Social Protection and Multidimensional Poverty: Lessons from Ethiopia, India and Peru

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Abstract

We investigate the impact of three large-scale social-protection schemes in Ethiopia, India, and Peru on multidimensional poverty. Using data from the Young Lives cohort study, we show the trend, changes and evolution of multidimensional poverty for individuals in program participant households. We follow a number of strategies to produce estimates that deal with non-random program placement. Our findings show that both the incidence and intensity of multidimensional poverty declined in all three countries over the period 2006 - 2016, more so for program participants than non-participants. We find positive short-term impact on asset formation, livestock holding, and some living standard indicators. In all three countries these positive impacts are sustained even in the medium and longer-term.

Keywords: Social protection, Multidimensional poverty, PSNP, NREGA, Juntos, Young lives

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1. Introduction

Many developing countries in Africa, Asia, and Latin America have adopted social protection schemes as a means to address extreme poverty, rising inequality, risk and vulnerability. These social-protection schemes, implemented through a system of transfers in cash or in kind, aim to reduce poverty in the long term and help vulnerable households cope with economic shocks in the short term. In developing and transition countries, 2.5 billion people are covered by safety net programs which include cash or in-kind transfers, social pensions, public works, and school feeding programs (World Bank, 2018).

The wealth of interest from policy makers, donors, and researchers notwithstanding, there is a paucity of evidence about the distributional incidence of these programs and very little is known on their effects on multidimensional poverty (Seth and Tutor, 2021). Poverty is multifaceted and well-being can also be measured by many other dimensions. Empirical studies have shown that significant percentages of those who are multidimensionally deprived are not monetary poor and vice versa (see for example Alkire and Jahan, 2018). Hence, tracking the poverty reduction role of social-protection programs in a multidimensional framework is of high policy relevance. A multidimensional approach also provides an alternative solution to address some of the known blind spots of monetary poverty measures such as missing markets, problems with measuring consumption, and the distinctive difference between transient and chronic poverty.

There is, however, a dearth of evidence as to whether social protection programs have reduced multidimensional poverty. Furthermore, due to data limitations and restrictions imposed by robust empirical estimation strategies, we still know very little about the medium and long run effects of public works and conditional cash transfer programs on poverty and inequality.[1]

This paper intends to fill some of the evidence gap on social-protection and its effects on multidimensional poverty using information from a cohort survey in Ethiopia, India, and Peru combined with information on participation in national social-protection schemes. We evaluate three large-scale social-protection schemes - 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. Our aim is to identify the role of the programs in protecting the basic levels of consumption among vulnerable individuals, and how well the programs facilitate investment in productive assets. Hence, we focus on the hitherto understudied questions and provide cross country evidence on how large scale redistributive policies affect multidimensional poverty both in the short and medium run. Our approach allows us to causally measure the impact of the programs and draw relevant policy recommendations in light of the experiences and lessons learnt from these programs.

We start by asking whether program participants are less poor and less vulnerable after taking part in the social-protection program than before. Does the impact persist in the medium to longer-term? We use a rich panel data from the Young Lives Survey that follows children, and their families, across a span of fifteen years in all the three countries. The longitudinal nature of the data that we use allows us to compare the same individuals at different times to see how their lives and their communities are changing over time. We are also able to compare and contrast the efficacy of the two main types of targeted interventions: conditional cash transfers and public work

[1] Throughout this paper we use the terms public works, workfare, and employment guarantee schemes interchangeably.

programs. For causal identification, we exploit the staged roll-out of the program across districts in India, and construct a counterfactual comparison group based on the probability of being treated given observable covariates in Ethiopia and Peru.

Our paper adds to a growing literature that attempts to document the effectiveness of poverty alleviation programs. We go beyond the traditional money metric poverty assessment, and rather focus on multiple non-income based measures that are equally vital for improving the design and effectiveness of poverty reduction policies. To our knowledge, this is the first paper to document the effects of three large scale social-protection programs using multidimensional poverty indicators and employing panel data that is conducted simultaneously in all the study countries.[2] This dataset allows us to explore the similarity of patterns across those countries, and draw conclusions that are relevant for other countries with similar circumstances. We follow UNDP (2010), Alkire and Santos (2014), and Alkire and Jahan (2018) in our measurement of multidimensional poverty and construct indicators based on health, education and living standards dimensions.

We find that multidimensional poverty declined in all three countries over the period 2006 - 2016, with program participants benefiting the most. Our estimation results indicate a significant decline in multidimensional poverty incidence and intensity, particularly for the severely poor individuals in program participant households in all the three countries. We also find a positive sustained impact on asset formation, livestock holding, and some living standard indicators. The effects of the social programs mainly emanate from the direct income effect of benefits. The conditionalities attached in the *Juntos* CCT program also have a positive long term impact

[2] Only a few other studies have used multidimensional poverty indicators to evaluate anti-poverty programs, including Seth and Tutor (2021) for the Philippines, Song and Imai (2019) for Kenya, and Azevedo and Robles (2013) for Mexico.

on child school attendance and schooling.

The remainder of this paper proceeds as follows. In Section 2 we layout a theoretical framework and review the related literature. Section 3 provides background information about the study countries and the three programs. Section 4 presents the data and summary statistics. We outline the empirical strategy of the paper and present the results in Section 5. Section 6 concludes.

2. Theoretical Frameworks and Existing Literature

Poverty reduction has often relied on either economic growth or the intentional redistribution of resources to the poor. Even though the largest reductions in extreme poverty worldwide in the past few decades have resulted from substantial economic growth in many emerging economies, continued reduction of extreme poverty will require targeted interventions to help the poorest households increase their standards of living (Hanna and Olken, 2018; Page and Pande, 2018).

Social safety-net programs protect vulnerable households from impacts of economic shocks, natural disasters, and other crises. According to the World Bank (2018) 36% of the very poor escaped extreme poverty because of social safety nets. This fact offers clear evidence that social safety net programs are making a substantial impact in the global fight against poverty. While most social protection programs have the common goal of reducing extreme poverty, the mechanisms of achieving that goal depend on the various designs, forms and sizes of the programs. Hence, comparing the effectiveness of different types of social protection programs is critical.

Conditional Cash Transfers (CCTs)

Conditional cash transfers are payments that are targeted to the poor and made conditional on certain behaviours of recipient households. CCTs have two clear objectives: 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).

Systematic reviews of evidence on the impacts of cash transfer programmes indicate that transfers generally have been well targeted to poor households, have raised consumption levels, and have reduced poverty – by a substantial amount in some countries (Fiszbein and Schady, 2009; Saavedra et al., 2012).

CCTs, for all their evident success, have been criticized at least for a few valid reasons.[3] First, some of the neediest households might find the associated conditions too costly to comply with thereby excluding some of the people the program aims to reach. Second, those households that do opt for the benefit may incur a costly

[3]Mexico's conditional cash transfer program, Prospera, previously known as Progresa (1997 - 2002) and Oportunidades (2002 - 2014), has been replaced in 2019 after 21 years. The end of the programme can be attributed to multiple critiques: Poor targeting, high exclusion error, corruption, low public support, and conditionalities that incur unintended negatives effects.

distortion to their own behaviour for the sake of the short-run financial gain. In addition, CCTs cannot serve the elderly poor, childless households, or households whose children are outside the age range covered by the CCT (Fiszbein and Schady, 2009).

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 twofold. They help reduce poverty by transferring income to the poor and vulnerable, while using the labour provided by program participants to contribute to the creation of public assets (Gehrke and Hartwig, 2018; Alderman and Yemtsov, 2014).

A conceptual framework outlined by Gehrke and Hartwig (2018) distinguishes four 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. Second, workfare programs may affect labour market equilibrium by either crowding out the labour supply of other household members or, if the workfare wages are not set low enough, by crowding out informal work by the participant. Third, the implicit, and sometimes explicit, training component of the programs may improve the employability of participants or boost the chances of earning income from self-employment. Fourth, through the productive assets created, market access could be improved through road construction which in turn increase trade and production.

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., 2019; Berg et al., 2018), labour 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. 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., 2021; Galasso and Ravallion, 2004). However, they are demanding from an administrative perspective and comparatively expensive to run (Gehrke and Hartwig, 2018). The World Bank's Atlas of Social Protection: Indicators of Resilience and Equity (ASPIRE) database shows that public works programs have an average Benefit-Cost-Ratio (BCR), defined as the reduction in the poverty gap obtained for each dollar spent in the program, of 0.31. The average BCR for Conditional Cash Transfer programs is 0.42 (World Bank, 2018). There is also some argument that participants' welfare losses from forgone income maybe considerably higher in public works programs than in other poverty reduction programs (Murgai et al., 2016).

Studies find that social-protection programs may have both intended and unintended consequences. Although empirical analyses typically show that public works programs in developing countries reach their target group of poor households (see Zimmermann, 2014, for a review), some also find unintended consequences of these programs, notably on human capital accumulation (Shah and Steinberg, 2019; Li and Sekhri, 2020).

Effects of Social Protection Design

We here evaluate three different designs of social protection: a conditional cash transfer, an employment guarantee and a cash for work programs. Important design features such as targeting and conditionality, transfer type and amount, main recipient, frequency and duration of payments, as well as supply-side circumstances influence outcomes and impacts of social protection programs. Ideally, an experimental design with a conditional, unconditional, and pure control arms would allow to learn whether the conditionality changes behaviour, or whether the CCT changes behaviour simply through its income effect (Hanna and Karlan, 2017). Criteria for choosing between conditional and unconditional transfers critically depend on the state of social services delivery, administrative capacity, and availability and utilisation of health and school services.

Even though the variations in program design and contexts make comparison difficult, we offer empirical evidence that highlights how different transfer programs work across different countries in reducing multidimensional poverty. We exploit the Young Lives dataset that offers a unique opportunity to report on trends, explore how patterns are similar or different across those countries, and make comparisons that are relevant for other countries with similar circumstances.

Our outcome variable is composed of living conditions, health and education categories. Irrespective of their design, all three transfer programs we evaluate have potential for reducing poverty through increasing households' disposable income and hence improving living conditions. Increased resources allow households to make improvements to sanitation facilities and housing conditions (such as replacing dirt floors with cement floors) thereby improving their health conditions (Cattaneo et al., 2009).

Education outcomes, as measured by schooling and attendance dimensions, can be affected by both conditional and unconditional transfer programs through the positive income effects emanating from direct transfers, short-term employment, and income from productive activities. Similarly, conditionalities associated with CCTs could lower the opportunity cost of schooling and hence further increase school attendance. It is difficult to isolate the effects of the conditionality from the liquidity or income effect of the program. Public work programs, on the other hand, may induce intrahousehold labour substitution effects that could positively or negatively affect child labour. An increase in participation of adults in the labour market may force children to take part in household enterprises and household chores previously carried out by the adults. The net effect of labour market-oriented programs on child labour will depend on whether the income effect dominates the substitution effect, which in turn is conditioned on many factors, among them the need of labour required under the program, the opportunity cost of adult household member time, requirements of the program, changes in income due to the program, opportunity cost of schooling, and child's productivity in household activities. A priori, it is not possible to determine which effect will dominate (see Dammert et al., 2018, for an extensive review).

Related Literature

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 show that public sector hiring crowded out private sector work and increased private sector wages. Gehrke (2017) finds that households with access to the program are more likely to take riskier agricultural investment decisions. Evidence from Andhra Pradesh in India suggests that a mother's participation in the labour force increases her children's time spent in school and leads to better grade progression (Afridi et al., 2016).

Using the Young Lives survey data, Andersen et al. (2015) estimate the link between participation in Peru's *Juntos* CCT with anthropometry, language development, and school achievement among young children and report that participation was associated with better height-for-age growth among boys. Similarly, using the same sample of children, Sánchez et al. (2020) highlight 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. Dasgupta (2017) also uses the Young Lives data and examines 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.

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 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 PSNP. Similarly, Andersson et al. (2011) report some evidence that participation in PSNP increased the number of trees planted, but there was no increase in their livestock holdings.

Our paper complements this rich body of work. The literature is scant when it comes to evaluating the effect of social-protection schemes on multidimensional poverty. In addition, the current state of knowledge about the impacts of the schemes is mostly restricted to outcomes measured in the short run. We show the trend, changes and evolution of the well-being of individuals in program participant households in the medium and longer-term using multidimensional poverty measures.

3. Study Context

Ethiopia: The Productive Safety Net Program (PSNP)

The Productive Safety Net Program (PSNP) is a public program that was 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. Examples of public works through PSNP include working on soil and water conservation, road building, and construction of schools and clinics. The aim is to enable households smooth consumption without the need to sell productive assets in lean periods. The public works segment of the program pays selected beneficiaries for their labour on labour-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).

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 labour available for work. Communities select beneficiaries in collaboration with the *kebeles* refining the selection based on household assets (landholdings), and income from nonagricultural activities and from alternative sources of employment (Gilligan et al., 2009; Berhane et al., 2014).

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 labour 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, 2019).

The act was 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).

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 guerilla 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 ($\sim$ 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).

4. 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 follow-up waves in 2006, 2009, 2013 and 2016.

One of the advantages of the Young Lives survey 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 basic services. The longitudinal nature of the data allows us to document the evolution of poverty over time.

4.1. Survey Design and Sampling

According to the survey documentation of Young Lives,[4] the 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.

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. Between three and five *woredas* (districts) were selected in each region, with a balanced representation of poverty levels, urban and rural areas, and a selection of urban site types. Among the *woredas* with food deficit status within each region, three with the highest proportion and one with the lowest proportion were selected. 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

[4] See https://www.younglives.org.uk/ for further details.

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[5] 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; and the selection of one poor and one non-poor district in each region based on a ranking of economic, human development and infrastructure development indicators (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 as described above). 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

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

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).

4.2. Variable Definition

Multidimensional Poverty Indicators

To study multidimensional poverty, we follow the global Multidimensional Poverty Index (MPI) methodology outlined in the United Nation's multiple human development reports since 2010 (UNDP, 2010; Alkire and Jahan, 2018). The global MPI looks at three dimensions of well-being (health, education, and living standards) and measures them with ten indicators: nutrition and child mortality for health; school attendance and years of schooling for education; cooking fuel, sanitation, drinking water, electricity, housing, and assets for living standards.

These indicators were selected after a thorough consultation process involving experts in all three dimensions, and building on recent advances in theory and data. The relevance of these dimensions and indicators is well documented in the literature (see for instance, Alkire and Jahan, 2018; Alkire and Seth, 2015; Alkire and Foster, 2011). Their purpose is to assess multidimensional poverty levels in specific countries or regions in the indicators most relevant and feasible locally (Alkire and Jahan, 2018).

Young Lives contains information that allows us to compute the MPI. A detailed description of the variables considered in each indicator is contained in Table A.5. In particular, for the health dimension we consider if any household member is undernourished and if any child has died in the family in the five-year period prior to the survey. For education we consider if no household member above age 10 has completed six years of schooling and if any child is not attending school.

For the living conditions dimension, we use information on whether the household cooks with dung, wood or charcoal; whether the household has a shared or unimproved sanitation facility; whether or not the household has access to safe drinking water; whether or not the household has access to electricity; whether or not the quality of main materials of dwelling (walls, roof and floor) satisfy basic norms of quality; and whether or not the household owns more than one of these assets: radio, TV, telephone, computer, animal cart, bicycle, motorbike, refrigerator, a car or truck.

The data providers also offer a *wealth index* computed from indicators of housing quality, access to services, and consumer durables (all of which have equal weights). The average produces a value between 0 and 1, where a higher wealth index indicates a higher socio-economic status. The wealth index is intended to be the primary measure of socio-economic status and material well-being of households within the Young Lives sample. We will also appeal to this wealth index in our robustness analysis.

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. Other characteristics such as gender of household members, ethnicity, religion, and language are also available.

Shocks and adverse events

The data also records detailed information on the occurrence of events that have affected negatively the economic situation of the household. An event is recorded as a shock only if the respondent perceives the event to have affected the welfare of the household negatively. These events include natural disasters, changes in economic conditions, changes in regulation, crime (e.g. theft) and other disasters (both natural and man-made). All shock-related variables are binary (either the shock was reported, or it was not).

4.3. Program Participation

Households in the sample were asked to describe their participation status in several country-specific public programs, including duration of participation, and the benefits acquired. Details about households' participation in PSNP, NREGA and *Juntos* programs, such as duration and type of support as well as identification of members who participated are available in the dataset. We use the first two rounds of survey (2002 and 2006) for the pre-program period and rounds 3-5 (2009 - 2016) for the post-program period.[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 Young Lives survey is conducted in six rural districts of Andhra Pradesh state, of which four received NREGA programming between April 2006 and March

[6]In Ethiopia a health extension program, in India Rajiv Aarogyasri healthcare program, and in Peru a pension program for over 65s (Bonograt) and a scholarship program for high school graduates (Beca 18) are reported in our sample. However, the three main programs evaluated here (PSNP, NREGA, *Juntos*) remain the major public programs. In addition, both healthcare programs in Ethiopia and India are almost universal. The Beca 18 and Bonograt programs in Peru are only reported in waves 4 and 5 and constitute a small share of support.

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 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.

4.4. Summary Statistics

We present summary statistics for the main variables and controls used in the paper in Tables A.1 - A.3 in Appendix A. We split the sample by participation status (program participants, and non-participants) as well as into pre- and post-program implementation periods. We use wave 2 survey (2006) for the pre-program period and averaged outcomes reported in waves 3-5 for the post-program period. We also present program coverage over time in Table A.4.

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. This pattern indicates that the social security programs reach their target group of poor households as more of the poorer households get coverage on average. This is in line with the findings from other studies cited above. Although some fraction of the non-poor often benefits as well, targeting seems to be fairly successful in most public works programs and to work better in this respect than a number of traditional cash transfer programs for the poor (Zimmermann, 2014).

5. Social Protection and Multidimensional Poverty

5.1. Measuring Multidimensional Poverty

Poverty measurement is still an active area of debate. The traditional money metric poverty assessment that mainly uses income or consumption based measures is deemed incomplete as it disregards some non-income based aspects of life that are equally vital for improving the design and effectiveness of poverty reduction policies. Researchers prefer an approach that proposes a broad, rich, and multidimensional view of human well-being paying much attention to the links between the economic, social, and political dimensions of life.

In measuring multidimensional poverty, researchers need to select the relevant dimensions and their corresponding indicators; aggregate the indicators within and across dimensions; and assign cut-off points to delineate the poor from the non-poor. The empirical framework in this paper follows the counting approach of measuring multidimensional poverty (Atkinson, 2003) as implemented by Alkire and Foster (2011) (henceforth AF). Building on the Foster-Greer-Thorbecke poverty measures, the AF proposal involves counting the different types of deprivation that individuals experience, such as a lack of education, employment, poor health and living standards. These deprivation profiles are analysed to identify who is poor, and then used to construct a multidimensional index of poverty.

The basic definitions and notation for multidimensional poverty in the AF method are as follows. Suppose we have n individuals in the population, and let $d \geq 2$ be the number of dimensions under consideration. Let $Y = [Y_{ij}]$ denote the $n \times D$ matrix of well-being outcomes, where the typical entry Y_{ij} is the achievement of the individual $i = 1, 2, \ldots, n$ in dimension $j = 1, 2, \ldots, D$. Let z_j denote the cut-off below which a person is considered to be deprived in dimension j. Expressing the data in terms of deprivations rather than achievements, for any given Y, let $g_{ij}^0 = 1$ when $Y_{ij} \leq z_j$, and $g_{ij}^0 = 0$ otherwise. From the matrix g^0 we can construct a column vector c of deprivation counts, whose i^{th} entry $c_i = |g_i^0|$ represents the number of deprivations suffered by person i. The deprivation of each person may also be weighted by the indicator's weight, given by w_j with $\sum_j w_j = 1$. From this, a deprivation score is computed for each individual, defined as the weighted sum of deprivations $c_i = \sum_{j=1}^{d} w_j g_{ij}^0$ (Alkire and Foster, 2011).

In order to identify who is poor and who is not, Alkire and Foster (2011) propose to follow the intermediate identification method, such that individual i is poor when the number of dimensions in which i is deprived is at least k, where k is chosen by the researcher.

Different indices are used in the last step to measure poverty: (i) the incidence of poverty, H; (ii) the intensity of poverty, A; and (iii) the Adjusted Headcount ratio, MPI. The index H measures the *incidence of poverty*, that is, the incidence of multiple deprivations or the incidence of experiencing k or more disadvantages. It is calculated by dividing the total number of individuals who are experiencing k or more deprivations (q) by the total number of individuals (n): $H = 1/n \sum_{i=1}^{n} \mathbf{1}[c_i \geq k] = q/n$, where $\mathbf{1}[c_i \geq k]$ is an indicator function with a value of 1 for $c_i \geq k$ and 0 otherwise. The index A measures the *intensity* of their deprivation - the average proportion of (weighted) deprivations they experience. That is, for multidimensionally poor individuals only (those with a deprivation score c greater than or equal to the cutoff), the deprivation scores are summed and divided by the total number of multidimensionally poor individuals ($A = \sum_{i=1}^{q} c_i/q$). The Adjusted Headcount ratio (MPI) combines information on the incidence and intensity of multidimensional poverty among the poor ($MPI = H \cdot A$). It represents the share of the population that is multidimensionally poor adjusted by the intensity of the deprivation suffered. This adjustment is necessary because if we only look at H we will only know what percent of the population is poor. The MPI sheds more light on whether or not they are all equally poor, or deprived in all the considered deprivations.

5.2. Descriptive Evidence

We measure the MPI on 10 indicators grouped into three dimensions: Education, Health, and Standard of Living. The education dimension consists of years of schooling and school attendance; the health dimension consists of nutrition and child mortality; and the standard of living dimension consists of electricity, sanitation, water, flooring material, cooking fuel, and asset ownership. Table A.5 in Appendix A summarizes the dimensions, cutoff criteria and corresponding weights of the indicators selected.

To identify the multidimensionally poor people, the deprivation scores for each indicator are summed to obtain the individual's deprivation score. We consider three different cutoff levels: 20%, 33% and 50% of the weighted indicators. We follow Alkire and Seth (2015) and identify a person as poor if their deprivation score c_i is greater than or equal to 33% of the weighted indicators. Individuals with a deprivation score of 20% or higher but less than 33% of the weighted indicators are considered to be *vulnerable* to multidimensional poverty. Individuals with a deprivation score of 50% of the weighted indicators or higher are considered to be in *severe* multidimensional poverty.

We report our descriptive results in tables 1 and 2 below. Table 1 presents the trends of multidimensional poverty in Ethiopia, India, and Peru by program participation status across four waves of survey. Table 2 complements these results by reporting the two components of the MPI (H and A) using k = 33% of the weighted indicators. Multidimensional poverty has declined steadily between 2006 and 2016 in all the three countries. The reduction in the MPI is robust to the different deprivation cutoffs. Although all three countries experienced poverty reduction, the magnitude varies across countries as well as by participation status in social-protection programs.

The largest decrease in multidimensional poverty is experienced by *Juntos* participants in Peru where the MPI declined from 0.57 in 2006 to 0.17 in 2016. Decomposing its total across the incidence and intensity of poverty, we observe a decrease in poverty incidence by 54 percentage points over the 10 years, and a decrease in poverty intensity by 18 percentage points. We also observe a sizeable drop in the MPI and its components for both PSNP and NREGA participants in Ethiopia and India. The reduction in the MPI for individuals living in households not covered by the programs is lower in all the three countries. Similarly, the proportion of multidimensionally poor that are in severe poverty shows a marked decline over the decade. Overall, participation in social safety-net is associated with a larger decline in all the multidimensional poverty indicators.

The bulk of the reduction in poverty in all the three countries occurred between the second and third waves (2006-2009), a period that coincides with the launching of the social safety-net programs in the countries. Further decline in multidimensional poverty was registered between 2009 and 2013, but poverty levels have plateaued from there on. Intensity of poverty remains high in all the samples considered with the average multidimensionally poor person deprived in at least 40% of the weighted indicators.

We also calculated the contribution of each dimension to multidimensional poverty. The full result is reported in Table A.6 in Appendix A. This decomposition provides information that can be useful for revealing a country's deprivation structure and can help with policy targeting. In this regard, deprivation in the education dimension accounts for over half of multidimensional poverty in Ethiopia and Peru, and two thirds in India. Deprivation in living conditions is the second dimension that contributes the most to overall poverty. In line with the initial results from our descriptive statistics, and asserting our finding regarding targeting, program participants in all the three countries are more deprived in living condition indicators than non-participants.

Table 1: The Multidimensional Poverty Index (MPI)

	2006		2009		2013		2016	
	Part.	Non-Part.	Part.	Non-Part.	Part.	Non-Part.	Part.	Non-Part.
Ethiopia								
$k = 20\%$	0.57	0.44	0.45	0.34	0.41	0.29	0.39	0.29
$k = 33\%$	0.56	0.40	0.42	0.30	0.38	0.23	0.36	0.24
$k = 50\%$	0.48	0.29	0.25	0.19	0.19	0.11	0.18	0.10
India								
$k = 20\%$	0.35	0.32	0.25	0.22	0.20	0.19	0.20	0.19
$k = 33\%$	0.31	0.27	0.18	0.15	0.12	0.12	0.15	0.14
$k = 50\%$	0.19	0.16	0.07	0.07	0.02	0.04	0.03	0.03
Peru								
$k = 20\%$	0.58	0.26	0.36	0.12	0.30	0.10	0.25	0.08
$k = 33\%$	0.57	0.21	0.29	0.08	0.23	0.07	0.17	0.05
$k = 50\%$	0.51	0.14	0.14	0.03	0.09	0.02	0.06	0.07

Number of observations: Ethiopia $N = 2892$ households (805 PSNP participants and 2087 non-participants) and 17739 individuals; India $N = 2944$ households (1738 NREGA participants, 1206 non-participants) and 15889 individuals; Peru $N = 2766$ households (427 *Juntos* participants, 2339 non-participants) and 14206 individuals. Columns labelled "Part." and "Non-Part" denote program participants and non-participants respectively. In all the countries the program implementation started after the 2006 survey. Rows labelled $k = 20\%, 33\%, 50\%$ represent the MPI level at the respective deprivation cutoff.

Table 2: Incidence and Intensity of Multidimensional Poverty (MPI)

	2006		2009		2013		2016	
	Part.	Non-Part.	Part.	Non-Part.	Part.	Non-Part.	Part.	Non-Part.
Ethiopia								
Incidence	97.2	74.7	87.1	61.5	82.1	51.2	81.5	56.2
Intensity	57.9	53.0	48.7	48.6	45.8	45.0	44.2	43.5
India								
Incidence	62.1	52.6	40.2	33.6	28.1	26.6	36.5	33.9
Intensity	49.2	51.0	44.4	46.0	42.1	44.1	41.2	41.6
Peru								
Incidence	94.4	42.8	64.8	18.7	52.3	15.7	40	12.4
Intensity	60.5	50.2	45.5	44.2	43.6	41.7	42.3	41.0

Number of observations: Ethiopia $N = 2892$ households (805 PSNP participants and 2087 non-participants) and 17739 individuals; India $N = 2944$ households (1738 NREGA participants, 1206 non-participants) and 15889 individuals; Peru $N = 2766$ households (427 *Juntos* participants, 2339 non-participants) and 14206 individuals. Columns labelled "Part." and "Non-Part" denote program participants and non-participants respectively. In all the countries the program implementation started after the 2006 survey. Incidence and intensity of poverty are computed based on a deprivation cutoff of $k = 33\%$.

We next analyse which deprivations have been reduced the most and contributed to the overall decline in multidimensional poverty. Our findings, reported in Table 3, show a statistically significant reduction in multidimensional poverty between 2006 and 2009 in all the three countries. The reductions are largest in school attendance (38%) and access to improved sanitation (19%) indicators in Ethiopia followed by significant reductions in the other living condition and nutrition indicators, each of which fell upto 6%. Similarly for India, deprivation in school attendance falls by 45% while deprivations in assets drops by 14%. In Peru, reduction in school attendance deprivation once again is the largest with a 72% decline, but significant reductions are also achieved in most other indicators almost all of which declined by more than 6%. Tables A.7 – A.9 in Appendix A report the percentage of people who are poor and deprived in each indicator and the percentage contribution of each indicator in the MPI for the three countries.

The descriptive evidence that both PSNP and NREGA result in reduced deprivation in child schooling is interesting. It points to the fact that optimal investment in child education may not be achieved in poor resource-constrained households. This result is consistent with the theoretical predictions of earlier works on child labour where poor, credit constrained households are more likely to resort to child labour to meet subsistence needs, even if parents have preferences for schooling (Baland and Robinson, 2000; Basu and Van, 1998). Using a randomised control trial with both a CCT and an unconditional transfer (UCT) design, Baird et al. (2011) show that both designs result in improved schooling outcomes. They conclude that even though schooling CCTs are a much more cost-effective means of reducing dropouts than are UCTs, in the absence of a market failure, such a distortion is inefficient.

Table 3: Dimensional Decomposition and the Contribution of the Indicators of the MPI, by Participation Status

	All			Participants			Non-participants		
	2006	2009	Difference	2006	2009	Difference	2006	2009	Difference
Ethiopia: PSNP									
Electricity	57.8%	52.3%	-5.5%***	80.6%	72.9%	-7.7%***	49.1%	44.1%	-5.0%***
Sanitation	57.8%	38.3%	-19.4%***	67.8%	33.6%	-34.2%***	53.7%	40.2%	-13.5%***
Water	49.6%	48.5%	-1.0%***	49.6%	57.8%	-8.3%***	49.7%	44.8%	-4.8%***
Housing	69.8%	65.6%	-4.3%***	78.8%	75.8%	-3.0%***	66.5%	61.5%	-5.0%***
Cooking fuel	93.0%	94.0%	0.9%***	99.9%	99.8%	-0.1%***	90.5%	91.6%	-1.1%***
Assets	19.5%	13.2%	-6.2%***	41.7%	30.7%	-11.0%***	10.8%	6.3%	-4.5%***
Attendance	66.0%	27.8%	-38.2%***	67.6%	26.7%	-40.9%***	65.3%	28.3%	-37.0%***
Schooling	75.8%	76.4%	0.6%	95.4%	95.3%	-0.1%	68.2%	68.8%	0.6%
Nutrition	31.0%	24.8%	-6.1%***	38.1%	29.3%	-8.8%***	28.1%	23.1%	-5.0%***
India: NREGA									
Electricity	9.4%	2.8%	-6.6%***	6.5%	2.1%	-4.4%***	15.2%	4.3%	-11.0%***
Sanitation	67.5%	66.0%	-1.5%***	69.1%	68.4%	-0.7%	64.3%	61.6%	-2.8%***
Water	5.0%	3.1%	-1.8%***	2.8%	1.4%	-1.4%***	9.3%	6.7%	-2.6% ***
Housing	28.6%	22.1%	-6.6%***	29.3%	22.1%	-7.2%***	27.5%	22.3%	-5.2%***
Cooking fuel	74.6%	70.9%	-3.8%***	77.5%	74.0%	-3.6%***	68.9%	64.8%	-4.1%***
Assets	21.5%	7.7%	-13.9%***	22.4%	7.0%	-15.4%***	19.8%	8.9%	-10.9%***
Attendance	56.7%	11.8%	-44.9%***	58.1%	13.7%	-44.4%***	53.8%	7.8%	-46.0%***
Schooling	59.3%	56.7%	-2.6%***	60.7%	58.3%	-2.4%***	56.6%	53.7%	-2.9%***
Nutrition	34.8%	31.4%	-3.4%***	36.4%	33.5%	-2.9%***	31.7%	27.5%	-4.3%***
Peru: *Juntos*									
Electricity	24.9%	14.3%	-10.6%***	52.4%	32.4%	-20.0%***	18.7%	10.2%	-8.5%***
Sanitation	15.1%	8.9%	-6.2%***	31.7%	11.6%	-20.1%***	11.4%	8.3%	-3.2%***
Water	38.9%	19.5%	-19.4%***	57.3%	28.0%	-29.3%***	34.9%	17.6%	-17.3%***
Housing	60.4%	54.3%	-6.2%***	95.6%	95.5%	-0.1%	52.4%	44.9%	-7.5%***
Cooking fuel	54.0%	48.3%	-5.6%***	99.1%	95.5%	-3.6%***	44.0%	37.6%	-6.4%***
Assets	23.7%	12.9%	-10.8%***	62.7%	33.9%	-28.7%***	14.9%	8.1%	-6.8%***
Attendance	74.4%	3.0%	-71.5%***	82.0%	1.2%	-80.8%***	71.8%	3.1%	-68.6%***
Schooling	40.3%	39.1%	-1.2%**	77.5%	77.8%	-0.3%	31.4%	30.0%	-1.4%**
Nutrition	35.5%	23.9%	-11.6%***	61.6%	43.8%	-17.8%***	29.8%	19.4%	-10.4%***

Statistical tests of differences reported under columns labelled "Difference". * $p < 0.01$, ** $p < 0.05$, *** $p < 0.001$. Number of observations are as described in Tables 1 and 2. The indicators are defined in Table A.5.

5.3. Causal Impact of the Programs

In the analysis so far, we showed that all the three social-protection schemes we considered are associated with significant reduction in multidimensional poverty. However, we cannot draw any causal conclusions from these exercises for two main reasons. First, we observe that poverty declined overtime irrespective of the programs. Second, program participation was not random. The fundamental challenge with causal inference is that we never observe what would have happened to the treated had the treatment not occurred. Many studies so far have been handicapped from making causal inferences due to this problem. In this paper, we propose to overcome the latter with a unique longitudinal dataset that enables us to employ robust estimation techniques in a quasi experimental setup.

We evaluate program impact estimating difference-in-differences (DID) models using matching methods to construct a credible control group. The DID estimator provides the average change in the outcome in a treatment group minus the average change in the outcome in a control group.

5.3.1. Identifying impact of PSNP and Juntos

To estimate program effects of PSNP in Ethiopia and *Juntos* in Peru while dealing with non-random program assignment, we use variations of the following regression model:

$$Y_{it} = \beta_0 + \beta_1 Prog_i + \beta_2 Post_t + \beta_3 Prog_i \cdot Post_t + \beta_4 \boldsymbol{X}_{it} + \lambda_t + \varepsilon_{it} \quad (1)$$

where Y_{it} is the outcome variable for individual i in year t, $Prog_i$ is an indicator of program participation status. $Post_t$ is a dummy variable equal to one in post program periods; $\boldsymbol{X}_{it}$ is a vector of covariates that we control for including household and community characteristics; λ_t denotes year fixed effects, and ε_{it} is the error term. β_3 is our coefficient of interest, and it measures the effect of program participation on the outcome variable Y. For evaluating H (the incidence of multidimensional poverty) the outcome variable Y_i is a binary indicator, such that $Y_i = 1$ if individual i experiences deprivation and 0 otherwise. For evaluating A (intensity of poverty), the outcome variable Y_i is the weighted sum of the number of deprivations that each individual suffers. We cluster standard errors at the community level.

In order to separately estimate the short-run, medium-run, and longer-run effects of the programs, we expand equation 1 as follows:

$$\begin{aligned} Y_{it} = \beta_0 + \beta_1 Round3_t + \beta_2 Round4_t + \beta_3 Round5_t + \beta_4 Prog_i + \\ \beta_5 Prog_i \cdot Round3_t + \beta_6 Prog_i \cdot Round4_t + \beta_7 Prog_i \cdot Round5_t + \\ \beta_8 \boldsymbol{X}_{it} + \varepsilon_{it} \end{aligned} \quad (2)$$

where $Round\ k = 3, 4, 5$ represent post program survey waves (see Section 4 for data description).

To assess how participation in each of the social-protection programs affects well-being of participants, we employ different strategies that address potential threats to identification. A common such threat to all the programs we are evaluating in this paper is the potential problem of selection bias. A key assumption of the DID estimation strategy is that, at baseline, the treatment and comparison groups are as comparable as possible. In other words, the mean change in outcomes for both groups would have been the same in the absence of the program. Unless treatment is randomly assigned, comparison of the outcome between the participants and non-participants will yield biased estimates.

To validate the plausibility of this assumption, we need to assess whether the pre-treatment trends were the same between the treatment and control groups. If selection is done based on observable characteristics, then one can circumvent the problem of selection bias by using a method of matching on observables. Hence, we conduct propensity score matching methods to construct a comparison group of households with a similar probability of being treated based on these observable characteristics. This method controls for confounding by matching observations on the basis of their predicted probability of treatment using the set of observable characteristics assumed not to be affected by the treatment.

In the PSNP case, 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. We use the following sets of covariates to match households defined as participants with non-participants: pre-program demographic characteristics of the household (age and gender of head, and household size), ownership of land and livestock, experiences of shocks (drought, illness, theft); and household location (urban, rural).

Similarly, in *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. Figures B.4 and B.5 in Appendix B show that the common support is complete; that is, for each participant household in PSNP and *Juntos*, we have a sufficiently high number of close matches from non-participant households.

5.3.2. Identifying impact of NREGA

In the case of NREGA, we exploit the staggered roll-out of the social-protection programs across districts to causally identify the impact of the schemes on a set of well-being indicators. This plausibly exogenous, temporal sub-district level variation in the intensity of implementation allows us to estimate the *intent-to-treat* effects of the program. We estimate the following difference-in-differences (DID) regression specification:

$$Y_{ijt} = \beta_0 + \beta_1 Prog_{ij} + \beta_2 Post_t + \beta_3 Prog_{ij} \cdot Post_t + \beta_4 \boldsymbol{X}_{ijt} + \gamma_j + \lambda_t + \varepsilon_{ijt} \quad (3)$$

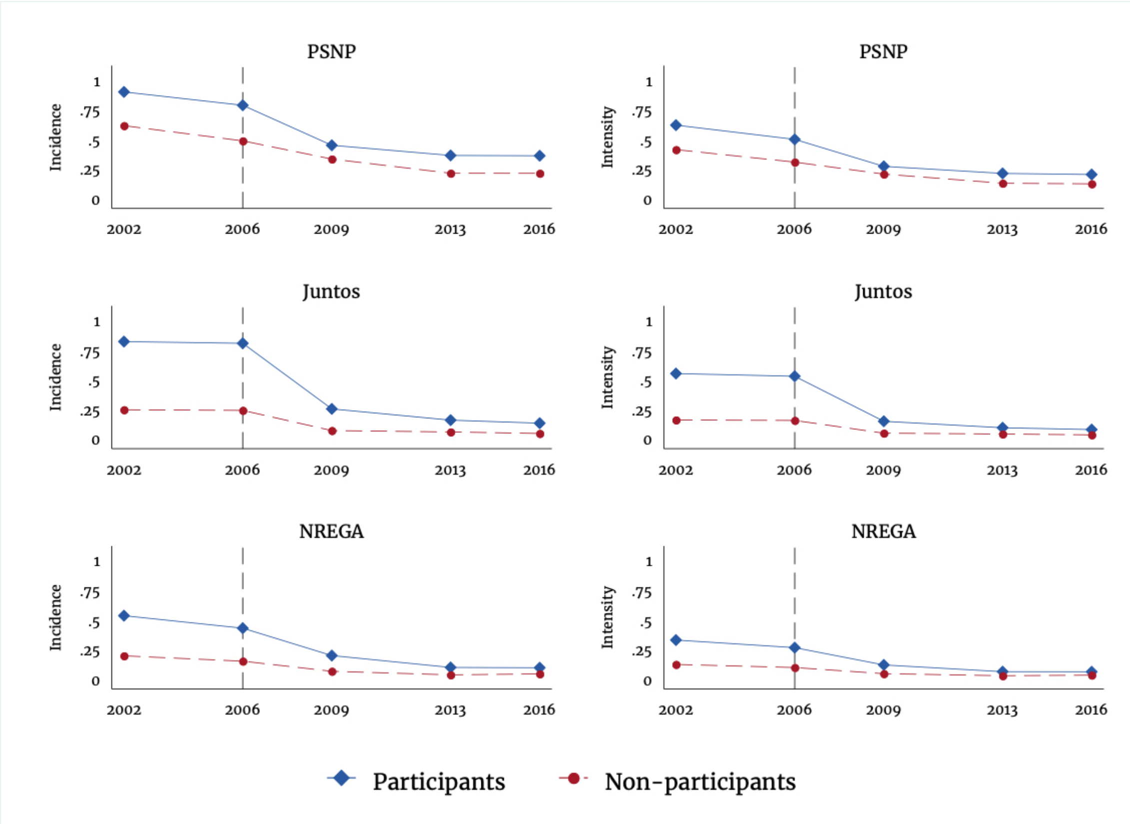
where j represents district and γ_j denotes district fixed effects.

Since the surveys that we use directly ask household members whether they participate in NREGA or not, we could also estimate average treatment effects. However, this strategy may suffer from potential endogeniety as households that take up NREGA may simultaneously make other decisions that could result in reduced poverty. For the sake of easier comparison, we also employ a similar strategy as the one of the first two programs and construct a comparison group of households using propensity score matching. The results from these latter two methods are reported in Appendix A (Tables A.14 and A.15), and are qualitatively similar to our main results.

5.3.3. Time trends

Our identification still relies on the assumption that in the absence of the programs, households that received the program and those that do not participate did not have systematically different time patterns in our outcome variables. Although there is no statistical test for this assumption, visual inspection often can show that the assumption seems to hold in the pre-treatment period. If the treatment and control groups are observationally similar at baseline, then we have higher confidence that the two groups preserve exchangeability in the post-treatment future. Two rounds of pre-intervention data (2002 and 2006 waves) allow us to test if the parallel trend assumption holds.

Figure 1 presents the trends of some selected outcomes, incidence and intensity of poverty, for program participants and non participants. As we established in Section 4, participant households are relatively poorer than non-participants. These differences are apparent in the plots for the two outcome variables as well. However, reassuringly, we can see that the trend of pre-program dynamics for participants and non participants is not systematically different and complies with the parallel trend assumption of our identification strategy. We report additional plots in Appendix B that depict parallel trends using different cutoffs of multidimensional poverty and other well-being indicators such as asset ownership and wealth index.



Note: Incidence and intensity of the MPI are computed based on the deprivation cutoff of 50% of the weighted indicators.

Figure 1: Trends in Incidence and Intensity of Multidimensional Poverty, by Participation Status

5.3.4. Results

Estimation results from DID estimates for short-term (2009) and medium and longer-term (2013 and 2016) impacts of all the three programs are reported in Table 4. In all of the estimations, we control for variables that might be affected by the programs and might influence household well-being. These variables include household head's age, education and gender, household size, as well as place of residence (urban/rural). Since effects on the deprivation scores of the poor maybe differentially affected for different poverty cutoffs (for example $k = 33\%$ and higher poverty cutoff, such as $k = 50\%$), we also focus on subsets of the poor who experience intense poverty (using $k = 50\%$). This approach allows us to clearly indicate the distributional impact of the programs on multiple deprivations.

For each country, in the first rows labelled $Program \times Post$, we present the average effect of the programs over the five survey waves. In the subsequent rows we separately estimate program effect on the short, medium and longer run using data from the third wave ($Program \times 2009$), fourth wave ($Program \times 2013$) and fifth wave ($Program \times 2016$) of the survey. We report program effects on the incidence (H) and intensity (A) of multidimensional poverty. A reduction in both H and A reflects a positive program impact.

Three general findings are evident from Table 4. First, the programs significantly reduced the incidence and intensity of poverty for the severely poor individuals in all the three countries. Second, the intensity of poverty of individuals experiencing multiple deprivations is significantly reduced in all of the samples we analyse. Third, program effects were sustained in the medium and longer run period in all three cases.

In Ethiopia and Peru, when we consider deprivations in three or more indicators ($k = 33\%$), we observe that PSNP and *Juntos* do not have a statistically significant impact in reducing the incidence of poverty. However, the corresponding intensities have shown a large reduction. NREGA, on the other hand, resulted in a reduction in the incidence of multidimensional poverty by 9.8 percentage-points (from the 51% of baseline control average). At the same time, the intensity of poverty of those experiencing three or more deprivations is lower by 6 percentage-points on average.

When we consider the cutoff level $k = 50\%$, we find that all three programs significantly reduced the incidence and intensity of poverty. PSNP, NREGA and *Juntos* resulted in 13% (from 60%), 9% (from 26%), and 21% (from 50%) decline in incidence of multidimensional poverty respectively. The corresponding intensities of poverty also showed significant reduction for all three programs ranging from 6 – 17%. These findings suggest that the reductions in multidimensional poverty are largely obtained by alleviating poverty among those with five or more deprivations, and also improving the poverty profiles of those experiencing a larger number of deprivation.

We next analyse which deprivations have been reduced the most. We estimate the program impact on all 10 censored deprivation indicators.[7] Table 5 presents the dimensional decomposition and the contribution of indicators to the overall poverty. The reductions in deprivation are not uniform across indicators. In all the three programs, reduction in multidimensional poverty has been accomplished by large reductions in deprivations in "asset ownership", "school attendance" and "sanitation". There has been statistically significant reductions in "schooling" and "housing" in India and "electricity" in Peru. We detect no significant reductions in "cooking fuel" and "clean water" indicators in all three countries.

The short and longer term effects of the three programs on the censored indicators are presented in Tables A.10 – A.12 in the Appendix A. The probability of not owning two or more durable assets declined by 31 percentage points for PSNP program participants in Ethiopia almost 10 years after the introduction of the program. Similarly for NREGA and *Juntos* participants in India and Peru, deprivation in asset holding decreased by 8 and 33 percentage points respectively.

It appears as though that the positive effect we detected from the two public works programs mainly captures the direct income-effect of the benefits (wages and

[7]The deprivations experienced by people who have not been identified as poor (i.e. those whose deprivation score is below the poverty cutoff) are censored, hence not included.

Table 4: DID Estimations: Short and Longer term effects

	Incidence of Poverty		Intensity of Poverty	
	$k = 33\%$	$k = 50\%$	$k = 33\%$	$k = 50\%$
Ethiopia				
Program×Post	0.084	-0.128***	-0.030**	-0.106***
	(0.053)	(0.029)	(0.014)	(0.016)
Program×2009	0.005	-0.210***	-0.072***	-0.160***
	(0.040)	(0.040)	(0.016)	(0.025)
Program×2013	0.086*	-0.124***	-0.030*	-0.101***
	(0.047)	(0.034)	(0.016)	(0.020)
Program×2016	0.066*	-0.091*	-0.024	-0.091***
	(0.035)	(0.050)	(0.023)	(0.032)
Observations	45161	45095	44989	45667
Control mean	0.86	0.59	0.48	0.37
India				
Program × Post	-0.098***	-0.092*	-0.063***	-0.058*
	(0.029)	(0.047)	(0.018)	(0.030)
Program × 2009	-0.071**	-0.074*	-0.043**	-0.050*
	(0.025)	(0.042)	(0.018)	(0.026)
Program × 2013	-0.134***	-0.128**	-0.057**	-0.069*
	(0.035)	(0.051)	(0.024)	(0.035)
Program × 2016	-0.106***	-0.106*	-0.056**	-0.048
	(0.032)	(0.056)	(0.026)	(0.037)
Observations	54600	54538	54720	54576
Control mean	0.51	0.26	0.26	0.16
Peru				
Program × Post	0.004	-0.211***	-0.072***	-0.162***
	(0.035)	(0.061)	(0.025)	(0.038)
Program × 2009	0.105	-0.166**	-0.047*	-0.140***
	(0.059)	(0.062)	(0.025)	(0.043)
Program × 2013	0.034	-0.228***	-0.056*	-0.163***
	(0.051)	(0.071)	(0.028)	(0.046)
Program × 2016	-0.021	-0.228***	-0.080**	-0.166***
	(0.057)	(0.064)	(0.031)	(0.041)
Observations	38274	38601	38318	38717
Control mean	0.74	0.50	0.41	0.32

Each cell is from a separate DID estimation of the outcome variable indicated in the column headings. Cluster robust standard errors in parenthesis. * $p < 0.01$, ** $p < 0.05$, *** $p < 0.001$ *Program* × *Post* presents the average effect of the programs over all waves. *Program* × 2009, *Program* × 2013 and *Program* × 2016 are results for each corresponding year.

in-kind transfers) received. These results are consistent with most findings in the related literature. Similar to our findings for NREGA and PSNP, a systematic review of 28 studies that evaluated public works programs in Africa and the middle east by Beierl and Grimm (2018) find that public works programs facilitate a moderate increase in asset accumulation and have limited success in consumption smoothing. They find little evidence of program impact on child nutrition.

With regard to *Juntos*, the two key characteristics of a CCT program are that they simultaneously act upon the short and long term dimensions of poverty. Our results highlight both the impact of a cash transfer on current poverty and the impact of conditioning the transfer upon school attendance. We show that *Juntos* resulted in reduced overall incidence and intensity of multidimensional poverty particularly through improvement in asset ownership and school attendance of children.

5.4. Robustness Checks

We run several sensitivity checks to assert the robustness of our main analyses. First, we augment the main analysis of the effects on multidimensional poverty by examining program impact on other indicators of wellbeing such as the wealth index of the household, livestock holdings, and susceptibility to natural and economic shocks. Table A.13 in Appendix A presents these results. We find that all three programs have a positive sustained impact on livestock holdings in Ethiopia and Peru. In addition, in India, susceptibility to drought induced shocks significantly declined for program participants over the 10 years considered.

As a robustness test of the validity of the parallel trend assumptions, we consider a placebo program implementation that started three years earlier than the actual implementation date. We use data from the first three waves of the survey for this exercise. We maintain the original assignment of districts to program in India and

Table 5: Dimensional decomposition and contribution of indicators to the overall poverty

	Schooling	Attendance	Nutrition	Electricity	Sanitation	Water	Housing	Fuel	Asset
PSNP × Post	0.008	-0.122***	-0.048	-0.080	-0.235***	0.226**	0.031	0.042	-0.240***
	(0.032)	(0.034)	(0.038)	(0.084)	(0.063)	(0.083)	(0.045)	(0.035)	(0.024)
Observations	45077	45821	45824	44986	45729	45063	45317	45454	45330
Control mean	0.77	0.63	0.33	0.66	0.49	0.53	0.72	0.85	0.16
NREGA × Post	-0.070**	-0.089**	-0.022	0.026	-0.091*	0.024	-0.096**	-0.091	-0.090**
	(0.031)	(0.040)	(0.016)	(0.037)	(0.051)	(0.043)	(0.036)	(0.055)	(0.042)
Observations	54855	54879	54918	54690	54626	54319	54488	54677	54537
Control mean	0.44	0.34	0.27	0.13	0.43	0.09	0.24	0.45	0.17
Juntos × Post	-0.064	-0.223***	0.031	-0.190**	-0.168***	-0.023	0.016	-0.030	-0.283***
	(0.041)	(0.050)	(0.047)	(0.084)	(0.053)	(0.064)	(0.034)	(0.053)	(0.035)
Observations	37994	38948	38707	38708	38866	38075	38531	38671	38779
Control mean	0.50	0.61	0.49	0.35	0.19	0.50	0.66	0.66	0.30

Each cell is from a separate DID estimation of the outcome variable indicated in the column headings. Standard errors clustered at community level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Program × *Post* presents the average effect of the programs over all waves.

participant households in Ethiopia and Peru. We then re-estimate our model on this sample. Table A.16 in Appendix A reports the results. The estimated placebo effects are statistically insignificant across the three programs lending support to our claim that there were no confounding differential trends in the pre-program period.

We also checked the robustness of our results to different deprivation and poverty cutoffs. We compute the MPI for the three countries using slightly different deprivation and poverty cutoffs as well as weights attached to indicators. The results are largely consistent with our main findings and are available from the authors upon request.

6. Conclusion

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. However, the empirical evidence on the effectiveness of these programs remains mixed.

In this paper we go beyond the analysis of average outcomes and investigate the impact on multidimensional poverty of three large-scale social-protection schemes - the Productive Safety Net Program (PSNP) in Ethiopia, the Mahatma Gandhi National Rural Employment Guarantee Act (NREGA) in India, and the *Juntos* conditional cash-transfer program in Peru. We use panel data collected in five surveys from 2002 to 2016 simultaneously in all three countries.

The novelty of our study is the evaluation of the social-protection schemes using multidimensional poverty measures. Following the Alkire-Foster method of measuring multidimensional poverty, we evaluate the role of the three schemes on poverty using 10 indicators grouped into three dimensions: Education, Health, and Standard of Living. We consider different poverty cutoffs to clearly indicate the distributional impact of the programs on multiple deprivations. We report program effects on the incidence and intensity of multidimensional poverty.

We find descriptive evidence that, on average, poorer households are successfully targeted by the programs. We show that multidimensional poverty (both its incidence and intensity) declined in all three countries over the period 2006 - 2016. The magnitude of decline varies across countries as well as by participation status in social protection programs. Overall, participation in social safety-net is associated with a larger decline in all the multidimensional poverty indicators. We also calculated the contribution of each dimension to multidimensional poverty. Decomposition of multidimensional poverty into the three dimensions shows that deprivation in education dimension accounts for over half of multidimensional poverty in Ethiopia and Peru, and two thirds in India. Deprivation in living conditions is the second dimension that contributes the most to overall poverty.

We then show the effect of these programs on the multidimensional well-being of individuals in program participant households in a difference-in-difference framework and over both the shorter- and longer-run. We find that the programs significantly reduced incidence and intensity of poverty for the severely poor individuals in all the three countries. The intensity of poverty of individuals experiencing multiple deprivations is significantly reduced in all of the samples we analyse. These program effects were sustained in the medium and longer run period in all three cases. The estimation results further indicate a positive short-term impact on asset formation, livestock holding, and some living standard indicators.

In all three countries these positive impacts are sustained even in the medium and longer-term. In contexts where chronic poverty and underemployment are widespread and persistent throughout the year, having public work programs that pay adequate wages over an extended period may enable beneficiaries to accumulate assets and make productive investments. These results show that the use of multidimensional poverty indicators, in addition to relying only on monetary ones, may assist in monitoring the trends and understanding the dynamics of poverty and evaluate the efficacy of policy measures such as the social-protection schemes evaluated in this study. In addition, these findings provide information that can be useful for revealing a country's deprivation structure and can help with policy targeting.

Our study evaluates the overall effects of two different transfer designs (a CCT and public works programs) on multidimensional poverty. Contrasting the relative effectiveness of the two main interventions is difficult as these programs have different design parameters such frequency and size of transfer, identity of the transfer recipient, as well as monitoring and enforcement of conditionalities. However, the similarity of our empirical findings across the three programs where the effect is largest among individuals in severely poor households, suggest that both the CCT and the two public works programs are effective in reducing poverty for individuals experiencing multiple deprivations.

The key advantages of a workfare program are its self-targeting and countercyclicality, but it comes at a huge administrative cost. CCTs on other hand could be effective in obtaining the desired behaviour change among targeted beneficiaries. However, they can also undermine the social protection dimension of cash transfer programs as the conditions attached to transfers tend to exclude the poorest families. Our results call for the careful consideration of social protection strategies. The state of social service delivery in health and education, local labour market conditions, as well as the administrative capacity of governments need to be holistically considered in designing an effective social protection program.

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Appendix A. Additional Tables

Table A.1: Summary Statistics (by Treatment Status): Ethiopia

	Pre-program (2006)			Post-program (2009-2016)		
	All	P	NP	All	P	NP
Household head:						
Education	3.57	1.70	4.29	4.73	2.56	5.29
	(3.78)	(2.23)	(4.01)	(3.92)	(2.44)	(4.03)
Age	42.91	43.16	42.82	47.11	47.36	47.05
	(11.45)	(11.84)	(11.30)	(12.07)	(11.62)	(12.19)
Male	0.79	0.73	0.81	0.75	0.68	0.76
	(0.41)	(0.44)	(0.39)	(0.44)	(0.47)	(0.42)
Household size	6.20	6.23	6.19	5.80	5.87	5.78
	(2.08)	(1.95)	(2.13)	(2.10)	(1.99)	(2.12)
Wealth index	0.29	0.21	0.32	0.37	0.28	0.40
	(0.18)	(0.12)	(0.18)	(0.17)	(0.13)	(0.18)
Access to services						
Water	0.50	0.50	0.51	0.55	0.37	0.60
	(0.50)	(0.50)	(0.50)	(0.50)	(0.48)	(0.49)
Sanitation	0.40	0.31	0.44	0.63	0.65	0.62
	(0.49)	(0.46)	(0.50)	(0.48)	(0.48)	(0.48)
Electricity	0.44	0.20	0.53	0.60	0.41	0.65
	(0.50)	(0.40)	(0.50)	(0.49)	(0.49)	(0.48)
Household owns						
Livestock	0.66	0.81	0.60	0.69	0.87	0.64
	(0.47)	(0.39)	(0.49)	(0.46)	(0.34)	(0.48)
Land	0.77	0.86	0.73	0.81	0.88	0.78
	(0.42)	(0.35)	(0.45)	(0.40)	(0.32)	(0.41)
House	0.72	0.85	0.67	0.73	0.88	0.69
	(0.45)	(0.35)	(0.47)	(0.44)	(0.33)	(0.46)
Shock-drought	0.29	0.51	0.21	0.22	0.41	0.17
	(0.45)	(0.50)	(0.41)	(0.42)	(0.49)	(0.38)
Observations	2892	805	2087	8304	1753	6551

Mean coefficients of household level indicators; s.d in parentheses. "P" and "NP" stand for participants and non-participants respectively. 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.

Table A.2: Summary Statistics (by Treatment Status): India

	Pre-program (2006)			Post-program (2009-2016)		
	All	P	NP	All	P	NP
Household head:						
Education	4.82	3.54	6.67	5.67	4.36	7.67
	(5.77)	(5.82)	(5.17)	(5.71)	(5.71)	(5.10)
Age	39.86	40.00	39.66	42.62	42.79	42.36
	(11.31)	(11.22)	(11.44)	(9.31)	(9.26)	(9.38)
Male)	0.93	0.93	0.92	0.88	0.89	0.88
	(0.26)	(0.25)	(0.27)	(0.32)	(0.32)	(0.32)
Household size	5.41	5.49	5.29	4.97	5.08	4.80
	(2.11)	(2.08)	(2.14)	(1.95)	(1.98)	(1.90)
Wealth index	0.46	0.36	0.60	0.58	0.51	0.69
	(0.20)	(0.14)	(0.18)	(0.17)	(0.16)	(0.14)
Access to services						
Water	0.95	0.93	0.99	0.98	0.97	0.99
	(0.22)	(0.26)	(0.12)	(0.13)	(0.16)	(0.08)
Sanitation	0.33	0.09	0.68	0.43	0.19	0.79
	(0.47)	(0.29)	(0.47)	(0.50)	(0.40)	(0.41)
Electricity	0.90	0.86	0.95	0.97	0.97	0.98
	(0.31)	(0.35)	(0.22)	(0.16)	(0.18)	(0.13)
Household owns						
Livestock	0.40	0.55	0.17	0.41	0.59	0.13
	(0.49)	(0.50)	(0.38)	(0.49)	(0.49)	(0.34)
Land	0.83	0.94	0.67	0.93	0.99	0.81
	(0.38)	(0.24)	(0.47)	(0.26)	(0.10)	(0.39)
House	0.81	0.93	0.65	0.82	0.95	0.61
	(0.39)	(0.26)	(0.48)	(0.39)	(0.21)	(0.49)
Shock-drought	0.28	0.40	0.11	0.11	0.16	0.03
	(0.45)	(0.49)	(0.31)	(0.31)	(0.37)	(0.18)
Observations	2944	1738	1206	8611	5200	3411

Mean coefficients of household level indicators; s.d in parentheses. "P" and "NP" stand for participants and non-participants respectively. 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.

Table A.3: Summary Statistics (by Treatment Status): Peru

	Pre-program (2006)			Post-program (2009-2016)		
	All	P	NP	All	P	NP
Household head:						
Education	7.76	4.31	8.41	8.38	5.05	9.14
	(4.28)	(3.10)	(4.15)	(4.27)	(3.37)	(4.08)
Age	39.82	39.07	39.96	43.24	44.06	43.06
	(11.27)	(11.03)	(11.31)	(11.32)	(10.39)	(11.50)
Male	0.87	0.90	0.86	0.82	0.86	0.81
	(0.34)	(0.30)	(0.34)	(0.39)	(0.35)	(0.39)
Household size	5.52	6.20	5.40	5.18	5.75	5.05
	(2.06)	(1.94)	(2.05)	(1.94)	(1.85)	(1.93)
Wealth index	0.48	0.25	0.52	0.60	0.40	0.64
	(0.23)	(0.12)	(0.22)	(0.19)	(0.12)	(0.18)
Access to services						
Water	0.62	0.44	0.66	0.82	0.69	0.84
	(0.48)	(0.50)	(0.47)	(0.39)	(0.46)	(0.36)
Sanitation	0.85	0.68	0.89	0.94	0.91	0.95
	(0.35)	(0.47)	(0.32)	(0.24)	(0.28)	(0.23)
Electricity	0.77	0.48	0.83	0.93	0.85	0.94
	(0.42)	(0.50)	(0.38)	(0.26)	(0.36)	(0.23)
Household owns						
Livestock	0.63	0.98	0.57	0.57	0.95	0.48
	(0.48)	(0.15)	(0.50)	(0.49)	(0.21)	(0.50)
Land				0.77	0.87	0.74
				(0.42)	(0.33)	(0.44)
House	0.71	0.86	0.68	0.78	0.90	0.75
	(0.45)	(0.35)	(0.47)	(0.42)	(0.30)	(0.43)
Shock-drought	0.07	0.22	0.04	0.05	0.18	0.02
	(0.25)	(0.41)	(0.19)	(0.22)	(0.38)	(0.15)
Observations	2766	427	2339	7771	1378	6393

Mean coefficients of household level indicators; s.d in parentheses. “P” and “NP” stand for participants and non-participants respectively. 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.

Table A.4: Summary Statistics: Program coverage over time

Wave	PSNP				*Juntos*			
	Non-participant		Participant		Non-participant		Participant	
	Households	Indiv.	Households	Indiv.	Households	Indiv.	Households	Indiv.
2006	2,055	12,724	805	5,015	2,182	11,595	427	2,611
2009	2,055	12,793	805	5,076	2,182	11,513	427	2,613
2013	2,218	12,731	564	3,174	2,035	10,106	480	2,722
2016	2,275	12,353	384	2,045	1,974	9,683	471	2,590

Indiv. denotes total number of individuals in the sample.

Table A.5: Multidimensional Poverty Indicators: Dimensions, cutoffs, and weights

Dimension	**Indicator**	**Cuttoff: Considered deprived if ...**	**Weight**
Health	Nutrition	Any member (adult or child) for whom there is nutritional information is undernourished	1/6
	Child mortality	Any child has died in the family in the five-year period preceding the survey	1/6
Education	Years of schooling	No household member aged 10 years or older has completed six years of schooling	1/6
	School attendance	Any school-aged child is not attending school	1/6
Living Standards	Cooking fuel	The household cooks with dung, wood, charcoal or coal	1/18
	Sanitation	Household lacks adequate sanitation or their toilet is shared	1/18
	Water	No access to improved drinking water or safe drinking water is at least a 30-minute walk from home, round trip	1/18
	Electricity	The household has no electricity	1/18
	Housing	Floor, roof or walls of dwelling are constructed using natural materials	1/18
	Assets	The household does not own more than one of these assets: radio, TV, telephone, computer, animal cart, bicycle, motorbike or refrigerator, and does not own a car or truck.	1/18

Source: Adopted from Alkire and Jahan (2018).

Table A.6: Multidimensional Poverty Index and contribution of dimensions

	Ethiopia					India					Peru				
Full Sample	All	2006	2009	2013	2016	All	2006	2009	2013	2016	All	2006	2009	2013	2016
MPI	0.37	0.45	0.34	0.26	0.26	0.22	0.29	0.17	0.12	0.15	0.18	0.30	0.12	0.10	0.08
Headcount ratio (H) [%]	71.2	81.6	68.9	57.2	59.6	47.0	58.9	38.0	27.5	35.6	36.8	54.8	27.4	23.4	18.4
Intensity of poverty (A) [%]	51.7	54.6	48.6	45.2	43.6	47.2	49.8	44.9	42.8	41.3	50.1	54.3	44.8	42.6	41.6
Contribution of:															
Education [%]	47.4	49.2	45.8	44.1	48.7	51.3	51.5	44.5	41.9	65.8	45.2	46.8	36.3	43.8	51.1
Health [%]	11.5	11.3	11.7	12.7	10.4	18.1	18.0	23.3	28.6	14.1	18.4	18.6	22.9	22.6	18.1
Living Conditions [%]	41.1	39.5	42.5	43.3	41.0	30.6	30.5	32.3	29.5	20.1	36.4	34.6	40.8	33.6	30.7
Program Participants															
MPI	0.49	0.56	0.42	0.38	0.36	0.23	0.31	0.18	0.12	0.15	0.36	0.58	0.29	0.23	0.17
Headcount ratio (H) [%]	90.9	97.0	87.1	82.1	81.5	49.0	62.1	40.2	28.1	36.5	68.6	95.1	64.8	52.3	40
Intensity of poverty (A) [%]	54.4	57.8	48.7	45.8	44.2	46.7	49.2	44.4	42.1	41.2	53.1	60.7	45.5	43.6	42.3
Contribution of:															
Education [%]	46.2	47.9	43.8	43.7	47.3	52.0	52.1	45.7	42.7	65.6	42.0	45.0	35.1	38.5	42.6
Health [%]	11.3	11.3	11.4	12.2	9.62	18.4	18.3	23.5	29.3	15.0	19.1	17.7	23.1	23.6	22.2
Living Conditions [%]	42.5	40.7	44.8	44.1	43.1	29.5	29.6	30.8	28.0	19.4	38.9	37.3	41.8	37.8	35.2
Non Participants															
MPI	0.33	0.40	0.30	0.23	0.24	0.21	0.27	0.15	0.12	0.14	0.14	0.23	0.08	0.07	0.05
Headcount ratio (H) [%]	65.0	75.4	61.5	51.2	56.2	43.3	52.6	33.6	26.6	33.9	28.6	45.3	18.7	15.7	12.4
Intensity of poverty (A) [%]	50.5	52.9	48.6	45.0	43.5	48.4	51.0	46.0	44.1	41.6	48.1	51.2	44.2	41.7	41.0
Contribution of:															
Education [%]	48.0	49.9	47.0	44.2	49.0	49.5	50.1	41.4	40.5	65.4	47.0	47.5	37.3	48.7	59.2
Health [%]	11.5	11.3	11.9	12.8	10.6	17.5	17.2	23.0	27.2	12.8	47.0	47.5	37.3	48.7	59.2
Living Conditions [%]	40.5	38.8	41.2	42.9	40.5	33.0	32.6	35.6	32.3	21.8	34.9	33.3	39.9	29.6	26.5

MPI stands for Multidimensional Poverty Index. $MPI = H \cdot A$
In all the countries program implementation started after the 2006 survey.

Table A.7: Deprivation in Multidimensional Poverty Index: Ethiopia

	2006		2009		2013		2016	
	Part.	Non-Part.	Part.	Non-Part.	Part.	Non-Part.	Part.	Non-Part.
Censored Headcount: Percentage of people who are poor and deprived in:								
Schooling	93.5	62.0	85.7	56.9	79.7	48.7	77.7	52.6
Attendance	68.5	56.8	25.9	27.2	18.8	12.5	24.6	19.2
Nutrition	38.5	27.1	29.0	21.2	27.6	17.7	20.8	15.5
Electricity	79.6	45.8	71.2	40.9	45.9	33.3	44.9	28.6
Sanitation	67.9	45.5	29.2	26.6	25.5	19.1	30.6	24.3
Water	49.0	43.7	53.5	35.8	62.3	29.7	59.2	29.5
Housing	75.0	57.1	71.6	51.1	64.7	38.0	55.0	39.3
Fuel	97.0	71.0	87.1	60.5	81.8	50.4	81.0	53.2
Assets	43.1	11.0	29.9	6.30	18.6	7.36	8.85	2.92
Dimensional Contribution: % Contribution in MPI of indicator:								
Schooling	27.7	26.1	33.6	31.8	35.3	35.2	35.9	35.9
Attendance	20.3	23.9	10.2	15.2	8.33	9.01	11.4	13.1
Nutrition	11.4	11.4	11.4	11.9	12.2	12.8	9.62	10.6
Electricity	7.86	6.44	9.31	7.62	6.77	8.04	6.92	6.51
Sanitation	6.70	6.39	3.82	4.95	3.76	4.61	4.71	5.53
Water	4.84	6.15	6.99	6.67	9.19	7.17	9.12	6.72
Housing	7.40	8.03	9.37	9.50	9.56	9.16	8.48	8.94
Fuel	9.58	9.98	11.4	11.3	12.1	12.2	12.5	12.1
Assets	4.26	1.55	3.91	1.17	2.75	1.78	1.36	0.67

"Part" and "Non-Part" stand for participants and non-participants respectively.

Number of observations are as described in Tables 1 and 2.

Table A.8: Deprivation in Multidimensional Poverty Index: Peru

	2006		2009		2013		2016	
	Part.	Non-Part.	Part.	Non-Part.	Part.	Non-Part.	Part.	Non-Part.
Censored Headcount: Percentage of people who are poor and deprived in:								
Schooling	75.1	25.7	61.1	16.3	48.0	12.9	37.3	11.0
Attendance	79.7	36.1	0.99	2.17	4.75	6.17	5.91	7.07
Nutrition	60.5	24.2	40.8	11.3	32.3	8.51	22.6	4.37
Electricity	51.3	15.9	27.8	7.17	7.09	2.81	4.44	2.09
Sanitation	31.2	9.61	9.74	3.81	8.86	2.48	3.69	1.54
Water	55.4	25.5	25.6	9.20	25.8	6.67	19.6	5.33
Housing	90.6	33.6	63.8	16.2	51.2	11.1	38.4	7.79
fuel	93.5	31.5	63.4	16.5	50.4	9.88	35.6	6.30
asset	60.8	12.8	31.7	6.44	11.9	1.95	5.52	1.14
Dimensional Contribution: % Contribution in MPI of indicator:								
Schooling	21.9	19.9	34.5	33.0	35.1	32.9	36.7	36.0
Attendance	23.2	28.0	0.56	4.38	3.47	15.7	5.82	23.2
Nutrition	17.7	18.8	23.1	22.8	23.6	21.7	22.2	14.3
Electricity	4.99	4.12	5.25	4.82	1.73	2.38	1.46	2.29
Sanitation	3.04	2.48	1.84	2.57	2.16	2.11	1.21	1.69
Water	5.39	6.59	4.82	6.19	6.28	5.67	6.45	5.84
Housing	8.80	8.67	12.0	10.9	12.5	9.42	12.6	8.53
Fuel	9.09	8.14	11.9	11.1	12.3	8.39	11.7	6.89
Assets	5.91	3.31	5.98	4.33	2.90	1.66	1.81	1.25

"Part" and "Non-Part" stand for participants and non-participants respectively.
Number of observations are as described in Tables 1 and 2.

Table A.9: Deprivation in Multidimensional Poverty Index: India

	2006		2009		2013		2016	
	Part.	Non-Part.	Part.	Non-Part.	Part.	Non-Part.	Part.	Non-Part.
Censored Headcount: Percentage of people who are poor and deprived in:								
Schooling	51.9	45.5	37.1	31.9	26.9	25.8	35.0	33.2
Attendance	43.7	35.1	11.8	6.45	3.42	2.65	24.2	22.1
Nutrition	33.6	27.7	25.2	21.2	20.9	19.1	13.5	10.8
Electricity	6.20	14.0	1.44	3.89	1.20	2.93	1.05	1.18
Sanitation	51.6	43.8	35.7	30.8	24.1	23.8	24.4	25.8
Water	2.35	8.51	0.85	5.52	0.17	2.30	0.13	1.97
Housing	25.7	25.1	17.0	19.0	8.99	10.8	7.91	8.79
Fuel	55.6	46.6	37.6	31.3	23.3	23.2	18.6	16.7
Assets	21.4	19.4	6.35	8.41	1.90	5.07	0.47	1.00
Dimensional Contribution: % Contribution in MPI of indicator:								
Schooling	28.3	28.3	34.7	34.4	37.9	36.7	38.8	39.3
Attendance	23.8	21.8	11.1	6.97	4.81	3.77	26.8	26.1
Nutrition	18.3	17.2	23.5	23.0	29.3	27.2	15.0	12.8
Electricity	1.13	2.91	0.45	1.40	0.56	1.39	0.39	0.46
Sanitation	9.38	9.08	11.1	11.1	11.3	11.3	9.02	10.1
Water	0.43	1.76	0.26	1.99	0.077	1.09	0.048	0.78
Housing	4.67	5.20	5.28	6.86	4.22	5.12	2.92	3.46
Fuel	10.1	9.66	11.7	11.3	10.9	11.0	6.87	6.57
Assets	3.89	4.01	1.98	3.03	0.89	2.41	0.17	0.39

"Part" and "Non-Part" stand for participants and non-participants respectively.
Number of observations are as described in Tables 1 and 2.

Table A.10: Dimensional decomposition and the contribution of indicators to the overall poverty: PSNP

	Schooling	Attendance	Nutrition	Electricity	Sanitation	Water	Housing	Fuel	Asset
Program × Post	0.008	-0.122***	-0.048	-0.080	-0.235***	0.226**	0.031	0.042	-0.240***
	(0.032)	(0.034)	(0.038)	(0.084)	(0.063)	(0.083)	(0.045)	(0.035)	(0.024)
Program × 2009	-0.021	-0.224***	-0.071**	-0.048	-0.242***	0.111	-0.053	0.004	-0.177***
	(0.034)	(0.069)	(0.030)	(0.078)	(0.060)	(0.096)	(0.048)	(0.037)	(0.038)
Program × 2013	0.027	-0.080**	-0.030	-0.164*	-0.217***	0.304**	0.109**	0.082	-0.273***
	(0.036)	(0.037)	(0.050)	(0.086)	(0.059)	(0.133)	(0.050)	(0.049)	(0.037)
Program × 2016	0.006	-0.065	-0.056	-0.083	-0.225**	0.331***	-0.038	0.102**	-0.313***
	(0.039)	(0.048)	(0.062)	(0.085)	(0.087)	(0.110)	(0.061)	(0.042)	(0.059)
Observations	45077	45821	45824	44986	45729	45063	45317	45454	45330
Control mean	0.766	0.628	0.326	0.658	0.489	0.533	0.717	0.852	0.156

Standard errors clustered at community level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Program × *Post* presents the average effect of the programs over all waves. *Program* × 2009, *Program* × 2013 and *Program* × 2016 are results for each corresponding year.

Table A.11: Dimensional decomposition and the contribution of indicators to the overall poverty: NREGA

	Schooling	Attendance	Nutrition	Electricity	Sanitation	Water	Housing	Fuel	Asset
Program × Post	-0.070**	-0.089**	-0.022	0.026	-0.091*	0.024	-0.096**	-0.091	-0.090**
	(0.031)	(0.040)	(0.016)	(0.037)	(0.051)	(0.043)	(0.036)	(0.055)	(0.042)
Program × 2009	-0.064**	-0.084*	-0.031	0.015	-0.054	0.013	-0.094***	-0.080**	-0.084**
	(0.028)	(0.042)	(0.029)	(0.031)	(0.046)	(0.034)	(0.030)	(0.037)	(0.035)
Program × 2013	-0.110**	-0.118**	-0.025	0.022	-0.119*	0.025	-0.077	-0.118**	-0.113**
	(0.049)	(0.046)	(0.018)	(0.037)	(0.061)	(0.043)	(0.049)	(0.056)	(0.045)
Program × 2016	-0.095***	-0.110***	-0.030	0.038	-0.119*	0.025	-0.079	-0.118	-0.076
	(0.032)	(0.036)	(0.022)	(0.044)	(0.061)	(0.047)	(0.053)	(0.072)	(0.060)
Observations	54855	54879	54918	54690	54626	54319	54488	54677	54537
Control mean	0.441	0.337	0.271	0.125	0.426	0.086	0.242	0.452	0.174

Standard errors clustered at community level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Program × *Post* presents the average effect of the programs over all waves. *Program* × 2009, *Program* × 2013 and *Program* × 2016 are results for each corresponding year.

Table A.12: Dimensional decomposition and the contribution of indicators to the overall poverty: *Juntos*

	Schooling	Attendance	Nutrition	Electricity	Sanitation	Water	Housing	Fuel	Asset
Program × Post	-0.064	-0.223***	0.031	-0.190**	-0.168***	-0.023	0.016	-0.030	-0.283***
	(0.041)	(0.050)	(0.047)	(0.084)	(0.053)	(0.064)	(0.034)	(0.053)	(0.035)
Program × 2009	-0.001	-0.209***	0.050	-0.115	-0.146***	-0.078	0.037	-0.014	-0.174***
	(0.032)	(0.052)	(0.052)	(0.072)	(0.040)	(0.058)	(0.030)	(0.043)	(0.042)
Program × 2013	-0.010	-0.219***	0.026	-0.221**	-0.134**	0.024	0.045	0.028	-0.297***
	(0.059)	(0.050)	(0.046)	(0.090)	(0.064)	(0.074)	(0.048)	(0.053)	(0.055)
Program × 2016	-0.076	-0.234***	-0.008	-0.231**	-0.156**	-0.019	-0.034	-0.046	-0.331***
	(0.056)	(0.049)	(0.054)	(0.096)	(0.062)	(0.083)	(0.068)	(0.068)	(0.061)
Observations	37994	38948	38707	38708	38866	38075	38531	38671	38779
Control mean	0.499	0.610	0.448	0.347	0.189	0.498	0.661	0.660	0.297

Standard errors clustered at community level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Program × *Post* presents the average effect of the programs over all waves. *Program* × 2009, *Program* × 2013 and *Program* × 2016 are results for each corresponding year.

Table A.13: DID Estimations: Short and Longer term effects

	Livestock	"Wealth"	Susceptibility to shock: Natural	Susceptibility to shock: Economic
Ethiopia				
Program×Post	0.122**	-0.005	-0.031	0.123
	(0.047)	(0.015)	(0.065)	(0.072)
Program×2009	0.137***	0.020	-0.016	0.035
	(0.033)	(0.015)	(0.086)	(0.082)
Program×2016	0.157***	0.006	0.036	0.016
	(0.055)	(0.021)	(0.110)	(0.084)
India				
Program×Post	0.051	0.013	-0.162**	-0.125*
	(0.032)	(0.021)	(0.076)	(0.062)
Program×2009	0.070***	0.017	-0.192**	-0.091
	(0.019)	(0.014)	(0.077)	(0.065)
Program×2016	-0.021	0.017	-0.062	-0.106
	(0.033)	(0.029)	(0.109)	(0.084)
Peru				
Program×Post	0.232***	-0.019	-0.007	-0.005
	(0.045)	(0.016)	(0.066)	(0.031)
Program×2009	0.122***	0.013	-0.014	0.023
	(0.025)	(0.014)	(0.081)	(0.040)
Program×2016	0.296***	-0.021	0.103	-0.006
	(0.056)	(0.019)	(0.089)	(0.042)

Each cell is from a separate DID estimation of the outcome variable indicated in the column headings. Cluster robust standard errors in parenthesis. * $p < 0.01$, ** $p < 0.05$, *** $p < 0.001$
$Program \times Post$ presents the average effect of the programs over all waves. $Program \times 2009$ and $Program \times 2016$ are results for each corresponding year.

Table A.14: Short and Longer term effects of NREGA: ATE estimations

	Incidence of Poverty		Intensity of Poverty	
	$k = 33\%$	$k = 50\%$	$k = 33\%$	$k = 50\%$
Program × Post	-0.104***	-0.194***	-0.090***	-0.121***
	(0.023)	(0.024)	(0.012)	(0.016)
Program × 2009	-0.033*	-0.148***	-0.055***	-0.095***
	(0.019)	(0.024)	(0.009)	(0.015)
Program × 2013	-0.157***	-0.231***	-0.116***	-0.143***
	(0.036)	(0.029)	(0.018)	(0.020)
Program × 2016	-0.173***	-0.241***	-0.124***	-0.147***
	(0.033)	(0.030)	(0.018)	(0.020)
Observations	49002	49002	49002	49002
Control mean	0.548	0.263	0.264	0.159

Each cell is from a separate DID estimation of the outcome variable indicated in the column headings. Cluster robust standard errors in parenthesis. * $p < 0.01$, ** $p < 0.05$, *** $p < 0.001$

$Program \times Post$ presents the average effect of the programs over all waves. $Program \times 2009$, $Program \times 2013$ and $Program \times 2016$ are results for each corresponding year.

Table A.15: Short and Longer term effects of NREGA: PS-DID Estimations

	Incidence of Poverty		Intensity of Poverty	
	$k = 33\%$	$k = 50\%$	$k = 33\%$	$k = 50\%$
Program × Post	-0.091***	-0.103**	-0.055**	-0.049
	(0.030)	(0.049)	(0.020)	(0.032)
Observations	54354	54472	54447	54384
Program × 2009	-0.082**	-0.087*	-0.042**	-0.048*
	(0.032)	(0.043)	(0.018)	(0.026)
Observations	35931	35797	35837	35894
Program × 2013	-0.114**	-0.124**	-0.071***	-0.073**
	(0.049)	(0.050)	(0.023)	(0.035)
Observations	30703	30544	30556	30670
Program × 2016	-0.122***	-0.093	-0.054*	-0.050
	(0.035)	(0.058)	(0.026)	(0.037)
Observations	33907	33672	33717	33827
Control mean	0.506	0.257	0.259	0.159

Each cell is from a separate DID estimation of the outcome variable indicated in the column headings. Cluster robust standard errors in parenthesis.
* $p < 0.01$, ** $p < 0.05$, *** $p < 0.001$
Program × *Post* presents the average effect of the programs over all waves. *Program* × 2009, *Program* × 2013 and *Program* × 2016 are results for each corresponding year.

Table A.16: Robustness check: Placebo program implementation

	Incidence of Poverty		Intensity of Poverty	
	$k = 33\%$	$k = 50\%$	$k = 33\%$	$k = 50\%$
PSNP × Post	-0.043	-0.002	-0.042**	-0.027
	(0.027)	(0.042)	(0.017)	(0.028)
Observations	28015	28219	27937	27863
NREGA × Post	0.026	0.053	0.012	0.025
	(0.030)	(0.040)	(0.017)	(0.026)
Observations	30792	30792	30792	30792
Juntos × Post	-0.102**	0.039	-0.026	0.060
	(0.037)	(0.058)	(0.023)	(0.041)
Observations	22487	22575	22422	22462

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix B. Additional Figures

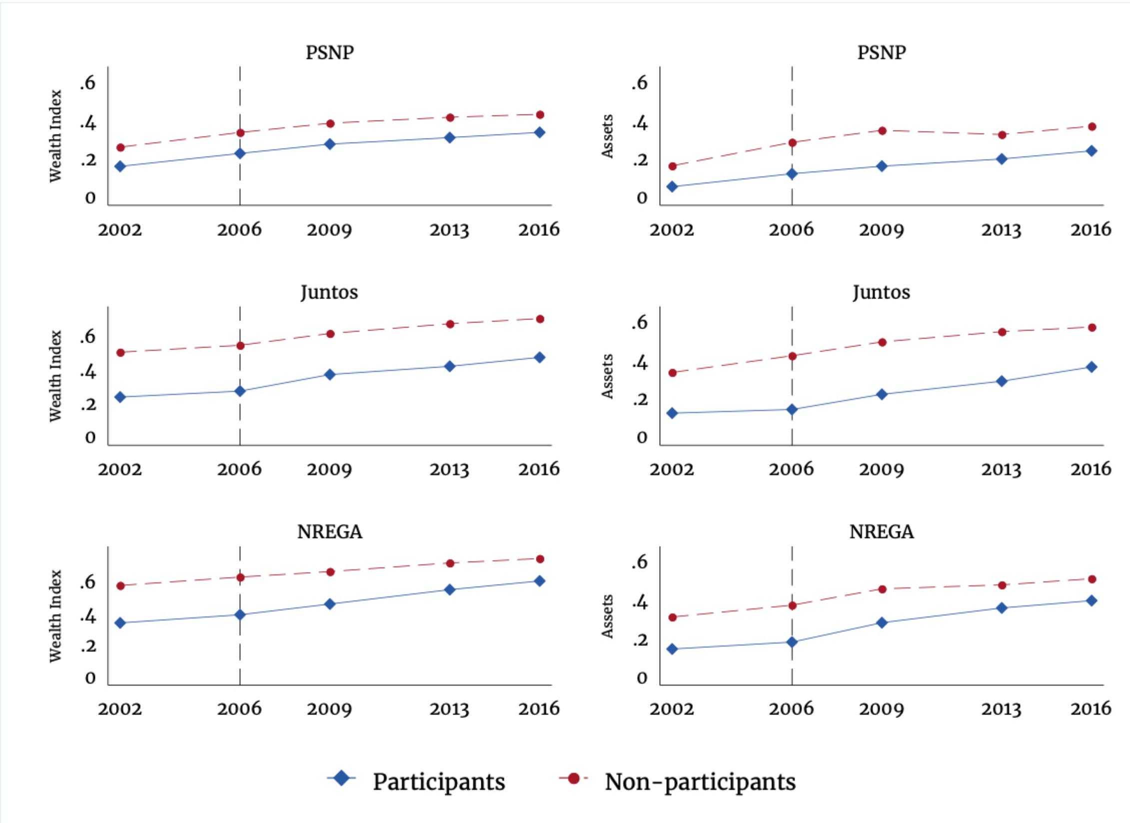
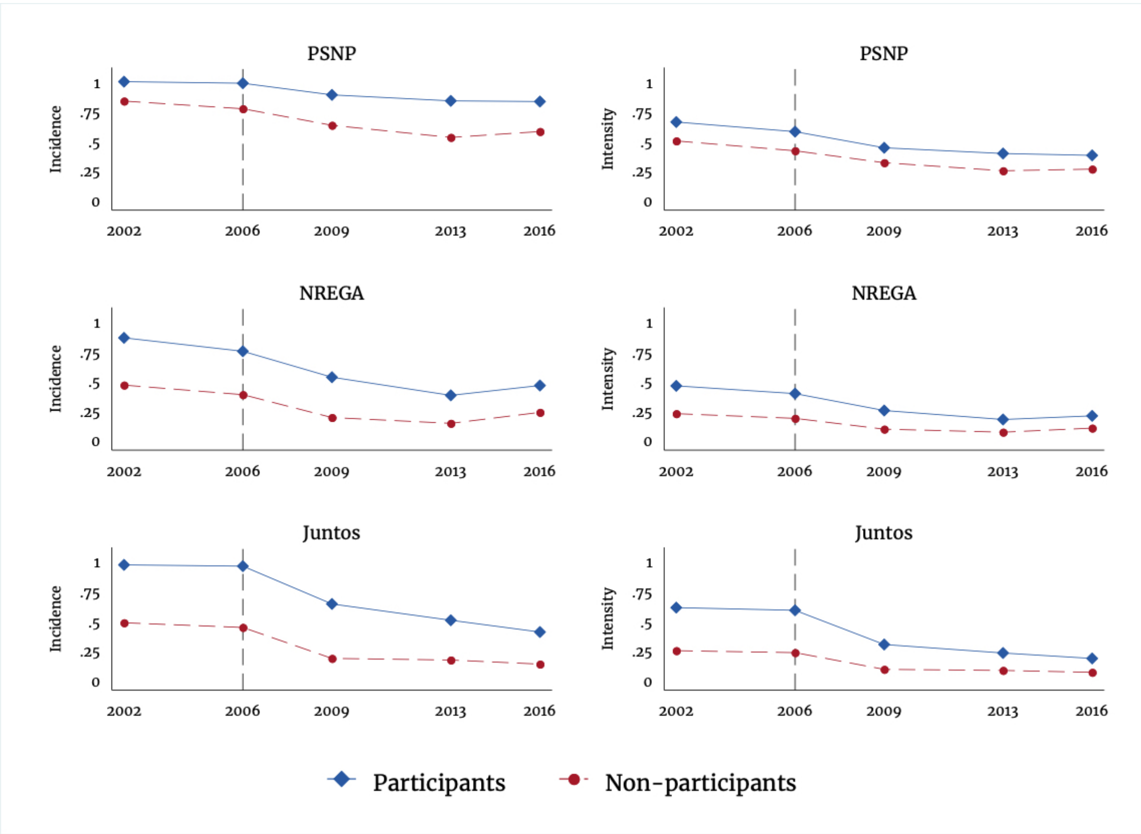
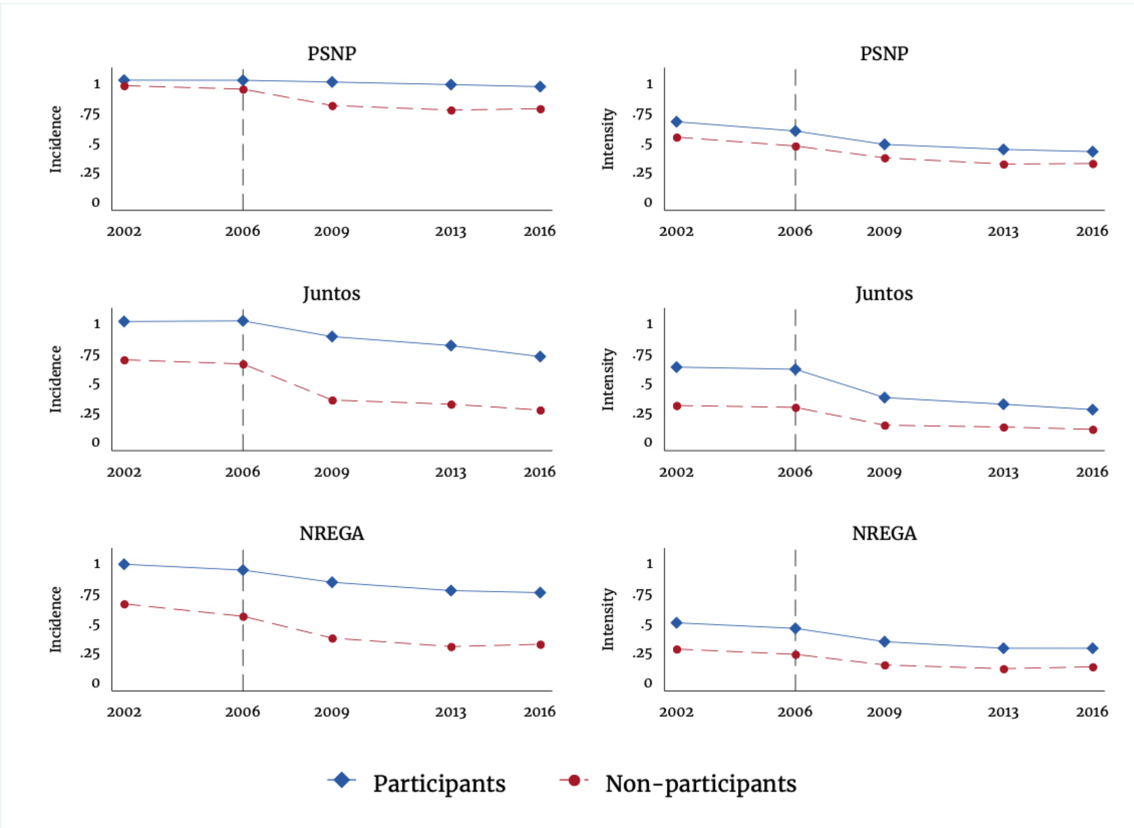


Figure B.1: Trends in Wealth Index and Asset Ownership, by Participation Status



Note: Incidence and intensity of MPI are computed based on deprivation cutoff of 33% of the weighted indicators.

Figure B.2: Trends in Incidence and Intensity of Multidimensional Poverty, by Participation Status



Note: Incidence and intensity of MPI are computed based on deprivation cutoff of 20% of the weighted indicators.

Figure B.3: Trends in Incidence and Intensity of Multidimensional Poverty, by Participation Status

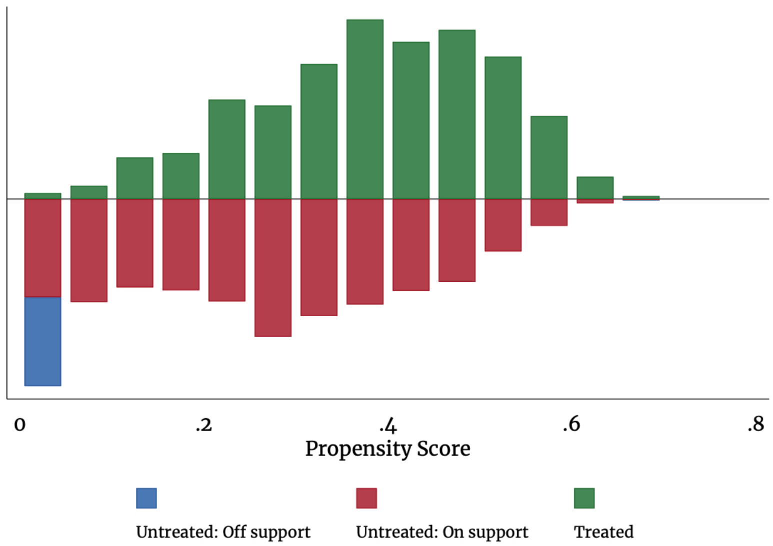


Figure B.4: Common Support: PSNP

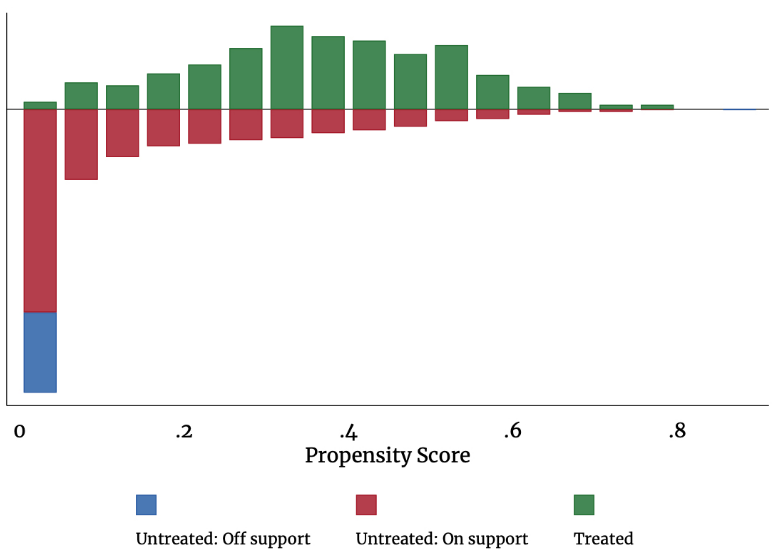


Figure B.5: Common Support: Juntos