Working Paper Series

#2022-012

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Published 4 April 2022

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UNU-MERIT Working Papers
ISSN 1871-9872

Maastricht Economic and social Research Institute on Innovation and Technology UNU-MERIT

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The multidimensional impacts of the Conditional Cash Transfer program *Juntos* in Peru

Ricardo Morel* and Liz Girón‡

22 February 2020

Abstract

Policy decisions are sensitive to the conceptualization of poverty and, in line with the growing demand for multidimensional poverty measurement, we conducted an impact evaluation of Peru's largest social protection intervention – the conditional cash transfer program 'Juntos' – to further understand its effects on multidimensional poverty. We combine a propensity score matching with a difference-in-difference approach to estimate and compare two multidimensional indices created using the Alkire-Foster method. The first replicates the Global Multidimensional Poverty Index (MPI) while the other is a Juntos-tailored MPI. We do not find robust and statistically significant effects of the program in either index. Despite finding steeper reductions among Juntos beneficiaries, particularly in education and health indicators, these changes cannot be statistically attributed to the program. We further conclude that using a multidimensional poverty index can be a highly useful evaluation tool when thoroughly adapted to the theory of change of the intervention under assessment. JEL codes: I32, I38.

Keywords: conditional cash transfers, multidimensional poverty, Juntos, Peru

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Introduction

The eradication of poverty is a priority in the development agenda, and it is no coincidence that appears as the first of the Sustainable Development Goals (SDG). Probably, the largest commitment by multilateral organizations and governments towards improving the lives of people. Development actors, including donor agencies and implementing organizations that range from local civil society organizations to government departments and international non-governmental organizations (NGOs), measure their progress in relation to their impacts on poverty reduction. The predominant way to measure poverty has been using monetary terms, such as income and consumption. However, there are different ways to interpret and measure this concept. For Amartya Sen (1999), poverty is not just the lack of money. It is about not having the capability to realise one's full potential as a human being. This approach has inspired a growing body of literature on measuring the multiple dimensions of wellbeing to understand *who* is poor and *why* and *how* they are poor. It has moved beyond the 'traditional' money metrics – such as resource or utility-based approaches – to incorporate the different deprivations that the poor and the extreme poor face. The operationalization of this concept has been particularly developed by the measures proposed by Alkire and Foster (2011a), leading to the development of the Multidimensional Poverty Index (MPI) (Alkire et al., 2015b). This applied work has become intrinsic to the social policy debate, which is reflected in its incorporation into the Human Development Report since 2010 (UNDP, 2010), the SDGs (United Nations, 2015) as mentioned above, and, more recently, the World Bank's (2017, 2018) approach for monitoring global poverty.

Our hypothesis is that measuring poverty using only monetary metrics can miss relevant information of people's lives. The efficient use of resources or the maximisation of utility are indeed important, but in a scenario with a multidimensional poverty measure can provide a more comprehensive measure of wellbeing. The efficient use of resources or the maximisation of utility are certainly important, but these are not comprehensive measures of wellbeing, less so in contexts of exclusion, vulnerability, and poverty, where social programs usually take place. Instead, Amartya Sen (1976, 1992, 1999) proposes that wellbeing be measured in terms of *functionings* and *capabilities*. Functionings are the activities or situations we recognise as intrinsically important (e.g. being healthy, having a good job, building knowledge, dignity, etc.). Capabilities are the 'real opportunity' that we have to accomplish our functionings. In short, the capability approach defines wellbeing (or poverty) with regard to the freedom (or deprivation) that we have to lead the type of life that we want, a 'good' life. This approach has been enormously important in conceptualising and operationalising the idea of multidimensional poverty (Alkire, 2002; Arrow, 1999; Atkinson, 1999; Bourguignon & Chakravarty, 2003; Robeyns, 2005; Sen & Anand, 2004).

Studies that compare monetary and multidimensional poverty measures generally find that these concepts do not significantly overlap (Ataguba, Ichoku, & Fonta, 2013; Bader et al., 2016; Khan et al., 2015; Levine, Muwonge, & Batana, 2014; Maltzahn & Durrheim, 2008; Roelen, Gassmann, & de Neubourg, 2012). As a result, policy and programmatic decisions are extremely sensitive to the conceptualization and measurement of poverty (Ruggeri Laderchi, Ruhi, & Stewart, 2003). For instance, from a targeting perspective, different population sets might be selected for an anti-poverty program. Similarly, from an evaluation standpoint, results could lead to misinformed decisions to shut down or scale up a program.

In that light, this study aims to assess what effects *Juntos* has on multidimensional poverty. To answer this question, we conduct an impact evaluation to assess the causal impacts of the national conditional cash transfer (CCT) program in Peru, *Juntos*, to understand its ability to fight poverty in a multidimensional setting. For this purpose, we use propensity score matching in combination with a difference-in-difference framework based on panel data collected by the Government of Peru between 2011 and 2015. We measure the effects of *Juntos* on multidimensional poverty and, more particularly, examine the channels and contributions of each of the dimensions and its indicators using the Alkire-Foster method.

Juntos is the largest national poverty eradication program in Peru, both in terms of beneficiaries and budget. As with most cash transfer programs, *Juntos* aims to impact different dimensions of people's life, such as their nutrition, health, and education status, specifically, as well as their living standards and sustainable livelihoods, more broadly. Therefore, despite income playing a central role in the theory of change of cash transfers programs (i.e. cash as an input), the impact pathway associated with the conditionalities is arguably more closely linked to human capital. Therefore, it is relevant to evaluate its impact using a measure that reflects the improvement in multiple dimensions at the same time. There is abundant evidence of cash transfer programs worldwide and a set of rigorous studies of *Juntos* in Peru looking at a myriad of outcomes, including both monetary and non-monetary indicators. However, the relevance of this paper relies on the fact that there is scarce evidence on the use of aggregate measures to assess the impact on the joint deprivations of individuals. In addition to the literature gap, there is an important policy demand. The Government of Peru has shown interest in embracing multidimensional poverty measures as it signed a cooperation agreement with the Oxford Poverty and Human

Development Initiative (OPHI) and the World Bank in 2016 to use the Alkire-Foster method to develop a national MPI (INEI, 2016b).

Methodologically, we use the Alkire-Foster method, relevant to Sen's approach, as it makes it possible to capture the proportion of people who are multidimensionally poor (incidence) as well as the multiple deprivations that they face at the same time (intensity) with respect to the program's outcomes. Therefore, this approach provides a comprehensive picture of poverty (Alkire et al., 2015b). This method is operational and replicable as well as an understandable and descriptive measure of poverty, allowing us to estimate treatment effects on multiple dimensions but also to track changes over time. For instance, showing the contributions of different deprivations to poverty can inform policymakers about the importance of dimensions often missed by monetary measures.

This research is particularly relevant in the context of the growing demand for multidimensional poverty measurement and evidence-based policy by governments, donors, and NGOs. We take a new approach to assess the most important anti-poverty initiative led by the Government of Peru in the last two decades. While there is abundant literature analysing the effects of *Juntos* on different dimensions of poverty, there no study that examines the impact on the joint distribution of these multiple dimensions. Ideally, a program such as *Juntos* would be expected to improve different dimensions simultaneously but that is not guaranteed. This evidence gap is crucial as all these dimensions constantly affect and reinforce one another. Moreover, the recent trend of empirical studies looking at the impacts of programs and policy on multidimensional poverty (Loschmann, Parsons, & Siegel, 2015; Mitchell & Macció, 2018; Ouili et al., 2017; Pasha, 2016; Robano & Smith, 2014), suggests that there is growing interest in this approach among scholars as well as policymakers. Nevertheless, the applied use of multidimensional measurement in the impact evaluation literature remains at an early phase and the ground is still fertile for academic contributions.

In sum, this impact evaluation of *Juntos* aims to understanding the capacity of the program to reduce poverty moving from a single metric to multiple dimensions. Furthermore, it is our motivation that the findings here will support better-informed policy decision-making in line with the government's move towards multidimensional poverty measures.

The paper is organized in six main sections. The following one, section 2, provides relevant background on the status of the existing literature on cash transfer programs. Section 3 describes Peru's socio-economic context as well as the intervention in question, *Juntos*. Section 4 describes the data, focuses on the identification and empirical strategy, and provides a detailed approach to the Alkire-Foster method and the building of the multidimensional indices. Section 5 shares the evaluation findings, discusses of the results, and identified the limitations of the study. Section 6 concludes.

1. Literature review

Cash transfers programs are a solution to poverty that provide poor and extreme poor households with small and regular payments to smooth consumption, improve diet diversity, and increase investment in children's human capital, mainly healthcare and education. In the long-run, such payments or cash transfers tend to increase the capabilities of children to grow up healthier, better educated, and more productive, breaking the chronic poverty trap from one generation to the other (Arnold, Conway, & Greenslade, 2011). This approach has received broad attention globally, particularly among social protection initiatives. An important reason is because it aims to tackle directly some of the top-priority SDGs[1] while focusing on one the most vulnerable populations (UN Inter-agency Group for Child Mortality, 2017).

The theory of change behind this poverty solution can seem logical and straightforward. However, moving from health visits and school attendance to increasing productivity and, even further, breaking the cycle of inter-generational poverty covers a long causal timeline. Therefore, the framework of such programs must consider a large variety of outcomes not only in terms of time but also on the different deprivations that the poor face.

In their comprehensive report on conditional cash transfers, Fiszbein and Schady (2009) point out that, in the short- to intermediate-term (immediate effects), cash transfers trigger two main channels of effects, one associated with the program's conditionalities to receiving the subsidy and the other directly linked to the monetary transfer itself. If we take the case of *Juntos*, the chain linked to complying with the program's conditionalities focuses on human capital accumulation as households are required to enrol children in school and attend regular pre-natal and child development checks to receive the cash transfer.

[1] Food security and improved nutrition, health and wellbeing, education, and productive employment and decent work.

Hence, it is expected that households would invest in education and health dimensions. This investment can take the form of (1) direct costs, such as paying school fees, buying uniforms or textbooks (education) as well as medical fees and medicines (health); (2) indirect costs, such as transport to reach the school or health centre; and (3) opportunity costs, reduce household income by sending children who work to school. In the medium-term, these mechanisms lead to higher rates of school attendance, more years of schooling, and better school performance, in relation to the education dimension. By contrast, expected outcomes in the health dimension are adequate birth weight, reduction in stunting, and better physical and cognitive development. The channel directly linked to the income effect of the cash transfer refers to the actions that households take on how to use that cash. Liquidity is expected to help households to smooth consumption and increase expenditure in terms of more quantity and variety of food items, leading to a more diverse diet. These effects are interconnected with education outcomes, such as school performance, as well as health indicators, such as nutrition status. As a result, extreme poverty is expected to drop and, in the long run, the combination of these processes should increase labour productivity, leading to higher income, reducing poverty, and, ultimately, breaking the intergenerational transmission of poverty.

Cash transfers as a social protection strategy to invest in human capital have started relatively recently but spread quickly in low and middle-income countries due to the supporting positive evidence that was generated globally on short-term monetary poverty reduction and higher access to health and education services. In 1997, only the governments of Brazil and Mexico had conditional cash transfers programs, but the number had increased to 27 countries by 2008, and 64 by 2015 (Honorati, Gentilini, & Yemtsov, 2015). In terms of non-contributory conditional, unconditional, and pension transfers, up to 130 low- and middle-income countries have at least one such transfer program (Bastagli et al., 2016).

This rapid expansion has been prompted by positive results from a vast pool of rigorous impact evaluations. Most of these studies have examined outcomes on monetary poverty, consumption, health or education (Attanasio et al., 2010; Barham, Macours, & Maluccio, 2013; de Brauw et al., 2015; Martorano & Sanfilippo, 2012; Skoufias, 2005). Another important research line has analysed the effects on employment and productivity (Banerjee et al., 2015; Blattman, Fiala, & Martínez, 2014; Gertler, Martinez, & Rubio-Codina, 2012), while others have focused on social outcomes, such as nutrition, food security, and wellbeing of children (Gahlaut, 2011; Miller, Tsoka, & Reichert, 2011; Tiwari et al., 2016). There have even been more specific areas studies, such as impacts on indigenous populations (Gajate-

Garrido, 2014), child labour (del Carpio, Loayza, & Wada, 2016), or the psychosocial wellbeing of beneficiaries (Macours & Vakis, 2009; Samuels & Stavropoulou, 2016).

Important syntheses and meta-analyses efforts have been produced in the literature about the expansion and impacts of cash transfers. For instance, Fiszbein and Schady (2009) synthetized the existing evidence on conditional cash transfers in, probably, the first attempt to systematically understand the wave of such programs. Arnold, Conway, and Greenslade (2011) summarised the literature on conditional and unconditional cash transfer programs. Kabeer and Waddington (2015) conducted the first meta-analysis of the causal effects of CCT programs based on 46 studies. More recently, Bastagli et al. (2016) authored a report that reviewed more than 200 studies of conditional and unconditional cash transfers between 2000 and 2015.

The global evidence on cash transfers programs consistently shows increases in household expenditure, mainly on food items, and decreases in the monetary poverty headcount (Bastagli et al., 2016; Fiszbein & Schady, 2009; Kabeer & Waddington, 2015). When looking at the education dimension, the literature suggests a causal link between cash transfers and school enrolment and attendance. However, results on learning outcomes, in the longer term, are quite limited (Arnold, Conway, & Greenslade, 2011; Baird et al., 2013; Bastagli et al., 2016; Fiszbein & Schady, 2009). A similar trend can be observed in the health dimension. While the causality link is strong on access to health services, such as pregnancy and child development checks, the results tend to weaken once the analysis moves further in the theory of change (Arnold, Conway, & Greenslade, 2011; Fiszbein & Schady, 2009) or uses more precise measures such as anthropometrics (Bastagli et al., 2016). Studies on labour intensity do not report significant changes, which suggests that the adults in the household continue working, on average, about the same number of hours independent of receiving a cash transfer (Fiszbein & Schady, 2009; Kabeer & Waddington, 2015). However, there is a general trend of reduced child labour and child work intensity, particularly among boys. There is also a correlation between an increase in school enrolment and attendance and reduction in absenteeism with lower rates of child labour (Baird et al., 2013; Bastagli et al., 2016; Fiszbein & Schady, 2009; Kabeer & Waddington, 2015).

In Peru, evaluations of *Juntos* have found an increase in per capita expenditure and consumption, where, as in the global literature, food seems to be the main driver (Escobal & Benites, 2012; Monge, Seinfeld, & Campana, 2017; Perova & Vakis, 2009, 2012). Studies into education outcomes have reported an increase in school enrolment and attendance and a reduction in drop-out. While Perova and Vakis (2009) observed these changes among primary students (between 6 to 14 years old); Monge et al. (2017) detected larger effects among secondary students (between 11 and 19 years old). This discrepancy could be due to the time when the studies took place. Primary enrolment rates would probably have been lower in the 2000s compared to the following decade due to larger investment of the government in access to education of vulnerable children. Results on health indicators are more ambiguous. Both the studies by Perova and Vakis (2009) and Sánchez and Jaramillo (2012) found higher access to health services and improved nutritional status, but Díaz and Saldarriaga (2014) and Monge et al. (2017) found no significant effects on health status. These contrasting findings could be linked to the already high pre-treatment values of these indicators in certain areas and – as with education – the timing of the evaluations. Regarding employment, Fernández and Saldarriaga (2014) found a reduction in labour supply following the cash transfer date among married women and mothers of children under five years of age. Focusing on child labour, Escobal and Benites (2012) found a small but statistically significant reduction in time dedicated to paid work; however, they also observed an increase in unpaid labour.

As seen throughout this chapter, the literature on the impacts of cash transfer program is extensive. Indeed, it could be argued that previous studies have already looked at each of the deprivations and poverty dimensions of the MPI. However, these impact evaluations measure the average effect of the program on each of the outcome indicators separately. Cash transfer programs expect to impact different dimensions of people's life, such as their nutrition, health, and education status as well as their living standards and sustainable livelihoods. Ideally, the program should tackle all these dimensions but in practice, that is not always the case as each household participating in the program not only experiences different deprivations at different levels and times but also have different functionings and capabilities. Consequently, we argue that it is relevant to also assess whether a household has reduced more than one deprivation at the same time. There is an evidence gap on studies of conditional cash transfers that combine a myriad of indicators in an MPI, which allows to dig deeper to find synergies and determine the values driving the changes.[2]

This study contributes to improving data on poverty measurement and, most importantly, broadens the understanding of which deprivations the poor and the extreme poor face in Peru. Moreover, it provides relevant information to the current policy debate on cash transfer programs.

[2] There is only one project, still work in progress, by Vaz, Malaeb, and Quinn (2019) to evaluate PROGRESA in Mexico adopting the Alkire-Foster method.

2. Background on Peru and *Juntos*

Juntos – translates as 'all together' from Spanish – is the Government of Peru's conditional cash transfer (CCT) program. Before describing the program, we first set the background by providing an economic, social, and political overview of the country.

Prudent macroeconomic reforms and policies have led Peru, an upper-middle income country, to a stable environment of sustained growth and low inflation. According to the World Bank (2019b), between 2002 and 2013 Peru was one of the fastest-growing countries in Latin America with an average annual GDP growth rate of 6.1%. Moreover, the percentage of the population below the (monetary) poverty line dropped from 58.7% in 2004, the second highest in South America only after Bolivia, to 20.7% in 2016. In terms of multidimensional poverty, Peru significantly reduced the share of people with deprivations in education, health, and living standards, and it was highlighted as one of the best performing countries in UNDP and OPHI's (2019) recent report. Despite these promising statistics, when compared to its neighbours, Peru lags behind Ecuador, Colombia, Brazil, and Chile when it comes to GDP per capita (World Bank, 2019b) and several poverty measures, including the national poverty rate, the extreme poverty line, defined as percentage of people living on less than USD 1.90 a day (Ritchie et al., 2019), the Human Development Index (HDI)[3] (UNDP, 2018), and multidimensional poverty (UNDP & OPHI, 2019). Additionally, in terms of wellbeing indicators (e.g. health, education, basic services, connectivity, and labour to government social expenditure), Peru is one of the worst-performing countries in South America. For instance, it has the highest incidence of tuberculosis, the second highest prevalence of anaemia, the lowest scores in the PISA test[4] despite high rates of school enrolment, the lowest access to basic sanitation services, the second lowest internet penetration, and the highest employment vulnerability. Additionally, it was the country that dedicated the lowest proportion of its GDP to education and the second lowest to social protection in 2015 (Deneulin & Clausen, 2018).

In 2016, INEI signed an agreement with OPHI to create a multidimensional poverty measure tailored to Peru adopting the Alkire-Foster method, following the steps of Colombia and Chile, who created a tailored MPI that, unlike the Global MPI, includes indicators on employment and social protection. Despite this important step, changes in government prevented the national MPI to be fully rolled out.

[3] Using data from 2017. Peru is only slightly above Colombia with an HDI of 0.75 versus 0.747 of Colombia.

[4] Program for International Student Assessment (PISA) is global test completed by 15-year old students that aims to assess countries' quality of education. More information at http://www.oecd.org/pisa/aboutpisa

Meanwhile, OPHI and UNDP still report statistics on Peru's multidimensional poverty using the Global MPI.

3.1 The intervention

Juntos is managed by the Ministry of Development and Social Inclusion (MIDIS) and is embedded within the national anti-poverty and social inclusion policy. Created in 2005, the program aims to incentivise investment in human capital through accessing health and education services as well as increase household consumption capacity by injecting liquidity, with the long-term objective of breaking intergenerational poverty. *Juntos* is the top priority social program led by the government in its goal to eradicate poverty. By 2016, the program had reached 814,533 households in 1,178 districts of the country's 1,846 districts. Coverage has focused on poverty levels, thus these districts include the 20 poorest, mostly concentrated in the Andean region (MIDIS, 2016). *Juntos* represents 28% of the budget for development and social inclusion (MEF, 2016) and the government expenditure on cash transfers is equivalent to 0.5% of the GDP (World Bank, 2019a). The targeting process has two main sequential steps, one at the district level and the other at the household level. These steps have changed over time as the program was scaled-up. By the time of the baseline survey used in this paper, in 2011, vulnerable districts were identified based on the following criteria:

- Households with two or more unsatisfied basic needs (based on the 2005 household census).
- Incidence of monetary poverty – poverty gap (based on INEI's 2004 Poverty Map).
- Severity of monetary poverty – extreme poverty (based on INEI's 2004 Poverty Map).
- Incidence of chronic child malnutrition among children between 6 and 9 years of age (based on the 2005 household census).
- Percentage of villages affected by political violence (collected by the Resettlement Support Program).

The indicators had different weights. Villages that had suffered from political violence during the active years of terrorist groups had the highest weight (1/3), followed by the malnutrition index (3/10), the average of basic needs (1/6), and both monetary poverty measures (1/10).

In the second phase, households within the eligible districts were classified as poor and extremely poor according to the Household Targeting System (SISFOH).[5] This index is calculated by a weighted average of household wellbeing, income, and expenditure indicators. Additionally, households must have a pregnant household member or at least one of the household members must be 14 years old or younger. In July 2012, the program relaxed the targeting criteria as part of its expansion strategy. Changes affected the first filter by targeting districts with a poverty rate equal or higher than 40% of their population (based on INEI's 2009 Poverty Map). A categorical criterion was added to prioritize rural districts by adding villages with fewer than 400 households or 2,000 inhabitants. In the second filter, SISFOH was still applied but the age cutoff increased to 19 years old or younger to account for completion of secondary schooling (Galdó, 2014; Meléndez & Guerrero, 2016).

Households participating in the program receive a cash transfer equivalent to PEN 100 monthly (approximately USD 30). The payments are delivered every two months to reduce logistical and administrative costs. The amount is fixed and does not change across households as it is the case with other cash transfer programs. The value of the transfer represents 15% of the average household expenditure by 2015, which has reduced from an estimated 23% in 2011, when baseline survey was conducted (Monge, Seinfeld, & Campana, 2017). Another comparative measure is that the transfer amount is about 8% of the cost of the national household basic goods basket, estimated at USD 378 per month (INEI, 2016a). The transfers stream will continue if the household meets the targeting criteria and complies with the conditions established. There is no time limit for being a *Juntos* beneficiary. Payments are delivered if households comply with the following conditionalities:

1. School enrolment and attendance at kindergarten for children between three and six years old, and primary or secondary education for those between six and 19 years old.[6]
2. Maternal monthly prenatal checks.
3. Height and development checks for children up to 36 months.[7]

[5] SISFOH – acronym for *Sistema de Focalización de Hogares.* The composition of the index is not publicly available.
[6] Attendance means having at most three unjustified absent days in school.
[7] Frequency is monthly for children between 0 to 11 months old, once every two months between 12 and 23 months, and once every three months between 24 and 36 months.

These conditions aim to direct investment into education and health services, which makes it a multi-sectoral program, thus the relevant of using a multidimensional approach when assessing impacts.

3. Methodology and data

The purpose of this study is to assess the impact of Peru's CCT program *Juntos* on multidimensional poverty. This chapter explains the methodology to identify a counterfactual and describes the data as well as the empirical strategy to measure treatment effects.

4.1 Identification strategy

Before an important expansion of *Juntos* to new districts in 2012, MIDIS designed an evaluation methodology based on matching techniques. As the expansion plan had already strategically identified the new areas of work, the strategy employed to identify a counterfactual was through the quasi-experimental method of propensity score matching (PSM). According to Rosenbaum and Rubin (1983), the propensity score is the conditional probability of receiving a treatment given pre-treatment characteristics. PSM relies on the strong assumption that non-observed characteristics are not significantly different between treatment and comparison groups (Gertler et al., 2016; Ravallion, 2007).

The first filter used by the government was to identify districts within the 14 eligible regions[8] where the program was not yet operating. The second step was to match 'untreated' villages with those participating in the program based on an algorithm that considered geographical characteristics and monetary poverty levels. For sampling reasons, only villages with more than 10 households were considered. Finally, households were sampled if they met *Juntos* targeting criteria, that is, to be poor according to SISFOH and have at least one member aged 19 or younger (Meléndez & Guerrero, 2016).

4.1.1 Propensity score weighting

In addition to matching, we added propensity score weighting (PSW) to guarantee that treatment and comparison groups have a similar distribution and reduce bias in estimates under the assumption of unconfoundedness (Imbens & Wooldridge, 2009). PSW uses propensity scores to weight differentially observations in treatment and comparison groups when estimating the treatment effect. In the average

[8] Region is the highest-level circumscription in Peru.

treatment effect on the treated (ATET) specification, weights are equal to 1 for observations in the treatment group whereas for observations in the comparison group, the weights are inversely proportional to the distance between the propensity scores of beneficiaries and non-beneficiaries (Becker & Ichino, 2002; Stone & Tang, 2013). An advantages of PSW is that by combining regression and propensity score methods, it reduces the correlation between omitted and included variables, providing a more robust estimator (Imbens & Wooldridge, 2009). Another benefit of this approach is that it allows keeping the whole sample since all observations in the comparison group are assigned weights, thus statistical power is not compromised (Olmos & Govindasamy, 2015). PSW, however, has also limitations. For instance, it is sensitive to misspecification of the propensity score model, which, if not specified carefully, can increase the bias in treatment effects (Freedman & Berk, 2008).

We selected the variables for the model based on their potential to explain treatment effects according to the literature review. We only used baseline values, and data for both the treatment and comparison groups came from the same source (Caliendo & Kopeinig, 2008). We also ensured variables had no missing values and checked Spearman's correlation coefficients and statistical differences between the mean values of the treatment and comparison groups at baseline (correlation test results are shown in Appendix Table 2). We chose 16 variables that have incidence at the individual level, namely the household head (i.e. age, no formal education); at the household level (i.e. household size, having children under five and in school age, being beneficiary of another social program, member affiliated to social security, and deprived in a number of household assets); and at village level (i.e. living in rural area, poverty rate). We use Kernel matching after considering the sample size, the share of treatment and control observations, and the distribution of the propensity score. Kernel provided the best fit compared to other algorithms in reducing bias and increasing efficiency. Appendix Tables 3 and 4 show the balancing property of the means of control and outcomes variables respectively, comparing the untreated and treated groups before and after the matching. Balance is achieved among covariates and outcome indicators. Appendix Table 5 compares results from all models tested. The mean and median bias reduce substantially by 86% and 87% respectively and the p-value of this model increased the most (0.922). Appendix Figures 1 and 2 show the comparison and the distribution of the propensity score among matched versus unmatched observations.

4.2 Data

The baseline survey was conducted between February and August 2011 and the sample used for this study only includes households that joined *Juntos* from the third quarter of 2011 onwards. The effective sample for analysis restricted to common support under the PSW model, which is a panel of 1,568 households, of which 777 are in the treatment group and 791 are in the comparison group.[9] Attrition between the two rounds of data collection represents 11% of the baseline sample. We tested for differential attrition on a large set of socio-economic and demographic variables and did not find significant evidence with the only exception of quality of electricity and ownership of a television set (see Appendix Table 1).[10] The sample is spread along the 14 eligible regions at the time of baseline and 77 districts.[11] Most households are in rural areas of the Andean region, which is a priority focus of the program due to its high poverty concentration.

Table 1 shows the weighted baseline mean values of a set of socio-economic and demographic variables for households in both the treatment and the comparison groups to check of balance. We only use the sample in common support and include 14 variables, which include demographic characteristics, such as household size, gender of household head, and children in pre (newborn to five years old) and school age (six to 19 years old). We also consider relevant socio-economic variables, namely literacy and education level of the household head as well as work frequency. At the household level, we checked ownership of tv and mobile sets and whether the household receives benefits from other governmental social programs as well as their affiliation status on the national social security scheme. Finally, at the district level, we input poverty rate and rural location. Without the propensity score weights, 10 out of the 14 selected variables had statistically significant differences. After applying PSW, balance was achieved in all 14 of them.

[9] Statistical power tests were conducted based on two previous impact evaluations of *Juntos*. Results show that the sample holds statistical power at 80% to detect a minimum effect size of 3.06%. Parameters and results of these power calculations can be found in Appendix Table 11.

[10] We ran linear regression with a 20 dummy-variable set absorbing by district.

[11] Appendix Table 12 shows the distribution of the sample by region and geographic domain and Appendix Figure 3 maps the location of treatment and control districts.

Table 1. Baseline means (with and without propensity score weighting) (n=1,569)

Variable	Pre/Post-matching	Mean Treatment	Mean Control	p-value
HH in rural area	Pre-matching	0.698	0.709	0.489
(1=rural)	Post-matching	0.698	0.692	0.757
Poverty rate in district	Pre-matching	0.645	0.589	0.001
	Post-matching	0.646	0.648	0.923
Age of hh head	Pre-matching	39.290	40.731	0.001
	Post-matching	39.305	39.183	0.774
HH size	Pre-matching	4.652	4.517	0.023
	Post-matching	4.653	4.615	0.528
Gender of hh head	Pre-matching	0.855	0.829	0.051
(1=male)	Post-matching	0.855	0.853	0.889
HH with children 0-5	Pre-matching	0.046	0.030	0.020
(1=Yes)	Post-matching	0.046	0.033	0.054
HH with children 6-19	Pre-matching	0.670	0.618	0.003
(1=Yes)	Post-matching	0.669	0.663	0.702
HH head is literate	Pre-matching	0.821	0.831	0.494
(1=Yes)	Post-matching	0.822	0.821	0.905
HH head has no formal education	Pre-matching	0.387	0.363	0.164
(1=Yes)	Post-matching	0.386	0.353	0.055
HH benefits from social other programs	Pre-matching	0.925	0.874	0.000
(1=Yes)	Post-matching	0.925	0.928	0.797
HH affiliated to social security	Pre-matching	0.059	0.115	0.000
(1=Yes)	Post-matching	0.059	0.053	0.431
HH owns tv	Pre-matching	0.832	0.752	0.000
(1=Yes)	Post-matching	0.831	0.834	0.840
HH owns mobile phone	Pre-matching	0.779	0.746	0.030
(1=Yes)	Post-matching	0.779	0.787	0.561
HH head worked last week	Pre-matching	0.314	0.453	0.000
(1=Yes)	Post-matching	0.314	0.328	0.418

HH stands for household

4.3 Empirical strategy

Using this matched sample, the empirical strategy in this study is based on difference-in-difference regressions to assess program impacts based on the ATET estimate. Therefore, we compare changes in the outcomes between household receiving *Juntos* cash transfers (treatment group) and eligible in their characteristics but non-participant households (comparison group) before (baseline in 2011) and after the intervention (endline in 2015). Formally, we have:

$$Y_{it} = \alpha + \beta 1T + \beta 2t + \beta 3T_{i1}t + X_{i0} + \varepsilon_{it}$$

Where Y_{it} is the outcomes of interest, T_{i1} indicates the binary treatment assignment, t is dummy that represents the time (0 refers to the baseline in 2011, and 1 refers to the endline in 2015), $T_{i1}t$ is the interaction between time and treatment, X_{i0} is a vector of matching baseline individual and household covariates and village characteristics (age of household head, household size, children under five years old, children in school age, household head has no formal education, household owns television set, household owns mobile phone, household has access to decent sanitation services, household has access to drinkable water, household has access to electricity, household has access to good quality fuel, household member registered in social security, household is beneficiary of another social program, household located in rural area, poverty rate of the district). ε represents the error term. We estimated robust standard errors. The unit of analysis in this study is the household, thus all individual-level data was transformed into indicators at the household level (e.g. nutrition, school attendance) in order to create the multidimensional poverty indices. Another reason for choosing the household as the analysis unit is derived from the theory of change of *Juntos*. First, targeting criteria use household-level indicators. Second, despite targeting different individuals within the household, the success of the program is measured on a household escaping from the poverty trap rather than a particular household member.

4.4 Multidimensional poverty

The main outcome under analysis is multidimensional poverty. It is commonly agreed that poverty is a multidimensional phenomenon. Yet, debate arises when it comes to its definition and measurement. Approaches are based on different social constructs, and these translate into a variety of poverty definitions and measures, which leads to identifying individuals and groups as poor in dissimilar ways. For instance, a person identified as poor in one approach might not be identified as poor in another. The two dominant approaches are monetary poverty, defined in terms of economic resources such as income and consumption; and multidimensional poverty, defined in terms of a broader set of 'dimensions' that capture wellbeing. Poverty has generally been measured by resource or utility approaches that use indicators of income, expenditure, and consumption as proxies of wellbeing. These measures have prevailed for decades and remain widely used tools for informing social policy. Indeed, assessment of cash transfers programs has also followed this approach. In recent years, however, the discourse in development economics and social policy has embraced the broader notion of multidimensional approaches that go beyond material indicators and aim to tackle different deprivations to fight poverty and have a 'good' life (Banerjee & Duflo, 2019). This conundrum is particularly relevant due to the policy implications for antipoverty policies and interventions targeting the poor (Ruggeri Laderchi, Ruhi, & Stewart, 2003).

The new 2030 Agenda for Sustainable Development, subscribed to by 193 countries, acknowledges that poverty eradication "in all its forms and dimensions" is the greatest challenge to achieving sustainable development and people's freedoms (United Nations, 2015). A multidimensional poverty index will be used to report SDG 1.2.2.[12] This steps reflect the combined efforts by the United Nations Development Programme (UNDP), the Oxford Poverty and Human Development Initiative (OPHI), national governments, and the research work of Sabina Alkire and James Foster (OPHI, 2018). In this line, the Commission on Global Poverty aims to advise "on other dimensions of poverty that the [World] Bank should collect data on, track, analyse and make available to policy-makers for evidence-based decisions" (World Bank, 2015). The World Bank, which promoted the use of monetary poverty lines,[13] has also committed to aggregating "dimensions using a member of the class of multidimensional poverty indices proposed by Alkire and Foster" (World Bank, 2017) understanding that "a growing toolbox for the assessment of well-being enhanced the understanding of poverty" (World Bank, 2018). Moreover, the MPI[14] has been included in the Human Development Reports since 2010 (UNDP, 2010). The MPI is an international poverty measure that uses data from more than 100 countries to assess poverty trends based on ten indicators split in three dimensions – namely, health, education, and standards of living. Other examples of influential policy publications on poverty are the World Development Report 2000/2001

[12] SDG 1.2.2: Proportion of men, women, and children of all ages living in poverty in all its dimensions according to national definitions (United Nations, 2015).
[13] For more information, see Ravallion (1998).
[14] The Multidimensional Poverty Index (MPI) is developed using the Alkire-Foster method and it provides a ranking of countries and sub-national divisions according to their multidimensional poverty level (OPHI, 2018).

(World Bank, 2001), the Development Cooperation Report by the OECD (2013), and the Stiglitz-Sen-Fitoussi Commission (2009). Governments are evidently adopting national multi-dimensional poverty indexes to complement monetary measurements and report progress on the SDGs.[15] In the debate on poverty measures, Ravallion (2010, 2011) questions the need for a "mashup" index to capture 'all' aspects of poverty, highlighting that there is no consensus on what dimensions to include and how these should be weighted. In response, Alkire and Foster (2011b) state that the selection of dimensions and parameters are normative judgements. They argue that there is no 'right' poverty index, but estimations should adapt to specific policy contexts and be open to public scrutiny.

The literature shows that there is a policy space for incorporating better wellbeing metrics for the evaluation of poverty in all its dimensions. This study aims to go beyond the 'typical' resource or utility-based outcomes to integrate a broader set of wellbeing dimensions, emphasising those related to human and social indicators. In the last decade, there has been a rise in the number of studies examining the differences in outcomes between monetary and multidimensional poverty, most of which have shown that the overlap between the two is not strongly correlated (Ataguba, Ichoku, & Fonta, 2013; Bader et al., 2016; Khan et al., 2015; Levine, Muwonge, & Batana, 2014; Maltzahn & Durrheim, 2008; Roelen, Gassmann, & de Neubourg, 2012). This mismatch has significant policy implications. For instance, from an evaluation perspective, treatment effects on outcomes and impacts will be different depending on which measure is used. Even when the study design and methodology are rigorous, if the information is partial – no matter the result – it may misinform and bias policy decisions. This is a reason is why Alkire et al. (2015b) advocate for the use of the MPI as a complementary tool in poverty targeting and assessment.

There is literature that links the Alkire-Foster method with poverty reduction interventions (Azevedo & Robles, 2013; Bouillon & Yáñez-Pagans, 2011; Trani, Biggeri, & Mauro, 2013). However, empirical evidence on the use of multidimensional poverty in the Alkire-Foster method in the impact evaluation literature remains scarce and provides a fertile ground for evidence generation on the usefulness of this tool to assess the impacts of social programs and policies. Robano and Smith (2014) calculated the difference-of-difference of the Alkire-Foster method to assess BRAC's Targeting the Ultra Poor Program in Bangladesh. Their multidimensional index includes health status, housing quality, clothing, and food

[15] Some of these include Bhutan, Colombia, Indonesia, Mexico, Philippines, Peru, Sierra Leone, Vietnam (OPHI, 2017).

security dimensions and find positive effects on the latter. They report that effect sizes were stronger among households that had higher deprivation scores at baseline. Loschmann, Parsons, and Siegel (2015) used matching techniques to evaluate the impacts of a program by the United Nations High Commissioner for Refugees (UNHCR) in Afghanistan with returning internally displaced populations. They created a tailored MPI with economic welfare, health and education, and basic services dimensions using the Alkire-Foster method. The study found that shelter assistance reduces multidimensional poverty, a change that is mainly driven by better diet diversity and improved food security (in the health and education dimension) and heating (in the basic services dimension). In South Africa, Pasha (2016) used secondary data to examine the impact of social grants using regression discontinuity and instrumental variables. The study employed the 'classic' MPI with its education, health, and living standard dimensions as well as the Correlation Sensitive Poverty Index (CSPI). Results show a reduction in multidimensional poverty in both composite indices. Ouili et al. (2017) conducted a randomized control trial (RCT) of Malawi's national unconditional cash transfer program in the framework of the Transfer Project. They developed a child poverty index with eight dimensions and 20 indicators using the Alkire-Foster method. Findings showed strong impacts on monetary poverty and somewhat limited effects on multidimensional poverty. The impacts on the latter were mainly driven by health, nutrition, and sanitation outcomes, specifically among boys. More recently, Mitchell and Macció (2018) used a quasi-experimental approach to analyse the impacts of the emergency housing program by TECHO in Argentina. They adapted the MPI dimensions to physical health, psychological health, sleep, privacy, interpersonal relations, and security. The results showed a reduction of multidimensional poverty by more than half on average. Effects were larger among households that were in the poorest quintiles at baseline.

Although these studies have also used indices based on the Alkire-Foster method, there are important differences with our approach, namely in the identification and empirical strategies, the target populations, the type of interventions, and the geographical locations. While the literature on impact evaluations and multidimensional poverty measurement is growing, it remains limited. There is fertile ground to further test and understand the implications and contributions of this approach in evaluating the impacts of anti-poverty programs.

4.5 The Alkire-Foster method

To analyse multidimensional poverty, this study uses the Alkire-Foster method, based on the foundations of Sen's (1976) axiomatic approach and an extension of the Foster, Greer, and Thorbecke (1984) measure. This method allows us to capture the proportion of people who are multidimensionally poor (incidence) as well as the multiple deprivations that they face at the same time (intensity) with respect to the program's outcomes, namely education, health, and living standards, providing a comprehensive picture of poverty (Alkire et al., 2015b). Furthermore, the method is operational and replicable as well as an understandable and descriptive measure of poverty, allowing us to capture the joint distribution of these deprivations as well as decomposing them by each indicator. As a result, we can report poverty trends over time on aggregate and by subgroups. Despite the mashup indices debate (Ravallion, 2010), the Alkire-Foster method is one of the most contrasted and more accepted tools to measure multidimensional poverty. This statement is backed by the formalisation of the method as the multidimensional poverty measure for the SDGs[16] by the United Nations (2015) and its institutional acknowledgement in recent poverty reports by the World Bank (2017, 2018).

Juntos, like all CCT programs, is a poverty solution that aims to tackle multiple outcomes over time. Therefore, it seems intuitive to use a measure that allows to assess the impact of such a program on the joint deprivations of individuals and households rather than analysing multiple and scattered indicators. Most impact evaluations of cash transfer programs measure the average effect of the intervention on separate outcomes (e.g. school attendance, nutrition, food consumption). The value added of the Alkire-Foster method is that it allows to evaluate whether each household has benefited on one or more outcomes or dimensions at the same time. There are synergies between deprivations in education, health, and living standards, and this approach enables scholars as well as policymakers to understand the drivers of multidimensional poverty, the association and contributions of these deprivations, and their changes over time.

The first step to build an MPI using the Alkire-Foster method is to choose the unit of identification depending on the objectives of the program and data available. Indicators are then selected and built based on the expected outcomes of the program. These indicators represent functionings (e.g. access to

[16] Under SDG indicator 1.2.2: proportion of men, women and children of all ages living in poverty in all its dimensions according to national definitions (Ritchie et al., 2019).

schooling and health services). Using a counting approach, which entails counting the number of dimensions in which people are deprived (Atkinson, 2003), the Alkire-Foster method is a direct and intuitive approach that works with a 'dual-cutoff' strategy to identify the poor. To give a practical example, we use the case of *Juntos*. First, we set the dimensions (e.g. education and health) composed by a set of indicators (e.g. access to school and access to health services) based on the theory of change of the program. Second, each indicator is defined in terms of a normative achievement set by the program, which is the deprivation cutoff (z) that determines who is deprived and who is not in a binary sense. The raw or uncensored headcount ratio is the proportion of the population deprived in a particular dimension. Third, indicators are given relative weights in terms of their importance to the programmatic objectives. Fourth, a poverty cutoff (k) is created based on the proportion of sum of weighted deprivations. This second cutoff point will identify who is multidimensionally poor and who is not and represents the incidence of poverty (H). In other words, the incidence of poverty (H) is the proportion of the population that is identified as multidimensionally poor. Moreover, the censored headcount ratio is the proportion of the population deprived in a particular dimension and that is, at the same time, multidimensionally poor. The intensity of poverty (A) is the average share of deprivations among those who are multidimensionally poor. Finally, the adjusted headcount ratio (M_0) is the product of the partial indices of the incidence and intensity of poverty ($H * A$) (Alkire, 2015; Alkire et al., 2015b; Alkire & Foster, 2011a; Alkire & Santos, 2014). Statistical robustness and sensitivity tests were considered as suggested by Athey and Imbens' (2017) paper on developments in econometrics.

4.6 The multidimensional poverty index

As Ruggeri Laderchi, Ruhi, and Stewart (2003) argue, conceptualization and measurement of poverty have direct implications in the way a policy is defined and implemented. In this paper, we create a tailored MPI to the objectives of *Juntos* and the local context, which we call *Juntos* MPI. Additionally, we also calculated the Global MPI, developed by OPHI (Alkire S., Chatterjee M, Conconi A., Seth S., 2015), which has set general parameters for all contexts to allow for extensive comparability. Having these two indices will permit better understanding the trade-offs between a measure that is limited to a specific policy or context against a more global and generic one.

Juntos MPI is inspired by the global index – establishing the same dimensions of health, education and living standards because these are also the main areas where *Juntos* expects impacts. However, the indicators that conform those dimensions have been tailored to *Juntos'* theory of change and the CCT policy-relevant outcomes as identified by Bastagli et al. (2016). As a result, each of the chosen indicators is relevant to the objectives of the program and, therefore, the wellbeing of its beneficiaries. The unit of observation and analysis is the household and the data used for the purpose of this paper comes from the same source, which is the household panel survey described in the "Data" sub-section. We have carefully define the indicators based on the data availability and reliability. Considering the time of exposure to *Juntos* or treatment intensity, we prioritize short-term outcomes that are expected to have direct impacts on education, health, and basic living standards.

The first two dimensions – education and health – resonate with the program's focus on human capital. Moreover, the living standards dimension is general enough to keep the denomination but rethink its components based on *Juntos'* short-term outcomes. The indicators in education (school attendance in each primary and secondary levels) and health (maternal and child checks) are all directly linked to *Juntos* conditionalities, so these are indeed fundamental to assess the effectiveness of the program early in the causal chain. Moreover, for the 'living standards' dimension, we include child labour because the program would expect, as an early outcome, that children would dedicate more time to school, thus, less to work. We also include ownership of large assets considering that the income effect of the cash transfers could trigger the purchase of important assets for the households' wellbeing. We work under the assumption that a household is more likely to access directly and in the short run as the result of the cash transfer as opposed to being able to change services such as electricity or sanitation facilities, which are part of the Global MPI. The deprivation cutoffs (z) for each indicator have been defined based on *Juntos* minimum goals and the local context. We give equal weights to all three dimensions (1/3) in the *Juntos* MPI and define the poverty cutoff (k) at 33%, which means that a household will be multidimensional poor if it is deprived in at least one of the dimensions. This follows the structure of the Global MPI, described also in this section. With regards to the indicators, each one has a weight of 1/6. Table 2 show the dimensions and indicators of the *Juntos* MPI.

Table 2. Juntos MPI: Dimensions and indicators

Dimensions	***Juntos MPI Indicators***
Education	**Primary school attendance.** Any household member in school age (between six and 11 years old) has missed school or is not enrolled.
	Secondary school attendance. Any household member in school age (between 12 and 17 years old) has missed school or is not enrolled.
Health	**Pre-natal checks.** The main female of the household did not complete the minimum requirement of six prenatal checks during last pregnancy.
	Child development. Any child below five years old has not made any visits to a health centre in the last six months or has never visited once.
Living standards	**Assets.** The household does not own any of these assets: TV, refrigerator, kitchen with oven.
	Child labour. At least one child between five- and 17-years old works.[17]

The Global MPI is constructed by ten weighted indicators, divided into three dimensions. The multidimensional poverty line is set at 33%, which means that a household is multidimensionally poor if it is deprived in at least one third of the weighted indicators. The index is built using the following weights: each indicator in the 'education' and 'health' dimension has a weight of 1/6 whereas indicators in the 'living standards' dimension have a weight of 1/18. Table 3 shows the description of the dimensions and indicators in the Global MPI.

To ensure robustness, we test the association and similarity across deprivations (binary indicators). To measure the association of coefficients, we use Cramer's V test, which is the mean square canonical correlation between two variables. Additionally, to measure the strength of the association, we use R^0 to test for redundancy. As explained by Alkire et al. (2015a, p.18), R^0 "shows the matches between deprivations as a proportion of the minimum of the marginal deprivation rates." We have considered that a value higher than 0.8 indicates a high redundancy rate. This means that more than 80% of the sample who are deprived in one indicator were also deprived the other indicator. In *Juntos* MPI, we observe no strong correlation or redundancy between indicators in neither Cramer's V nor R^0 tests. In the Global MPI, we also observe no high correlation between the indicators; however, in the R^0 test, the indicators

[17] Uses ILO definition in terms of the age range (ILO, n.d.). Regarding number of hours, we consider a household is deprived if at least one child has worked more than one hour during the school year, either paid or unpaid. During vacations, we incorporate the definition by the Ministry of Labour that considers children between 12 to 17 (secondary school age) can work up to 35 hours weekly.

in the 'living standards' dimension seem to have a high redundancy among each other. This high level of association is not necessarily positive or negative. We keep it as we are replicating the Global MPI to compare results with a tailored made multidimensional index. Results of both Cramer V and R^0 tests in relation to the *Juntos* MPI can be found in Appendix Tables 6 and 7.

Table 3. Global MPI: Dimensions and indicators[18]

Dimensions	***Global MPI Indicators***
Education	**Years of schooling.** No household member older than 10 years old has not completed six years of education (equivalent to primary education).
	School attendance. Any school-aged child is not attending school up to the age at which he/she would complete class 8 (2nd year of secondary school in Peru).
Health	**Nutrition.** Any child under 5 years of age in the household with nutritional information is either stunted or underweight (below minus two standard deviations from the median).
	Child mortality. Any child below five years old has died in the household in the last five years.
Living standards	**Cooking fuel.** A household cooks with dung, agricultural crops, shrubs, wood,
	Sanitation. The household's sanitation facility is not improved (according to SDG guidelines) or it is improved (flush toilet or latrine or ventilated improved pit or composting toilet) but shared with other households.
	Electricity. The household has no electricity
	Housing. The household has inadequate housing: the floor is made of natural materials (mud/clay/earth, sand, or dung), or if the dwelling has no roof or walls or if either the roof or walls are constructed using natural materials (cane, palm/trunks, sod/mud, dirt, grass/reeds, thatch, bamboo, sticks) or rudimentary materials (carton, plastic/polythene sheeting, bamboo with mud, stone with mud, loosely packed stones, adobe not covered, raw/reused wood, plywood, cardboard, unburnt brick, or canvas/tent)
	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.
	Drinking water. The household does not have access to improved drinking water (piped water, public tap, borehole or pump, protected well, protected spring or rainwater).

[18] Some indicators have been adapted to the availability of variables in the dataset.

4. Analysis and results

This chapter shows the results of the difference-in-difference regressions using the weighted values and controlling for individual, household, and village characteristics included in the PSW model. We first show the results for the *Juntos* MPI, followed by the Global MPI analysis. For each index, we explain the results at the aggregate level before breaking down the indicators.

Juntos MPI

Between 2011 and 2015, the proportion of the population that was multidimensionally poor (H) fell in both the treatment and the comparison groups by 16 and 13 percentage points respectively. The adjusted headcount (M_0) also decreased over time in both groups, by seven percentage points in the treatment group and five percentage points in the comparison group. However, the impact analysis on H and M_0 found no significant differences between households in the treatment and comparison groups under the iteration of treatment and time. Results are shown in Table 4.[19]

Table 4. Juntos MPI: Impact on aggregate measures (Estimations weighted of propensity scores) (n=1,568)

VARIABLES	(1) Headcount ratio (H)	(2) Adjusted Headcount Ratio (M_0)
Diff-in-diff	-0.00575	-0.00536
	(0.0280)	(0.0110)
Observations	3,136	3,136
R-squared	0.041	0.038
Mean control t(0)	0.214	0.0787
Mean treated t(0)	0.228	0.0847
Diff t(0)	0.0142	0.00605
Mean control t(1)	0.0726	0.0283
Mean treated t(1)	0.0811	0.0290
Diff t(1)	0.00848	0.000685

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Using the same regression model as with the aggregate measures (see more details in the "Methodology and data" section), Tables 5 and 6 show the impacts on the outcome indicators using the uncensored and

[19] We do not report results on the intensity of poverty (A) because the denominator is not the same among groups, hence it is not possible to make a direct comparison. Appendix Table 15 reports the incidence of the covariates at the aggregate level for *Juntos* MPI.

the censored headcount ratios respectively. The uncensored refers to the ratio of all households deprived in a given dimension whereas the censored estimations refer to the ratio of only poor households deprived in a given dimension. To calculate the censored deprivation score, we use the poverty cutoff (*k*) of 33%, which, as explained in the previous section, is equivalent to a household being deprived in at least one third of the weighted indicators. When comparing Tables 5 and 6, the values in the censored headcount are lower because these represent the proportion of who is deprived in a particular indicator (i.e. uncensored headcount) and, at the same time, is also multidimensional poor. The common trend in all indicators is that rates of deprived households reduce at endline in both uncensored and censored headcounts. It is worth noting that the trend is similar for both treatment and comparison groups. However, the difference-in-difference estimations in the uncensored headcount ratio (see Table 5) do not report any statistically significant reduction in the tailored indicators. When censoring the headcount ratio (see Table 6), despite observing a similar trend with a stronger reduction among treated households in most indicators, we still do not find any statistically significant difference between groups.

Table 5. Juntos MPI: Impact on indicators – Uncensored Headcount Ratios (Weighted) (n=1,568)

VARIABLES	(4) Attendance (primary)	(5) Attendance (Secondary)	(6) Antenatal checks	(7) Child health checks	(8) Child labor	(9) Large Asset Ownership
Diff-in-diff	-0.0175	-0.0157	0.00355	-0.0302	0.0519	-0.0131
	(0.0175)	(0.0192)	(0.0223)	(0.0260)	(0.0351)	(0.0269)
Observations	3,136	3,136	3,136	3,136	3,136	3,136
R-squared	0.002	0.006	0.035	0.016	0.011	0.025
Mean control t(0)	0.0506	0.0815	0.145	0.165	0.303	0.165
Mean treated t(0)	0.0463	0.0682	0.142	0.153	0.331	0.198
Diff t(0)	-0.00422	-0.0133	-0.00309	-0.0115	0.0274	0.0336
Mean control t(1)	0.0526	0.0586	0.0356	0.103	0.204	0.0683
Mean treated t(1)	0.0309	0.0296	0.0360	0.0618	0.283	0.0888
Diff t(1)	-0.0217	-0.0290	0.000456	-0.0417	0.0793	0.0205

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6. Juntos MPI: Impact on indicators – Censored Headcount Ratios (Weighted) (n=1,568)

VARIABLES	(10) Attendance (primary)	(11) Attendance (Secondary)	(12) Antenatal checks	(13) Child health checks	(14) Child labor	(15) Large Asset Ownership
Diff-in-diff	-0.00491	0.00297	-0.00608	-0.0234	0.0196	-0.0203
	(0.0133)	(0.0166)	(0.0178)	(0.0184)	(0.0221)	(0.0205)
Observations	3,136	3,136	3,136	3,136	3,136	3,136
R-squared	0.002	0.006	0.026	0.013	0.022	0.024
Mean control t(0)	0.0331	0.0627	0.0878	0.0727	0.125	0.0910
Mean treated t(0)	0.0296	0.0489	0.0914	0.0888	0.125	0.125
Diff t(0)	-0.00354	-0.0137	0.00356	0.0161	9.12e-05	0.0338
Mean control t(1)	0.0239	0.0327	0.0180	0.0343	0.0344	0.0264
Mean treated t(1)	0.0154	0.0219	0.0154	0.0270	0.0541	0.0399
Diff t(1)	-0.00845	-0.0108	-0.00252	-0.00723	0.0196	0.0135

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Global MPI

At the aggregate level, as shown in Table 7, both groups report similar decreasing trends. The incidence of multidimensional poverty (*H*) reduced by 22.5 percentage points in the comparison group and by 22.7, in the treatment group. The adjusted headcount ratio (M_0) dropped by 10.7 percentage points in the comparison group and by 9.9 in the treatment group. As a result of the parallel decreasing trends over time for both *Juntos* and non-*Juntos* beneficiaries, the difference-in-difference regression analysis shows that the program did not have any statistically significant effect in neither of the aggregate multidimensional poverty measures.[20]

Table 7. Global MPI: Impact on aggregate measures (Estimations weighted of propensity scores)

VARIABLES	(1) Headcount ratio (*H*)	(2) Adjusted Headcount Ratio (M_0)
Diff-in-diff	-0.00138	0.00735
	(0.0384)	(0.0167)
Observations	3,136	3,136
R-squared	0.053	0.059
Mean control t(0)	0.574	0.246

[20] Appendix Table 18 reports the incidence of the covariates at the aggregate level for the Global MPI.

Mean treated t(0)	0.614	0.255
Diff t(0)	0.0399	0.00942
Mean control t(1)	0.349	0.139
Mean treated t(1)	0.387	0.156
Diff t(1)	0.0386	0.0168

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The Global MPI indicators also show a downward trend where, overall, households on both the treatment and comparison groups reduce their deprivations. In this scenario, the indicators concentrating a larger proportion of deprived households are the quality of cooking fuel and sanitation facilities in the living standards dimension, reaching more than 95% on average in both treatment and comparison groups in the uncensored headcount at baseline and averaging 58% in the censored headcount. Years of schooling follows with a still important proportion of deprived households of about two thirds (63%), also on the uncensored headcount at baseline, and 50% on average under the censored headcount (see Tables 8 and 9). Deprivation in child mortality is extremely low (below 1% in both the uncensored and censored headcounts), and its contribution to the construction of the MPI is insignificant,[21] which reinforces the need for a tailored index to the context where *Juntos* operates.

At the indicator level in the uncensored headcount ratio, the Global MPI does not show any significant decrease among *Juntos* beneficiaries compared to those that did not receive the cash transfers on the education and health dimensions. In the living standards dimension, however, we encounter a statistically significant reduction ($p < 0.05$) in the deprivation of quality of fuel used for cooking. Households in the comparison group, on average, reduced their deprivation in this indicator by 18.6 percentage points compared to a slower reduction of 14 percentage points in the treatment group. This trend could be explained by the fact that *Juntos* beneficiaries might have focused more on education and health outcomes rather than other living conditions. Conversely, non-beneficiaries might have found it more effective to drive their scarce resources towards outcomes that are less expensive, such as cooking fuel, and have more immediate and tangible returns compared to education and health-related investments. Both these results are observed only using the uncensored headcount ratio. When censoring the headcount to

[21] Appendix Table 13 and 14 show the percentage contributions of each indicator in both the Juntos MPI and the Global MPI respectively.

consider only those who are deprived in each dimension and, at the same time, are multidimensionally poor, we do not find any statistically significant effects.

Moreover, we also find a significant effect ($p < 0.1$) in the deprivation of access to drinking water, which considerably fell by 12.3 percentage points in the treatment group compared to only 4.8 percentage points in the comparison group (see Table 8). After applying the censored headcount, we do not observe any statistically significant difference in the indicators that compose the Global MPI (see Table 9).[22] An important aspect to discuss is that, in most cases, improving the quality of the water source (e.g. building pipes, a pump, or a protected well) is not a task that is often carried out by a single household due to the high costs and level of effort involved. These are usually the result of government interventions in a group of villages, support from non-governmental organizations to targeted populations, or a coordinated effort by a group of villagers. Therefore, the question on the role of *Juntos* played to reduce the deprivation of beneficiaries in the access to safe water can be subject of further discussion.[23]

To analyse in more depth how the decision of the cutoff point ($k=33\%$) might affect the results of the censored headcount ratio, Appendix Tables 8 and 9 list the different poverty cutoffs in more detail for M_0 for both the *Juntos* and the Global MPI respectively. Results indicate that even if we lower the cutoff value, there are no significant differences, thus it is unlikely that the results will change should we adjust k.

[22] It is worth mentioning that we did not have data to exactly replicate the composition of this indicator following the Global MPI's definition. As mentioned in Table 4, we do not have information about the source of water, hence we built this indicator only with the type of the water source but not distance.

[23] Appendix Tables 19 and 20 shows the inference of the included covariates in the regression model for the uncensored and censored headcounts in the Global MPI, respectively.

Table 8. Global MPI: Impact on indicators – Uncensored Headcount Ratios (Weighted)

VARIABLES	(4) Years of Schooling	(5) School attendance	(6) Nutrition	(7) Child mortality	(8) Fuel	(9) Sanitation	(10) Safe water	(11) Electricity	(12) Housing Materials	(13) Small assets ownership
Diff-in-diff	0.0455	-0.00966	0.0133	0.00110	0.0452**	0.0199	-0.0758*	0.0444	0.00572	0.00551
	(0.0385)	(0.0156)	(0.0303)	(0.00535)	(0.0227)	(0.0271)	(0.0391)	(0.0337)	(0.0164)	(0.0383)
Observations	3,136	3,136	3,136	3,136	3,136	3,136	3,136	3,136	3,136	3,136
R-squared	0.004	0.002	0.029	0.001	0.074	0.074	0.011	0.046	0.008	0.043
Mean control t(0)	0.640	0.0403	0.246	0.00334	0.977	0.939	0.489	0.291	0.0677	0.491
Mean treated t(0)	0.627	0.0309	0.248	0.00129	0.978	0.934	0.485	0.320	0.0772	0.541
Diff t(0)	-0.0134	-0.00939	0.00203	-0.00205	0.00133	-0.00443	-0.00370	0.0290	0.00950	0.0497
Mean control t(1)	0.565	0.0435	0.109	0.00481	0.791	0.727	0.441	0.100	0.0272	0.290
Mean treated t(1)	0.597	0.0245	0.125	0.00386	0.838	0.743	0.362	0.174	0.0425	0.345
Diff t(1)	0.0321	-0.0190	0.0154	-0.000952	0.0465	0.0154	-0.0795	0.0734	0.0152	0.0552

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 9. Global MPI: Impact on indicators – Censored Headcount Ratios (Weighted)

VARIABLES	(14) Years of Schooling	(15) School attendance	(16) Nutrition	(17) Child mortality	(18) Fuel	(19) Sanitation	(20) Safe water	(21) Electricity	(22) Housing Materials	(23) Small assets ownership
Diff-in-diff	0.0160	-0.00537	0.0141	0.00110	0.00733	1.44e-06	-0.0200	0.0318	0.00702	0.0287
	(0.0385)	(0.0153)	(0.0287)	(0.00503)	(0.0382)	(0.0381)	(0.0355)	(0.0309)	(0.0147)	(0.0358)
Observations	3,136	3,136	3,136	3,136	3,136	3,136	3,136	3,136	3,136	3,136
R-squared	0.027	0.002	0.028	0.001	0.061	0.061	0.030	0.039	0.007	0.050
Mean control t(0)	0.492	0.0403	0.217	0.00334	0.569	0.557	0.372	0.227	0.0543	0.389
Mean treated t(0)	0.512	0.0296	0.219	0.000	0.611	0.596	0.363	0.261	0.0631	0.421
Diff t(0)	0.0203	-0.0107	0.00138	-0.00334	0.0428	0.0386	-0.00904	0.0338	0.00878	0.0315
Mean control t(1)	0.324	0.0392	0.0888	0.00481	0.322	0.314	0.227	0.0708	0.0202	0.174
Mean treated t(1)	0.360	0.0232	0.104	0.00257	0.372	0.353	0.198	0.136	0.0360	0.234
Diff t(1)	0.0363	-0.0160	0.0154	-0.00224	0.0501	0.0386	-0.0291	0.0656	0.0158	0.0601

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

On a comparative note, when observing the variance at the indicator level across both indices – *Juntos* MPI and the Global MPI – we observe that trends and effects differ depending on the parameters used, supporting the idea that a tailored index is a better measure for assessing the effects of a program rather than using a standard and generic one. In the Global MPI, some proportions at baseline are either too high or too low to provide useful information in an impact assessment. Take, for example, the mean deprivation in access to quality cooking fuel at 98% or the mean deprivation of child mortality at 0.2%. *Juntos* MPI indicators range from 31% mean deprivation in child labour and 5% in primary school attendance. The data to build a Global MPI might be available but its relevance for the assessment of a specific social protection policy is questionable. The *Juntos* MPI, being aligned with the program's theory of chain, is a more reliable index for an impact evaluation.

In order to situate our explanations within existing literature on *Juntos* we refer to the study by Monge et al. (2017) that evaluated the impacts of *Juntos* using a broader version of the same dataset and a different methodological approach.[27] In line with the national (Perova & Vakis, 2009) and global (Bastagli et al., 2016) evidence, they found positive effects on school attendance among *Juntos* beneficiaries. However, despite showing an improvement in this indicator in our analysis, it does not result in significant changes among the treated and comparison households over time. With regards to health indicators, Monge et al. (2017) neither find significant changes in nutrition nor child mortality. Our results are in line with these findings but differ from the previous impact assessments of *Juntos* by Sánchez and Jaramillo (2012). We argue that the magnitude of the effect size is too small, and the limited statistical power of the sample does not allow us to detect these changes. Monge et al. (2017) find positive impacts on child development health visits but no significant effects on antenatal checks. Díaz and Saldarriaga (2014) show impacts on pre-natal checks and also child development visits, but these are rather small as baseline values were already quite high. To support this point, our data shows that pre-natal checks seem to be a widespread and common practice among the population, for both *Juntos* beneficiaries and non-beneficiaries. It has, in fact, the lowest percentage of deprived households at baseline and endline in both treatment and comparison groups. Furthermore, across different indicators we repeatedly observe that the trend in the comparison group is similar to that of *Juntos* beneficiaries, which could suggest spillovers effects from

[27] An important note to consider is that even though it is the same dataset, there are differences in the way the data was treated. First, we only worked with a prospective sample and, therefore, did not include those that became *Juntos* beneficiaries in 2010, before baseline. Second, we dropped observations with missing values in the variables relevant for the creation of the indicators for the MPI. Third, to enhance the accuracy of our empirical strategy, we incorporated propensity score weighting to our sample and only kept observations under common support (see section 4 for more details).

other economic and social policies or universal governmental interventions that could ultimately dissipate the effects of the program.

5.1 Limitations

The statistical power obtained with the sample size used in the analysis could potentially limit the findings by stating a false negative (type II error). In other words, there could be indicators that *Juntos* is effectively improving, but the magnitude of the difference between groups is so small that we cannot detect its significance and, thus, do not reject the null hypothesis. Considering the trends observed in our data and the existing literature (Bastagli et al., 2016; Díaz & Saldarriaga, 2014), child mortality and nutrition, could be having effects that are too small to be captured with our statistical power.

Besides effect size limitations, another challenge we face is the exposure to the intervention. The mean exposure to the treatment was 32 months, with a median of 35 months. During this period, early-stage outcomes, such as health visits or school enrolment, are expected to happen. However, outcomes that are further in the theory of change, such as nutrition or learning outcomes, should take longer. As a result, despite being important outcomes of the program and relevant for an impact evaluation, we do not include these indicators in the *Juntos* MPI. A way to capture mid to long-term effects of the treatment group is to match sampled households with schools and health centres records. Furthermore, the panel can be expanded into more survey rounds that will allow to track households even beyond their status of program beneficiaries.

It is important and useful to compare multidimensional poverty to monetary poverty as the government often uses the latter as the main measure to make policy decisions. However, the data did not include monetary poverty indicators or consumption data to calculate it. To overcome this limitation, we turned to the analytical report by Monge et al. (2017) that considered consumption panel data.[28] Their analysis showed a reduction in the incidence of extreme poverty among households that have between 24 and 48 months of exposure to the program and are in the lowest poverty percentile, whereas the results are null if the whole sample is considered together. According to Monge et al. (2017), the results suggest that the program targeting would have helped to reduce inequalities among those poorest. Furthermore, their study shows that there is an increase in consumption as a direct output from the income effect, but they do not observe a reduction in monetary poverty.

[28] Official *Juntos* impact evaluation report prepared for the Ministry of Economy and Finance.

Finally, we find a significant increase in the number of children in school age (6 to 19 years old) in the treatment group from baseline to endline. A possible explanation is that households may retain children at home for longer (to still receive the cash transfer) rather than sending them away for work or other activities. We raise this point because, when building the MPI, households that do not fit into a specific indicator are automatically considered non-deprived. This estimation allows households in the comparison group to have higher non-deprivation rates as fewer of them have children in school age. This is a limitation only relevant for the indicators in the education dimension. When testing for differences on children below five years of age and pregnant women, relevant for the health dimension, we observe no differences across groups (see Appendix Table 10).

5. Conclusions

Most of the evidence on the effectiveness of social interventions and policy to fight poverty focuses on resource or utility-based outcomes, such as income, expenditure, and consumption. Aligned with the post-2015 demand for alternative and complementary wellbeing measurements led by the United Nations and supported by the World Bank, the hypothesis in this paper has been that money metrics alone can be complemented when framing and defining poverty. Therefore, we use the Multidimensional Poverty Index (MPI), built with the Alkire-Foster method, to evaluate the impact of Peru's national cash transfer program, *Juntos*. Even though there is ongoing debate on multidimensional poverty indices, there are multiple reasons for choosing the MPI: methodologically, it is one of the most widely accepted approaches for this purpose (e.g. included in the SDG poverty indicators); technically, it allows reporting and analysis of poverty trends by aggregate measures as well as decomposing them by indicators (which suits a difference-in-difference impact evaluation design); and, finally, contextually, it supports testing of different index compositions, one using the standard international and comparable 'Global MPI' and another using a tailored measure for the particular policy under evaluation, the '*Juntos* MPI.'

Active for 15 years, *Juntos* has established itself as the most important anti-poverty initiative led by the Government of Peru, both in terms of budget investment and population reach. The existing literature on the impacts of *Juntos* is mainly based on quasi-experimental studies as the program never followed a randomized rollout. Studies generally agree that cash transfers lead expenditure increase; however, it does not seem to translate into a significant decrease in monetary poverty. Effects on poverty reduction are observed only among households that have been exposed to the program for longer. Evidence on education and health, in line with the literature, shows an increase in the demand and use of these services (e.g., medical check-ups or school enrolment), likely due to the intrinsic conditional aspect; however, in longer-term outcomes (e.g. nutrition or learning), the effects are much smaller or tend to dissipate (Díaz & Saldarriaga, 2014; Escobal & Benites, 2012; Monge, Seinfeld, & Campana, 2017; Perova & Vakis, 2009; Sánchez & Jaramillo, 2012).

In addition to these studies, MIDIS and MEF launched an impact evaluation of the program, demonstrating the demand from policymakers for rigorous evidence. As part of this initiative, it was agreed with MIDIS and *Juntos* that our study would provide a complementary view to the findings from the government-led assessment by using a multidimensional poverty approach. We use data collected by the government in the framework of an impact evaluation of *Juntos* between 2011 (baseline) – right before one of the largest programmatic expansion periods of the program – and 2015 (endline). The team in charge of the evaluation at MIDIS used PSM to generate a comparison group and, for the purpose of this paper, we used difference-in-difference regressions augmented with PSW to estimate ATET.

There is abundant evidence of cash transfer programs worldwide looking at a myriad of outcomes and using both monetary and non-monetary indicators. However, the relevance of this paper lies on the fact that there is scarce knowledge on the use of aggregate measures to assess the impact on the joint deprivations of individuals. In this context, we consider relevant to use the Alkire-Foster method to construct a composite index of multidimensional poverty to better understand how this tool could be applied to impact evaluation and, ultimately, inform policy. To learn more about this tool, we compare two different indices, the standard Global MPI – currently used in the same way (dimensions, indicators, and parameters) for more than 100 countries – with an MPI tailored to the theory of change of *Juntos*.

Results indicate that, at the aggregate level, there is a reduction in the adjusted headcount ratio and the incidence of multidimensional poverty in both multidimensional indices; however, these differences are not statistically significant between the treatment and comparison groups over time. Therefore, we cannot attribute the observed decrease on multidimensional poverty to *Juntos*. At the indicator-level, when using the Global MPI, we observe a statistically significant faster reduction in the deprivation of access to safe water among those received *Juntos* cash transfers, while households in the comparison group had a significantly higher reduction in their deprivation of quality of cooking fuel. A potential interpretation is that access to better sources of water might be linked to targeted programming on *Juntos* districts due to their poverty levels rather than households' own efforts to install new pipelines or pumps, which are expensive and require largely coordinated efforts. Regarding cooking fuel, a potential explanation is that *Juntos* households are channelling their money towards education and health expenses, which are *Juntos* conditionalities, while households that are not part of the program would rather invest in less expensive items with short-term returns. It is important to note, however, that we only find these outcomes to be statistically significant using the raw headcount. When applying the censored headcount (those who are deprived in a dimension and are multidimensionally poor), these results are not significant. Moreover, we do not observe significant differences among the treatment and comparison groups over time in any of the *Juntos* MPI indicators. However, despite the null results, we observe how trends and effects differ depending on the MPI parameters. Based on the descriptive statistics, we consider the tailored index to be a better measure for assessing the effects of the program.

We conclude that using a multidimensional poverty index can be a useful evaluation tool. At the same time, any index must be thoroughly adapted to the theory of change of the intervention or policy under evaluation. In other words, it should be tailored to provide a more accurate reading as opposed to a general or standard index. While we consider it a useful outcome measure for evaluation purposes, the MPI may tell us one side of the story, thus, it should be complemented with other measures so that the context and impacts are better understood. In this study, it was not possible to include monetary poverty or consumption data, but we advise to include such indicators either as part of a dimensions in the MPI or as a separate benchmark indicator.

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Appendix

Appendix Table 1. Correlates of attrition

Variables	Prospective sample only	Variables	Prospective sample only
HH head is male	-0.0198	HH has children between 3 to 14 years old	-0.0253
	[0.0227]		[0.0229]
HH head mother tongue is Spanish	-0.1215	HH size	-0.0055
	[0.1271]		[0.0046]
HH head mother tongue is Quechua	-0.1597	HH uses good quality fuel	0.0522
	[0.1253]		[0.0352]
HH head knows how to read & write	-0.0330	HH has access to good quality toilet facilities	-0.0100
	[0.0497]		[0.0182]
HH head has no formal education	-0.0243	HH has access to safe drinking water	-0.0018
	[0.0505]		[0.0205]
HH head completed primary education	0.0144	HH has reliable source of electricity	-0.0368*
	[0.0160]		[0.0222]
House is owned	-0.0234	HH has good flooring materials	-0.0058
	[0.0171]		[0.0251]
HH head worked last week	-0.0631*	HH has radio	0.0153
	[0.0363]		[0.0176]
HH head has a permanent job	-0.0445	HH has television set	0.0324*
	[0.0478]		[0.0166]
HH has at least one pregnant woman	0.0333	Beneficiary of a social program	-0.0103
	[0.0418]		[0.0201]
Constant	0.4008***		
	[0.1442]		
Observations	1,780		
R-squared	0.126		
F Stat	1.318		

Robust standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 2. Spearman correlations (n=1,569)

Children 6-19	No edu	Rural area	Social security	Poverty rate	Owns tv	Owns mobile	Social program	Sanitation	Water	Electr.	Housing	Fuel
1.000												
0.059	**1.000**											
0.059	0.028	**1.000**										
-0.019	0.019	0.054	**1.000**									
0.050	0.025	**0.824**	0.013	**1.000**								
-0.011	-0.119	0.007	-0.034	0.042	**1.000**							
0.011	-0.084	-0.034	-0.042	0.027	0.262	**1.000**						
-0.124	-0.069	-0.148	0.005	-0.078	-0.018	0.046	**1.000**					
-0.039	0.031	-0.030	-0.011	-0.050	-0.113	-0.090	0.044	**1.000**				
0.038	-0.002	-0.199	-0.073	-0.208	-0.155	-0.133	-0.010	0.043	**1.000**			
0.027	-0.053	-0.015	0.037	-0.131	-0.389	-0.195	0.054	0.108	0.111	**1.000**		
-0.002	-0.052	0.079	0.059	-0.157	-0.143	-0.066	0.016	0.050	0.010	0.209	**1.000**	
0.081	0.041	0.017	0.097	-0.019	-0.195	-0.114	0.001	0.065	0.020	0.106	0.068	**1.000**

r than -0.5.

Appendix Table 3. Control variables: Comparison of matched and unmatched baseline statistics after PSW (n = 1,569)

Variable	Unmatched Matched	Mean Treated	Mean Control	%bias	%reduct bias	t-test t	p>t V(C)
Age of HH head	U	39.290	40.731	-11.8		-3.31	0.001
	M	39.305	39.183	1	91.5	0.29	0.774
HH size	U	4.6517	4.5171	8.1		2.28	0.023
	M	4.6525	4.6147	2.3	71.9	0.63	0.528
Children 0-5	U	0.66967	0.6182	10.8		3.01	0.003
	M	0.66924	0.66276	1.4	87.4	0.38	0.702
Children 6 -19	U	0.82134	0.83059	-2.4		-0.68	0.494
	M	0.82239	0.82075	0.4	82.3	0.12	0.905
No education	U	0.05913	0.11504	-19.9		-5.57	0.000
	M	0.0592	0.0527	2.3	88.4	0.79	0.431
Rural area	U	0.69794	0.70923	-2.5		-0.69	0.489
	M	0.69755	0.69244	1.1	54.7	0.31	0.757
Social security	U	0.77892	0.74589	7.8		2.17	0.03
	M	0.77864	0.78723	-2	74	-0.58	0.561
Poverty rate	U	0.64524	0.58913	11.6		3.24	0.001
	M	0.64607	0.64774	-0.3	97	-0.1	0.923
Owns tv	U	0.31362	0.45259	-28.9		-8.08	0.000
	M	0.31403	0.3276	-2.8	90.2	-0.81	0.418
Owns mobile	U	0.38303	0.43869	-11.3		-3.17	0.002
	M	0.38224	0.41629	-6.9	38.8	-1.94	0.053
Social programs	U	0.83162	0.75221	19.6		5.5	0.000
	M	0.8314	0.83411	-0.7	96.6	-0.2	0.84
Sanitation	U	0.93445	0.89381	14.5		4.07	0.000
	M	0.93436	0.93917	-1.7	88.2	-0.55	0.582
Water	U	0.48586	0.54109	-11.1		-3.1	0.002
	M	0.4852	0.48933	-0.8	92.5	-0.23	0.818
Electricity	U	0.32005	0.19469	29		8.12	0.000
	M	0.32046	0.29462	6	79.4	1.56	0.119
Housing	U	0.07841	0.12389	-15.1		-4.23	0.000
	M	0.07722	0.06745	3.2	78.5	1.05	0.293
Fuel	U	0.97686	0.90265	31.6		8.82	0.000
	M	0.97812	0.97686	0.5	98.3	0.24	0.812

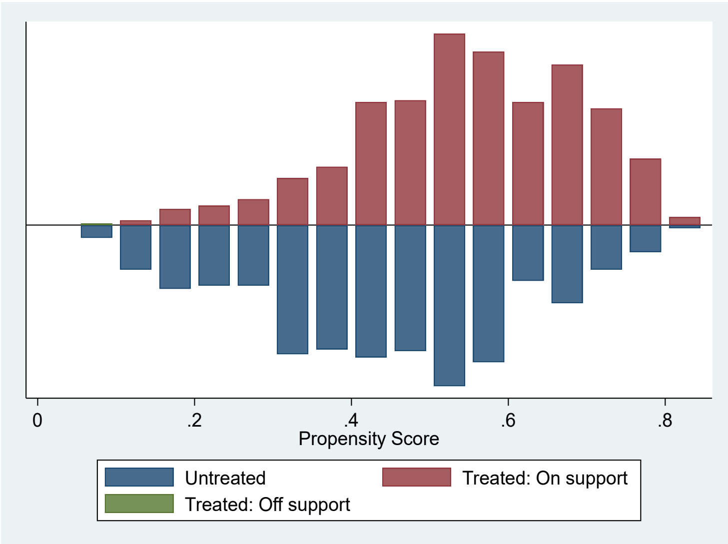
Appendix Table 4. Outcome variables: Comparison of matched and unmatched baseline statistics after PSW (n = 1,569)

Variable	Unmatched Matched	Mean Treated	Mean Control	%bias	%reduct bias	t-test t	p>t	V(C)
School Attendance (primary)	U	0.04627	0.04172	2.2		0.62	0.534	
	M	0.04633	0.05077	-2.2	2.4	-0.58	0.565	
School Attendance (secondary)	U	0.06812	0.06827	-0.1		-0.02	0.987	
	M	0.06821	0.08185	-5.4	-9328.6	-1.44	0.149	
Antenatal checks	U	0.14139	0.13274	2.5		0.7	0.482	
	M	0.14157	0.14516	-1	58.5	-0.29	0.775	
Child health checks	U	0.15296	0.15424	-0.4		-0.1	0.921	
	M	0.15315	0.16423	-3.1	-766.4	-0.85	0.398	
Child labor	U	0.33033	0.26675	13.9		3.9	0.000	
	M	0.33076	0.30365	5.9	57.4	1.62	0.104	
Large Asset Ownership	U	0.19794	0.14918	12.9		3.61	0.000	
	M	0.1982	0.16411	9	30.1	2.47	0.014	
Years of Schooling	U	0.62596	0.64096	-3.1		-0.87	0.384	
	M	0.62677	0.63994	-2.7	12.2	-0.76	0.446	
School attendance	U	0.03085	0.03287	-1.2		-0.32	0.747	
	M	0.03089	0.04037	-5.4	-369.3	-1.43	0.154	
Nutrition	U	0.24936	0.22882	4.8		1.35	0.178	
	M	0.24839	0.24657	0.4	91.1	0.12	0.906	
Child mortality	U	0.00129	0.00253	-2.8		-0.8	0.426	
	M	0.00129	0.00342	-4.9	-71.8	-1.23	0.219	
Fuel	U	0.97686	0.90265	31.6		8.82	0.000	
	M	0.97812	0.97686	0.5	98.3	0.24	0.812	
Sanitation	U	0.93445	0.89381	14.5		4.07	0.000	
	M	0.93436	0.93917	-1.7	88.2	-0.55	0.582	
Safe water	U	0.48586	0.54109	-11.1		-3.1	0.002	
	M	0.4852	0.48933	-0.8	92.5	-0.23	0.818	
Electricity	U	0.32005	0.19469	29		8.12	0.000	
	M	0.32046	0.29462	6	79.4	1.56	0.119	
Housing Materials	U	0.07841	0.12389	-15.1		-4.23	0.000	
	M	0.07722	0.06745	3.2	78.5	1.05	0.293	
Small assets ownership	U	0.53985	0.43489	21.1		5.91	0.000	
	M	0.54054	0.49128	9.9	53.1	2.75	0.006	

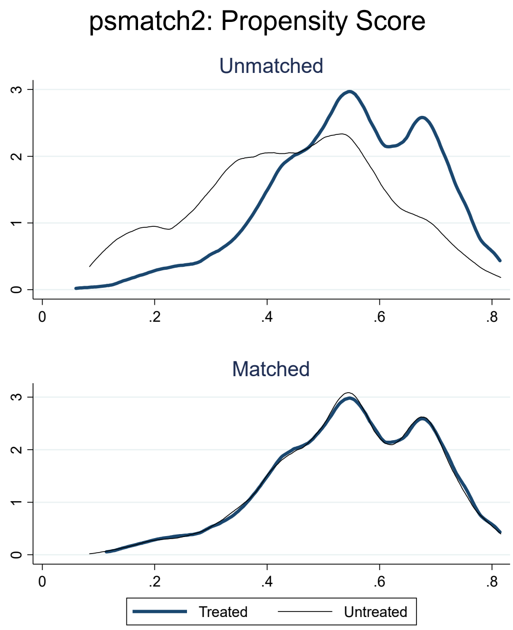
Appendix Table 5. Comparison of PSM models tested (n = 1,569)

	Ps R2	LR chi2	p>chi2	Mean bias	Median bias	B	R	off support (n)
Unmatched	0.079	345.05	0.000	14.7	11.7	68.1	0.65	-
PSM	0.002	9.38	0.897	2.1	2.0	11.0	1.15	1
NN	0.002	9.38	0.897	2.1	2.0	11.0	1.15	1
Kernel	0.002	8.78	0.922	2.1	1.5	10.6	1.1	1
NN + caliper	0.007	28.58	0.027	4.1	3.7	19.2	1.09	1

Appendix Figure 1. Comparison of treatment and control households using Kernel PSM (n = 1,569)



Appendix Figure 2. Density using Kernel PSM (n = 1,569)



Appendix Table 6. Cramer V test

Variable	Baseline	Variable	Endline
attendance primary	**1.0000**	attendance primary	**1.0000**
attendance secondary	0.0406	attendance secondary	0.0925
ante-natal checks	0.0230	ante-natal checks	0.0412
child development checks	-0.0655	child development checks	0.0344
child labour	0.0496	child labour	0.0460
assets	-0.0243	assets	-0.0377
attendance primary	0.0406	attendance primary	0.0925
attendance secondary	**1.0000**	attendance secondary	**1.0000**
ante-natal checks	-0.0049	ante-natal checks	0.0492
child development checks	0.0180	child development checks	0.0573
child labour	-0.0037	child labour	0.0206
assets	0.0613	assets	0.0192
attendance primary	0.0230	attendance primary	0.0412
attendance secondary	-0.0049	attendance secondary	0.0492
ante-natal checks	**1.0000**	ante-natal checks	**1.0000**
child development checks	0.0975	child development checks	0.1375
child labour	0.0623	child labour	-0.0126
assets	-0.0532	assets	-0.0276
attendance primary	-0.0655	attendance primary	0.0344
attendance secondary	0.0180	attendance secondary	0.0573
ante-natal checks	0.0975	ante-natal checks	0.1375
child development checks	**1.0000**	child development checks	**1.0000**
child labour	0.0337	child labour	0.0525
assets	-0.1000	assets	-0.0769
attendance primary	0.0496	attendance primary	0.0460
attendance secondary	-0.0037	attendance secondary	0.0206
ante-natal checks	0.0623	ante-natal checks	-0.0126
child development checks	0.0337	child development checks	0.0525
child labour	**1.0000**	child labour	**1.0000**
assets	-0.0704	assets	0.0047
attendance primary	-0.0243	attendance primary	-0.0377
attendance secondary	0.0613	attendance secondary	0.0192
ante-natal checks	-0.0532	ante-natal checks	-0.0276
child development checks	-0.1000	child development checks	-0.0769
child labour	-0.0704	child labour	0.0047
assets	**1.0000**	assets	**1.0000**

Appendix Table 7. R^0 test

Variable	Baseline	Variable	Endline
attendance primary	**1.0000**	attendance primary	**1.0000**
attendance secondary	0.1159	attendance secondary	0.1404
ante-natal checks	0.1739	ante-natal checks	0.0784
child development checks	0.0435	child development checks	0.1228
child labour	0.2609	child labour	0.1404
assets	0.2464	assets	0.1579
attendance primary	0.1159	attendance primary	0.1404
attendance secondary	**1.0000**	attendance secondary	**1.0000**
ante-natal checks	0.1308	ante-natal checks	0.0980
child development checks	0.1776	child development checks	0.1471
child labour	0.1682	child labour	0.1029
assets	0.4019	assets	0.2794
attendance primary	0.1739	attendance primary	0.0784
attendance secondary	0.1308	attendance secondary	0.0980
ante-natal checks	**1.0000**	ante-natal checks	**1.0000**
child development checks	0.2419	child development checks	0.2745
child labour	0.2326	child labour	0.0588
assets	0.2372	assets	0.1765
attendance primary	0.0435	attendance primary	0.1228
attendance secondary	0.1776	attendance secondary	0.1471
ante-natal checks	0.2419	ante-natal checks	0.2745
child development checks	**1.0000**	child development checks	**1.0000**
child labour	0.2033	child labour	0.1261
assets	0.1909	assets	0.1261
attendance primary	0.2609	attendance primary	0.1404
attendance secondary	0.1682	attendance secondary	0.1029
ante-natal checks	0.2326	ante-natal checks	0.0588
child development checks	0.2033	child development checks	0.1261
child labour	**1.0000**	child labour	**1.0000**
assets	0.2279	assets	0.2479
attendance primary	0.2464	attendance primary	0.1579
attendance secondary	0.4019	attendance secondary	0.2794
ante-natal checks	0.2372	ante-natal checks	0.1765
child development checks	0.1909	child development checks	0.1261
child labour	0.2279	child labour	0.2479
assets	**1.0000**	assets	**1.0000**

Appendix Table 8. Juntos MPI: Impact on Censored Counting Vector

(Estimations weighted of propensity scores)

VARIABLES	(1) **10%**	(2) **20%**	(3) **33%**	(4) **40%**	(5) **50%**	(6) **60%**	(7) **70%**	(8) **80%**	(9) **90%**	(10) **100%**
Diff-in-diff	-0.00350	-0.00536	-0.00536	-0.00617	-0.00617	-0.00673	-0.00268	-0.00268	0.000	0.000
	(0.0105)	(0.0110)	(0.0110)	(0.00760)	(0.00760)	(0.00457)	(0.00267)	(0.00267)	(0.000)	(0.000)
Observations	3,136	3,136	3,136	3,136	3,136	3,136	3,136	3,136	3,136	3,136
R-squared	0.061	0.038	0.038	0.009	0.009	0.001	0.002	0.002	0.000	0.000
Mean control t(0)	0.152	0.0787	0.0787	0.0214	0.0214	0.00220	0.000	0.000	0.000	0.000
Mean treated t(0)	0.156	0.0847	0.0847	0.0242	0.0242	0.00429	0.000	0.000	0.000	0.000
Diff t(0)	0.00482	0.00605	0.00605	0.00287	0.00287	0.00209	0.000	0.000	0.000	0.000
Mean control t(1)	0.0871	0.0283	0.0283	0.00823	0.00823	0.00635	0.00268	0.00268	0.000	0.000
Mean treated t(1)	0.0884	0.0290	0.0290	0.00493	0.00493	0.00172	0.000	0.000	0.000	0.000
Diff t(1)	0.00132	0.000685	0.000685	-0.00330	-0.00330	-0.00463	-0.00268	-0.00268	0.000	0.000

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 9. Global MPI: Impact on Censored Counting Vector

(Estimations weighted of propensity scores)

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
VARIABLES	10%	20%	33%	40%	50%	60%	70%	80%	90%	100%
Diff-in-diff	0.0116	0.0131	0.00735	0.0109	0.0224	0.0147	-0.00164	0.000	0.000	0.000
	(0.0111)	(0.0138)	(0.0167)	(0.0160)	(0.0137)	(0.00910)	(0.00456)	(0.000)	(0.000)	(0.000)
Observations	3,136	3,136	3,136	3,136	3,136	3,136	3,136	3,136	3,136	3,136
R-squared	0.080	0.068	0.059	0.028	0.020	0.008	0.002			
Mean control t(0)	0.335	0.314	0.246	0.132	0.0899	0.0292	0.00568	0.000	0.000	0.000
Mean treated t(0)	0.336	0.315	0.255	0.123	0.0638	0.0227	0.00601	0.000	0.000	0.000
Diff t(0)	0.000811	0.00177	0.00942	-0.00852	-0.0261	-0.00655	0.000324	0.000	0.000	0.000
Mean control t(1)	0.248	0.214	0.139	0.0596	0.0348	0.00481	0.00224	0.000	0.000	0.000

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 10. Treatment effects (n = 1,568)

VARIABLES	(1) Children 0 to 5 years old	(2) Children 6 to 19 years old	(3) Pregnant woman
Diff-in-diff	0.0320	0.0691**	-0.0243
	(0.0379)	(0.0278)	(0.0148)
Observations	3,136	3,136	3,136
R-squared	0.074	0.016	0.001
Mean control t(0)	0.614	0.820	0.0332
Mean treated t(0)	0.595	0.822	0.0463
Diff t(0)	-0.0192	0.00233	0.0131
Mean control t(1)	0.327	0.858	0.0407
Mean treated t(1)	0.340	0.929	0.0296
Diff t(1)	0.0128	0.0715	-0.0111

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 11. Power calculations

Parameters	**8.5%[a]**	**4.25%**	**5.0%[b]**	**2.50%**
Significance level	0.05	0.05	0.05	0.05
Mean of poverty rate in baseline control group	42.22	42.22	42.22	42.22
Standard deviation	21.61	21.61	21.61	21.61
Number of observations in treatment	782	782	782	782
Number of observations in control	785	785	785	785
Power	1.00	0.97	1.00	0.63
Minimum effect size	6.20	4.03	4.03	4.03

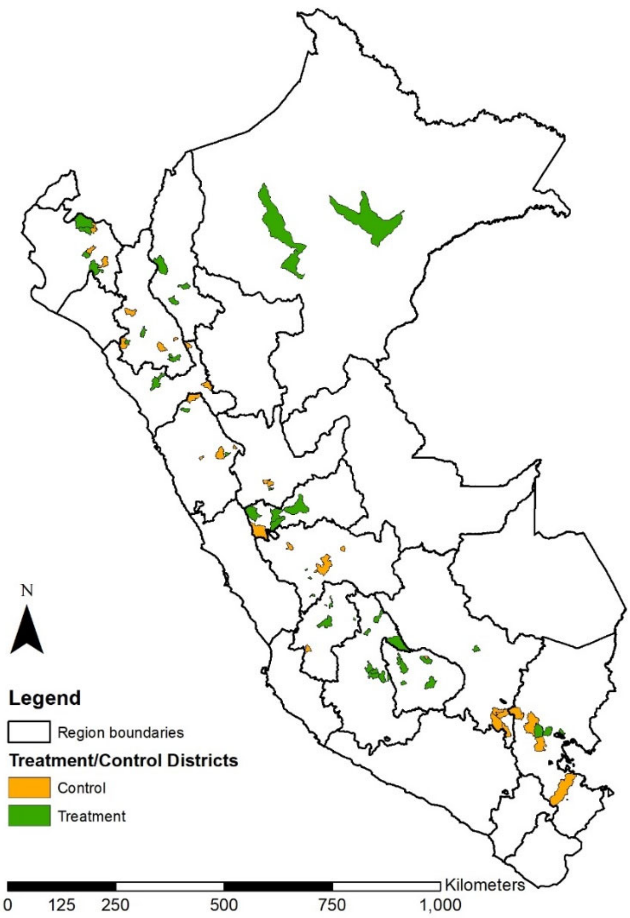
[a] (Sánchez & Jaramillo, 2012), [b] (Perova & Vakis, 2009)

Appendix Table 12. Summary statistics: Sampled households and districts by region (n=1,598)

Region	Percent
Amazonas	6.69
Ancash	8.54
Apurimac	5.99
Ayacucho	6.95
Cajamarca	7.71
Cusco	4.65
Huancavelica	6.25
Huánuco	8.03
Junín	7.46
La Libertad	7.65
Loreto	6.31
Pasco	7.65
Piura	8.16
Puno	7.97

Area	Percent
Coast (rural)	7.27
Coast (urban)	2.29
Amazon (rural)	8.86
Amazon (urban)	2.87
Andes (rural)	54.24
Andes (urban)	24.47

Appendix Figure 3. Map of districts in treatment and comparison groups



Appendix Table 13. Juntos MPI: Percentage contribution to M_0 (n=1,568)

		Baseline	**Endline**
Education	Primary school attendance	6.2%	10.7%
	Secondary school attendance	11.0%	15.5%
Health	Antenatal checks	18.8%	9.1%
	Child development visits	17.3%	17.1%
Living Standards	Child labor	22.1%	19.8%
	Large asset ownership	24.6%	27.8%

Appendix Table 14. Global MPI: Percentage contribution to M_0 (n=1,568)

		Baseline	**Endline**
Education	Years of schooling	33.5%	39.3%
	School attendance	2.2%	3.1%
Health	Nutrition	14.4%	10.8%
	Child mortality	0.1%	0.3%
Living Standards	Cooking fuel	13.0%	13.2%
	Sanitation	12.8%	12.7%
	Drinking water	8.6%	7.9%
	Electricity	4.8%	3.9%
	Flooring	1.9%	1.2%
	Assets	8.8%	7.7%

Appendix Table 15. Report on covariates: Juntos MPI, aggregate measures

	(1)	(2)
VARIABLES	H	M
Age	-0.0008	-0.0003
	[0.0006]	[0.0002]
	[-0.002 ; 0.000]	[-0.001 ; 0.000]
HH size	0.0329***	0.0129***
	[0.0052]	[0.0020]
	[0.023 ; 0.043]	[0.009 ; 0.017]
Children 0 to 5	0.0677***	0.0302***
	[0.0169]	[0.0062]
	[0.035 ; 0.101]	[0.018 ; 0.042]
Children 6 to 19	0.0809***	0.0326***
	[0.0176]	[0.0065]
	[0.046 ; 0.115]	[0.020 ; 0.045]
No education	0.0771***	0.0287***
	[0.0273]	[0.0103]
	[0.024 ; 0.131]	[0.009 ; 0.049]
Rural	-0.0749***	-0.0285***
	[0.0279]	[0.0105]
	[-0.130 ; -0.020]	[-0.049 ; -0.008]
Social security	-0.0140	-0.0039
	[0.0159]	[0.0061]
	[-0.045 ; 0.017]	[-0.016 ; 0.008]
Poverty rate	0.0399	0.0172*
	[0.0261]	[0.0099]
	[-0.011 ; 0.091]	[-0.002 ; 0.037]
Owns TV	-0.0592***	-0.0231***
	[0.0132]	[0.0048]
	[-0.085 ; -0.033]	[-0.032 ; -0.014]
Owns mobile	-0.0527***	-0.0205***
	[0.0130]	[0.0048]
	[-0.078 ; -0.027]	[-0.030 ; -0.011]
Social program	-0.0172	-0.0091
	[0.0166]	[0.0065]
	[-0.050 ; 0.015]	[-0.022 ; 0.004]
Sanitation	0.0031	0.0014
	[0.0212]	[0.0079]
	[-0.038 ; 0.045]	[-0.014 ; 0.017]
Safe water	0.0092	0.0026
	[0.0135]	[0.0051]
	[-0.017 ; 0.036]	[-0.007 ; 0.013]
Electricity	0.0467***	0.0183***
	[0.0175]	[0.0067]
	[0.012 ; 0.081]	[0.005 ; 0.031]
Housing	-0.0248	-0.0089
	[0.0261]	[0.0100]
	[-0.076 ; 0.026]	[-0.029 ; 0.011]
Fuel	0.0294	0.0111
	[0.0207]	[0.0073]
	[-0.011 ; 0.070]	[-0.003 ; 0.025]
Constant	0.0168	-0.0023
	[0.0471]	[0.0172]
	[-0.076 ; 0.109]	[-0.036 ; 0.032]
Observations	3,136	3,136
R-squared	0.124	0.128

Appendix Table 16. Report on covariates: Juntos MPI, uncensored headcount

	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Attendance Pri	Attendance Sec	Ante-natal	Child checks	Child Labour	Large assets
Age	-0.0014***	-0.0001	-0.0014***	-0.0012**	0.0013*	-0.0005
	[0.0003]	[0.0004]	[0.0005]	[0.0006]	[0.0008]	[0.0006]
	[-0.002 ; -0.001]	[-0.001 ; 0.001]	[-0.002 ; -0.000]	[-0.002 ; -0.000]	[-0.000 ; 0.003]	[-0.002 ; 0.001]
HH size	0.0067**	0.0263***	0.0034	0.0100**	0.0257***	0.0088*
	[0.0030]	[0.0042]	[0.0037]	[0.0044]	[0.0061]	[0.0046]
	[0.001 ; 0.013]	[0.018 ; 0.035]	[-0.004 ; 0.011]	[0.001 ; 0.019]	[0.014 ; 0.038]	[-0.000 ; 0.018]
Children 0 to 5	0.0021	-0.0355**	0.1223***	0.1170***	-0.1316***	0.0335**
	[0.0103]	[0.0138]	[0.0122]	[0.0137]	[0.0231]	[0.0148]
	[-0.018 ; 0.022]	[-0.063 ; -0.008]	[0.098 ; 0.146]	[0.090 ; 0.144]	[-0.177 ; -0.086]	[0.004 ; 0.063]
Children 6 to 19	0.0276**	0.0157	0.0099	-0.0053	0.2222***	0.0161
	[0.0108]	[0.0097]	[0.0186]	[0.0200]	[0.0174]	[0.0189]
	[0.006 ; 0.049]	[-0.003 ; 0.035]	[-0.026 ; 0.046]	[-0.045 ; 0.034]	[0.188 ; 0.256]	[-0.021 ; 0.053]
No education	0.0272*	-0.0007	0.0282	0.0179	-0.0106	0.1411***
	[0.0160]	[0.0161]	[0.0187]	[0.0207]	[0.0314]	[0.0296]
	[-0.004 ; 0.059]	[-0.032 ; 0.031]	[-0.008 ; 0.065]	[-0.023 ; 0.059]	[-0.072 ; 0.051]	[0.083 ; 0.199]
Rural	-0.0276*	-0.0126	-0.0232	-0.0591***	-0.0496	-0.0742***
	[0.0150]	[0.0212]	[0.0220]	[0.0220]	[0.0340]	[0.0280]
	[-0.057 ; 0.002]	[-0.054 ; 0.029]	[-0.066 ; 0.020]	[-0.102 ; -0.016]	[-0.116 ; 0.017]	[-0.129 ; -0.019]
Social security	-0.0083	-0.0014	0.0195	-0.0166	-0.0168	0.0152
	[0.0102]	[0.0108]	[0.0120]	[0.0147]	[0.0194]	[0.0143]
	[-0.028 ; 0.012]	[-0.023 ; 0.020]	[-0.004 ; 0.043]	[-0.046 ; 0.012]	[-0.055 ; 0.021]	[-0.013 ; 0.043]
Poverty rate	0.0183	-0.0117	0.0353*	0.0784***	-0.0309	0.0734***
	[0.0134]	[0.0198]	[0.0204]	[0.0210]	[0.0323]	[0.0272]
	[-0.008 ; 0.044]	[-0.050 ; 0.027]	[-0.005 ; 0.075]	[0.037 ; 0.120]	[-0.094 ; 0.032]	[0.020 ; 0.127]
Owns TV	-0.0134*	-0.0009	-0.0296***	0.0121	-0.0224	-0.0996***
	[0.0079]	[0.0093]	[0.0115]	[0.0139]	[0.0184]	[0.0109]
	[-0.029 ; 0.002]	[-0.019 ; 0.017]	[-0.052 ; -0.007]	[-0.015 ; 0.039]	[-0.058 ; 0.014]	[-0.121 ; -0.078]
Owns mobile	-0.0143*	0.0017	0.0206*	-0.0063	0.0454***	-0.1537***
	[0.0079]	[0.0090]	[0.0115]	[0.0128]	[0.0171]	[0.0105]
	[-0.030 ; 0.001]	[-0.016 ; 0.019]	[-0.002 ; 0.043]	[-0.031 ; 0.019]	[0.012 ; 0.079]	[-0.174 ; -0.133]
Social program	0.0014	-0.0120	-0.0339**	0.0122	0.0170	-0.0198
	[0.0101]	[0.0130]	[0.0136]	[0.0126]	[0.0230]	[0.0162]
	[-0.018 ; 0.021]	[-0.037 ; 0.013]	[-0.061 ; -0.007]	[-0.012 ; 0.037]	[-0.028 ; 0.062]	[-0.052 ; 0.012]
Sanitation	0.0094	-0.0080	0.0074	0.0044	0.0001	-0.0060
	[0.0124]	[0.0161]	[0.0174]	[0.0205]	[0.0300]	[0.0188]
	[-0.015 ; 0.034]	[-0.039 ; 0.024]	[-0.027 ; 0.041]	[-0.036 ; 0.045]	[-0.059 ; 0.059]	[-0.043 ; 0.031]
Safe water	0.0140*	0.0189**	0.0230**	0.0280**	-0.0866***	-0.0097
	[0.0077]	[0.0088]	[0.0113]	[0.0128]	[0.0168]	[0.0129]
	[-0.001 ; 0.029]	[0.002 ; 0.036]	[0.001 ; 0.045]	[0.003 ; 0.053]	[-0.120 ; -0.054]	[-0.035 ; 0.016]
Electricity	0.0225**	0.0245**	0.0063	-0.0001	-0.0009	0.0694***
	[0.0108]	[0.0113]	[0.0141]	[0.0152]	[0.0202]	[0.0178]
	[0.001 ; 0.044]	[0.002 ; 0.047]	[-0.021 ; 0.034]	[-0.030 ; 0.030]	[-0.040 ; 0.039]	[0.035 ; 0.104]
Housing	-0.0165	-0.0258	0.0103	0.0189	-0.0586**	0.0185
	[0.0129]	[0.0158]	[0.0214]	[0.0239]	[0.0294]	[0.0262]
	[-0.042 ; 0.009]	[-0.057 ; 0.005]	[-0.032 ; 0.052]	[-0.028 ; 0.066]	[-0.116 ; -0.001]	[-0.033 ; 0.070]
Fuel	-0.0016	-0.0042	0.0547***	0.0288	0.0924***	-0.0062
	[0.0176]	[0.0194]	[0.0184]	[0.0273]	[0.0260]	[0.0211]
	[-0.036 ; 0.033]	[-0.042 ; 0.034]	[0.019 ; 0.091]	[-0.025 ; 0.082]	[0.042 ; 0.143]	[-0.048 ; 0.035]
Constant	0.0517*	-0.0043	0.0286	0.0392	0.0262	0.2027***
	[0.0285]	[0.0331]	[0.0374]	[0.0496]	[0.0582]	[0.0457]
	[-0.004 ; 0.107]	[-0.069 ; 0.061]	[-0.045 ; 0.102]	[-0.058 ; 0.137]	[-0.088 ; 0.140]	[0.113 ; 0.292]
Observations	3,136	3,136	3,136	3,136	3,136	3,136
R-squared	0.024	0.056	0.090	0.066	0.121	0.153

Appendix Table 17. Report on covariates: Juntos MPI, censored headcount

VARIABLES	(9) Attendance Pri	(10) Attendance Sec	(11) Ante-natal	(12) Child checks	(13) Child Labour	(14) Large assets
Age	-0.0005**	0.0000	-0.0011***	-0.0003	0.0004	-0.0004
	[0.0002]	[0.0004]	[0.0004]	[0.0004]	[0.0005]	[0.0005]
	[-0.001 ; -0.000]	[-0.001 ; 0.001]	[-0.002 ; -0.000]	[-0.001 ; 0.001]	[-0.001 ; 0.001]	[-0.001 ; 0.001]
HH size	0.0055**	0.0202***	0.0050	0.0135***	0.0212***	0.0118***
	[0.0023]	[0.0037]	[0.0031]	[0.0036]	[0.0044]	[0.0040]
	[0.001 ; 0.010]	[0.013 ; 0.027]	[-0.001 ; 0.011]	[0.006 ; 0.021]	[0.013 ; 0.030]	[0.004 ; 0.020]
Children 0 to 5	0.0106	-0.0260**	0.0758***	0.0671***	0.0117	0.0420***
	[0.0079]	[0.0116]	[0.0095]	[0.0098]	[0.0139]	[0.0112]
	[-0.005 ; 0.026]	[-0.049 ; -0.003]	[0.057 ; 0.094]	[0.048 ; 0.086]	[-0.015 ; 0.039]	[0.020 ; 0.064]
Children 6 to 19	0.0293***	0.0054	0.0411***	0.0157	0.0660***	0.0379***
	[0.0065]	[0.0079]	[0.0137]	[0.0130]	[0.0108]	[0.0135]
	[0.017 ; 0.042]	[-0.010 ; 0.021]	[0.014 ; 0.068]	[-0.010 ; 0.041]	[0.045 ; 0.087]	[0.012 ; 0.064]
No education	0.0161	-0.0030	0.0391**	0.0388**	0.0069	0.0739***
	[0.0133]	[0.0133]	[0.0173]	[0.0188]	[0.0209]	[0.0244]
	[-0.010 ; 0.042]	[-0.029 ; 0.023]	[0.005 ; 0.073]	[0.002 ; 0.076]	[-0.034 ; 0.048]	[0.026 ; 0.122]
Rural	-0.0279**	-0.0072	-0.0332*	-0.0099	-0.0436*	-0.0491**
	[0.0127]	[0.0191]	[0.0178]	[0.0175]	[0.0228]	[0.0206]
	[-0.053 ; -0.003]	[-0.045 ; 0.030]	[-0.068 ; 0.002]	[-0.044 ; 0.024]	[-0.088 ; 0.001]	[-0.090 ; -0.009]
Social security	-0.0023	-0.0092	0.0072	-0.0148	-0.0063	0.0020
	[0.0078]	[0.0097]	[0.0099]	[0.0112]	[0.0127]	[0.0119]
	[-0.018 ; 0.013]	[-0.028 ; 0.010]	[-0.012 ; 0.027]	[-0.037 ; 0.007]	[-0.031 ; 0.019]	[-0.021 ; 0.025]
Poverty rate	0.0140	-0.0163	0.0285*	0.0239	0.0084	0.0447**
	[0.0113]	[0.0176]	[0.0160]	[0.0171]	[0.0211]	[0.0197]
	[-0.008 ; 0.036]	[-0.051 ; 0.018]	[-0.003 ; 0.060]	[-0.010 ; 0.057]	[-0.033 ; 0.050]	[0.006 ; 0.083]
Owns TV	-0.0041	-0.0079	-0.0229***	-0.0181**	-0.0267**	-0.0586***
	[0.0056]	[0.0072]	[0.0085]	[0.0088]	[0.0109]	[0.0082]
	[-0.015 ; 0.007]	[-0.022 ; 0.006]	[-0.040 ; -0.006]	[-0.035 ; -0.001]	[-0.048 ; -0.005]	[-0.075 ; -0.042]
Owns mobile	-0.0171***	-0.0051	0.0059	-0.0132	-0.0086	-0.0852***
	[0.0054]	[0.0074]	[0.0088]	[0.0088]	[0.0106]	[0.0081]
	[-0.028 ; -0.006]	[-0.020 ; 0.009]	[-0.011 ; 0.023]	[-0.030 ; 0.004]	[-0.029 ; 0.012]	[-0.101 ; -0.069]
Social program	-0.0067	-0.0072	-0.0147	-0.0031	-0.0150	-0.0078
	[0.0081]	[0.0105]	[0.0102]	[0.0093]	[0.0138]	[0.0123]
	[-0.023 ; 0.009]	[-0.028 ; 0.013]	[-0.035 ; 0.005]	[-0.021 ; 0.015]	[-0.042 ; 0.012]	[-0.032 ; 0.016]
Sanitation	0.0097	-0.0006	0.0043	0.0135	-0.0057	-0.0130
	[0.0072]	[0.0121]	[0.0137]	[0.0122]	[0.0182]	[0.0151]
	[-0.004 ; 0.024]	[-0.024 ; 0.023]	[-0.023 ; 0.031]	[-0.010 ; 0.037]	[-0.041 ; 0.030]	[-0.043 ; 0.017]
Safe water	0.0096*	0.0182**	0.0033	-0.0066	0.0013	-0.0099
	[0.0056]	[0.0073]	[0.0090]	[0.0096]	[0.0107]	[0.0102]
	[-0.001 ; 0.021]	[0.004 ; 0.032]	[-0.014 ; 0.021]	[-0.025 ; 0.012]	[-0.020 ; 0.022]	[-0.030 ; 0.010]
Electricity	0.0127	0.0246**	0.0046	0.0113	0.0148	0.0417***
	[0.0081]	[0.0099]	[0.0109]	[0.0113]	[0.0139]	[0.0143]
	[-0.003 ; 0.029]	[0.005 ; 0.044]	[-0.017 ; 0.026]	[-0.011 ; 0.034]	[-0.012 ; 0.042]	[0.014 ; 0.070]
Housing	0.0008	-0.0263**	0.0054	0.0035	-0.0179	-0.0189
	[0.0120]	[0.0127]	[0.0180]	[0.0180]	[0.0204]	[0.0198]
	[-0.023 ; 0.024]	[-0.051 ; -0.001]	[-0.030 ; 0.041]	[-0.032 ; 0.039]	[-0.058 ; 0.022]	[-0.058 ; 0.020]
Fuel	0.0068	-0.0043	0.0226	0.0107	0.0237*	0.0069
	[0.0073]	[0.0156]	[0.0154]	[0.0160]	[0.0143]	[0.0125]
	[-0.008 ; 0.021]	[-0.035 ; 0.026]	[-0.008 ; 0.053]	[-0.021 ; 0.042]	[-0.004 ; 0.052]	[-0.018 ; 0.031]
Constant	-0.0047	0.0009	0.0085	-0.0429	-0.0266	0.0512
	[0.0189]	[0.0289]	[0.0280]	[0.0346]	[0.0347]	[0.0351]
	[-0.042 ; 0.032]	[-0.056 ; 0.057]	[-0.046 ; 0.063]	[-0.111 ; 0.025]	[-0.095 ; 0.041]	[-0.018 ; 0.120]
Observations	3,136	3,136	3,136	3,136	3,136	3,136
R-squared	0.025	0.054	0.066	0.056	0.064	0.108

Appendix Table 18. Report on covariates: Global MPI, aggregate measures

VARIABLES	(1) H	(2) M
Age	0.0007	0.0001
	[0.0008]	[0.0003]
	[-0.001 ; 0.002]	[-0.000 ; 0.001]
HH size	0.0443***	0.0221***
	[0.0057]	[0.0024]
	[0.033 ; 0.056]	[0.017 ; 0.027]
Children 0 to 5	0.0439*	0.0368***
	[0.0227]	[0.0092]
	[-0.001 ; 0.088]	[0.019 ; 0.055]
Children 6 to 19	0.0879***	0.0432***
	[0.0260]	[0.0108]
	[0.037 ; 0.139]	[0.022 ; 0.064]
No education	0.1760***	0.0728***
	[0.0294]	[0.0118]
	[0.118 ; 0.234]	[0.050 ; 0.096]
Rural	-0.0266	-0.0090
	[0.0345]	[0.0152]
	[-0.094 ; 0.041]	[-0.039 ; 0.021]
Social security	0.0239	0.0158*
	[0.0198]	[0.0082]
	[-0.015 ; 0.063]	[-0.000 ; 0.032]
Poverty rate	0.0084	0.0030
	[0.0323]	[0.0143]
	[-0.055 ; 0.072]	[-0.025 ; 0.031]
Owns TV	-0.1265***	-0.0482***
	[0.0196]	[0.0079]
	[-0.165 ; -0.088]	[-0.064 ; -0.033]
Owns mobile	-0.1097***	-0.0512***
	[0.0179]	[0.0073]
	[-0.145 ; -0.075]	[-0.066 ; -0.037]
Social program	-0.0704***	-0.0299***
	[0.0226]	[0.0091]
	[-0.115 ; -0.026]	[-0.048 ; -0.012]
Sanitation	0.1941***	0.0798***
	[0.0273]	[0.0109]
	[0.141 ; 0.248]	[0.058 ; 0.101]
Safe water	0.1406***	0.0683***
	[0.0177]	[0.0073]
	[0.106 ; 0.175]	[0.054 ; 0.083]
Electricity	0.1562***	0.0911***
	[0.0215]	[0.0092]
	[0.114 ; 0.198]	[0.073 ; 0.109]
Housing	0.1061***	0.0555***
	[0.0304]	[0.0138]
	[0.046 ; 0.166]	[0.028 ; 0.082]
Fuel	0.0889***	0.0312**
	[0.0344]	[0.0142]
	[0.021 ; 0.156]	[0.003 ; 0.059]
Constant	-0.0210	-0.0424*
	[0.0624]	[0.0256]
	[-0.143 ; 0.101]	[-0.093 ; 0.008]
Observations	3,136	3,136
R-squared	0.243	0.299

Appendix Table 19. Report on covariates: Global MPI, uncensored headcount

VARIABLES	(3) Schooling	(4) Attendance	(5) Nutrition	(6) Child mortality	(7) Fuel
Age	0.0042***	-0.0010***	-0.0028***	-0.0001	0.0006
	[0.0008]	[0.0003]	[0.0006]	[0.0001]	[0.0005]
	[0.003 ; 0.006]	[-0.002 ; -0.000]	[-0.004 ; -0.002]	[-0.000 ; 0.000]	[-0.000 ; 0.001]
HH size	0.0571***	0.0079***	0.0250***	0.0009	0.0112***
	[0.0055]	[0.0027]	[0.0051]	[0.0009]	[0.0035]
	[0.046 ; 0.068]	[0.003 ; 0.013]	[0.015 ; 0.035]	[-0.001 ; 0.003]	[0.004 ; 0.018]
Children 0 to 5	-0.0534**	0.0092	0.1832***	-0.0015	-0.0192
	[0.0227]	[0.0086]	[0.0158]	[0.0024]	[0.0124]
	[-0.098 ; -0.009]	[-0.008 ; 0.026]	[0.152 ; 0.214]	[-0.006 ; 0.003]	[-0.044 ; 0.005]
Children 6 to 19	0.1603***	0.0218**	-0.0029	-0.0039	0.0308*
	[0.0269]	[0.0094]	[0.0236]	[0.0039]	[0.0171]
	[0.107 ; 0.213]	[0.003 ; 0.040]	[-0.049 ; 0.043]	[-0.012 ; 0.004]	[-0.003 ; 0.064]
No education	0.3037***	0.0065	0.0301	-0.0016	0.0339**
	[0.0207]	[0.0119]	[0.0223]	[0.0010]	[0.0146]
	[0.263 ; 0.344]	[-0.017 ; 0.030]	[-0.014 ; 0.074]	[-0.004 ; 0.000]	[0.005 ; 0.063]
Rural	-0.0346	0.0002	-0.0390	-0.0056*	0.0361*
	[0.0356]	[0.0177]	[0.0294]	[0.0033]	[0.0210]
	[-0.104 ; 0.035]	[-0.035 ; 0.035]	[-0.097 ; 0.019]	[-0.012 ; 0.001]	[-0.005 ; 0.077]
Social security	0.0258	0.0173**	0.0140	0.0035**	0.0243*
	[0.0204]	[0.0073]	[0.0166]	[0.0017]	[0.0126]
	[-0.014 ; 0.066]	[0.003 ; 0.032]	[-0.019 ; 0.047]	[0.000 ; 0.007]	[-0.000 ; 0.049]
Poverty rate	0.0223	-0.0094	0.0356	0.0033*	0.0175
	[0.0333]	[0.0164]	[0.0281]	[0.0017]	[0.0187]
	[-0.043 ; 0.088]	[-0.042 ; 0.023]	[-0.019 ; 0.091]	[-0.000 ; 0.007]	[-0.019 ; 0.054]
Owns TV	-0.0631***	-0.0144**	0.0054	0.0003	-0.0251**
	[0.0203]	[0.0066]	[0.0158]	[0.0014]	[0.0121]
	[-0.103 ; -0.023]	[-0.027 ; -0.001]	[-0.025 ; 0.036]	[-0.002 ; 0.003]	[-0.049 ; -0.001]
Owns mobile	-0.0387**	-0.0078	-0.0038	-0.0023	-0.0011
	[0.0183]	[0.0068]	[0.0147]	[0.0016]	[0.0108]
	[-0.075 ; -0.003]	[-0.021 ; 0.005]	[-0.033 ; 0.025]	[-0.005 ; 0.001]	[-0.022 ; 0.020]
Social program	-0.0128	-0.0074	-0.0214	0.0021*	0.0116
	[0.0232]	[0.0090]	[0.0158]	[0.0012]	[0.0126]
	[-0.058 ; 0.033]	[-0.025 ; 0.010]	[-0.052 ; 0.010]	[-0.000 ; 0.005]	[-0.013 ; 0.036]
Sanitation	0.0695**	0.0011	0.0310	0.0022**	0.0227
	[0.0301]	[0.0114]	[0.0227]	[0.0009]	[0.0193]
	[0.010 ; 0.129]	[-0.021 ; 0.023]	[-0.014 ; 0.076]	[0.000 ; 0.004]	[-0.015 ; 0.061]
Safe water	-0.0090	0.0182***	0.0373**	0.0008	-0.0082
	[0.0180]	[0.0066]	[0.0145]	[0.0018]	[0.0106]
	[-0.044 ; 0.026]	[0.005 ; 0.031]	[0.009 ; 0.066]	[-0.003 ; 0.004]	[-0.029 ; 0.013]
Electricity	0.0317	0.0296***	0.0188	0.0046	0.0160
	[0.0215]	[0.0096]	[0.0182]	[0.0029]	[0.0120]
	[-0.010 ; 0.074]	[0.011 ; 0.048]	[-0.017 ; 0.054]	[-0.001 ; 0.010]	[-0.008 ; 0.039]
Housing	0.0006	-0.0190	0.0645**	-0.0042**	-0.0002
	[0.0326]	[0.0121]	[0.0281]	[0.0020]	[0.0159]
	[-0.063 ; 0.064]	[-0.043 ; 0.005]	[0.009 ; 0.120]	[-0.008 ; -0.000]	[-0.031 ; 0.031]
Fuel	0.0403	-0.0072	-0.0102	-0.0079	0.6588***
	[0.0396]	[0.0156]	[0.0324]	[0.0073]	[0.0372]
	[-0.037 ; 0.118]	[-0.038 ; 0.023]	[-0.074 ; 0.053]	[-0.022 ; 0.006]	[0.586 ; 0.732]
Constant	0.0262	0.0151	0.0830	0.0088	0.1621***
	[0.0669]	[0.0249]	[0.0544]	[0.0085]	[0.0487]
	[-0.105 ; 0.157]	[-0.034 ; 0.064]	[-0.024 ; 0.190]	[-0.008 ; 0.026]	[0.067 ; 0.258]
Observations	3,136	3,136	3,136	3,136	3,136
R-squared	0.150	0.032	0.124	0.007	0.214

Report on covariates: Global MPI, uncensored headcount (continued)

VARIABLES	(8) Sanitation	(9) Water	(10) Electricity	(11) Housing	(12) Small assets
Age	-0.0007	0.0003	0.0002	-0.0000	0.0008
	[0.0006]	[0.0008]	[0.0005]	[0.0003]	[0.0007]
	[-0.002 ; 0.000]	[-0.001 ; 0.002]	[-0.001 ; 0.001]	[-0.001 ; 0.001]	[-0.001 ; 0.002]
HH size	0.0035	-0.0035	0.0063*	0.0002	0.0075
	[0.0040]	[0.0052]	[0.0037]	[0.0022]	[0.0054]
	[-0.004 ; 0.011]	[-0.014 ; 0.007]	[-0.001 ; 0.014]	[-0.004 ; 0.004]	[-0.003 ; 0.018]
Children 0 to 5	-0.0049	0.0117	0.0037	0.0048	0.0123
	[0.0156]	[0.0201]	[0.0135]	[0.0080]	[0.0202]
	[-0.036 ; 0.026]	[-0.028 ; 0.051]	[-0.023 ; 0.030]	[-0.011 ; 0.020]	[-0.027 ; 0.052]
Children 6 to 19	0.0113	0.0024	0.0044	0.0118	-0.0000
	[0.0181]	[0.0241]	[0.0159]	[0.0098]	[0.0244]
	[-0.024 ; 0.047]	[-0.045 ; 0.050]	[-0.027 ; 0.036]	[-0.007 ; 0.031]	[-0.048 ; 0.048]
No education	0.0077	-0.0610**	0.0004	0.0092	0.0637**
	[0.0232]	[0.0286]	[0.0182]	[0.0086]	[0.0281]
	[-0.038 ; 0.053]	[-0.117 ; -0.005]	[-0.035 ; 0.036]	[-0.008 ; 0.026]	[0.009 ; 0.119]
Rural	-0.0683***	0.0208	0.0466	-0.0061	0.0443
	[0.0247]	[0.0318]	[0.0286]	[0.0232]	[0.0327]
	[-0.117 ; -0.020]	[-0.041 ; 0.083]	[-0.009 ; 0.103]	[-0.052 ; 0.039]	[-0.020 ; 0.108]
Social security	-0.0337***	-0.0446***	0.0085	-0.0001	0.0185
	[0.0126]	[0.0173]	[0.0126]	[0.0079]	[0.0176]
	[-0.059 ; -0.009]	[-0.079 ; -0.011]	[-0.016 ; 0.033]	[-0.016 ; 0.015]	[-0.016 ; 0.053]
Poverty rate	0.0658***	-0.0255	-0.0250	-0.0011	-0.0268
	[0.0235]	[0.0302]	[0.0273]	[0.0219]	[0.0313]
	[0.020 ; 0.112]	[-0.085 ; 0.034]	[-0.078 ; 0.029]	[-0.044 ; 0.042]	[-0.088 ; 0.035]
Owns TV	-0.0018	-0.0485***	0.0043	-0.0014	-0.2239***
	[0.0144]	[0.0174]	[0.0090]	[0.0053]	[0.0180]
	[-0.030 ; 0.026]	[-0.083 ; -0.014]	[-0.013 ; 0.022]	[-0.012 ; 0.009]	[-0.259 ; -0.189]
Owns mobile	0.0047	0.0554***	-0.0082	-0.0088	-0.4111***
	[0.0123]	[0.0159]	[0.0109]	[0.0067]	[0.0169]
	[-0.019 ; 0.029]	[0.024 ; 0.087]	[-0.030 ; 0.013]	[-0.022 ; 0.004]	[-0.444 ; -0.378]
Social program	-0.0075	-0.0409*	0.0044	-0.0001	-0.0476**
	[0.0163]	[0.0215]	[0.0139]	[0.0073]	[0.0210]
	[-0.039 ; 0.024]	[-0.083 ; 0.001]	[-0.023 ; 0.032]	[-0.015 ; 0.014]	[-0.089 ; -0.007]
Sanitation	0.6756***	0.0485*	0.0073	0.0077	0.0250
	[0.0306]	[0.0267]	[0.0156]	[0.0053]	[0.0263]
	[0.616 ; 0.736]	[-0.004 ; 0.101]	[-0.023 ; 0.038]	[-0.003 ; 0.018]	[-0.027 ; 0.076]
Safe water	0.0143	0.5605***	0.0172	0.0015	-0.0098
	[0.0123]	[0.0160]	[0.0112]	[0.0067]	[0.0160]
	[-0.010 ; 0.038]	[0.529 ; 0.592]	[-0.005 ; 0.039]	[-0.012 ; 0.015]	[-0.041 ; 0.022]
Electricity	0.0776***	0.0476**	0.6746***	0.0258***	0.1189***
	[0.0145]	[0.0197]	[0.0165]	[0.0088]	[0.0193]
	[0.049 ; 0.106]	[0.009 ; 0.086]	[0.642 ; 0.707]	[0.009 ; 0.043]	[0.081 ; 0.157]
Housing	0.0252	-0.0506*	0.0479*	0.5675***	-0.0217
	[0.0169]	[0.0291]	[0.0246]	[0.0306]	[0.0269]
	[-0.008 ; 0.058]	[-0.108 ; 0.007]	[-0.000 ; 0.096]	[0.508 ; 0.627]	[-0.074 ; 0.031]
Fuel	-0.0086	0.0100	0.0033	0.0036	0.0243
	[0.0251]	[0.0332]	[0.0206]	[0.0052]	[0.0307]
	[-0.058 ; 0.041]	[-0.055 ; 0.075]	[-0.037 ; 0.044]	[-0.007 ; 0.014]	[-0.036 ; 0.085]
Constant	0.3220***	0.2280***	-0.0126	0.0178	0.5927***
	[0.0499]	[0.0571]	[0.0377]	[0.0171]	[0.0584]
	[0.224 ; 0.420]	[0.116 ; 0.340]	[-0.086 ; 0.061]	[-0.016 ; 0.051]	[0.478 ; 0.707]
Observations	3,136	3,136	3,136	3,136	3,136
R-squared	0.299	0.353	0.624	0.448	0.354

Appendix Table 20. Report on covariates: Global MPI, censored headcount

	(13)	(14)	(15)	(16)	(17)
VARIABLES	Schooling	Attendance	Nutrition	Child mortality	Fuel
Age	0.0025***	-0.0010***	-0.0020***	-0.0001	0.0009
	[0.0008]	[0.0003]	[0.0006]	[0.0001]	[0.0008]
	[0.001 ; 0.004]	[-0.002 ; -0.000]	[-0.003 ; -0.001]	[-0.000 ; 0.000]	[-0.001 ; 0.002]
HH size	0.0476***	0.0084***	0.0280***	0.0013	0.0430***
	[0.0061]	[0.0027]	[0.0049]	[0.0008]	[0.0057]
	[0.036 ; 0.059]	[0.003 ; 0.014]	[0.018 ; 0.038]	[-0.000 ; 0.003]	[0.032 ; 0.054]
Children 0 to 5	-0.0063	0.0094	0.1655***	-0.0024	0.0449**
	[0.0232]	[0.0084]	[0.0148]	[0.0022]	[0.0226]
	[-0.052 ; 0.039]	[-0.007 ; 0.026]	[0.136 ; 0.194]	[-0.007 ; 0.002]	[0.000 ; 0.089]
Children 6 to 19	0.1146***	0.0199**	0.0145	-0.0049	0.0985***
	[0.0254]	[0.0092]	[0.0214]	[0.0035]	[0.0257]
	[0.065 ; 0.164]	[0.002 ; 0.038]	[-0.027 ; 0.056]	[-0.012 ; 0.002]	[0.048 ; 0.149]
No education	0.2019***	0.0084	0.0349	-0.0019*	0.1668***
	[0.0306]	[0.0118]	[0.0221]	[0.0010]	[0.0295]
	[0.142 ; 0.262]	[-0.015 ; 0.032]	[-0.008 ; 0.078]	[-0.004 ; 0.000]	[0.109 ; 0.225]
Rural	-0.0292	-0.0008	-0.0320	-0.0058*	-0.0278
	[0.0360]	[0.0177]	[0.0292]	[0.0033]	[0.0346]
	[-0.100 ; 0.041]	[-0.035 ; 0.034]	[-0.089 ; 0.025]	[-0.012 ; 0.001]	[-0.096 ; 0.040]
Social security	0.0263	0.0206***	0.0210	0.0036**	0.0262
	[0.0202]	[0.0069]	[0.0157]	[0.0016]	[0.0197]
	[-0.013 ; 0.066]	[0.007 ; 0.034]	[-0.010 ; 0.052]	[0.001 ; 0.007]	[-0.012 ; 0.065]
Poverty rate	0.0213	-0.0106	0.0298	0.0034**	0.0148
	[0.0339]	[0.0163]	[0.0280]	[0.0017]	[0.0324]
	[-0.045 ; 0.088]	[-0.043 ; 0.021]	[-0.025 ; 0.085]	[0.000 ; 0.007]	[-0.049 ; 0.078]
Owns TV	-0.1037***	-0.0093	-0.0131	-0.0011	-0.1210***
	[0.0194]	[0.0062]	[0.0147]	[0.0009]	[0.0195]
	[-0.142 ; -0.066]	[-0.021 ; 0.003]	[-0.042 ; 0.016]	[-0.003 ; 0.001]	[-0.159 ; -0.083]
Owns mobile	-0.1046***	-0.0122*	-0.0164	-0.0026**	-0.1111***
	[0.0179]	[0.0064]	[0.0139]	[0.0013]	[0.0179]
	[-0.140 ; -0.069]	[-0.025 ; 0.000]	[-0.044 ; 0.011]	[-0.005 ; -0.000]	[-0.146 ; -0.076]
Social program	-0.0717***	-0.0074	-0.0306**	0.0019	-0.0667***
	[0.0231]	[0.0088]	[0.0153]	[0.0012]	[0.0225]
	[-0.117 ; -0.027]	[-0.025 ; 0.010]	[-0.061 ; -0.001]	[-0.000 ; 0.004]	[-0.111 ; -0.023]
Sanitation	0.1846***	-0.0013	0.0490**	0.0014**	0.1898***
	[0.0264]	[0.0113]	[0.0193]	[0.0007]	[0.0272]
	[0.133 ; 0.236]	[-0.024 ; 0.021]	[0.011 ; 0.087]	[0.000 ; 0.003]	[0.137 ; 0.243]
Safe water	0.1088***	0.0198***	0.0508***	0.0014	0.1338***
	[0.0179]	[0.0064]	[0.0139]	[0.0017]	[0.0175]
	[0.074 ; 0.144]	[0.007 ; 0.032]	[0.024 ; 0.078]	[-0.002 ; 0.005]	[0.099 ; 0.168]
Electricity	0.1281***	0.0327***	0.0325*	0.0048	0.1509***
	[0.0222]	[0.0095]	[0.0178]	[0.0029]	[0.0215]
	[0.085 ; 0.172]	[0.014 ; 0.051]	[-0.002 ; 0.067]	[-0.001 ; 0.010]	[0.109 ; 0.193]
Housing	0.0442	-0.0213*	0.0651**	-0.0041**	0.1034***
	[0.0327]	[0.0114]	[0.0275]	[0.0020]	[0.0304]
	[-0.020 ; 0.108]	[-0.044 ; 0.001]	[0.011 ; 0.119]	[-0.008 ; -0.000]	[0.044 ; 0.163]
Fuel	0.0613*	-0.0009	0.0056	-0.0030	0.2079***
	[0.0337]	[0.0132]	[0.0288]	[0.0046]	[0.0326]
	[-0.005 ; 0.127]	[-0.027 ; 0.025]	[-0.051 ; 0.062]	[-0.012 ; 0.006]	[0.144 ; 0.272]
Constant	-0.1374**	0.0054	-0.0243	0.0040	-0.1579***
	[0.0625]	[0.0229]	[0.0499]	[0.0055]	[0.0605]
	[-0.260 ; -0.015]	[-0.039 ; 0.050]	[-0.122 ; 0.074]	[-0.007 ; 0.015]	[-0.277 ; -0.039]
Observations	3,136	3,136	3,136	3,136	3,136
R-squared	0.195	0.037	0.128	0.010	0.250

Report on covariates: Global MPI, censored headcount (continued)

VARIABLES	(18) Sanitation	(19) Water	(20) Electricity	(21) Housing	(22) Small assets
Age	0.0003	0.0010	0.0008	0.0001	0.0011
	[0.0008]	[0.0007]	[0.0005]	[0.0003]	[0.0007]
	[-0.001 ; 0.002]	[-0.000 ; 0.002]	[-0.000 ; 0.002]	[-0.000 ; 0.001]	[-0.000 ; 0.003]
HH size	0.0435***	0.0181***	0.0166***	0.0011	0.0191***
	[0.0057]	[0.0051]	[0.0041]	[0.0022]	[0.0054]
	[0.032 ; 0.055]	[0.008 ; 0.028]	[0.009 ; 0.025]	[-0.003 ; 0.005]	[0.009 ; 0.030]
Children 0 to 5	0.0339	0.0191	0.0172	0.0088	0.0399**
	[0.0226]	[0.0200]	[0.0147]	[0.0074]	[0.0199]
	[-0.010 ; 0.078]	[-0.020 ; 0.058]	[-0.012 ; 0.046]	[-0.006 ; 0.023]	[0.001 ; 0.079]
Children 6 to 19	0.0815***	0.0561**	0.0211	0.0163*	0.0713***
	[0.0257]	[0.0218]	[0.0171]	[0.0095]	[0.0230]
	[0.031 ; 0.132]	[0.013 ; 0.099]	[-0.012 ; 0.055]	[-0.002 ; 0.035]	[0.026 ; 0.116]
No education	0.1462***	0.0545**	0.0275	0.0129	0.1722***
	[0.0300]	[0.0271]	[0.0189]	[0.0088]	[0.0286]
	[0.087 ; 0.205]	[0.001 ; 0.108]	[-0.010 ; 0.065]	[-0.004 ; 0.030]	[0.116 ; 0.228]
Rural	-0.0366	0.0056	0.0557*	0.0215	0.0231
	[0.0343]	[0.0327]	[0.0313]	[0.0232]	[0.0336]
	[-0.104 ; 0.031]	[-0.059 ; 0.070]	[-0.006 ; 0.117]	[-0.024 ; 0.067]	[-0.043 ; 0.089]
Social security	0.0139	-0.0113	0.0084	0.0052	0.0276
	[0.0197]	[0.0175]	[0.0136]	[0.0072]	[0.0175]
	[-0.025 ; 0.052]	[-0.046 ; 0.023]	[-0.018 ; 0.035]	[-0.009 ; 0.019]	[-0.007 ; 0.062]
Poverty rate	0.0230	-0.0446	-0.0267	-0.0243	-0.0194
	[0.0322]	[0.0310]	[0.0298]	[0.0221]	[0.0319]
	[-0.040 ; 0.086]	[-0.105 ; 0.016]	[-0.085 ; 0.032]	[-0.068 ; 0.019]	[-0.082 ; 0.043]
Owns TV	-0.1183***	-0.0558***	-0.0038	-0.0029	-0.1844***
	[0.0193]	[0.0158]	[0.0088]	[0.0049]	[0.0159]
	[-0.156 ; -0.081]	[-0.087 ; -0.025]	[-0.021 ; 0.014]	[-0.013 ; 0.007]	[-0.216 ; -0.153]
Owns mobile	-0.0969***	0.0184	-0.0109	-0.0099	-0.3034***
	[0.0177]	[0.0153]	[0.0116]	[0.0064]	[0.0153]
	[-0.132 ; -0.062]	[-0.012 ; 0.048]	[-0.034 ; 0.012]	[-0.022 ; 0.003]	[-0.333 ; -0.273]
Social program	-0.0548**	-0.0318	-0.0106	-0.0040	-0.0468**
	[0.0224]	[0.0209]	[0.0150]	[0.0070]	[0.0207]
	[-0.099 ; -0.011]	[-0.073 ; 0.009]	[-0.040 ; 0.019]	[-0.018 ; 0.010]	[-0.087 ; -0.006]
Sanitation	0.3340***	0.1213***	0.0158	0.0114**	0.0632***
	[0.0246]	[0.0231]	[0.0156]	[0.0050]	[0.0236]
	[0.286 ; 0.382]	[0.076 ; 0.167]	[-0.015 ; 0.046]	[0.002 ; 0.021]	[0.017 ; 0.110]
Safe water	0.1405***	0.3979***	0.0226*	0.0067	-0.0141
	[0.0174]	[0.0152]	[0.0120]	[0.0064]	[0.0157]
	[0.106 ; 0.175]	[0.368 ; 0.428]	[-0.001 ; 0.046]	[-0.006 ; 0.019]	[-0.045 ; 0.017]
Electricity	0.1462***	0.0629***	0.5279***	0.0275***	0.1298***
	[0.0213]	[0.0194]	[0.0181]	[0.0084]	[0.0203]
	[0.104 ; 0.188]	[0.025 ; 0.101]	[0.492 ; 0.563]	[0.011 ; 0.044]	[0.090 ; 0.170]
Housing	0.1132***	-0.0018	0.0539*	0.4508***	0.0275
	[0.0307]	[0.0282]	[0.0282]	[0.0313]	[0.0284]
	[0.053 ; 0.173]	[-0.057 ; 0.053]	[-0.001 ; 0.109]	[0.389 ; 0.512]	[-0.028 ; 0.083]
Fuel	0.0944***	0.0547*	-0.0166	-0.0008	0.0324
	[0.0325]	[0.0300]	[0.0208]	[0.0048]	[0.0273]
	[0.031 ; 0.158]	[-0.004 ; 0.114]	[-0.057 ; 0.024]	[-0.010 ; 0.009]	[-0.021 ; 0.086]
Constant	-0.1535**	-0.1143**	-0.1039***	-0.0142	0.2373***
	[0.0597]	[0.0544]	[0.0397]	[0.0167]	[0.0548]
	[-0.271 ; -0.036]	[-0.221 ; -0.008]	[-0.182 ; -0.026]	[-0.047 ; 0.019]	[0.130 ; 0.345]
Observations	3,136	3,136	3,136	3,136	3,136
R-squared	0.256	0.284	0.488	0.362	0.306

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