IMPACT ASSESSMENT REPORT

Ethiopia

Participatory Small Irrigation Development Programme I (PASIDP I)
Results from a High Frequency Data Collection

Authors:
Alessandra Garbero, Bezawit Beyene Chichaibelu

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Executive summary

This report presents the results of an ex-post impact assessment of the Participatory Small-scale Irrigation Development Programme (PASIDP), a project financed by IFAD and implemented in Ethiopia between 2008 and 2015. This agricultural project aimed at improving food security and increasing income of beneficiaries by providing access to small-scale irrigation infrastructure systems in four regions of Ethiopia.

The objective of the impact assessment was to investigate both the sustainability of the impacts and the resilience capacity of beneficiaries in a context characterized by adverse weather conditions. An innovative data collection was put in place to study the impact on areas where a protracted drought was taking place. In particular, using panel data that allowed one to follow household over time, the analysis tested whether the irrigation schemes were able to provide a protective and sustained effect towards reducing vulnerability and enhancing smallholders households resilience capacity to cope with the longer term variability of the climatic shocks.

In the face of recurrent climatic shocks across many countries that negatively affect farmers income, undermine the impact of investments, IFAD has been promoting the resilience of vulnerable smallholders through investments that enhance farmers capacity to mitigate, recover and adapt to shocks and chronic stresses.

Smallholders households and community level responses to shocks often differ widely. Some can mitigate the effect of a shock and recover rapidly to a level of welfare at or above pre-shock levels. Others may find themselves stuck in a lower level of welfare permanently, a “poverty trap” (Carter & Barrett 2006). What allows some households to recover, even prosper, in a shock prone environment while others sink deeper into poverty?

In the context of such welfare dynamics the concept of resilience has gained prominence, and increased popularity in development policy. Barrett and Constas (2014) propose a new theory that conceives resilience as “the capacity … to avoid poverty in the face of various stressors and in the wake of myriad shocks. If and only if that capacity is and remains high over time, then the unit is resilient.”

Measuring projects’ impact on resilience requires adequate data. One data snapshot does not allow one to assess dynamics - e.g. changes - whether households are more resilient after a shock occurring and whether the intervention is having a protective impact after the shock in question. Research questions of such kind, require at least two data points, one at the time of the shock and one after the shock in question. The reality is that a number of impact assessments have sought to measure resilience, but are constrained in their reliance on traditional annual datasets, mostly post-shock. Concurrently, governments and aid agencies have pioneered "early warning systems", collecting monthly data on food-prices and other indicators of a potential crisis. Yet this data is rarely good enough to answer the questions of interest, and fail to track individual households over time.

The panel data collection consisted of four rounds, the first, a first round (or baseline) survey collected in November 2016, followed by three follow-up surveys conducted every three months until November 2017 precisely with the objective to investigate both the evolution of well-being outcomes, agricultural productivity and farmers resilience capacity over four seasons and monitor the effectiveness of the irrigation systems over time.

The findings from this impact assessment offer unique insights both concerning the transformative benefits of irrigation projects, the sustainability of such benefits overtime, and also vis a vis the measurement of resilience in the context of ex-post impact assessments with quasi-experimental designs, using high-frequency data.

Notably, it was found that in terms of agricultural production indicators, treatment farmers seem to remarkably invest on agricultural inputs, have higher yields and this is particularly evident in the Dry season which, intuitively, should be the season where the benefits of irrigation systems should be felt the most.

Impacts are also evident across the crop portfolio where value of sales of specific crops (notably, grains and cereals, but also vegetables and fruit), are significantly higher for those accessing modern irrigation compared to their rain-fed counterparts. While treated farmers seem to intensify, and mostly rely on crop production as their major source of income, their counterfactual counterparts resort to non-agricultural income sources, specifically livelihoods activities such as wage employment and self-employment .

As far as economic mobility and poverty indicators are concerned, treated farmers have a higher return from productive assets, are more likely to be above the poverty line, and are less likely to be transiently poor particularly during the Dry season. In terms of poverty and welfare dynamics, treatment farmers are also more likely to exit poverty - relative to persisting in poverty – in the Dry season – compared to their rain-fed counterpart, especially when the poverty metric is based on productive assets.

Concerning food security indicators, a key finding is the reduction in the negative coping strategies to which households resort in times of distress. Such reduction is particularly significant in the Belg season (or the short rainy season), the season immediately following the Dry season, implying that there is lagged effect in the food security benefits, whereby treated farmers are resilient after the dry season. In addition, this finding also underlines the persistence of the treatment effect – or impact sustainability - which goes beyond the season of interest, notably the Dry season, and manifest itself also in the following season.

As far as market access indicators are concerned, market participation regarding crop sales is consistently larger for treated farmers compared to rain-fed counterparts, particularly in the Dry season and to a lesser extent in the following Belg season.

A number of resilience metrics were also compared. The PRIME based methodology – a capacity based approach – that aggregates three capacities notably, adaptive, transformative and absorptive - indicates gains across all seasons for treated farmers compared to counterfactual farmers. These resilience gains seem to be consistently larger in the Dry season compared with the other rounds. Such findings are not evident in the other resilience metrics, although impacts are present to a lesser extent in the Dry season and warrant further investigation.

Thanks to the panel structure of the dataset, which allows one to examine households status in the outcomes of interest across the seasons, and the role of PASIDP, this impact assessment was able to study impact dynamics through a growth model where a dynamic panel data model was employed, notably the Blundell-Bover system GMM estimator, to assess the impact of PASIDP on asset growth, as well as resilience gains, overtime, making full use of the four rounds of data. The findings there also unequivocally show the benefits of irrigation on assets growth - which are largely positive contingent on the variability of the drought over the seasons. Assets growth is also inversely related to initial assets, indicating the wealthier the farmer is at the first round the slower the assets growth. This indicate that there is convergence in assets growth. Results also point to the fact that the treatment increases resilience capacity gains and that that resilience capacity is a function of the previous status and increases over the various seasons.

This study clearly portrays strong evidence that investing in irrigation is highly transformative for farmers, particularly for those at the lower end of the welfare distribution and that implicitly the irrigation systems act as a risk management strategy that allows farmers to exhibit positive returns even during the climatic shock. In addition, this study highlights the added value of high frequency data collections. This data collection system has the potential to allow one to assess the seasonal variation as well as the sustainability of benefits overtime in a context where the drought spells are protracted and affect households differentially across the seasons.

The policy recommendations from this study are multi-fold. First, focused projects such as the ones with irrigation investments are effective at generating returns for smallholder farmers and increasing production of high value crops. However, commercialization and marketing support continue to be areas of improvement and should be bundled to interventions aimed at improving agricultural production to maximize the potential benefits of this increased production. Also, from an M&E and operational perspective, projects that aim at enhancing resilience and protecting smallholders from climatic shocks need to have different data systems from standard conventional M&E. Resilience data must be collected at high frequency in order to capture the impacts of stressors and shocks (and responses to shocks) using shock-sensitive indicators. The data must be collected over the long term, therefore ex-ante, rather than ex-post, because vulnerability to shocks is the product of slower-moving stressors as well as of long-term, multisector interventions for building resilience such as the ones implemented by IFAD-supported projects. In order to minimize the costs of such a data collection, specific data should be collected in sentinel sites, or small samples, e.g. sites that are strategically selected to monitor risk, shocks and welfare outcomes, while maintaining representativeness of key structural characteristics, such as specific agro-ecologies or livelihood zones, that can be collected in the standard annual surveys such as mid-term or completion surveys. Remote sensed data (GIS) can be used to provide objective shocks metrics on a more frequent basis.

Defined by a much sharper focus on altering the dynamics of welfare, resilience-building projects require this kind of data structure e.g. high frequency, sustained, long-term surveying of a network of sentinel sites combined with standard annual and more occasional surveys such as the usual baseline, midterm and completion surveys.

Sentinel surveys could be implemented on a collaborative basis among the Rome-based Agencies (RBAs) as well as nongovernmental organizations (NGOs), and national governments, given their mutual interest in monitoring resilience.

1. Introduction

A handful of studies have documented that public investments in agriculture, designed, and rolled-out to suit local conditions, contribute to increased agricultural productivity and resilience capacity of farmers (Asfaw et al., 2012; Azzarri et al., 2015; Minde et al., 2008). Investment in irrigation facilities is a common example, which illustrates how public investments in agriculture can improve the performance of farmers in the form of increased productivity, across rural areas in the developing world. Several empirical studies have found irrigation to have a positive impact on agriculture and poverty amongst small-scale farmers (Hussain and Hanjra, 2004; Lipton et al., 2003; Smith, 2004). Although the returns on investments in irrigation can be potentially high, the World Bank (2007) reports that irrigation coverage in Sub-Saharan Africa remains low. With this information in mind, a strong case could be made for investing in the expansion of irrigation coverage across Sub-Saharan Africa as a means of improving agricultural productivity and alleviating rural poverty (Dillon, 2011).

Out of the approximately 100 million ha of Ethiopia's land area, according to 2007 country estimates from the Food and Agriculture Organisation (FAO), only about 35% were considered arable. Crop production represents about 70% of the entire agricultural sector contribution to about 45% of the GDP of Ethiopia. Notwithstanding laudable growth rates averaging 6.7% between 1996 and 2006, poverty level in Ethiopia is still considered very high, worse off in the rural areas. The cause of this high level of rural poverty in Ethiopia among other reasons, is often attributed to the widespread low-input, low-output rain dependent subsistence farming systems, diminishing farm sizes, drought and drought induced famines, rapid population growth, environmental and land degradation and poor irrigation and water facilities.

Ethiopia's geographical and climatic attributes provide a greater amount of rainfall than the rest of Africa on average (Kassahun, 2007). Nonetheless, the agricultural sector in the country is constantly stricken by frequent drought and soil degradation (Matouš et al., 2013). These peculiar shocks to agricultural production are closely linked to the persistence of poverty in rural Ethiopia. Also, insufficient or lack of functioning irrigation infrastructures exacerbates the presence of poverty amongst rural farmers, especially among the poorest of the poor (Del Carpio et al., 2011; Escobal, 2005). Despite having relatively abundant water resources with irrigation potential, a report by the World Bank (2006) shows that only 5% of irrigable land are covered with irrigation in Ethiopia.

Poverty eradication being the main developmental objective, in September 2006 the government of Ethiopia adopted the Plan for Accelerated and Sustained Development to End Poverty (PASDEP) document, drafted by the country's ministry of finance and economic development in consultation with other stakeholders and development partners. The plan was to be Ethiopia's guiding strategic framework for a five-year period 2005/06 – 2009/10, with an ultimate objective to eradicating poverty and outlining the major focus programs and policies to achieve that. According to the plan, it was expected that in order to achieve the goal of halving poverty in Ethiopia by 2015, the economy of Ethiopia must sustain a growth rate of 6 to 7% annually, to be upheld by simultaneous sustained growths in the agricultural sector. In view of that, the major plans focused on to secure sustained development in the agricultural sector including the expansion of small and medium scale irrigation and water conservation programmes, and ensuring that natural resources are utilized judiciously. At the end of the defined period in the PASDEP plan, the government of Ethiopia planned to support the development of irrigation schemes covering about 322,630 ha of irrigable land in Ethiopia.

Tailored around the PASDEP – a plan that projects an incorporation of an additional 1.2 million hectares of land under irrigation by 2015, the Participatory Small-Scale Irrigation Development Project (PASIDP) was crafted. The primary goal of the PASIDP was to improve welfare and food security of rural households residing in drought prone areas of selected districts in four regional states of Ethiopia, through participatory small-scale irrigation development. Amongst others, some of the PASIDP approaches to achieving the goal were to: innovatively build on indigenous knowledge; promote beneficiary participation in the selection, construction, operation, maintenance and management of irrigation schemes; and secure communal ownership through grassroots organisations such as water users' association. Implemented from March 2008 to September 2015, the PASIDP project constructed a total of 121 irrigation schemes and benefitted about 62,000 households.

It is often argued that access to adequate water supply through irrigation infrastructures can help rural farmers improve their welfare, agricultural production and resilience. In the case of rural Ethiopia, several studies have reported positive effects of small-scale irrigation on food security and income from agricultural production (Ersado, 2005; Van Den Burg and Ruben, 2006; Tesfaye et al., 2008; Bacha et al., 2011; Aseyehegu et al., 2012). Howbeit, most of these studies assessing impact of investments in rural irrigation infrastructure do not incorporate either valid comparison groups or randomize the allocation of individuals or local communities that receive benefits from irrigation projects. Accordingly, to supplement an ex-post impact assessment for the PASIDP project that was conducted as part of the IFAD9 Impact Assessment Initiative , a high-frequency data was collected to particularly assess the sustainability of impact and estimate poverty and resilience outcomes. This study is thus an additional impact assessment where a lab-in-the-field experiment was run and a high-frequency dataset was collected to investigate the relationship between farmers' resilience profiles, risk preferences and agricultural productivity and well-being outcomes. The novel high-frequency dataset consists of a baseline survey collected in November 2016, and three follow-up surveys conducted every three months until November 2017.This study thus complements the small but growing literature that analyse the impact of irrigation projects (Del Carpio et al., 2011; Dillon, 2011; Rejesus et al., 2011).

This study examines whether the small-scale irrigation schemes, along with other capacity building and training activities offered as part of the PASIDP project, sustainably impacted beneficiaries in terms of providing them with more stable and increased income through increased agricultural production and household consumption, and enhanced smallholders resilience capacity to adverse shocks over a period of 12 months.

The following sections of this report, highlight in details the specifics of the project, including the theory of change and research questions used to assess the project's impact, the data and methodology utilized to appraise the impact of the project and finally the results and the discussion of the findings on the project's impact.

2. Theory of change and main research questions

2.1 PASIDP theory of change

The PASIDP project was launched, as part of Ethiopia's second-generation Poverty Reduction Strategy Paper (also referred to as the Plan for Accelerated and Sustainable Development to End Poverty (PASDEP)), with an overall objective of reducing rural poverty. To reduce rural poverty, the project aimed at improving rural household food consumption and agricultural revenue mainly through expansion of traditional irrigation systems and development of new small-scale irrigation systems.

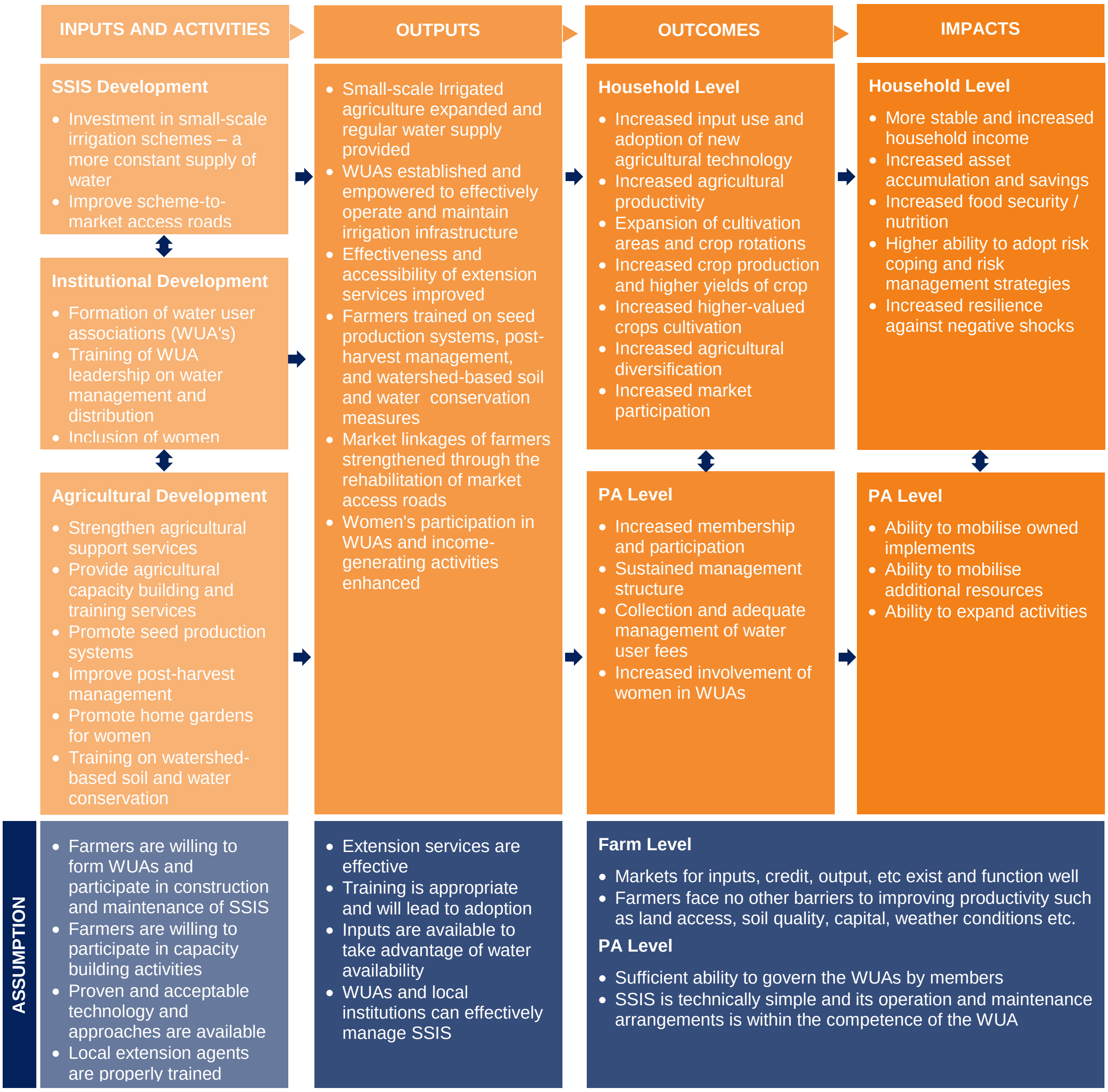
The project comprised of three main components namely (a) institutional development, (b) small-scale irrigation scheme development and (c) agricultural development. The institutions' development component supported a highly participatory approach to small-scale irrigation development through the formation of WUA's and community empowerment, while strengthening institutional capacity at the grassroot level and at the regional level. The small-scale irrigation development component improved the catchments area planning of small-scale irrigation schemes covering over 12,000 hectares of irrigable land, supported the construction of small-scale irrigation schemes and improved scheme-to-market access roads. The agricultural development component involved activities that strengthened agricultural support services, improved farming practices particularly in seed production systems, post-harvest management, watershed-based soil and water conservation and promoted home gardens for women.

For the development and management of the small-scale irrigation schemes, the project followed a participatory approach to ensure a sense of ownership and control in the management of the irrigation structures created and the soil conservation works to take care of the pitfalls of irrigated farming. At the start, food-deficit woredas (districts) under the Productive Safety Net Programme (PSNP) that are high density, drought prone and food insecure were selected to participate in the project. Then, following a participatory approach, the woreda and kebele (sub-districts) officials along with community leaders, selected the type of small-scale irrigation scheme most appropriate for the area based on the local conditions and implementation capacity of the targeted beneficiaries. To supplement the development of the small-scale irrigation schemes, the project implementation officials and the community leaders selected the most suitable training activities to offer to project beneficiaries.

Project's interventions, which include constructing irrigation schemes, forming WUA's, training of WUA leaders and members, and providing capacity building and training activities to farmers, should have helped the beneficiaries of the project in the following ways. First, the WUA's were formed within each community that receives the project. Second, the project's extension agents trained WUA leaders and members on ways to efficiently and effectively manage and distribute water. Third, capacity building activities and skills training were provided to the beneficiaries to increase their knowledge and awareness on agricultural technologies and improved practices. And finally, with a well-functioning irrigation system in place, project beneficiaries would obtain (1) a more constant supply of water, (2) substantially higher supply of water overall, and (3) timely water supply for agricultural production over the course of the cultivation seasons.

Given the components of the project and the details of activities involved, the project's theory of change can be summarized as in Figure 1.

Figure 1: PASIDP's theory of change



The agricultural development component of the project was designed to stimulate the adoption of agricultural technologies and improved practices among smallholder farmers. These technologies and practices were expected to sustainably increase productivity, boost adaptive capacity, food security, resilience of small holder farmers and enhance achievement of national food security and development goals (FAO, 2009). The small-scale irrigation schemes, along with other capacity building and training activities offered as part of the project were expected to help their beneficiaries have more stable and higher income level by increasing agricultural production, increase household consumption, and improve their resilience to negative shocks, notably drought, by allowing them to cope and recover from them (Ersado, 2005; Van Den Burg and Ruben, 2006; Tesfaye et al., 2008; Bacha et al., 2011; Aseyehegu et al., 2012). Project interventions of such kind should also have allowed beneficiaries, at the bottom end of the income distribution to move out of poverty.

Within the context of the PASIDP project, the development of small-scale irrigation schemes should have allowed farmers with access to irrigation to take advantage of the improvements in water supply to adopt risk management (ex-ante) strategies in preparation for shocks, and adopt risk coping (ex-post) strategies in response to shocks. As climate is rapidly becoming a major constraint to farmers who rely heavily on agriculture, the reliance on sustained irrigation water supply for agriculture is seen as one adaptation option to the variability in climate (Di Falco and Veronesi, 2014). Other forms of adaptation may include soil conservation measures (Kurukulasuriya, 2011) and switch of crop choices to more higher-valued crops (Seo and Mendelsohn, 2008). On the one hand, as a means to foster the adoption of risk management strategies, farmers with access to irrigation are better able to grow crops throughout the year, allowing them to have greater opportunities to earn income from selling their crops rather than relying mostly on water from rainfall. On the other hand, irrigation may also help beneficiaries reduce the need to adopt negative risk coping strategies such as sale of assets, reduction of consumption, or migration to other areas in search of other wage opportunities.

The effects of small scale irrigation scheme development can have a heterogeneous impact on project beneficiaries (Tucker and Yirgu, 2010). Specifically in the case of small-scale irrigation in Ethiopia, Kaur et al. (2010) identify that pastoralists are the ones most affected by increasing climate variability as they require water for their grazing land and livestock herds. Tucker and Yirgu (2010) report that more well-off farmers usually receive higher benefits from an irrigation project, since they have greater means to take advantage of the improvements in the supply of water by investing in productive farm inputs, renting additional land, and hiring additional labour to work on their farms.

However, for the irrigation development to have an impact on the beneficiaries, an important assumption is the adoption of agricultural technologies and practices that are complementary to irrigation. The lack of adoption of other agricultural technologies complementary to irrigation, which might be necessary to fully harness the potential of irrigation, might hinder the full potential impact of irrigation projects (Byerlee and Polanco, 1986; Mann, 1978). Also, a sizable body of literature has documented that the decision to adopt a new technology may be driven by individual unobserved characteristics (Bandiera and Rasul, 2006; Liverpool and Winter-Nelson, 2012; Songsermsawas et al., 2016). One component of the individual unobserved characteristics of the household is their risk preferences. Research has shown that the adoption (or lack, thereof) of other technologies complimentary to irrigation is correlated with individual risk preferences or ambiguity aversion (Leathers and Smale, 1991; Esrado et al., 2004). Thus, differential risk preferences or ambiguity aversion behaviour among farmers might help explain the heterogeneity in the impact of irrigation projects.

2.2 Project coverage and targeting

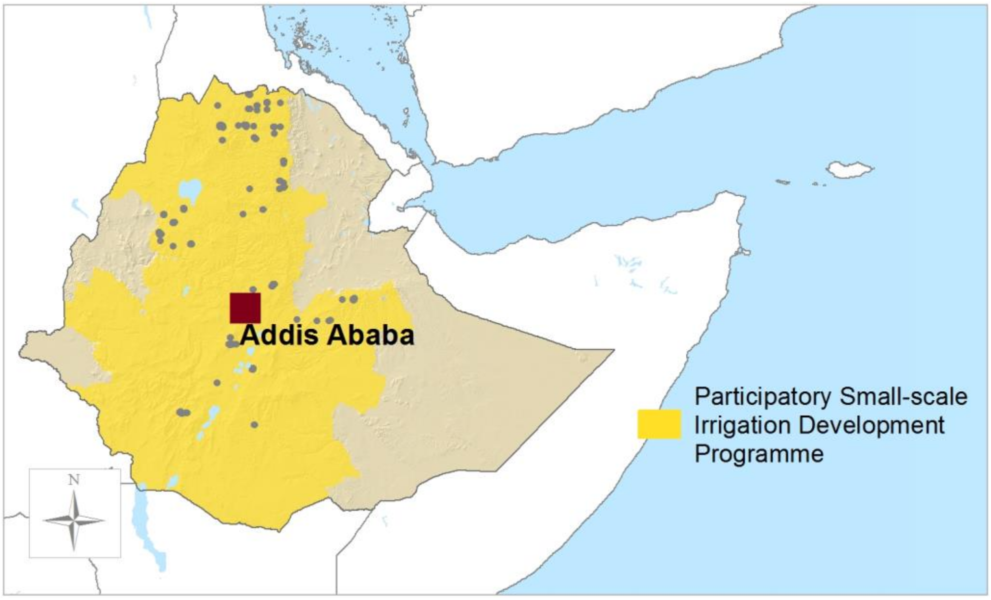
The PASIDP project was approved in 2008, and closed in 2015. During this time, 121 schemes were constructed and the total land area under irrigation increased by more than 12,000 hectares. The PASIDP project is estimated to have benefited 311,000 individuals in 62,000 households. With a total cost of US$ 57.8 million, the activities implemented by the project reached more than 62,000 beneficiary households in four regions (Amhara, Oromia, SNNPR, and Tigray) of Ethiopia, which were selected by the Government of Ethiopia (GOE). In Table 1, the distribution of PASIDP irrigation schemes is presented by region and by type of irrigation schemes chosen to be constructed. Figure 1 presents the locations of the irrigation facilities constructed and upgraded as part of the PASIDP project.

The targeting strategy of PASIDP project was designed to ensure the inclusion of resource poor and vulnerable farmers and women. Poor households rarely own land and have sufficient access to agricultural inputs and are hence rarely included in irrigation schemes. To overcome this constraint, the project introduced a range of small scale and relatively low-cost irrigation schemes that pose low entry barriers to the poor. Additionally, the project had a capacity-building component on irrigated farming and water management to promote irrigation schemes that are owned and fully operated by poor farmers. As women are the most vulnerable group of people in the communities covered by the project, the project also specifically designed a number of activities for women.

Table 2.1: Distribution of PASIDP Irrigation Schemes

Region	Scheme Type	Number of Locations
Amhara (28 schemes)	River Diversion	26
	Spate	2
Oromia (30 schemes)	River Diversion	20
	Spate	8
	Spring	2
SNNPR (17 schemes)	River Diversion	12
	Spate	4
	Spring	1
Tigray (46 schemes)	River Diversion	21
	Spate	4
	Pump Supported	14
	Shallow Well	7
Total		**121**

Figure 2.1: PASIDP small-scale irrigation locations (Source: IIASA)



2.3 Research questions

Drawing from the theory of change explained above, this impact assessment seeks to assess the sustainability of the impacts over a 12 months period. This periods spans 4 agricultural seasons. Specifically:

Question 1: What is the impact of PASIDP on beneficiaries' levels of cash input expenditures over the 12 months period and the four seasons of observation?

Question 2: Have the cultivation areas of PASIDP beneficiaries expanded as a result of the project? Is there a differential impact by season?

Question 3: Have the agricultural productivity levels of PASIDP beneficiaries increased as a result of the project? Are these levels affected by seasonal variation?

Question 4: Have the PASIDP beneficiaries diversified their crop cultivation (growing more types of crop) as a result of the project? What is this impact by season?

Question 5: Have the levels of agricultural revenue among PASIDP beneficiaries increased as a result of the project?

Question 6: Have the consumption levels of food and non-food items among PASIDP beneficiaries increased as a result of the project?

Question 7: Has the ability to adopt risk coping and risk management strategies among PASIDP beneficiaries increased as a result of the project? Is this different across seasons?

Question 8: Has the resilience level of PASIDP beneficiaries increased thanks to the interventions received? What are the resilience levels over the course of the seasons?

Question 9: Are there seasonal variations vis a vis PASIDP beneficiaries capability to move out of poverty compared to their counterfactual farmers? What is the evidence on economic mobility indicators?

3. Impact assessment design: Data and methodology

3.1 Data

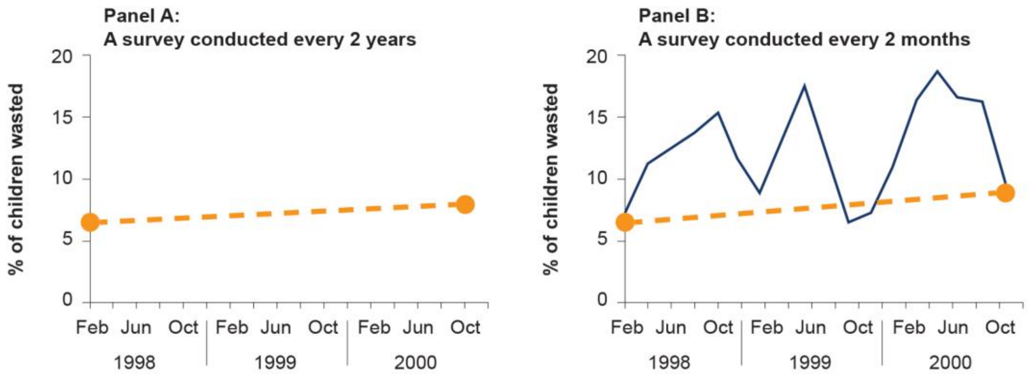
Identifying the impact of the PASIDP project was challenging due to several reasons. First, the project contained multiple components, and the details of project delivery and project implementation varied according to the capacity of local institutions, timing, geographical landscape, characteristics of beneficiary, and selection of capacity building or training activities offered. Second, there was insufficient documentation about the project's target group, targeting strategy, list of activities offered, and list of beneficiaries. Third, project interventions were delivered in an ad-hoc fashion, which is not uncommon in the case of irrigation or other investments related to infrastructure that are subject to varying uncertainty regarding engineering complexity, procurement process of construction firms, length of construction times, among others. The non-random nature of project placement is particularly important for impact evaluation since the presence of an irrigation project is likely to be correlated with geographical suitability, unobservable characteristics of households that lead to participation in the project, and pre-existing local conditions such as access to markets and roads (Dillon, 2011).

Hence, the ex-post impact assessment of PASIDP adopted a mixed method approach, collecting both qualitative and quantitative data in order to strengthen its design. This impact assessment began with a qualitative survey that was done in 2016 to create a better understanding of the project targeting strategy, the implementation details, and the channels through which the project activities affect the changes in the key outcome indicators, followed by a quantitative survey, also conducted in 2016, which aimed at providing an assessment of the overall impact of the project (see Garbero and Songsermsawas: IFAD9 Impact Assessment Brief - Ethiopia).The methodology of the qualitative study included a series of narratives from focus-group discussions (FGD's) and key-informant interviews (KII's). The results from the qualitative study documented positive impacts of the project on agricultural production, both in terms of yields, crop income, and diversification.

This study complemented the quantitative survey that was conducted in 2016, and had an innovative data collection strategy where high frequency data (e.g. quarterly data) was collected across four rounds over a 12-month period . Data was collected on one entire year to capture the seasonal variation of the outcomes within different agricultural cycles and assess to what extent seasonal variation in the climatic shocks could affect agricultural outcomes and smallholders resilience Previous studies have documented that traditional household surveys conducted annually are necessary to estimate the impact of irrigation projects (Dillon, 2011; Del Carpio et al. 2011). However, the study of resilience warrants high-frequency, resilience-related data, e.g. low burden monthly or quarterly surveys administered by local village-based enumerators. Equipped with tablets, enumerators in the field administer a survey about a household's well-being, shocks experienced, and asset levels. The data are immediately uploaded to a remote server, allowing near real-time monitoring which can be used by agencies to launch targeted policy interventions. Annual surveys may be inadequate to assess the impact of irrigation projects on project outcomes such as agricultural production and income, household's consumption, and resilience as such outcomes usually vary greatly within the same year or cropping season in response to agro-climatic or economic shocks. ,

The increased volatility and variability of weather shocks in Ethiopia and the seasonal response of agricultural outcomes of smallholders beneficiaries therefore provides the rationale for conducting this study to capture the sustainability of the irrigation benefits. The literature has also stressed the need for more frequent data collection systems, in a context of an evaluation of the Nutrition Surveillance Program (NSP) in Bangladesh (Barrett and Headey, 2014). There, a high-frequency dataset revealed a considerable difference in measuring child nutritional outcomes, once compared with traditional annual data measured at two points in time (Figure 3.1 – panel A). Note how, high-frequency household surveys can lead the policy maker to complete different conclusions regarding trends in nutritional outcomes (Figure 3.1 –panel B). Another study by McKenzie (2012) called for multiple rounds of data collection at short intervals to measure outcomes that were relatively noisy, and less correlated with time such as business profits, and household expenditures. This can allow researchers to assess the variability of treatment effects overtime

Figure 3.1: Wasting prevalence of children in Bangladesh from a study by Bloem, Moench-Pfanner, and Panagides (2003)



As far as this study is concerned, a high-frequency survey collected information from randomly selected beneficiary and non-beneficiary households from the four regions covered by the project. The process through which the beneficiary and non-beneficiary households were sampled was designed to identify direct impacts; comparison farmers were selected as those who were not exposed to the project activities both directly and indirectlyin such regions. Given that households that reside in the same kebele as the treatment group have a higher probability of being exposed to the project activities indirectly, the impact assessment relied on an identification strategy that randomized the selection at the kebele level. To overcome the problem of contamination, the control group was selected from kebeles that did not benefit from the project, but were located in the same woreda as the kebeles that benefited from the project to account for similarities in the agro-ecological context. The random selection of the Kebeles was also implemented with a selection-on-observables design to ensure the estimation of the impact was free from selection bias. Therefore, the sampling frame of the control kebeles included kebeles which had similar characteristics as the beneficiary kebeles in terms of agro-climatic conditions and agricultural practices as indicated by NDVI and precipitation levels. To further confirm the similarity of the kebeles in the treatment and control groups, the local project management units were consulted to validate the selection of the counterfactual.

In general, the selection of beneficiary and non-beneficiary households followed a two-stage stratified sampling by region, agro-ecological zone, and precipitation levels. First, from the full list of 105 kebeles with small-scale irrigation schemes built by PASIDP as shown earlier in Table 1, a number of selection criteria were applied to arrive at the final list of candidate locations that the survey would have covered. These selection criteria were:

- The scheme was considered to be functional by the program management unit (PMU) for more than one year.
- The projected abstraction rate of the irrigation scheme was not too high (no greater than the 90th percentile ranks of all irrigation schemes); which would prevent the random selection of irrigation schemes that may not be representative of the majority of the schemes built by PASIDP.
- The information regarding the size of command areas after the construction of the irrigation scheme was available.

After applying these three criteria, 93 kebeles remained in the sampling frame of the beneficiary kebeles from a total of 105 kebeles in the four regions. Then, to select a counterfactual Kebele with similar NDVI and precipitation levels as the sampled project kebeles, average normalized difference vegetation index (NDVI) and average precipitation data of each kebele was matched to the list of project kebeles. After verifying that all the kebeles in each region had similar NDVI and precipitation values, equal number of beneficiary and non-beneficiary kebeles were randomly selected by stratifying the kebeles according to precipitation levels. Approximately 10 beneficiary kebeles were randomly selected per region from the 93 treated Kebeles to obtain a sufficiently representative sample of all kebeles covered by the project. In addition, 10 control kebeles were randomly sampled from non-beneficiary kebeles that had similar agro-climatic indicators, geographical landscape, and agricultural activities. After selecting the Kebeles, around 13 households were randomly selected out of the total 300 to 400 households living in each beneficiary and non-beneficiary kebeles. In total, 1,033 beneficiary and non-beneficiary households were sampled from the four regions, as shown in Table 3.1 below.

Table 3.1: Sample distribution by region before matching

Region	Treatment		Control		Total
	HHs	Kebeles	HHs	Kebeles	
Amhara	130	10	130	10	260
Oromia	129	10	130	10	259
SNNPR	128	10	126	10	254
Tigray	130	10	130	10	260
Total	517	40	516	40	1,033

In summary, the beneficiaries (treatment group) resided in areas that had a functioning PASIDP irrigation scheme in place for at least one year to ensure that the benefits from irrigation to their agricultural activities could be observed. The non-beneficiaries (control group) resided instead in areas without any PASIDP-related activities, but with similar agro-climatic indicators, geographical landscape, and agricultural activities.

3.2 Questionnaire and impact indicators

The high-frequency data contained detailed information on access to irrigation water supply, agricultural production and household expenditure, along with a full set of household-level data such as household demographics, social and economic characteristics, and special modules on risk management strategies, coping strategies and self-perceived shocks which were measured across four rounds. This information was used to construct a number of impact indicators and generate a wide range of household level explanatory variables to be used in the analysis. Self-reported shocks in the survey were also complemented with an objective shock measure, notably the Standardized Precipitation Evapotranspiration Index (SPEI), which was used as a covariate in the analysis. Such indicator is an extension of the widely used Standardized Precipitation Index (SPI). The SPEI is designed to take into account both precipitation and potential evapotranspiration (PET) in determining the extent and severity of drought. The parameters of the SPEI are a time-series of total monthly precipitation (P) and monthly potential evapotranspiration (PET).

This impact assessment focused on measuring impact of the PASIDP project on two main sets of outcomes. While the first set of outcomes related closely to the main goal of the project, which is to reduce poverty by raising income, measured in terms of agricultural production and household consumption, the second set of outcomes, though less examined in previous literature, focused on resilience metrics.

Agricultural production, intensification and input use

To measure agricultural production, indicators concerning crop and livestock production were employed. The crop production related variables were constructed for each season covering the crop cultivation season prior to each survey round. As far as crop production was concerned, crop input, crop yield (kg/ha) and value of crop production were used. To measure agricultural productivity, the rate of production for given inputs such as seeds, fertilizers, and pesticides was used. For livestock production, household livestock ownership and the number of livestock units owned were used. As a measure of livestock units owned, the tropical livestock unit was constructed by assigning weights to each livestock type.

In addition to generating an increase in agricultural production, better irrigation infrastructure and reliable water supply also enhance use of other inputs like land, fertilizers and pesticides. To estimate the projects impacts on such outcomes, agricultural intensification was additionally assessed. Agricultural intensity is broadly referred to as the ratio of inputs and outputs within an agricultural system either in terms of yield per land area and per input unit (Herzog et al., 2006). Alternatively, it can be defined as the sum of various categories of input costs and the total cultivated area of the farm (Teillard et al., 2012). Hence, both output-oriented and input-oriented measures were used to assess the agricultural intensity.

Economic mobility: income, savings and assets-based indicators

This impact assessment measures the impact of the project on economic mobility over time using household income, savings and assets as a proxy. All three indicatorswere calculated at the household level with a reference period of four months representing the season prior to each data collection round. For assets, additional 12 month recalled data was collected for the period preceding the first round of data collection.

The total household income was calculated as the sum of gross income from crop production, livestock production, agricultural and non-agricultural wage employment, self-employment, transfer and other income source. Savings include household's total amount of cash savings in both formal and informal financial institutions. As far as assets indicators were concerned, durable, productive, livestock and overall assets indices were computed using principal components analysis

(PCA) and polychoric factor analysis. Such data reduction methods assign weights to the counts of each asset item based on the household distributions for each round.

Poverty reduction indicators

Although it is well recognized that poverty is a multidimensional concept, prior empirical work on poverty measurement is mostly based on income, consumption or assets-based indicators. While acknowledging the importance of non-monetary dimensions of poverty, the focus in this impact assessment is on asset-based poverty. Asset-based poverty measures measure the extent to which households have a stock of assets that is sufficient to sustain a minimum level of consumption during periods of transitory shocks.

Asset based poverty indicators were constructed based on the indices discussed above for each round of data collection using relative poverty lines that were calculated based on the assets distribution at baseline (obtained through recall data), setting the poverty thresholds at 40th and 60th percentiles of such distributions. All four asset indices are used to check the sensitivity of the poverty classification to the inclusion of different assets in the indices.

Based on the asset-based poverty indicator variables, households were then classified into four groups: (1) households who moved out of poverty in each consecutive round (if households were below the poverty line in the previous round and were above the poverty line at the next round), (2) households who stayed poor (if households remained below the poverty line in two consecutive rounds), (3) households who stayed non-poor (if households remained above the poverty line in two consecutive rounds), and (4) households who moved into poverty (if households are above the poverty line in the previous round and are below the poverty line in the consecutive round). These indicators are particularly relevant for an analysis of poverty dynamics over the different seasons.

Resilience

Resilience, similar to other well-being indicators, is a multidimensional concept (Sen, 1985). Following the definition of resilience provided by Barrett and Constas (2014), where resilience is conceptualized as smallholders capacity to positively react from shocks and recover their pre-shock level of income or food security, there can be at least three possible types of capacity strengthening mechanisms that can help increase farmers resilience (Mitchell 2013). Absorptive capacity refers to "the ability of a system to prepare for, mitigate or prevent the impacts of negative events" (Cutter et al. 2008). For example, farmers might harvest their crops earlier than usual during a bad year to prevent additional crop losses. Adaptive capacity may be defined as "the ability of a system to adjust, modify or change its characteristics and actions to moderate potential future damage and to take advantage of opportunities" to maintain the same level of well-being (Béné et al. 2012). For instance, farmers might adopt drought-tolerant crop varieties in response to growing climate vulnerability. Transformative capacity is the "ability to create a fundamentally new system so that the shock will no longer have any impact" (Béné et al. 2012). Farmers within a community may increase their transformative capacity by engaging in a community-based forest conservation program to prevent excessive logging within the community. It is important to note these three types of mechanisms that enhance resilience are not mutually exclusive, and in many instances, may take place concurrently.

To date, scholars have developed several approaches that collect a range of indicators to estimate resilience. The wide range of methodologies allow researchers and practitioners to estimate resilience indexes wherebythe relevant indicators are collapse into a single indicator variable, which is then employed either as a predictor variable or as a dependent variable contingent on whether resilience is an outcome or an explanatory variable in the analysis of interest. Given the different methodologies available to date, this impact assessment undertook an innovative approach by including in the survey instrument various indicators that could lead to the different estimation procedures underlying the various resilience metrics available in the literature. The first approach, referred to as the Resilience Index Measurement and Analysis (RIMA) model, employs a multidimensional poverty analysis approach using a multivariate statistical technique (Alinovi et al., 2010; Bauer et al., 2011; FAO, 2013). A second approach, which is an updated version of the RIMA model, is the Resilience Index Measurement and Analysis – II (RIMA II) model (d'Errico et al., 2015a; d'Errico et al. 2015b; Kozlowska et al., 2015; d'Errico et al., 2016; FAO, 2016) which refined the estimation framework for the resilience model. The third approach, employed as part of a household survey conducted in Ethiopia from the Pastoralist Areas Resilience Improvement and Market Expansion (PRIME) project (Frankenberger, 2015) is to use a principle component analysis (PCA) to combine different sub-indices to form a single resilience index. Last, we present a fourth approach which employs a conditional moment-based econometric approach to compute household-level resilience index (Cissé and Barrett, 2016; Phadera et al., 2017). These resilience metrics are fairly similar in the data requirements needed for their computation. Therefore, given also, the lack of consensus for an endorsed resilience metric, a choice was made to compute and compare them, to provide recommendations on whether such metrics can lead to the same conclusions.

Food security

Several case studies in Ethiopia have already highlighted the positive impacts of enhanced access to irrigation water supply on household food security (Tesfaye et al., 2008; Bacha et al., 2011; Aseyehegu et al., 2012). Besides an extended growing season, with a higher variety in food and cash crop production and the resulting increase in cash income, food insecurity could be reduced. Hence, dietary diversity and food security outcomes are also among the key expected impacts of the PASIDP project. This impact assessment will examine to what extent there is a seasonal variation in food security outcomes over the course the different seasons.

To measure dietary diversity, the household dietary diversity score was used. The latter (HDDS) is a simple count of food groups that a household or an individual has consumed over the preceding 24 hours. To measure food insecurity, the Coping Strategies Index (CSI) was also calculated. The CSI takes an experiential approach to measure food security based on the behavioural coping strategies undertaken by households to manage food shortages. The CSI was constructed as a weighted average of the frequency and severity of various behavioural coping strategies (Carletto, Zezza, and Banerjee 2013).

Market access indicators

A proxy for market access was also computed based on household’s proximity to the market. Specifically, the travelling time to markets and information on market participation of the households, simply defined as whether or not a farmer sells its crops or livestock products for money, were used as market access indicators.

3.3 Impact estimation

Different estimators and approaches were employed contingent on the indicators of interest to estimate the impact of the project.

First it is important to stress the specific data structure. It is a high frequency data collection which involved four rounds of data collection, which actually capture the seasonality of both shocks and outcomes.

In order to first observe the evolution of treatment effects over the four rounds, cross-sectional regressions were estimated for the main outcomes: agricultural productivity and production outcomes, economic mobility, food security and market access outcomes. Recall that a treatment effect is the change in an outcome caused by an individual getting the treatment instead of another.

It is important to recall the basic quantities of interest. A potential outcome model specifies the potential outcomes that each individual would obtain under each treatment level, the treatment assignment process and the dependence of the potential outcomes on the treatment assignment process. When the potential outcomes do not depend on the treatment levels, after conditioning on covariates, regression estimators, inverse-probability-weighted estimators and matching estimators are commonly used. The term potential outcome model is equivalent to the Rubin causal model and the counterfactual model.[1]

Three parameters are often used to measure treatment effects: the average treatment effect (ATE), the average treatment effect on the treated (ATET), and the potential outcome means (POMs).

The ATE is the average effect of the treatment in the population:

$ATE = E(y_1 - y_0)$.

The POM for treatment level t is the average potential outcome for that treatment level:

$POM_t = E(y_t)$.

The ATET is the average treatment effect among those that receive the treatment:

$ATET = E(y_1 - y_0|T = 1)$.

The potential outcome model is crucial to the discussion: this model generates data in which y_i is the observed outcome variable, t_i is the treatment variable, x_i is a vector of covariates that affect the outcome, and w_i is a vector of covariates that affect treatment assignment. x_i and w_i can have variables in common.

Therefore, this potential outcome model specifies the observed outcome y as y_0 when treatment is equal to zero, $T = 0$ and y as y_1 when treatment is equal to one ($T = 1$). Analytically:

$y = (1 - T)y_0 + Ty_1$.

Note that the functional forms for y_0 and y_1 are:

$y_{0=}X'\beta_0 + \epsilon_0$,

$y_{1=}X'\beta_1 + \epsilon_1$,

where β_0 and β_1 are the coefficients to be estimated, and ϵ_0 and ϵ_1 are the error terms that are not related to x or w.

Therefore, the potential outcome model divides each potential outcome into a predictable component $X\beta_t$ and an unobservable error term ϵ_t.

The treatment assignment process can be specified as follows:

$$t = \begin{cases} 1, & \text{if } W'\gamma + \eta > 0 \\ 0, & \text{otherwise} \end{cases},$$

where γ is the vector of coefficients, and η is an unobservable error that is not related to x or w. Once again, the treatment assignment process is divided into a predictable term $W\gamma$ and an unobservable error term η.

The potential outcome model is specified through the functional forms of the potential outcomes and the treatment assignment process. The linear functional form is presented in the example above, but other functional forms can also be used, depending on the nature of the outcome variable. In the remainder of this section, the set of functional forms for the potential outcomes is

[1] See Rubin (1974); Holland (1986); Robins (1986); Heckman (1997); Heckman and Navarro-Lozano (2004); Imbens (2004); Cameron and Trivedi (2005); Imbens and Wooldridge (2009); and Wooldridge (2010) for more detailed discussions.

referred to as the outcome model, and the treatment assignment process is referred to as the treatment model.

Three key assumptions underpin the different treatment effect estimators that we employ in this study, namely: (1) the conditional independence (CI) assumption, which restricts the dependence between the treatment model and the potential outcomes given the covariates; (2) the overlap assumption, which ensures that each individual could receive any treatment level; and (3) the independent and identically distributed (i.i.d.) sampling assumption, which ensures that the potential outcomes and the treatment status of each individual are unrelated to the potential outcomes and treatment statuses of all other individuals in the population. This third assumption is what is known as SUTVA, the *stable unit treatment value assumption* (Imbens and Woolridge 2009; Woolridge 2010). Note that these assumptions may vary across estimators. The SUTVA assumption states that the observed differences in outcomes between treatment and control units only depend on one's own treatment status, and not the treatment status of the other units.

The following five econometric methods are used to provide correct inference for causal parameters, for each round of the study specifically: (1) regression-adjustment (RA); (2) propensity score matching (PSM); (3) covariate matching (NN or NNM);[2] (4) inverse-probability weighting (IPW); and (5) the doubly robust estimator (IPWRA).

In addition, given the particular data structure, a high frequency dataset with four rounds of data, which is effectively panel data, an adaptation of the standard empirical growth model is used to estimate the impact of irrigation on resilience overtime (Dercon et al. 2012). Dercon et al. (2012) note that while the standard growth model (Temple 1999) does not account for transitory shocks (for example, changes in rainfall levels), previous studies using a panel dataset of Ethiopian households survey observed significant impacts of transitory shocks on household consumption levels (Dercon 2004, Dercon et al. 2005). According to this specification, one estimates the changes in outcomes from the first period, controlling for the initial conditions. This specification can be expressed as follows:

$$\Delta y_{it} = \beta_0 + \beta_1 I_i + \beta_2 \Delta S_{it} + \beta_3 I_i \Delta S_{it} + \beta_4 y_{i,t-1} + \beta_5 y_{i1} + \beta_6 X_{i1} + T_t + \varepsilon_{it},$$

where $\Delta y_{it} = y_{it} - y_{i1}$ is the change in outcome of interest overtime from the baseline round, I_i is the treatment status, $\Delta S_{it} = S_{it} - S_{i1}$ is the change in the prevalence of shocks over time from the first round, $y_{i,t-1}$ is the outcome of interest from the previous time period (first-ordered lag), X_{i1} is the household characteristics at the baseline round (initial conditions), T_t is the time dummy variable, and ε_{it} is the error term. The growth model is fitted through the Arellano-Bond (1991) and Arellano-Bover (1995)/Blundell-Bond (1998) Dynamic Panel data estimators. Two specifications are explored – a first one that doesn't include interactions and more saturated one. The covariates used in the model are age, gender, education level and marital status of the

[2] Both (2) and (3) are matching estimators.

household head, number of adult members, dependency ratio and the size of land owned by the household.

The Arellano-Bond (1991) and Arellano-Bover (1995)/Blundell-Bond (1998) estimators, also known as difference and system GMM (generalized method of moments), have gained increased recognition in the econometric literature (Bond, 2002, Roodman, 2005) recently. Both are designed for cases in which T (time) is at least equal to 3 and the number of observations is large (small T and large N). They are particularly recommended when there is a dynamic panel bias, when there are no good excluded instruments at hand, when other regressors are potentially endogenous in the model of interest and when there is the presence of heteroscedasticity and auto-correlation within households and not across them.

The difference GMM estimator was first proposed by Holtz-Eakin, Newey and Rosen (1988). The idea behind is to first-difference the data and then apply the generalized method of moments. Instead of using exogenous instruments, lagged levels of any endogenous repressors are added. This makes the endogenous variables predetermined and, therefore, not correlated with the error term in the equation.

The system GMM estimator was first suggested by Arellano and Bover in 1995 and further developed by Blundell and Bond in 1998. The estimator exploits further moment conditions and essentially fits a system of equations for each period, one in differences and one in levels, allowing for the instruments to change. The introduction of more instruments, improves efficiency. The equation in differences is instrumented with levels and the level equation is instrumented with the differences. It makes the additional assumption that the first differences of the instruments are uncorrelated with the fixed effects. System GMM is estimated in levels to be able to retain time invariant variables such as the treatment variable.

To ensure that the households in the treatment and the control groups are statistically comparable, matching estimators are employed first to obtain comparable groups and control for any selection on observable characteristics using the observations using data from the first round. This matched sample is used to set the sample for all analyses.

1. Profile of the project area and sample

Table 4.1 presents descriptive statistics of the survey sample, where average characteristics of treatment and control groups are presented. Note that average characteristics are quite balanced across the two groups – indicating that there are no systematic differences and therefore that the control represents a valid counterfactual. Minor differences are observed for variables such as education of household head (with the control slightly more educated then the treatment group); and for recalled assets such as number of livestock (e.g. oxen and donkeys) – where the treatment group seems to have a higher average number of animals 12 months ago.

Table 4.1: Summary statistics before, after matching and bias reduction

	Before matching				After matching				Reduction in Bias (%)
	Treat. Mean/SE	Control Mean/SE	p-value	Bias	Treat. Mean/SE	Control Mean/SE	p-value	Bias	
Male head	0.92	0.89	0.138	9.26	0.93	0.927	0.94	0.55	94.02
	0.01	0.02			0.01	0.014			
Age of head	44.28	45.26	0.280	3.40	44.20	44.256	0.95	0.45	86.89
	0.60	0.70			0.60	0.662			
Education of head (1= Elementary)	0.44	0.51	0.072*	12.41	0.44	0.433	0.78	2.25	81.83
	0.02	0.03			0.02	0.027			
Education of head (1=Secondary)	0.07	0.04	0.043**	10.74	0.06	0.057	0.90	1.22	88.66
	0.01	0.01			0.01	0.013			.
Number of adult HH members	6.01	5.67	0.053*	8.88	5.98	6.040	0.77	2.49	71.95
	0.12	0.13			0.12	0.139			
Dependency ratio	1.35	1.33	0.738	3.88	1.35	1.305	0.57	4.52	-16.43
	0.05	0.05			0.05	0.054			
Marital status of head (1=married)	0.92	0.89	0.141	8.16	0.93	0.926	0.91	0.86	89.52
	0.01	0.02			0.01	0.015			
Altitude	1859	1830	0.452	5.03	1857	1875	0.66	3.39	32.63
	23.88	30.68			24.42	28.836			
Total land owned	2.09	1.93	0.337	5.13	2.08	2.082	0.99	0.11	97.95
	0.12	0.12			0.12	0.123			
Improved wall	0.05	0.07	0.261	6.21	0.05	0.058	0.65	3.58	42.44
	0.01	0.01			0.01	0.013			
Improved floor	0.05	0.05	0.925	0.67	0.05	0.046	0.96	0.39	42.44
	0.01	0.01			0.01	0.012			
Modern kitchen	0.87	0.88	0.536	1.21	0.87	0.866	0.85	1.54	-27.41
	0.02	0.02			0.02	0.019			
Number of rooms	2.22	2.16	0.374	2.86	2.22	2.259	0.60	4.43	-55.23
	0.04	0.05			0.04	0.054			
Toilet	0.82	0.85	0.305	5.37	0.82	0.804	0.59	4.74	11.70
	0.02	0.02			0.02	0.022			

Improved oven	0.06	0.06	0.712	5.09	0.05	0.050	0.91	0.82	83.92
	0.01	0.01			0.01	0.012			
Improved waste	0.11	0.08	0.232	6.95	0.11	0.111	0.96	0.45	93.55
	0.02	0.01			0.02	0.017			
Number of oxen (12 months ago)	1.25	0.96	0.003***	13.56	1.16	1.211	0.70	3.83	71.74
	0.07	0.07			0.06	0.079			
Number of donkeys (12 months ago)	0.50	0.33	0.002***	14.60	0.45	0.463	0.79	2.46	83.14
	0.04	0.03			0.04	0.038			
Radio	0.39	0.31	0.058*	9.89	0.37	0.377	0.92	0.90	90.93
	0.03	0.03			0.03	0.030			
Incidence of all shocks experienced in the past five years	1.85	1.80	0.637	1.10	1.85	1.875	0.87	1.32	-20.03
	0.08	0.09			0.08	0.092			
Drought index (SPEI<=-1)	0.84	0.80	0.215	2.53	0.84	0.847	0.76	2.36	7.00
	0.02	0.02			0.02	0.020			
No. of observations	422	348			403	328			

Table 4.2 displays the sample distribution by region, after performing propensity score matching. The sample reduced from 770[3] to 731 after matching on a number of covariates, notably the ones presented in Table 4.1.

Table 4.2: Sample distribution by region after matching

Region	Treatment		Control		Total
	HHs	Kebeles	HHs	Kebeles	
Amhara	119	10	67	10	186
Oromia	99	10	71	10	170
SNNPR	73	9	91	10	164
Tigray	112	10	99	10	211
Total	403	39	328	40	731

Table 4.3 presents the distribution of the irrigation schemes financed by the project in the sampled kebeles across the four regions. The distribution is quite heterogeneous – with modern diversion prevalent across all regions and particularly in Amhara.

Table 4.3: Distribution of irrigation schemes among the treatment sample by region

Type of irrigation	Region				Total
	Amhara	Oromia	SNNPR	Tigray	
Modern river diversion	109	41	38	43	231
Traditional river diversion	2	6	5	3	16

[3] Note that around 25% of the initial 1,033 households were lost due to attrition and treatment contamination.

Spring	0	12	0	0	12
Spate	0	11	0	8	19
Pump-supported	0	2	1	36	39
Shallow-dug wells	0	0	0	11	11
Total	111	72	44	101	328

Table 4.4 shows descriptive statistics concerning the treatment sample, particularly reported costs concerning water users associations (WUA) membership (notably prevalence of WUA membership, reported WUA membership fees; WUA and irrigation costs in the last 12 months preceding the baseline round, by region. The proportion of households who participate in WUAs is larger in Amhara region, possibly a consequence of the larger number of schemes. Surprisingly reported fees are larger in Tigray, as well as costs related to the WUA and irrigation. However, the higher WUA membership fee and cost observed in Tigray can be explained by the evolution of WUAs in the four regions that was largely influenced by traditional irrigation practices, the political context of the villages and the interests of external actors (Yami, 2013). While with the introduction of 'modern schemes' of PASIDP, the set-up and by-laws of WUAs in Amhara, Oromo and SNNPR regions got replaced by the new institutional arrangements introduced by PASIDP and the cooperative agency, in Tigray region the traditional water distribution system and the WUA leadership persisted. The traditional WUA committees in the Tigray region continued to function at the lowest level of formal institutions to govern the irrigation schemes and administer WUA membership fees successfully, while the top-down approach followed by the cooperative agency in devising the formal by-laws of WUAs in the three regions reduced the common understanding of by-laws by users of schemes and weakened rule enforcement(Yami, 2013). The higher average cost of irrigation in Tigray mainly due to the presences of pump-supported irrigations schemes that usually have a significant electric costs.

Also, share of irrigated land is roughly similar – although irrigated land size seems to be higher in Amhara compared to the rest of the regions.

Table 4.4: Descriptive statistics of the cost of irrigation and WUA membership for the treatment sample by region at the baseline

	Region				Total
	Amhara	Oromia	SNNPR	Tigray	
WUA membership (%)	89.92	31.31	50.68	69.64	62.78
WUA membership fee (Birr)	33.12	28.70	34.46	87.35	49.49
WUA cost (Birr)	22.73	3.94	5.27	37.32	18.66
Irrigation cost (Birr)	65.74	31.51	20.17	217.84	91.46

Irrigated land (ha.)	0.92	0.31	0.16	0.33	0.44
Share of irrigated land (%)	0.33	0.33	0.13	0.22	0.25

Table 4.5 presents the percentage distribution of households by the type of major crops grown in each region, at the baseline round. Note that while maize is prevalent in Amhara and Oromia, teff is prevalent across all except Oromia, followed by sorghum which is grown, primarily in Oromia, and Tigray. Wheat is predominant instead in Tigray.

Table 4.5: Sample distribution by major types of crops grown by region at the baseline

	Region				Total
	Amhara	Oromia	SNNPR	Tigray	
Major crops (%)					
Maize	65.05	67.06	46.34	13.27	46.37
Teff	43.55	0.00	43.29	51.18	35.57
Sorghum	1.61	54.12	4.27	35.07	24.08
Wheat	13.44	4.71	12.20	45.50	20.38
Barley	29.03	0.59	10.98	31.28	19.02

Table 4.6 shows descriptive results on the various crop production indicators, for the matched samples, across the four rounds. Note that these statistics refer to the season preceding the data collection. Recall that Meher is the main rainy season, while Belg represents the short rainy season. Result on input expenditure for the first Meher season is not presented as expenditure data was not collected during the first round of data collection. Note that grain yield largely varies across seasons, while vegetables yields are larger in first Meher and Dry season. Crop diversification measured by the Simpson index seems to be larger in the first Meher season.

Table 4.6: Descriptive statistics of crop production for the matched sample across seasons

	Seasons				Total
	Meher 1	Dry	Belg	Meher2	
Crop production input use					
Cultivated land (ha.)	1.16	0.35	0.53	1.40	0.86
Share of irrigated land	0.25	0.25	0.22	0.23	0.24
Expenditure per ha. (Birr)	-	1907.7	677.9	1481.2	1016.7
Seed	-	754.7	168.3	416.5	446.5
Fertilizer	-	701.8	324.2	814.9	613.6

Pesticides	-	109.6	68.9	37.3	71.9
Labour	-	341.6	116.5	212.5	223.5
Crop yield (ha.)					
Grain	1531.5	1206.4	7055.3	1079.73	1806.3
Cereal	1593.3	1384.2	2988.4	1068.8	1478.2
Pulse	859.4	488.9	925.1	281.2	598.1
Fruit	1399.5	536.1	6924.8	2434.5	3225.7
Spice	-	1194.5	4830.3	1411.4	2106.5
Vegetable	6743.45	5079.9	1682.5	1245.7	3874.9
Root	4368.7	7085.9	35994.3	1613.3	12059.1
Perennial	2773.8	2501.7	12024.3	926.9	4371.4
Crop revenue	3250.7	2013.9	960.4	1269.6	1873.6
Total value of crop production	-	27,8	36,549	42,017	26,611
Crop diversification (Simpson's index)	0.412	0.181	0.224	0.272	0.272

Table 4.7 presents descriptive statistics on income indicators across the four rounds. Note that total gross income is larger in the Meher seasons, while the distribution of income sources exhibit similar patterns across the first and fourth round, and between the 2nd and 3rd round. Income diversification is descriptively marginally larger during the rounds corresponding to the dry and short rainy season. This implies that households participate in other income-generating activities in the lean seasons.

Table 4.7: Descriptive statistics of household income of the matched sample across seasons

	Seasons				Total
	Meher 1	Dry	Belg	Meher2	
Total gross income	6617.7	4319.4	3673.5	6815.7	5356.6
Per capita gross income	1238.7	811.7	675.4	1239.64	991.4
Income sources (% of total)					
Crop	43	28	26	39	34
Livestock	30	29	29	26	28
Agricultural wage	2	3	3	2	2
Non-agricultural wage	3	5	3	3	4
Self-employment	8	11	13	10	11
Transfer	2	2	2	2	2
Other	1	2	4	3	2

Income diversification	0.29	0.34	0.32	0.28	0.31

Table 4.8 reports food security indicators, as well as expenditure based indicators, across the four rounds. Per capita expenditures are recalled during the last four months preceding each round. Note how food security indicators are not consistent. While HDDS seems to increase in the Dry and Belg seasons, and decreases in the Meher seasons, the coping strategy index, which can be interpreted, as the more coping strategies a household employs, the worse off it is, seems to be remarkably low in the first Meher, the baseline round, to then deteriorate across the following rounds. These trends are explored in the subsequent multivariate analyses across treatment and control groups.

Table 4.8: Descriptive statistics of nutrition status of the matched sample across seasons

	Seasons				Total
	Meher 1	Dry	Belg	Meher2	
HDDS	4.63	5.72	6.21	5.85	5.60
CSI	0.52	3.51	3.69	3.59	2.83
Per capita household food expenditure	17.29	38.72	47.32	37.24	35.14
Per capita household non-food expenditure	30.47	46.11	40.10	45.81	40.63
Per capita total household expenditure	47.77	84.83	87.41	83.05	75.77

Turning to the resilience metrics proxied by the various indices, cross-sectional descriptive statistics are presented indicating the percentage of households being resilient using the median threshold of the index in question (contingent of each index distribution). Trends are quite different across the various metrics. Intuitively households seem to be less resilient in the dry season, except under RIMA II where the negative spike is during the third round.

Table 4.9: Descriptive statistics of the resilience status of the matched household sample across seasons (various resilience indicators).

	Seasons				Total
	Meher 1	Dry	Belg	Meher2	
Resilience indicators (%)					
RIMA I	47	48	61	49	51
RIMA II	47	24	08	16	23
PRIME	58	29	31	22	35
Development resilience (expenditure)	-	43	46	49	46
Development resilience (HDDS)	-	44	38	52	45

Development resilience (Assets)	65	47	62	52	57

Table 4.10 presents asset based indicators across the 4 rounds. Note an increase of average levels across seasons, as far as durable, productive and livestock assets are concerned, which is then reflected in the overall asset index distribution.

Table 4.10: Descriptive statistics of household assets of the matched sample across seasons

	Seasons				Total
	Meher 1	Dry	Belg	Meher2	
Overall assets	1.42	1.70	1.75	1.90	1.69
Durable assets	1.58	1.90	2.23	2.72	2.11
Productive assets	1.89	2.09	2.05	2.11	2.03
Livestock	1.20	1.62	1.53	1.57	1.48
Large livestock	1.19	1.44	1.38	1.47	1.37
Small livestock	0.57	1.15	1.06	0.98	0.940
TLU	7.33	4.18	4.12	4.25	4.97

As far as asset based poverty metrics, the number of households classified as poor are reported according to two relative poverty lines, the 40th and 60th percentile of assets distribution at baseline (Table 4.11 – poverty incidence indicator). The percentage of households classified as moving in, out, and in poverty persistence (either remaining below or above the specific poverty line) are also presented.

Table 4.11: Descriptive statistics of economic mobility based on different asset-based poverty lines for the matched sample (percentage)

	Seasons			
	Meher 1	Dry	Belg	Meher2
Overall asset-based poverty line, 40th percentile (%)				
Poverty incidence	30	22	24	19
Moving into poverty	2	9	11	7
Moving out of poverty	28	46	28	43
Remain below poverty line	72	54	72	57
Remain above poverty line	98	91	89	93
Overall asset-based poverty line, 60th percentile (%)				
Poverty incidence	50	37	40	31

Moving into poverty	4	13	17	9
Moving out of poverty	13	39	21	35
Remain below poverty line	87	61	79	65
Remain above poverty line	96	87	83	91
Productive asset-based poverty line, 40th percentile (%)				
Poverty incidence	30	25	28	21
Moving into poverty	1	11	16	11
Moving out of poverty	27	43	36	51
Remain below poverty line	73	57	64	49
Remain above poverty line	99	89	84	89
Productive asset-based poverty line, 60th percentile (%)				
Poverty incidence	49	40	46	42
Moving into poverty	2	19	25	17
Moving out of poverty	22	37	23	29
Remain below poverty line	78	63	77	71
Remain above poverty line	98	81	75	83

Last, indicators for market access are presented in Table 4.12. Livestock and crops sales seem to be more prevalent in the first season compared to the last round – except for livestock products. The average time to market in minutes across seasons exhibits similar values except for the short rainy season.

Table 4.12: Descriptive statistics of market participation of the matched sample across seasons

	Seasons				Total
	Meher 1	Dry	Belg	Meher2	
Market participation (%)					
Livestock	40	25	24	29	30
Livestock product	33	32	29	33	32
Crop	40	27	18	22	27
Time to market (minutes)	98	91	68	91	87

5. Results

In this section results are presented from the cross-sectional treatment effects estimators, notably IPWRA, IPW, NN, PSM and RA, across the various outcomes presented in the previous section. Results are reported across the seasons covered in each round of data collection, from Meher (rainy season) in the first round, to Dry in the second round, Belg (short rainy season) in the third round, and again, Meher in the fourth round. Note that IPWRA, the doubly robust estimator, is considered the one that is more robust and reliable from an econometric standpoint, hence it can be considered the preferred estimator for results reporting.

5.1 Agricultural production, intensification and input indicators

In this section, indicators such as crop area and expenditure on various inputs (notably seeds, fertilizers, pesticides and labor) are presented. For crop area observations are only available for two rainy seasons (Meher). For inputs expenditures, only three valid data points are available. The first data point corresponds to the one that is first in time (October 2016).

Results are quite consistent across the various estimators. Relative to the crop area under analysis, it is important to stress that irrigation has, intuitively, a stronger impact in the Dry season.

Expenditure on inputs seems to be consistently higher in the Dry season compared to the other seasons. Particularly for seeds expenditures, the highest impact is in the dry season where there is a coefficient of 1.76 (see column that refers to the IPWRA estimator). This corresponds to a 176% increase in seed expenditure with irrigation relative to farmers in the comparison group. Expenditure on fertilizers and labour exhibit a similar trend. This shows the extent of beneficiary farmers' labour participation in the dry season for crop production.

Table 5.1: Results on agricultural production indicators: crop input use

		(1)	(2)	(3)	(4)	(5)	(6)
		IPWRA	IPW	NN	PSM	RA	Control mean
Crop inputs use by season							
Crop area	Meher 1	0.133	0.0849	0.173*	0.128	0.182**	1.062
		(0.0823)	(0.0814)	(0.0955)	(0.0830)	(0.0824)	
	Dry	0.175***	0.206***	0.200***	0.219***	0.177***	0.237
		(0.0451)	(0.0434)	(0.0463)	(0.0417)	(0.0439)	
	Belg	0.0156	0.0127	0.0285	0.0307	-0.00869	0.536
		(0.0516)	(0.0514)	(0.0677)	(0.0489)	(0.0553)	
	Meher 2	0.119	0.0914	0.0926	0.0554	0.138	1.285
		(0.0900)	(0.0984)	(0.152)	(0.109)	(0.0982)	
Seed	Dry	1.758***	1.900***	1.874***	1.840***	1.772***	67.52

expenditure (Birr, log)		(0.208)	(0.194)	(0.206)	(0.197)	(0.201)	
	Belg	0.359**	0.354**	0.218	0.249	0.249	97.69
		(0.178)	(0.179)	(0.229)	(0.182)	(0.185)	
	Meher 2	0.555**	0.472**	0.392	0.528**	0.511**	268.4
		(0.222)	(0.228)	(0.283)	(0.240)	(0.220)	
Fertilizer expenditure (Birr, log)	Dry	1.960***	2.005***	2.074***	2.094***	2.026***	55.03
		(0.207)	(0.200)	(0.210)	(0.193)	(0.195)	
	Belg	0.572***	0.596***	0.540**	0.497***	0.481**	142.2
		(0.190)	(0.189)	(0.253)	(0.188)	(0.194)	
	Meher 2	0.398*	0.317	0.749**	0.422*	0.583**	854.5
		(0.233)	(0.235)	(0.322)	(0.241)	(0.251)	
Pesticide expenditure (Birr, log)	Dry	0.316***	0.349***	0.422***	0.371***	0.353***	11.82
		(0.120)	(0.107)	(0.118)	(0.102)	(0.104)	
	Belg	0.243***	0.244***	0.239**	0.241***	0.233***	2.418
		(0.0810)	(0.0813)	(0.0979)	(0.0823)	(0.0818)	
	Meher 2	0.207	0.172	0.101	0.145	0.249	37.20
		(0.153)	(0.156)	(0.192)	(0.170)	(0.153)	
Labor expenditure (Birr, log)	Dry	0.881***	0.888***	1.022***	0.983***	0.931***	26.92
		(0.165)	(0.158)	(0.165)	(0.143)	(0.152)	
	Belg	0.123	0.119	0.0709	0.162	0.127	40.87
		(0.123)	(0.124)	(0.147)	(0.118)	(0.125)	
	Meher 2	-0.0991	-0.177	0.0183	-0.0249	-0.0326	246.0
		(0.209)	(0.215)	(0.246)	(0.212)	(0.206)	
No. of observations		731	731	731	731	731	328

Notes:
1. Results are based four rounds of high frequency data.
2. Results only on crop expenditure are not reported for meher 1 as expenditure data was not collected in the first round.
3. *, **, & *** represent statistical significance at the 10%, 5%, & 1% level respectively.

In terms of crop yield gains, results are also very stable across estimators. Looking at the estimator of reference, IPWRA, impacts are larger in the Dry season for all seasonal crops under examinations, and notably grains, cereal, vegetables, root and fruit crops. Perennials also exhibit a significant impact across the first Meyer season, followed by the Dry season.

Table 5.2: Results on agricultural production indicators: crop yield

		(1)	(2)	(3)	(4)	(5)	(6)
		IPWRA	**IPW**	**NN**	**PSM**	**RA**	**Control mean**
Crop yield by season							
Grain crop yield (kg/ha, log)	Meher 1	0.332	0.284	0.312	0.569**	0.600**	707.0
		(0.243)	(0.238)	(0.350)	(0.276)	(0.270)	
	Dry	0.514***	0.565***	0.578***	0.642***	0.515***	41.24
		(0.154)	(0.152)	(0.165)	(0.139)	(0.154)	
	Belg	0.474***	0.490***	0.234	0.372**	0.396**	172.1
		(0.167)	(0.165)	(0.216)	(0.180)	(0.177)	

	Meher 2	-0.110	-0.252	-0.183	-0.0688	0.0793	574.8
		(0.237)	(0.241)	(0.319)	(0.258)	(0.251)	
Cereal crop yield (kg/ha, log)	Meher 1	0.340	0.321	0.269	0.643**	0.611**	717.2
		(0.245)	(0.240)	(0.353)	(0.278)	(0.272)	
	Dry	0.522***	0.584***	0.497***	0.577***	0.504***	29.70
		(0.136)	(0.129)	(0.157)	(0.129)	(0.140)	
	Belg	0.414***	0.425***	0.138	0.313*	0.347**	146.1
		(0.159)	(0.157)	(0.209)	(0.170)	(0.168)	
	Meher 2	-0.0923	-0.240	-0.134	-0.0863	0.111	555.2
		(0.237)	(0.240)	(0.318)	(0.257)	(0.252)	
Vegetable crop yield (kg/ha, log)	Meher 1	0.519***	0.506***	0.470***	0.465***	0.504***	57.37
		(0.130)	(0.125)	(0.144)	(0.142)	(0.130)	
	Dry	0.811***	0.811***	0.936***	0.847***	0.855***	48.18
		(0.157)	(0.149)	(0.137)	(0.141)	(0.140)	
	Belg	0.187*	0.177*	0.198*	0.115	0.166	39.34
		(0.106)	(0.107)	(0.117)	(0.134)	(0.108)	
	Meher 2	0.0491	0.0208	0.0190	0.0315	0.0259	38.27
		(0.105)	(0.111)	(0.128)	(0.122)	(0.107)	
Root crop yield (kg/ha, log)	Meher 1	0.471***	0.381**	0.439**	0.338*	0.472***	146.0
		(0.147)	(0.156)	(0.178)	(0.182)	(0.145)	
	Dry	0.686***	0.720***	0.705***	0.698***	0.619***	413.9
		(0.182)	(0.175)	(0.210)	(0.189)	(0.192)	
	Belg	-0.0642	-0.0916	-0.152	-0.0273	-0.0846	2153.0
		(0.174)	(0.184)	(0.260)	(0.177)	(0.181)	
	Meher 2	-0.200	-0.0905	-0.175	0.0720	-0.248	155.6
		(0.151)	(0.128)	(0.217)	(0.116)	(0.158)	
Pulses crop yield (kg/ha, log)	Meher 1	0.0879	-0.0101	0.186	-0.103	0.174	49.83
		(0.139)	(0.140)	(0.156)	(0.170)	(0.123)	
	Belg	0.0505	0.0584	0.0608	0.0323	0.0313	6.504
		(0.0628)	(0.0601)	(0.0674)	(0.0733)	(0.0684)	
	Meher 2	-0.0644	-0.0854	-0.187	-0.0413	-0.0784	18.44
		(0.104)	(0.108)	(0.146)	(0.114)	(0.104)	
Fruit crop yield (kg/ha, log)	Meher 1	0.200***	0.198***	0.201***	0.183***	0.195***	0.762
		(0.0626)	(0.0628)	(0.0631)	(0.0647)	(0.0636)	
	Belg	0.369***	0.366***	0.250*	0.437***	0.368***	28.50
		(0.113)	(0.114)	(0.133)	(0.101)	(0.111)	
	Meher 2	0.117	0.0850	0.0260	0.170*	0.0812	49.19
		(0.109)	(0.115)	(0.167)	(0.0953)	(0.112)	
Spices crop yield (kg/ha, log)	Meher 1	0.0109	0.0109	0.0109	0.0109	0.0109	7.927
		(0.0109)	(0.0109)	(0.0109)	(0.0107)	(0.0109)	
	Belg	0.0868	0.0942	0.163*	0.0961	0.0784	43.48
		(0.0889)	(0.0853)	(0.0988)	(0.0941)	(0.0899)	
	Meher 2	0.00563	-0.00172	0.0905	-0.0547	-0.0125	65.31
		(0.116)	(0.120)	(0.157)	(0.142)	(0.120)	
Perennial	Meher 1	0.380**	0.470***	0.467**	0.479***	0.325*	236.0

crop yield (kg/ha, log)		(0.175)	(0.166)	(0.235)	(0.163)	(0.190)	
	Dry	0.338**	0.360**	0.189	0.333*	0.251	278.1
		(0.167)	(0.160)	(0.217)	(0.172)	(0.184)	
	Belg	0.251	0.222	0.254	0.311*	0.220	376.2
		(0.166)	(0.170)	(0.211)	(0.162)	(0.166)	
	Meher 2	0.200	0.278**	-0.00758	0.279**	0.186	48.90
		(0.156)	(0.141)	(0.235)	(0.140)	(0.160)	
No. of observations		731	731	731	731	731	328

Notes:

1. Results are based four rounds of high frequency data.
2. Results for pulse, fruits, and spices for the dry season are not presented as they are not produced by most of the sample in the dry season.
3. *, **, & *** represent statistical significance at the 10%, 5%, & 1% level respectively.

Turning to indicators related to the value of crop production, strongly significant results are once again present which show that impacts of modern irrigation are larger for value of grain and cereal crops produce (in Birr and logarithmic form) in the Belg season (the short rains season), but also significant and high in second Meyer (large rainy season, preceding the 4th round) respectively. As far as value of vegetable crop produce, a higher impact was expected among the treated – in the dry season, and the findings corroborate this hypothesis.

Table 5.3: Results on agricultural production indicators: value of crop production

		(1)	(2)	(3)	(4)	(5)	(6)
		IPWRA	IPW	NN	PSM	RA	Control mean
Value of crop production by season							
Value of grain crop produce (Birr, log)	Meher 1	0.143	0.0333	0.335	0.569**	0.600**	1103.3
		(0.253)	(0.245)	(0.330)	(0.276)	(0.270)	
	Dry	0.572***	0.634***	0.597***	0.667***	0.553***	96.25
		(0.159)	(0.154)	(0.173)	(0.147)	(0.164)	
	Belg	1.340***	1.363***	1.164***	1.087***	1.201***	2715.1
		(0.281)	(0.281)	(0.354)	(0.326)	(0.290)	
	Meher 2	1.453***	1.244***	1.321***	1.349***	1.620***	9141.0
		(0.309)	(0.313)	(0.434)	(0.313)	(0.321)	
Value of cereal crop produce (Birr, log)	Meher 1	0.155	0.0956	0.254	0.643**	0.611**	949.2
		(0.240)	(0.233)	(0.324)	(0.278)	(0.272)	
	Dry	0.550***	0.574***	0.522***	0.579***	0.523***	57.06
		(0.136)	(0.135)	(0.154)	(0.134)	(0.142)	
	Belg	1.303***	1.320***	1.117***	1.069***	1.170***	2502.1
		(0.276)	(0.276)	(0.344)	(0.319)	(0.285)	
	Meher 2	1.253***	1.039***	1.181***	1.148***	1.449***	8445.4
		(0.313)	(0.316)	(0.437)	(0.315)	(0.327)	
Value of vegetable crop	Meher 1	0.497***	0.476***	0.477***	0.465***	0.504***	78.2
		(0.121)	(0.119)	(0.137)	(0.142)	(0.130)	

produce (Birr, log)	Dry	0.814***	0.832***	0.932***	0.854***	0.864***	88.81
		(0.161)	(0.152)	(0.139)	(0.145)	(0.141)	
	Belg	0.242	0.226	0.253	0.166	0.236	357.1
		(0.163)	(0.166)	(0.181)	(0.197)	(0.157)	
	Meher 2	0.658***	0.661***	0.258	0.645***	0.612***	525.3
		(0.194)	(0.192)	(0.280)	(0.205)	(0.200)	
Value of root crop produce (Birr, log)	Meher 1	0.288***	0.263**	0.313***	0.338*	0.472***	33.2
		(0.108)	(0.110)	(0.112)	(0.182)	(0.145)	
	Dry	0.651***	0.698***	0.698***	0.676***	0.603***	208.6
		(0.183)	(0.175)	(0.201)	(0.190)	(0.188)	
	Belg	0.0930	0.0526	0.0308	0.167	0.0268	1523.4
		(0.224)	(0.235)	(0.289)	(0.226)	(0.230)	
	Meher 2	0.442*	0.582***	0.236	0.828***	0.312	926.1
		(0.238)	(0.220)	(0.332)	(0.210)	(0.249)	
Value of pulse crop produce (Birr, log)	Meher 1	0.0443	-0.0390	0.147	-0.103	0.174	102.6
		(0.139)	(0.138)	(0.127)	(0.170)	(0.123)	
	Belg	0.193*	0.207*	0.217	0.149	0.151	135.3
		(0.113)	(0.109)	(0.136)	(0.132)	(0.123)	
	Meher 2	0.418**	0.391**	0.0929	0.372*	0.395**	452.2
		(0.191)	(0.195)	(0.262)	(0.210)	(0.194)	
Value of fruits crop produce (Birr, log)	Meher 1	0.172***	0.167***	0.180***	0.183***	0.195***	1.5
		(0.0547)	(0.0558)	(0.0543)	(0.0647)	(0.0636)	
	Belg	1.040***	1.033***	0.880***	1.231***	0.979***	1105.8
		(0.221)	(0.222)	(0.297)	(0.207)	(0.226)	
	Meher 2	1.474***	1.422***	1.333***	1.624***	1.386***	659.3
		(0.225)	(0.226)	(0.292)	(0.203)	(0.234)	
Value of spices crop produce (Birr, log)	Meher 1	0.0130	0.0130	0.0130	0.0109	0.0109	0
		(0.0130)	(0.0130)	(0.0130)	(0.0107)	(0.0109)	
	Belg	0.0532	0.0529	0.112	-0.0470	0.0292	763.8
		(0.178)	(0.177)	(0.242)	(0.206)	(0.186)	
	Meher 2	0.945***	0.943***	1.166***	0.925***	0.942***	1597.6
		(0.213)	(0.216)	(0.268)	(0.217)	(0.224)	
Value of perennial crop produce (Birr, log)	Meher 1	0.240	0.451**	0.459*	0.479***	0.325*	499.8
		(0.219)	(0.194)	(0.270)	(0.163)	(0.190)	
	Dry	0.517**	0.522**	0.261	0.490**	0.445*	1003.5
		(0.232)	(0.227)	(0.305)	(0.234)	(0.245)	
	Belg	1.719***	1.640***	1.993***	1.513***	1.690***	5300.1
		(0.313)	(0.319)	(0.410)	(0.350)	(0.327)	
	Meher 2	2.048***	2.036***	2.116***	2.064***	1.982***	2965.3
		(0.307)	(0.300)	(0.441)	(0.301)	(0.335)	
Crop diversification (Simpson's Index)	Meher 1	0.0799***	0.0794***	0.0943***	0.0757***	0.0891***	0.358
		(0.0205)	(0.0196)	(0.0251)	(0.0221)	(0.0207)	
	Dry	0.132***	0.145***	0.113***	0.154***	0.123***	0.103
		(0.0194)	(0.0181)	(0.0240)	(0.0179)	(0.0197)	
	Belg	0.0698***	0.0696***	0.0593**	0.0724***	0.0565***	0.196

		(0.0187)	(0.0186)	(0.0252)	(0.0206)	(0.0204)	
	Meher 2	0.157***	0.167***	0.173***	0.172***	0.147***	0.185
		(0.0203)	(0.0200)	(0.0283)	(0.0201)	(0.0220)	
No. of observations		731	731	731	731	731	328

Notes:
1. Results are based four rounds of high frequency data.
2. Results only on crop sales value are reported for meher 1 as data on the total value of crop production was not available.
3. Results for pulse, fruits, and spices for the dry season are not presented as they are not produced by most of the sample in the dry season.
4. *, **, & *** represent statistical significance at the 10%, 5%, & 1% level respectively.

5.2 Economic mobility indicators

Looking at the impact of irrigation on economic mobility indicators, specifically crop, livestock and agricultural wage income –results are remarkably positive for crop income – with the largest impacts in the second rainy season. The data seem to imply a significant reduction in both self-employment and non-agricultural wage income for treated farmers in the dry season, possibly corroborating the hypothesis that the treated do not diversify, focusing exclusively on the production of irrigated crops in the dry season.

In addition, total household income is significantly higher for the treatment groups compared to the counterfactual, stressing the positive effect of irrigation systems and the sustainability of impact across the period under observation.

Table 5.4: Results on economic mobility: income and savings indicators

		(1) IPWRA	(2) IPW	(3) NN	(4) PSM	(5) RA	(6) Control mean
Income indicators by season							
Crop income (Birr, log)	Meher 1	2.923***	3.124***	3.321***	3.134***	2.999***	2407.7
		(0.317)	(0.297)	(0.412)	(0.296)	(0.318)	
	Dry	2.125***	2.240***	2.029***	2.222***	2.032***	1508.4
		(0.296)	(0.288)	(0.360)	(0.303)	(0.299)	
	Belg	0.769***	0.740**	0.411	0.711**	0.650**	2595.2
		(0.285)	(0.289)	(0.375)	(0.288)	(0.290)	
	Meher 2	3.413***	3.743***	3.849***	3.880***	3.425***	2336.3
		(0.294)	(0.288)	(0.373)	(0.302)	(0.302)	
Livestock income (Birr, log)	Meher 1	-0.136	-0.0498	0.309	0.184	0.122	1757.3
		(0.291)	(0.277)	(0.391)	(0.309)	(0.291)	
	Dry	0.0887	0.106	0.780**	-0.0976	0.430	1567.7
		(0.285)	(0.281)	(0.342)	(0.299)	(0.278)	
	Belg	-0.187	-0.171	0.246	-0.309	0.0631	1625.9
		(0.280)	(0.286)	(0.346)	(0.314)	(0.281)	
	Meher 2	-0.123	-0.198	-0.0528	-0.225	-0.0860	2074.9
		(0.297)	(0.294)	(0.398)	(0.297)	(0.288)	
Agricultural wage income (Birr, log)	Meher 1	-0.0632	-0.0533	-0.0641	-0.0415	-0.113	80.79
		(0.101)	(0.0941)	(0.163)	(0.0894)	(0.112)	

	Dry	-0.157	-0.136	-0.401**	-0.0605	-0.149	79.88
		(0.133)	(0.117)	(0.201)	(0.114)	(0.121)	
	Belg	-0.158	-0.185	-0.139	-0.274**	-0.202*	141.7
		(0.114)	(0.121)	(0.182)	(0.133)	(0.119)	
	Meher 2	0.187*	0.167	0.0100	0.188*	0.141	69.70
		(0.0989)	(0.102)	(0.152)	(0.104)	(0.108)	
Non-agricultural wage income (Birr, log)	Meher 1	-0.0529	-0.108	-0.195	-0.0908	-0.112	233.7
		(0.113)	(0.122)	(0.147)	(0.111)	(0.126)	
	Dry	-0.391**	-0.475***	-0.476**	-0.426***	-0.442***	314.7
		(0.154)	(0.165)	(0.233)	(0.164)	(0.156)	
	Belg	0.0407	0.0496	0.0118	0.132	-0.00339	145.6
		(0.134)	(0.132)	(0.193)	(0.122)	(0.140)	
	Meher 2	-0.0687	-0.101	-0.0682	-0.0402	-0.0471	163.4
		(0.134)	(0.140)	(0.173)	(0.129)	(0.127)	
Self-employment income (Birr, log)	Meher 1	-0.333	-0.415**	-0.609**	-0.373*	-0.451**	636.0
		(0.205)	(0.201)	(0.275)	(0.204)	(0.209)	
	Dry	-0.898***	-0.598**	-0.801**	-0.626**	-0.759***	831.3
		(0.275)	(0.247)	(0.318)	(0.251)	(0.257)	
	Belg	-0.252	-0.276	-0.226	-0.352	-0.188	1139.0
		(0.246)	(0.254)	(0.311)	(0.284)	(0.242)	
	Meher 2	-0.696***	-0.794***	-0.682**	-1.082***	-0.699***	1167.6
		(0.237)	(0.241)	(0.296)	(0.274)	(0.231)	
Transfer income (Birr, log)	Meher 1	-0.255**	-0.358***	-0.283*	-0.268**	-0.290**	332.6
		(0.109)	(0.124)	(0.168)	(0.132)	(0.118)	
	Dry	0.0341	0.0195	0.0981	0.0600	0.0116	90.73
		(0.107)	(0.108)	(0.139)	(0.0934)	(0.108)	
	Belg	-0.0862	-0.0929	0.0323	-0.0773	-0.0908	57.36
		(0.111)	(0.115)	(0.121)	(0.129)	(0.112)	
	Meher 2	-0.179	-0.211	-0.0592	-0.339*	-0.181	138.7
		(0.127)	(0.137)	(0.153)	(0.176)	(0.121)	
Other sources of income (Birr, log)	Meher 1	-0.0541	-0.0704	-0.171	-0.0188	-0.0561	46.34
		(0.0729)	(0.0802)	(0.124)	(0.0749)	(0.0744)	
	Dry	0.0650	0.0738	0.199	0.0791	0.0645	46.83
		(0.116)	(0.110)	(0.130)	(0.106)	(0.113)	
	Belg	0.0470	0.0361	-0.135	0.0693	0.0831	84.67
		(0.140)	(0.145)	(0.194)	(0.150)	(0.133)	
	Meher 2	-0.110	-0.109	0.0697	-0.102	-0.0657	247.1
		(0.167)	(0.168)	(0.176)	(0.170)	(0.157)	
Total household income (Birr, log)	Meher 1	0.913***	0.962***	1.199***	1.046***	1.035***	5738.1
		(0.216)	(0.208)	(0.305)	(0.236)	(0.227)	
	Dry	0.548**	0.673**	0.846**	0.617**	0.707***	4611.3
		(0.270)	(0.272)	(0.343)	(0.293)	(0.269)	
	Belg	-0.250	-0.256	-0.0889	-0.419	-0.201	5419.7
		(0.256)	(0.259)	(0.317)	(0.263)	(0.257)	
	Meher 2	1.056***	1.158***	1.364***	0.996***	1.115***	6419.3
		(0.236)	(0.246)	(0.342)	(0.262)	(0.229)	
Income diversification	Meher 1	-0.0501*	-0.0544**	-0.0866**	-0.0380	-0.0604**	0.330
		(0.0257)	(0.0245)	(0.0363)	(0.0269)	(0.0256)	

(Simpson's index)	Dry	-0.0248	-0.0339	-0.0614	-0.0303	-0.0364	0.366
		(0.0295)	(0.0295)	(0.0387)	(0.0320)	(0.0297)	
	Belg	0.0377	0.0340	0.0135	0.0578**	0.0379	0.304
		(0.0287)	(0.0287)	(0.0356)	(0.0288)	(0.0286)	
	Meher 2	-0.0360	-0.0454*	-0.0556	-0.0173	-0.0374	0.311
		(0.0259)	(0.0269)	(0.0370)	(0.0281)	(0.0253)	
No. of observations		731	731	731	731	731	328

Notes:
1. Results are based four rounds of high frequency data.
2. *, **, & *** represent statistical significance at the 10%, 5%, & 1% level respectively.

Table 5.5 present impacts on wealth proxies, notably asset indices. The results show that average treatment effects on the treated, in the case of our best case estimator, IPWRA, are only positive and significant for productive assets, and consistently higher in the dry season, compared to the other rounds. Results are less stable for the other indicators; particularly, results for durables and livestock indicators, are only significant under the NN estimator, warranting further analysis.

Table 5.5: Results on economic mobility: asset indices

		(1)	(2)	(3)	(4)	(5)	(6)
		IPWRA	IPW	NN	PSM	RA	Control mean
Asset indicators by season							
Durable assets	Meher 1	-0.000130	0.0104	-0.0494	0.0996	0.118	1.523
		(0.0794)	(0.0738)	(0.127)	(0.0781)	(0.0869)	
	Dry	0.102	0.122	0.314**	0.162*	0.209**	1.790
		(0.0993)	(0.0868)	(0.125)	(0.0894)	(0.0998)	
	Belg	0.132	0.129	0.370***	0.138	0.223*	2.102
		(0.113)	(0.115)	(0.143)	(0.122)	(0.122)	
	Meher 2	0.0656	0.0585	0.326*	0.0656	0.178	2.619
		(0.124)	(0.127)	(0.168)	(0.120)	(0.130)	
Productive assets	Meher 1	0.115	0.111	0.224**	0.187**	0.236**	1.768
		(0.0912)	(0.0855)	(0.100)	(0.0753)	(0.0962)	
	Dry	0.413***	0.326***	0.566***	0.387***	0.502***	1.843
		(0.0763)	(0.0812)	(0.103)	(0.0877)	(0.0831)	
	Belg	0.274***	0.289***	0.503***	0.360***	0.380***	1.811
		(0.0837)	(0.0839)	(0.105)	(0.0838)	(0.0895)	
	Meher 2	0.197***	0.133*	0.220**	0.192***	0.284***	1.970
		(0.0738)	(0.0756)	(0.110)	(0.0708)	(0.0825)	
Livestock assets	Meher 1	-0.0797	-0.0517	0.176*	0.0425	0.0967	1.149
		(0.0926)	(0.0744)	(0.0930)	(0.0515)	(0.0790)	
	Dry	-0.232	-0.0849	0.211	0.0864	0.0549	1.544
		(0.235)	(0.186)	(0.151)	(0.101)	(0.150)	
	Belg	-0.0730	-0.0714	0.128	0.0241	0.0796	1.483
		(0.109)	(0.112)	(0.127)	(0.0845)	(0.0998)	
	Meher 2	-0.0281	-0.0380	0.0636	-0.0155	0.0640	1.528
		(0.0897)	(0.0917)	(0.131)	(0.100)	(0.0993)	
Large	Meher 1	-0.0797	0.0263	0.228**	0.114**	0.161**	1.105

livestock		(0.0926)	(0.0645)	(0.0917)	(0.0527)	(0.0758)	
	Dry	-0.232	0.0677	0.281***	0.150*	0.154	1.327
		(0.235)	(0.0846)	(0.109)	(0.0885)	(0.101)	
	Belg	-0.0730	0.0165	0.157	0.0711	0.121	1.298
		(0.109)	(0.0833)	(0.126)	(0.0844)	(0.0897)	
	Meher 2	-0.0281	0.107	0.271**	0.150*	0.191**	1.357
		(0.0897)	(0.0836)	(0.118)	(0.0846)	(0.0904)	
Small livestock	Meher 1	0.0125	-0.147	0.00204	-0.119	-0.0778	0.616
		(0.0698)	(0.103)	(0.110)	(0.0873)	(0.0906)	
	Dry	0.01000	-0.373	-0.0558	-0.0945	-0.204	1.195
		(0.0967)	(0.424)	(0.267)	(0.182)	(0.280)	
	Belg	0.0149	-0.176	0.0475	-0.0478	-0.00999	1.088
		(0.0824)	(0.194)	(0.179)	(0.120)	(0.139)	
	Meher 2	0.101	-0.318**	-0.409**	-0.358**	-0.242*	1.116
		(0.0830)	(0.133)	(0.174)	(0.164)	(0.132)	
Tropical livestock unit (TLU)	Meher 1	-0.182	-0.0281	1.271**	0.423	0.814*	6.876
		(0.130)	(0.370)	(0.547)	(0.311)	(0.459)	
	Dry	-0.645	0.269	0.857***	0.475**	0.500*	3.810
		(0.543)	(0.233)	(0.299)	(0.234)	(0.277)	
	Belg	-0.175	-0.0302	0.132	0.106	0.244	3.946
		(0.188)	(0.242)	(0.448)	(0.237)	(0.268)	
	Meher 2	-0.287**	0.347	0.706**	0.455*	0.525**	3.906
		(0.130)	(0.237)	(0.349)	(0.241)	(0.261)	
Total assets	Meher 1	0.0182	0.0274	0.114	0.104**	0.141**	1.349
		(0.0523)	(0.0469)	(0.0694)	(0.0442)	(0.0583)	
	Dry	0.108	0.124*	0.342***	0.203***	0.248***	1.557
		(0.0887)	(0.0734)	(0.0840)	(0.0595)	(0.0729)	
	Belg	0.112	0.117*	0.312***	0.170***	0.215***	1.613
		(0.0684)	(0.0695)	(0.0818)	(0.0636)	(0.0713)	
	Meher 2	0.0790	0.0518	0.183*	0.0807	0.165**	1.821
		(0.0646)	(0.0664)	(0.0981)	(0.0650)	(0.0727)	
No. of observations		731	731	731	731	731	328

Notes:

1. Results are based four rounds of high frequency data.
2. *, **, & *** represent statistical significance at the 10%, 5%, & 1% level respectively.

5.3 Poverty reduction indicators

Turning to poverty incidence indicators, based on asset indicators, Table 5.6 remarkably shows how treated farmers are consistently more likely to be above the poverty line almost across the board, and according to the different poverty lines in the dry season – where the benefits of irrigation should be felt the most. Beneficiaries farmers are also more likely to the above the poverty line in the season following the dry season, the Belg. These results are investigated further in the dynamic analysis, that are shown in Table 5.6 and 5.6a.Table 5.7 shows instead dynamic transitions across the various rounds, looking at movements in and out poverty.

Table 5.6: Results on economic mobility: poverty indicators

		(1) IPWRA	(2) IPW	(3) NN	(4) PSM	(5) RA	(6) Control mean
Poverty indicator by season							
Above the overall asset-based poverty line, 40th percentile	Meher 1	0.0557	0.00977	0.0270	0.0155	0.0686**	0.674
		(0.0341)	(0.0273)	(0.0396)	(0.0359)	(0.0346)	
	Dry	0.106***	0.0646**	0.0954**	0.0682**	0.118***	0.723
		(0.0310)	(0.0264)	(0.0377)	(0.0326)	(0.0321)	
	Belg	0.100***	0.0532**	0.0766**	0.0552*	0.0851***	0.701
		(0.0321)	(0.0267)	(0.0387)	(0.0312)	(0.0306)	
	Meher 2	0.0588**	0.0290	0.0605	0.0409	0.0690**	0.777
		(0.0295)	(0.0251)	(0.0370)	(0.0312)	(0.0304)	
Above the overall asset-based poverty line, 60th percentile	Meher 1	0.0560	-0.00213	0.0520	0.00372	0.0799**	0.473
		(0.0371)	(0.0307)	(0.0406)	(0.0369)	(0.0376)	
	Dry	0.115***	0.0610**	0.0964**	0.0639*	0.128***	0.570
		(0.0358)	(0.0305)	(0.0382)	(0.0370)	(0.0359)	
	Belg	0.114***	0.0569*	0.0522	0.0639*	0.0920***	0.537
		(0.0364)	(0.0315)	(0.0396)	(0.0373)	(0.0345)	
	Meher 2	0.0959***	0.0471	0.0666*	0.0571*	0.103***	0.631
		(0.0347)	(0.0287)	(0.0380)	(0.0330)	(0.0331)	
Above the durable asset-based poverty line, 40th percentile	Meher 1	0.0838**	0.0451	0.0891**	0.0409	0.0935**	0.643
		(0.0345)	(0.0302)	(0.0429)	(0.0342)	(0.0367)	
	Dry	0.0698**	0.0438	0.0603	0.0577*	0.0836**	0.732
		(0.0315)	(0.0292)	(0.0413)	(0.0323)	(0.0330)	
	Belg	0.0307	0.00147	0.0120	-0.0130	0.0279	0.768
		(0.0307)	(0.0282)	(0.0380)	(0.0308)	(0.0306)	
	Meher 2	0.0271	0.0118	0.00418	0.0136	0.0261	0.881
		(0.0229)	(0.0208)	(0.0306)	(0.0241)	(0.0239)	
Above the durable asset-based poverty line, 60th percentile	Meher 1	0.0491	0.0164	0.108***	0.00993	0.0663*	0.470
		(0.0371)	(0.0332)	(0.0415)	(0.0381)	(0.0384)	
	Dry	0.0836**	0.0461	0.0419	0.0837**	0.0978***	0.564
		(0.0363)	(0.0336)	(0.0429)	(0.0395)	(0.0372)	
	Belg	0.0942***	0.0612*	0.0568	0.0428	0.0858**	0.601
		(0.0355)	(0.0327)	(0.0440)	(0.0380)	(0.0348)	
	Meher 2	0.0233	-0.00118	0.0227	-0.00806	0.0232	0.768
		(0.0309)	(0.0282)	(0.0397)	(0.0315)	(0.0319)	
Above the productive asset-based poverty line, 40th percentile	Meher 1	0.0502	0.0333	0.0732*	0.0316	0.0813**	0.677
		(0.0340)	(0.0303)	(0.0418)	(0.0369)	(0.0352)	
	Dry	0.109***	0.0789***	0.114***	0.0962***	0.127***	0.692
		(0.0323)	(0.0285)	(0.0400)	(0.0329)	(0.0336)	
	Belg	0.135***	0.107***	0.0867**	0.122***	0.124***	0.649
		(0.0334)	(0.0302)	(0.0401)	(0.0353)	(0.0320)	

	Meher 2	0.0578*	0.0283	0.0101	0.0422	0.0758**	0.756
		(0.0306)	(0.0270)	(0.0341)	(0.0314)	(0.0300)	
Above the productive asset-based poverty line, 60th percentile	Meher 1	0.0648*	0.0152	0.0641	0.0205	0.0807**	0.479
		(0.0371)	(0.0329)	(0.0442)	(0.0386)	(0.0378)	
	Dry	0.139***	0.107***	0.111**	0.112***	0.164***	0.521
		(0.0363)	(0.0332)	(0.0447)	(0.0374)	(0.0364)	
	Belg	0.131***	0.0800**	0.0490	0.105***	0.103***	0.470
		(0.0368)	(0.0336)	(0.0427)	(0.0382)	(0.0354)	
	Meher 2	0.114***	0.0635**	0.0574	0.0943***	0.133***	0.521
		(0.0365)	(0.0305)	(0.0412)	(0.0358)	(0.0350)	
Above the livestock asset-based poverty line, 40th percentile	Meher 1	0.0749**	0.0182	0.0681	0.0471	0.0792**	0.598
		(0.0358)	(0.0300)	(0.0444)	(0.0357)	(0.0371)	
	Dry	0.0944***	0.0422	0.0760*	0.0440	0.0796**	0.613
		(0.0352)	(0.0310)	(0.0439)	(0.0347)	(0.0354)	
	Belg	0.0774**	0.0254	0.0409	0.0347	0.0598*	0.637
		(0.0348)	(0.0309)	(0.0416)	(0.0338)	(0.0345)	
	Meher 2	0.0910***	0.0457	0.0765*	0.0670*	0.0701**	0.631
		(0.0348)	(0.0314)	(0.0425)	(0.0382)	(0.0344)	
Above the livestock asset-based poverty line, 60th percentile	Meher 1	0.0639*	0.0135	0.0852*	0.0447	0.0541	0.390
		(0.0366)	(0.0336)	(0.0439)	(0.0402)	(0.0384)	
	Dry	0.0987***	0.0576*	0.0597	0.0806**	0.0886**	0.470
		(0.0370)	(0.0345)	(0.0437)	(0.0392)	(0.0378)	
	Belg	0.0205	-0.0346	-0.0115	-0.0155	0.00403	0.503
		(0.0372)	(0.0335)	(0.0416)	(0.0381)	(0.0367)	
	Meher 2	0.0278	-0.00934	0.0234	0.00744	0.0240	0.491
		(0.0372)	(0.0340)	(0.0425)	(0.0389)	(0.0367)	
No. of observations		731	731	731	731	731	328

Results are similar across estimators when considering the 40th percentile poverty line – indicating that treated farmers are more likely to move out of poverty in the dry season, when setting the threshold at a lower end of the asset based distribution. These results tend to be more sensitive to the choice of the poverty line and to the assets used to build the poverty metric – indicating that benefits might vary across the seasons contingent on households initial conditions in the asset-based distribution. For instance in the case of movements out of poverty using the 40th percentile poverty line and an overall asset index distribution, beneficiaries at the lower end of the distribution are more likely to move out of poverty in the dry season. Setting a higher cut off, gains are not large enough to warrant an exit out of poverty in the dry season. Better off farmers are more likely to move out of poverty in the second Meyer season for instance.

Table 5.7: Results on economic mobility: poverty reduction indicators

		(1) IPWRA	(2) IPW	(3) NN	(4) PSM	(5) RA	(6) Control mean
Poverty reduction indicators by season							
Moving out of poverty, overall asset-based poverty line, 40th percentile	Meher 1	0.0458	0.0485	0.0001	-0.00822	0.0422	0.257
		(0.0494)	(0.0501)	(0.0671)	(0.0578)	(0.0516)	
	Dry	0.127**	0.135**	0.110	0.147**	0.130*	0.402
		(0.0645)	(0.0640)	(0.0880)	(0.0715)	(0.0671)	
	Belg	0.0729	0.0659	0.217***	0.0145	0.0755	0.253
		(0.0703)	(0.0700)	(0.0726)	(0.0746)	(0.0712)	
	Meher 2	0.110	0.0925	0.194*	0.109	0.120	0.378
		(0.0770)	(0.0799)	(0.100)	(0.0774)	(0.0745)	
Moving out of poverty, overall asset-based poverty line, 60th percentile	Meher 1	0.0138	0.0197	0.0132	0.00658	0.0144	0.121
		(0.0368)	(0.0371)	(0.0568)	(0.0425)	(0.0383)	
	Dry	0.0742	0.0810*	0.147**	0.0632	0.0841*	0.347
		(0.0486)	(0.0485)	(0.0731)	(0.0555)	(0.0498)	
	Belg	0.0734	0.0696	0.134**	0.0650	0.0796	0.170
		(0.0491)	(0.0490)	(0.0597)	(0.0569)	(0.0491)	
	Meher 2	0.122**	0.123**	0.188***	0.124**	0.123**	0.289
		(0.0543)	(0.0552)	(0.0704)	(0.0584)	(0.0562)	
Moving out of poverty, durable asset-based poverty line, 40th percentile	Meher 1	0.121**	0.123**	0.0506	0.130***	0.111**	0.186
		(0.0503)	(0.0508)	(0.0730)	(0.0492)	(0.0504)	
	Dry	0.0312	0.0383	0.0909	0.0636	0.0507	0.564
		(0.0643)	(0.0644)	(0.0938)	(0.0653)	(0.0665)	
	Belg	0.0409	0.0394	0.0875	0.0281	0.0417	0.523
		(0.0726)	(0.0720)	(0.103)	(0.0840)	(0.0769)	
	Meher 2	0.0353	0.0380	0.0617	0.0401	0.0408	0.671
		(0.0739)	(0.0741)	(0.0978)	(0.0761)	(0.0734)	
Moving out of poverty, durable asset-based poverty line, 60th percentile	Meher 1	0.0164	0.0169	-0.0336	0.0179	0.0162	0.172
		(0.0370)	(0.0372)	(0.0538)	(0.0387)	(0.0370)	
	Dry	0.0421	0.0456	0.124*	0.0438	0.0513	0.414
		(0.0502)	(0.0501)	(0.0683)	(0.0542)	(0.0513)	
	Belg	0.150***	0.149***	0.134*	0.151***	0.156***	0.357
		(0.0535)	(0.0540)	(0.0733)	(0.0570)	(0.0563)	
	Meher 2	0.0406	0.0397	0.0244	0.0203	0.0396	0.527
		(0.0626)	(0.0622)	(0.0843)	(0.0615)	(0.0628)	
Moving out of poverty, productive asset-based poverty line, 40th percentile	Meher 1	0.0826*	0.0828*	0.0355	0.0645	0.0841*	0.234
		(0.0476)	(0.0481)	(0.0584)	(0.0573)	(0.0502)	
	Dry	0.126**	0.125**	0.123	0.0932	0.124*	0.377
		(0.0625)	(0.0619)	(0.0925)	(0.0634)	(0.0672)	
	Belg	0.160**	0.157**	0.150	0.103	0.158**	0.297
		(0.0691)	(0.0694)	(0.0943)	(0.0751)	(0.0711)	

	Meher 2	0.0689	0.0519	0.0345	0.0632	0.0494	0.496
		(0.0713)	(0.0718)	(0.0954)	(0.0748)	(0.0713)	
Moving out of poverty, productive asset-based poverty line, 60th percentile	Meher 1	0.0188	0.0164	-0.0472	-0.0107	0.0154	0.208
		(0.0370)	(0.0373)	(0.0518)	(0.0464)	(0.0389)	
	Dry	0.125**	0.128***	0.158**	0.133***	0.119**	0.310
		(0.0495)	(0.0490)	(0.0672)	(0.0507)	(0.0510)	
	Belg	0.0617	0.0619	0.161**	0.0912*	0.0476	0.210
		(0.0474)	(0.0479)	(0.0628)	(0.0487)	(0.0487)	
	Meher 2	0.0860*	0.0880*	0.106*	0.101**	0.0796	0.253
		(0.0482)	(0.0483)	(0.0573)	(0.0492)	(0.0490)	
Moving out of poverty, livestock asset-based poverty line, 40th percentile	Meher 1	-0.00941	-0.00833	0.0001	0.00345	-0.00638	0.177
		(0.0461)	(0.0456)	(0.0585)	(0.0467)	(0.0454)	
	Dry	0.153***	0.153***	0.102	0.125**	0.152***	0.242
		(0.0568)	(0.0559)	(0.0818)	(0.0601)	(0.0567)	
	Belg	0.0453	0.0458	0.110	0.0424	0.0409	0.260
		(0.0618)	(0.0614)	(0.0760)	(0.0711)	(0.0603)	
	Meher 2	0.126**	0.127**	0.191**	0.124**	0.113*	0.185
		(0.0572)	(0.0568)	(0.0756)	(0.0583)	(0.0583)	
Moving out of poverty, livestock asset-based poverty line, 60th percentile	Meher 1	0.0117	0.0122	0.0572*	-0.00543	0.0127	0.120
		(0.0337)	(0.0337)	(0.0342)	(0.0347)	(0.0332)	
	Dry	0.0646	0.0584	0.00909	0.0489	0.0670	0.265
		(0.0449)	(0.0443)	(0.0610)	(0.0458)	(0.0448)	
	Belg	-0.0187	-0.0186	0.0287	-0.0129	-0.0215	0.201
		(0.0433)	(0.0432)	(0.0538)	(0.0427)	(0.0422)	
	Meher 2	0.0405	0.0313	0.0964*	0.0521	0.0410	0.184
		(0.0424)	(0.0430)	(0.0494)	(0.0406)	(0.0430)	

Notes:
1. Results are based on four rounds of high frequency data.
2. *, **, & *** represent statistical significance at the 10%, 5%, & 1% level respectively.

5.4 Food security indicators

In terms of dietary diversity, there are also significant impacts of modern irrigation on the HDDS, indicating that treated farmers have a significantly higher dietary diversity score during the first round.

Turning to the CSI, a negative coefficient indicates a gain for treated farmers, and a positive coefficient, an increased use of (negative) coping strategies. Here results are less clear, with a strong and negative coefficient in the Belg season, after the dry season. This might indicate a lagged effect, e.g that the availability of food might benefit subsequent seasons, which might be interesting to investigate in a dynamic model.

Table 5.8: Results on food security indicators

		(1) IPWRA	(2) IPW	(3) NN	(4) PSM	(5) RA	(6) Control mean
Food security indicators by season							
Household dietary diversity score (HDDS)	Meher 1	0.288**	0.221	0.180	0.344**	0.331**	4.503
		(0.145)	(0.145)	(0.199)	(0.145)	(0.151)	
	Dry	0.169	0.0964	0.284	0.0993	0.206	5.610
		(0.190)	(0.192)	(0.257)	(0.181)	(0.184)	
	Belg	0.164	0.185	0.368*	0.283*	0.246	6.037
		(0.151)	(0.151)	(0.212)	(0.160)	(0.154)	
	Meher 2	-0.163	-0.186	-0.0116	-0.198	-0.115	5.933
		(0.128)	(0.128)	(0.180)	(0.134)	(0.131)	
Coping strategies index (CSI)	Meher 1	0.435*	0.317	0.480*	-0.00868	0.389	0.345
		(0.235)	(0.285)	(0.257)	(0.475)	(0.259)	
	Dry	-1.050	-0.873	-1.831*	-0.864	-1.361*	4.046
		(0.669)	(0.670)	(1.023)	(0.646)	(0.701)	
	Belg	-2.442***	-2.612***	-2.963***	-3.362***	-2.601***	4.985
		(0.711)	(0.741)	(0.972)	(0.899)	(0.713)	
	Meher 2	0.0545	-0.0272	0.626	-0.341	-0.276	3.643
		(0.657)	(0.665)	(0.706)	(0.718)	(0.713)	
Household expenditure (7 days, Birr, log)	Meher 1	0.0253	0.00230	2.285	0.0964	0.0350	3.536
		(0.0601)	(0.0593)	(3.963)	(0.0628)	(0.0621)	
	Dry	0.0603	0.0606	19.25**	0.0935	0.0818	3.985
		(0.0702)	(0.0646)	(8.466)	(0.0619)	(0.0659)	
	Belg	-0.0352	-0.0437	3.963	-0.0436	-0.0216	4.123
		(0.0628)	(0.0623)	(8.363)	(0.0565)	(0.0610)	
	Meher 2	-0.00684	-0.0127	-1.106	0.0227	0.0100	4.128
		(0.0540)	(0.0573)	(8.189)	(0.0524)	(0.0529)	
Household food expenditure (7 days, Birr, log)	Meher 1	0.0643	0.00609	-0.103	0.122	0.0122	2.212
		(0.101)	(0.0958)	(0.124)	(0.105)	(0.101)	
	Dry	-0.0426	-0.0393	0.0655	-0.0284	-0.0225	3.225
		(0.0714)	(0.0698)	(0.0902)	(0.0668)	(0.0708)	
	Belg	-0.0181	-0.0336	0.0662	-0.0567	-0.0299	3.463
		(0.0677)	(0.0682)	(0.0891)	(0.0678)	(0.0690)	
	Meher 2	-0.000238	-0.0104	0.156*	0.00734	0.00123	3.308
		(0.0626)	(0.0654)	(0.0891)	(0.0661)	(0.0627)	
No. of observations		731	731	731	731	731	328

Notes:

1. Results are based on four rounds of high frequency data.
2. *, **, & *** represent statistical significance at the 10%, 5%, & 1% level respectively.

5.5 Resilience indicators

Last, the impact of irrigation is investigated on the various resilience metrics over the various seasons. Here the results are less intuitive and are a function of the underlying methodology for the resilience metric. Results are largely significant in the case of the PRIME-based composite indicator where the results are consistently positive across the various rounds, and the coefficients are particularly high for the dry season. The latter finding is intuitive and implies that the benefits of irrigation should be at their maximum during the dry season and that treatment does strengthen resilience status.

Relative to other metrics, notably the RIMA I and the RIMA II, a positive result was also found in the dry season (however only under the NN estimator). Relative to food security based development resilience, results are different – and imply the households are more resilient in terms of food security in the second Meyer season – e.g. at the last round of the survey. Asset based development resilience is instead not significant – and this warrants further analysis. Note that this metrics are very different and further work is needed to unpack the metrics – to analyse the single components that compose the single resilience construct.

Table 5.9: Results on resilience indicators based on treatment effects estimation

		(1)	(2)	(3)	(4)	(5)	(6)
		IPWRA	IPW	NN	PSM	RA	Control mean
Resilience indicators by season							
RIMA I	Meher 1	-0.0458	-0.0306	0.0211	-0.0105	-0.00902	0.476
		(0.0346)	(0.0344)	(0.0468)	(0.0377)	(0.0368)	
	Dry	0.0341	0.0424	**0.109****	0.0428	0.0779**	0.442
		(0.0331)	(0.0323)	(0.0455)	(0.0319)	(0.0359)	
	Belg	-0.0389	-0.0354	-0.0360	0.00496	-0.0257	0.628
		(0.0343)	(0.0349)	(0.0461)	(0.0368)	(0.0362)	
	Meher 2	-0.0119	-0.00577	-0.0161	-0.00806	-0.00722	0.500
		(0.0347)	(0.0346)	(0.0488)	(0.0323)	(0.0352)	
RIMA II	Meher 1	-0.00212	0.000956	0.0513	0.0298	0.0485	0.454
		(0.0329)	(0.0316)	(0.0483)	(0.0335)	(0.0372)	
	Dry	0.00989	0.0323	**0.124*****	0.0354	0.0452	0.213
		(0.0326)	(0.0305)	(0.0328)	(0.0301)	(0.0318)	
	Belg	-0.0122	-0.0125	0.0199	-0.00310	-0.00109	0.0854
		(0.0209)	(0.0214)	(0.0196)	(0.0195)	(0.0193)	
	Meher 2	-0.00856	-0.0160	0.0397	-0.0205	-0.00351	0.168
		(0.0243)	(0.0265)	(0.0294)	(0.0274)	(0.0264)	
PRIME	Meher 1	**0.0998*****	**0.0989*****	0.0695	**0.146*****	**0.134*****	0.518
		(0.0348)	(0.0335)	(0.0505)	(0.0379)	(0.0379)	
	Dry	**0.191*****	**0.203*****	**0.186*****	**0.191*****	**0.195*****	0.174
		(0.0321)	(0.0310)	(0.0404)	(0.0320)	(0.0330)	
	Belg	**0.161*****	**0.163*****	**0.185*****	**0.164*****	**0.175*****	0.220

		(0.0335)	(0.0333)	(0.0394)	(0.0350)	(0.0336)	
	Meher 2	**0.0911*****	**0.0837*****	**0.145*****	**0.0757*****	**0.0994*****	0.162
		(0.0277)	(0.0286)	(0.0361)	(0.0287)	(0.0294)	
Development resilience (expenditure)	Dry	-0.0334	-0.0260	-0.0572	-0.0410	-0.0299	0.434
		(0.0384)	(0.0370)	(0.0504)	(0.0402)	(0.0381)	
	Belg	-0.0356	-0.0321	-0.0522	-0.00311	-0.0300	0.469
		(0.0380)	(0.0383)	(0.0474)	(0.0414)	(0.0377)	
	Meher 2	-0.0454	-0.0205	-0.0500	-0.00310	-0.0279	0.479
		(0.0376)	(0.0383)	(0.0481)	(0.0400)	(0.0366)	
Development resilience (HDDS)	Dry	-0.0107	-0.00104	0.0174	-0.0180	-0.00863	0.446
		(0.0397)	(0.0379)	(0.0481)	(0.0403)	(0.0388)	
	Belg	-0.0435	-0.0474	-0.0697	**-0.0852****	-0.0527	0.408
		(0.0373)	(0.0375)	(0.0478)	(0.0409)	(0.0366)	
	Meher 2	**0.0973****	**0.0945****	0.0529	**0.0862****	**0.0997****	0.466
		(0.0398)	(0.0384)	(0.0532)	(0.0397)	(0.0395)	
Development resilience (Assets)	Meher 1	-0.00201	-0.00497	0.0174	-0.00682	-0.0422	0.680
		(0.0364)	(0.0346)	(0.0492)	(0.0349)	(0.0376)	
	Dry	-0.0172	-0.0209	-0.0563	-0.0100	-0.0405	0.505
		(0.0389)	(0.0378)	(0.0508)	(0.0408)	(0.0392)	
	Belg	-0.0258	-0.0271	-0.0401	-0.0407	-0.0451	0.652
		(0.0368)	(0.0367)	(0.0490)	(0.0387)	(0.0368)	
	Meher 2	0.0309	0.0309	0.0174	0.0304	0.0169	0.512
		(0.0392)	(0.0383)	(0.0536)	(0.0408)	(0.0385)	
No. of observations		731	731	731	731	731	328

Notes:
1. Results are based on four rounds of high frequency data.
2. *, **, & *** represent statistical significance at the 10%, 5%, & 1% level respectively.

Last, assets growth is explored across the various rounds, and the extent to which resilience and treatment status have an impact on households assets growth trajectory over the seasons is assessed. To this end, estimates of the impact of the project on assets growth are presented in a dynamic framework based on the auto-regressive panel data estimator also known as the Blundell-Bover estimator or system GMM (Table 5.6). Here, the dynamic structure of the data is exploited (e..g an analysis which combines all rounds) and an asset based growth model is estimated conditional on treatment, initial conditions and lagged assets, and other key covariates (age, gender, education level and marital status of the household head, number of adult members, dependency ratio and the size of land owned by the household). Two specifications are presented, model 1 with a more parsimonious specification and model 2 with a richer set of covariates. The results show how the impact of treatment is remarkably positive, indicating that the effects of modern irrigation, contribute to positive asset growth over time. However initial conditions (e.g. asset levels at the first round) negatively impact assets growth, indicating that the highest the level of assets at "baseline" the lower the growth over time. This possibly corroborates the idea that the richest present a slower growth, but still positive – as showed by the fact that asset growth is also positively related to households' previous status.

Looking at coefficient of interest, e.g. the interaction term between drought and treatment status which proxies for resilience, the latter is positive and statistically significant, suggesting that the intervention increased beneficiary household welfare despite the negative incidence of the drought shock, therefore contributing to their increased resilience.

Last the season dummies presented in model 1, highlight the fact that asset growth is negatively impacted by the variability of weather shocks across the seasons. Specifically, the negative effects of weather on asset growth are larger in the dry season. The seasonal effects are collinear with the drought indicators in the second specification and the significance of the seasonal dummies fades away in the second specification.

Table 5.6: Impact don assets growth based on system GMM estimation

	(1)	(2)
	Basic asset growth model	Asset growth model with shock and PASIDP beneficiary interaction term
Lagged overall assets	0.41***	0.41***
	(0.03)	(0.03)
Initial overall assets	-0.63***	-0.45***
	(0.06)	(0.05)
PASIDP beneficiary status	0.22***	0.175***
	(0.03)	(0.03)
Drought		-0.02
		(0.0323)
PASIDP beneficiary status * Drought		0.13***
		(0.04)
Head age		0.012***
		(0.001)
Head Gender		0.19***
		(0.05)
Head education (1=Illiterate)		-0.16***
		(0.05)
Head education (1=Primary)		0.30***
		(0.06)
Head marital status		-0.08
		(0.05)
Number of adult members		0.08***
		(0.01)
Dependency ratio		0.03***
		(0.01)
HH owned land		0.001*
		(0.00)
Dry season (dummy)	-0.27***	-0.16

	(0.03)	(0.03)
Belg season (dummy)	-0.078**	-0.01
	(0.03)	(0.03)
Rainy season (dummy)	-0.14***	-0.09
	(0.03)	(0.03)
Constant	1.84***	-0.09
	(0.11)	(0.08)
Wald F statistic	183.54***	114.49***
Sargan test	2.78	1.51
AR (2) test	0.44	0.54
No. of observation	2924	2924

Notes:

1. Results are based on four rounds of high frequency data and 12 month recalled asset prior to Meher 1.
2. *, **, & *** represent statistical significance at the 10%, 5%, & 1% level respectively.

Table 5.6a presents instead the same asset growth model but this time adding lagged resilience (resilience measured at the previous wave/round), using the PRIME indicators as a proxy for resilience. Note how asset growth is a function of past resilience status, conditional on treatment, and the shock in question (e.g. drought). This essentially mean that a unit increase in household resilience in the previous season generates a higher asset growth in the subsequent season. Even under this specification, note how there is asset accumulation over the rounds (e.g. the higher the asset levels at the previous season, the higher the assets growth); asset growth increases also with a unit increase in past resilience status (e.g. if a household is resilient at the previous round – it is more likely to exhibit future asset growth); the treatment effect is positive and contributes to asset growth.

Table 5.6a: Impact of treatment controlling for resilience (PRIME) on asset growth, systems GMM estimation

	Asset growth model with lagged Resilience (2)
Lagged overall assets	0.532***
Lagged resilience (PRIME)	**0.223*** **
PASIDP beneficiary status	**0.064** **
Drought	-0.047*
Belg season (dummy)	-0.055
Rainy season (dummy)	-0.108***
Constant	0.136
Wald F statistic	91.88***

No. of observation	2193

Note:

1. .01 - ***; .05 - **; .1 - *; Standard errors not shown for sake of brevity.
2. Drought indicator is a dummy variable based on reported drought shock.
3. Initial conditions included, but not shown for the sake of brevity.

In table 5.6b, the same growth model is presented, this time modelling resilience gains as an outcome – as opposed to assets, using the same resilience index (the PRIME based index). This specification essentially looks at whether changes in resilience over time are positively affected by the treatment. This is indeed the case and the results point to the fact that the intervention, e.g. the PASIDP modern irrigation contributed to building resilience overtime – and this is path dependent, e.g. current resilience is a function of past resilience and increases over time, e.g. the more the household is resilient in the past seasons, the more likely to exhibit a higher resilience growth in the future, conditional on the negative impact of the drought.

Table 5.6b: Impact of treatment on resilience gains (PRIME) based on systems GMM estimation

	Resilience gains model (PRIME)
Lagged resilience (PRIME)	0.103***
PASIDP beneficiary status	**0.144*** **
Drought	-0.049***
Belg season (dummy)	0.065***
Rainy season (dummy)	0.109***
Constant	-0.029
Wald F statistic	17.37***
No. of observation	2193

Note:

1. .01 - ***; .05 - **; .1 - *; Standard errors not shown for sake of brevity.
2. Drought indicator is a dummy variable based on reported drought shock.
3. Initial conditions included, but not shown for the sake of brevity.

5.6 Market access indicators

Turning to a suite of indicators that proxies for market participation, modern irrigation increases market participation relative to crop sales, by 33% in the first Meher, and even 175% in the Dry season, compared to their counterfactual farmers. This shows how the irrigation benefits translated into market opportunities for farmers – in the dry season.

Table 5.6: Results on market access indicators by season

		(1) IPWRA	(2) IPW	(3) NN	(4) PSM	(5) RA	(6) Control mean
Market access indicators by season							
Market participation for crops	Meher 1	0.108***	0.112***	0.154***	0.116***	0.125***	0.326
		(0.0371)	(0.0355)	(0.0484)	(0.0362)	(0.0377)	
	Dry	0.235***	0.246***	0.232***	0.238***	0.232***	0.134
		(0.0331)	(0.0315)	(0.0408)	(0.0325)	(0.0328)	
	Belg	0.0895	0.0902***	0.0707**	0.0856***	0.0826***	0.137
		(.)	(0.0281)	(0.0358)	(0.0284)	(0.0280)	
	Meher 2	0.0269	0.0278	-0.0447	0.0378	0.00343	0.223
		(0.0317)	(0.0301)	(0.0484)	(0.0340)	(0.0332)	
Market participation for livestock	Meher 1	-0.0617	-0.0551	-0.00124	-0.0155	-0.0321	0.402
		(0.0383)	(0.0368)	(0.0506)	(0.0373)	(0.0382)	
	Dry	0.00523	-0.000844	0.0546	-0.0211	0.0311	0.244
		(0.0349)	(0.0343)	(0.0378)	(0.0379)	(0.0334)	
	Belg	-0.0284	-0.0289	-0.00993	-0.0199	-0.00572	0.241
		(0.0338)	(0.0345)	(0.0415)	(0.0380)	(0.0328)	
	Meher 2	-0.00975	-0.0142	-0.0517	-0.00124	-0.0142	0.293
		(0.0348)	(0.0351)	(0.0500)	(0.0359)	(0.0347)	
Market participation for livestock products	Meher 1	0.0104	0.0204	0.0112	0.0273	0.0349	0.296
		(0.0372)	(0.0361)	(0.0464)	(0.0369)	(0.0366)	
	Dry	0.0223	0.0264	0.0794*	0.00868	0.0541	0.284
		(0.0372)	(0.0360)	(0.0466)	(0.0374)	(0.0356)	
	Belg	0.0279	0.0314	0.0720*	0.000620	0.0449	0.265
		(0.0349)	(0.0348)	(0.0397)	(0.0378)	(0.0341)	
	Meher 2	0.0354	0.0324	0.122**	0.0136	0.0511	0.302
		(0.0364)	(0.0359)	(0.0492)	(0.0387)	(0.0358)	
Travel time to market	Meher 1	0.0709	-0.168	1.139	-0.854	-0.228	115.769
		(3.036)	(3.043)	(3.269)	(4.045)	(3.035)	
	Dry	-13.29	-18.32	-11.41	-16.06	-14.18	108.8
		(13.78)	(18.90)	(38.97)	(17.43)	(18.05)	
	Belg	8.059	7.386	5.467	8.095	5.056	66.20
		(6.146)	(6.555)	(8.952)	(6.600)	(6.657)	
	Meher 2	21.41**	29.46***	37.97***	29.84***	27.87***	66.32
		(10.62)	(10.72)	(11.03)	(10.41)	(9.962)	
No. of observations		731	731	731	731	731	328

Notes:

3. Results are based on four rounds of high frequency data.
4. *, **, & *** represent statistical significance at the 10%, 5%, & 1% level respectively.

6. Conclusion

The results from this impact assessment are based on an innovative high frequency dataset which was collected across four seasons and over 12 months in four Ethiopian regions, to assess the sustainability of impact of an irrigation project on economic mobility and resilience, as well as other relevant indicators such agricultural production and food security, across the seasons in questions. The added value of a data collection of such kind resides in the fact that allows one to take into account the variability of a protracted shock and its consequences on the recipients over time. It also allows one to assess whether PASIDP has the protective effect across the seasons and whether this impact varies.

It is therefore, of policy relevance, to assess how impacts vary long after a project closes, and address to what extent impact varies contingent on the variability of shocks in a context such as the Ethiopian one, which is characterized by high levels of vulnerability, spatial diversity and the existence of a number of large scale programs designed to build household and community level resilience.

The results convey a number of messages: first the sustainability of impact across the period of observation, which is the period following a major drought which occurred in 2016. PASIDP closed at the end of 2015 and impacts of irrigation schemes can still be felt and are particularly remarkable during the dry season.

In terms of agricultural production indicators, treatment farmers seem to remarkably invest on agricultural inputs, have higher yields and this is particularly evident in the Dry season which, intuitively, should be the season where the benefits of irrigation systems should be felt the most.

Impacts are also evident across the crop portfolio where value of sales of specific crops (notably, grains and cereals, but also vegetables and fruit), are significantly higher for those accessing modern irrigation compared to their rain-fed counterparts. While treated farmers seem to intensify, and mostly rely on crop production as their major source of income, their counterfactual counterparts resorts to non-agricultural income sources, specifically livelihoods activities such as wage employment and self-employment .

As far as economic mobility indicators are concerned, treated farmers have a higher return from productive assets, are more likely to be above the poverty line, and are less likely to be transiently poor particularly during the Dry season. In terms of movements out of poverty – treatment farmers are also more likely to exit poverty - relative to persisting in poverty – in the dry season – compared to their rain-fed counterpart, particularly when the poverty metric is based on productive assets.

In terms of food security indicators, a key finding is the reduction in the negative coping strategies to which households resort in times of distress. Such reduction is particularly significant in the Belg season, the season immediately following the Dry season, and are intuitive, implying treated farmers increased resilience. This finding also underlines the persistence of the treatment effect – which goes beyond the season of interest, notably the Dry season, and manifest itself also in the following season.

As far as market access indicators are concerned, it was found that market participation regarding crop sales, proxied by distance metrics, are consistently larger for treated farmers compared to rain-fed counterparts, particularly in the Dry season and to a lesser extent in the following Belg season.

A number of resilience metrics were also compared and tested with this data. The Prime methodology – a capacity based approach - indicates gains across all rounds for treated farmers compared to counterfactual farmers. These gains seem to be consistently larger in the Dry season compared with the other rounds. Such findings are not evident in the other resilience metrics, although impacts are present but to a lesser extent and only in the Dry season.

Defined as it is by a much sharper focus on altering the dynamics of human welfare, resilience building requires a very different empirical strategy, compared with standard impact assessment cross-sectional analysis. To this, an attempt to look at dynamics was made through the growth model presented in Table 5.6, 5.6a and 5.6b, where a dynamic panel data model, notably system GMM, the Blundell-Bover estimator, was employed to assess the impact of PASIDP on asset growth, across the seasons, as well as on resilience gains or growth, making full use of the four rounds of data. A dynamic model is more suitable given that one can estimate the impact of treatment on resilience controlling for past shocks and past welfare dynamics.

The findings once again unequivocally show the benefits of irrigation on assets growth - contingent on the drought shocks – where the benefits are overwhelmingly positive. Assets growth is also inversely related to initial assets, indicating that the growth rate is potentially slower for those with higher level of assets at the first round. Results also point to the fact that treatment is positively related to resilience gains and that the latter increase over time.

This study clearly portrays strong evidence that investing in irrigation is highly transformative for farmers, particularly for those at the lower end of asset distribution. In addition, through a high frequency data collection, it was possible to assess the seasonal variation in such benefits as well as the sustainability of such benefits over time in a context where the drought spells are protracted and affect households differentially across the various seasons.

The following policy recommendations can be offered based on the findings of this study. The first and most important one is that irrigation projects are transformative and generate returns that make farmers resilient to climatic shocks and to this end, irrigation may act as an effective risk management strategy increasing farmers income and building resilience. Shocks contexts that are highly volatile, may require interventions that are tailored to such volatility, bundling interventions to for instance index insurance or other informal insurance mechanisms, capable of having larger multiplier effects.

Focused projects such as the ones providing small scale irrigation infrastructure are very effective at increasing production of high value crops but need to be bundled with marketing and market access interventions, to allow farmers to maximize the benefits from increased production. Commercialization and marketing support continue to be areas of improvement and should be bundled to interventions aimed at improving agricultural production.

The last policy recommendation concerns the ideal data structure of M&E systems for resilience building projects. M&E systems for resilience-building projects necessarily need to differ from standard M&E. The former require high frequency data – e.g. data collected at shorter time intervals compared with standard baseline, midterm and completion surveys – to be able to assess whether the interventions have indeed a protective effects towards reducing farmers' vulnerability to shocks and longer-term stressors in times of need. In order to minimize the cost implications of collecting data of such kind – such granular data could be collected for specific sites and for sub-samples, and combined with the more standard M&E data, which can be instead collected bi-annually. In addition, higher cost-efficiency could be gained by forging alliances with other stakeholders on the ground – so that data collection efforts won't be duplicated – for instance between the Rome-based agencies – which have a vested interest in having joint early warning systems – but also with national governments and local NGOs – focusing on geographical areas that are particularly shocks prone.

References

Alinovi, L., d'Errico, M., Mane, E., and Romano, D. (2010). Livelihoods Strategies and Household Resilience to Food Insecurity: An Empirical Analysis to Kenya. *European Report on Development*.

Arellano. M., and Bond, S. (1991). Some test of specification for panel data: Monte Carlo evidence and application to employment equations. *The Review of Economic Studies, 58,* 277-97.

Arelleno, M., and Bover, O. (1995). Another Look at Instrumental Variable Estimation of Error Component Models, *Journal of Econometrics, 68,* 29-51.

Aseyehegu, K., Yirga, C., and Rajan, S. (2012). Effect of small-scale irrigation on the income of rural farm households: The case of Laelay Maichew District, Central Tigray, Ethiopia. *Journal of Agricultural Sciences*, 7(1).

Asfaw, S., Kassie, M., Simtowe, F., and Lipper, L. (2012). Poverty reduction effects of agricultural technology adoption: A micro-evidence from rural Tanzania. *Journal of Development Studies*, 48(9), 1288-1305.

Azzarri, C., Haile, B., Roberts, C., and Spielman, D. (2015). Targeting bias or early impact of agricultural innovations? A case study from Malawi. Working paper, International Food Policy Research Institute (IFPRI), Washington, DC.

Bacha, D., Namara, R., Bogale, A., and Tesfaye, A. (2011). Impact of small- scale irrigation on household poverty: Empirical evidence from the Ambo district in Ethiopia. *Irrigation and Drainage*, 60(1), 1-10.

Bandiera, O., and Rasul, I. (2006). Social networks and technology adoption in Northern Mozambique. *Economic Journal*, 116(514), 869-902.

Barrett, C. B., and Constas, M. A. (2014). Toward a theory of resilience for international development applications. *Proceedings of the National Academy of Sciences*, 111(40), 14625-14630.

Barrett, C. B., and Headey, D. D. (2014). Measuring resilience in a volatile world: A proposal for a multicountry system of sentinel sites. In 2020 Conference papers (No. 1). International Food Policy Research Institute, Washington, DC.

Béné, C., Wood, R. G., Newsham, A., and Davies, M. (2012). Resilience: new utopia or new tyranny? Reflection about the potentials and limits of the concept of resilience in relation to vulnerability reduction programmes. Working paper, Institute of Development Studies, Brighton, United Kingdom.

Blundell, R.S., and Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics 87:* 115–143.

Bond, S. R. (2002). Dynamic panel data models: a guide to micro data methods and practice. *Portuguese Economic Journal 1(2):* 141-162.

Byerlee, D., and De Polanco, E. H. (1986). Farmers' stepwise adoption of technological packages: Evidence from the Mexican Altiplano. *American Journal of Agricultural Economics*, 68(3), 519- 527.

Cameron, A. C., and P. K. Trivedi. 2005. *Microeconometrics: Methods and Applications*. New York: Cambridge University Press.

Carletto, C, A Zezza and R Banerjee (2013). Towards better measurement of household food security: Harmonizing indicators and the role of household surveys. *Global Food Security*, *2,* 30–40.

Cissé, J.D. and Barrett, C.B., (2016), March. Estimating development resilience: a conditional moments-based approach. Working paper, Cornell University, Ithaca, NY.

Cutter, S.L., Barnes, L., Berry, M., Burton, C., Evans, E., Tate, E. and Webb, J., (2008). A place-based model for understanding community resilience to natural disasters. *Global Environmental Change*, 18(4): 598-606.

D'Errico, M., Di Giuseppe, S., Pietrelli, R. and Grazioli, F. (2015a). Resilience analysis in Niger. Technical report, Rome, Italy.

D'Errico, M., Di Giuseppe, S., Pietrelli, R. and Grazioli, F. (2015b). Resilience analysis in Mali. Technical report, Rome, Italy.

D'Errico, M., Pietrelli, R. and Romano, D. (2016). Household resilience to food insecurity: evidence from Tanzania and Uganda. Working paper, Rome, Italy.

Del Carpio, X. V., Loayza, N., and Datar, G. (2011). Is Irrigation Rehabilitation Good for Poor Farmers? An Impact Evaluation of a Non- Experimental Irrigation Project in Peru. *Journal of Agricultural Economics*, 62(2), 449-473.

Del Carpio, X. V., Loayza, N., and Datar, G. (2011). Is Irrigation Rehabilitation Good for Poor Farmers? An Impact Evaluation of a Non- Experimental Irrigation Project in Peru. *Journal of Agricultural Economics*, 62(2), 449-473.

Dercon, S. (2004). Growth and shocks: Evidence from rural Ethiopia. *Journal of Development Economics*, 74(2): 309-329.

Dercon, S., Hoddinott. J., and Woldehanna, T. (2005). Consumption and shocks in 15 Ethiopian villages, 1999-2004. *Journal of African Economies*, 14: 559-585.

Dercon, S., Hoddinott. J., and Woldehanna, T. (2012). Growth and chronic Poverty: Evidence from rural communities in Ethiopia. *Journal of Development Studies*, 48(2): 238-253.

Di Falco, S., and Veronesi, M. (2014). Managing environmental risk in presence of climate change: the role of adaptation in the Nile Basin of Ethiopia. *Environmental and Resource Economics*, *57*(4), 553-577.

Dillon, A. (2011). The effect of irrigation on poverty reduction, asset accumulation, and informal insurance: Evidence from Northern Mali. *World Development*, 39(12), 2165-2175.

Ersado, L., Amacher, G., and Alwang, J. (2004). Productivity and land enhancing technologies in Northern Ethiopia: Health, public investments, and sequential adoption. *American Journal of Agricultural Economics*, 86(2), 321-331.

Escobal, J. (2005). The role of public infrastructure in market development in rural Peru. Working paper, Munich Personal RePEc Archive, Lima, Peru.

FAO (2013). Resilience Index Measurement and Analysis (RIMA). Technical report, FAO, Rome, Italy.

FAO (2016). Resilience Index Measurement and Analysis – II (RIMA II). Technical report, FAO, Rome, Italy.

Frankenberger, T., (2015). Ethiopia Pastoralist Areas Resilience Improvement and Market Expansion (PRIME) Project Impact Evaluation Report of the Interim Monitoring. Technical report, Westat, Rockville, MD.

Heckman, J. (1997). Instrumental variables: A study of implicit behavioral assumptions used in making program evaluations. *Journal of Human Resources 32:* 441–462.

Heckman, J., and Navarro-Lozano, S. (2004). Using matching, instrumental variables, and control functions to estimate economic choice models. *Review of Economics and Statistics 86:* 30–57.

Herzog, F., Steiner, B., Bailey, D., Baudry, J., Billeter, R., Bukácek, R., De Blust, G., De Cock, R., Dirksen, J., Dormann, C.F. and De Filippi, R. (2006). Assessing the intensity of temperate European agriculture at the landscape scale. *European Journal of Agronomy*, *24*(2), 165-181.

Holland, P. W. (1986). Statistics and causal inference. *Journal of the American Statistical Association 81:* 945–960.

Holtz-Eakin, D., W. K. Newey, and H. S. Rosen. 1988. Estimating vector autoregressions with panel data. *Econometrica, 56:* 1371–1395.

Hussain, I., and Hanjra, M. A. (2004). Irrigation and poverty alleviation: review of the empirical evidence. *Irrigation and Drainage*, 53(1), 1-15.

Imbens, G. W. (2004). Nonparametric estimation of average treatment effects under exogeneity: A review. *Review of Economics and Statistics 86:* 4–29.

Imbens, G. W., and Wooldridge, J. M. (2009). Recent developments in the econometrics of program evaluation. *Journal of Economic Literature 47:* 5–86.

Kassahun, D. (2007). Rainwater harvesting in Ethiopia: Capturing the realities and exploring opportunities. Technical report, Forum for Social Studies, Addis Ababa, Ethiopia.

Kaur, N., Getnet, M., Shimelis, B., Tesfaye, Z., Syoum, G., and Atnafu, E. (2010). Adapting to climate change in the water sector: Assessing the effectiveness of planned adaptation interventions in reducing local level vulnerability. Working paper, RiPPLE, Addis Ababa, Ethiopia.

Kurukulasuriya, P., Kala, N., and Mendelsohn, R. (2011). Adaptation and climate change impacts: a structural Ricardian model of irrigation and farm income in Africa. *Climate Change Economics*, 2(02), 149-174.

Leathers, H. D., and Smale, M. (1991). A Bayesian approach to explaining sequential adoption of components of a technological package. *American Journal of Agricultural Economics*, 73(3), 734- 742.

Lipton, M., Litchfield, J., and Faurès, J. M. (2003). The effects of irrigation on poverty: A framework for analysis. *Water Policy*, 5(5), 413-427.

Liverpool-Tasie, L. S. O., and Winter-Nelson, A. (2012). Social learning and farm technology in Ethiopia: Impacts by technology, network type, and poverty status. *Journal of Development Studies*, 48(10), 1505-1521.

Mann, C. K. (1978). Packages of practices: A step at a time with clusters. *Studies in Development*, 21, 73-81.

Matouš, P., Todo, Y., and Mojo, D. (2013). Roles of extension and ethno-religious networks in acceptance of resource-conserving agriculture among Ethiopian farmers. *International Journal of Agricultural Sustainability*, 11(4), 301-316.

McKenzie, M. (2012). Beyond baseline and follow-up: The case for more T in experiments. *Journal of Development Economics*, 99. 210-221.

Minde, I., Jayne, T.S., Crawford, E., Arega, J., and Govereh, J. (2008). Promoting fertilizer use in Africa: Current issues and empirical evidence from Malawi, Zambia, and Kenya. Working paper, Regional Strategic Analysis and Knowledge Support System, Southern Africa (ReSAKSS-SA), Pretoria, South Africa.

Mitchell, A. (2013). Risk and resilience: From good idea to good practice - A scoping study for the experts group on risk and resilience. Working paper, Organisation for Economic Co-operation and Development, Paris, France.

Phadera, L., Michelson, H., Winter-Nelson, A. E., and Goldsmith, P. D. (2017) Do Asset Transfers Build Household Development Resilience? Working paper, University of Illinois, Urbana, IL.

Rejesus, R. M., Palis, F. G., Rodriguez, D. G. P., Lampayan, R. M., and Bouman, B. A. (2011). Impact of the alternate wetting and drying (AWD) water-saving irrigation technique: Evidence from rice producers in the Philippines. *Food Policy*, 36(2), 280-288.

Robins, J. M. (1986). A new approach to causal inference in mortality studies with a sustained exposure period—application to control of the healthy worker survivor effect. *Mathematical Modeling 7:* 1393–1512.

Roodman, D. (2005). xtabond2: Stata module to extend xtabond dynamic panel data estimator. Center for Global Development, Washington.

Rubin, D. B. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of Educational Psychology 66:* 688–701.

Sen, A. (1985). *Commodities and Capabilities.* Oxford University Press.

Seo, S. N., and Mendelsohn, R. O. (2008). An analysis of crop choice: Adapting to climate change in Latin American farms. *Ecological Economics*, 69, 109-116.

Smith, L. E. D. (2004). Assessment of the contribution of irrigation to poverty reduction and sustainable livelihoods. *Water Resources Development*, 20(2), 243-257.

Smith, L., Frankenberger, T., Langworthy, B., Martin, S., Spangler, T., Nelson, S., and Downen, J. (2014). Ethiopia Pastoralist Areas Resilience Improvement and Market Expansion (PRIME)

Project Impact Evaluation: Baseline Survey Report. Technical report, United States Agency for International Development, Washington, DC.

Teillard, F., Allaire, G., Cahuzac, E., Leger, F., Maigne, E., and Tichit, M. (2012). A novel method for mapping agricultural intensity reveals its spatial aggregation: implications for conservation policies. *Agriculture, ecosystems & environment*, *149*, 135-143.

Temple, J. (1999). The new growth evidence. *Journal of Economic Literature*, 37(1): 112-156.

Tesfaye, A., Bogale, A., Namara, R. E., and Bacha, D. (2008). The impact of small-scale irrigation on household food security: The case of Filtino and Godino irrigation schemes in Ethiopia. *Irrigation and Drainage Systems*, 22(2), 145-158.

Tucker, J., and L. Yirgu. (2010). Small-scale irrigation in the Ethiopian highlands: What potential for poverty reduction and climate adaptation? Background paper, RiPPLE, Addis Ababa, Ethiopia.

Van Den Berg, M., and Ruben, R. (2006). Small-scale irrigation and income distribution in Ethiopia.*Journal of Development Studies*, 42(5), 868-880.

Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data*. 2nd ed. Cambridge, MA: MIT Press.

World Bank. (2006). *Ethiopia: Managing Water Resources to Maximise Sustainable Growth: A World Bank Water Resources Assistance Strategy for Ethiopia*. Washington, DC.

World Bank. (2007). *World Development Report 2008: Agriculture for Development*. Washington, DC.

Yami, M. (2013). Sustaining participation in irrigation systems of Ethiopia: what have we learned about water user associations?. *Water Policy*, *15*(6), 961-984.

Appendix 1: Agricultural production and economic mobility: Asset indices

Table 1A: List of crops included in each agricultural production indicator

Crop Agricultural production indicators	Items included
Grains	Cereals, pulse, oilseed
Cereals	Teff, barley, wheat, maize, sorghum, oats, rice
Vegetables	Haleko, onion, garlic, green leaf vegetables, tomato, cabbage, carrot, ginger, pumpkin, green pepper
Root	Potato, sweet potato, yam, beet root, cassava
Pulses	Horse beans, lentils, chick peas, cow peas, vetch, haricot beans, field peas
Fruits	Banana, pineapple, avocado, mango, orange, watermelon, cactus, apple, juniper
Spices	Black pepper, red pepper
Perennials	Coffee, chat, enset, eucalyptus, bamboo, dikerence, acacia

Table 2A: List of assets included in each economic mobility indicators: asset indicies

Economic mobility: Asset indicies	Items included
Durable assets	Numbers of kerosene stove, electric stove, bed, watch, mobile phone, TV, sofa, bicycle, motor bicycle, cart, sewing machine, electric mitad
Productive assets	Numbers of sickle, axe, pickaxe, hoe, traditional plough, modern plough, leather whip beehive, shovel, sprayer, pump
Livestock assets	Numbers of ox, cow, sheep, goat, horse, donkey, mule, camel, pig, chicken, duck
Large livestock assets	Numbers of ox, cow, sheep, goat, horse, donkey, mule, camel, pig
Small livestock assets	Numbers of chicken, duck

Appendix 2: Matching quality statistics

Figure 1A: Balance between treatment and control groups

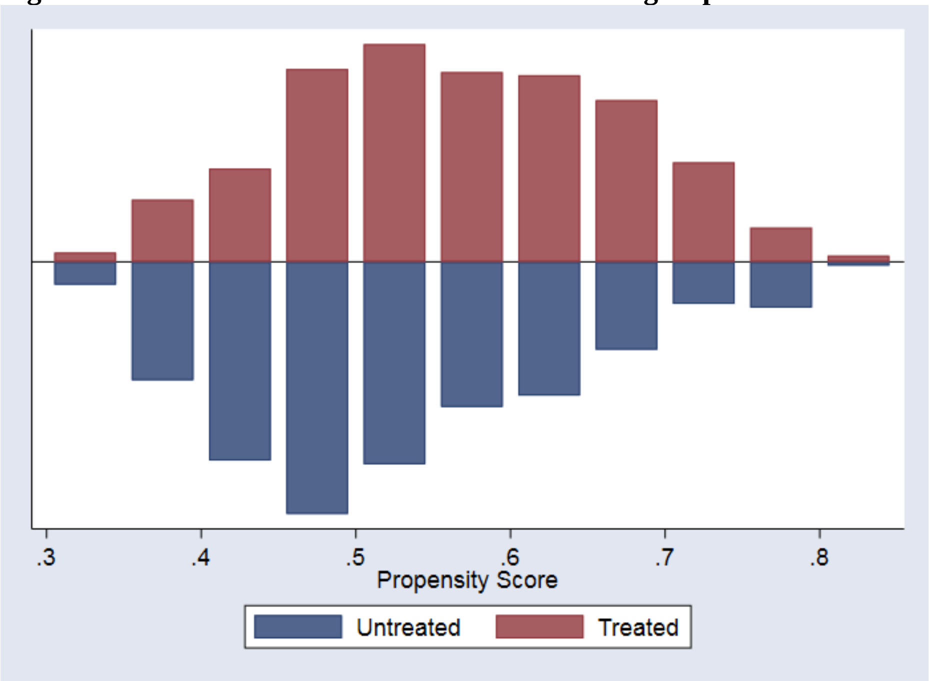


Figure 2A: Common support between treatment and control groups

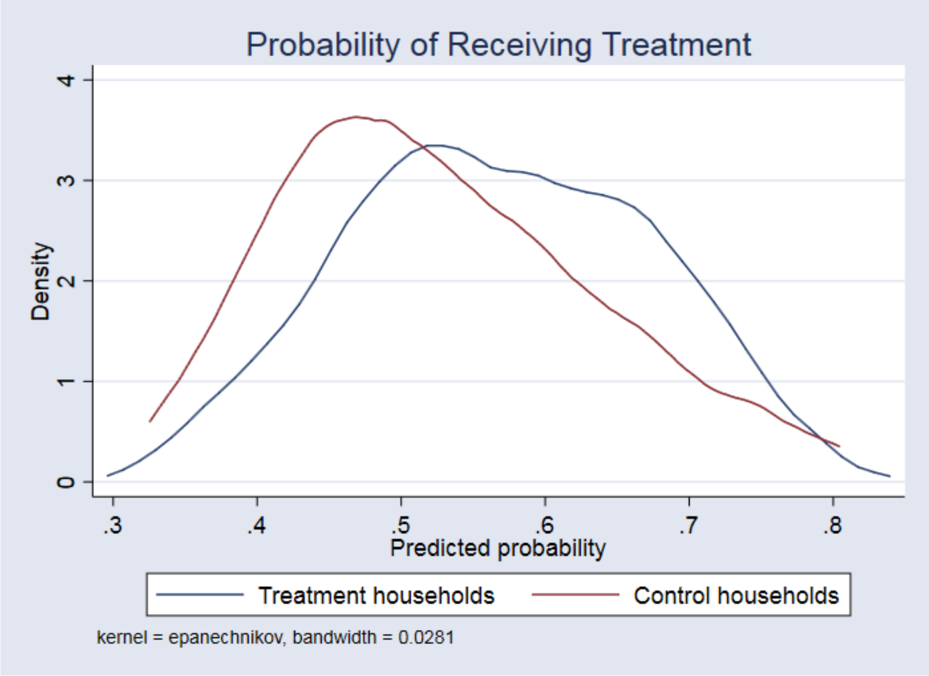
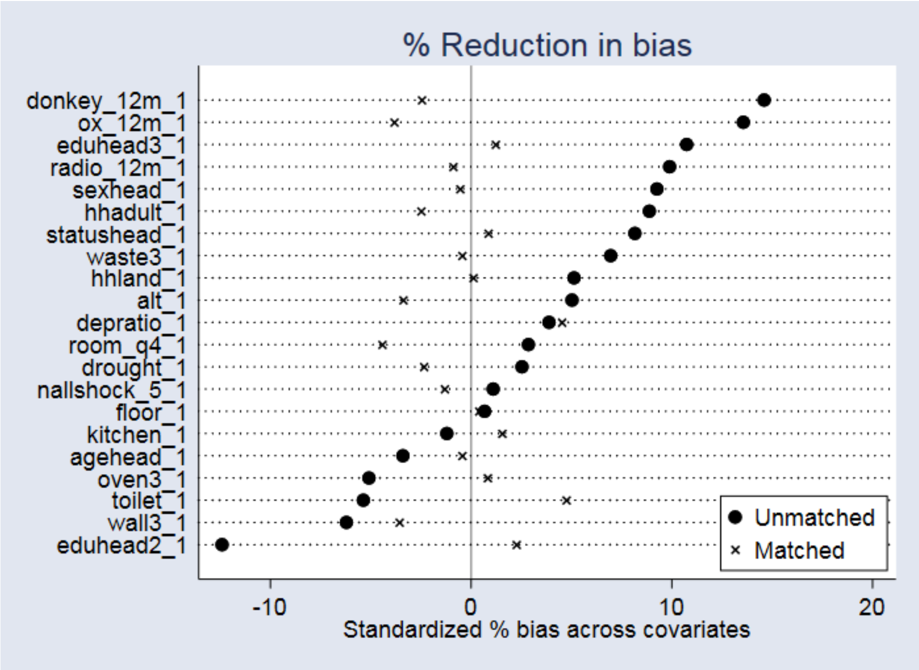


Figure 3A: Bias reduction between treatment and control groups



Appendix 3: Standardized Precipitation Evapotranspiration Index (SPEI)

The Standardized Precipitation Evapotranspiration Index (SPEI) is an extension of the widely used Standardized Precipitation Index (SPI). The SPEI is designed to take into account both precipitation and potential evapotranspiration (PET) in determining drought.

The parameters of the SPEI are a time-series of total monthly precipitation (P) and monthly potential evapotranspiration (PET). Monthly PET was calculated by the Thornthwaite equation that only relies on monthly mean temperature (T) and latitude (L) to calculate the monthly average day length.

A simple climate water balance was first calculated as the differences between precipitation P and PET for month j according to:

$$D = P_j - PET_j$$

where monthly PET is calculated by Thornthwaite equation:

$$PET = 16K\left(\frac{10T}{I}\right)^m$$

where T is monthly mean temperature (°C); I is heat index calculated as the sum of 12 monthly index values; m is the coefficient dependent on I: m=6.75 × 10^{-7} ·I^3 – 7.71 × 10^{-7} ·I^2 + 1.79 × 10^{-2} ·I + 0.492; and K is a correction coefficient computed as a function of the latitude and month.

The calculated D_i values are aggregated at different time scales, following the same procedure as used for the SPI. The difference , $D_{I,j}^{k}$ in month j and year i depends on the chosen time scale k. In our case, the accumulated difference for one month in a particular year i with a 4-month time scale was calculated to match the three seasons in Ethiopia using monthly precipitation and temperature data for the period January 1981 to December 2017. Then, the log-logistic distribution was used for normalizing the D series to obtain the SPEI.

SPEI has an intensity scale in which both positive and negative values are calculated, identifying wet and dry events. For the analysis, we used the continues negative SPEI values replacing the positive values to zero to capture drought. In the matching, we used the SPEI drought index for the 2015 Meher season, while for the outcome models we used the SPEI drought index for the four season in the period between June 2016 to September 2017.

The SPEI values for each season were computed using the SPEI command in R.

IFAD
International Fund for Agricultural Development
Via Paolo di Dono, 44 - 00142 Rome, Italy
Tel: +39 06 54591 - Fax: +39 06 5043463
Email: ifad@ifad.org
www.ifad.org
ifad-un.blogspot.com
www.facebook.com/ifad
instagram.com/ifadnews
www.twitter.com/ifadnews
www.youtube.com/user/ifadTV