IMPACT ASSESSMENT REPORT

People's Republic of China

Guangxi Integrated Agricultural Development Project (GIADP)

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Executive summary

Improving market access of smallholder farmers in the developing world is considered an important approach to moving them out of poverty and increasing their economic mobility. In China, rural poverty has declined at a phenomenal speed within just two decades, and much of this success story is attributable to rapid income growth in rural areas. Thus, having a good understanding of how development efforts in rural China may help alleviate poverty and improving economic mobility is of particular interest for policy, as they are instrumental in informing future project design and scaling-up of success stories to other regions in China as well as to other countries.

The Guangxi Integrated Agricultural Development Project (GIADP) is an example of a development effort aimed at increasing rural household income in China through three project components: community infrastructure development, agricultural production and marketing support, and rural environmental improvement. The project was approved by the Executive Board of the International Fund for Agricultural Development (IFAD) in December 2011, entered into effect in January 2012, and ran until March 2017. Interventions delivered covered three main components: community infrastructure improvements, agricultural production and marketing support, and interventions aimed at preserving the rural environment.

The overall goal of the impact assessment of GIADP is to attempt to measure the impact of the GIADP on four core dimensions: agricultural production, economic mobility, food security and resilience. Because these outcomes cannot always be measured directly, we use a set of proxy variables for each of these core outcomes. Moreover, since the GIADP included different sub-components, we attempt to measure the average effects of the project on the classes of outcomes listed above, along with trying to measure the impact of some specific components.

In order to measure the impact of GIADP primary data was collected from a representative pool of beneficiaries (treatment group) and non-beneficiaries (control group). The impact assessment methodology employs a non-experimental design. Because the impact assessment is conducted in an *ex post* manner, there are two primary estimation challenges: (1) to properly construct treatment and the counterfactual or control groups, and (2) to attempt to limit bias in impact estimates due to non-random placement of the program. To address these challenges, the identification strategy relies on a three stage matching approach, where the counterfactual is first determined at administrative village (AV) level where AVs are matched within counties (AVs); then at natural village level (NVs); and last, at household level where households are consequently matched within such AVs and NVs. In addition, the AVs and NVs sample selection was further validated through a consultation with key informants and experts, who confirmed the validity of the counterfactual.

In terms of impact estimation strategy, a number of estimators, namely the inverse probability weighting estimator with regression adjustment (IPWRA), the inverse probability weighting estimator (IPW), covariate matching (NN), propensity score matching (PSM), and the regression adjustment (RA) estimators were compared and employed to verify the robustness of results.

Impact estimates are computed for the whole sample, and for specific sub-samples, namely poor and vulnerable counties (the relatively better off ones) and samples of counties receiving different sets of interventions within the poverty category (specifically, AVs receiving (1) agricultural production and marketing support only, (2) infrastructural development only, (3) agricultural production and marketing support along with infrastructural development, and (4) agricultural production and marketing support along with rural environmental improvement). The sub-group analyses are essential to understand the heterogeneity of project impact, given that different treatment intensity occurred, i.e. the distribution of interventions was not homogeneous across all AVs.

The quantitative findings indicate that beneficiary households have higher yields and value from production of their crops, in particular fruit crops, and this finding is particularly strong for the vulnerable counties sample among those receiving agricultural support and infrastructure interventions. We also find higher yields and value from production of vegetable crops among those receiving agricultural support and environmental improvement interventions, an innovative intervention approach introduced by GIADP for potential scaling-up to other areas in the future. In terms of economic mobility and income returns, we do not observe a significant impact on the income aggregate, except for vulnerable counties (albeit marginally significant) while we also find a positive and significant impact on household savings for the same counties, highlighting the result that savings accumulation can only happen in context where there is sufficient income growth. On the other hand, given the strong pro-poor focus of the project, we find that households in poorer counties, exhibit positive and significant changes in assets ownership, specifically durable assets, and this finding is particularly strong for the sub-sample of households who receive the agricultural and marketing components, and even larger for those receiving infrastructure and agricultural interventions combined (albeit marginally significant in the latter case, given the small sample size). In addition, we find an impressive impact on poverty dynamics, where treated households are more likely to move out of poverty. These findings are consistent across almost all asset-based relative poverty lines, and across all sub-samples, and are particularly strong when using the durable assets index distribution to define the poverty lines.

While our results show lower dietary diversity for treated households in a number of instances, compared to households in the control group, such findings are particularly unstable across the different specifications and the sub-samples, warranting further research. Relative to the resilience dimension, proxied by both the coping strategy and the ability to recover indicators, we did not find any positive and significant impact except for households residing in poor counties and receiving the infrastructural component.

These results point out to at least two implications for future research and more generally for policy design of rural development efforts. First, the findings confirm that agricultural, marketing related and infrastructure interventions tailored to context-specific conditions can generate positive and significant impacts. However, further research, possibly with ex ante impact assessments, is still needed to understand the mechanisms and channels through which improvements in agricultural production and market access may help beneficiary farmers improve their welfare. For instance, additional investigation is required to understand farmers' decisions vis a vis marketing opportunities and the relevant constraints that might prevent farmers from taking full advantage of such opportunities. Second, the strong impacts on assets and particularly the ones on durable and productive assets for the less well-off households receiving both agricultural and infrastructural-related interventions combined, raise a point of consideration for future design of rural development projects. Particularly, it motivates the need to investigate the possibility of implementing integrated approaches covering two key aspects of rural development, namely the provision of agricultural and marketing support, along with infrastructural development geared towards the improvement of market access, price transmission and the reduction of transaction costs, particularly for those at the bottom end of the income distribution. This would maximise the benefits of individual interventions and would allow smallholders to fully benefit from the outcomes that can be brought about by production-oriented interventions, and thus permitting them to permanently move out of poverty and improve economic mobility.

Additionally, as further projects are developed with the Government of China, we suggest considering how the project will be evaluated for impacts as the project is designed. The type of ex post evaluation done here is quite imperfect because of the lack of a proper control group designed at project inception, and the inherent challenges of reconstructing it ex post, coupled with a lack of exact knowledge about to whom which products or components were offered, in other words, the imprecision of the treatment distribution, which was only identified at a high level of aggregation (administrative villages). In addition, in demand-driven programs it is important to understand and control for the types of unobservable factors that lead people to participate in the projects, and properly designed ex ante impact assessments can go a long way to address implementation and other issues in future projects mid-stream, so that proper impacts can be attained.

In addition, an important recommendation is worth making. M&E systems should be geared towards collecting granular data of both beneficiaries reached, along with their targeting characteristics and interventions delivered (quantity and timing), to be able to correctly monitor the treatment distribution over the life of the project particularly when the project is multi-components. These data are essential to the design of internally and externally valid impact assessments.

1. Introduction

In September 2015, the United Nations (UN) adopted the Sustainable Development Goals (SDGs) as an overarching framework for sustainable development. One of the SDGs, SDG 1, is to eradicate all forms of poverty by 2030. One current approach to alleviate poverty and fostering economic development among the rural poor is to improve their access to markets (Sachs, 2005; Smith, 2015). Earlier works on the topic have focused on analysing the role of domestic markets in instigating economic development (Rosenstein-Rodan, 1943; Murphy et al., 1989). However, more recent empirical studies have quantified the economic costs of being geographically remote, away from local markets (Jacoby, 2000; Minten and Kyle, 1999; Mu and van de Walle, 2007).

China presents a special example to investigate the efforts of rural poverty alleviation and economic development. Between 1980 and 2001, the prevalence of poverty in the rural areas of China declined from 76% to 13% (Ravallion and Chen, 2004). In particular, much of this incredible achievement is attributed to lifting income in the rural area (de Janvry et al., 2005). Existing evidence from China has indicated that increased access to rural infrastructures and markets is correlated with the improvement in poverty-related and wealth-related outcomes (Emran and Hou, 2013). Thus, rural development projects aimed at improving access to rural infrastructures and markets have the potential to alleviate poverty and foster economic development in rural areas. Therefore, having a good understanding of how rural development efforts in China may contribute to improving the livelihoods of the rural poor would definitely generate several lessons to be learned for future project design and implementation, and also to inform policy formulation to address rural poverty.

GIADP represents one attempt to address such development challenges by improving rural infrastructures and increasing access to markets of smallholder farmers in rural China. GIADP is a multi-component rural development project which took place in the Guangxi Zhuang Autonomous Region (GZAR) of the People's Republic of China. The project was approved by the Executive Board of IFAD in December 2011, and entered into effect in January 2012. The project completed its interventions and activities in March 2017. The main focus of the project is to foster rural development and poverty reduction. The project consists of three components: (1) community infrastructure (rural road and irrigation infrastructures), (2) agricultural production and marketing support, and (3) rural environmental improvement.[1] Through the activities implemented during the course of GIADP, project beneficiaries are expected to increase their revenue from agricultural production through innovative approaches. Thus, the focus of this impact assessment is to investigate the extent to which the project may help its beneficiaries increase their revenue from production and other related outcomes. Further, we are interested in impact heterogeneity, in other words, assessing the extent to whichthe different types of interventions implemented by GIADP generated an impact.

To construct a valid counterfactual , the backbone of non-experimental designs and counterfactual-based impact assessments, we use both statistical approaches and validation with expert advice . This combined effort resulted in a list of control areas which were statistically and contextually comparable to treatment areas. The dataset used in this impact assessment report came from primary household and community (conducted at the AV level) surveys, which were collected between July and September 2017. The surveys collected information from households and communities in project (treatment) and non-project (control) AVs. The dataset contained information about socioeconomic characteristics, livelihood and income-generating activities, and access to information, social capital, and social support.

[1] The GIADP project also consists of the project management component. The project activities in this component includes the recruitment of project staff members, procurement of project intervention tools and equipment necessary to deliver the project activities, monitoring and tracking of project activities, and overall management of the project activities. However, this component is not the focus of our impact assessment.

In this impact assessment report, results are presented in the following order. First, we present the analyses of the pooled or total sample. Then, we explore the heterogeneous impacts of the project: first by the poverty category at the county level, and second by type of project intervention received.

We start by presenting in the next section the project's theory of change including background of the project, targeting criteria and geographical coverage, the relevant research questions that were addressed in this impact assessment, and its relevance to existing literature. Then, we describe the overall empirical approach to assess the project, and the methodology to construct the counterfactual whose outcome and impact indicators would be compared to those of the project beneficiaries to quantify project impact. Following this section, we report the profile of the project beneficiaries from our sample. Next, we present the results from the full sample and from the sub-samples determined by type of project intervention received and the poverty status of the county, and discuss the findings. Finally, we conclude with a summary of lessons learned and policy implications.

2. Theory of change and research questions

2.1 GIADP theory of change

In Figure 1, we present the logical framework of the project from which derive the theory of change (TOC). The project activities, which included activities related to community infrastructure, agricultural production and marketing support, and rural environmental improvement, should help the project beneficiaries in the following ways. First, the project by constructing and improving community infrastructures, which included irrigation infrastructure systems, water supply sources, and village roads, should increase the productive capacity of its beneficiaries through improved water supply and allocation/management, and greater market access/participation. Second, project activities included various capacity building and training activities related to agricultural and livestock production to the beneficiaries.[2] As a result, beneficiaries should have greater access to information about agricultural practices and technology. Third, members of the beneficiary communities improve their access to agricultural markets through the establishment of local agricultural stations and the strengthening of rural market linkages by providing technical support related to processing and packaging to increase value of produce. Finally, project activities constructed biogas digester systems and improved sanitary systems in beneficiary communities, both of which may help the members of the communities have access to more sustainable agricultural practices and improve their ability to cope with negative exogenous shocks, in other words, shocks that cannot be controlled for by the individuals.[3]

The GIADP project activities can be categorized into three main components: (1) community infrastructure (e.g. paving of village roads, lining of irrigation canals, construction of safe water drinking sources, etc.), (2) agricultural production and marketing support (e.g. niche crops such as hawthorn, siraitia, pomegranate, pitaya, persimmon, macadamia nut, kiwi fruit, sugarcane, and litchi, etc.) and livestock trainings (e.g. pigs and goats), construction and improvements of local agricultural stations, support to cooperatives and complementary package for value chain development, etc.), and (3) rural environmental improvement (e.g. installation of biogas digester systems, improvements of sanitation facilities, upgrades of kitchens and latrines, etc.).

The activities under the community infrastructure component and the agricultural marketing support activities were delivered to all AVs covered by the project[4]. However, the activities under the agricultural production (both niche/cash crop and landrace livestock), and the rural environmental improvement components were designed to be tailored to the local needs and suitability of each AV. Specifically, the village implementation groups (VIGs) formed as part of the project in each AV discussed the types of crops and livestock to be cultivated and supported as part of the project with project staff members in each county. After the types of crops and livestock were agreed upon, the VIG leaders developed a context specific curricula related to the crops and livestock in question. After that, marketing activities were tailored to the types of niche/cash crops and landrace livestock mutually agreed and thus covered by the project.

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[2] The project activities related to agricultural and livestock production include training farmers on the cultivation and marketing of niche and cash crops (cultivation practices and improving crop values depending on the crop type) and landrace livestock (provision of improved livestock breed and cultivation of livestock products).

[3] Based on our discussions with the project staff, the project curriculum related to more sustainable agricultural practices mainly involves training the farmers to rely less on chemical fertilizers, and rely more on organic fertilizers for their crop cultivation. Further, the installation of biogas digester systems should make beneficiaries less reliant on firewood collection from the surrounding forest areas. However, we learned that the impact from the biogas system is expected to be small, and we decided not to focus on evaluating this impact of the project.

[4] The community infrastructure component of the project is designed to contain three types of infrastructure: roads, irrigation canals, and drinking water sources. However, our discussions with the project team revealed that the paving of village roads were delivered to all AVs covered by the project, whereas the lining of irrigation canals and the construction of drinking water sources were delivered to only a selected number of AVs.

While it is true that separate project components may lead to changes in the outcomes of beneficiary households and communities through distinct causal channels, it is important to recognize that project activities in each component may interact. Having a good understanding of how project components may interact allows researchers to design an impact assessment strategy, along with identifying comprehensive outcome and impact indicators relevant to the project logic. For example, improvements in road conditions allow farmers - who have been trained to raise their productivity - to access the agricultural markets at the right time and ensure the best prices for their harvest (Minten and Kyle, 1999; Mu and van de Walle, 2007). Further, farmers who have greater output levels due to improved production practices can take advantage of the improved road access to markets and the strengthened linkages to markets to raise their agricultural income (Banerjee et al., 2012; Casaburi et al., 2013; Datta, 2012; Faber, 2014; Aggrawal, 2016; Qin and Zhang, 2016). Similarly, it is expected that AVs receiving the project will be strengthened and empowered by being more able to accumulate and mobilize resources to address any occurring development challenges and initiate new income-generating activities through participating in project activities (Asfaw et al, 2012; Azzarri et al., 2015; Minde et al., 2008). This might imply that beneficiaries communities have greater organization skills and capacity to take advantage of investment opportunities related to agriculture and infrastructure in the future (Beath et al., 2018).

Two further considerations are important while designing impact assessments: the assumptions related to the project's logical framework, and the potential effects of the project interventions on non-beneficiaries, albeit named spillover effects. Regarding the former issue, Figure 1 outlines the assumptions within the logical framework necessary to generate the expected changes at the output, outcome, and impact levels. These assumptions include (1) having the project activities tailored to suit the local conditions and institutional context, (2) having sufficient demand and take-up of project activities by communities and households, (3) having sufficient market linkages between farms and markets, (4) having sufficient market demand for agricultural products in the area, (5) having continuous provision of project activities throughout the project life, and (6) beneficiaries not facing any unforeseen shocks or constraints that might prevent them from taking full advantage of project activities.

Figure 1: GIADP's logical framework

INPUTS AND ACTIVITIES

Institutional development

- Formation of VIGs
- Trainings related to agriculture and management

Comm. infrastructures/ rural environment

- Building and upgrade of irrigation, road, drinking water supply and sanitation facilities, biogas digesters
- Trainings related to operation, maintenance, and repair

Agricultural production and marketing support

- Trainings related to agricultural extension, niche crop production, and livestock rearing
- Improvement township agricultural stations
- Support to cooperatives
- Complementary packages for value-chain development

OUTPUTS

Comm. Infrastructures

- Canals lined, roads paved, water sources built
- Farmers trained to maintain facilities

Rural environment

- Biogas digesters built, latrines renovated, kitchens built, livestock sheds renovated
- Village sanitation facilities built

Ag. production

- Niche crops demonstrated and scaled-up
- Breeding stock provided
- Farmers trained by gender

Ag. marketing

- Ag. stations built, crop facilities built, coops built, markets built, equip. provided
- Farmers admitted to training programs and trained, support offered

OUTCOMES

Household Level

- Increased input use
- Expanded cultivation area
- Increased crop productivity
- Increased sales of crop (both quantity and value)
- Reduced vulnerability to production and climatic shocks

AV Level

- Increased membership and participation in AV activities
- Improved management of land and environmental resources
- Sustainable agricultural practices maintained

IMPACTS

Household Level

- Increased income
- Increased assets
- Increased food and non-food consumption
- Improved nutrition and dietary diversity
- Improved resilience to production and climatic shocks

AV Level

- Ability to mobilise owned implements
- Ability to mobilise additional resources
- Ability to expand activities

ASSUMPTION

Inputs and activities:

- Sufficient local capacity to form local project offices and deliver project activities
- Project support sustained throughout project duration
- Close supervision by project staff to ensure project effectiveness
- Infrastructures are functioning and well-maintained

Outputs:

- Minimal or no catastrophic shocks in project communities and households
- Sufficient means to receive information about agricultural production and marketing
- Sufficient market activities to sustain the operation of agricultural stations
- Sufficient linkages to markets and financial services

Outcomes and impacts:

Household Level

- Markets for inputs, credit, and outputs exist and function well with sufficient supply of inputs and credit and demand for agricultural products
- No other barriers to improving agricultural outcomes such as weather conditions or crop diseases

AV Level

- Sufficient ability to manage AV activities by leaders and members
- Sufficient capacity to accumulate and mobilize capital and labor resources for AV activities

One potential concern related to the specific sets of project interventions, is the inherent potential of infrastructure-related interventions to generate spillover effects at community level. In other words, the upgrading of village roads might benefit non-beneficiaries living in nearby communities. Based on our review of project documents and the discussions with the project team, the upgrading of village roads mostly involved short-distance or "last-mile roads," which are feeder roads, linking the project AVs to the main road and replacing traditional walking paths. As a result, we expect that the spillovers to other non-beneficiaries to be minimal given the fact that these roads are highly localized and for specific use of the AV residents.[5] However this hypothesis may be contested on grounds that it may be possible that the project interventions might have impacts on the local economy beyond the project AVs, generating spillover effects that are in the realm of general equilibrium effects, that might impact the nearby AVs. For example, Aggarwal (2016) shows that road construction in India had an effect on local crop prices in the project districts. Project activities can indeed generate greater demand for agricultural labour from non-beneficiaries through the improvements of irrigation canals and the strengthening of marketing linkages, as highlighted in the literature (Del Carpio et al. 2011; Headey et al., 2010). However, we try and address this, by excluding in our selection of eligible counterfactual AVs, those that are connected to the treatment AVs.

Regarding all other project components, all farmers within each AV receive project activities with different intensity. Thus, it is likely that the majority of the impacts of the project should be contained within the project AVs. Finally, while it is likely that farmers who receive training activities offered by the project may share the knowledge with those who do not receive any training, we anticipate that the extent to which this knowledge sharing takes place is minimal, and thus is not a major concern in this impact assessment (Witt et al., 2008; Songsermsawas et al., 2016).

2.2. Project coverage and targeting

Eight counties in GZAR have been selected to be covered by GIADP. The GIADP project focuses on targeting the poor and vulnerable households in 509 AVs of 50 townships. Based on the project's database, a total of approximately 1,339,189 people are expected to have benefitted from the project. It is estimated that 60% of all beneficiaries are considered poor and vulnerable according to subjective wealth ranking which is used to rank households within each the project areas. The list of counties and townships selected to be part of the GIADP project is as follows in Table 1. The areas which received the project are illustrated in Figure 2.

The targeting strategy of the beneficiary communities and households was conducted in a participatory manner. First, eligible counties (a total of eight) and townships (a total of 50 in eight counties) were selected to receive the project through a participatory poverty assessment approach.[6] Next, the AVs selected to receive project interventions (a total of approximately 509 AVs) were identified through the poverty assessment in a participatory manner. Within each AV, a participatory subjective wealth-ranking assessment was conducted to identify the poor and vulnerable households, in order to prioritize them for project inclusion. Finally, the project activities were designed and implemented to meet the local demands of the beneficiaries, and to ensure benefits to the targeted population through extensive consultations among the VIG members in each AV.

[5] To further rule out the possibility of spillovers to indirect beneficiary AVs, the PPMO provided us a list of indirect beneficiary AVs. We exclude these indirect beneficiary AVs from our sample.

[6] Based on our discussions with the project staff members, CPMO and TPMO staff members were invited to participate in the poverty assessment exercise as part of the selection process to be included in the GIADP project. Invited staff members were asked to assess the poverty levels of their counties and townships based on the number of households in each poverty category, as defined by the PAO. After that, the counties and townships were selected to receive the project based on their assessed poverty levels.

Figure 2: GIADP project areas

Source: IFAD

Table 1: List of project counties and townships

County	Township
Beiliu (6)	Beiliu, Dali, Tangan, Liuma, Mingle, Xinrong
Cenxi (6)	Botang, Malu, Nuotong, Anping, Cencheng, Guiyi
Du'an (6)	Gaoling, Bao'an, Chengjiang, Longwan, Disu, Daxing
Leye (4)	Luosha, Xinhua, Gantian, Tongle
Longzhou (5)	Xiadong, Binqiao, Jinlong, Shuikou, Xiangshui
Pingle (6)	Pingle, Zhangjia, Shazi, Yangan, Qinglong, Dafa
Tengxian (10)	Jinji, Mengjiang, Heping, Taiping, Gulong, Tongxin, Langnan, Tianping, Tengzhou, Xiangqi
Yongfu (7)	Longjiang, Baishou, Sanhuang, Baoli, Yongfu, Luojin, Yongan

Table 2: Distribution of project areas at the township and at the AV levels

County	GIADP township	Non-GIADP township	GIADP AV	Non-GIADP AV	GIADP beneficiary	GIADP non-beneficiary
Beiliu	6	8	84	197	395,813	945,517
Cenxi	6	8	90	182	298,314	517,564
Du'an	7	11	20	228	65,032	578,876
Leye	4	4	13	85	26,955	127,774
Longzhou	5	6	40	76	78,530	168,941
Pingle	6	3	62	72	176,749	218,754
Tengxian	10	1	118	73	474,647	257,640
Yongfu	6	2	82	17	238,862	53,139
Overall	50	43	509	930	1,754,902	2,868,205

In Table 2, we present the distribution of the number of GIADP and non-GIADP project areas at the township and at the AV level by each county. Also, we present the number of GIADP beneficiaries and non-beneficiaries in each project county.

2.3 Research questions

In this impact assessment study, the key research questions follow the project's TOC as suggested in White (2009). The main research questions as part of this impact assessment are as follows.

Question 1: Do households in project areas have higher use of physical inputs (seed, fertilizer, and pesticide) as a result of the project? Do they have larger crop cultivation areas relative to those in non-project areas?

Question 2: Do households in project areas experience higher crop yields than those in non-project areas? If yes, which types of crops have higher yields?

Question 3: Do households in project areas generate greater levels of income from crop and livestock production than those in non-project areas?

Question 4: Do households in project areas have dietary diversity than those of non-project areas? Are they more able to cope with food insecurity incidents?

Question 5: Are households more resilient to negative exogenous shocks than those in non-project areas? Specifically, do they experience less frequent and less severe shocks, and are able to recover better from shocks than those in non-project areas?

Question 6: Do households in project areas move out of poverty as a result of the project?

3. Impact assessment design: Data and methodology

3.1 Data

Addressing the research questions for the ex post impact assessment of the GIADP project requires collecting extensive data. In this impact assessment, we employ a mixed-method approach, with a non-experimental design which relies mainly on quantitative methods of enquiry and qualitative interviews. The quantitative investigation consists of two main surveys with specific questionnaires: a household survey and a community survey administered at the AV and NV levels. The household survey collects information mainly on household-level indicators related to agricultural production and household consumption expenditure and income. The community survey focuses mainly on indicators related to access to community-level infrastructure, roads, agricultural markets, environmental conditions, and resilience. The qualitative interviews consist of key informant interviews administered to project staff and village leaders in the project areas.

Obtaining a valid counterfactual is a necessary condition for a rigorous impact assessment, or the estimates derived from the analysis will contain bias, in other words, will not reflect adequately the project impact. To account for selection on observables, i.e. due to features that can be controlled for and identified in this impact assessment, we employ a three-level matching approach where we reconstruct the counterfactual at three levels. This statistical approach is further validated with an expert consultation with key informants, which consist mainly of project staff who are familiar with the project and the areas covered by the project. They were requested to validate the quality of the matched treatment and control locations to ensure that they are similar at baseline, and thus could serve as the appropriate comparison group. This validation exercise resulted in the final list of treatment and control AVs to be included in our sample.

Potential biases such as non-random placement of the project locations could have a direct implication on the validity of the counterfactual. This is an important consideration for this impact assessment since agricultural projects are often placed in context where there is a need, hence this factor is likely to be correlated with agro-climatic factors, and pre-existing local conditions such as limited access to markets and roads (Dillon, 2011).[7] However, we account for these potential sources of bias by addressing selection on observables, i.e. due to features that can be controlled for and identified in this impact assessment, through a three-level matching strategy where we reconstruct the counterfactual at three levels. This statistical approach is further validated with an expert consultation with key informants.

The steps for the three level matching are the following: first, we matched or paired project and non-project AVs, based on similar baseline characteristics. This first level of matching ensures that AVs face similar conditions, in terms of, for instance, similar agro-ecologic conditions, initial poverty levels and population density. Second we matched treatment and control NVs. Third, we matched households in both treatment and comparison AVs to determine the final analyses sample.

In order to understand the targeting mechanism, we held various discussions with project staff members. It was revealed that the key criteria for selecting beneficiaries AVs into the project was their poverty levels, as measured by the shares of household belonging to each poverty category.[8] Therefore, the counterfactual determination focused on mimicking the targeting strategy, by finding

[7] A subset of regions which received the GIADP project activities were already part of an earlier IFAD-supported project in GZAR, the West Guangxi Poverty Alleviation Project (WGPAP), which was closed in 2008. These regions originally under WGPAP were selected to also be part of GIADP to strengthen the impact of the WGPAP project as they were areas with high poverty rates. However, there was insufficient information about which areas/communities under WGPAP were also part of GIADP.

[8] More details about the poverty classification for households in rural China can be found later in this document.

non-project AVs with similar poverty levels, along with similar baseline characteristics that might ensure that that treatment and comparison AVs are comparable.

The Provincial Project Management office (PPMO) staff members provided us with a comprehensive dataset containing the list of all beneficiaries AVs in every township of all eight counties based on the project's M&E system. In this dataset, there was detailed AV-level baseline information on a number of key variables such the number of natural villages (NVs), the number of households, the total male and female population, the total Han and ethnic minority population, the size of dryland and irrigated areas, the annual precipitation level, the number of cooperatives, and the numbers of households in each poverty category: A, B, or C.[9] The sampling strategy employed to determine the final number of treatment and the comparison AVs followed a two-stage approach. First, we asked the PPMO staff members to provide us with a complete list of AVs (both project and non-project). From this comprehensive list of AVs obtained from the M&E system, we ranked the beneficiaries AVs in each county by the extent of project activities received and divided this distribution into quartiles. Then, we randomly selected a number of project AVs, within each strata, which is determined by the level of project activities or intensity delivered in each AV.[10]

The heterogeneity in the distribution, or intensity, of project activities delivered in each AV, is an important element in our sampling strategy. This means that the project essentially consisted of three components with different treatment intensity. In Table 3, we present the heterogeneity in the treatment intensity e.g. in the distribution of project's interventions of the AVs that we included in the impact assessment sample. Of the 63 project AVs we collect data from, community infrastructure interventions were implemented in 40 AVs, agricultural production and marketing support interventions were delivered in 32 AVs, and interventions related to rural environmental improvement were delivered in 23 AVs. This implies that there are different interventions combinations within AVs and counties and that the interventions were not equally distributed within AVs. Therefore there is differential dosage, resulting in AVs receiving more and different sets of interventions than others. In addition, project delivery and project implementation may be also heterogeneous in different areas conditional on the capacity of local institutions, timing, geographical attributes, and beneficiary characteristics.

Table 3: Project intervention intensity by component

Project component	Number of AVs implemented
Community infrastructures	40 (63%)
Agricultural production and marketing support	32 (51%)
Rural environmental improvement	23 (37%)
Total	**63 (100%)**

Source: GIADP project database and primary data collected for this impact assessment

After randomly selecting the AVs within the strata, we ran propensity score matching (PSM, with five nearest neighbours and with kernel) to pair up the GIADP AVs (treatment) with the non-GIADP

[9] Households in China can be classified into three categories in terms of poverty level, according to the classification published by the Poverty Alleviation Office (PAO) of the People's Republic of China. Category A consists of households whose per capita income level are greater than CNY 3,000 a year. Category B consists of households whose per capita income level are between CNY 1,196-3,000 a year. Category C consists of households whose per capita income level are less than CNY 1,196 a year.

[10] Detailed information about the sampling strategy can be found in the impact assessment plan of the GIADP project (Garbero and Songsermsawas, 2017) .

AVs according to a number of AVs attributes that mimicked the targeting strategy. This led us to a number of non-GIADP AVs deemed suitable to serve as the counterfactual or comparison group. PSM was run within each of the eight counties separately, to ensure that suitable counterfactual AVs would only be found within the same county.[11] PSM ultimately ensures that GIADP AVs are similar to non-GIADP AVs in terms of observable characteristics, notably the ones available in the project's M&E data system. In Table 5, we report the variables used for matching project and non-project AVs. As the project targeted AVs mainly based on poverty levels, such variables include the share of households belonging to either B or C category along with other AV-level characteristics.

To validate the counterfactual, and ensure the appropriateness of the selected non-GIADP AVs as an adequate comparison group, we held discussions with the PPMO and County Project Management Office (CPMO) staff members to help us verify the selection of the non-GIADP AVs to be included in the analyses of the project impact.

In addition, we had to ensure a procedure for selecting NVs within AVs, and consequently sample households within such NVs. The following strategy was designed.

1. From the list of treatment and control AV's, we asked the PPMO to provide us with a complete list of NVs in order to select the households within the NV within each AV. The list contained the following information related to:
    - Name of household head
    - Sex of household head
    - Poverty indicator at household level (whether the household was below or above the poverty line at baseline (year 2012) or earlier)
    - NV name
    - Variables for geographical and agro-ecological conditions for the NV (whether the NV was in a plain/mountainous area, slope, elevation, total arable area, total dry area)
    - Variables related to population composition (number of Han population and number of ethnic minority population, number of male and female population, number of households, population density of NV)
    - Administrative village name
    - Township name
    - County name

This was necessary to both select households that were comparable in poverty levels prior to the start of the project (2012) and to select NVs with similar agro-ecological and population density conditions.

2. We selected 15 households per NV to interview in treatment and control AVs. Once the treatment and control NVs had been selected, we paired them by "similarity" and assuming that a good match of NVs between treatment and control locations was obtained, we selected households in the NV's in a systematic way.
3. To solve the potential issue that selected households to be interviewed might not have been available for interviews, our strategy entailed the selection of another 5-10 additional households as reserves. This list was only employed if the households in the first list were not available for interviews. To ensure that there was a sufficient number of households in each selected NV, NVs with fewer than 20 households were removed from the list of eligible NVs to be selected for interviews.

The final dataset is therefore a cross-sectional household survey collected from 1,875 households (929 treatment and 946 control households) from 119 AVs in 119 NVs.[12] Propensity score matching makes sure that a sound counterfactual is determined provided that there is sufficient common

[11] PSM is conducted at the county level for all counties except for Yongfu county where PSM was not possible. This is because in Yongfu county, there are 82 AVs which received the project activities, and only 17 AVs without the project activities. Due to the small number of non-project AVs, we cannot match project and non-project AVs. Instead, we ask the project staff members at the county level to help us select the most appropriate non-project AVs to be part of our control locations.

[12] Initially, we had planned to collect data from 1,890 households. However, due to incomplete or missing data, we were able to use information collected from only 1,875 households.

support between households in treatment and control groups. Common support means that we statistically ensure that people with the same characteristics in treatment and control groups have a positive probability of being both participants and non-participants (Heckman et al., 1999). Implementing the common support condition ensures that any combination of characteristics observed in the treatment group (ideally prior to the project) can also be observed among the control group (Bryson et al. , 2002).

Matching results as shown in Figures 3 and 4 of Appendix 2 show that sufficient common support is achieved between households in treatment and control NVs and AVs, essentially confirming that the comparison group was constructed appropriately. In addition, Figure 5 in Appendix 2 demonstrates that matching substantially reduces the standardized percent of bias across all matching covariates. Specifically, a key statistics that assesses the quality of the counterfactual achieved through the matching, i.e. the Rosenbaum and Rubin bias, shows a reduction from 30.7% before matching to 16.8% after matching, which is lower than the recommended threshold of 25% as suggested in the literature (Rubin, 2001). Further, the relative ratio between the variances of all covariates in treatment and control groups is 0.83, which is within the recommended bound of (0.8, 1.25), also suggested in the literature (Rubin, 2001). The matched sample is further trimmed at the 2% lowest and the 98% highest propensity scores to improve the common support, a standard practice in the literature (Leuven and Sianesi, 2003).

After matching, 1,801 households were left in the full sample and used for analysis (892 treatment and 909 control households).

Descriptive statistics of the households in our sample are presented in Table 4, before and after matching. The latter confirms that there is a greater balance in the characteristics of the households in treatment and control groups after matching. Specifically, in the matched sample, across all variables considered, the only household-level characteristic that remains statistically different between treatment and control groups is the age of the household head. However, considering the magnitude of the difference is only 1.20 years, it is possible to conclude that an appropriate counterfactual group to estimate the project impact of GIADP was determined.

Table 4: Descriptive statistics of the sample before and after matching

Variable	Before matching			After matching		
	Treat. Mean	Control Mean	Diff.	Treat. Mean	Control Mean	Diff.
Household size	5.03	5.12	-0.09	5.06	5.11	-0.05
Sex of head (=1 if male)	0.92	0.91	0.01	0.92	0.91	0.01
Age of head	54.30	55.78	-1.47***	54.09	55.62	-1.52***
Education of head	1.58	1.57	0.01	1.59	1.58	0.01
Religion of head	1.233	1.138	0.094**	1.225	1.122	0.103***
Land owned (hectare)	4.45	4.55	-0.10	4.45	4.42	0.03
Distance to road (km.)	0.28	0.20	0.08**	0.20	0.17	0.03
Distance to market (km.)	7.37	7.73	0.47	6.80	6.93	-0.13
Number of children	1.152	1.258	-0.106	1.16	1.25	-0.09
Number of adults 15-64 years	3.36	3.31	0.05	3.385	3.318	0.067
Number of adults older than 65 years	0.46	0.48	-0.02	0.46	0.48	-0.01
Number of observations	929	946		892	909	

Note: .01 - ***; .05 - **; .1 - *; Level of education is coded as 0 = none, 1 = primary, 2 = secondary, and 3 = university or higher; Religion is coded as 1 = agnostic and 2= other.

To capture any potential project spillovers effects, there are at least three key considerations: identify the type of spillovers of interest (namely whether they are externalities, general equilibrium effects, interactions, or behavioural effects), the appropriate approach to account for the presence of spillovers possibly at design (in an ex ante fashion), and the identification of a valid counterfactual that adequately takes into account the presence of spillovers to non-beneficiaries if the spillovers cannot be neglected. Collecting detailed data from non-beneficiaries to investigate the presence of spillovers would imply a larger sample size, which also has a direct cost implication. However, as discussed earlier, we rule out the presence of spillover effects in our sample and we expect that spillovers of project activities to non-beneficiaries at AVs –level to be minimal, given the size of the infrastructure delivered and the size of the AV.

When the presence of spillovers due to project activities is likely to be high and spatially determined, it is advised that comparison locations in the sample are selected from areas located far enough from treatment locations to avoid any contamination bias.

3.2 Questionnaire and impact indicators

The household and the community questionnaires cover a broad range of information. This collected information is used to construct outcome and impact indicators to estimate the impact of GIADP.

The household-level questionnaire collects detailed information on agricultural production and marketing stratified by season, parcel, and crop from the most recent full agricultural season preceding the time of survey. It also consists of information about socio-economic characteristics, other sources of income, asset ownership, exposure to exogenous shocks, access to credit, savings, and other rural financial services, sources of information, social assistance programs, and social groups. The AV-level questionnaire includes information related to access to rural infrastructures, services, markets, sources of information, social assistance programs, and social groups.

In this impact assessment, we focus on estimating the project impact on four sets of indicators. We now turn to describing the specific key outcome and impact indicators that have been carefully analysed as part of this impact assessment based on the project logic described in the project's TOC as shown in Figure 1.

3.2.1 Agricultural production indicators

The first set of indicators considered in this impact assessment are those related to agricultural or crop production, which involve both crop inputs and crop outputs. All agricultural-production related variables cover a full agricultural season (12 months) preceding the time of survey. In particular, they cover the period between June 2016 and May 2017. For crop inputs, the first variable considered is the total area allocated to crop cultivation. In China, the unit of land measurement (mu) is standardized throughout the country, which ensures that there would be no measurement error arising from differences in local land measurement units across counties in our sample.[13] Then, the total rate of input use (kg./ha.) was calculated for the following physical inputs: seeds, fertilizers, and pesticides.

For crop outputs, we first calculated crop yields (kg./ha.) separately by crop type: grains, roots, vegetables, and fruits.[14] Values of crop production were then separately computed by crop type. Calculating the total gross value of crop production (crop revenues plus value of crops saved for home consumption) is appropriate in our setting because approximately only 33% of the households in our sample had sold their crops for cash at the time of the survey. Thus, computing the values of crops allocated for home consumption as well as crop revenues would be more appropriate in our setting than just focusing on crop revenues alone.

3.2.2 Economic mobility: income and savings indicators

Economic mobility indicators are defined as wealth proxies that may measure "income" changes from one time period to another. In this impact assessment, we include, income, savings, and asset based-indices. While changes in income and savings are assessed against the control group, for assets, we are able to look at dynamics, since we elicited recall data.

All indicators related to income and savings were collected at household level, with a reference period of 12 months preceding the time of data collection. The aggregated household income indicator was computed as the sum of the total value of crop production, the total income from livestock, the total income from livestock products, the total income from wage employment, and the total income from transfers. Savings was computed as the total amount of cash savings the household arising from access to either a financial institution or to other informal groups.

3.2.3 Economic mobility: other wealth indicators

To complement income and savings indicators, we also investigate project impact on household wealth proxies using asset-based indicators in order to provide a more comprehensive picture of project impact on household wealth and economic mobility. We compute asset indices by assigning

[13] A hectare is equivalent to 15 mu.

[14] The full list of crops included in each type of crop output variables is presented in Appendix 3.

weights to the counts of each asset item based on their distributions in the dataset. In the absence of reliable data on household expenditures, which are usually difficult and time-consuming to collect, building an asset index by reducing the different variables into a single indicator, is well established in the literature and can be a viable alternative to measure household wealth (Filmer and Pritchett, 2001; Sahn and Stifel, 2003).

A number of asset indices are computed in order to provide a comprehensive illustration of asset ownership namely housing assets, durable assets, productive assets, and livestock assets (the latter was also broken down into large and small livestock).[15] As the information on housing and durable assets have been collected as categorical variables, the literature recommends using multiple correspondence analysis (MCA) to compute these indeces. As the information on other types of assets have been collected as continuous variables, the respective asset indices were computed using the principal components analysis (PCA) methodology. The overall asset index was then computed by using the polychoric factor analysis methodology which is particularly powerful when aggregating different indices (Kolenikov and Angeles, 2004). Specifically, this method allows one to incorporate categorical variables into the PCA methodology.

3.2.4 Food security and resilience indicators

The dietary diversity indicator is calculated following FAO's household dietary diversity score (HDDS), which is a measure of the ability to access different food groups by a household (FAO, 2010). In our survey, HDDS was calculated from a set of 16 item responses which reflect the household's consumption experience of each food group during the 24 hours preceding the time of survey.

The coping strategy indicator is calculated following WFP's coping strategies index (CSI), which is a measure of the severity of the coping strategies implemented by households when facing food shortages.

Last, based on a subjective measure of shock incidence, i.e. households own perception of the occurrence and severity of shocks, we calculated the perceived ability to recover as a proxy for resilience. The latter is a measure that takes into account both the frequency, the severity of shocks, as well as the ability of households to cope both with idiosyncratic, namely household specific shocks and covariant shocks (community level ones).

3.2.5 Poverty reduction indicators

Poverty metrics are constructed based on the above mentioned asset-based indicators, to measure the probability of moving out of poverty. Asset-based poverty lines are relative poverty lines which are calculated using asset information from households' recalled responses at baseline. Asset-based poverty lines are set at the 40th and the 60th percentiles of the baseline asset index distribution (Booysen et al., 2008). To ensure that our asset-based poverty lines are not driven by the choice of the assets used in the calculation of the poverty lines, poverty indicators are calculated based on several types of asset indices namely overall, durable, productive, and livestock asset indices. In other words, this is equivalent to running a sensitivity analysis to the inclusion of different assets in the indices, and assess their implication for poverty classifications.

An indicator variable that indicates whether a household is below or above the poverty line is constructed based on the distribution of the asset index at baseline and at the time of survey. Households can be classified into four states: either moving out of poverty (if households are below the poverty line at baseline and are above the poverty line at the time of survey); remaining poor(if households are below the poverty line in both periods); remaining out of poverty (if a household is

[15] The full list of asset items included in each asset index is presented in Appendix 3.

above the poverty line in both periods); and last, moving into poverty (if households are above the poverty line at baseline, but are below the poverty line at the time of survey).

Following this classification, the distribution of households in our sample according to their poverty status is reported in Table 5, contingent on the asset index definition. In addition, estimating movement out of poverty requires comparing these dynamics against a threshold.

It is reassuring to see that there are only a handful of households in the sample moving into poverty, therefore we omit these observations from our estimation of treatment effects. Further, in our estimates of the impact of the project, we assess the probability of moving out of poverty only against the sample that was actually poor at baseline, hence the reference category is remaining in poverty. Consequently, given the smaller sample size, we only estimate the impact of the project on the likelihood of moving out of poverty using the pooled sample, and the stratified sample by county poverty category.

Table 5: Descriptive statistics of poverty categories based on different asset-based poverty lines

Poverty category	Treatment	Control	Total
Overall asset-based poverty line, 40th percentile			
Moving into poverty	5	3	8
Moving out of poverty	236	196	432
Remain below poverty line	131	157	288
Remain above poverty line	520	553	1,073
Overall asset-based poverty line, 60th percentile			
Moving into poverty	0	7	7
Moving out of poverty	206	249	455
Remain below poverty line	313	313	426
Remain above poverty line	333	380	413
Durable asset-based poverty line, 40th percentile			
Moving into poverty	0	2	2
Moving out of poverty	277	236	513
Remain below poverty line	90	117	207
Remain above poverty line	525	554	1,079
Durable asset-based poverty line, 60th percentile			
Moving into poverty	1	2	3
Moving out of poverty	322	245	567
Remain below poverty line	233	282	515
Remain above poverty line	336	380	716
Productive asset-based poverty line, 40th percentile			
Moving into poverty	1	2	3

Moving out of poverty	129	135	264
Remain below poverty line	242	240	482
Remain above poverty line	520	532	1,052
Productive asset-based poverty line, 60th percentile			
Moving into poverty	3	3	6
Moving out of poverty	113	99	212
Remain below poverty line	464	432	896
Remain above poverty line	312	375	687
Livestock asset-based poverty line, 40th percentile			
Moving into poverty	2	4	6
Moving out of poverty	278	233	511
Remain below poverty line	244	239	483
Remain above poverty line	368	433	801
Livestock asset-based poverty line, 60th percentile			
Moving into poverty	33	39	72
Moving out of poverty	242	233	465
Remain below poverty line	317	301	618
Remain above poverty line	300	346	646
Number of observations	892	909	1,801

3.3 Impact estimation

Impact estimates are computed relying mainly on the results derived from the inverse-probability-weighting regression-adjustment (IPWRA) estimator (Wooldridge, 2007; Wooldridge, 2010). This approach models both the outcome and the treatment probability, and has the property of being "doubly robust", which means that only one of the two models must be correctly specified to consistently estimate the treatment effects (in other words the impact of the program) (Bang and Robins, 2005). The IPWRA estimator uses the inverse of the estimated treatment-probability weights to estimate missing-data-corrected regression coefficients that are subsequently used to compute the potential outcome means. Due to this property, this estimator generates the most reliable and accurate results and is thus used as the preferred one in our final discussion.

All estimates reported are average treatment effect on the treated (ATT). Mathematically, in the context of the IPWRA estimator, the weighted-least squares regression equation to estimate ATT with the addition of covariates can be written as follows:

$$Y_i = \alpha_0 + \tau T_i + \alpha_1 X_i + \alpha_2 (X_i - \bar{X}) T_i + \varepsilon_i,$$

where Y_i is our outcome variable of interest, T_i is our indicator for treatment, X_i is a vector of co-variates in the outcome equation, $\bar{X}$ is the sample average of X for the subsample of treated households, ε_i is the error term, and τ, α_1, and α_2 are parameters to be estimated. The matrix containing the weights assigned to observations in the sample to estimate the ATT effects can be specified as follows:

$$\omega(t, x) = t + (1 - t)\frac{\hat{P}(X)}{1 - \hat{P}(X)},$$

where $\omega(t, x)$ is the weight applied, t represents $T_i = 1$, $\hat{P}(X)$ is the estimated propensity score, and X is a vector of covariates (Lee, 2005).

The estimated ATT, or the households which received the GIADP project (with the necessary scaling due to the ATT estimates being the intention-to-treat or ITT estimates) can be expressed as follows:

$$ATT = E(\delta_i | T = 1) = E(\frac{Y_{i1}}{m_i} - \frac{Y_{i0}}{m_i} | T = 1).$$

In addition, to assess the robustness of our results, we present results obtained from five different estimators as in Garbero (2016). The four other estimators considered are (1) the inverse probability weighting estimator (IPW), (2) covariate matching (NN), (3) propensity score matching (PSM), and (4) regression adjustment estimator (RA). The latter is considered the base case estimator. For further details on these estimators, please refer to Garbero (2016).

4. Profile of the project area and sample

GIADP covers eight counties in GZAR. We present the distribution of sampled households and AVs by county, as shown in Table 6 below.

Table 6: Sample distribution by county

County	Poverty category of county	Treatment		Control	
		Households	AVs/NVs	Households	AVs/NVs
Beiliu	Vulnerable	141	10	133	10
Cenxi	Vulnerable	156	11	163	11
Duan	Poor	42	3	44	3
Leye	Poor	30	2	28	2
Longzhou	Poor	66	5	65	5
Pingle	Vulnerable	120	8	120	8
Tengxian	Vulnerable	190	14	206	14
Yongfu	Vulnerable	147	10	150	10
Total		**892**	**63**	**909**	**63**

While our main analysis uses the pooled sample from all eight counties, we explore potentially heterogeneous impacts of the project based on the poverty category of the county defined at the national level. Of all eight counties, three are considered poor or worse off (Du'an, Leye, Longzhou), and five are considered as vulnerable or relatively better off (Beiliu, Cenxi, Pingle, Tengxian, Yongfu). Further, we report the proportions of the households in the sample, by type of project intervention received. The types of interventions received are broken down into three mutually exclusive groups based on the two main types of project interventions delivered as part of this project: (1) agricultural production and marketing support, and (2) community infrastructure.[16] Thus, the three mutually exclusive groups based on the types of project interventions received are: (1) agricultural production and marketing support interventions only, (2) community infrastructure interventions only, and (3) agricultural production and marketing support and community infrastructure interventions. In addition, we examined a forth group of interventions, namely the agricultural production and marketing support interventions along with the rural environmental improvement interventions given the country the project team interests in learning lessons from the innovative approach of GIADP.. Thus, the fourth sub-group consists of households receiving these two interventions implemented together within the same AVs.[17] In Table 7 below, we present the distribution of sample based on the types of interventions according to each poverty category at the county level.

[16] The other component of theproject, rural environmental improvement, represents a small portion of the project's total budget relative to the other two components.

[17] It is not possible to conduct a sub-group analysis of households receiving rural environmental improvement interventions only. This is because the project actvities delivered under this component were not delievered exclusively in any AV as part of GIADP. Rather, they were always delievered along with other interventions along with one of the two or both components of GIADP.

Table 7: Sample distribution by type of intervention received

Type of intervention received (%)	Pooled sample	Poor county sample	Vulnerable county sample
Agricultural and marketing support only	35.7%	31.5%	38.5%
Community infrastructure only	25.9%	30.4%	23.0%
Agricultural and marketing support with community infrastructure	16.0%	12.8%	18.1%
Agricultural and marketing support with rural environmental improvement	19.1%	12.8%	27.0%
Number of observations	892	352	540

Note: Treatment sample only

To provide a brief overview of the types of crops grown by the households in our sample, we present the breakdown of the proportions of the households in our sample that grow the main crops in our sample. This information is reported in Table 8 below.

Table 8: Sample distribution by type of crops grown

Type of crops cultivated (%)	Pooled sample	Poor county sample	Vulnerable county sample
Rice (=1 if yes)	0.66	0.70	0.63
Maize (=1 if yes)	0.12	0.16	0.10
Wheat (=1 if yes)	0.03	0.00	0.01
Root (=1 if yes)	0.07	0.12	0.04
Vegetable (=1 if yes)	0.20	0.19	0.20
Fruit (=1 if yes)	0.26	0.15	0.33
Number of observations	1,801	722	1,079

In Table 9, descriptive statistics of the households in our sample are reported. Among the GIADP beneficiaries and the corresponding counterfactual group, an average household consists of five members, and most of them are male-headed. The average age of the household head is 54-55 years old, and household heads tend to be slightly younger (only by an average of 1.47 years) in the treatment group. Households heads have completed at least primary education, and observe similar religious affiliation. Overall, the characteristics of the dwelling of households in treatment and control groups appear to be similar, and so are the demographic characteristics of the households in both groups.

We then split the pooled sample into two groups, based on observations collected from households in poor and vulnerable counties. In both sub-samples, the household-level characteristics are quite balanced, except for a number of variables including the age of head, the religious affiliation of the head, and the distance to the nearest market. While statistically different, it is important to note that the magnitude of the differences is still small, and thus we remain confident that we obtained a credible counterfactual.

Table 9: Descriptive statistics of the households in the pooled sample, and stratified by poverty category of county

Household characteristics	Pooled sample			Poor county sample			Vulnerable county sample		
	Treat. Mean	Control Mean	Diff.	Treat. Mean	Control Mean	Diff.	Treat. Mean	Control Mean	Diff.
Household size	5.03	5.12	-0.09	5.05	5.01	0.04	5.07	5.19	-0.12
Sex of head (=1 if male)	0.92	0.91	0.01	0.93	0.91	0.02	0.91	0.91	0.00
Age of head	54.30	55.78	-1.5***	54.27	55.91	-1.6***	53.98	55.42	-1.4***
Education of head	1.58	1.57	0.01	1.56	1.62	-0.06	1.60	1.55	0.05
Religion of head	1.233	1.138	0.094**	1.142	1.089	0.41**	1.278	1.145	0.134**
Land owned (hectare)	4.45	4.55	-0.10	3.07	2.67	-0.10	5.35	5.62	-0.27
Distance to road (km.)	0.28	0.20	0.08**	0.18	0.14	0.04	0.21	0.19	0.02
Distance to market (km.)	7.37	7.73	0.47	7.22	6.20	1.02***	6.53	7.44	-0.9***
Number of children	1.152	1.258	-0.106	1.09	1.14	0.58	1.20	1.33	-0.12
Number of adults 15-64 years	3.36	3.31	0.05	3.43	3.29	0.14	3.36	3.34	0.02
Number of adults older than 65 years	0.46	0.48	-0.02	0.48	0.50	-0.02	0.45	0.46	-0.01
Number of observations	929	946		352	370		540	539	

Note: .01 - ***; .05 - **; .1 - *; Level of education is coded as 0 = none, 1 = primary, 2 = secondary, and 3 = university or higher; Religion is coded as 1 = agnostic and 2= other.

5. Results

We now turn to presenting the impact estimates on various outcome and impact indicators. First, we present the overall projects impacts using the pooled sample. While measuring overall impacts, results from five different estimators are displayed to verify the robustness of our results. The five estimators presented include (1) inverse probability weighting with regression adjustment (IPWRA) estimator, (2) inverse probability weighting (IPW) estimator, (3) covariate matching estimator based on five nearest neighbours (NN), (4) propensity score matching estimator based also on five nearest neighbours (PSM), and (5) last, regression adjustment (RA) estimator, which is included as it represents the base-case estimator.[18]

Based on the specific definitions of the indicators, the magnitudes of impact estimates reported are either expressed in percentages or in levels. When relevant, our narration of results converts impact estimates from percentages to levels to illustrate the magnitude of project impact relative to the control groups means.[19] The control group represents the valid counterfactual, i.e. what would have happened to households in treatment areas in the absence of the project. To this end, the means of the control group in absolute terms are reported in corresponding tables and in the appendix, for reference. The discussions of results also include information from anecdotal evidence elicited from our review of project documents, discussions and interviews with project staff, and secondary analysis of project's administrative database. Last, two sets of additional analyses that explore heterogeneous project impacts are presented: first, we disaggregate the sample by the county poverty status; second, the sample is split by both mutually exclusive categories of project interventions received and the county poverty category.

All impact estimates reported in the additional analyses are based on the IPWRA estimator. It is important to note that estimates of heterogeneous project impact might be prone to an endogeneity bias, due to self-selection in to participation and strategic targeting. Further, in order to determine samples of mutually exclusive interventions, we might incur a potential small sample size bias, that might affect the significance of the results. Thus, results from our additional sub-group analyses should be interpreted with caution.

5.1 Overall impacts of GIADP

5.1.1 Agricultural production indicators

We begin by investigating project impacts on crop production, as illustrated in Table 10. Note that the direction and magnitude of impact estimates is similar across estimators, strengthening the robustness of our results. Overall, households in treated areas do not expand their crop cultivation areas relative to the control group. In terms of physical inputs namely fertilizers and pesticides, treated households do not use higher amounts of overall physical inputs. However, households in treated areas appear to be using lower levels of seeds for crop production. In particular, their seed use is approximately 15.9% lower than the one of the control group, which corresponds to approximately 6.3 kg./ha. lower than of the level of their control counterpart. This reduction in seed use could be attributed to beneficiaries farmers improved efficiency due to the project. Evidence from the qualitative key informants interviews confirms that farmers in treated villages received a

[18] Control variables used for all specifications include household size, sex of household head, age of household head, education of household head, religion of household head, land ownership, type of wall, type of roof, type of floor, number of rooms, size of dwelling, type of bath, source of fuel, distance to road, access to irrigation, access to credit, access to various types of social assistance programs, and membership in agricultural cooperatives.

[19] All control group means are presented in levels.

number of trainings on agricultural production technologies, especially on seed use. Their participation in these training sessions resulted in more effective uses of seeds, which have led to lower seed uses in absolute terms. This is especially important as existing evidence in the literature has reported accuracy of seed varieties between self-reported information and DNA fingerprinting tests (Kosmowski et al., 2018). In particular, the literature has noted the substantial level of inaccuracies of self-reported seed quality from personal interviews when compared against tested seed samples for their actual varieties.

In terms of crop yields, households in treated areas have significantly lower grain and root yields compared to their control counterparts by approximately 40%, which corresponds to 220 kg./ha. and 19.4 kg./ha less than the level measured in the control. The qualitative findings corroborated the fact that farmers in project areas reallocate their arable land from growing grain and root crops to higher-valued crops including vegetables and fruits instead. However, beneficiaries have significantly higher yields of fruit crops by 19.3%, about 17 kg./ha more than the control. The significant impacts on yields of fruit crops are of particular importance, as the project focused on promoting best practices of fruit crop production and marketing (especially citrus crops). The qualitative interviews also confirmed that GIADP delivered interventions specifically designed to upgrade the production and marketing of fruit crops through trainings related to improving farmers management and marketing practices of such crops. This finding is in line with existing evidence in the literature, which reports significant impacts of agricultural interventions designed to focus on crops suitable for production in the region (Asfaw et al., 2012; Azzarri et al., 2015). Turning to the crop production, treatment households have significantly lower values of grain production, but the value of root production does not significantly change despite the decrease in yields. In terms of fruit crops, the value of fruit crops produced significantly increase by 29.1%, which translates to approximately 976 Chinese yuan (CNY) higher per year relative to the level observed in the control group.[20] This finding support the argument that the project focus on both production support and marketing of fruit crops not only helps increasing yields, but also the value of the crops produced. This finding provides evidence that that market-focused activities can maximize the benefits received from agricultural production technical support to beneficiaries.

[20] One US$ is equivalent to approximately 6.32 CNY in March 2018.

Table 10: Results on agricultural production indicators from the pooled sample

	(1)	(2)	(3)	(4)	(5)	(6)
	IPWRA	IPW	NN	PSM	RA	Control mean
	Pooled sample	Pooled sample	Pooled sample	Pooled sample	Pooled sample	Pooled sample
Agricultural production indicators						
Crop area (ha)	0.260	0.278	0.278	0.617	0.258	16.97
	(0.38)	(0.40)	(0.40)	(0.83)	(0.37)	
Seed use per ha (kg/ha, log)	-0.159**	-0.164**	-0.164**	-0.146**	-0.160**	39.75
	(-2.38)	(-2.44)	(-2.44)	(-2.07)	(-2.39)	
Fertilizer use per ha (kg/ha, log)	0.0649	0.0640	0.0640	0.0604	0.0675	103.12
	(0.93)	(0.92)	(0.92)	(0.79)	(0.97)	
Pesticide use per ha (kg/ha, log)	0.0573	0.0527	0.0527	0.0800	0.0600	160.04
	(0.60)	(0.55)	(0.55)	(0.77)	(0.62)	
Grain yield (kg/ha, log)	-0.399***	-0.407***	-0.41***	-0.38***	-0.402***	555.04
	(-3.07)	(-3.14)	(-3.14)	(-2.64)	(-3.10)	
Root yield (kg/ha, log)	-0.399***	-0.407***	-0.41***	-0.38***	-0.402***	48.67
	(-3.07)	(-3.14)	(-3.14)	(-2.64)	(-3.10)	
Vegetable yield (kg/ha, log)	-0.0529	-0.0550	-0.0550	0.0113	-0.0501	210.14
	(-0.42)	(-0.44)	(-0.44)	(0.09)	(-0.40)	
Fruit yield (kg/ha, log)	0.193**	0.201**	0.201**	0.174*	0.195**	90.68
	(2.25)	(2.36)	(2.36)	(1.89)	(2.28)	
Value of grain production (CNY, log)	-0.502***	-0.500***	-0.50***	-0.52***	-0.501***	2,969.91
	(-3.39)	(-3.38)	(-3.38)	(-3.30)	(-3.39)	
Value of root production (CNY, log)	-0.107*	-0.108*	-0.108*	-0.0912	-0.109*	60.38
	(-1.87)	(-1.90)	(-1.90)	(-1.45)	(-1.91)	
Value of vegetable production (CNY, log)	0.0495	0.0486	0.0486	0.0934	0.0521	247.80
	(0.59)	(0.58)	(0.58)	(1.14)	(0.63)	
Value of fruit production (CNY, log)	0.291**	0.301***	0.301***	0.261**	0.294**	3,355.70
	(2.49)	(2.59)	(2.59)	(2.05)	(2.53)	
Number of observations	1,801	1,801	1,801	1,801	1,801	909

Note: .01 - ***; .05 - **; .1 - *; t-statistics in parentheses

5.1.2 Economic mobility: income and savings indicators

In Table 11, results on income and savings indicators are presented for the whole sample. Total annual household income was calculated taking the sum of value of crop production, livestock income, livestock product income, wage employment income, and transfer income (e.g. pensions, remittances, etc.). However significant project impacts on total household income, or on any components of household income are not observed in the pooled sample. On the other hand, households in treatment areas have significantly higher level of household savings compared to the control sample. In particular, the increase in savings is 40.9%, corresponding to approximately 961 CNY more than the counterfactual level. This finding is consistent with existing evidence in the literature for instance Jalan and Ravallion (2001) and Chamon and Prasad (2010) which found that savings increase when there is substantive income growth. In our survey, we also asked about the rationale for savings: the majority of households with active savings stated that the latter are intended for precautionary measures in the case of emergency. Likewise, this is in line with previous findings about the motivation behind savings in rural China (Kraay, 2000; Giles and Yoo, 2007).

Table 11: Results on economic mobility: income and savings indicators from the pooled sample

	(1)	(2)	(3)	(4)	(5)	(6)
	IPWRA	IPW	NN	PSM	RA	Control mean
	Pooled sample	Pooled sample	Pooled sample	Pooled sample	Pooled sample	Pooled sample
Economic mobility: income and savings indicators						
HH income (CNY, log)	0.0547	0.0567	0.0567	0.0692	0.0540	55,066.70
	(0.55)	(0.58)	(0.58)	(0.66)	(0.55)	
Value of crop production (CNY, log)	0.283*	0.280*	0.280*	0.327*	0.287*	17,317.13
	(1.71)	(1.69)	(1.69)	(1.88)	(1.74)	
Livestock income (CNY, log)	0.127	0.121	0.121	0.0692	0.125	487.86
	(1.22)	(1.15)	(1.15)	(0.58)	(1.20)	
Livestock product income (CNY, log)	0.00189	0.000500	0.000500	-0.0289	0.00194	91.20
	(0.03)	(0.01)	(0.01)	(-0.38)	(0.03)	
Wage income (CNY, log)	-0.164	-0.155	-0.155	-0.124	-0.163	36,021.21
	(-0.84)	(-0.79)	(-0.79)	(-0.57)	(-0.83)	
Transfer income (CNY, log)	0.155	0.147	0.147	0.289*	0.163	1,425.93
	(0.92)	(0.87)	(0.87)	(1.67)	(0.97)	
Savings (CNY, log)	0.409**	0.412**	0.412**	0.412**	0.408**	2,351.08
	(2.36)	(2.37)	(2.37)	(2.26)	(2.35)	
Number of observations	1,801	1,801	1,801	1,801	1,801	909

Note: .01 - ***; .05 - **; .1 - *; t-statistics in parentheses

5.1.3 Economic mobility: other wealth indicators

Analyses of project impacts on income and savings indicators are complemented by exploring results on additional wealth indicators (Table 12), namely asset-based indicators. In the literature, asset-based indicators have been used to study poverty, economic mobility, and growth in the absence of monetary- based indicators such as income or expenditures (Filmer and Pritchett, 2001; Sahn and Stifel, 2003). Using information about recalled asset ownership at baseline (before GIADP started), and current asset ownership, we computed changes in asset indices between baseline and current values. In the pooled sample, weobserve a significant impact of the project on durable assets. Specifically, the value of asset indices among treated households is higher than that of the control households by 10.7%. This finding is not surprising because any improvements in economic mobility among smallholder households tend to reflect in greater investments in durable asset items like TV, radio, motorcycle, etc. However, we do not observe any significant impacts on other assets, either on overall assets, or durable productive , small and large livestock assets.

Table 12: Results on economic mobility: other wealth indicators from the pooled sample

	(1)	(2)	(3)	(4)	(5)	(6)
	IPWRA	IPW	NN	PSM	RA	Control mean
	Pooled sample	Pooled sample	Pooled sample	Pooled sample	Pooled sample	Pooled sample
Economic mobility: other wealth indicators						
Change in overall asset index	0.0304	0.0308	0.0308	0.0174	0.0311	0.37
	(1.54)	(1.56)	(1.56)	(0.81)	(1.58)	
Change in durable asset index	0.0763**	0.0786**	0.0786**	0.0623	0.0766**	0.71
	(2.07)	(2.15)	(2.15)	(1.57)	(2.08)	
Change in productive asset index	0.00463	0.00311	0.00311	-0.0189	0.00595	0.32
	(0.14)	(0.10)	(0.10)	(-0.52)	(0.19)	
Change in livestock asset index	-0.0467	-0.0484	-0.0484	-0.0663	-0.0487	0.20
	(-0.80)	(-0.82)	(-0.82)	(-1.08)	(-0.83)	
Change in large livestock asset index	-0.0604	-0.0623	-0.0623	-0.0761	-0.0621	0.16
	(-1.04)	(-1.06)	(-1.06)	(-1.26)	(-1.06)	
Change in small livestock asset index	0.0704	0.0716	0.0716	0.0546	0.0683	0.28
	(1.38)	(1.41)	(1.41)	(1.05)	(1.34)	
Number of observations	1,801	1,801	1,801	1,801	1,801	909

Note: .01 - ***; .05 - **; .1 - *; t-statistics in parentheses

5.1.4 Food security and resilience indicators

Project impacts are also explored on other indicators which include dietary diversity, the coping strategy index, and resilience, as reported in Table 13. Using the pooled sample, we do not observe any significant impacts on the coping strategy index and on resilience. While the results show that there is evidence of a negative impact on dietary diversity among treated households, the impact is only significant at 10% level. In addition, the qualitative evidence indicated that households in project regions purchase only a small portion of their food from the market and rely mainly on own-produced food items. Thus, it is not surprising that there is not much difference in the dietary diversity between households in treatment and control groups.

Table 13: Results on food security and resilience indicators from the pooled sample

	(1)	(2)	(3)	(4)	(5)	(6)
	IPWRA	IPW	NN	PSM	RA	Control mean
	Pooled sample	Pooled sample	Pooled sample	Pooled sample	Pooled sample	Pooled sample
Dietary diversity, coping strategy, Food security and resilience indicators						
Dietary diversity score	-0.114*	-0.103	-0.103	-0.100	-0.113*	5.81
	(-1.78)	(-1.62)	(-1.62)	(-1.55)	(-1.78)	
Coping strategy index score	0.101	0.0997	0.0997	0.0666	0.1000	0.32
	(0.58)	(0.57)	(0.57)	(0.37)	(0.57)	
Ability to recover from shock score	-0.0015	-0.0012	-0.0012	-0.0028	-0.0017	0.07
	(-0.31)	(-0.24)	(-0.24)	(-0.56)	(-0.34)	
Number of observations	1,801	1,801	1,801	1,801	1,801	909

Note: .01 - ***; .05 - **; .1 - *; t-statistics in parentheses

5.1.5 Poverty reduction indicators

Results from the estimation of the likelihood of moving out of poverty are presented in Table 14. Among the households who were already below the asset-based poverty line at baseline, treated households are more likely to move out of poverty according to the overall and durable asset-based poverty lines than their control counterpart. Using the overall asset-based poverty lines, treated households are 7.2% and 6.8% more likely to move out of poverty when setting the poverty lines at the 40th and the 60th percentiles of the baseline distribution. The results are even stronger when using durable asset-based poverty lines, where treated households are 6.8% and 11.8% more likely to move out of poverty. These results are in line with our findings on the changes in asset indices, where we find the most significant project impact on the increase in durable assets.

Table 14: Results on poverty reduction indicators from the pooled sample

	(1)	(2)	(3)	(4)	(5)	(6)
	IPWRA	IPW	NN	PSM	RA	Control mean
	Pooled sample	Pooled sample	Pooled sample	Pooled sample	Pooled sample	Pooled sample
Poverty reduction indicators						
Moving out of poverty, overall asset-based poverty line, 40th percentile	0.0728**	0.0796**	0.0272	0.0725**	0.0678*	0.56
	(2.04)	(2.12)	(0.68)	(2.03)	(1.89)	
Moving out of poverty, overall asset-based poverty line, 60th percentile	0.0678**	0.0594	0.0327	0.0672*	0.0656*	0.29
	(1.97)	(1.58)	(0.81)	(1.94)	(1.87)	
Moving out of poverty, durable asset-based poverty line, 40th percentile	0.0685**	0.0616*	0.0126	0.0691**	0.0656**	0.67
	(2.10)	(1.80)	(0.36)	(2.12)	(2.00)	
Moving out of poverty, durable asset-based poverty line, 60th percentile	0.118***	0.112***	0.122***	0.118***	0.113***	0.39
	(3.24)	(2.81)	(2.95)	(3.22)	(3.10)	
Moving out of poverty, productive asset-based poverty line, 40th percentile	-0.0204	-0.0216	-0.0480	-0.0208	-0.0350	0.36
	(-0.59)	(-0.56)	(-1.18)	(-0.60)	(-1.02)	
Moving out of poverty, productive asset-based poverty line, 60th percentile	-0.00279	0.00647	-0.00452	-0.00350	-0.00902	0.22
	(-0.09)	(0.20)	(-0.13)	(-0.12)	(-0.29)	
Moving out of poverty, livestock asset-based poverty line, 40th percentile	0.0452	0.0410	0.0305	0.0452	0.0576*	0.49
	(1.41)	(1.22)	(0.84)	(1.40)	(1.81)	
Moving out of poverty, livestock asset-based poverty line, 60th percentile	0.0174	0.0134	0.0138	0.0170	0.0326	0.42
	(0.55)	(0.40)	(0.39)	(0.54)	(1.05)	
Number of observations	994	994	994	994	994	472

Note: .01 - ***; .05 - **; .1 - *; t-statistics in parentheses

5.2 Heterogeneous impacts of GIADP by poverty category of the county

5.2.1 Agricultural production indicators

Turning to impact estimates that attempt to tease out heterogeneous impacts, results on crop production indicators are presented in Table 15. When disaggregating the sample into two groups, namely the county poverty status as defined nationally-defined poverty category, we observe that households in treatment areas in poor counties have significantly higher levels of fertilizer and pesticide uses. However, as observed in the pooled sample, the same finding of significantly lower level of seeds used is found. This finding might hint towards inputs substitution among these households. On the other hand, households in treatment areas located vulnerable counties do not exhibit any significantly different use levels of seeds, fertilizers, or pesticides relative to their counterfactual counterpart.

For crop yields, there are positive and significant impacts on vegetable and fruit yields among treated households in vulnerable counties. Specifically, their vegetable and fruit yields are 47.8% and 22.4% higher than those of control households, where this translates to approximately 74.34 kg./ha. and 17.10 kg./ha increases in yields in absolute terms, respectively. Among households in poor counties, we do not find any significant changes in crop yields, except for a decrease in vegetable yields.

Coherently to the observed increases in yields, treatment households in vulnerable counties also report higher values of vegetable and fruit production by 44.3% and 34.4%. These increases correspond to approximately 76.44 CNY and 1525.64 CNY increases in values of vegetables and fruits harvested. Similar to the finding on vegetable yields among treated households in poor counties, the value of vegetable production are also lower relative to the levels observed in the control group.

Table 15: Results on agricultural production indicators by poverty category of the county

	(1)	(2)	(3)	(4)
	IPWRA	Control mean	IPWRA	Control mean
	Poor county	Poor county	Vulnerable county	Vulnerable county
Crop Agricultural production indicators				
Crop area (ha)	1.630	11.53	-0.743	20.71
	(1.93)		(-0.70)	
Seed use per ha (kg/ha, log)	-0.304**	62.63	-0.0790	24.03
	(-2.78)		(-0.89)	
Fertilizer use per ha (kg/ha, log)	0.113	98.46	0.00269	106.31
	(1.03)		(0.03)	
Pesticide use per ha (kg/ha, log)	0.357*	173.36	-0.203	150.90
	(2.21)		(-1.63)	
Grain yield (kg/ha, log)	-0.0707	583.01	-0.64***	535.83
	(-0.35)		(-3.36)	
Root yield (kg/ha, log)	-0.0707	63.45	-0.64***	38.52
	(-0.35)		(-3.36)	
Vegetable yield (kg/ha, log)	-0.896***	289.67	0.478**	155.54
	(-4.61)		(2.94)	
Fruit yield (kg/ha, log)	0.138	111.57	0.224*	76.35
	(0.91)		(2.09)	
Value of grain production (CNY, log)	-0.249	1,972.97	-0.66***	3,654.27
	(-1.04)		(-3.37)	
Value of root production (CNY, log)	-0.236*	112.80	-0.00567	24.40
	(-2.16)		(-0.10)	
Value of vegetable production (CNY, log)	-0.571***	357.41	0.443***	172.56
	(-4.59)		(4.02)	
Value of fruit production (CNY, log)	0.187	1,782.57	0.344*	4,435.58
	(0.94)		(2.27)	
Number of observations	722	370	1,079	539

Note: .01 - ***; .05 - **; .1 - *; t-statistics in parentheses

5.2.2 Economic mobility: income and savings indicators

Impacts on income and savings by county-level poverty status are presented in Table 16. In the poor counties sample, we do not observe any significant impacts on income, either on aggregate household income or on separate income components. In vulnerable counties, the income of treated households is instead 22% higher than that of control households (albeit only significant at 10% level), which translates to an increase of approximately 13,333 CNY per year.

Similar to the findings from the pooled sample, we observe a positive and significant impact on savings. The magnitude of the increase is 65.5%, which translates to 1490 CNY, which is much higher than the magnitude of the increase observed in the pooled sample of 961 CNY. This finding is consistent with existing evidence in the literature, which also reports increased savings in the presence of income growth (Chamon and Prasad, 2010).

Table 16: Results on economic mobility: income and savings indicators by poverty category of the county

	(1)	(2)	(3)	(4)
	IPWRA	Control mean	IPWRA	Control mean
	Poor county	Poor county	Vulnerable county	Vulnerable county
Economic mobility: income and savings indicators				
HH income (CNY, log)	-0.177	46,998.03	0.220*	60,605.50
	(-1.03)		(1.66)	
Value of crop production (CNY, log)	0.310	4,675.42	0.282	25,995.12
	(1.21)		(1.21)	
Livestock income (CNY, log)	-0.0661	323.09	0.203	600.97
	(-0.46)		(1.29)	
Livestock product income (CNY, log)	-0.0272	110.81	0.0133	77.74
	(-0.28)		(0.16)	
Wage income (CNY, log)	-0.344	40,100.41	-0.0475	33,221.01
	(-1.11)		(-0.17)	
Transfer income (CNY, log)	0.140	1,788.31	0.166	1,177.19
	(0.52)		(0.76)	
Savings (CNY, log)	0.0965	2,460.00	0.655**	2,276.31
	(0.35)		(2.90)	
Number of observations	722	370	1,079	539

Note: .01 - ***; .05 - **; .1 - *; t-statistics in parentheses

5.2.3 Economic mobility: other wealth indicators

In terms of other wealth indicators, such as asset-based indicators (Table 17), we find that the poor counties treatment group exhibits a positive and significant increase in changes of overall assets by about 25% (relative to the control mean). This notable increase in overall assets can be explained by significant increases in both durable and small livestock assets (29% and 128%) compared to the baseline period.

On the contrary, households in vulnerable countries don't exhibit any significant changes in assets compared to baseline level. It is interesting to note that all asset gains are subsumed by the poor counties sample. Such findings on assets across households in the two groups are not surprising, and they are consistent with existing findings in the literature which point out to the fact that, asset-based indicators are better-suited to capture changes in wealth at the lower end of the income distribution (Filmer and Scott, 2012).

Table 17: Results on economic mobility: other wealth indicators by poverty category of the county

	(1)	(2)	(3)	(4)
	IPWRA	Control mean	IPWRA	Control mean
	Poor county	Poor county	Vulnerable county	Vulnerable county
Economic mobility: other wealth indicators				
Change in overall asset index	0.0971**	0.35	-0.0143	0.38
	(3.04)		(-0.57)	
Change in durable asset index	0.207***	0.70	-0.0160	0.72
	(3.68)		(-0.33)	
Change in productive asset index	0.0589	0.28	-0.0273	0.35
	(1.15)		(-0.66)	
Change in livestock asset index	-0.0414	0.19	-0.0551	0.21
	(-0.37)		(-0.84)	
Change in large livestock asset index	-0.0807	0.17	-0.0497	0.15
	(-0.73)		(-0.78)	
Change in small livestock asset index	0.219**	0.17	-0.0470	0.35
	(2.80)		(-0.71)	
Number of observations	722	370	1,079	539

Note: .01 - ***; .05 - **; .1 - *; t-statistics in parentheses

5.2.4 Food security and resilience indicators

Turning to project impacts on food security and resilience (Table 18), we find similar results as reported in the impact estimates for the pooled sample, where no significant impacts on the coping strategy index or resilience indicators are observed. While we find no impact on dietary diversity among treated households in poor counties, treated households in vulnerable counties have less diverse diets. In particular, their dietary diversity score is on average 4% lower than that of the control group.

Table 18: Results on dietary diversity, coping strategy, and resilience indicators by poverty category of the county

	(1)	(2)	(3)	(4)
	IPWRA	Control mean	IPWRA	Control mean
	Poor county	Poor county	Vulnerable county	Vulnerable county
Food security and resilience indicators				
Dietary diversity score	0.104	5.74	-0.248**	5.85
	(1.14)		(-2.75)	
Coping strategy index score	-0.131	0.23	0.192	0.38
	(-0.69)		(0.70)	
Ability to recover from shock score	0.00401	0.08	-0.00565	0.07
	(0.48)		(-0.93)	
Number of observations	722	370	1,079	539

Note: .01 - ***; .05 - **; .1 - *; t-statistics in parentheses

5.2.5 Poverty reduction indicators

In Table 19, the impact of the project on the likelihood or probability of moving out of poverty by the county poverty category is presented. We find consistently positive and significant impacts on the likelihood of being moved out of poverty among treated households in poor counties across different asset-based poverty lines, both at the 40th and the 60th percentiles of the baseline distribution. Compared to the pooled sample, the magnitudes of the impacts on the overall asset-based poverty lines and the durable asset-based poverty lines are even larger than those of the pooled sample, notably 13% and 18% and 13.4% and 16% respectively.

Table 19: Results on poverty reduction indicators by poverty category of the county

	(1)	(2)	(3)	(4)
	IPWRA	Control mean	IPWRA	Control mean
	Poor county	Poor county	Vulnerable county	Vulnerable county
Poverty reduction indicators				
Moving out of poverty, overall asset-based poverty line, 40th percentile	0.130**	0.56	0.0451	0.55
	(2.17)		(0.98)	
Moving out of poverty, overall asset-based poverty line, 60th percentile	0.180***	0.27	0.00682	0.31
	(3.12)		(0.16)	
Moving out of poverty, durable asset-based poverty line, 40th percentile	0.134***	0.69	0.0172	0.65
	(2.65)		(0.40)	
Moving out of poverty, durable asset-based poverty line, 60th percentile	0.160***	0.40	0.0826*	0.38
	(2.66)		(1.75)	
Moving out of poverty, productive asset-based poverty line, 40th percentile	0.113*	0.32	-0.075*	0.39
	(1.96)		(-1.70)	
Moving out of poverty, productive asset-based poverty line, 60th percentile	0.108**	0.18	-0.0495	0.24
	(2.15)		(-1.32)	
Moving out of poverty, livestock asset-based poverty line, 40th percentile	0.128***	0.46	-0.0299	0.51
	(2.61)		(-0.70)	
Moving out of poverty, livestock asset-based poverty line, 60th percentile	0.0867*	0.36	-0.0537	0.45
	(1.76)		(-1.28)	
Number of observations	419	190	575	282

Note: .01 - ***; .05 - **; .1 - *; t-statistics in parentheses

5.3 Heterogeneous impact of GIADP by type of intervention[21]

We now turn to subgroup analyses, where we explore the heterogeneity of impacts by county poverty category, on households that received separate sets of interventions. Recall that estimates are reported for the sample of households receiving agricultural production and marketing support only, community infrastructure only and all these interventions at the same time. However the reader should bear in mind that the disaggregated samples might incur a small sample size bias.

5.3.1 Agricultural production indicators

Results on crop production are reported in Table 20. Interestingly, we now see an increase in the cultivated area among treated households receiving interventions related to agricultural production and marketing support in the poor counties sample. Consistently, within the same group of households, fertilizer use increased by 69.5% , corresponding to an increase of approximately 92.4 kg./ha. more than their control counterpart. In terms of yields, we observe a significant increase in fruit yields among treated households receiving a combination of agricultural and infrastructure interventions. Specifically, treated households receiving both interventions witness increases of 94.6% and 70.0% in fruit yields in poor counties and in vulnerable countries, respectively. Significant increases in fruit yields are also observed among treated households receiving agricultural interventions in poor counties, and among households receiving infrastructure interventions in vulnerable counties. Similar to the project impacts on fruit yields, treated households receiving a combination of agricultural and infrastructure interventions observe significant increases in the value of harvested fruits by 120% and 126% in poor and vulnerable counties respectively. These positive results on fruit yields and on value of fruit production provide evidence that agricultural and infrastructure interventions combined can generate significant impacts on the production of targeted crops (in this case fruits). This finding is further corroborated by the qualitative evidence which also confirmed that through the trainings offered by the project to improve the production and marketing of fruit crops, farmers benefited of higherfruit yields and value of fruit production. . However given the extremely small sample size particularly for this group (column 5), these findings need to be interpreted with caution..

GIADP tested an innovative intervention delivery approach by combining agricultural support with interventions aimed at improving the rural environment. Among the AVs which received this combination of interventions, we observe higher vegetable yields, particularly in the vulnerable county sample. We also find a higher value of vegetable production. Given the small sample size available for this sub-group analysis, our results may warrant additional research to further support the claim for scaling-up similar approaches to deliver agricultural interventions in the future.

[21] The relevant descriptive statistics of the control group means for the indicators for the analyses of the heterogeneous impacts of GIADP by type of intervention are reported in Tables 27-30 Appendix 4.

Table 20: Results on agricultural production indicators by type of intervention received

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	IPWRA	IPWRA	IPWRA	IPWRA	IPWRA	IPWRA	IPWRA	IPWRA
	Ag. only, Poor county	Ag. only, Vulnerable county	Infra. only, Poor county	Infra. only, Vulnerable county	Ag. and infra., Poor county	Ag. and infra., Vulnerable county	Ag. and env., Poor county	Ag. and env., Vulnerable county
Agricultural production indicators								
Crop area (ha)	5.721***	-1.179	0.690	-3.284	-9.293	0.0535	-9.293	1.762
	(4.14)	(-1.11)	(0.44)	(-1.22)	(-1.03)	(0.02)	(-1.03)	(0.70)
Seed use per ha (kg/ha, log)	-0.0961	-0.270*	0.0619	0.601**	-0.784	-0.211	-1.993***	-0.00580
	(-0.68)	(-2.36)	(0.30)	(2.57)	(-0.46)	(-0.64)	(-2.76)	(-0.03)
Fertilizer use per ha (kg/ha, log)	0.695**	-0.0342	-0.198	-0.0394	-3.83***	-0.281	-0.784	-0.356*
	(3.11)	(-0.25)	(-0.93)	(-0.19)	(-2.64)	(-1.22)	(-0.46)	(-1.88)
Pesticide use per ha (kg/ha, log)	0.598	-0.139	0.340	0.168	-0.919**	-0.387	-3.833***	0.344*
	(1.78)	(-0.70)	(0.99)	(0.68)	(-1.98)	(-1.29)	(-2.64)	(1.95)
Grain yield (kg/ha, log)	0.681	-0.521*	-0.233	-0.845**	-3.65***	-2.17***	-3.645***	-1.090***
	(1.81)	(-2.20)	(-0.62)	(-2.19)	(-7.10)	(-4.54)	(-7.10)	(-3.01)
Root yield (kg/ha, log)	0.681	-0.521*	-0.233	-0.845**	-3.65***	-2.17***	-3.645***	-1.090***
	(1.81)	(-2.20)	(-0.62)	(-2.19)	(-7.10)	(-4.54)	(-7.10)	(-3.01)

Vegetable yield (kg/ha, log)	-0.627*	0.0538	-1.66***	0.182	0.885***	-0.145	0.885***	1.299***
	(-2.28)	(0.20)	(-4.09)	(0.64)	(2.62)	(-0.36)	(2.62)	(3.39)
Fruit yield (kg/ha, log)	0.549*	0.207	0.275	0.469	0.946***	0.700***	0.946***	-0.0825
	(2.55)	(1.62)	(1.37)	(1.48)	(2.62)	(2.87)	(2.62)	(-0.47)
Value of grain production (CNY, log)	1.405**	-0.87***	-0.441	-0.559	-3.508	-3.22***	-3.508	-0.996**
	(3.17)	(-3.61)	(-1.15)	(-1.15)	(-1.41)	(-5.29)	(-1.41)	(-2.17)
Value of root production (CNY, log)	-0.122	0.127	-0.205	-0.00945	6.518*	-0.110	6.518*	-0.0761
	(-1.22)	(1.37)	(-0.98)	(-0.24)	(1.68)	(-0.83)	(1.68)	(-0.60)
Value of vegetable production (CNY, log)	-0.255	0.159	-1.06***	0.101	0.349***	-0.00745	0.349***	1.090***
	(-1.75)	(1.15)	(-3.75)	(0.43)	(2.62)	(-0.03)	(2.62)	(3.63)
Value of fruit production (CNY, log)	0.627*	0.299*	0.451	0.866*	1.198***	1.259***	1.198***	-0.0638
	(2.48)	(2.29)	(1.62)	(1.77)	(2.62)	(3.20)	(2.62)	(-0.24)
Number of observations	215	408	253	257	60	194	60	283

Note: .01 - ***; .05 - **; .1 - *; t-statistics in parentheses

5.3.2 Economic mobility: income and savings indicators

Project impacts on income and savings indicators are reported in Table 21. Note that households receiving a combination of GIADP interventions related to agricultural production and marketing support along with rural environmental improvement have significantly higher household income, and this significant increase in income may be explained by the increased value of their crop production. The qualitative evidence also supports this finding that households receiving this combination of interventions benefitted from higher prices for their crops sold (especially for vegetable and fruit crops). Statistically significant increases in the value of crop production among those receiving agricultural production and marketing only, and among those receiving both agricultural and infrastructure interventions are observed in the poor counties. There are also statistically significant increases in livestock income among those receiving infrastructure interventions only. In particular, livestock income increases by 39.0% 22.2% in poor and vulnerable counties, respectively. These magnitudes correspond to approximately 25 and 45 CNY of increased livestock income per year. In terms of savings, we only see a significant increase in total savings among treated households receiving infrastructure interventions only in vulnerable counties. The magnitude of the increase is 74.5%, which translate to an increase in savings of approximately 1,647 CNY.

Table 21: Results on economic mobility: income and savings indicators by type of intervention received

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	IPWRA	IPWRA	IPWRA	IPWRA	IPWRA	IPWRA	IPWRA	IPWRA
	Ag. only, Poor county	Ag. only, Vulnerable county	Infra. only, Poor county	Infra. only, Vulnerable county	Ag. and infra., Poor county	Ag. and infra., Vulnerable county	Ag. and env., Poor county	Ag. and env., Vulnerable county
Economic mobility: income and savings indicators								
HH income (CNY, log)	0.245	0.157	-0.352	-0.278	-4.57***	-0.185	-4.56***	0.477**
	(0.57)	(0.75)	(-1.28)	(-1.32)	(-3.21)	(-0.72)	(-3.21)	(2.32)
Value of crop production (CNY, log)	2.111***	-0.375	0.187	0.316	-1.230	-1.99***	-1.230	1.380***
	(4.28)	(-1.56)	(0.47)	(0.52)	(-0.49)	(-3.00)	(-0.49)	(2.82)
Livestock income (CNY, log)	-0.614	0.678*	0.390*	0.222*	N/A	0.104	N/A	-0.624**
	(-1.69)	(2.19)	(1.90)	(1.75)		(0.58)		(-2.23)
Livestock product income (CNY, log)	-0.0807	0.112	0.185	0.109	N/A	N/A	N/A	N/A
	(-0.33)	(0.84)	(1.24)	(1.24)				
Wage income (CNY, log)	-0.335	0.242	-0.401	-0.643	N/A	0.745	N/A	0.0393
	(-0.55)	(0.56)	(-0.65)	(-1.29)		(1.13)		(0.07)

Transfer income (CNY, log)	0.481	0.460	0.226	-0.372	0.339	0.196	0.339	0.159
	(0.87)	(1.24)	(0.50)	(-0.84)	(0.16)	(0.37)	(0.16)	(0.36)
Savings (CNY, log)	0.0792	0.608	-0.525	0.745*	-4.946	0.0277	-4.946	0.0783
	(0.15)	(1.71)	(-0.94)	(1.74)	(-1.13)	(0.05)	(-1.13)	(0.16)
Number of observations	215	408	253	257	60	194	60	283

Note: .01 - ***; .05 - **; .1 - *; t-statistics in parentheses

5.3.3 Economic mobility: other wealth indicators

Table 22 presents the results on assets-based indicators. Households receiving agricultural interventions have statistically significant increases in overall assets, and in particular durable and small livestock assets. Consistently, the significant impacts are only a prerogative of households in the poor counties sample. Further, the magnitudes of the impacts on overall assets are even larger for households receiving both types of interventions (thus including infrastructure) in the poor counties Moreover, we also observe statistically significant increases in changes in productive assets, for the same sample.

Such findings are consistent with our earlier findings that asset-based indicators are more likely to detect dynamics at the lower tail of the wealth distribution, corroborating evidence from existing literature (Filmer and Scott, 2012). Larger impacts on assets can be observed among those receiving the agricultural-related interventions (Column 1). Relative to the combined agricultural and infrastructure interventions (column 5) a positive results is also obtained particularly on the overall and productive asset indeces. However the size of this sample is too small to make conclusive statements about the benefits of all interventions combined. Thus additional research with possibly larger sample sizes is needed to validate this claim.

Table 22: Results on economic mobility: other wealth indicators by type of intervention received

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	IPWRA	IPWRA	IPWRA	IPWRA	IPWRA	IPWRA	IPWRA	IPWRA
	Ag. only, Poor county	Ag. only, Vulnerable county	Infra. only, Poor county	Infra. only, Vulnerable county	Ag. and infra., Poor county	Ag. and infra., Vulnerable county	Ag. and env., Poor county	Ag. and env., Vulnerable county
Economic mobility: other wealth indicators								
Change in overall asset index	0.210**	0.00537	-0.0284	0.00683	0.911*	-0.0161	0.911*	0.00352
	(2.71)	(0.13)	(-0.53)	(0.14)	(1.80)	(-0.28)	(1.80)	(0.08)
Change in durable asset index	0.374**	0.114	0.0202	0.0281	-0.0252	-0.0422	-0.0252	-0.0619
	(3.21)	(1.41)	(0.20)	(0.35)	(-0.09)	(-0.42)	(-0.09)	(-0.74)
Change in productive asset index	0.197	-0.0971	-0.0953	-0.00957	2.538*	-0.0250	2.538*	0.0621
	(1.50)	(-1.34)	(-1.09)	(-0.11)	(1.73)	(-0.22)	(1.73)	(0.81)
Change in livestock asset index	-0.132	0.0328	0.0575	-0.00385	-0.244*	-0.335	-0.244*	-0.144*
	(-0.51)	(0.24)	(1.84)	(-0.06)	(-1.72)	(-1.25)	(-1.72)	(-1.67)
Change in large livestock asset index	-0.190	0.0341	0.0218	0.00190	-0.0445	-0.318	-0.0445	-0.145*
	(-0.74)	(0.26)	(1.23)	(0.03)	(-0.40)	(-1.19)	(-0.40)	(-1.75)

Change in small livestock asset index	0.395*	-0.0987	0.216	-0.0467	-1.27***	-0.0599	-1.27***	0.0872
	(2.31)	(-0.70)	(1.50)	(-0.43)	(-3.10)	(-0.50)	(-3.10)	(0.87)
Number of observations	215	408	253	257	60	194	60	283

Note: .01 - ***; .05 - **; .1 - *; t-statistics in parentheses

5.3.4 Food security and resilience indicators

Turning to the impacts on dietary diversity, presented in Table 23, we find that households receiving agricultural interventions in vulnerable counties have greater dietary diversity relative to control households (7.2% higher dietary diversity score on average compared to the control group mean). This finding is consistent with the limited evidence investigating the relationship between agricultural interventions and dietary outcomes (Banerjee et al., 2015; Zeweld et al., 2015; Jodlowski et al., 2016; Upton et al., 2016). However a significant decrease in dietary diversity is exhibited for households benefiting from infrastructure related interventions in the vulnerable county sample (13.2% lower dietary diversity score on average compared to the control group mean), and also for households receiving both types of interventions. This finding might hint to the fact that in such counties, households might shift to less varied diets.

Some evidence of positive impact on the ability to recover from negative shocks can also be observed particularly for the infrastructure-related sample in poor counties. Finally these additional analyses do not show any significant impact on the coping strategy index.

Table 23: Results on food security and resilience indicators by type of intervention received

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	IPWRA	IPWRA	IPWRA	IPWRA	IPWRA	IPWRA	IPWRA	IPWRA
	Ag. only, Poor county	Ag. only, Vulnerable county	Infra. only, Poor county	Infra. only, Vulnerable county	Ag. and infra., Poor county	Ag. and infra., Vulnerable county	Ag. and env., Poor county	Ag. and env., Vulnerable county
Dietary diversity, coping strategy, andFood security resilience indicators								
Dietary diversity score	0.419*	0.186	0.179	-0.85***	-1.560*	-0.347*	-1.560*	-0.0406
	(2.04)	(1.32)	(1.09)	(-4.72)	(-1.91)	(-1.66)	(-1.91)	(-0.30)
Coping strategy index score	-0.0424	-0.313	0.0155	-0.00163	N/A	N/A	N/A	N/A
	(-0.10)	(-1.43)	(0.07)	(-0.02)				
Ability to recover from shock score	-0.0100	0.00837	0.0757***	-0.00933	-0.08***	0.0273*	-0.08***	-0.022**
	(-0.71)	(0.78)	(4.42)	(-0.90)	(-2.77)	(1.88)	(-2.77)	(-2.22)
Number of observations	215	408	253	257	60	194	60	283

Note: .01 - ***; .05 - **; .1 - *; t-statistics in parenthes

6. Conclusion

This ex post impact assessment is an example of the greater efforts made to reduce rural poverty and increase economic mobility in the rural areas of China by improving market access and increasing agricultural production. The project implemented interventions related to community infrastructures, agricultural production and marketing support, as well as investments to benefit the environment in rural areas. Primary data was collected from around 1,801 households in 119 AVs in order to quantify the project impacts on a number of key outcome and impact indicators, namely crop production, income and savings, assets, movements out of poverty, dietary diversity, and resilience.

Consistent with the existing literature, we find that project interventions that are tailored to context - specific conditions contribute to a significant improvements in yields and value of crop production, particularly for fruit crops, and to a lesser extent for vegetable crops (Asfaw et al., 2012; Azzarri et al., 2015).

Given that the project had a specific poverty targeting, it is reassuring to see that households do witness increases in assets, in particular durable assets, while not experiencing increases in monetary income. This might be justified on grounds that increases in income might be translated directly in assets improvements and might not be sufficient to warrant an income increase as yet for those that are relatively worse off. Improvements in assets can be best detected by asset indices for households at the very bottom of the income distribution, as noted in the literature (Filmer and Scott, 2012). In addition such finding is also reinforced by the sub-group analyses where we found that impacts on assets are larger among the households in poor counties as opposed to the ones observed for vulnerable counties. In addition, the results on poverty dynamics are particularly robust, where the likelihood or probability of being moved out of poverty is positive and significant. Treated households are in fact more likely to move out of poverty based on two relative poverty lines set at the 40^{th} and 60^{th} percentile of the overall asset-index distribution. This probability is even higher when poverty lines defined by durable asset indices are employed.

Additionally, impacts on savings are evident among better-off households in line with existing evidence in the literature that supports the argument that savings represent a form of insurance and are consequence of substantive income growth (Chamon and Prasad, 2010).

However, when studying the heterogeneity of treatment effects, we found a number of data limitations, which prevented us from making more conclusive statements about impact attribution at intervention level, as well as providing an assessment of the interactions between community infrastructure development, agricultural production and marketing support interventions, and their synergistic impact on agricultural outcomes and welfare of beneficiary households and communities. Specifically, we need to note the challenges related to the identification of the treatment distribution, in other words the distribution of activities in the sample, which was reconstructed, ex post, from the M&E data.

Specifically, the treatment intensity distribution was determined at AV level. This essentially means – that we were only able to determine the distribution of activities at such unit. This might dilute the impact estimates, leading to a downward bias as effectively estimates are an intention to treat. An intention to treat is what the literature defines as the causal effect of “assignment” to the treatment group and therefore it reflects the intended assignment and not the actual treatment. In other words, not all NVs within AVs are treated and not all households within such NVs are assigned to the treatment. This implies that the distribution of treatment at NVs and household level is unknown, hence we are not able to determine take up levels or the level of “compliance” across those units. Therefore it may be possible that the NVs and households included in the sample, although residing in AVs that are officially part of the treatment sample, might not have received the specific treatment in question. This leads to potential underestimation of project impact. These issues becomes particularly complicated when there are multiple components – and there is heterogeneity at implementation level, within the AV. This is a major limitation of the M&E data provided, which is particularly problematic in an ex post framework, and leads us to the important recommendation that granular data on the distribution of the interventions at AV, NV, and household levels need to be collected as part of the routinely collected project specific M&E data system.

Last, note how the results were particularly “fuzzy” or imprecise, when the infrastructural component was examined. To this end, it is important to note, that the Government of China mimicked the infrastructural component – e.g. the construction of village level roads - in other AVs that were not necessarily targeted by GIADP.. This may further dilute the magnitude of impact estimates, particularly the ones related to the infrastructure component, given that the counterfactual might have benefited of similar interventions, leading to potential “contamination”, confounding, underestimation and even lack of significant project impact.

Cognizant of these limitations, the results do corroborate the project theory of change, particularly the strong poverty reduction impact, which is particularly consistent, across the set of asset indices, and coherent with the poverty targeting in poor counties. This also leads to the important conclusion that combined interventions where infrastructure is provided along technical assistance and marketing support, are more effective for households at the lower end of the income distribution. While those at the lower end do translate their income improvements into assets, the relative better off do witness an improvement in savings. It would be important to invest in ex ante impact assessments to test further these hypotheses, namely understanding the pathways through which tailored agricultural and marketing support, coupled with focused infrastructure that improves access to markets, and allow farmers to get better prices for their produce, affect beneficiaries’ welfare and well-being outcomes. Addressing these important questions is crucial to understand how smallholder households may move out of poverty and improve their economic mobility through improved market access.

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Appendix 1: List of variables used for matching AVs by county

Table 24: List of variables used for matching AVs by county

County	Variables used for matching AVs
Beiliu	No. of natural villages, No. of female population, Paddy area (ha.), Dry area (ha.), No. of households in categories B and C
Cenxi	No. of natural villages, No. of population, Paddy area (ha.), Dry area (ha.), No. of households in categories B and C
Du’an	No. of natural villages, No. of population, No. of minority population, Paddy area (ha.), Dry area (ha.), Share of households in category C
Leye	No. of natural villages, No. of population, No. of minority population, Paddy area (ha.), Dry area (ha.), No. of households in categories B and C
Longzhou	No. of population, Paddy area (ha.), Share of households in category C
Pingle	No. of natural villages, No. of population, Paddy area (ha.), Dry area (ha.), Rainfall level, No. of households in categories A, B and C
Tengxian	No. of natural villages, No. of population, Paddy area (ha.), Dry area (ha.), No. of households in categories B and C
Yongfu	N/A as matching is not possible

Appendix 2: Matching quality statistics

Figure 3: Balance between treatment and control groups

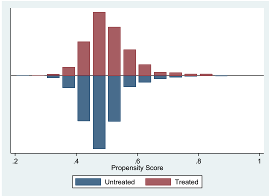


Figure 4: Common support between treatment and control groups

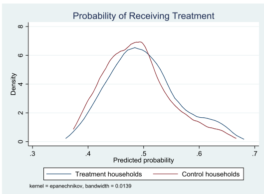
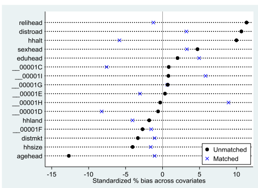


Figure 5: Bias reduction between treatment and control groups



Appendix 3: Agricultural production and economic mobility: other wealth indicators

Table 25: List of crops included in each agricultural production indicator

Crop Agricultural production indicators	Items included
Grains	Rice, corn, wheat, sorghum, millet
Roots	Potato, sweet potato, taro, cassava, Chinese yam
Vegetables	Cowpea, green leaf vegetables, tomato, cucumber
Fruits	Monk fruit, dragon fruit, passion fruit, guava, banana, litchi, longan, plum, pomelo, jujube, persimmon, grape, papaya, kiwi, peach, orange

Table 26: List of assets included in each economic mobility: other wealth indicator

Economic mobility: other wealth indicator	Items included
Housing assets	Type of wall, type of floor, type of kitchen, number of rooms, size of dwelling, source of fuel
Durable assets	Numbers of kerosene stove, electric stove, bed, watch, mobile phone, TV, sofa, bicycle, motor bicycle, cart, sewing machine
Productive assets	Numbers of tractor, tricycle, animal cart, harvester, thresher, beater, sprayer, pump
Livestock assets	Numbers of ox, cow, goat, horse, pig, chicken, duck
Large livestock assets	Numbers of ox, cow, goat, horse, pig
Small livestock assets	Numbers of chicken, duck

Appendix 4: Descriptive statistics (control group means) relevant to the analyses of the heterogeneous impacts of GIADP by type of intervention

Table 27: Descriptive statistics of agricultural production indicators by type of intervention received

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Control mean	Control mean	Control mean	Control mean	Control mean	Control mean	Control mean	Control mean
	Ag. only, Poor county	Ag. only, Vulnerable county	Infra. only, Poor county	Infra. only, Vulnerable county	Ag. and infra., Poor county	Ag. and infra., Vulnerable county	Ag. and env., Poor county	Ag. and env., Vulnerable county
Agricultural production indicators								
Crop area (ha)	10.56	16.35	12.68	30.76	15.00	28.38	15.00	20.52
Seed use per ha (kg/ha, log)	10.78	16.42	57.70	20.28	49.65	39.66	49.65	31.84
Fertilizer use per ha (kg/ha, log)	132.19	96.20	99.82	130.13	81.61	106.91	81.61	95.56
Pesticide use per ha (kg/ha, log)	10.98	149.66	187.89	126.33	142.07	136.26	142.07	145.56
Grain yield (kg/ha, log)	544.60	706.99	634.45	291.71	840.16	416.87	840.16	431.42
Root yield (kg/ha, log)	29.92	21.08	82.31	2.56	125.99	77.85	125.99	26.69

Vegetable yield (kg/ha, log)	211.58	123.88	424.73	137.87	0.00	217.85	0.00	232.60
Fruit yield (kg/ha, log)	13.81	12.30	216.14	197.89	0.00	90.00	0.00	87.54
Value of grain production (CNY, log)	189.60	1,788.16	1,631.11	8,253.52	7,030.28	10,506.86	7,030.28	2,596.70
Value of root production (CNY, log)	32.94	3.88	145.51	0.17	437.99	53.48	437.99	5.80
Value of vegetable production (CNY, log)	5.56	5.22	638.48	8,253.51	0.00	706.24	0.00	170.09
Value of fruit production (CNY, log)	92.00	36.54	4,009.63	13,038.38	0.00	5,074.65	0.00	4,636.91
Number of observations	104	200	146	133	15	96	15	140

Note: .01 - ***; .05 - **; .1 - *; t-statistics in parentheses

Table 28: Descriptive statistics of economic mobility: income and savings indicators by type of intervention received

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Control mean	Control mean	Control mean	Control mean	Control mean	Control mean	Control mean	Control mean
	Ag. only, Poor county	Ag. only, Vulnerable county	Infra. only, Poor county	Infra. only, Vulnerable county	Ag. and infra., Poor county	Ag. and infra., Vulnerable county	Ag. and env., Poor county	Ag. and env., Vulnerable county
Economic mobility: income and savings indicators								
HH income (CNY, log)	37,759.33	44,866.39	48,411.36	88,269.75	42,917.16	93,110.28	42,917.16	70,947.79
Value of crop production (CNY, log)	477.88	12,018.22	5,767.895	53,161.18	6,409.827	56,263.93	6,409.827	31,495.64
Livestock income (CNY, log)	890.13	722.435	56.16438	204.4662	218.00	129.1667	218.00	743.86
Livestock product income (CNY, log)	259.61	56.00	61.64384	45.11278	0.00	0.00	0.00	117.86
Wage income (CNY, log)	34,448.37	30,857.18	40,744.11	35,553.31	34,840.00	37,822.81	34,840.00	37,608.14
Transfer income (CNY, log)	1,683.33	1,463.835	1,781.548	818.4662	1,449.33	707.2917	1,449.33	982.29
Savings (CNY, log)	1,490.38	2,103.165	2,729.452	2,211.278	2,800.00	2,064.583	2,800.00	2,699.29
Number of observations	104	200	146	133	15	96	15	140

Note: .01 - ***; .05 - **; .1 - *; t-statistics in parentheses

Table 29: Descriptive statistics of economic mobility: other wealth indicators by type of intervention received

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Control mean	Control mean	Control mean	Control mean	Control mean	Control mean	Control mean	Control mean
	Ag. only, Poor county	Ag. only, Vulnerable county	Infra. only, Poor county	Infra. only, Vulnerable county	Ag. and infra., Poor county	Ag. and infra., Vulnerable county	Ag. and env., Poor county	Ag. and env., Vulnerable county
Economic mobility: other wealth indicators								
Change in overall asset index	0.31	0.39	0.46	0.37	0.29	0.37	0.29	0.35
Change in durable asset index	0.67	0.73	0.85	0.59	0.45	0.62	0.45	0.70
Change in productive asset index	0.22	0.36	0.42	0.43	0.35	0.40	0.35	0.28
Change in livestock asset index	0.45	0.37	0.04	0.11	0.06	0.10	0.06	0.10
Change in large livestock asset index	0.43	0.29	0.01	0.07	0.00	0.05	0.00	0.07
Change in small livestock asset index	0.21	0.48	0.21	0.33	0.39	0.30	0.39	0.15
Number of observations	104	200	146	133	15	96	15	140

Note: .01 - ***; .05 - **; .1 - *; t-statistics in parentheses

Table 30: Descriptive statistics of food security and resilience indicators by type of intervention received

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Control mean	Control mean	Control mean	Control mean	Control mean	Control mean	Control mean	Control mean
	Ag. only, Poor county	Ag. only, Vulnerable county	Infra. only, Poor county	Infra. only, Vulnerable county	Ag. and infra., Poor county	Ag. and infra., Vulnerable county	Ag. and env., Poor county	Ag. and env., Vulnerable county
Dietary diversity, coping strategy,Food security and resilience indicators								
Dietary diversity score	5.55	5.59	5.79	6.44	5.73	5.89	5.73	5.69
Coping strategy index score	0.56	0.58	0.19	0.11	0.00	0.16	0.00	0.00
Ability to recover from shock score	0.10	0.06	0.38	0.65	0.13	0.07	0.13	0.089
Number of observations	104	200	146	133	15	96	15	140

Note: .01 - ***; .05 - **; .1 - *; t-statistics in parentheses

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