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Agricultural and Rural Development Interventions and Poverty Reduction: Global Evidence from 16 Impact Assessment Studies

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Abstract

Agricultural and rural development interventions significantly reduce global poverty by providing growth-oriented tools, including but not limited to access to finance, training, and markets. While such interventions effectively reduce monetary poverty (e.g., $1 a day poverty line), there is increasing interest in incorporating non-monetary poverty indicators, such as education, health, and living standards, to capture inherent multidimensionality in poverty. This study analyzes data from 16 impact evaluation studies conducted between 2019 and 2023 to examine whether and to what extent agricultural and rural development interventions affect the multidimensional poverty of small-scale producers. Our analysis reveals a 4 percent reduction in multidimensional poverty for treatment households compared to comparison households. Our findings suggest that agricultural and rural development interventions play a positive role in reducing poverty and have the potential to improve the long-term well-being of poor households.

JEL Codes: O13, Q18, R51

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1. Introduction

Agriculture plays a vital role in reducing poverty worldwide by increasing wages and jobs, lowering food prices, and creating multiplier effects in other sectors (Idan et al., 2004; World Bank, 2022). Previous research shows that agricultural sector growth has a two to three times greater impact on poverty reduction than growth in other sectors, particularly in the poorest countries (Christiaensen and Martin, 2018). This is primarily due to the pro-poor nature of agricultural growth, which enhances the capacity of poor households to generate independent incomes (De Janvry and Sadoulet, 2010, 2022).

Agricultural interventions typically aim to promote the uptake of project components among targeted farm populations to improve their welfare. In this context, welfare is generally measured using monetary indicators such as income or consumption. Although some studies have examined the role of the agricultural sector in reducing poverty at the national level (Anríquez and Stamoulis, 2007; Christiaensen and Martin, 2018), there is limited literature on how agricultural projects contribute to poverty reduction at the household level in rural areas. To understand the agricultural sector's contribution to poverty reduction, it is crucial to consider the choice of poverty measure. While monetary-based, one-dimensional indicators (e.g., consumption-based and income-based poverty indicators) are often used, they fail to capture the multiple sources of deprivation that poor households face, such as limited access to education, healthcare, and basic infrastructure (OPHI, 2022). Therefore, it is important to measure poverty using a multidimensional indicator that captures the full spectrum of poverty to provide a more comprehensive analysis of the impact of agricultural interventions on poverty alleviation. In this regard, the multidimensional poverty index (MPI) has emerged as a prominent tool in filling these gaps in poverty measurement by capturing various deprivations and measuring who is considered poor and according to which dimension.

This study examines the impact of agricultural support interventions on the multidimensional poverty of small-scale producers worldwide. We analyze data from 16 impact assessment studies carried out between 2019 and 2023 in 16 countries, including Djibouti, Ghana, India, Kenya, Kyrgyzstan, Mali, Nepal, Nicaragua, Nigeria, Papua New Guinea, Pakistan, Peru, Philippines, Tajikistan, Tanzania, and Zambia. The respective national governments implement these projects with a common goal of rural development thorough different agriculture activity-oriented interventions with co-financing by the International Fund for Agricultural Development (IFAD). The study includes 34,779 households, of which 18,072 are treatment households and the rest are comparison households. We used most commonly used the Alkire-Foster method to measure MPI, which measures the percentage of people who are poor based on three dimensions (i.e., living standard, education, and health) and the intensity of poverty experienced by households, without relying on income or expenditure data (Alkire and Foster, 2011).

We calculate the post-intervention MPI score and the percentage of people who are poor using indicators representing all three dimensions of the MPI (i.e., living standard, education, and health). To assess the causal impact of these interventions, we employ linear regressions followed by inverse probability-weighted regression adjustment (IPWRA), entropy balancing, and difference-in-difference (DiD) methods. Our findings indicate a significant reduction in multidimensional poverty among households that received agricultural support interventions compared to those that did not. The interventions resulted in a reduction of 4% in multidimensional poverty. We also find that projects implemented in African countries, project-targeted household enterprise activities, households headed by a male and younger-aged person, and smaller households experienced the most significant poverty reduction.

The findings of this study confirm the hypothesis that agricultural support interventions effectively reduce poverty and food security (De Janvry and Sadoulet, 2022; Garbero and Jäckering, 2021; Christiaensen and Martin, 2018). Additionally, they support the idea that multi-package agricultural support interventions are necessary to achieve higher-level outcomes, such as productivity and income, rather than single-input interventions. Most of the interventions examined in this study had multiple components that addressed various constraints faced by small-scale producers, including access to finance, training, markets, and infrastructure development. Previous studies show that single-input interventions are not enough to bring about holistic changes in the economic activities of small-scale producers. For instance, microcredit interventions often create a substitution between economic activities and may not always increase household income (Hossain et al., 2022; Banerjee et al., 2015). Similarly, extension interventions such as farmer field schools may only improve farmers' knowledge or adoption of new technologies if delivered correctly and not necessarily increase profits (JPAL, 2018; VoxDev, 2019). Therefore, multi-package interventions that target the entire value chain through the development of infrastructure, storage capacity, and market links are essential for improving household welfare (Fuglie et al., 2020; Swinnen and Kuijpers, 2020; Bizikova et al., 2020; Kafle et al., 2022).

This study contributes to the literature on the relationship between agriculture and poverty reduction, relying on aggregated cross-country data (Fuglie et al., 2020; Christiaensen and Martin, 2018). Our findings offer a more comprehensive understanding of household well-being across different continents by including welfare measures beyond monetary poverty, such as education, health, and access to basic infrastructure. This finding contrasts earlier evidence that agricultural development can combat poverty only in the short term (Victor & Akadiri 2019). Our study also contributes to the existing literature by demonstrating how household welfare can be assessed for monitoring and evaluation purposes when detailed data on income or consumption is unavailable. Many development programs gather basic household information as part of performance monitoring and evaluation initiatives. These indicators can be used to measure multidimensional poverty, highlighting the impact of programs on household welfare without significantly altering the current monitoring and evaluation framework or incurring additional data collection expenses.

The results of this study suggest that agricultural and rural development interventions should consider the multidimensional nature of poverty from the planning stage and target households accordingly to achieve the highest impact on poverty reduction. To effectively reach the most vulnerable small-scale producers, targeting strategies should not solely rely on income but also incorporate more comprehensive indicators, such as wealth ranking, housing quality, and proxy means tests, as detailed in Karlan & Thuysbaert (2019) and Hanna & Olken (2018). This approach will enable target groups to benefit from project outcomes for sustainable livelihoods fully. Moreover, since development practitioners and donor agencies are interested in measuring the sustainability of project impacts, using multidimensional poverty indices as a proxy for well-being may provide a more accurate reflection than income or consumption-based indicators.

The reminder of this paper is organized as follows. We provide the background of the MPI measure in Section Two. We describe the data used for this study in Section Three. Section Four details the identification strategy. Section Five contains the main results, and we discuss the results and conclude in Section Six.

2. Multidimensional Poverty Index

The Multidimensional Poverty Index (MPI) was developed to provide a holistic view of poverty by capturing various deprivations households face. This is motivated by the finding that single indicator-based welfare indicators, such as income or poverty, which often fail to fully capture the nuances of households' living standards (OPHI, 2022). MPI's foundation lies in the Alkire-Foster method, formulated by the Oxford Policy and Human Development Initiative (OPHI) and United Nations Development Programme (UNDP). It has gained widespread recognition for its application in measuring poverty (Alkire and Foster, 2011). The United Nations Development Programme's Human Development Report Office has used the OPHI methodology since 2010 to compare multidimensional poverty across over 100 developing countries.

The OPHI methodology incorporates three dimensions to measure household-level MPI scores—living standards, education, and health—each weighted equally (OPHI, 2018). Within these dimensions, multiple binary indicators capture deprivation. For example, the living standards dimension consists of indicators related to housing, assets, and utilities; the education dimension is based on adult literacy and children's school attendance; and the health dimension considers child mortality and nutrition. Each indicator within a dimension carries an equal weight. Finally, a weighted sum of these indicators is calculated to compute the overall MPI score, which ranges from 0 to 1. Additionally, a binary MPI indicator can also be used, with a value of 1 indicating poverty (a score of 0.33 or higher) and 0 otherwise, in line with the original OPHI methodology.

The measurement of MPI and associated indicators has evolved to align with theoretical advancements, data availability, and policy relevance (Alkire et al., 2021). Notably, the asset indicator has been scrutinized due to the challenge of obtaining comparable data, even within a single country (Vollmer and Alkire, 2022). The World Bank has extended the scope of MPI by integrating a monetary aspect—such as consumption or income-based poverty headcount—into its framework (World Bank, 2018). Moreover, the Food and Agriculture Organization (FAO), in collaboration with OPHI, has introduced indicators focusing on rural livelihoods and resources, creating a rural-specific MPI (FAO and OPHI, 2022).

We adapted the OPHI approach to calculate MPI scores. One notable difference is that we used household food insecurity status instead of child mortality and nutrition to calculate the health dimension of MPI, also used by the Food and Agriculture Organization to measure rural MPI (FAO and OPHI, 2022).[1] The only difference is that the FAO/OPHI uses two proxy indicators for the health dimension, food insecurity and child malnutrition, while we use only the food insecurity indicator. Detailed definitions and weights for each indicator can be found in Tables A1 and A2 in the Appendix.

3. Data

This study uses data from 16 impact assessment studies conducted in Djibouti, Ghana, India, Kenya, Kyrgyzstan, Mali, Nepal, Nicaragua, Nigeria, Papua New Guinea, Pakistan, Peru, Philippines, Tajikistan, Tanzania, and Zambia. These projects were implemented by the national governments of these countries with financial and technical support from IFAD. As part of IFAD's development effectiveness framework, 25 projects were selected to undergo an impact assessment. We dropped nine countries from this analysis as they did not collect the required indicators for measuring MPI scores. Appendix C presents a brief overview of each study and Table A3 in the Appendix provides specific reasons for dropping these nine countries. Data collections are done by independent institutions in each IA study. For instance, the International Food Policy Research Institute (IFPRI) collected data for eight countries, and the Center for Evaluation and Development

[1] The food insecurity indicator is based household responses to their Food Insecurity Experience Scale (FIES). FIES indicators focus on self-reported food-related behaviours and experiences of households/respondents in accessing food due to resource constraints. There is total 8 indicators on difficulties in accessing food due to lack of money or other resources by individual respondent or of the respondent's household.

(C4ED) collected data for 6 countries. The rest of the data was collected by a few other institutions, including Oxford Policy Management (OPM), Sistemas Integrales, and the Southeast Asian Regional Center for Graduate Study and Research in Agriculture (SEARCA).

The impact assessment studies collected detailed household and community-level data from randomly selected beneficiaries and comparison households (IFAD, 2022). The sample selection process typically employs multi-stage matching techniques and stakeholder consultations to identify comparable beneficiaries and comparison households within similar geographical areas. Comparison households are selected based on the same targeting strategy that the project team used to select program beneficiaries. Additionally, geospatial data (such as rainfall, temperature, population density, and travel time to the nearest city) along with development indicators (like night lights) are frequently used to match and select communities or villages. Table A4 shows sample size, treatment and comparison sample ratio, project target sector, project launch and closing periods, and data collection periods. Most of the interventions began after 2011, lasted an average of eight years, and ended between 2019 and 2022. Data was collected from 2019 to 2023.

In addition to collecting data from the current period, each study collected retrospective data on easily recallable indicators, such as asset holdings and housing quality. In this regard, interviewers used a structured questionnaire that first recorded respondents' responses from the current period, followed by a question of whether respondents had the same asset or housing condition during the baseline period. In cases of no change, the endline values were recorded as the baseline. Otherwise, baseline values were documented based on recall. Although retrospective data is not ideal, in the case of assets and housing quality, it is expected to be less error-prone than data on income or production input/output (for details, see Moreno-Serra et al., (2022); Wollburg, Tiberti, and Zezza (2021); Assaad, Krafft, and Yassin (2018); De Nicola and Gine (2014); Howard (2011)). We use these recalled indicators primarily as additional control variables.

4. Identification Strategy

We construct a pooled sample by combining data from all the countries to conduct an aggregate analysis, followed by a country-level analysis. Given the similar conceptual frameworks, sampling designs, survey instruments, and a shared focus on rural development across individual IA studies, pooling data increases statistical power to test additional hypotheses (Bangdiwala et al., 2016). We begin with the following linear regression to estimate aggregate and country-level causal effects:

$$y_{hc} = \alpha_0 + \alpha_1 \times \text{Treat}_{hc} + \mu X_{hc} + \eta C + \xi_{hc} \qquad (1)$$

where y_{hc} is the MPI poverty score of household h from country c; Treat_{hc} is a dummy variable taking a value of 1 if the household h from country c is a beneficiary household and 0 otherwise. X_{hc} presents household-level control variables (e.g., household size, number of male members, whether headed by a female, age of household head, baseline indicators related asset, housing quality, and access to sanitation, water, electricity) to capture for any differences at the households level; C consists of fixed effects for countries (to account for country level difference), year of the start of the intervention (to account the variation in interventions' duration), and quarter of data collection (to account seasonal pattern in the data). Finally, ξ_{hc} captures household-level unobservable factors. α_3 is the coefficient of interest, showing whether the interventions have any impact on the MPI poverty level or not. We cluster standard errors at the level of treatment assignment. The full list of cluster information is available in Table A5. Missing independent variable values are replaced by the mode value of country and region/province, with a dummy variable for missing status included.[2]

[2] For household-level control variables (e.g., household size, number of male members, whether headed by a female, and age of household head), there are missing information for less than 1 percent of sample. We replace the missing

For unbiased impact estimation in Equation (1), we assume that beneficiary and comparison households were comparable during the pre-program period regarding both observable and unobservable characteristics. We present standardized differences for demographic, household head characteristics, and baseline deprivation indicators between treatment and control groups in Table 1. These differences are not substantial, well within the 0.10 rule-of-thumb (Austin, 2009), suggesting comparability in observable characteristics. While each study uses a similar targeting strategy to control household selection, the absence of a randomized control trial or natural experiment may raise the possibility of unbalanced, unobserved characteristics.

In addition to linear regressions, we employ inverse probability-weighted regression adjustment (IPWRA), entropy balancing, and difference-in-difference (DiD) methods. IPWRA and entropy balancing calculate pre-intervention similarities between beneficiary and comparison households and apply weighted regressions for causal effect estimation. Between the two approaches, the entropy balancing method provides flexibility in regression functional forms and criteria for balancing (e.g., mean, variance, skewness) compared to IPWRA (Apeti and Edoh, 2023). Lastly, we use the DiD method, acknowledging that the baseline MPI score relies only on living standards indicators like assets, dwelling quality, and access to sanitation, water, electricity, and cooking fuel. The DiD method helps control any pre-intervention differences between treatment and control households. We provide further details on these alternative methods in Appendix B.

5. Results

5.1 Summary Results

value with country and admin level 1 mode values. In addition, we control dummy variables indicating the missing data status in regressions. Results do not change if we drop these observations from the analysis.

Table 1 shows that the average MPI score is 0.31 for beneficiary households and 0.33 for non-beneficiary households. Looking at the binary indicators of MPI, we find that about 45% and 47% of the treatment and control households are poor respectively. Figure 1 shows that the cumulative distribution of MPI scores for treatment households is lower than for control households. Examining specific deprivation indicators of MPI, we find that treatment households were better off in terms of sanitation, electricity, housing, asset, education, and food security indicators.

Table A6 shows country-level MPI scores and MPI poverty status by treatment status of households. Notably, treatment households in Ghana show a significantly lower MPI score (0.29) than the control group (0.47), with a corresponding MPI poverty status of 44% versus 67%. Other countries like Pakistan, Peru, Tajikistan, Tanzania, and Zambia also show a noticeably lower MPI score and MPI poverty rate among the treatment households compared to control groups. This contrasts with countries like Kyrgyzstan, Mali, and Nigeria, where treatment households have higher MPI scores and poverty status than their control counterparts. Columns 9 and 10 show the official MPI poverty rates published by OPHI and World Bank for our study countries for the same periods. In most cases, poverty concentration is much higher in our study sample compared to the national-level statistics published by these two sources.

5.2 Impact on MPI Score and multidimensional poverty rate

Table 2 presents the impact on MPI score and MPI poverty status. The pooled analysis shows that beneficiary households experienced a 4% decrease in their MPI score relative to comparison households, as highlighted in Column 1. A similar reduction in the poverty rate, using the binary poverty indicator, is evident in Column 2. Methods such as Inverse Probability Weighted Regression Adjustment (IPWRA), entropy balancing, and Difference in Differences (DiD) consistently demonstrate significant reductions of similar magnitudes in both MPI scores and poverty rates for treatment households compared to controls.

Country-specific results are shown in Figure 1. We find significant variances in outcomes by country. Beneficiary households in Ghana experienced the most substantial decrease in MPI score by 27%, followed by Pakistan with a 15% reduction, Peru at 9%, and Zambia at 8%. Conversely, in Kyrgyzstan and Mali, beneficiary households' MPI scores were 16% and 13% higher than those of comparison households. The binary poverty indicator revealed a similar trend, with the most notable reductions in poverty rates among beneficiaries observed in Ghana (25%), Pakistan (15%), Peru (13%), Zambia (9%), and Tanzania (5%). In Mali, however, there was a 9% increase in the poverty rate among beneficiary households compared to control groups. We present the associated OLS regression results in Table A7.

The results across all countries were either positive or showed no significant effect, except in Mali, where the MPI score and poverty rate increased for treatment households. In Mali, providing credit and training services to beneficiary households led to more off-farm self-employment but reduced agricultural production and sales, as detailed by Toma et al. (2020). Additionally, higher Food Insecurity Experience Scale (FIES) scores, indicating greater food insecurity or nutrition-related deprivation, were recorded for beneficiary households in Mali. These factors likely contributed to the observed rise in MPI score and poverty rate. Overall, our findings confirm that interventions effectively reduced multidimensional poverty. This evidence reinforces the argument that investments in agriculture serve as a potent mechanism for poverty alleviation, particularly for the most impoverished populations (FAO, 2017; Christiaensen and Martin, 2018).

5.3 Impact on MPI by sub-groups

The findings of this study highlight the effectiveness of agricultural interventions in reducing poverty among beneficiary households. As previous research suggests that the contribution of the agricultural sector to poverty reduction may vary by target group and geography (De Janvry and Sadoulet, 2010; Christiaensen et al., 2011), it is important to examine whether the impacts of these interventions differ across sub-groups. We analyze the impact of interventions on different sub-groups.

We examine if poverty reduction was significant across all geographical regions. Results in Figure 3 indicate that the East and Southern Africa (ESA) and West and Central Africa (WCA) regions experienced a significant reduction in MPI scores by 4% and 7%, respectively. Poverty rates also decreased significantly in the ESA region by 4%. Overall, interventions had the highest impact on poverty reduction in Africa, where poverty concentration is relatively high with low productivity and factor market failures (Christiaensen, Demery, and Kuhl, 2011; Castaneda et al., 2018; Fugile et al., 2020). The interventions target specific sectors, such as farming, coffee and cocoa, fishery, livestock, or enterprise activity, and households are selected based on their involvement in those activities. Figure 3 shows that interventions targeting household enterprises (20%) were particularly successful, followed by livestock activity.

We also conducted a sub-sample analysis based on household characteristics, such as headship, size, and head age (Figure 3). Male-headed households show better outcomes, as evidenced by their MPI scores and poverty rates, compared to female-headed households. Household size also plays a role, with smaller households (6 or fewer members) benefiting more from the interventions than larger households (more than six members). Furthermore, younger household heads (34 or less years old) and middle-aged (35 to 54 years) exhibit more substantial reductions in MPI scores and poverty, possibly indicating a greater ability to leverage the benefits of the provided interventions. We present the associated OLS regression results in Table A8.

6. Discussion and conclusion

Our study shows that agricultural and rural development interventions significantly reduce multidimensional poverty among beneficiary households relative to comparison households. As expected, the extent of this impact varies depending on which indicators are used to construct the MPI score, region, and project target activities. Since all impact assessment studies conducted were after the closure of the interventions, which had an average duration of eight years, the results of this study reflect the long-term impact of agricultural interventions. In addition, the variations in impact across different regions and household characteristics highlight the need for contextually adapted strategies. As such, development interventions could be flexible and sensitive to the unique socioeconomic dynamics of each region to maximize effectiveness. Overall, thus, this study provides valuable insights that can inform policymakers and practitioners in designing and implementing targeted interventions.

Our findings are consistent with previous research demonstrating the critical role of the agricultural sector in reducing poverty in rural areas (Abro et al. 2014). Although most earlier studies have focused on the role played by agricultural interventions to reduce monetary poverty, they document that agricultural interventions are successful poverty reduction tools. For instance, Kassie et al. (2011) show that promoting new agricultural technologies can reduce rural poverty through increased farm household income. Hanjra et al. (2009) have argued that a comprehensive approach, including investments in agricultural water management, rural infrastructure, and related policies, is essential to break the poverty trap in smallholder African agriculture. Similarly, Abro et al. (2014) have suggested that a growth plus approach, which designs policies to enhance agricultural productivity, protect assets, and improve market access, is crucial for poverty reduction. Finally, Dercon et al. (2009) showed that improvements in roads and access to agricultural extension reduced poverty in rural Ethiopia. Some studies also documented the significant role of investment in agricultural research as an effective tool for poverty reduction (Fan et al., 2000; Ainembabazi et al., 2018).

It is important to consider the factors that may have contributed to poverty reduction. Table A9 shows that deprivation in access to electricity, asset ownership, adequate housing facilities, and food insecurity reduced for beneficiary households compared to comparison households, while there is an increase in deprivation related to cooking fuel. Overall, these results imply that agricultural intervention can not only improve current or short-run welfare (e.g., food security) but can also improve the long-term capacity and welfare of households, further enhancing their resilience to face risks (Tirivayi, Knowles, and Davis, 2016).

The pre-intervention data on a few indicators, such as asset counts, dwelling quality, and sanitation access, were collected based on recall. These indicators are used as additional control variables in regressions and to measure baseline MPI in the case of DiD regressions. One concern is whether the recall error can bias the treatment effects. The former may happen if the recall errors vary by household treatment status. To test this, we use data from the Nepal study, with original and recalled baseline data. We find no statistically significant differences in error rates between the treatment and control groups when comparing MPI scores based on actual and recalled baseline data. Results are presented in Table A10. The former implies that it is less likely that recalled baseline data will bias the impact estimates.

Future research could investigate the channels through which agricultural interventions reduce poverty, such as job creation, improved wages, lower food or input prices, multiplier effects, or other means. Our study is also limited to retrospective data and partial replication of MPI estimation methods due to the absence of randomized control trial experiments and the lack of proper baseline data. In addition, it is important to tailor the MPI indicators to the agricultural context to reflect the poverty status of agricultural households accurately. For example, the current MPI indicators mainly use durable assets in MPI score calculation rather than agricultural assets. Nevertheless, in a world facing multiple crises, addressing global poverty remains a critical challenge, and agriculture is expected to play an increasingly important role in reducing poverty and improving food security. Our study provides global evidence to support this claim.

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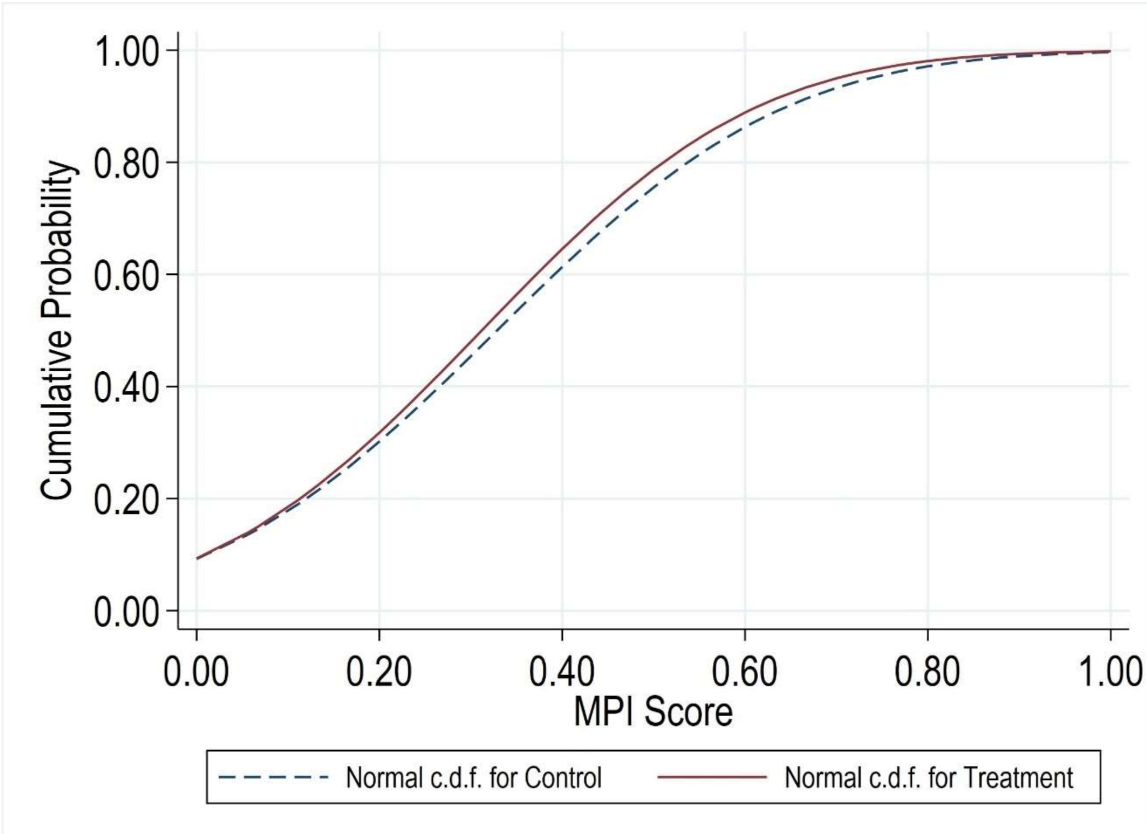

Figure 1. Cumulative probability distribution of MPI score

Notes: The graph shows cumulative distributions of MPI scores by treatment status. MPI score is measured based on all three dimensions. For instance, the graph shows the probability of having an MPI score of 0.40 or below, which is about 60% for control households and about 65% for treatment households. This implies that the treatment households have a lower probability of possessing high MPI scores compared to the control households. Total sample size is 31,968, of which 16,674 are beneficiary households and the rest of the 15,294 households are comparison households.

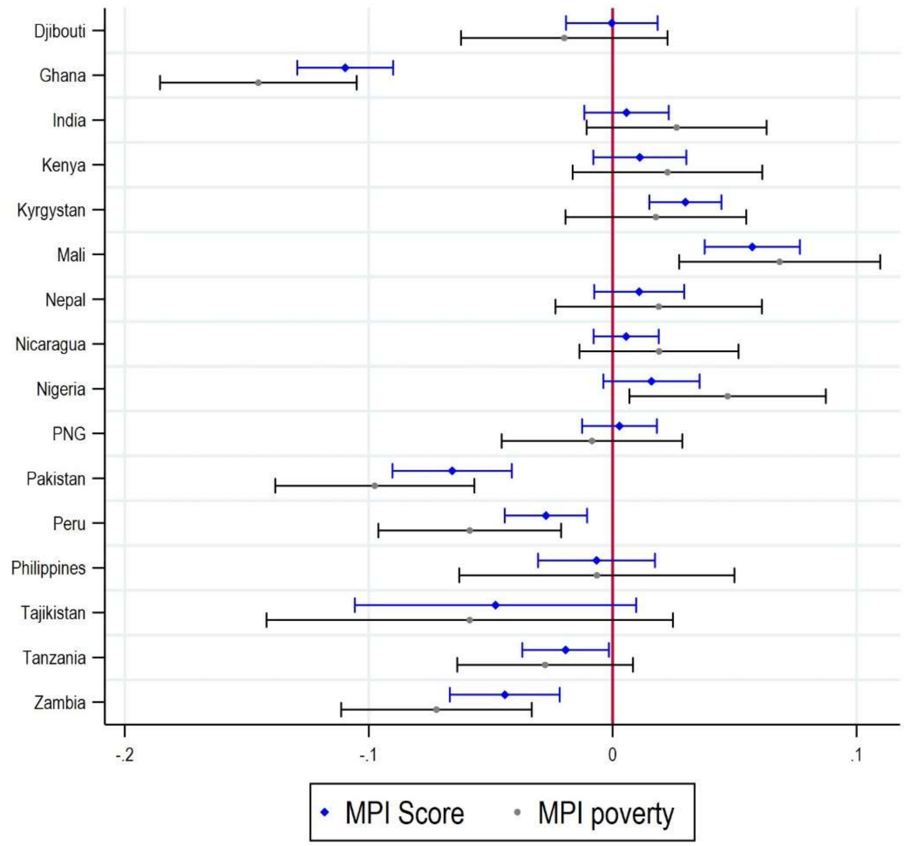

Figure 2. Impact on MPI score and MPI poverty rate by country.

Notes: The graph shows impact estimates and associated 90% confidence interval from country-level analysis. MPI score is a continuous indicator, and MPI poor is a binary indicator (whether a household's MPI score is equal or above 0.33). Each impact estimate is based on a separate linear regression. Each regression controls household-level variables (household size, male members, sex of household head, and head's age) as well as fixed effects for the country of intervention, data collection year, and data collection quarters. Standard errors are clustered at the intervention placement level.

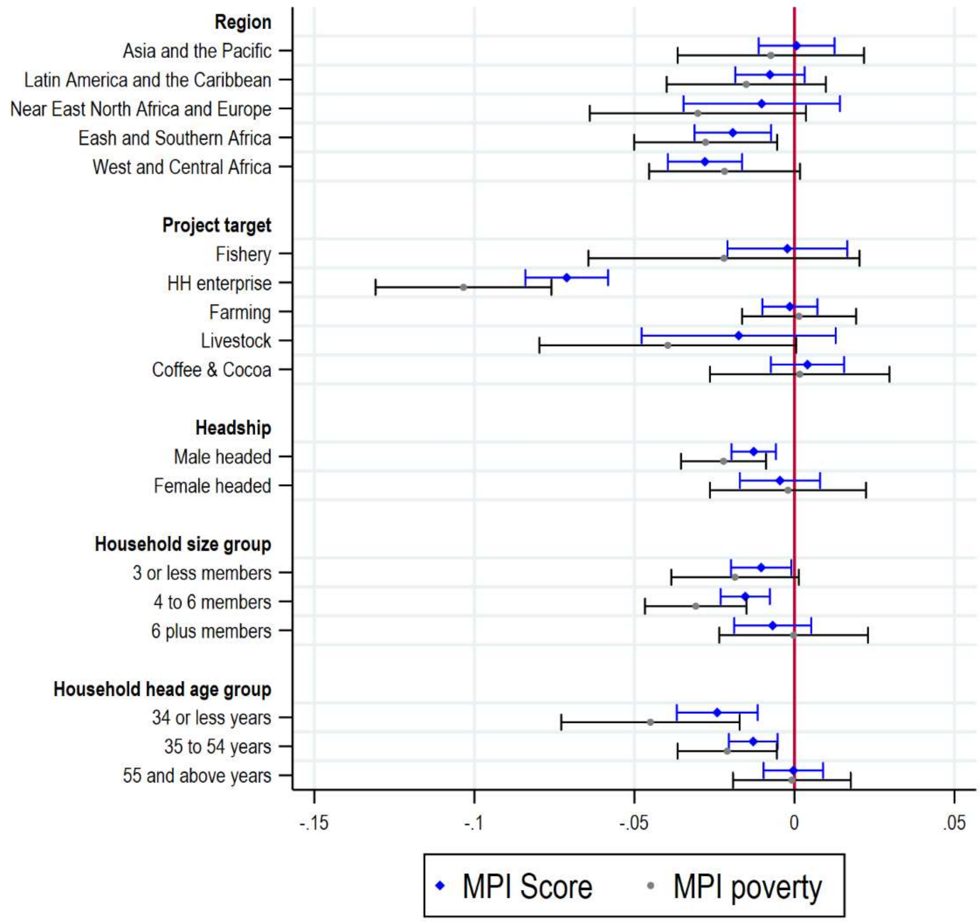

Figure 3. Impact on MPI score and MPI poverty rate by subsample.

Notes: The graph shows impact estimates and associated 90% confidence interval from country-level analysis. MPI score is a continuous indicator, and MPI poor is a binary indicator (whether a household's MPI score is equal or above 0.33). Each impact estimate is based on a separate linear regression. Each regression controls household-level variables as well as fixed effects for the country of intervention, data collection year, and data collection quarters. Standard errors are clustered at the intervention placement level.

Table 1. Summary Statistics

	All Mean	Treatment Mean	Control Mean	Standardized differences
	(1)	(2)	(3)	(4)
Demographic indicators				
Total number of household members	4.95	4.93	4.97	-0.02
Total number of male household members	2.61	2.58	2.64	-0.04
Total number of female household members	2.53	2.51	2.55	-0.03
No. of household members aged >=15 and <24	0.89	0.89	0.89	0.00
No. of household members >=65	0.28	0.28	0.28	0.00
No. of household members <15	1.79	1.77	1.81	-0.02
Female household head (1=yes)	0.17	0.17	0.16	0.01
Age of household head in years	50.04	50.01	50.06	0.00
Education of household head in years	5.50	5.49	5.51	0.00
Endline MPI indicators				
MPI score	0.32	0.33	0.31	0.07
MPI poor	0.46	0.47	0.45	0.05
Cooking fuel	0.76	0.74	0.77	-0.07
Sanitation	0.62	0.64	0.61	0.06
Electricity	0.20	0.21	0.19	0.06
Drinking water	0.20	0.20	0.21	-0.03
Housing	0.57	0.57	0.56	0.02
Assets	0.38	0.39	0.37	0.04
Child education	0.19	0.19	0.20	-0.01
Adult education	0.28	0.29	0.27	0.05
Food insecurity	0.26	0.27	0.25	0.05
Baseline MPI indicators				
Cooking fuel	0.91	0.84	0.98	-0.02
Sanitation	0.74	0.75	0.73	0.05
Electricity	0.50	0.54	0.46	0.01
Drinking water	0.46	0.48	0.43	0.01
Housing	0.56	0.55	0.56	-0.03
Assets	0.52	0.54	0.51	0.05

Notes: All MPI indicators except the MPI scores are binary variables. MPI score is a continuous indicator, and MPI poor is a binary indicator (whether a household's MPI score is equal to or above 0.33). For MPI-related indicators, variables other than "MPI score" and "MPI poor" indicate whether a household is deprived of that category or not. Education and food insecurity data are missing for the baseline period. Total sample size is 31,968, of which 16,674 are beneficiary households and the rest of the 15,294 households are comparison households.

Table 2. Impact of interventions on multidimensional poverty

	MPI score				MPI poor			
	OLS	IPWRA	Entropy	DID	OLS	IPWRA	Entropy	DID
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	-0.012***	-0.011**	-0.011**	-0.008	-0.018**	-0.020**	-0.019**	0.020**
	(0.004)	(0.005)	(0.004)	(0.017)	(0.007)	(0.009)	(0.009)	(0.008)
Post				-0.268***				-0.372***
				(0.016)				(0.007)
Post X Treatment				-0.005				-0.046***
				(0.019)				(0.010)
Constant	0.201***		0.163***	1.414*	0.578***		0.235*	0.853***
	(0.041)	(0.043)	(0.045)	(0.827)	(0.117)		(0.130)	(0.077)
Observations	31,968	24097	24,097	63,936	31,968	24097	24,097	63,936
R-squared	0.300	0.309	0.259	0.025	0.193	0.489	0.189	0.275
Counterfactual value	0.324		0.323	0.317	0.465		0.466	0.494

Notes: MPI score is a continuous indicator, and MPI poor is a binary indicator (whether a household's MPI score is equal to or above 0.33). Each regression controls household-level variables (household size, male members, sex of household head, and head's age) as well as fixed effects for the country of intervention, data collection year, and data collection quarters. Standard errors are clustered at the intervention placement level. The counterfactual mean is measured as the average among the treatment group minus the estimated treatment effect for the OLS, Entropy, and DID columns. IPWRA method estimates the counterfactual value by default. Asterisks indicate the level of statistical significance: * at 10 percent; ** at 5 percent; *** at 1 percent. Treatment effect is in the row titled "Treatment" for the OLS, Entropy, and IPWRA specifications and in the row titled "Post X Treatment" for the DiD specification.

Table 3. Impact on multidimensional poverty deprivation indicators

	OLS		IPWRA		Entropy	
	Coeff	SE	Coeff	SE	Coeff	SE
	(1)	(2)	(3)	(4)	(5)	(6)
Cooking fuel	0.035***	(0.009)	0.017	(0.012)	0.017*	(0.010)
Sanitation	-0.012**	(0.006)	-0.009	(0.007)	-0.008	(0.007)
Electricity	-0.021***	(0.007)	-0.015**	(0.008)	-0.017**	(0.008)
Drinking water	0.007	(0.009)	0.006	(0.010)	0.016	(0.011)
Housing	-0.014**	(0.006)	-0.020***	(0.006)	-0.019***	(0.006)
Assets	-0.018***	(0.007)	-0.014**	(0.006)	-0.014**	(0.006)
Child education	-0.002	(0.008)	0.003	(0.007)	0.003	(0.007)
Adult education	-0.010*	(0.006)	-0.020**	(0.009)	-0.019**	(0.008)
Food insecurity	-0.022***	(0.007)	-0.016*	(0.009)	-0.016*	(0.008)

Notes: All the variables are binary indicators, indicating whether a household is deprived in that indicator or not. Each regression controls household-level variables (household size, male members, sex of household head, and head's age) as well as fixed effects for the country of intervention, data collection year, and data collection quarters. Standard errors are clustered at the intervention placement level. The counterfactual mean is measured as the average among the treatment group minus the estimated treatment effect. Asterisks indicate the level of statistical significance: * at 10 percent; ** at 5 percent; *** at 1 percent.

Appendix A

Table A1. Definition of MPI dimensions and deprivation indicators used.

Dimensions	Indicator	Deprived if…
Living Standards	Cooking fuel	A household cooks using solid fuel such as dung, crops, shrubs, wood, charcoal, or coal.
	Sanitation	The household has unimproved or no sanitation facility, or it is improved but shared with other households.
	Drinking water	The household's source of drinking water is not safe, and drinking water is a 30-minute or longer walk from home roundtrip.
	Electricity	The household has no electricity.
	Housing	The household has inadequate housing materials in any of the three components: floor, roof, or walls.
	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.
Education	Years of schooling	No eligible household member has completed six years of schooling.
	School attendance	Any school-aged child is not attending school up to the age at which he/she would complete class 8.
Health	Food security	The probability of being moderate to severely food insecure exceeds 50 percent.

Notes: Definitions are based on the OPHI notes on MPI methodology.

Table A2. Comparison of deprivation indicators (and dimensions) used to estimate MPI and the corresponding weights.

	OPHI		This study (all dimensions)	
	Dimensions	Weight	Dimensions	Weight
Living standard	Housing Assets Electricity Drinking water Sanitation Cooking fuel	1/18 1/18 1/18 1/18 1/18 1/18	Housing Assets Electricity Drinking water Sanitation Cooking fuel	1/18 1/18 1/18 1/18 1/18 1/18
Education	Adult school attainment Child school attendance	1/6 1/6	Adult school attainment Child school attendance	1/6 1/6
Health and nutrition	Nutrition Child mortality	1/6 1/6	Food insecure	1/3

Notes: OPHI shows the original method proposed by OPHI, (2018). The "all dimensions" indicates the MPI score calculated using indicators of three dimensions. The "Living standard dimension" indicates the MPI score calculated using indicators of only the living standard dimension.

Table A3. Full list of impact assessment studies

	Region	Country	Project full name	Why dropped
1	APR	India	Post-Tsunami Sustainable Livelihoods Programme for the Coastal Communities of Tamil Nadu	NA
2		Nepal	Adaptation for Smallholders in Hilly Areas Project	NA
3		Pakistan	Southern Punjab Poverty Alleviation Project	NA
4		Papua New Guinea	Productive Partnerships in Agriculture Project	NA
5		Philippines	Second Cordillera Highland Agricultural Resource Management Project	NA
6		Solomon Islands	Rural Development Programme - Phase II	Education data only for household heads.
7	ESA	Ethiopia	Rural Financial Intermediation Programme II	Education, infrastructure, and housing are missing. No FIES data
8		Lesotho	Smallholder Agriculture Development Project	Baseline data is missing
9		Kenya	Upper Tana Catchment Natural Resource Management Project	NA
10		Malawi	Sustainable Agricultural Production Programme	Baseline data is missing
11		Mozambique	Pro-Poor Value Chain Development in the Maputo and Limpopo Corridors	Asset, education, infrastructure, and housing data are missing. No FIES data.
12		Tanzania	Marketing Infrastructure, Value Addition and Rural Finance Support Programme	NA
13		Zambia	Smallholder Productivity Promotion Programme	NA
14	LAC	Argentina	Inclusive Rural Development Programme	Education data only for household head.
15		Bolivia	Economic Inclusion Programme for Families and Rural Communities in the Territory of Pluractional State of Bolivia	Education data only for household head. No FIES data.
16		Nicaragua	Adapting to Markets and Climate Change Project	NA
17		Peru	Strengthening Local Development in the Highlands and High Rainforest Areas Project	NA
18	WCA	Ghana	Rural Enterprises Programme III	NA
19		Mali	Rural Microfinance Programme	NA
20		Mauritania	Poverty Reduction Project in Aftout South and Karakoro - Phase II	FIES variables are not correctly constructed.
21		Nigeria	Value Chain Development Programme	NA
22	NEN	Djibouti	Programme to Reduce Vulnerability in Coastal Fishing Areas	NA
23		Kyrgyzstan	Livestock and Market Development Programme II	NA
24		Tajikistan	Livestock and Pasture Development Project II	NA
25		Tunisia	Agropastoral Development and Local Initiatives Promotion Programme for the Southeast - Phase II	Education data only for household head.

Table A4. List of impact assessment studies

		Intervention characteristics			Survey information		
Region	Country	Main target sector/activity	Start year	End year	Survey year	Sample size	Treatment (N)/ Control (N)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
APR	India	Fishery	2005	2020	2020-2021	2598	1.27
	Nepal	Farming	2016	2022	2022-2023	2409	1.01
	PNG	Coffee & cocoa	2011	2019	2020-2021	3348	1.30
	Pakistan	Livestock	2011	2023	2021	3273	1.35
	Philippines	Farming	2011	2020	2021-2022	2000	1.00
LAC	Nicaragua	Coffee & cocoa	2014	2021	2021	1854	1.09
	Peru	HH enterprise	2013	2019	2019	1803	0.97
NEN	Djibouti	Fishery	2014	2020	2021	1327	0.93
	Kyrgyzstan	Livestock	2014	2021	2021	2729	1.04
	Tajikistan	Livestock	2017	2021	2021	1228	0.94
ESA	Kenya	Farming	2012	2022	2021	1597	0.97
	Tanzania	Farming	2011	2020	2021	1806	1.15
	Zambia	Farming	2014	2019	2020	1971	1.13
WCA	Ghana	HH enterprise	2012	2022	2021	1674	0.89
	Mali	Farming	2010	2019	2019	1080	1.01
	Nigeria	Farming	2012	2022	2020	1271	0.99

Notes: Total sample size is 31,968, of which 16,674 are beneficiary households and the rest of the 15,294 households are comparison households. Column 8 shows the ratio of treatment and control households by country. Region indicates IFAD's operational hub, where APR stands for Asia and the Pacific; ESA stands for East and Southern Africa; LAC stands for Latin America and the Caribbean; NEN stands for Near East North African and Europe; and WCA stands for West and Central Africa.

Table A5. Cluster information

Region	Country	Cluster	Level
APR	India	Yes	Panchayat
	Nepal	Yes	Ward
	PNG	Yes	Ward
	Pakistan	Yes	village
	Philippines	Yes	Barangay
LAC	Nicaragua	Yes	cooperative
	Peru	No	No
NEN	Djibouti	No	No
	Kyrgyzstan	Yes	village
	Tajikistan	Yes	Municipality (Jamoat)
ESA	Kenya	No	No
	Tanzania	No	No
	Zambia	Yes	Ward
WCA	Ghana	No	No
	Mali	No	No
	Nigeria	No	No

Note: Cluster indicates the level of intervention placement.

Table A6. MPI score and poverty rate by country.

	MPI Score All Mean	MPI Score Treatment Mean	MPI Score Control Mean	Std diff.	MPI Poor All Mean	MPI Poor Treatment Mean	MPI Poor Control Mean	Std diff.	OPHI	World Bank
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Djibouti	0.37	0.37	0.37	0.01	0.56	0.58	0.55	0.06	.	0.29
Ghana	0.39	0.47	0.29	0.70	0.57	0.67	0.44	0.47	0.25	0.33
India	0.18	0.19	0.17	0.08	0.33	0.33	0.32	0.01	0.16	.
Kenya	0.39	0.39	0.39	0.01	0.57	0.57	0.57	0.00	0.38	0.45
Kyrgyzstan	0.18	0.14	0.21	-0.48	0.17	0.14	0.21	-0.18	0.00	0.01
Mali	0.46	0.43	0.48	-0.25	0.77	0.74	0.80	-0.13	0.68	0.44
Nepal	0.26	0.25	0.27	-0.08	0.25	0.24	0.27	-0.06	0.18	0.27
Nicaragua	0.22	0.21	0.23	-0.09	0.28	0.26	0.30	-0.08	0.17	0.16
Nigeria	0.41	0.39	0.42	-0.11	0.64	0.61	0.67	-0.14	0.46	0.42
PNG	0.35	0.35	0.35	-0.02	0.47	0.47	0.47	0.01	0.57	0.75
Pakistan	0.40	0.44	0.37	0.27	0.59	0.66	0.55	0.23	0.38	0.17
Peru	0.31	0.33	0.29	0.17	0.42	0.46	0.38	0.16	0.07	0.07
Philippines	0.12	0.13	0.12	0.07	0.18	0.19	0.18	0.04	0.06	0.08
Tajikistan	0.40	0.43	0.37	0.27	0.64	0.68	0.60	0.17	0.07	0.07
Tanzania	0.39	0.41	0.37	0.15	0.57	0.60	0.54	0.12	0.57	0.55
Zambia	0.50	0.53	0.48	0.24	0.77	0.81	0.73	0.18	0.48	0.67

Notes: MPI poor is a binary indicator showing whether a household's MPI score is equal to or above 0.33. OPHI and World Bank statistics are taken from their official website for the latest available period.

Table A7. Impact on MPI score and MPI poverty rate by country.

	MPI score		MPI poverty	
	Coeff	SE	Coeff	SE
	(1)	(2)	(3)	(4)
Djibouti	-0.000	(0.011)	-0.020	(0.026)
Ghana	-0.110***	(0.012)	-0.145***	(0.025)
India	0.006	(0.010)	0.026	(0.022)
Kenya	0.011	(0.012)	0.022	(0.024)
Kyrgystan	0.030***	(0.009)	0.018	(0.022)
Mali	0.057***	(0.012)	0.068***	(0.025)
Nepal	0.011	(0.011)	0.019	(0.025)
Nicaragua	0.006	(0.008)	0.019	(0.020)
Nigeria	0.016	(0.012)	0.047*	(0.024)
PNG	0.003	(0.009)	-0.008	(0.022)
Pakistan	-0.066***	(0.015)	-0.098***	(0.025)
Peru	-0.027***	(0.010)	-0.059**	(0.023)
Philippines	-0.007	(0.014)	-0.006	(0.034)
Tajikistan	-0.048	(0.034)	-0.059	(0.049)
Tanzania	-0.019*	(0.011)	-0.028	(0.022)
Zambia	-0.044***	(0.014)	-0.072***	(0.024)

Notes: The graph shows impact estimates and associated 90% confidence interval from country-level analysis. MPI score is a continuous indicator, and MPI poor is a binary indicator (whether a household's MPI score is equal to or above 0.33). Each impact estimate is based on a separate linear regression. Each regression controls household-level variables (household size, male members, sex of household head, and head's age) as well as fixed effects for the country of intervention, data collection year, and data collection quarters. Standard errors are clustered at the intervention placement level.

Table A8. Impact on MPI score and MPI poverty rate by sub-sample.

		MPI score		MPI poverty	
		Coeff	SE	Coeff	SE
	(1)	(2)	(3)	(4)	(5)
Region	APR	0.001	(0.007)	-0.007	(0.018)
	LAC	-0.008	(0.007)	-0.015	(0.015)
	NEN	-0.010	(0.015)	-0.030	(0.021)
	ESA	-0.019***	(0.007)	-0.028**	(0.014)
	WCA	-0.028***	(0.007)	-0.022	(0.014)
Project target	Fishery	-0.002	(0.011)	-0.022	(0.026)
	HH enterprise	-0.071***	(0.008)	-0.103***	(0.017)
	Farming	-0.001	(0.005)	0.001	(0.011)
	Livestock	-0.017	(0.018)	-0.040	(0.024)
	Coffee & cocoa	0.004	(0.007)	0.002	(0.017)
Headship	Male	-0.013***	(0.004)	-0.022***	(0.008)
	Female	-0.005	(0.008)	-0.002	(0.015)
Household size group	3 or less members	-0.010*	(0.006)	-0.019	(0.012)
	4 to 6 members	-0.015***	(0.005)	-0.031***	(0.010)
	6 plus members	-0.007	(0.007)	-0.000	(0.014)
Household head age group	34 or less years	-0.024***	(0.008)	-0.045***	(0.017)
	35 to 54 years	-0.013***	(0.005)	-0.021**	(0.009)
	55 and above years	-0.000	(0.006)	-0.001	(0.011)

Notes: The graph shows impact estimates and associated 90% confidence interval from country-level analysis. MPI score is a continuous indicator, and MPI poor is a binary indicator (whether a household's MPI score is equal to or above 0.33). Each impact estimate is based on a separate linear regression. Each regression controls household-level variables as well as fixed effects for the country of intervention, data collection year, and data collection quarters. Standard errors are clustered at the intervention placement level.

Table A9. Impact on multidimensional poverty deprivation indicators

	Cooking fuel	Sanitation	Electricity	Drinking water	Housing	Assets	Child education	Adult education	Food insecurity
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment	0.035***	-0.012**	-0.021***	0.007	-0.014**	-0.018***	-0.002	-0.010*	-0.022***
	(0.009)	(0.006)	(0.007)	(0.009)	(0.006)	(0.007)	(0.008)	(0.006)	(0.007)
Constant	0.650***	-0.014	0.380***	-0.343**	0.155*	0.147	0.143	0.367***	0.084
	(0.046)	(0.107)	(0.115)	(0.157)	(0.082)	(0.128)	(0.191)	(0.092)	(0.082)
Observations	26,695	31,968	31,968	31,968	31,968	31,968	18,572	31,968	31,968
R-squared	0.448	0.517	0.235	0.182	0.504	0.463	0.161	0.231	0.175
Counterfactual value	0.737	0.619	0.209	0.201	0.573	0.384	0.197	0.275	0.271

Notes: All the variables are binary indicators, indicating whether a household is deprived in that indicator or not. Each OLS regression controls household-level variables (household size, male members, sex of household head, and head's age) as well as fixed effects for the country of intervention, data collection year, and data collection quarters. Standard errors are clustered at the intervention placement level. The counterfactual mean is measured as the average among the treatment group minus the estimated treatment effect. Asterisks indicate the level of statistical significance: * at 10 percent; ** at 5 percent; *** at 1 percent.

Table A10. Recall data comparison

	(1) Actual- Recall baseline MPI score	(2) Actual- Recall baseline MPI status
Treatment	0.027	-0.044
	(0.029)	(0.230)
Constant	0.243***	0.044
	(0.025)	(0.181)
Observations	1,112	1,112

Notes: Dependent variable in column one (two) shows the absolute differences in MPI score (MPI poverty status) based on original baseline data and recalled baseline data. Only the sample from the Nepal study is used in this analysis. Standard errors are clustered at the intervention placement level for all regression specifications.

Appendix B:

Inverse probability-weighted regression adjustment (IPWRA)

In IPWRA, inverse probability weights are combined with regression adjustment to improve the comparability of beneficiary and comparison groups (Wooldridge 2010). After computing the inverse probability weights (matching Equation), the IPWRA method employs a weighted regression (outcome equation) to estimate the predicted value of the outcome for the beneficiary and comparison households:

$$y_{hc} = \alpha_0 + \alpha_1 \times \text{Treat}_{hc} + \mu X_{hc} + \eta \left(X_{hc} - E[X_{hc} | \text{Treat}_{hc} = 1]\right)\text{Treat}_{hc} + \xi_{hc}$$

All the notations are the same as in Equation (1). In the matching Equation that estimates probability weight (i.e., probability of program participation), X_{hc} includes household-level control variables and dummy indicators for country and region/provincial administrative level.

Entropy balancing method.

The entropy balancing method matches treatment households with control households based on observable attributes. This approach calculates weights for control households in line with predefined balanced constraints (for example, achieving balance in the mean, variance, or skewness of characteristics). Following this, entropy balancing uses these weights in a regression framework.

The approach, formulated by Hainmueller (2012), presents several benefits compared to traditional matching methods. It eliminates the iterative process of matching and balance verification, which can be inefficient and may sometimes result in suboptimal covariate balance. Instead, entropy balancing achieves balance by constructing a synthetic control group that mirrors the treatment group based on the constraint imposed by the users. Additionally, this method does not require an empirical model to determine the probability of project participation, unlike the requirements of other propensity score matching techniques (Apeti and Edoh, 2023). We used the same set of matching variables used in the IPWRA method for this analysis.

Difference-in-difference (DiD)

The regression model is as follows:

$$y_{hc} \ = \alpha_0 + \alpha_1 \times \ \text{Post}_t + \alpha_2 \times \ \text{Treat}_{hc} + \alpha_3 (\text{Post}_t \times \ \text{Treat}_{hc}) + \ \mu\, X_{hc} + \ \eta\, C + \ \xi_{hct}$$

where y_{hc} is the MPI poverty score of household h from country c in time t (i.e., endline or baseline); Post_t is a dummy variable equal to 1 if endline (post-program period) and zero otherwise; Treat_{hc} is a dummy variable taking a value of 1 if the household h from country c is a beneficiary household and 0 otherwise. X_{hc} presents household-level control variables (e.g., household size, number of male members, whether headed by a female, and age of household head) to capture for any differences at the household level; C consists of fixed effects for countries (to account for country level difference), year of the start of the intervention (to account the variation in interventions' duration), and quarter of data collection (to account seasonal pattern in the data). Finally, ξ_{hct} captures household-level unobservable factors. α_3 is the coefficient of interest, showing whether the interventions have any impact on the MPI poverty level or not. The baseline MPI score is based only on the living standard dimension. The two missing dimensions in the baseline data are education and food security.

Appendix C: Brief overview of Impact Assessment Studies

India: Post-Tsunami Sustainable Livelihoods Programme (PTSLP) for the Coastal Communities of Tamil Nadu

Objective

Develop viable enterprises and resource management systems in the coastal communities affected by the 2004 tsunami. Build self-reliant coastal communities that are resilient to shocks and able to manage their livelihood base in a sustainable manner.

Timeline

IFAD approved PTSLP in 2005, launched it in July 2007 with an original completion date of May 2014, and went on to grant approvals for two additional financing spates. These extended the project implementation, expanded geographic coverage, and moved the final project completion date to 30 March 2020.

Data

Data were collected from 2,741 households (1,527 beneficiaries and 1,214 comparison households) residing in 147 panchayats (89 beneficiary panchayats and 58 comparison panchayats). To select a valid counterfactual of households, the impact assessment study replicated the same criteria used to select the beneficiaries of the PTSLP during its initial design and rollout. The impact assessment data collection was implemented between December 2020 and January 2021.

Nepal: Adaptation for Smallholders in Hilly Areas Project (ASHA)

Objective

The ASHA was an eight-year long project aimed at improving the adaptation capacity of smallholders and institutions. The project promoted natural resource management and climate-resilient agricultural and forestry practices and technologies. Specifically, the project supported the construction and rehabilitation of climate-resilient communal infrastructures such as irrigation canals, rainwater harvesting systems, water ponds, and landslide control infrastructures.

Timeline

ASHA is an 8-year project that began in 2014 and completed in 2022.

Data

Data were collected from 2,414 households (1,215 treated and 1,199 control). Control households were selected randomly from wards located in the same area where the ASHA project was not implemented.

Pakistan: Southern Punjab Poverty Alleviation Project (SPPAP)

Objective

The Southern Punjab Poverty Alleviation Project (SPPAP) aims at reducing poverty and improving the living conditions of the rural population of the poorest households in six districts with the highest incidence of poverty in Punjab. It does so by enhancing the employment potential and boosting agricultural productivity and production for the target population of poor and ultra-poor households identified using a poverty scorecard, with a special focus on women. SPPAP initially targeted the districts Bahawalnagar, Bahawalpur, Muzaffargarh and Rajanpur and later extended activities to Dera Ghazi Khan and Rahim Yar Khan.

Timeline

The project is an ongoing intervention, which began in 2010 and will be completed by 2023.

Data

The IA of SPPAP employs a mixed methods approach by combining qualitative and quantitative primary data. The qualitative data was collected through 15 key informant interviews, 77 in-depth interviews, and 12 transect walks. The quantitative data was gathered through 3,321 beneficiary and non-beneficiary household interviews and 126 interviews with community leaders, across the districts Bahawalnagar, Bahawalpur, Muzaffargarh, and Rajanpur. The quantitative IA identifies SPPAP's impact with an ex-post non-experimental approach by matching and comparing beneficiaries and non-beneficiaries similar in their characteristics before the SPPAP intervention started. The IA of SPPAP focused on the two components livestock package and vocational and entrepreneurial training, which are considered two separate treatment arms.

Papua New Guinea: Productive Partnerships in Agriculture Project (PPAP)

Objective

Improve the livelihoods of cocoa and coffee small-scale producers in Papua New Guinea by enhancing the performance and sustainability of the respective value chains.

Timeline

The PPAP entered into force in 2010 with original completion planned for 2016. In 2014, IFAD approved additional financing for PPAP leading to an extension of the project with completion in 2021.

Data

The impact assessment relied on combining quantitative data from 3,500 farmers (1,750 cocoa and 1,750 coffee), 277 community surveys, and qualitative data from 53 focus group discussions, key informant interviews, and in-depth discussions. Analysts created a valid counterfactual using statistical matching together with geospatial data and machine learning.

Philippines: Second Cordillera Highland Agricultural Resource Management Project (CHARMP2)

Objective

To improve the livelihoods of poor households of indigenous communities living in the Cordillera Administrative Region (CAR) through introducing sustainable agricultural and agri-business development, improved land tenure security and food security, and conservation of watersheds and highland forests.

Timeline

IFAD approved financing of the CHARMP2 project in April 2008 with an original completion date set for December 2015. However, in 2016, IFAD approved additional financing for the project, extended the completion date to June 2021.

Data

Data were collected from 2,000 households (1,000 beneficiaries and 1,000 comparisons) and 100 barangays (50 beneficiaries and 50 comparisons). To select comparison households, the IA study used a GPS coordinates-based household listing complemented by a screening interview.

Republic of Kenya: Upper Tana Catchment Natural Resources Management Project (UTaNRMP)

Objective

Contribute to the reduction of rural poverty in the Upper Tana River catchment area. Enhance the area's sustainable use and management of natural resources – land, water, and biodiversity – for greater environmental services and increase sustainable food production and income.

Timeline

UTaNRMP is a 10-year project that began in 2012 and will complete towards the end of 2022.

Data

Data were collected from 1,608 households (792 treated and 816 control). Control households were selected randomly in wards located in counties at least partially falling within the Tana River basin where no project activities were conducted.

Tanzania: Marketing Infrastructure, Value Addition and Rural Finance Support (MIVARF) program

Objective

Sustainably enhance income and food security of smallholders by increasing their access to a wider range of financial services and output markets and promote the adoption of productivity-increasing sustainable agricultural technologies.

Timeline

IFAD approved MIVRAF in December 2010 as a seven-year nationwide programme. In 2018, it was extended for two years with the completion date set for March 2020. An additional extension was made in October 2020 with the completion and closing date set for 31 December 2020.

Data

To mimic the targeting scheme of MIVARF, comparison wards were selected through statistical matching within MIVARF targeted LGAs/districts, and producer groups involved in MIVARF's relevant value chains were identified within these wards. The final selection of the control group then occurred among households belonging to these groups. The final sample size was 1,828 households (968 treated and 860 control).

Republic of Zambia: Smallholder Productivity Promotion Programme (S3P)

Objective

The S3P aimed to increase the incomes and food and nutrition security of small-scale farmers who cultivated no more than 5 hectares by boosting agricultural production, productivity and sales of cassava, groundnut, and mixed-beans systems. It also promoted farmers' group participation and adoption of agricultural practices such as improved planting materials as well as conservation agriculture which encompasses minimum/zero tillage, soil cover, crop rotation or intercropping.

Timeline

The programme, approved in 2011, was implemented in Zambia's Luapula, Muchinga, and Northern provinces by the Ministry of Agriculture (MoA) through a public-private partnership strategy from 2013 to 2019.

Data

The estimation of the S3P's impact was based on an ex-post non-experimental sample design that covered 198 communities and 2,052 households (both beneficiaries and non-beneficiaries). Surveys, implemented in October–November 2020, collected detailed livelihood data for the 2019/2020 agricultural season. Two levels of matching ensured that control households represented a good counterfactual, i.e., treated households had they not received the S3P interventions.

Peru: Strengthening Local Development in the Highlights and High Rainforest Areas Project (PSSA)

Objective

The PSSA aimed to unlock rural development and poverty reduction in Peru through three components: i) supporting the formation of producer associations (PAs) and advising on development and implementation of business plans (PDNs); ii) supporting the development of community natural resource management plans (PGTs), and iii) strengthening local governance. The impact assessment focused on the first component, which encouraged producers to form producer groups and provided support in developing business plans. Once the plans were developed, PSSA provided financial support and training on business management and production techniques to implement the plans.

Timeline

The project was implemented from 2013 to 2019 in 85 districts across four departments – Cajamarca, Lima, Amazonas, and San Martin.

Data

The impact assessment of the PSSA project used project M&E data and Peru's 2012 National Agricultural Census (CENAGRO) to identify well-matched treatment, control, and spillover communities. Significant spillover impacts were expected; therefore, the sample frame included a spillover group. Once identified, a household questionnaire was administered to 982 PA members, 1,047 control households, and 1,074 spillover households – all of which had been randomly sampled. In addition, a community questionnaire was administered to the 97 treated, 90 control, and 106 spillover communities from which the households had been sampled. Finally, a third questionnaire was administered to 167 PA leaders.

Republic of Nicaragua: Adapting to Markets and Climate Change Project (NICADAPTA)

Objective

Sustainably improve the living conditions of small-scale coffee and cocoa producers by increasing their competitiveness and reducing their vulnerability to climate shocks. To achieve these objectives, the project introduced producers' organizations to productive investments and technical assistance with a specific focus on women, youth, indigenous and Afro-descendant communities.

Timeline

Approved in 2013 and then implemented from 2014 until 2020.

Data

The estimation of NICADAPTA's impact was based on an ex-post quasi-experimental sample design that covered 2,107 coffee and cocoa producer households in 100 of the NICADAPTA cooperatives and 100 non-NICADAPTA cooperatives. A comprehensive baseline farmer survey was conducted in 2014 and the endline household questionnaire was administered between March and May 2021. The comparison farmer group was defined as being a member of a cooperative that never received any funding from NICADAPTA through PIs. Two levels of matching ensured that comparison households represented a good counterfactual: i.e., what would have happened to treated households if they had not received the NICADAPTA interventions on key indicators of production, resilience, and livelihoods.

Ghana: Rural Enterprises Programme – Phase III (REP III)

Objective

Improve livelihoods and income of poor rural micro- and small enterprise (MSE) entrepreneurs by increasing the number of rural MSEs that generate profit, growth, and employment opportunities.

Upscale and mainstream a district-based support system for rural MSEs implemented during REPs I and II, which preceded REP III.

Timeline

REP III was approved in 2011 and implemented in 2012. The programme's original completion date of 2020 has been extended until 2024.

Data

REP III's IA, conducted from 2019 to 2021, focused on its activities from 2011 to 2019, which was the original financing portion of the project. As an ex-post IA, it used a quasi-experimental design that required the construction of a comparison group to serve as a counterfactual. Identification of a valid counterfactual for REP III was challenging given the programme's national coverage and self-targeting. It entailed use of geospatial data to set physical distance buffers and statistical matching. Final sample size was 1,738 households (817 beneficiaries and 921 comparison).

Republic of Mali: Rural Microfinance Programme (PMR)

Objective

Improve the livelihoods of people living in poverty and extreme poverty in marginalized areas, especially women and youth, by increasing access to financial services and credit markets. Focus activities on strengthening existing credit unions and expanding their geographic coverage to provide easier access to financial services for people in rural areas.

Timeline

IFAD approved PMR on 25 March 2009 and it became effective on 21 July 2010. Project Implementation lasted eight years and was completed on 30 September 2018.

Data

The ex-post IA used a quasi-experimental statistical matching design that required construction of a valid comparison group to serve as a counterfactual. Based on beneficiary data provided by the NGOs involved in project implementation, two treatment arms and a control arm were created: (i) the credit group that received both training and group-based credit, (ii) the training group, which received only training, and (iii) the comparison group. The final sample size was 1,161 households, including 575 treated (383 in the credit group and 192 in the training group) and 586 in the comparison group.

Federal Republic of Nigeria: Value Chain Development Programme (VCDP)

Objective

Sustainably enhance the income and food security of poor rural households engaged in production, processing, and marketing of rice and cassava in targeted states through an inclusive strategy. Focus activities on strengthening the capacity of producers, processors, and other actors along the value chains, as well as public and private institutions, service providers, policymakers, and regulators.

Timeline

VCDP was implemented in the six states of Anambra, Benue, Ebonyi, Niger, Ogun, and Taraba across southern and central Nigeria from 2013 to 2019. As a recall, this period covers the original phase of the project before it received additional financing in 2018 and 2019. The project has now been extended and will close in 2024.

Data

The IA focused on the activities supported as part of VCDP's original financing portion which was from 2012 to 2019. The ex-post IA used a quasi-experimental design that could be formalized within the potential outcome framework of a binary treatment case that requires construction of a counterfactual. The following conditions were considered when identifying the non-beneficiary FOs to include in the control group: focus crop, geography, agroecological conditions, proximity to VCDP locations, and FO size. The final sample size was 1,784 households (879 treatment and 905 comparisons).

Republic of Djibouti: Programme to Reduce Vulnerability in Coastal Fishing Areas (PRAREV)

Objective

PRAREV- aimed to support poor and vulnerable populations affected by climate change in coastal localities and promote the fishing value chain by increasing beneficiaries' access to fishing equipment, fish landings, and infrastructure to make them more productive and resilient to climate change. In addition, the project aimed to improve the welfare of the target population by strengthening the fish value chain and creating a supportive environment by including climate adaptation policies in national strategies.

Timeline

PRAREV was approved on 12 December 2013 and remained active until 2021.

Data

The IA of PRAREV was conducted between October 2021 and January 2022. The ex-post IA used a quasi-experimental design requiring the construction of a control group. Sampling involved a full enumeration of households belonging to fishing cooperatives and fishers in the targeted regions. Since the listing exercise covered just enough households to reach the targeted sample based on power calculations, no sample selection was done. All households listed were selected based on full beneficiaries' enumeration. Final household data were collected from 1,385 households (637 treated and 748 non-beneficiaries).

Kyrgyzstan: Livestock and Market Development Project II (LMDP II)

Objective

LMDP II aimed to enhance livestock productivity and strengthen the climate resilience of Kyrgyzstan's pasture communities by supporting community-based associations in managing local pastures, livestock health, and the development of income-generating activities.

Timeline

The project was implemented in Batken, Osh and Jalal-Abad regions of southern Kyrgyzstan from 2014 to 2020.

Data

The estimation of the LMDP II's impact was based on quantitative and qualitative data collected between August 2019 and April 2020. The quantitative analysis relied on an ex-post quasi-experimental sample design that included both beneficiaries and non-beneficiaries from 3,002 households across 158 villages.

Having two levels of matching ensured that initial differences between LMDP II and comparison areas were accounted for.

Republic of Tajikistan: Livestock and Pasture Development Project Phase II (LPDP II)
Objective
The LPDP II, which targeted poor small-scale livestock farmers, private veterinary service providers, and vulnerable women-headed households, was designed to improve the living conditions and enhance the food and nutrition security of livestock farmers by boosting livestock productivity and improving the productive capacity of pastures.
Timeline
During its 5-year operation – from 2017 to 2021 – the project established rotational pasture plans, water points, veterinary services, breeding techniques, and fodder production, alongside the capacity building and strengthening of social capital implemented through Pasture Users' Unions (PUUs).
Data
The appraisal of the LPDP II impact was based on an ex-post quasi-experimental sample design that covered 82 communities in 9 districts and 1,496 households (both beneficiaries and non-beneficiaries). Surveys to collect detailed livelihood data were undertaken from August through October 2021. Matching ensured that comparison households characterized a good counterfactual by representing the situation of treated households if they had not received the LPDP II interventions.
