancing test on differences between PW treated and control households in mean of observed variables before and after matching

Variable	Unmatched/ matched sample	Mean Treated	Mean Control	t-value for diff.	Bias (%)	Bias reduction after matching (%)
Head is female	Unmatched	0.12	0.12	-0.04	-0.1	
	Matched	0.12	0.14	*-0.96*	-4.7	-3332.1
Head's age	Unmatched	42.67	42.64	0.07	0.2	
	Matched	42.67	42.67	*0.00*	0.0	96.3
Number of adults aged 18-60y	Unmatched	2.20	2.18	0.41	1.5	
	Matched	2.20	2.14	*1.32*	6.1	-302.7
Land size (ha)	Unmatched	0.63	0.82	-5.51	-21.8	
	Matched	0.63	0.66	*-0.67*	-2.8	87.1
Livestock holdings (TLU)	Unmatched	2.28	2.41	-1.4	-5.0	
	Matched	2.28	2.22	*0.52*	2.5	50.6
Received income from nonfarm enterprise	Unmatched	0.25	0.25	-0.09	-0.3	
	Matched	0.25	0.27	*-0.82*	-3.9	-1101.5
Living in Amhara region	Unmatched	0.09	0.19	-7.3	-28.9	
	Matched	0.09	0.11	*-1.44*	-6.0	79.3
Living in Oromia region	Unmatched	0.04	0.23	-13.75	-60.7	
	Matched	0.04	0.05	*-1.34*	-3.9	93.6
Living in SNNP region	Unmatched	0.19	0.29	-6.21	-23.5	
	Matched	0.19	0.15	*1.88*	8.0	66.1
Living in Tigray region	Unmatched	0.22	0.09	12.36	37.6	
	Matched	0.22	0.20	*1.03*	5.6	85.1

Summary of the balancing test:

Unmatched/ matched sample	*Ps R2*	*LR chi2*	*p>chi2*	*Mean Bias*	*Med. Bias*	*B*	*R*
Unmatched	0.111	601.57	0	18	13.4	95.8	0.61
Matched	0.005	12.51	0.252	4.4	4.3	16.8	0.94

Notes: The balancing test is based on radius matching with a caliper of 0.05.

Table A.8.: Impacts of PSNP & allied programs on children's resources and well-being: PSM methods

(a) Impacts of PSNP public work

Outcome variable	Kernel	Radius
Child's share in household resources	-0.014*** (0.002)	-0.014*** (0.003)
Log of child's household resources	-0.035 (0.028)	-0.039 (0.028)
Child is monetarily-poor	0.057*** (0.010)	0.055*** (0.011)
Household is monetarily-poor	0.005 (0.017)	0.006 (0.017)
Child is multidimensionally-deprived	0.051** (0.018)	0.052** (0.019)
Child works	0.021*** (0.017)	0.152*** (0.017)
A school-age child not enrolled	0.005 (0.009)	0.005 (0.009)
U-7 child is multidimensionally-deprived	0.004 (0.022)	-0.006 (0.022)
U-7 child is stunted	0.0152 (0.029)	0.014 (0.029)

(b) Impacts of PSNP direct support

Outcome variable	Kernel	Radius
Child's share in household resources	-0.002 (0.006)	-0.008 (0.006)
Log of child's household resources	-0.020 (0.038)	-0.059 (0.039)
Child is monetarily-poor	0.039** (0.018)	0.049** (0.018)
Household is monetarily-poor	-0.083** (0.029)	-0.065** (0.029)
Child is multidimensionally-deprived	0.083*** (0.030)	0.081*** (0.030)
U-7 child is multidimensionally-deprived	-0.010 (0.039)	-0.026 (0.039)
U-7 child is stunted	-0.038 (0.463)	-0.025 (0.470)

(c) Impacts of allied transfers

Outcome variable	Kernel	Radius
Child's share in household resources	0.004 (0.003)	0.007* (0.0035)
Log of child's household resources	-0.086*** (0.028)	-0.080*** (0.029)
Child is monetarily-poor	0.026** (0.013)	0.021* (0.013)
Household is monetarily-poor	0.072*** (0.018)	0.077*** (0.018)
Child is multidimensionally-deprived	0.009 (0.021)	-0.003 (0.021)
U-7 child is multidimensionally-deprived	0.049** (0.021)	0.039 (0.025)
U-7 child is stunted	0.053 (0.029)	0.037 (0.036)

(d) Joint impacts of PSNP and allied transfers

Outcome variable	Kernel	Radius
Child's share in household resources	-0.021*** (0.005)	-0.017*** (0.005)
Log of child's household resources	0.025 (0.042)	-0.018 (0.042)
Child is monetarily-poor	0.037* (0.020)	0.038* (0.020)
Household is monetarily-poor	-0.027 (0.033)	0.005 (0.033)
Child is multidimensionally-deprived	0.074** (0.035)	0.064* (0.036)
U-7 child is multidimensionally-deprived	0.067** (0.034)	0.032 (0.035)
U-7 child is stunted	0.091* (0.057)	0.113* (0.058)

Notes: *, ** and *** imply statistical significance at 10%, 5% and 1% levels respectively. Standard errors in parentheses. All estimates are weighted to make them representative of the corresponding population. U-7=Under-7-year-old. PW=Public work. DS=Direct support. PSNP=Productive safety net program. PSM=Propensity score matching.