AUGUST 2020
No. 138

Authors
Liyousew Borga
Conchita D'Ambrosio
Coordination
Cécilia Poggi (AFD)

Research papers

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Social Protection and Intrahousehold Resource Allocation: Evidence from Three Large-scale Programs

Liyousew G. Borga
Conchita D'Ambrosio
Department of Behavioural and Cognitive Sciences,
University of Luxembourg

Résumé

Les programmes de protection sociale sont devenus une forme populaire d'intervention gouvernementale dans les pays en développement. Les preuves empiriques sont encore rares sur leur efficacitéàréduire les inégalités et la pauvretéau sein des ménages. Àcette fin, nous utilisons des données du projet Young Lives pour évaluer le rôle jouépar trois régimes de protection sociale àgrande échelle - le Productive Safety Net Program (PSNP) en Éthiopie, le National Rural Employment Guarantee Scheme (NREGS) en Inde et le programme conditionnel de transfert monétaire Juntos au Pérou. Nous constatons que ces programmes ne parviennent pas àatteindre tous individus pauvres car sous-alimentés, donc on retrouve aussi des enfants pauvres répartis dans la courbe de distribution des dépenses des ménages par habitant. Toutefois, la participation aux programmes a un impact positif. Les ménages participants au programme connaissent une réduction de la dénutrition infantile une fois inscrits aux programmes. En même temps, ces programmes réussissent àdétourner les ressources des adultes vers les enfants et donc àréduire les inégalités au sein du ménage.

Mots-clés: Protection sociale; Allocation intra-ménage des ressources; Sous nutrition; PSNP; NREGS; Juntos; Young Lives

Abstract

Social-protection schemes have become a popular form of government intervention in developing countries. The empirical evidence is still scant on their effectiveness in reducing within-household inequality and poverty. To this aim we use data from the Young Lives cohort study, and evaluate the role played in it by three large-scale social-protection schemes – the Productive Safety Net Program (PSNP) in Ethiopia, the National Rural Employment Guarantee Scheme (NREGS) in India, and the Juntos conditional cash-transfer program in Peru. We find that these programs fail to reach all poor individuals since undernourished aseven poor children are spread across the distribution of household per capita expenditure. Participating in the programs, however, has some positive impact. Program participant households do experience a reduction in child undernutrition once enrolled in the programs. At the same time, these programs are successful to divert resources from adults to children, and hence to reduce within-household inequality.

Keywords: Social protection; Intra-household resource allocation; Undernutrition; PSNP; NREGS; Juntos; Young lives

Acknowledgements

We acknowledge financial support from the Fonds National de la Recherche Luxembourg and the European Union (EU-AFD Research Facility on Inequalities). We thank Cecilia Poggi, Anda David, Carlos Soto Iguaran, Raphael Cottin and seminar participants at the 2020 International Workshop on the Distributional Impact of Social Protection in Addis Ababa for their helpful comments. All errors are our own. The data used in this study come from Young Lives, a 15-year study of the nature of childhood poverty. Young Lives is funded by UK aid from the Department for International Development (DFID), with co-funding by the Netherlands Ministry of Foreign Affairs and Irish Aid. The views expressed herein must in no way be considered to reflect the official position of the European Union, AFD, Young Lives, the University of Oxford, DFID or other funders.

JEL Classification: D13, I32, I38, J12

Original version: English

Accepted: July 2020

Introduction

Social-protection schemes have become a popular form of government intervention in developing countries. There is also a renewed emphasis on these programs within the international-development community as they are seen as a tool to combat the adverse impacts of natural and economic crises. Many developing countries have adopted social-protection schemes as a means to address extreme poverty, rising inequality, risk and vulnerability. 2.5 billion people in developing and transition countries are covered by safety net programs of various designs, forms and sizes (World Bank, 2018).

A key component for a successful social protection program is proper "targeting" of beneficiaries. Accurate identification of the poor, however, is often difficult in developing countries since income is difficult to observe and consumption data is hard to collect and prone to measurement error (Brown et al., 2019). A further concern with targeting is the presence of intrahousehold inequality. Even though standard poverty measures are based on household percapita consumption, it is individuals that obtain utility from consumption and thus poverty is experienced by individuals not households. If the within-household distribution of resources is skewed, inequality between individuals will be very different from inequality between aggregate households (Cherchye et al., 2018). As a result, conventional measures may underestimate poverty rates for individuals who have less power within the household. Social protection programs that target beneficiaries based on such measures may fail to reach their intended targets, particularly if disadvantaged individuals live in households with percapita consumption above the poverty threshold (Brown et al., 2019).

Households are simply the economic environments in which individuals live. Policy targeting of poor individuals, monitoring of movements in and out of poverty and evaluation of policies designed to reduce poverty would be better if we measured poverty at the individual level (Lechene et al., 2019). Program effectiveness depends not only on the ability to reach households that include deprived individuals, but also on the ability to reach deprived individuals within those households, which will depend on how resources are allocated internally (Brown et al., 2018).

In this paper, using information from a cohort survey in Ethiopia, India, and Peru, we evaluate the role of three large scale social protection programs in reducing intrahousehold inequality and assess the presence and scope of poverty mistargeting. The three programs are the Productive Safety Net Program (PSNP) in Ethiopia, the National Rural Employment Guarantee Act (NREGA) in India, and the Juntos conditional cash-transfer program in Peru.

In particular, we attempt to discover to what extent the programs reduce within-household inequality, and how these programs may lead to a reallocation of intrahousehold resources. We begin by quantifying the extent of nutritional inequality both across and within households. Reducing undernutrition is deemed central to reducing poverty. We then document how total consumption is divided among family members. We further investigate how households' decision making respond to program participation in terms of observed budget allocation on assignable private goods. We identify and compute the share of household resources devoted to children, women and men by observing how each family member's expenditures on a single private good like clothing vary with income, family size, and program coverage.

We find a large incidence of undernutrition in all the three countries. In Ethiopia and India, over 40 percent of children are underweight. To examine how the incidence of undernutrition among children varies with percapita household expenditure, we ranked households from poorest to richest and compared the concentration of undernourished children residing in those households. We find that children in our sample faced similar probability of being undernourished at any point of the percapita expenditure distribution. These findings echo the results in Brown et al. (2018) where they warn that targeting poor households does not necessarily reach poor individuals. Limiting our analysis to the period prior to program implementation, we observe that the incidence of child undernutrition is quite similar between targeted and untargeted (but otherwise comparable) households. We also find that the relationship between household wealth and child nutritional outcomes is very weak. Participating in the programs, however, has some positive impact. Program participant households do experience a reduction in child undernutrition once enrolled in the programs.

In addition, our analysis of the allocation of total resources within families shows that resources are not shared equally with men consuming a larger share of resources as measured by a private assignable good. We estimated the main determinants of the resource shares of men, women, and children and find that program participation induces reallocation of resources from parents to children. We find that the channels through which the programs affect intrahousehold resource allocation are different across the three programs.

Our contribution is twofold. First, we bring together two growing and important strands of literature: the collective household models and estimates of resource shares, and the impact evaluation of social protection programs. The framework of collective model of the household has become the main tool to study intrahousehold resource allocation. We combine this new and evolving method of estimating intrahousehold dynamics with standard impact evaluation methods. Second, evaluation of the three programs is of a wider interest since the programs have various designs, forms and sizes, and they are implemented at scale in a low income context in three countries. Our analyses are based on a unique dataset that collects comparable and comprehensive information in all the three countries. The data offers rich child and household level longitudinal information which allows us to evaluate program impacts over time.

The remainder of the paper is organized as follows. In Section 1 we review the related literature and outline the causal mechanisms of social safety-net. The institutional framework of our study context is introduced in Section 2. We describe the dataset and justify our empirical strategy in Section 3. Our results are discussed in Section 4, while Section 4.5 concludes.

1. Literature Review and Theoretical Framework

There is a potentially important role for redistributive social policies to help poor families in developing countries. Missing insurance markets, imperfect access to credit, behavioral constraints such as present bias and difficulty resisting immediate temptations, and household bargaining constraints can lead to undersaving and subsequently underinvestment. Vulnerable households smooth consumption by making long-term sacrifices that can lead to suboptimal outcomes for the underpowered, often women and children (Hanna and Karlan, 2017)

Social safety-net programs protect vulnerable households from impacts of economic shocks, natural disasters, and other crises. An estimated 36 percent of the very poor escaped extreme poverty because of social safety nets, providing clear evidence that social safety net programs are making a substantial impact in the global fight against poverty (World Bank, 2018).

While most social protection initiatives have the common goal of reducing extreme poverty, the specificity of interventions and the intended pathways out of extreme poverty differ (Sulaiman, 2016). Hence, comparing the effectiveness of different types of social protection programs is critical.

1.1. Causal Mechanisms of the Impact of Social Protection

Conditional Cash Transfers (CCTs): Conditional cash transfers are payments that are targeted to the poor and made conditional on certain behaviors of recipient households. The objective is providing poor households with a minimum consumption floor and encouraging the accumulation of human capital to tackle intergenerational transmission of poverty (Fiszbein and Schady, 2009).

Three causal mechanisms can be identified through which CCTs may impact the household economy. The first is through an income effect whereby CCTs provide liquidity constrained poor households the means to undertake human capital investments. The second is through a substitution effect as the conditions attached to the transfer increase the opportunity costs of not taking children to health clinics and sending them to school. Third, there may be a distributional effect where the transfers lead to an effect on intrahousehold resource allocation (Kabeer and Waddington, 2015).

In the case of *Juntos*, the mechanisms through which beneficiary children could improve their nutritional status are an increase in growth monitoring controls and vaccinations; an increase in child consumption due to the cash transfers; and an increase in health inputs such as access to clean water and sanitation due to the cash transfers (Sanchez et al., 2020).

Systematic reviews of evidence on the impacts of cash transfer programs indicate that transfers generally have been well targeted to poor households, have raised consumption levels, and have reduced poverty (Fiszbein and Schady, 2009). On the other hand, qualitative evidence reveals multiple challenges facing CCTs such as extra-official conditionalities, elite capture, or failure to comply with instructions by beneficiaries (Olivier de Sardan and Piccoli, 2017; Cookson, 2015). CCTs also force some beneficiary households to incur a costly distortion to their own behavior for the sake of short-run financial gain. In addition, despite their positive short-term impacts, few studies investigate whether these short-term gains eventually translate into sustained long-term benefits.

Public Works Programs: Public works programs are public interventions that provide employment to poor households and individuals at relatively low wages (Gehrke and Hartwig, 2018). The primary goal of most workfare programs is to help reduce poverty by transferring income to the poor and vulnerable, while using the labor provided by program participants to contribute to the creation of public assets (Gehrke and Hartwig, 2018; Alderman and Yemtsov, 2014).

There are a few mechanisms through which public works programs could trigger productive effects. First, the programs provide employment on demand and the wage paid to those working may have a more or less effective insurance function thereby improving individual risk management and increasing productive investments (Gehrke and Hartwig, 2018). Second, workfare programs may affect labor market equilibrium. The programs could crowd out the labor supply of other household members, or if the workfare wages are not set low enough they may crowd out informal work by the participant. Third, some programs include an implicit or explicit training component, through which participants may improve their employability or boost the chances of earning income from self-employment. Fourth, through the productive assets created, which are intended to benefit the wider community, market access could be improved through road construction which in turn increase trade and production (Gehrke and Hartwig, 2018).

There is a growing literature that attempts to document the different effects of public works programs such as the general equilibrium price and wage effects (Cunha et al., 2017; Berg et al., 2018), labor market responses (Afridi et al., 2016; Imbert and Papp, 2015; Zimmermann, 2014), and effects on risk-sharing networks (Angelucci and De Giorgi, 2009). A few other papers also investigate the effects of social-protection programs on household consumption (Bose, 2017), and household's management of production risks (Gehrke, 2017).

The empirical evidence on the effectiveness of these programs is mixed.[1] There is evidence showing that workfare programs have been successful in alleviating the negative effects of food price hikes, economic downturns and other crises (Bertrand et al., 2017; Galasso and Ravallion, 2004). However, they are demanding from an administrative perspective and comparatively expensive to run (Gehrke and Hartwig, 2018). Studies also find that public works programs may have some unintended consequences, notably on human capital accumulation (Shah and Steinberg, 2015; Li and Sekhri, 2019).

[1]Most evidence to date comes from NREGA, and uses the same method (Difference-in-Differences approach between districts).

1.2. Individual Deprivation and Resource Shares

Living standards, such as income poverty and material deprivation, are often assessed using household level indicators with the underlying assumption that household resources are shared to the equal benefit of all household members. While it is true that poverty is an individual deprivation, social protection programs are also targeted on the basis of expenditure surveys that generally collect consumption data at the level of households (Brown et al., 2018). Equating the household with the individual, however, is particularly problematic since household level measures are gender blind and ignore intrahousehold differences in resource allocation.

One of the key components of social protection programs is reducing undernutrition as it is deemed central to reducing poverty. Undernutrition is implicated in child mortality, causes much illness, and leads to cognitive underdevelopment. The evidence regarding the impact of income on nutritional outcomes is mixed. Deaton and Drèze (2009) find that higher percapita incomes in India do not translate into higher caloric intake or better nutritional outcomes on average. While Hong et al. (2006) show that children in the poorest 20 percent of households in Bangladesh are more than three times as likely to suffer from stunting as children from the top 20 percent of households; Brown et al. (2019) highlight that undernourished individuals are spread across the household percapita expenditure distribution.

Dunbar et al. (2013) find poverty rates for children in Malawi that are much higher than those of men. Calvi (2019) shows that intrahousehold gender inequality and gender asymmetry in poverty can account for a substantial fraction of Indian "missing women". She finds that poverty rate among older married women in India increases with age, primarily because their share of household resources declines with age. De Vreyer and Lambert (2018) report that intrahousehold consumption inequalities are shown to account for nearly 14 percent of total inequality in Senegal. Brown et al. (2018) document that around one half of undernourished women and children in sub-Saharan Africa are not found in the poorest 40 percent of households. D'Souza and Tandon (2019) and Brown et al. (2019) both find substantial inequities in the intrahousehold distribution of calories and nutrients as well as within-household differences in total consumption in Bangladesh.

Although intuitively compelling, it is not easy to disentangle household expenditure from individual consumption. An important tool for measuring the within-household distribution of consumption is the "resource share", defined as the fraction of total household consumption consumed by each member (Lechene et al., 2019). These shares are often interpreted as measures of the bargaining power of each household member (Dunbar et al., 2019).[2]

Resource shares are key components of collective household models, going back to the earliest frameworks of Chiappori (1988, 1992). Identification of resource shares, however, is difficult since consumption is typically measured at the household level, and many goods

[2] Resource share are sometimes determined by altruism, particularly the shares claimed by children. See Dunbar et al. (2019) for a thorough review and formal identification.

are jointly consumed or shared. Browning et al. (2013) demonstrate that under the assumption of preference stability, we can identify the household's resource sharing rule or members' bargaining power. With a weaker preference restriction and an assignable good, Dunbar et al. (2013, hereafter denoted DLP) show how to identify levels of resource shares semi-parametrically for adults and children without price variation.

In the DLP model resource shares in a given household type are identified under the assumption that resource shares don't vary with household expenditure and preferences are similar across people, or similar across types. The first restriction that resource shares are independent of household expenditure seems a strong assumption. However, Menon et al. (2012) for Italian households, Bargain et al. (2018) for Bangladesh, and Cherchye et al. (2015) for Dutch households, all find that resource shares appear to be independent of total household expenditure.

Identifying resource share levels help address policy questions such as uncovering the prevalence of women's poverty or child deprivation. A growing literature has applied Engel curve comparisons to quantify intrahousehold inequality in developing countries. These methods have been used to study inequality between children and adults (Dunbar et al., 2013; Bargain et al., 2018; Dunbar et al., 2019), control of resources and bargaining power (Tommasi, 2019), and the wellbeing of older women (Calvi, 2019).

1.3. Empirical Evidence

A number of impact evaluations have studied the effects of the three social safety-net programs that we are investigating. Imbert and Papp (2015) estimate the effect of NREGA on private employment and wages and find that public sector hiring crowded out private sector work and increased private sector wages. Gehrke (2017) reports that households with access to the program are more likely to take riskier agricultural investment decisions. Evidence from Andhra Pradesh India suggests that a mother's participation in the labor force increases her children's time spent in school and leads to better grade progression (Afridi et al., 2016). However, there is also contrary evidence of children dropping out of school to help with household chores (Li and Sekhri, 2019).

Dasgupta (2017) also uses the Young Lives data from India to examine the causal impact of NREGA in mitigating effects of negative rainfall shocks in early life on children's long-term health outcomes and finds significant positive impact.

Using the Young Lives survey data from Peru, Andersen et al. (2015) estimate the link between participation in the *Juntos* CCT with anthropometry, language development, and school achievement among young children and show that participation was associated with better height-for-age scores among boys. Similarly, using the same sample of children, Sanchez et al. (2020) find that exposure to *Juntos* led to an improvement in nutritional status and in cognitive achievement, both of which were larger for those initially exposed during the first 4 years of life.

Porter and Goyal (2016) investigate the impact of PSNP in Ethiopia on child nutritional outcomes and find a small but positive medium-term impact for children aged 5–15. Berhane et al. (2014) study the impact of the duration of participation in Ethiopia's PSNP and show that five years participation raises livestock holdings when compared to one year participation. Gilligan et al. (2009) also estimate the impact of the PSNP on household welfare, asset ownership, and agricultural and economic activity in 2006, after the first year of the project and find only weak impacts of the PSNP. Similarly, Andersson et al. (2011) find some evidence that participation in PSNP increased the number of trees planted, but there was no increase in their livestock holdings. A review by GIZ (2018) concludes that none of the studies conducted on the PSNP provides convincing and robust empirical evidence that the program can sustainably boost the total income, expenditure or (non-food) consumption of beneficiary households.

Our paper complements this rich body of work. The literature is scant when it comes to evaluating the effect of social-protection schemes in reducing intrahousehold inequalities and poverty. In addition, the current state of knowledge about the impacts of the schemes is mostly restricted to outcomes measured in the short run.

2. Institutional Background

We examine the effects of three large scale social protection programs in reducing within-household inequalities and poverty to provide a holistic understanding on the drivers and consequences of these phenomena and how they are influenced by public policies. We chose these programs for a number of reasons. First, they are very large projects that involve a coordinated effort of governments, donors local authorities, and individual households. Second, the programs cover three countries that uniquely offer diverse social, cultural, political, and economic context to draw lessons from. Third, the assessment will provide a rich knowledge and understanding of the targeting, incidence, and heterogeneity of effects of the programs that future policies can be based on.

2.1. Ethiopia: The Productive Safety Net Program (PSNP)

The Productive Safety Net Program (PSNP) is a public program that started in 2005 by the government of Ethiopia and a consortium of donors as a safety net, targeting transfers to poor households through either public works or direct support. The aim is to enable households to smooth consumption without the need to sell productive assets in lean periods. The public works segment of the program pays selected beneficiaries for their labor on labor-intensive projects designed to build community assets. In addition, by reducing seasonal liquidity constraints, it is intended to stimulate investments as well (Andersson et al., 2011; Gilligan et al., 2009).

PSNP transfers are provided to households on a monthly basis for six consecutive months. All PSNP beneficiaries receive the same transfer regardless of whether they participate in Public

Works or Direct Support. The cash and food transfers are set at the level required to smooth household consumption or fill the food gap. In 2009 (our first post-program period), the daily cash wage rate was 10 birr ($\approx 1USD$) and the food transfer was 3 kg of cereal. Each Public Works household member is entitled to receive a transfer based on 5 days of work at the prevailing cash or food wage rate (Wiseman et al., 2010).

The selection of beneficiaries for both the public works and direct support components of the safety net program uses a mix of administrative criteria and community input. When the program began in 2005, historical data on food aid allocations were used to select beneficiary districts (*woredas*). Within the *woredas*, local administrators selected the chronically food-insecure *kebeles* (lowest administrative unit), assigning the *woreda*'s "PSNP quota" among these areas (Berhane et al., 2014). Eligibility for the PSNP at the household-level focused on the household's chronic history of food need, level of the food gap or unmet need, and household labor available for work. Communities selected beneficiaries in collaboration with the *kebeles* refining the selection based on household assets (landholdings), and income from non-agricultural activities and from alternative sources of employment (Gilligan et al., 2009; Berhane et al., 2014).

2.2. India: The National Rural Employment Guarantee Act (NREGA)

The National Rural Employment Guarantee Act (NREGA) was passed in 2005, and the scheme began to roll-out in February 2006. The act entitles every household in rural India to 100 days of work per year at a state-level minimum wage to rural households willing to supply manual labor on local public works. To obtain work on a project, interested adult applicants lodge an application for a job card at their local *Gram Panchayat* (the lowest government administrative units). Following verification, a Job Card is issued and workers can start applying for work. If an applicant is not assigned to a project, they are eligible for unemployment compensation. Applicants cannot choose the project (Shah and Steinberg, 2015).

The program was implemented in a phased manner using a "backwardness index" developed by the planning commission. The index was computed on the basis of agricultural productivity per worker, agricultural wage rate, and composition of scheduled caste/scheduled tribe in the population. The act was then gradually introduced throughout India starting with 200 of the poorest districts in February 2006, extending to 130 districts in April 2007, and to the rest of rural India in April 2008. In the Andhra Pradesh region, where our data is from, four of the Young Lives sample districts (comprising 66% of the sample) were covered by the NREGA in the first phase of implementation in 2006 (Dasgupta, 2017).

2.3. Peru: Juntos

The conditional cash transfer program *Juntos* was established in 2005 targeting poor families mainly in rural areas in Peru. Its geographical coverage has increased gradually over time, after initially serving 70 districts in the southern highlands, to include other areas of the highlands and the Amazonian jungle. *Juntos* eligibility is based on a three stage selection process: selection of eligible districts, selection of eligible households within those districts, and a community level validation. Exposure to violence due to guerrilla activity, poverty level, unmet basic needs, and level of child malnutrition are the main variables considered in district selection. Household eligibility within districts was determined by a proxy means test formula that is computed based on census data. In addition, only households with children under the age of 14 years or at least one pregnant woman were selected. The final stage is a community level validation that was performed by community members, local authorities and representatives of the Ministries of Education and Health. Beneficiary households received transfers of 100 soles ($\approx$ 30 US dollars) each month regardless of household composition, representing about 15% of beneficiary household spending (Andersen et al., 2015; Perova and Vakis, 2012).

The conditions for transfers under *Juntos* depend on the age and eligibility of the participant. Members of households with children younger than five years of age as well as households with a pregnant or lactating woman are required to attend regular health care visits. Children aged between six and 14 years who had not completed primary school are required to attend school at least 85% of the days (Andersen et al., 2015).

3. Methods

3.1. Data

The data for this study are from the *Young Lives Project*, a study tracking the lives of children in four countries: Ethiopia, India (in the states of Andhra Pradesh and Telangana), Peru and Vietnam over 15 years. In each study country, the *Young Lives* surveys involve tracking 3,000 children in two cohorts. The younger cohort consists of 2,000 children who were born between January 2001 and May 2002. The older cohort consists of approximately 1,000 children from each country born in 1994-95. Currently, five survey waves are available: the baseline round in 2002 and four followup waves in 2006, 2009, 2013 and 2016.

One of the advantages of the Young Lives data is that it covers a wide range of well-being indicators including asset holdings, consumption expenditure, physical and emotional health, nutrition, education and material wealth, as well as child development indicators. This range of well-being indicators is seldom covered in national representative samples, which typically need to narrow their focus towards people's ability to access to basic services. The longitudinal nature of the data allows us to document the evolution of poverty and inequality over time. More detailed information about the sample design, study sites, attrition, and characteristics of the sample is given in appendix A.

3.1.1. Variable Definition

Household Expenditure: The Young Lives survey documents detailed information regarding the household wealth, consumption aggregates and ownership of land and livestock.[3] The *wealth index* is estimated from three sub indexes (all of which have equal weights) – the housing quality index, the access to services index, and the consumer durable index.[4]

The household questionnaire collects detailed data on expenditures within the last 12 months. The 12 month recall has the disadvantage of recall bias but this is likely to be outweighed by the advantage of more complete reporting compared to diary-based data collection that only records expenditures over a few weeks. Consumption aggregates data include total percapita expenditure, percapita food consumption, and percapital non-food expenditure, all in both nominal and real terms. Food consumption is aggregated based on self-reported food items consumed in the last 2 weeks from different sources (e.g. purchased, home-produced, from stock). Non-food consumption sums up all non-food items, such as expenditure on education, health, clothing and footwear, or other non-food items.

We use household expenditures on clothing and shoes for the men, women, boys, and girls as our assignable goods. We exclude expenditures on school uniforms from the analysis as they are less likely to be discretionary expenditures shaped by children's preferences but rather parental investment decisions.

Household characteristics: Information on the characteristics of the household head (age, gender, education), the number of household members by sex and age groups, and size of the household is also available in the dataset, together with information on other time-invariant characteristics such as gender of household members, ethnicity, religion, and language.

Health and nutrition: Health and anthropometric information contained in the dataset includes weight, height, and the body mass index from which z-scores for weight-for-height, height-for-age, and BMI-for age were estimated using WHO references tables. We use these information to compute stunting, wasting and underweight indicators. Stunting, or low height for age, is caused by long-term insufficient nutrient intake and

[3] In two of the five waves, annual household income and its potential sources are recorded in the data.

[4] The housing quality index is a simple average of the sleeping rooms per person, indicator variables that take the value of 1 if the quality of main materials of dwelling (walls, roof and floor) satisfy basic norms of quality. The access to services index is a simple average of indicators such as access to electricity, safe drinking water, sanitation and adequate fuels for cooking. The consumer durable index averages a set of dummy variables which take the value of 1 if a household member owns at least one of each consumer durable.

frequent infections. Wasting, or low weight for height, is usually the result of acute significant food shortage and/or disease.[5]

3.2. Descriptive Statistics

We present summary statistics for the main variables and controls used in the paper in Tables B.1-B.3 in appendix B. We split the sample by participation status (program participants, and non-participants) as well as into pre and post program implementation periods. We consult round two survey (2006) for the pre-program period and averaged outcomes reported in rounds 3-5 (2009 - 2016) for the post-program period.[6]

Similar patterns are apparent in all the three samples. On average, program participant households have heads with fewer years of education, larger household size, and lower access to basic services. Participant households are also relatively poorer with smaller wealth index figures, and more susceptible to drought induced shocks.

3.3. Identification

To identify program treatment status of households, we employ different strategies that address potential threats to identification. We exploit the roll-out of the social-protection programs across districts in India to causally identify the impact of the schemes on a set of well-being indicators. We use a propensity score matching technique for the other countries to construct a valid control group by using a set of characteristics assumed not to be affected by the treatment. This method is especially useful in situations in which few unexposed units of observation are comparable to the exposed units across all covariates, and when the units of observation can be compared across a high number of pre-program covariates (Dehejia and Wahba, 2002).

NREGA: We first exploit the differences in timing and geography between early and late treatment districts to estimate the *intent-to-treat* effects of the program. Furthermore, the surveys that we use directly ask household members whether they participate in NREGA which allows us to estimate average treatment effects as well. The Young Lives survey is conducted in six rural districts of the Andhra Pradesh state, of which four received NREGA programming between April 2006 and March 2007. The remaining two districts did not receive programming until April 2007, after the second Young Lives survey, allowing for clean identification of program treatment status in the data. The Phase I districts compose

[5] The Stata commands zscore06 and zanthro are used to convert height (in centimeters) and weight (in kilograms) along with age in months into a standardized variable using the WHO 2006 classification.

[6] Respondents were asked to report their month and year of *Juntos* initiation in the data. *Juntos* officially started in 2005, and about 2% of our sample started receiving transfers in 2006. Hence, in our pre-post program analysis we exclude these households due to lack of sufficient baseline data. Similarly Gilligan et al. (2009) and Porter and Goyal (2016) show that PSNP transfers were delayed during the first year of implementation of the PSNP (2005/6), and impact was not experienced until after wave 2 of our data was collected, justifying the use of 2006 as our baseline.

the treatment group in our study, while the Phase II and III districts serve as the control group. The subsequent three waves of the Young Lives survey will allow us to measure the short, medium term and longer-term effects of NREGA treatment.

PSNP: Treatment is largely based on asset and income variables that are observable both to the policy makers and to the analyst. According to the PSNP implementation manual and previous studies (Berhane et al., 2014; Hoddinott et al., 2012; Andersson et al., 2011; Sharp et al., 2006), the variables used for selection are status of assets, income from non-agricultural activities and alternative employment, and support from relatives or community. Hence, we conducted propensity score matching methods to construct a comparison group of households with a similar probability of being treated based on these observable characteristics. Porter and Goyal (2016) use similar approach to ours to study the impact of PSNP on child nutrition.

Juntos: We identify controls based on propensity score matching techniques. Following Andersen et al. (2015), exposure to the Juntos program was predicted by using a probit model based on round one characteristics including household wealth, number of household members, rural or urban household location, number of household members who were age six and younger (and age 6-14), indigenous language as a first language, mother's characteristics, and interaction and polynomial terms.

Figure C.1 in Appendix C shows that the common support for both Ethiopian and Peruvian sample is complete; that is, for each beneficiary household, we have a sufficient number of close matches from the "control" group.

3.4. Analysis of Undernutrition and Household Expenditure

Undernutrition denotes insufficient intake of energy and nutrients to meet an individual's needs to maintain good health. It is often a result of poor dietary intake or disease and is usually a consequence of food insecurity or poor health environments. It is also an important dimension of individual poverty. Combating undernutrition in developing countries is a key component of the Sustainable Development Goals which stresses that making headway against undernutrition will have wide-reaching consequences for improving health and working to end poverty (Brown et al., 2019).

One way to measure undernutrition is to use anthropometric indicators as they are more sensitive over the full spectrum of malnutrition than other indicators. The basic measurements taken from children include age, sex, weight, length, and height, which are then compared to the sex-specific and WHO-guided international reference population as a way to assess the level of undernutrition. We analyze the relationship between anthropometric measures and household expenditure, and assess the extent of nutritional inequality within households. We then construct concentration curves using an approach similar to Brown et al. (2018) to examine how the incidence of undernutrition, and hence poverty, varies with percapita household expenditure.

3.5. Resource Shares

Following Chiappori (1988), several studies use a collective household model, where each individual has their own utility function and the household reaches a Pareto efficient allocation of goods. DLP show how to obtain a measure of individual-level consumption by identifying resource shares. They demonstrate that resource shares can be identified by observing how expenditure on assignable goods varies with household income and size. A good is assignable if it is consumed exclusively by a particular type of person in the household (e.g., men's clothing). DLP obtain identification by comparing Engel curves for the assignable goods within the framework of a structural model.

Browning et al. (2013, hereinafter BCL) provide a general efficient collective household model with scale economies in consumption, preference heterogeneity across people, and possibly unequal distributions of household resources. DLP take that model and impose sufficient restrictions on it to make it implementable with real-world data via nonlinear estimation of household-level Engel curves for assignable goods. In the subsequent paragraphs we outline the estimation procedure of this model made simple by Lechene et al. (2019).

Let $h = 1, \ldots, H$ index households. Let t index the types of individuals in the household (m for adult male, f for adult female and c for children). Let the household consist of n_h^t individuals of each type t, and let $n_h = \sum_t n_h^t$ be the total number of individuals in household h. Let y_h denote the observed household expenditure (budget). Each type of person gets a shadow budget, and these shadow budgets must add up to the full household budget.

The share of the household budget allocated to a type t person is called their resource share, denoted by η_h^t. Resource shares sum to 1 in each household h so that $\sum_t \eta_h^t = 1$. They may in general depend on household budgets, prices, household and individual characteristics (including so-called "distribution factors"). They can vary across the types of individuals in the household, but we assume that resources are here distributed equally.[7] We wish to identify resource shares from household-level consumption data without observing market prices.

Resource shares provide a measure of consumption within the household: higher resource shares mean higher consumption. Second, they identify inequality within the household: if resource shares are very unequal, then there is a lot of inequality within the household. Third, resource shares may respond to policy variables in the context of poverty reduction. If we can find policy variables that shift resource shares upwards for disadvantaged individuals, then their poverty rates may decrease.

Following DLP, we define private goods as those that cannot be shared or consumed jointly

[7] For example, in a household with two children where the children's resource share is $\eta_h^t = 0.40$, we have that 40 percent of the household budget is allocated to children, with 20 percent going to each child.

by more than one person, and assignable goods if they are consumed by an observable individual household member. Let $\eta^t(y)$ be the resource share of person t when the household faces a fixed market price vector $\mathbf{p}$. Assume that shadow prices are linear in market prices, with $\mathbf{p}_h = \mathbf{A}_h\mathbf{p}$ for some diagonal matrix $\mathbf{A}_h$.[8] BCL provide identification results for more general relationships, but this restriction substantially simplifies the Engel curves. Let a private assignable good (e.g., clothing) be observed for each type of person in a collective household. Let $w^t(y)$ be the Engel curve function for a person of type t for their assignable good. This gives the fraction of total expenditure commanded by that good for a person of that type if they lived alone and faced the shadow price vector $\mathbf{p}$ and a budget y.

The household Engel curve for an assignable good, evaluated at the market price vector $\mathbf{p}$, is given by:

$$W^t(y) = \eta^t(y)w^t(\eta^t(y)y/n^t). \tag{1}$$

The relationship in equation 1 states that the household's Engel curves (at market prices, held fixed) for an assignable good consumed by $t = m, f, c$ is equal to the resource shares of the relevant people times their Engel curves.

BCL show that if we observed the functions $w^t(y)$ and the functions $W^t(y)$, then the resource shares $\eta^t(y)$ are identified. DLP provide sufficient restrictions on the model such that resource shares are identified from data on just Engel curve functions of collective households facing a single price vector. They impose the following assumptions: i) resource shares do not depend on the household budget, so that $\eta^t(y) = \eta^t$; ii) individual Engel curve functions are given by an Almost Ideal demand system of Deaton and Muellbauer (1980), so that $w^t(y) = \alpha^t + \beta^t \ln y$; and iii) that preferences are similar, but not identical, across people, such that $\beta^t = \beta$.

Substituting these assumptions into (1) gives

$$W^t(y) = \eta^t \left(\alpha^t + \beta^t \left(\ln y + \ln \eta^t - \ln n^t\right)\right). \tag{2}$$

Lechene et al. (2019) provide a theory-consistent linearisation of the DLP model and extend it to accommodate multiple household types and demographic characteristics. To achieve this linearisation, we rewrite equation (2) with a subscript h on all observed variables, and an additive error term as:

$$W_h^t = a_h^t + b^t \ln y_h + \varepsilon_h^t \tag{3}$$

where

$$a_h^t = \eta^t\alpha^t + \eta^t\beta \ln \eta^t - \eta^t\beta \ln n_h^t$$

and

$$b^t = \eta^t\beta.$$

[8]Shadow prices for goods are the within-household prices of consumption. They are assumed be the same for all household members. Shadow prices differ from market prices because some goods may be shared. The more shareable is the good, the lower is its shadow price of consumption within the household. For goods that are not shared, the shadow price equals the market price.

Lechene et al. (2019) suggest that we can approximate the a_h^t term with

$$a_h^t = a_0^t + a_n^t \ln n_h^t.$$

With this approximation the model may be estimated by a linear regression of the observed household-level assignable good expenditure share. Lechene et al. (2019) further show how we can extend this model to include demographic preference shifters and distribution factors. Distribution factors, are defined as variables which affect bargaining power, but which do not affect preferences over goods or scale economies (Dunbar et al., 2013).

Let **z** be all variables that affect preferences, and let **d** be distribution factors that affect resource shares but not preferences. Denote $\mathbf{m} = [\mathbf{z} \quad \mathbf{d}]$ as the vector of all variables affecting resource shares η^t. Substituting this into equation (2), and expanding out the terms, we get:

$$\begin{aligned} W^t(y,m) = \eta^t(\mathbf{m})\alpha^t(\mathbf{z}) + \eta^t(\mathbf{m})\beta(\mathbf{z})\ln y + \eta^t(\mathbf{m})\beta(\mathbf{z})\ln \eta^t(\mathbf{m}) - \\ \eta^t(\mathbf{m})\beta(\mathbf{z})\ln n^t. \end{aligned} \tag{4}$$

Lechene et al. (2019) discuss in great detail how this model may be estimated by ordinary least squares (OLS), or with seemingly unrelated regression (SUR). We estimate equation (2) using seemingly unrelated regression method.

4. Results

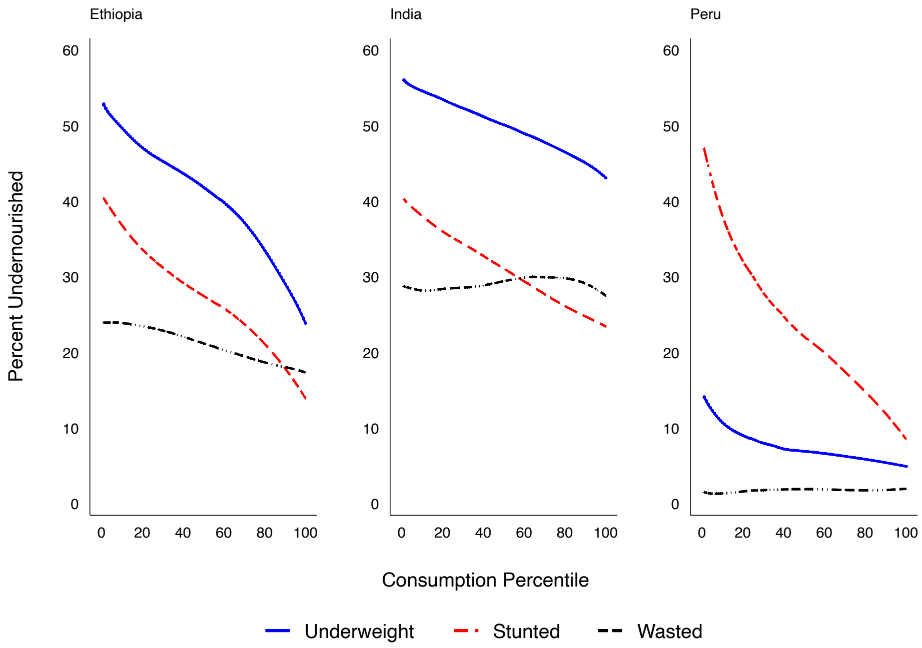
4.1. Social Protection and Nutrition Inequality

We begin our evaluation by measuring individual poverty using nutritional outcomes. We analyze the relationship between anthropometric measures and household wealth and expenditure and assess the extent of nutritional inequality among children.

Figure 1 plots the incidence of the three anthropometric indices against percentiles of the household per capita expenditure for Ethiopia, India and Peru. We observe a large incidence of undernutrition in all the three countries. In Ethiopia and India, over 40 percent of children are underweight. More than 30 percent are categorized as stunted and wasted in India. Figures C.2 and C.6 in Appendix C further show that program participation status both before and after the program implementation does not alter the overall incidence of undernutrition in the two countries. We find slightly different results for Peru. Incidence of child undernutrition is lower; particularly the incidence of wasting and underweight. Stunting on the other hand is relatively prevalent, where about 30 percent of children were stunted prior to *Juntos* implementation. Post program incidence, however, declined markedly (figure C.6). Since CCTs attach conditionalities on health, it is not surprising that we find a positive impact of *Juntos* on undernutrition.

There is some evidence of a wealth effect in which nutritional status improves with a higher wealth index. However, the wealth effect is very weak in Ethiopia and India, as well as for the wasting and underweight indicators in Peru.[9] Our results are consistent with the finding of Brown et al. (2018) where they showed that three-quarters of underweight women and undernourished children are not found in the poorest 20 percent of households in 30 countries in sub-Saharan Africa.

Figure 1: Nutritional Outcomes and Household Consumption



Notes: The graphs show proportions of underweight, stunted and wasted children across the distribution of household per capita expenditure percentiles in 2006. Households are ranked by their pre-progam expenditure level and placed into consumption percentiles.

One concern with the the relatively weak relationship between household wealth and undernutrition, particularly among poorer households, could be selection bias due to child mortality among the undernourished. However, this is not the case in our sample as child mortality is extremely low in the cohort data. Our results are robust to restricting the sample to children who survived until the fifth wave (age 15 for the younger cohort).[10]

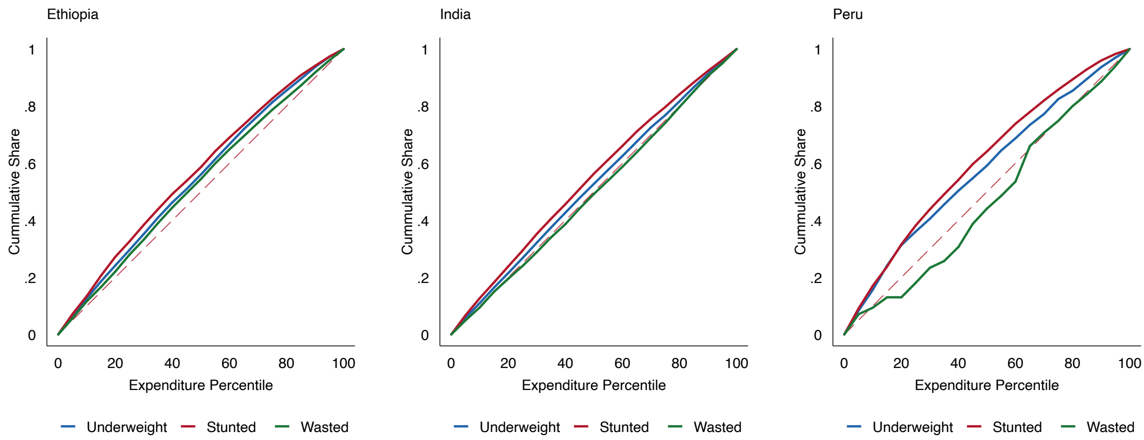
Next, we ask if undernourished children tend to be concentrated in the poorer strata of household expenditure or not. To examine how the incidence of undernutrition among children varies with percapita household expenditure, we construct concentration curves using an approach similar to Brown et al. (2018). These curves show the cumulative share of undernourished individuals by cumulative household expenditure and wealth percentile (that is, households ranked from poorest to richest). A higher degree of concavity implies that a larger share of undernourished children are found in the poorest households.

Figure 2 presents concentration curves for children in Ethiopia, India and Peru. We rank

[9]We also plot the undernutrition indicators using household consumption data and find similar results. These plots are reported in Appendix C.

[10]A second concern regarding our results is potential measurement error in anthropometric measures. However, according to Barnett et al. (2012) these measurements were undertaken by trained fieldworkers who overall produced high-quality fieldwork.

Figure 2: Undernutrition Concentration Curves



Notes: The graphs show the concentration curves for the cumulative proportion of children who are underweight, stunted and wasted at each household consumption percentile. Households are ranked by their pre-progam expenditure level and placed into consumption percentiles.

households based on their total expenditure prior to the program. We report similar plots for both pre and post program periods and by participation status in Appendix C. In Ethiopia and India, while there is some concavity, the curves tend to be fairly close to the diagonal line. Children in our sample faced similar probability of being undernourished at any point of the percapita expenditure distribution. For instance, only around 60 percent of undernourished children in Ethiopia are found in the bottom half of the percapita expenditure distribution. In Peru, however, the concentration curve for stunting exhibits a marked concavity implying stunted children tend to be concentrated in the poorer strata of household wealth. We find no evidence indicating that undernutrition status varies with gender. The results are also largely similar when using household wealth percentiles instead of consumption (see Appendix C for these figures).

Our results cast some doubt on relying solely on household consumption and wealth measures to target nutritionally-deprived individuals. Given the greater emphasis placed on undernutrition as a measurement of individual poverty, and given the strong evidence on the longer-term costs of undernutrition in children, it is imperative that targeting should be considered from a broader perspective. Policy effectiveness in this regard crucially depends on other factors such as the local health environment and intrahousehold resource allocation (Brown et al., 2018).

4.2. Resource Shares

The results in the previous section show that undernutrition of children is spread widely across the household wealth and consumption distributions, and this can be attributed to intrahousehold inequality in resource allocation. In this subsection, we estimate how total household expenditure is divided among family members to further investigate the presence and extent of intrahousehold inequality and how participation in social protection programs mediates this effect.

Table D.2 in Appendix D gives summary statistics of our assignable good for the sample families with up to four children. Our private assignable good is the sum of clothing and footwear expenditures. In all three countries, men have more resource share than women on average. As the number of children residing in the household increases, it appears that resources are diverted from the parents, but more from the mother.

We estimate equation (2) using seemingly unrelated regression method as outlined in Section 3.5. We include some demographic variables, which may affect preferences, and "distribution factors" that may affect resource shares and not preferences (Dunbar et al., 2013). Our demographic variables include household head characteristics (age, gender, years of eduction), time dummies, region dummies, and indicators for the number of female and male children and adults present by age groups. Our distribution factor is a dummy indicating whether the household is a PSNP or Juntos participant (or in the Indian sample, the household resides in districts that implemented NREGA early).

Dunbar et al. (2019) argue that some interesting policy questions can be addressed with this approach, such as identifying whether a policy that changes a distribution factor (for example, participation in social protection program) actually increases women's and children's share of resources within the household.

Tables 1 - 3 report the estimated coefficients of the main covariates for the resource shares of men (η_m), women (η_f) and children (η_c).[11] We report only coefficients relating to a few key demographic variables and our distribution factor which have potential policy implications.

The first four rows of tables 1 - 3 reveal that the total resources of men and women decline with the number of children. However, it is also evident that this decline is not shared evenly across men and women. For three or fewer children, women mostly bear the decline in resource shares, particularly in India and Peru. In Ethiopia, men's resource shares also decline for the third and fourth child.

The variable of interest for our study is the program participation indicator (PSNP in Table 1, NREGA in Table 2, and *Juntos* in Table 3). We find that the programs divert resources from adults to children. In all three specifications, the effect is negative for the father, and always significant. In India and Peru, the coefficient is negative for the mother as well. The effect on the men is larger in magnitude in Ethiopia and Peru, which implies that more resources are redistributed from men to children (and also to the women in Ethiopia). In India, however, the

[11] The rest of the estimated coefficients of the model are reported in table D.3 in appendix D.

magnitude is slightly larger for women.

Table 1: Resource shares of men, women and children: Ethiopia

	Men	Women	Children
One child	-0.004	-0.024***	0.027***
	(0.008)	(0.007)	(0.009)
Two children	-0.004	-0.023***	0.026***
	(0.007)	(0.006)	(0.008)
Three children	-0.014**	-0.016**	0.029***
	(0.007)	(0.006)	(0.009)
Four children	-0.010	-0.015**	0.024**
	(0.008)	(0.007)	(0.010)
PSNP	-0.029***	0.004	0.027***
	(0.006)	(0.005)	(0.007)
2009 Wave	-0.009	-0.009*	0.017**
	(0.006)	(0.005)	(0.008)
2012 Wave	-0.009	-0.015***	0.024***
	(0.006)	(0.006)	(0.008)
2016 Wave	-0.014**	-0.032***	0.044***
	(0.007)	(0.006)	(0.008)
Regional Dummies	Yes	Yes	Yes
Other controls.	Yes	Yes	Yes

Controls include: household head characteristics, age groups of adult and children by gender, dummy for rural residence, regional indicators.
$N = 6856$. * $p < 0.01$, ** $p < 0.05$, *** $p < 0.001$

With respect to the demographic variables, three observations stand out. First, the coefficients of the time dummies are always negative for both men and women and positive for children, implying that children gain more resources over time into the program. Second, we find that household composition matters (the results are reported in D.3 in Appendix D). Women's (men's) resource shares increase with the number of women (men) in the household, and decrease as the numbers of children increase. Third, household head's education, gender, and age also matters: not surprisingly, women get lower resource shares in households headed by men.

4.3. Discussion

There is a growing concern in the related literature that standard household level poverty measures maybe hiding the true extent of deprivation as many poor individuals reside in non-poor households. We use anthropometric measures to see whether household poverty might provide a reliable guide for policy targeting of nutritionally-deprived individuals.

We show that undernourished children are spread across the distribution of household percapita expenditure. The incidence of child undernutrition is very high in all the three countries and the magnitude is comparable between social protection program participant and non participant households. Hence the three social protection programs did not reach all households with nutritionally-deprived children. However, program

Table 2: Resource shares of men, women and children: India

	Men	Women	Children
One child	−0.022***	−0.033***	0.061***
	(0.004)	(0.004)	(0.005)
Two children	−0.038***	−0.048***	0.096***
	(0.005)	(0.005)	(0.007)
Three children	−0.036***	−0.055***	0.102***
	(0.007)	(0.007)	(0.010)
Four children	−0.041***	−0.029***	0.079***
	(0.012)	(0.011)	(0.016)
NREGA	−0.010*	−0.016***	0.025***
	(0.006)	(0.006)	(0.008)
2009 Wave	−0.023***	−0.018***	0.043***
	(0.004)	(0.004)	(0.005)
2012 Wave	−0.063***	−0.056***	0.123***
	(0.004)	(0.004)	(0.005)
2016 Wave	−0.090***	−0.088***	0.181***
	(0.004)	(0.004)	(0.005)
Regional Dummies	Yes	Yes	Yes
Other controls.	Yes	Yes	Yes

Controls include: household head characteristics, age groups of adult and children by gender, dummy for rural residence, regional indicators.
$N = 7507$. * $p < 0.01$, ** $p < 0.05$, *** $p < 0.001$

Table 3: Resource shares of men, women and children: Peru

	Men	Women	Children
One child	−0.019***	−0.031***	0.051***
	(0.005)	(0.004)	(0.007)
Two children	−0.031***	−0.040***	0.072***
	(0.005)	(0.005)	(0.007)
Three children	−0.027***	−0.038***	0.066***
	(0.007)	(0.006)	(0.010)
Four children	−0.023**	−0.025***	0.048***
	(0.009)	(0.008)	(0.013)
Juntos	−0.031***	−0.007	0.040***
	(0.005)	(0.005)	(0.007)
2009 Wave	−0.011**	−0.017***	0.029***
	(0.005)	(0.004)	(0.007)
2012 Wave	−0.019***	−0.033***	0.053***
	(0.005)	(0.005)	(0.007)
2016 Wave	−0.041***	−0.048***	0.090***
	(0.005)	(0.005)	(0.007)
Regional Dummies	Yes	Yes	Yes
Other controls.	Yes	Yes	Yes

Controls include: household head characteristics, age groups of adult and children by gender, dummy for rural residence, regional indicators.
$N = 7160$. * $p < 0.01$, ** $p < 0.05$, *** $p < 0.001$

participant households do experience a reduction in child undernutrition once enrolled in the programs. This is evident from the figures in Table D.1 in Appendix D where height-for-age of children in participating households improved significantly.

The magnitude of improvement in the nutritional indicators vary by program type. This is not surprising since the three social protection schemes we investigate have different causal mechanisms through which they affect indicators of poverty and deprivation. The largest improvement is registered in Peru where stunting incidence declines by 20% among *Juntos* participants. In addition to the direct income effect of social protection, CCTs attach conditionalities such as growth monitoring controls and vaccinations. PSNP participants also enjoyed a sizable reduction in the incidence of stunting. This too is expected as the main objective of the program is shielding households from the adverse impacts of shocks induced by vagaries of nature and other socioeconomic shocks.[12]

Our analysis of the allocation of total resources within families shows that resources are not shared equally. Men are always enjoying the larger share of resources as measured by private assignable good. We estimated the main determinants of the resource shares of men women and children and find that program participation induces reallocation of resources from parents to children. However, this does not imply that parents become poorer due to the programs, because total household resources also increase (see summary tables in Appendix B).

In all the three programs that we here evaluated, participants are not selected randomly in experimental settings. The programs also do not explicitly redistribute benefits to the father or the mother. However, it is encouraging to see that the programs induce reallocation of resources to children. We cannot generalize if redistribution favoring mothers versus favoring fathers is more effective in reducing intrahousehold inequality.

4.4. Policy Implications

Our findings indicate that accounting for intrahousehold inequalities is crucial for a comprehensive assessment of poverty and inequality. Targeting poor households does not necessarily reach poor individuals. Households are simply the economic environments in which individuals live. Policy targeting of poor individuals, monitoring of movements in and out of poverty and evaluation of policies designed to reduce poverty would be better if we measured poverty at the individual level. We recommend a careful consideration of local health environment and intrahousehold resource allocation.

[12] One channel of effect could be increased expenditure on better quality food. We observe a supporting descriptive evidence from Table B.1 where the share of household expenditure on high protein foods increased in post-program periods.

4.5. Limitations and Extensions

There are a few caveats to our approach that require further analysis and robustness checks.[13] First, for identification of resource shares, we followed the DLP approach and assume that resource shares are invariant to expenditure. Second, we assumed that clothing is an observable private assignable good. One may be concerned that privateness may be violated by the direct sharing of clothing by household members. Even though several studies establish that clothing is generally considered to be an assignable good with a low degree of publicness (Dunbar et al., 2013), we can still verify the robustness of our results by looking only at footwear and check if estimated resource shares are similar to the case where we considered both goods.

A third concern with our analysis is potential endogeneity in household expenditure measures emanating from measurement error, either due to infrequency of purchases or because of recall errors. Dunbar et al. (2013) suggest instrumenting expenditure with household wealth data to account for this endogeneity. Since wealth is measured by enumerating physically observed assets of the households it is less prone to recall and measurement error. Another potential source of endogeneity is the number of children in the household. Unobserved preference heterogeneity may simultaneously affect both fertility decisions and expenditure decisions.

An important extension of our analysis is measuring individual poverty. In order to do that, we propose to use the resource share estimates and calculate poverty rates that take into account the unequal resource allocation within the household. We can then compare these levels with those derived from the standard poverty line used by the World Bank (a PPP adjusted equivalent of the US$1.90 per person per day threshold). This approach will allow us to quantify the welfare effects of the social protection programs both in terms of change in individual consumption and poverty of each household member.

Conclusions

Using data from a cohort survey in Ethiopia, India, and Peru, we evaluate the role of three large scale social protection programs in reducing intrahousehold inequality. Recent work has emphasized that a comprehensive assessment of poverty and inequality should take into account intrahousehold inequalities. Targeting poor households by anti-poverty programs cannot guarantee reaching poor individuals as many poor individuals reside in non-poor households (Brown et al., 2018, 2019).

We find that the incidence of undernutrition, as measured by anthropometric indices, is very high in all three countries. We also observe that program participation status both before and after the program implementation does not alter the overall incidence of undernutrition in Ethiopia and India where the social protection program is workfare. However, program

[13] Work is underway to extend the current analysis and include these robustness checks. We are also extending the analysis to check for heterogeneity by gender.

participant households do experience a reduction in child undernutrition once enrolled in the programs. There is also some evidence of a weak wealth effect in which nutritional status improves with a higher wealth index.

We also investigate how total household expenditure is divided among family members to see the presence and extent of intrahousehold inequality. Our findings reveal that total resources of men and women decline with the number of children. However, it is also evident that this decline is not shared evenly across men and women. For three or fewer children, women mostly bear the decline in resource shares, particularly in India and Peru. We find that the programs divert resources from adults to children. In all three countries, the effect is negative for the father which implies that more resources are redistributed from men to children.

Our findings indicate that accounting for intrahousehold inequalities is crucial for a comprehensive assessment of poverty and inequality. The results echo the concern raised in recent studies that anti-poverty programs that rely on household level poverty indicators may miss out deprived individuals residing in otherwise non-poor households.

References

Afridi, F., Mukhopadhyay, A., and Sahoo, S. (2016). Female labor force participation and child education in India: Evidence from the National Rural Employment Guarantee Scheme. *IZA Journal of Labor & Development*, 5:7.

Alderman, H. and Yemtsov, R. (2014). How can safety nets contribute to economic growth? *World Bank Economic Review*, 28:1–20.

Andersen, C. T., Reynolds, S. A., Behrman, J. R., Crookston, B. T., Dearden, K. A., Escobal, J., Mani, S., Sánchez, A., Stein, A. D., and Fernald, L. C. (2015). Participation in the Juntos Conditional Cash Transfer Program in Peru Is Associated with Changes in Child Anthropometric Status but Not Language Development or School Achievement. *Journal of Nutrition*, 145:2396–2405.

Andersson, C., Mekonnen, A., and Stage, J. (2011). Impacts of the Productive Safety Net Program in Ethiopia on livestock and tree holdings of rural households. *Journal of Development Economics*, 94:119–126.

Angelucci, M. and De Giorgi, G. (2009). Indirect effects of an aid program: how do cash transfers affect ineligibles' consumption? *American Economic Review*, 99:486–508.

Bargain, O., Lacroix, G., and Tiberti, L. (2018). Validating the collective model of household consumption using direct evidence on sharing. *Partnership for Economic Policy Working Paper*, (2018-06).

Barnett, I., Ariana, P., Petrou, S., Penny, M. E., Duc, L. T., Galab, S., Woldehanna, T., Escobal, J. A., Plugge, E., and Boyden, J. (2012). Cohort profile: the young lives study. *International Journal of Epidemiology*, 42:701–708.

Berg, E., Bhattacharyya, S., Rajasekhar, D., and Manjula, R. (2018). Can public works increase equilibrium wages? Evidence from India's National Rural Employment Guarantee. *World Development*, 103:239–254.

Berhane, G., Gilligan, D. O., Hoddinott, J., Kumar, N., and Taffesse, A. S. (2014). Can social protection work in Africa? The impact of Ethiopia's productive safety net programme. *Economic Development and Cultural Change*, 63:1–26.

Bertrand, M., Crépon, B., Marguerie, A., and Premand, P. (2017). Contemporaneous and Post-Program Impacts of a Public Works Program: Evidence from Côte d'Ivoire. Mimeo.

Bose, N. (2017). Raising Consumption Through India's National Rural Employment Guarantee Scheme. *World Development*, 96:245–263.

Brown, C., Calvi, R., and Penglase, J. (2019). Sharing the pie: Undernutrition, intra-household allocation, and poverty. Mimeo.

Brown, C., Ravallion, M., and van de Walle, D. (2018). Most of Africa's nutritionally-deprived women and children are not found in poor households. *Review of Economics and Statistics*.

Browning, M., Chiappori, P.-A., and Lewbel, A. (2013). Estimating consumption economies of scale, adult equivalence scales, and household bargaining power. *Review of Economic Studies*, 80:1267–1303.

Calvi, R. (2019). Why are

older women missing in India? the age profile of bargaining power and poverty. *Journal of Political Economy*, Forthcoming.

Cherchye, L., Cosaert, S., De Rock, B., Kerstens, P. J., and Vermeulen, F. (2018). Individual welfare analysis for collective households. *Journal of Public Economics*, 166:98–114.

Cherchye, L., De Rock, B., Lewbel, A., and Vermeulen, F. (2015). Sharing rule identification for general collective consumption models. *Econometrica*, 83:2001–2041.

Chiappori, P.-A. (1988). Rational household labor supply. *Econometrica*, 56:63–90.

Chiappori, P.-A. (1992). Collective labor supply and welfare. *Journal of Political Economy*, 100:437–467.

Cookson, T. P. (2015). *Rural women and the uneven process of inclusion: an institutional ethnography of Peru's conditional cash transfer programme*. PhD thesis, University of Cambridge.

Cunha, J. M., De Giorgi, G., and Jayachandran, S. (2017). The Price Effects of Cash Versus In-Kind Transfers. *Review of Economics and Statistics*.

Dasgupta, A. (2017). Can the Major Public Works Policy Buffer Negative Shocks in Early Childhood? Evidence from Andhra Pradesh, India. *Economic Development and Cultural Change*, 65:767–804.

De Vreyer, P. and Lambert, S. (2018). By ignoring intra-household inequality, do we underestimate the extent of poverty? Working Paper 2018 – 12.

Deaton, A. and Drèze, J. (2009). Food and nutrition in India: facts and interpretations. *Economic and Political Weekly*, 44:42–65.

Dehejia, R. H. and Wahba, S. (2002). Propensity score-matching methods for nonexperimental causal studies. *Review of Economics and Statistics*, 84(1):151–161.

D'Souza, A. and Tandon, S. (2019). Intrahousehold nutritional inequities in rural Bangladesh. *Economic Development and Cultural Change*, 67:625–657.

Dunbar, G. R., Lewbel, A., and Pendakur, K. (2013). Children's resources in collective households: identification, estimation, and an application to child poverty in Malawi. *American Economic Review*, 103:438–71.

Dunbar, G. R., Lewbel, A., and Pendakur, K. (2019). Identification of random resource shares in collective households without preference similarity restrictions. *Journal of Business & Economic Statistics*, pages 1–46.

Escobal, J. and Flores, E. (2008). An assessment of the young lives sampling approach in Peru. Technical report, Young Lives.

Fiszbein, A. and Schady, N. R. (2009). *Conditional cash transfers: reducing present and future poverty*. The World Bank.

Galasso, E. and Ravallion, M. (2004). Social protection in a crisis: Argentina's Plan Jefes y Jefas. *World Bank Economic Review*, 18:367–399.

Gehrke, E. (2017). An Employment Guarantee as Risk Insurance? Assessing the Effects of the NREGS on Agricultural Production Decisions. *World Bank Economic Review*, 1:23.

Gehrke, E. and Hartwig, R. (2018). Productive effects of public works programs:

What do we know? What should we know? *World Development*, 107:111–124.

Gilligan, D. O., Hoddinott, J., and Taffesse, A. S. (**2009**). The impact of Ethiopia's Productive Safety Net Programme and its linkages. *Journal of Development Studies*, 45:1684–1706.

Hanna, R. and Karlan, D. (**2017**). Designing social protection programs: Using theory and experimentation to understand how to help combat poverty. In Banerjee, A. V. and Duflo, E., editors, *Handbook of Economic Field Experiments*, volume 2 of *Handbook of Economic Field Experiments*, pages 515 – 553. North-Holland.

Hoddinott, J., Berhane, G., Gilligan, D. O., Kumar, N., and Seyoum Taffesse, A. (**2012**). The impact of Ethiopia's Productive Safety Net Programme and related transfers on agricultural productivity. *Journal of African Economies*, 21:761–786.

Hong, R., Banta, J. E., and Betancourt, J. A. (**2006**). Relationship between household wealth inequality and chronic childhood under-nutrition in bangladesh. *International Journal for Equity in Health*, 5:15.

Imbert, C. and Papp, J. (**2015**). Labor Market Effects of Social Programs: Evidence from India's Employment Guarantee. *American Economic Journal: Applied Economics*, 7:233–263.

Kabeer, N. and Waddington, H. (**2015**). Economic impacts of conditional cash transfer programmes: a systematic review and meta-analysis. *Journal of Development Effectiveness*, 7:290–303.

Kumra, N. (**2008**). An assessment of the Young Lives sampling approach in Andhra Pradesh, India. Technical report, Young LivesTechnical Note 2. Oxford: Young Lives.

Lechene, V., Pendakur, K., and Wolf, A. (**2019**). OLS estimation of the intra-household distribution of consumption. Technical report, IFS Working Paper W19/19.

Li, T. and Sekhri, S. (**2019**). The spillovers of employment guarantee programs on child labor and education. *The World Bank Economic Review*.

Menon, M., Pendakur, K., and Perali, F. (**2012**). On the expenditure-dependence of children's resource shares. *Economics Letters*, 117(3):739–742.

Olivier de Sardan, J.-P. and Piccoli, E. (**2017**). Cash transfers: the revenge of contexts, an anthropological approach. Mimeo.

Outes-Leon, I. and Dercon, S. (**2008**). Survey attrition and attrition bias in young lives. Technical report, Young Lives Technical Note 5, Oxford: Young Lives.

Outes-Leon, I. and Sanchez, A. (**2008**). An assesment of the young lives sampling approach in ethiopia. Technical report, Young Lives Technical Notes 1. Oxford: Young Lives.

Perova, E. and Vakis, R. (**2012**). 5 Years in Juntos: New Evidence on the Program's Short and Long-Term Impacts. *Revista Economía*, 35:53–82.

Porter, C. and Goyal, R. (**2016**). Social protection for all ages? Impacts of Ethiopia's productive safety net program on child nutrition. *Social Science & Medicine*, 159:92–99.

Sanchez, A., Melendez, G., and Behrman, J. (**2020**). Impact of juntos conditional cash transfer program on nutritional and cognitive outcomes in peru: Comparison between younger and older initial exposure. *Economic Development and Cultural Change*, 68:865–897.

Shah, M. and Steinberg, B. M. (**2015**). Workfare and Human Capital Investment: Evidence from India. Technical report, National Bureau of Economic Research.

Sharp, K., Brown, T., and Teshome, A. (**2006**). Targeting Ethiopia's Productive Safety Net Programme (PSNP). *Overseas Development Institute and the IDL Group: London and Bristol, UK*.

Sulaiman, M. (**2016**). Making sustainable reduction in extreme poverty: A comparative meta-analysis of livelihood, cash transfer and graduation approaches. Technical report, Washington, DC: CGAP.

Tommasi, D. (**2019**). Control of resources, bargaining power and the demand of food: Evidence from progresa. *Journal of Economic Behavior & Organization*, 161:265–286.

Wiseman, W., Van Domelen, J., and Coll-Black, S. (**2010**). Designing and implementing a rural safety net in a low income setting: Lessons learned from ethiopia's productive safety net program 2005-2009. *World Bank, Washington DC*, 56.

World Bank (**2018**). *The State of Social Safety Nets 2018*. World Bank, Washington, DC.

Zimmermann, L. (**2014**). Public works programs in developing countries have the potential to reduce poverty. *IZA World of Labor*.

A. The Young Lives Survey: Design and Sampling

Young Lives respondents were selected from 20 clusters that were specifically designed in each country. Each cluster is deemed to represent a certain type of population, and is expected to show typical trends affecting those people or areas. In each country, the study sites were selected in 2001 using a semi-purposive sampling strategy. The districts were selected first, then 20 sentinel sites within these were appointed according to an agreed set of criteria. In each sentinel site, 100 households with a child born in 2001-02 and 50 households with a child born in 1994-95 were randomly selected.[14]

In Ethiopia, five out of the country's nine states and two city administrations were selected. These five regions account for 96% of the national population. Even though Young Lives is not intended to be a nationally representative survey, compared to the Demographic and Health Survey (DHS) or Welfare Monitoring Survey (WMS), the sample includes a wide range of living standards, similar to the variability found in the Ethiopian population as a whole (Outes-Leon and Sanchez, 2008; Outes-Leon and Dercon, 2008).

Similar to the sampling design in Ethiopia, the sampling strategy followed by Young Lives in Andhra Pradesh was semi-purposive. The selection process of districts for the survey ensured that all geographical regions were surveyed, as too were the poor and non-poor districts of each region (based on indicators of economic, human development, and infrastructure). Undivided Andhra Pradesh[15] had three distinct agro-climatic regions: Coastal Andhra, Rayalaseema, and Telangana. The sampling scheme adopted was designed to identify regional variations with the following priorities: a uniform distribution of sample districts across the three regions to ensure full regional representation; the selection of one poor and one non-poor district in each region, based on a ranking of development indicators; and considering issues that might impact on childhood poverty in poor districts and mandals (Gehrke, 2017; Kumra, 2008).

In Peru, slightly differently from Ethiopia and India, the sampling of clusters was random (in the other countries it was semi-random/semi-purposive). The district level was used as the sample frame. The most recent poverty map of all districts in Peru in 2001 was used to select the 20 clusters. Factors such as infant mortality, housing, schooling, road networks and access to services determined the ranking of districts. To achieve the aim of over-sampling poor areas, the highest ranking 5% of districts (all located in Lima) were excluded. The resulting districts were examined to cover rural, urban, peri-urban, coastal, mountain and Amazon areas and for logistical feasibility, and one of them was selected for the sampling. Following the selection of districts, a random population centre (i.e. a village or hamlet) was chosen within the district. A comparison to the DHS from 2000 (the year closest to the first wave of Young Lives in 2002), indicates that the Young Lives sample covers the diversity of children and families in Peru (Escobal and Flores, 2008).

[14]The official Young Lives website (url: https://www.younglives.org.uk/) documents the sampling, attrition and tracking, selection of research tools, piloting and research design, as well as background literature reviews of the survey in great details.

[15]The State of Andhra Pradesh was divided into the states of Andhra Pradesh and Telangana in 2013.

B. Summary Statistics

Table B.1: Summary Statistics (by PSNP Participation Status)

	Pre-program (2006)			Post-program (2009-2016)		
	All	Part.	Non-part	All	Part.	Non-part
Household head's characteristics:						
Years of education	3.44	1.62	4.28	4.63	2.82	5.47
	(3.84)	(2.33)	(4.11)	(3.91)	(2.50)	(4.15)
Age	41.03	40.89	41.18	46.81	46.86	46.79
	(11.02)	(11.10)	(11.00)	(10.99)	(11.02)	(10.98)
Gender ($Male = 1$)	0.81	0.77	0.83	0.76	0.74	0.77
	(0.39)	(0.42)	(0.37)	(0.42)	(0.44)	(0.42)
Household size	6.05	6.13	6.02	5.95	6.01	5.92
	(2.08)	(1.91)	(2.15)	(1.95)	(1.92)	(1.97)
Wealth index	0.28	0.20	0.32	0.37	0.29	0.41
	(0.18)	(0.12)	(0.19)	(0.18)	(0.13)	(0.18)
Total monthly expenditure	663.28	497.35	742.48	810.36	554.90	933.60
	(540.87)	(295.69)	(610.13)	(1189.94)	(426.08)	(1401.78)
Non-food	257.01	136.47	314.55	408.94	205.28	507.19
	(355.85)	(97.76)	(415.83)	(1226.27)	(395.52)	(1457.48)
Food	408.91	361.92	431.32	432.76	367.03	464.47
	(291.59)	(254.80)	(305.76)	(305.04)	(189.21)	(342.91)
Share of food exp.	65.94	72.29	62.89	61.05	68.38	57.51
	(15.68)	(12.49)	(16.10)	(15.56)	(12.68)	(15.58)
Share of protein	8.71	7.70	9.22	10.33	8.75	11.08
	(11.20)	(10.39)	(11.58)	(11.98)	(11.50)	(12.14)
Share of cereals	56.28	60.07	54.50	36.04	38.20	35.00
	(21.10)	(19.71)	(21.47)	(23.94)	(26.49)	(22.54)
Share of veggies	10.60	11.08	10.41	25.79	28.25	24.61
	(9.12)	(9.51)	(8.95)	(23.29)	(26.55)	(21.45)
Share of other food	24.41	21.15	25.87	27.33	24.33	28.78
	(15.77)	(14.49)	(16.03)	(14.56)	(13.98)	(14.62)
Observations	1912	611	1281	5579	1813	3766

Mean coefficients; s.d in parentheses.
Monthly total consumption expenditure, in 2006 eth. birr

Table B.2: Summary Statistics (by NREGA Participation Status)

	Pre-program (2006)			Post-program (2009-2016)		
	All	Part.	Non-part	All	Part.	Non-part
Household head's characteristics:						
Years of education	4.40	3.07	7.24	5.36	4.06	8.23
	(4.59)	(3.90)	(4.65)	(4.70)	(4.17)	(4.54)
Age	38.51	38.80	37.89	41.10	40.98	41.37
	(11.86)	(12.01)	(11.48)	(8.52)	(8.62)	(8.28)
Gender ($Male = 1$)	0.95	0.95	0.94	0.90	0.90	0.91
	(0.22)	(0.22)	(0.23)	(0.30)	(0.30)	(0.29)
Household size	5.52	5.62	5.27	5.03	5.09	4.92
	(2.23)	(2.24)	(2.16)	(1.95)	(1.95)	(1.95)
Wealth index	0.46	0.37	0.64	0.58	0.52	0.71
	(0.20)	(0.15)	(0.15)	(0.17)	(0.16)	(0.12)
Total monthly expenditure	4373.92	4065.78	5014.35	5164.99	4746.64	6103.31
	(3392.27)	(3103.74)	(3836.93)	(5326.89)	(5494.59)	(4800.69)
Non-food	2201.33	1845.22	2955.66	3015.40	2639.59	3858.29
	(2286.80)	(1739.16)	(3012.94)	(4692.56)	(4879.97)	(4120.65)
Food	2172.59	2220.56	2058.69	2149.59	2107.05	2245.01
	(1958.43)	(2074.75)	(1681.70)	(1457.14)	(1539.75)	(1247.33)
Share of food exp	52.50	56.21	44.48	47.92	50.57	41.97
	(14.79)	(14.05)	(13.13)	(15.74)	(15.68)	(14.18)
Share of protein	19.34	17.15	24.12	21.98	20.50	25.26
	(11.15)	(10.79)	(10.39)	(10.78)	(10.78)	(10.02)
Share of cereals	37.20	39.87	31.27	29.14	29.64	28.03
	(14.18)	(14.40)	(11.72)	(12.54)	(13.07)	(11.18)
Share of veggies	18.74	18.33	19.66	24.47	24.91	23.50
	(7.39)	(7.28)	(7.56)	(9.65)	(10.23)	(8.14)
Share of other food	24.73	24.65	24.95	24.41	24.94	23.22
	(11.95)	(12.16)	(11.47)	(11.91)	(12.24)	(11.08)
Observations	1950	1328	606	5755	3966	1789

Mean coefficients; s.d in parentheses.
Monthly total consumption expenditure, in real 2006 rupees

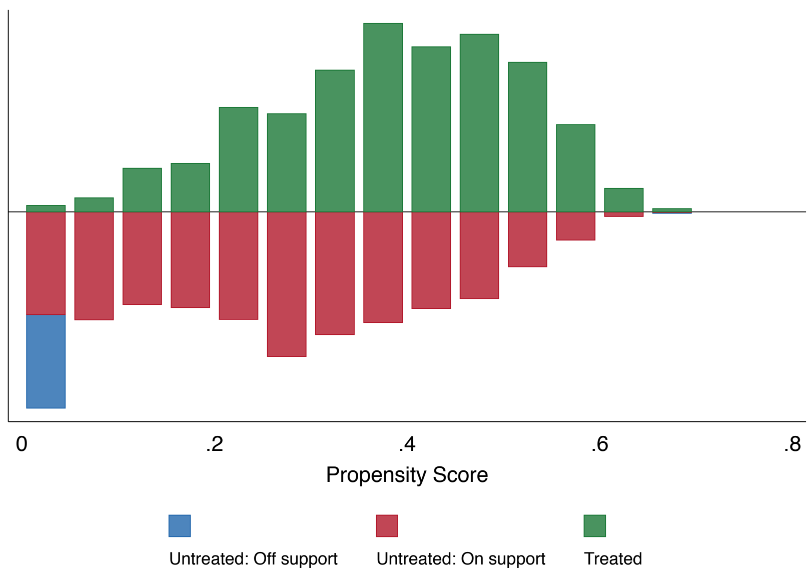
Table B.3: Summary Statistics (by *Juntos* Participation Status)

	Pre-program (2006)			Post-program (2009-2016)		
	All	Part.	Non-part	All	Part.	Non-part
Household head's characteristics:						
Years of education	7.79	4.87	9.05	8.22	5.26	9.58
	(4.31)	(3.33)	(4.07)	(4.32)	(3.44)	(3.99)
Age	38.48	38.51	38.46	42.98	43.33	42.83
	(11.21)	(11.38)	(11.09)	(10.44)	(10.63)	(10.35)
Gender ($Male = 1$)	0.89	0.92	0.88	0.84	0.87	0.82
	(0.31)	(0.27)	(0.32)	(0.37)	(0.34)	(0.38)
Household size	5.51	6.11	5.23	5.30	5.69	5.13
	(2.08)	(2.04)	(2.03)	(1.87)	(1.85)	(1.85)
Wealth index	0.47	0.26	0.56	0.59	0.41	0.67
	(0.23)	(0.12)	(0.21)	(0.20)	(0.14)	(0.17)
Total monthly expenditure	933.92	634.99	1067.08	1303.54	969.82	1452.92
	(742.95)	(363.36)	(828.90)	(1676.44)	(583.17)	(1959.65)
Non-food	345.45	128.99	441.12	615.93	257.24	776.59
	(499.60)	(165.66)	(566.36)	(1004.86)	(326.65)	(1153.34)
Food	530.35	459.59	561.81	645.96	602.37	665.87
	(288.08)	(226.01)	(305.86)	(314.08)	(282.18)	(325.03)
Share of food exp	63.59	74.45	58.78	57.31	65.87	53.50
	(16.26)	(13.20)	(15.06)	(16.67)	(14.71)	(16.07)
Share of protein	29.36	24.82	31.39	32.06	28.47	33.67
	(12.61)	(13.15)	(11.82)	(11.89)	(12.13)	(11.43)
Share of cereals	27.88	32.19	25.90	23.78	26.90	22.39
	(11.56)	(12.24)	(10.59)	(9.94)	(10.59)	(9.30)
Share of veggies	18.72	21.62	17.40	18.84	21.88	17.48
	(8.79)	(9.98)	(7.87)	(8.33)	(9.06)	(7.59)
Share of other food	24.07	21.36	25.34	25.32	22.76	26.47
	(13.42)	(10.67)	(14.32)	(15.73)	(13.81)	(16.39)
Observations	1963	593	1337	5705	1766	3933

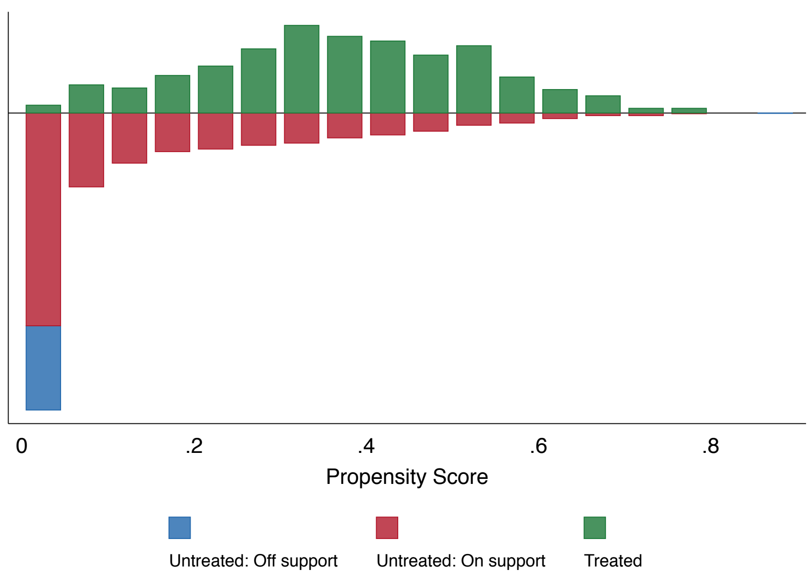
Mean coefficients; s.d in parentheses.
Monthly total consumption expenditure, in real 2006 soles

C. Additional Graphs

Propensity Score Plots



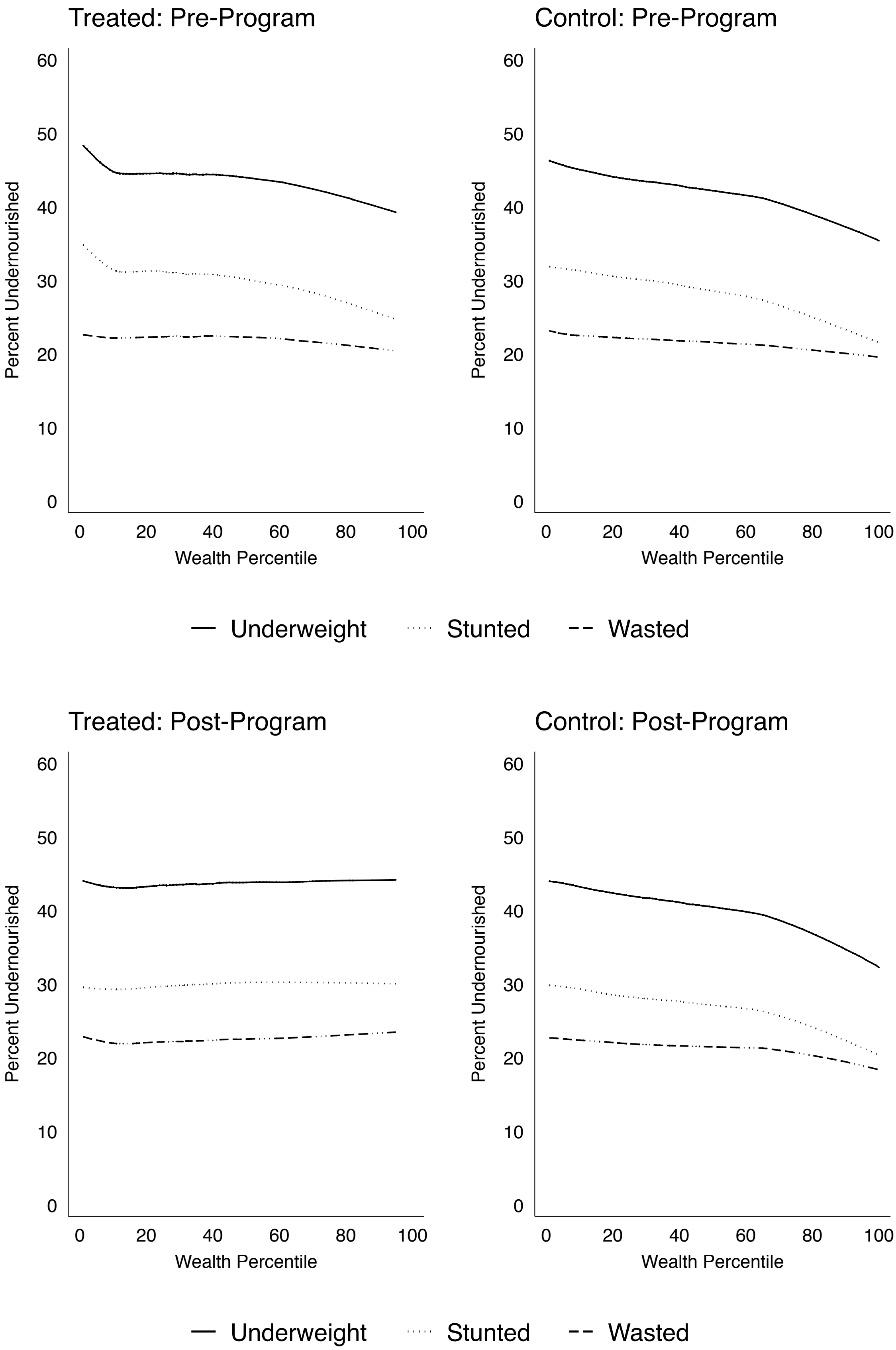
(a) PSNP



(b) *Juntos*

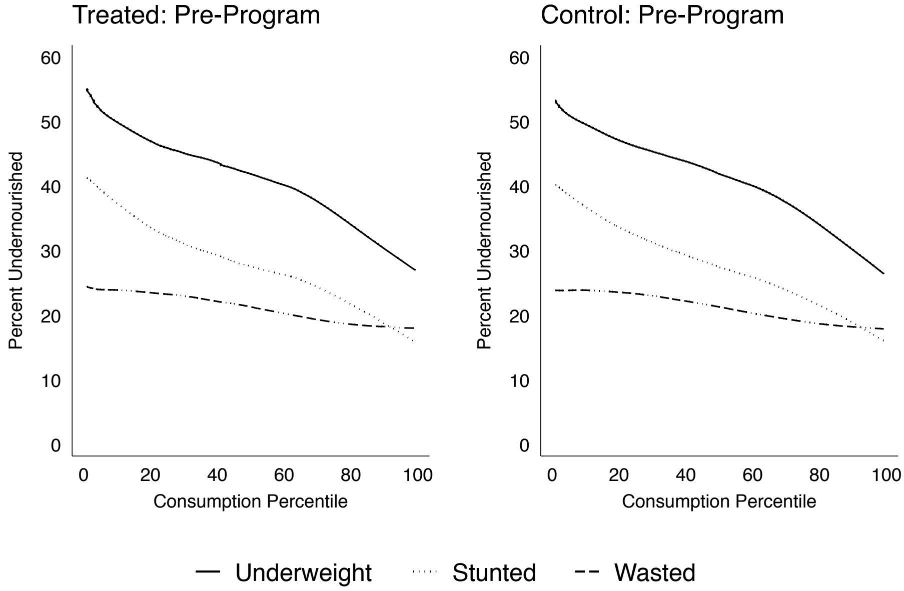
Figure C.1: The Propensity Score Common Support

Figure C.2: Nutritional Outcomes and Household Wealth: Ethiopia



Notes: The graphs show proportions of underweight, stunted and wasted children across the distribution of household wealth percentiles by participation status and pre and post program roll-out. Wealth percentile is based on pre-progam ranking of each group.

Nutritional Outcomes and Household Consumption: Ethiopia



Nutritional Outcomes and Household Consumption: Ethiopia

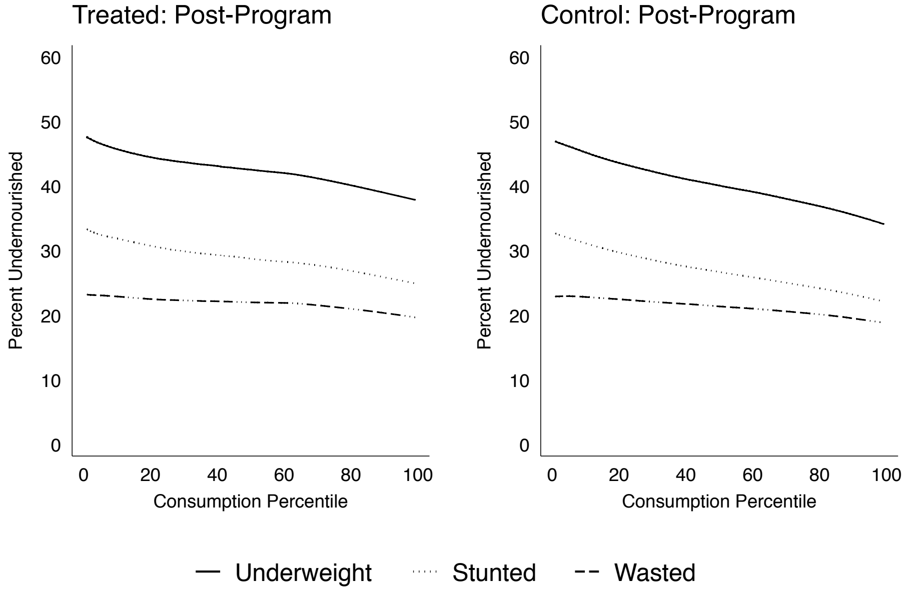
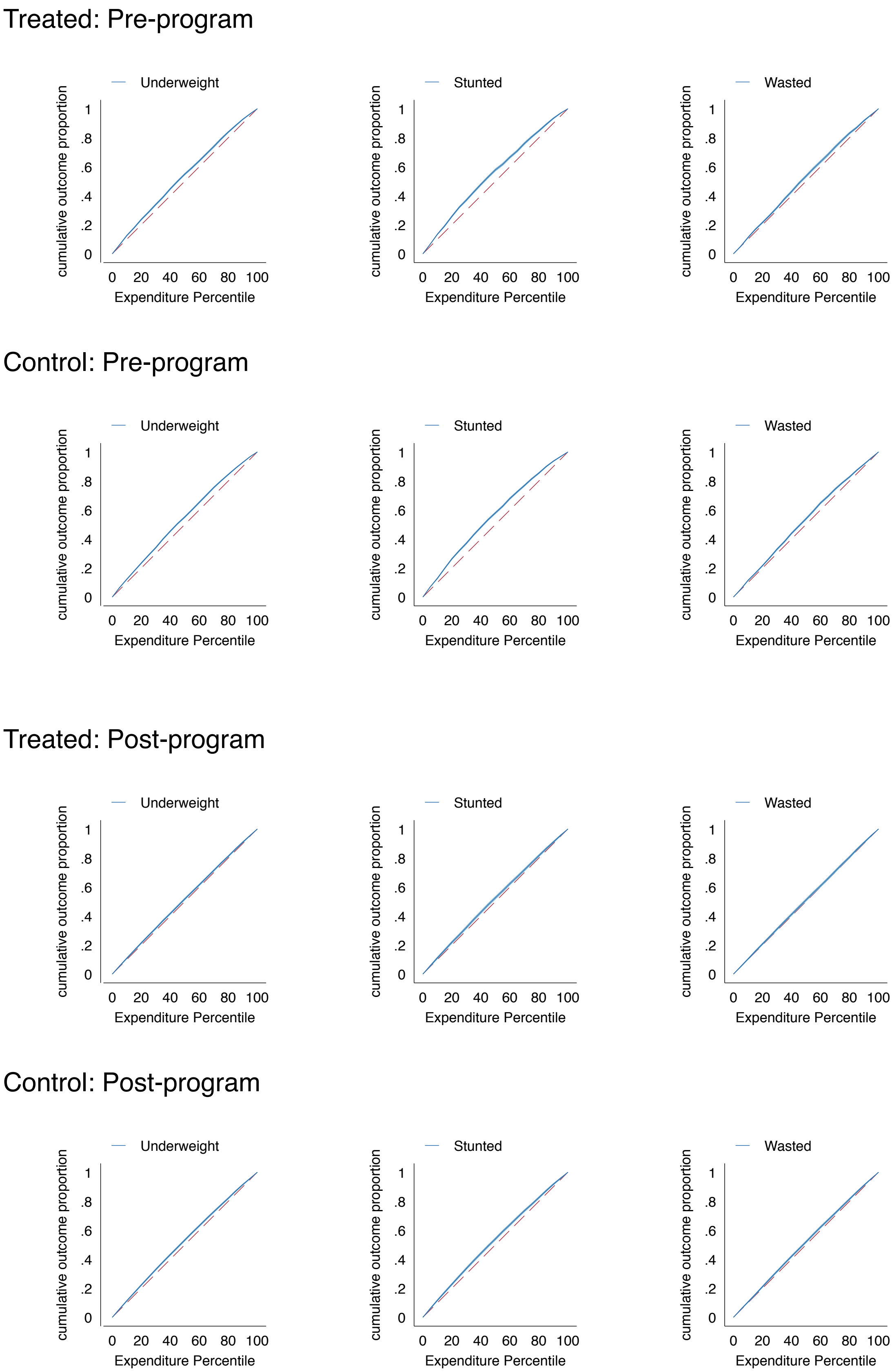


Figure C.3: Undernutrition Concentration Curves: Ethiopia



Notes: The graphs show the concentration curves for the cumulative proportion of children who are underweight, stunted and wasted at each household consumption percentile. Households are ranked by their pre-progam expenditure level and placed into consumption percentiles.

Figure C.4: Undernutrition Concentration Curves by Gender (Pre-program)

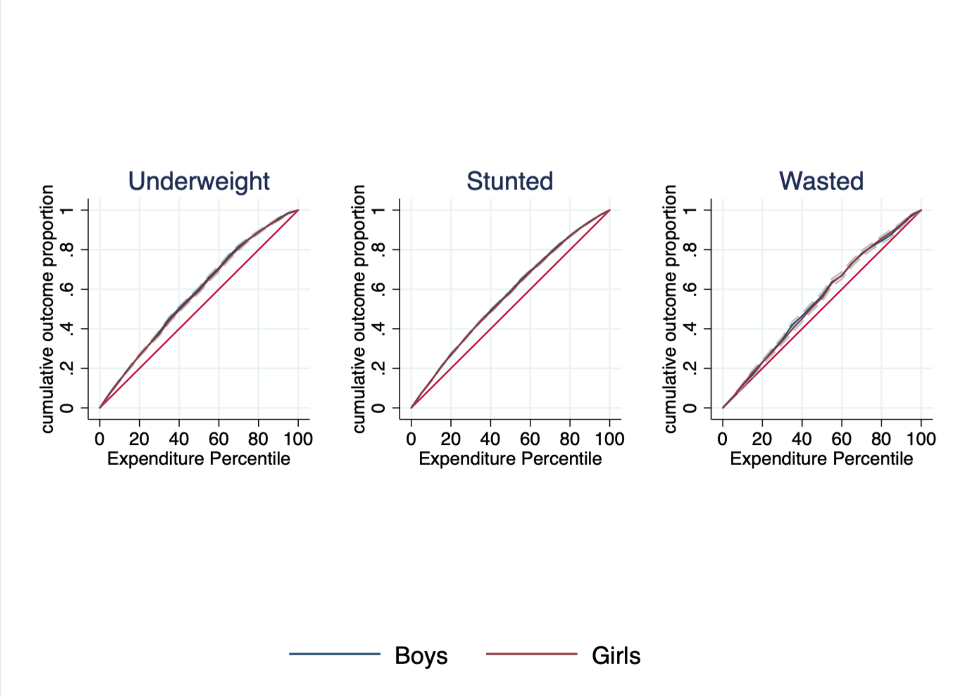


Figure C.5: Undernutrition Concentration Curves by Gender (Post-program)

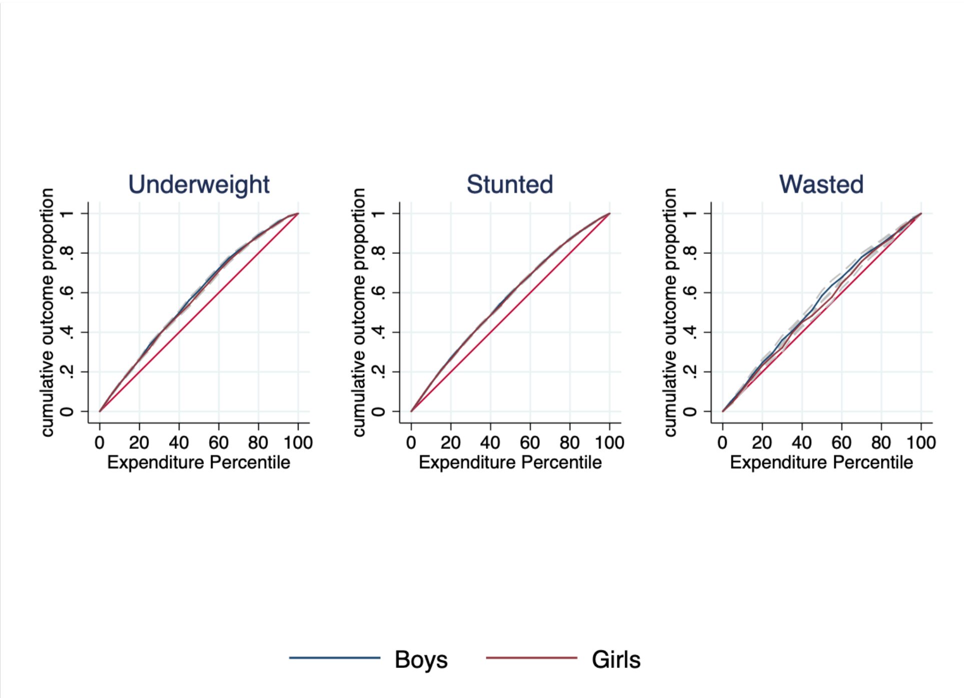
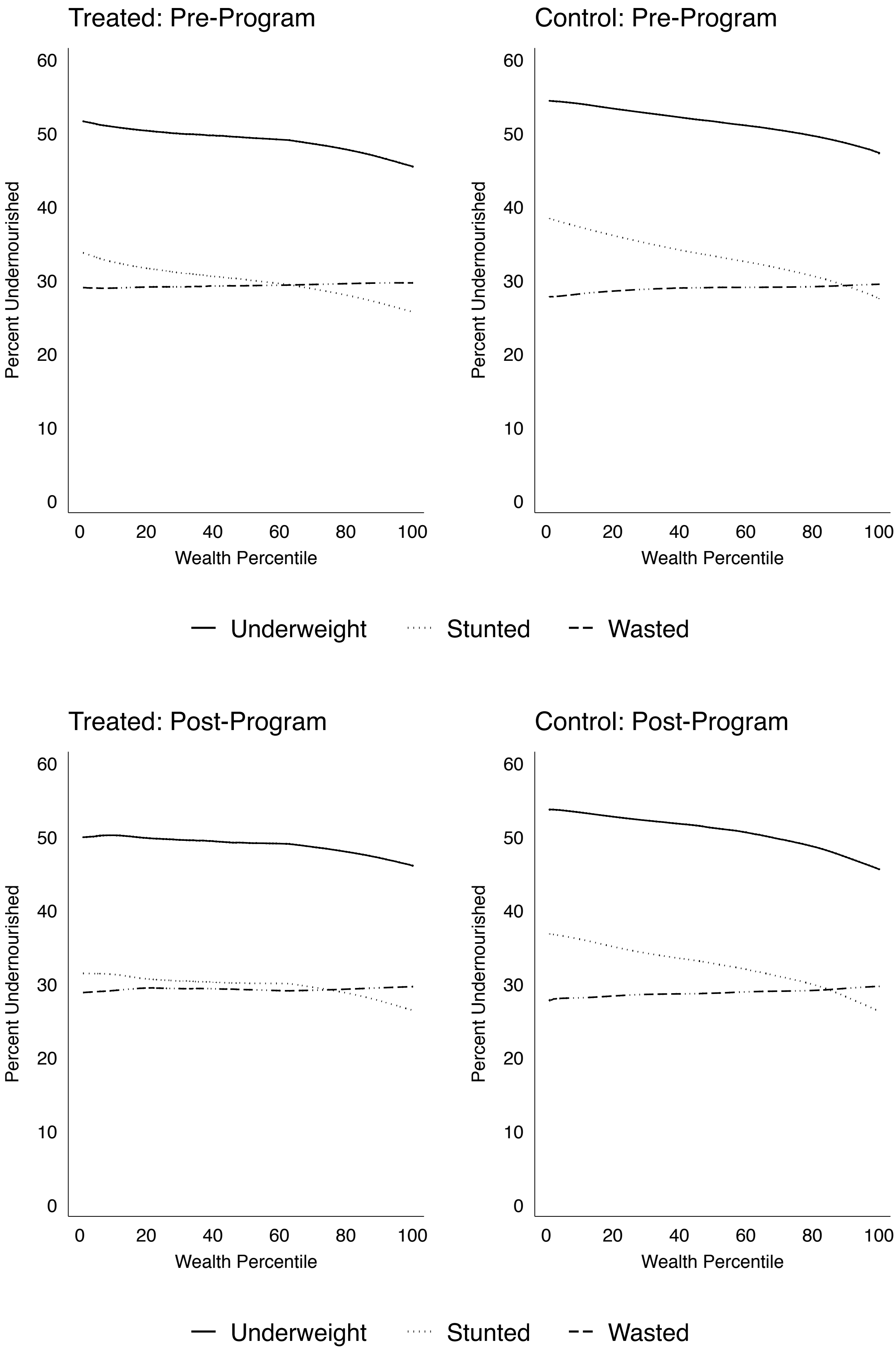
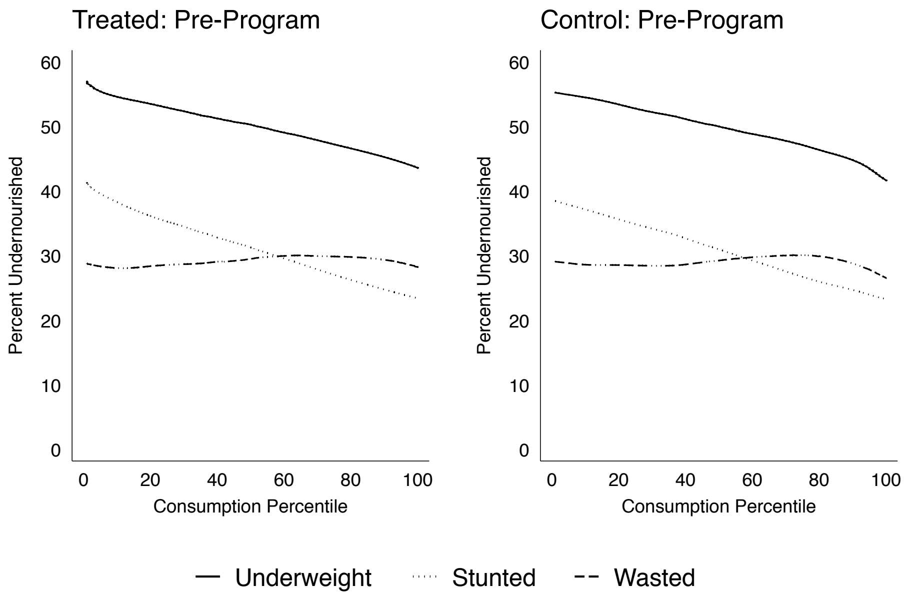


Figure C.6: Nutritional Outcomes and Household Wealth: India



Notes: The graphs show proportions of underweight, stunted and wasted children across the distribution of household wealth percentiles by participation status and pre and post program roll-out. Wealth percentile is based on pre-progam ranking of each group.

Nutritional Outcomes and Household Consumption: India



Nutritional Outcomes and Household Consumption: India

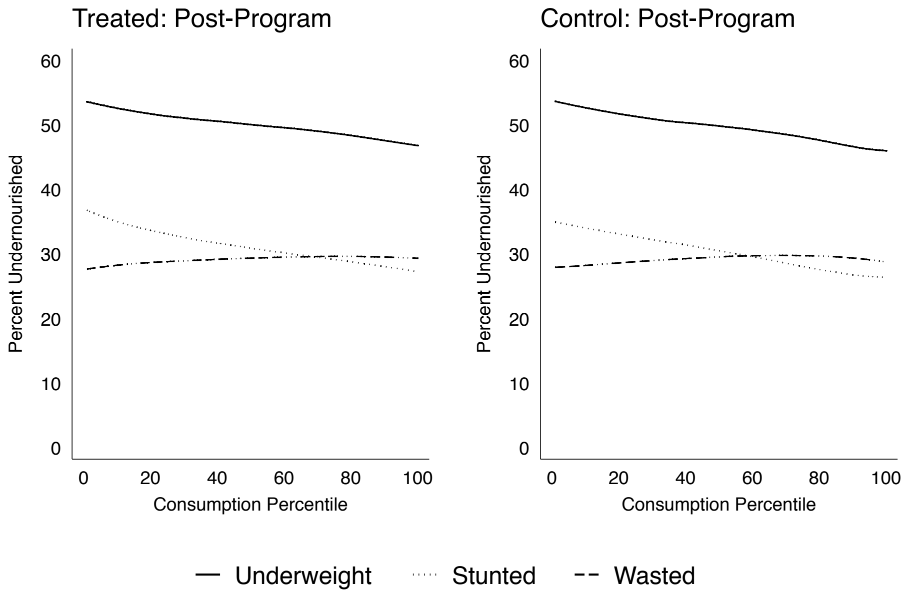
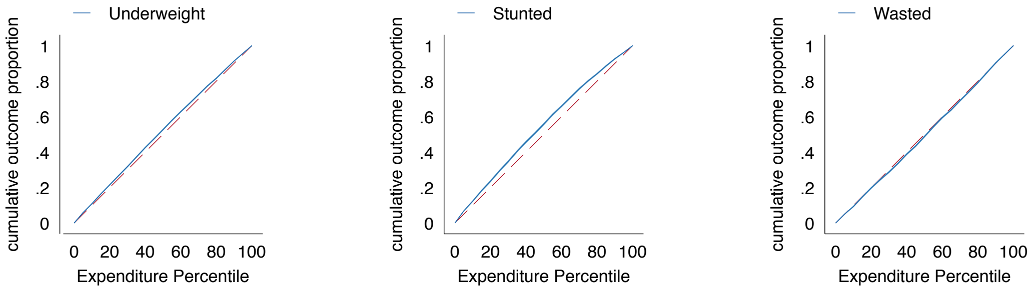
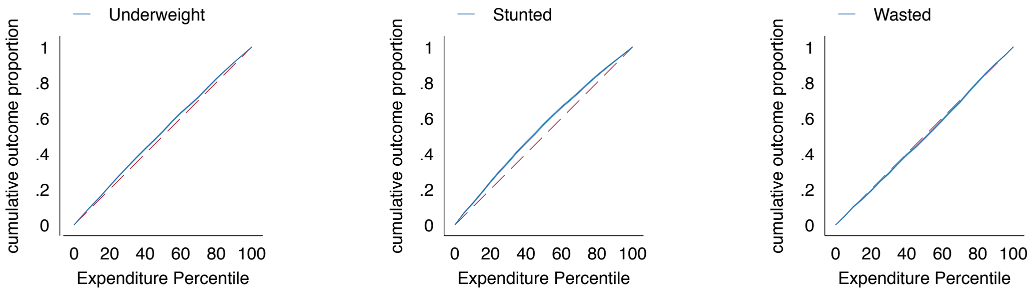


Figure C.7: Undernutrition Concentration Curves: India

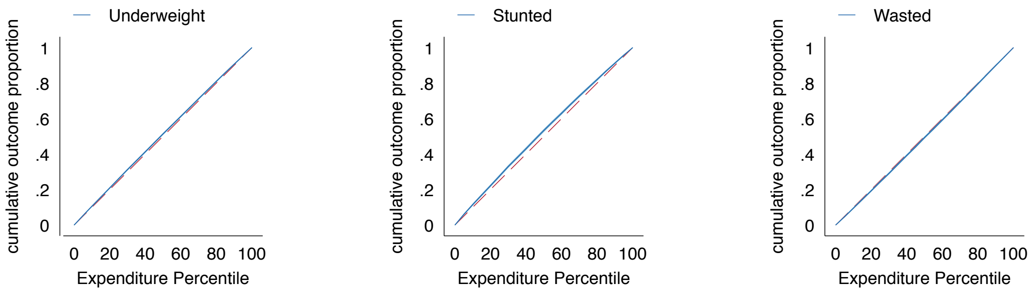
Treated: Pre-program



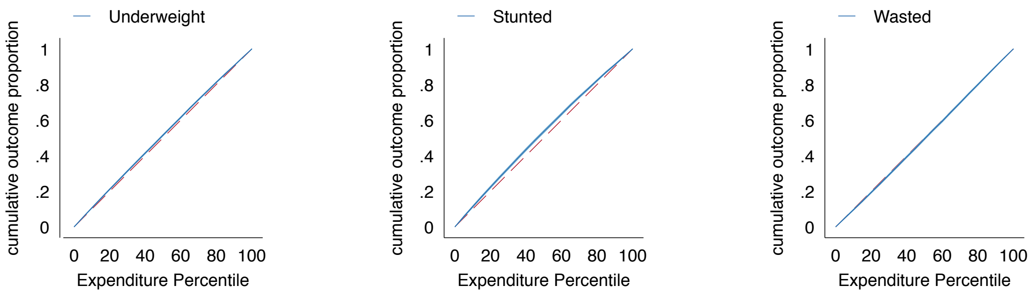
Control: Pre-program



Treated: Post-program



Control: Post-program



Notes: The graphs show the concentration curves for the cumulative proportion of children who are underweight, stunted and wasted at each household consumption percentile. Households are ranked by their pre-progam expenditure level and placed into consumption percentiles.

Figure C.8: Undernutrition Concentration Curves by Gender (Pre-program)

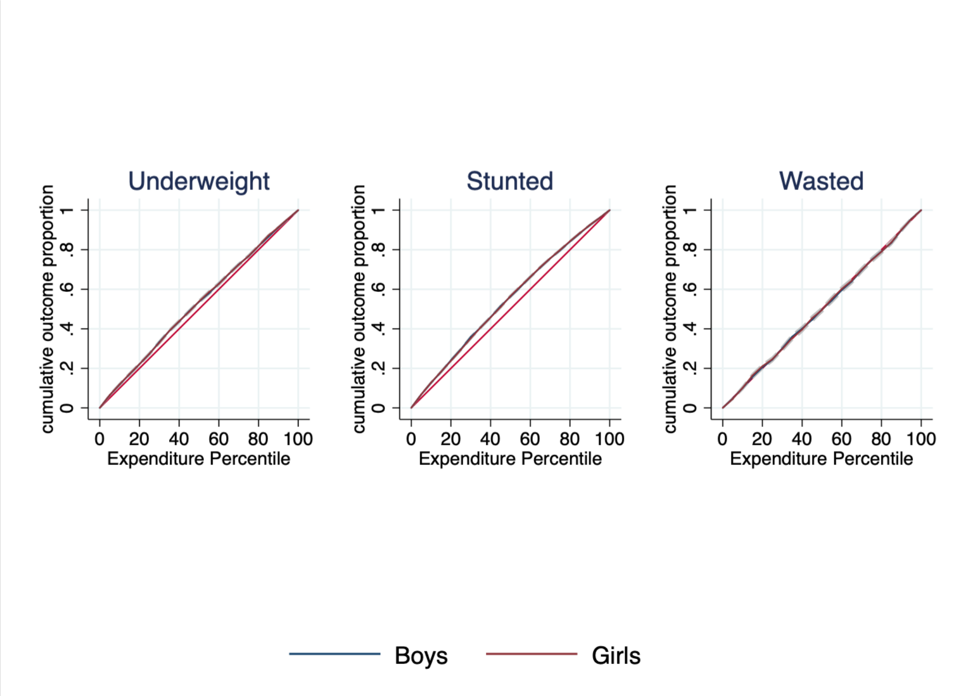


Figure C.9: Undernutrition Concentration Curves by Gender (Post-program)

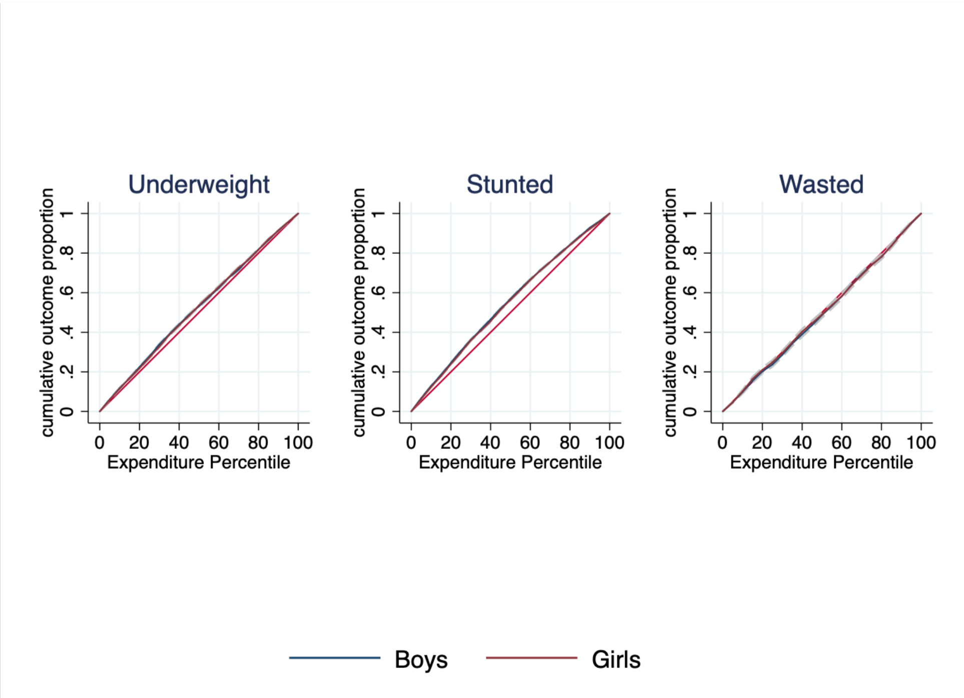
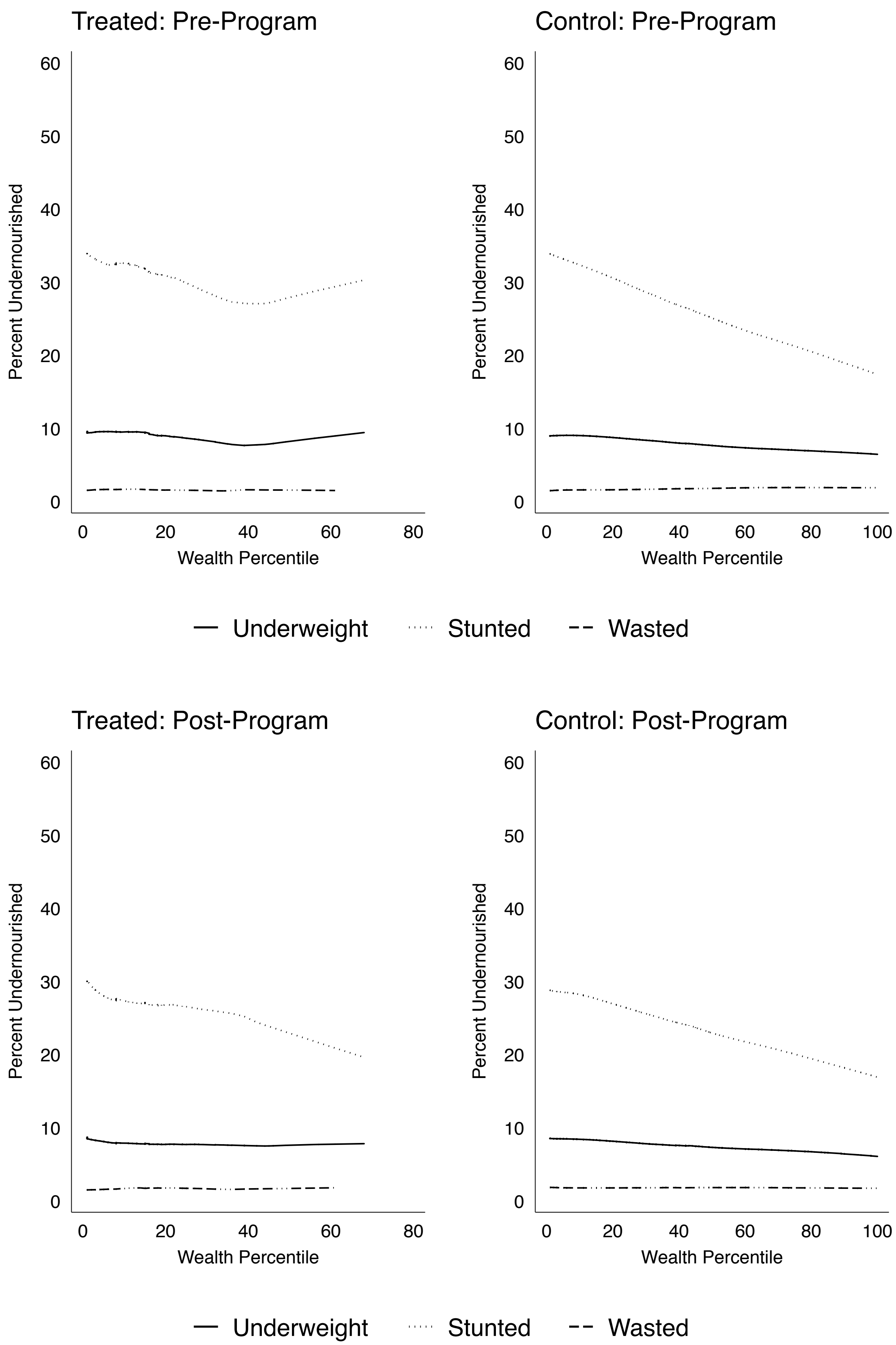
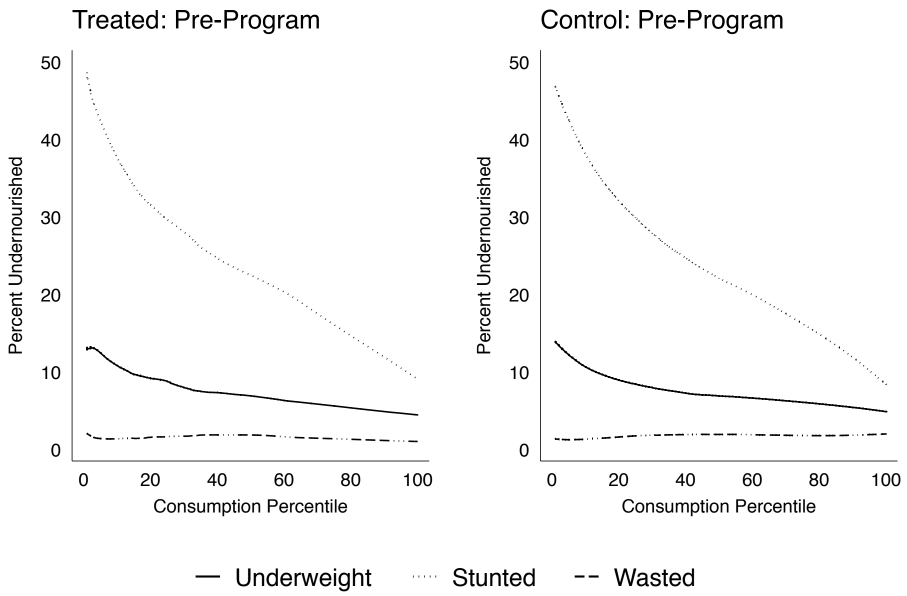


Figure C.10: Nutritional Outcomes and Household Wealth: Peru



Notes: The graphs show proportions of underweight, stunted and wasted children across the distribution of household wealth percentiles by participation status and pre and post program roll-out. Wealth percentile is based on pre-progam ranking of each group.

Nutritional Outcomes and Household Consumption: Peru



Nutritional Outcomes and Household Consumption: Peru

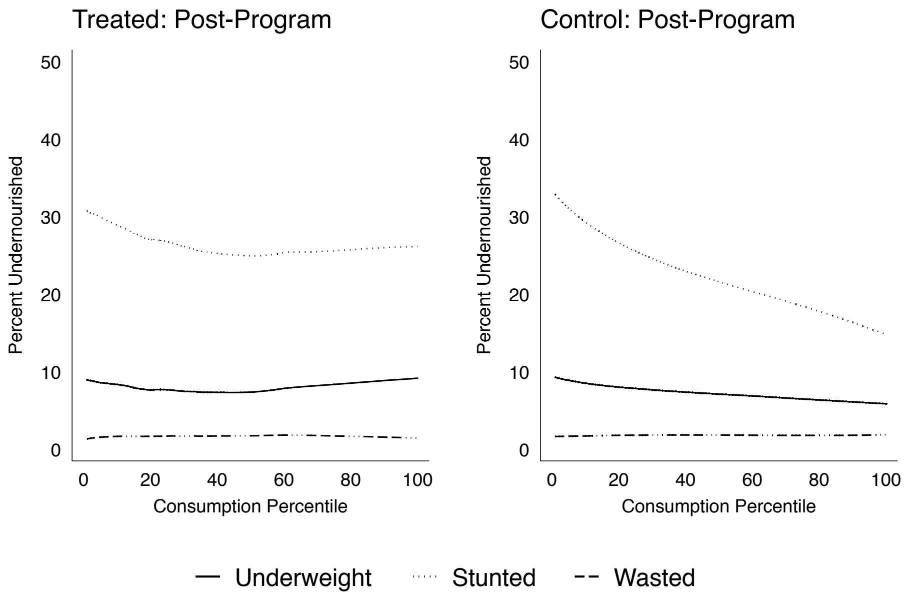
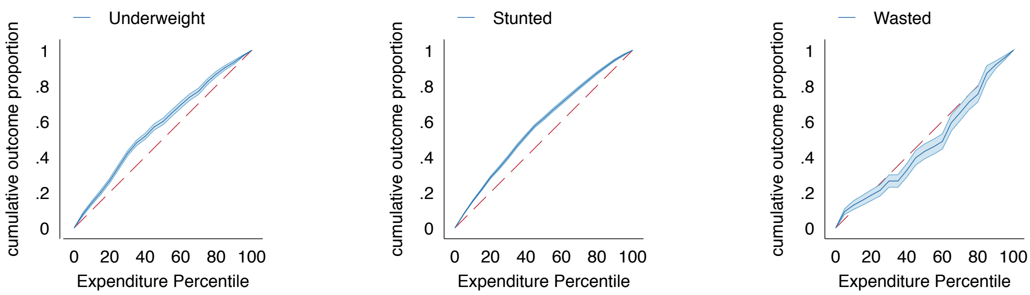
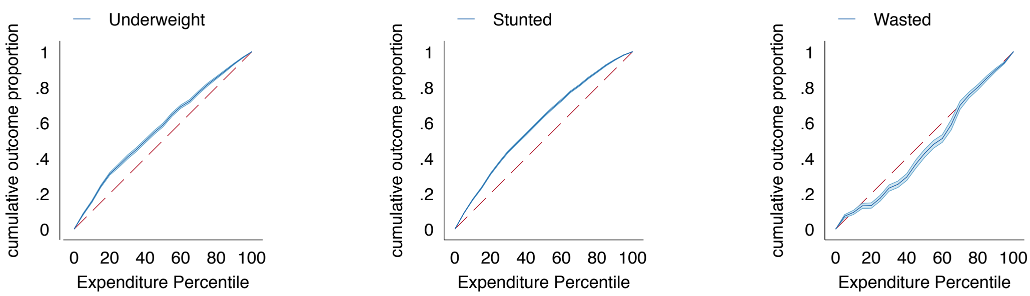


Figure C.11: Undernutrition Concentration Curves: Peru

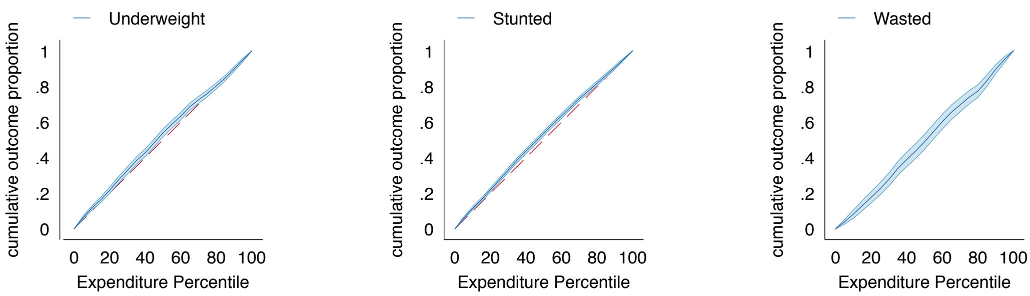
Treated: Pre-program



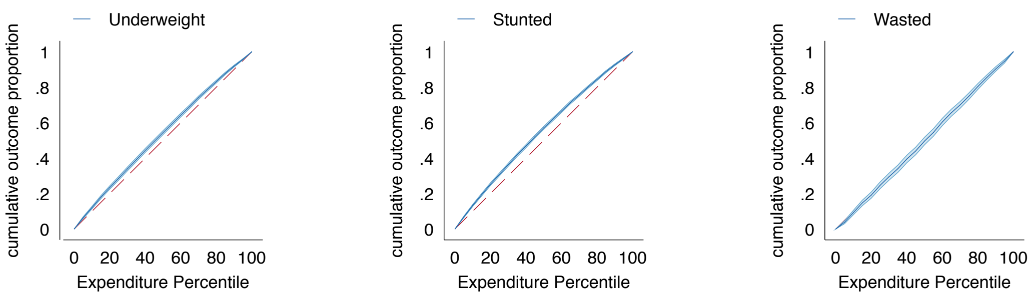
Control: Pre-program



Treated: Post-program



Control: Post-program



Notes: The graphs show the concentration curves for the cumulative proportion of children who are underweight, stunted and wasted at each household consumption percentile. Households are ranked by their pre-progam expenditure level and placed into consumption percentiles.

Figure C.12: Undernutrition Concentration Curves by Gender (Pre-program)

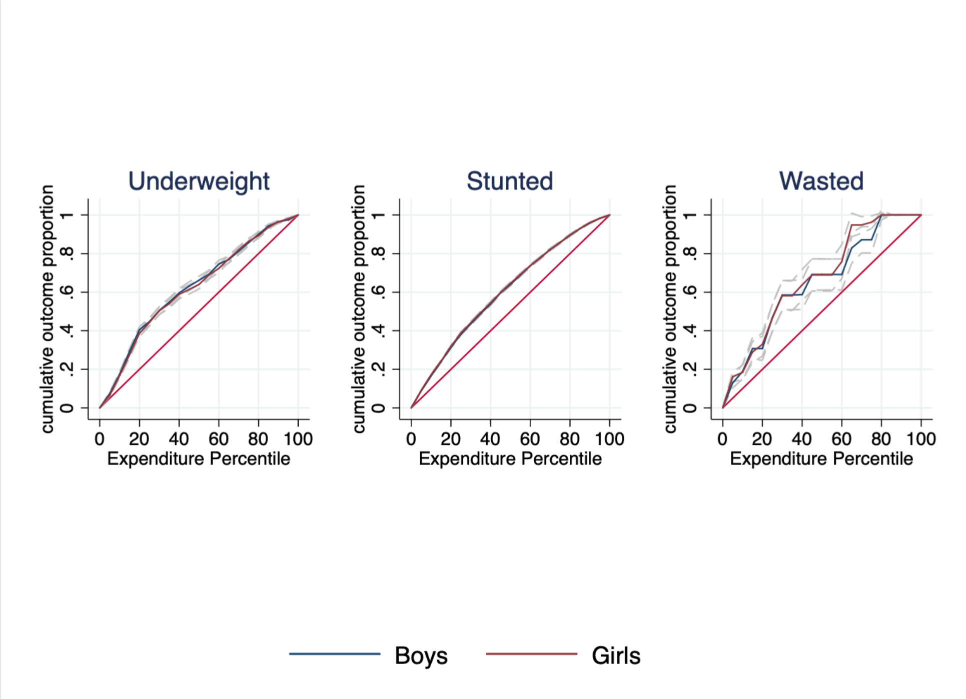
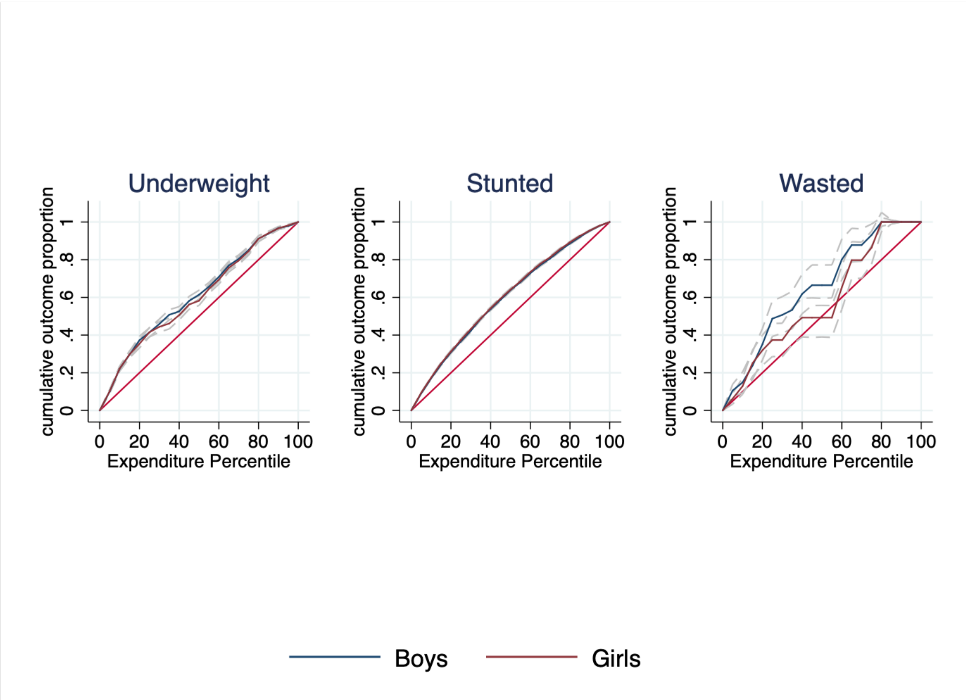


Figure C.13: Undernutrition Concentration Curves by Gender (Post-program)



D. Additional Tables

Table D.1: Summary Statistics of Nutritional Outcomes (by Treatment Status)

	2006			2009		
	Non part.	Part	All	Non part.	Part	All
Ethiopia – PSNP						
Height-for-age z-score	-1.29	-1.65	-1.39	-1.21	-1.47	-1.28
	(1.20)	(1.10)	(1.18)	(1.27)	(1.21)	(1.26)
Stunted	0.27	0.37	0.30	0.23	0.29	0.25
	(0.44)	(0.48)	(0.46)	(0.42)	(0.45)	(0.43)
Observations	2855			2851		
India – NREGA						
Height-for-age z-score	-1.46	-1.68	-1.60	-1.35	-1.56	-1.48
	(1.29)	(1.34)	(1.33)	(1.06)	(1.19)	(1.15)
Stunted	0.30	0.36	0.34	0.27	0.33	0.31
	(0.46)	(0.48)	(0.47)	(0.44)	(0.47)	(0.46)
Observations	2921			2882		
Peru – *Juntos*						
Height-for-age z-score	-1.35	-2.33	-1.51	-1.09	-1.87	-1.22
	(1.12)	(0.99)	(1.16)	(1.01)	(0.86)	(1.03)
Stunted	0.26	0.60	0.32	0.17	0.41	0.21
	(0.44)	(0.49)	(0.46)	(0.38)	(0.49)	(0.41)
Observations	2571			2599		

mean coefficients; sd in parentheses

Table D.2: Budget Share of Assignable goods: Summary Statistics

	All	1 child	2 children	3 children	4 children
Ethiopia					
Man	0.269	0.274	0.275	0.270	0.259
	(0.208)	(0.223)	(0.195)	(0.171)	(0.161)
Woman	0.251	0.255	0.246	0.235	0.222
	(0.173)	(0.183)	(0.153)	(0.134)	(0.124)
Children	0.481	0.471	0.479	0.496	0.519
	(0.236)	(0.249)	(0.223)	(0.202)	(0.192)
Observations	7405	2058	1973	1321	494
India					
Man	0.280	0.290	0.281	0.288	0.307
	(0.134)	(0.129)	(0.115)	(0.129)	(0.126)
Woman	0.278	0.284	0.268	0.264	0.284
	(0.120)	(0.116)	(0.108)	(0.102)	(0.117)
Children	0.441	0.427	0.451	0.449	0.409
	(0.174)	(0.167)	(0.164)	(0.171)	(0.205)
Observations	7658	3311	1240	347	90
Peru					
Man	0.229	0.228	0.218	0.211	0.197
	(0.165)	(0.157)	(0.152)	(0.146)	(0.140)
Woman	0.229	0.228	0.200	0.198	0.183
	(0.148)	(0.137)	(0.131)	(0.125)	(0.126)
Children	0.542	0.544	0.581	0.591	0.620
	(0.217)	(0.206)	(0.206)	(0.208)	(0.208)
Observations	7401	2697	1637	649	263

Mean coefficients; s.d in parentheses. Observations are pooled over all survey waves.

Table D.3: Resource shares of men, women and children

	(Ethiopia)			(India)			(Peru)		
	Men	Women	Children	Men	Women	Children	Men	Women	Children
Head: years of edu.	0.001**	-0.001	-0.001	0.001**	0.001***	-0.002***	0.000	0.002***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Head: Male	0.160***	-0.052***	-0.113***	0.122***	-0.060***	-0.069***	0.138***	-0.071***	-0.075***
	(0.006)	(0.006)	(0.008)	(0.005)	(0.005)	(0.007)	(0.005)	(0.005)	(0.007)
No. of female children	-0.018***	-0.019***	0.036***	-0.014***	-0.014***	0.023***	-0.016***	-0.015***	0.030***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
No. of female children	-0.017***	-0.025***	0.041***	-0.010***	-0.008***	0.013***	-0.010***	-0.021***	0.030***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
No. of adult male	0.011***			0.012***			0.012***		
	(0.001)			(0.001)			(0.001)		
No. of adult female		0.006***			0.007***			0.008***	
		(0.001)			(0.001)			(0.001)	
N	6856			7507			7160		

Mean coefficients; s.e in parentheses.

Agence française
de développement
5, rue Roland Barthes
75012 Paris l France
www.afd.fr

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Publication Director Rémy Rioux
Editor-in-Chief Thomas Melonio

Legal deposit 3rd quarter 2020
ISSN 2492 - 2846
Graphic design MeMo, Juliegilles, D. Cazeils
Layout AFD
Printed by the AFD reprography service

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