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The Impact of Using Small-Scale Irrigation Motor Pumps on Farmers' Household Incomes in Ethiopia: A Quasi-Experimental Approach

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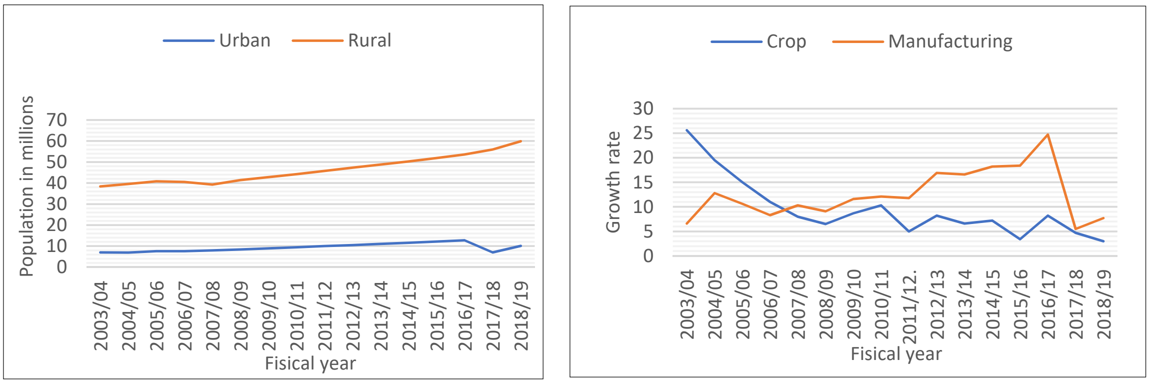
Abstract: Sectoral economic growth data in Ethiopia show that the agriculture sector has the lowest growth, which is caused by frequent drought and inefficient technologies, among other factors. As a result, the productivities of land and labor, as well as the income of small-scale farm households, are very low, and rural areas have a relatively high poverty rate. A quasi-experiment was applied to understand the impact of using small-scale irrigation motor pumps on farmers' livelihood improvement. Specifically, a survey was conducted in 2019 on a sample of 92 small-scale irrigation motor pump and canal irrigation users as the treatment and control groups. The weighted propensity score matching method was applied to eliminate initial differences and adjust sampling proportions across the groups. Based on the average treatment effect on the treated estimation results, we cannot state that the mean income difference in small-scale irrigation motor pump users and canal irrigation system users is different from zero. This indicates that countries with little capital to invest in large-scale irrigation projects can introduce household-level small-scale irrigation motor pumps to improve farmers' incomes.

Keywords: impact evaluation; irrigation motor pump; propensity score matching (PSM); quasi-experiment; treatment effect

1. Introduction

Ethiopia has been one of the fastest-growing economies worldwide since 2003/2004, with an average real gross domestic product (GDP) growth rate of 10.1% [1,2]. From Figure 1a,b, sectoral economic growth data show that agriculture has the lowest growth in Ethiopia, despite the large labor force involved in it [1].

One reason for the slower growth of agriculture is the low share of investment in this sector, which only accounts for 4.2% of the total investment capital in the country [1,3]. As a result, the productivities of land and labor, as well as the income of farm households (HH), are very low. Furthermore, agriculture is dependent on natural rainfall and is easily affected by drought, which negatively affects production and productivity. This results in the prevalence of a relatively high poverty rate in rural areas, an average of 25.6%, whereas the urban poverty rate is 14.8% [4,5]. Additionally, in Table 1, cross-sectional data from the World Bank show that Ethiopian farmers have the lowest farm income [6]. Therefore, Ethiopian farmers must make more efforts to transform the agriculture sector so that it reaches the level of modern agriculture and set long-term targets to achieve higher incomes.



(**a**): Rural–urban working population

(**b**): Crop vs. manufacturing value of products

Figure 1. (**a**) Rural–urban working population; (**b**) crop vs. manufacturing value of products.

Table 1. Labor productivity in Canada, China, and Ethiopia.

	Farm Population (000)	Gross Income (Billion USD)	Gross per Capita Income (USD)
Canada	322.74	26.56	82,283.64
China	224,237.85	927.88	4137.95
Ethiopia	32,282.66	23.28	721.28

Source: World Development Indicators (2016).

The advancement of irrigation technologies can boost these extremely low levels of production and productivity by creating alternative sources of water for agricultural production [7,8]. This is expected to improve the income of small-scale farm HH. Recently, the Ethiopian government has started paying attention to the expansion of irrigation projects to increase production and productivity. Specifically, it planned to increase the area of land covered by irrigation from 2.34 million hectares in 2014/2015 to 4.14 million hectares by the end of 2019/2020 and provide access to at least one alternative water point for 1.74 million ha of additional irrigated land [9].

Many researchers found that using irrigation motor pumps or canal irrigation has a positive impact on HH income [10–13]. Therefore, we hypothesized that there is no significant difference between the mean incomes of small-scale irrigation motor pump (SSIMP) users and small-scale canal irrigation system (SSCIS) users (H_0: ATT_{SSIMP}-ATT_{SSCIS} = 0). This is due to the similarity in soil types, technology level, agricultural extension awareness, and availability of alternative water sources for both groups. Alternatively, we argued that, because of differences in farm size and the number of people in the labor force, there will be a significant difference between the mean incomes of SSIMP users and SSCIS users (H_1: ATT_{SSIMP}-$ATT_{SSCIS} \neq 0$).

This study compared the difference between the impacts of the two treatment groups, SSIMP users and SSCIS users, instead of the differences between SSIMP users and non-irrigation users. It also measured the benefits of using household-level alternative SSIMP when SSCIS is not accessible. Specifically, we measured the impact of using SSIMP on farmers' livelihood improvement. The types of small-scale irrigations are presented in Figure 2.

As discussed below, most studies have tried to evaluate the impact of irrigation on livelihood improvement based on data from irrigation users and non-users. Ahmed et al. [14] used a random sample of 200 HHs and employed propensity score matching (PSM) to determine the impact of irrigation on HH income and food security status in the Oromia region in Ethiopia. The estimation results showed that the farm income and calorie intake of irrigation users improved compared with non-users. Gebregziabher et al. [15] used a sample of 613 farm HHs to measure the impact of irrigation participation on income in the Tigray region in Ethiopia. They applied an experimental method and found that irrigation users' income is higher than the regional average, whereas non-users' income is 50% lower. Enyew et al. [16] found, based on a sample of 313 HHs from the Rift Valley Lake Basins in Ethiopia, that irrigation improved HH income and contributed to poverty reduction.

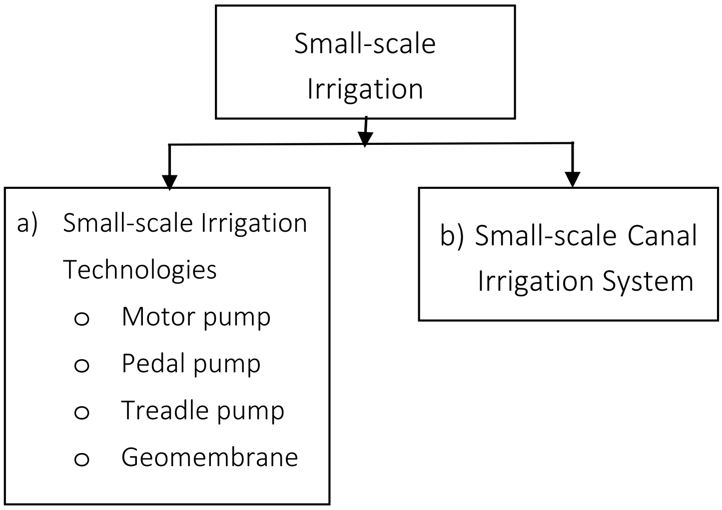


Figure 2. Types of small-scale irrigation in the study area.

Differing from earlier research, this study used a quasi-experimental approach to evaluate the comparative advantage of using SSIMPs in cases where SSCIS is not available. The study enhances the current understanding of: (1) the expanded application of experimental methods using two treated groups instead of the conventional treated and non-treated groups; and (2) the benefit of using HH-level alternative irrigation technologies in cases where canal irrigation is not applicable.

2. Materials and Methods

2.1. Sampling and Data Collection

This study was conducted in the Debre Eliyas district, Ethiopia. Debre Eliyas is located in the East Gojjam administrative zone in the Amhara national regional state. In the study area, for 12 existing small-scale canal irrigation projects, the total size of irrigable land before 2007 had increased sixfold by 2018, which improved the income of an additional 831 HHs. Furthermore, household-level small-scale irrigation technologies (SSIT) were also distributed, which improved the livelihood of 705 HHs with no access to an SSCIS.

Our target population was naturally placed under two different treatments (see Figure 3). One is located near the Gedeb river, which is not used for canal irrigation, and the other near a canal irrigated area, namely the Shimburit II small-scale irrigation dam. All 17 HHs located near the Gedeb river have started using SSIMP. In total, 324 HHs are located within the command area of the Shimburit II small-scale irrigation dam. Based on this, we constructed a study sample by randomly selecting 75 HHs from the SSCIS users and all 17 SSIMP users. Because of the low number of SSIMP users in the population, applying random selection would mean the probability of selecting an SSIMP user would be nearly zero. Furthermore, P_{SSIMP} = 17/341 = 5%, which is too small to use in the estimation. Instead, we attached weights to the selected samples to balance the sampling rate and representation [17,18], (Table 2).

We used a structured questionnaire containing questions on HH demographic characteristics, sources of income, components of expenditure, savings, and credit information. It was challenging to collect the income of rural HHs directly, as they are engaged in multiple livelihood activities whose contributions are difficult to quantify [19,20]. Furthermore, because of the strong association between income and expenditure in low-income countries, and the fact that GDP is estimated with an expenditure survey, we used HH expenditure as a proxy measure for HH income [19–23].

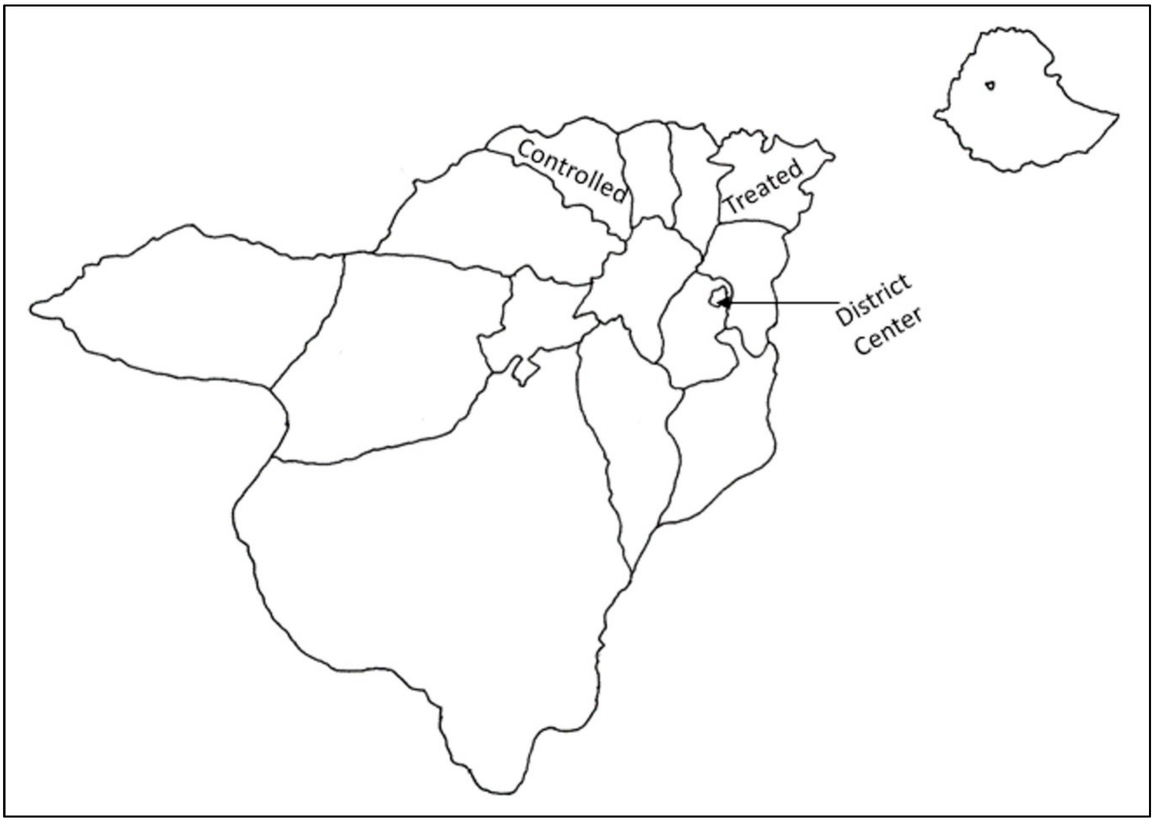


Figure 3. Map of Debre Eliyas district. Source: Debre Eliyas office of chief administration.

Table 2. Sample weights.

	Target Population	Sample	Probability	Weight
Motor pump	17	17	17/17 = 1	1/(17/17) = 1
Cana irrigation	324	75	75/324 = 0.23	1/(75/324) = 4.32

In the expenditure section of the survey, we included food consumption expenditure (e.g., purchased foods, own production, donations), non-food consumption expenditure, non-consumption expenditure (e.g., remittance, gamming), savings, and credit information. Therefore, the expenditure approach to the HH income represents the sum of all expenditures made by a HH, including savings, investment, and credit repayment [19,20].

The questionnaire was pretested with 10 randomly selected farmers, and we found that it is suitable for the survey. Next, in consultation with the Debre Eliyas district office of agriculture and the office of the district chief administration, we selected five enumerators to conduct face-to-face interviews in the selected kebeles. Detailed practical training was given to the enumerators, and survey guidelines were prepared for quick reference. Then, the house-to-house survey was conducted during 5–9 June 2019 (i.e., over five days). The authors conducted daily follow-ups during the survey period.

2.2. Data Analysis Method

We adopted a quasi-experimental method to scale the treatment effect of using SSIMP on farmers' HH incomes. For each SSIMP user, we have an expected income of y_1, and y_0 otherwise. As such, the difference between the two expected incomes ($y_1 - y_0$) is the treatment effect of using SSIMP [24]. However, an individual cannot be in two states (user and non-user) during the survey. Therefore, from the non-users, we constructed a comparison group using PSM, that is, the probability of being in the SSIMP user group, to estimate the average treatment effect (ATE) of using SSIMP [25–28]. Since

SSIMPs are distributed by the office of agriculture in a district, we did not conduct a baseline survey for each farmer to measure the initial differences across treatment and control groups.

Assume $M = 1$ for SSIMP users, and $M = 0$ otherwise.

The expected income of farmer i is given by:

$$Y_i = M_i Y_{1i} + (1 - M_i) Y_{0i} \quad (1)$$

We cannot observe both outcomes for an individual farmer as he/she will be either in the treatment or the control group. Therefore, the expected income of any individual farmer is given by:

$$Y_i = \begin{cases} y_{1i}, & if M_i = 1 \\ y_{0i}, & if M_i = 0 \end{cases} \quad (2)$$

We constructed a comparison group of non-SSIMP users conditional on propensity scores, *P(X)*. Then, the ATE is given by:

$$\begin{aligned} ATE &= E[y_1 | M = 1, P(X)] - E[y_0 | M = 0, P(X)], \\ ATE &= \{E[y_1 | \mathrm{M} = 1, P(X)] - E[y_0 | M = 1, P(X)]\} + \{E[y_0 | M = 1, P(X)] - E[y_0 | M = 0, P(X)]\}. \end{aligned} \quad (3)$$

Selection bias was eliminated by PSM, and SSIMP and non-SSIMP users became observationally similar, conditional on the observed covariates [29].

$$\begin{aligned} ATE_{SSIMP} &= E[y_1 | M = 1, P(X)] - E[y_0 | M = 0, P(X)], \\ ATE_{SSIMP} &= ATT_{SSIMP}, \end{aligned} \quad (4)$$

where $E[y_0 | M = 1, P(X)] = E[y_0 | M = 0, P(X)]$.

Mostly, ATE is used in cases where there are both treated and untreated groups [30]. However, we applied ATE to evaluate the impact differences between two experimental groups with different treatments: SSIMP and SSCIS users.

Assume D = 1 for SSIMP users and D = 0 otherwise, and B = 1 for SSCIS users and B = 0 otherwise. Then, the difference between the two ATEs conditional on observed covariates is given by:

$$\begin{aligned} \mathrm{ATE_{SSIMP\&SSCIS}} = \mathrm{E}(y_1 | D = 1) - \mathrm{E}(y_1 | B = 1) &= \{[\mathrm{E}(y_1 | D = 1) - \mathrm{E}(y_0 | D = 1)] + [\mathrm{E}(y_0 | D = 1) - \mathrm{E}(y_0 | D = 0)]\} \\ &- \{[\mathrm{E}(y_1 | B = 1) - \mathrm{E}(y_0 | B = 1)] + [\mathrm{E}(y_0 | B = 1) - \mathrm{E}(y_0 | B = 0)]\}, \end{aligned}$$

$$\mathrm{ATT(E)} = \mathrm{ATT(E)_{SSIMP}} - \mathrm{ATT(E)_{SSCIS}} \quad (5)$$

Selection bias was cleared by PSM, and the difference in the average treatment effect on the treated (ATT(E)) of the two groups is the ATT(E) of using SSIMPs on motor pump users [25,26]. Then, assuming $M = 1$ for SSIMP users and 0 for SSCIS users, Equation (5) will be equal to Equation (4), on the condition of the observed covariates.

However, the magnitude of ATT(E) in Equation (5) shows only the income differences between SSIMP and SSCIS users, not the actual income difference between SSIMP users and irrigation non-users. Variable definitions are shown in Table 3.

Table 3. Variable definitions.

x	Definition	Unit
HH head gender	Sex of HH head (0 = female, 1 = male)	Dummy
HH head age	Age of HH head	Number
Family size	Number of family members	Number
HH head marital status	Marital status of HH head (1 = married, 0 = single)	Dummy
Full-time workers	Number of full-time workers in the family	Number
Part-time workers	Number of part time workers in the family	Number
Not working	Number of family members who are not working either under working age or retired	Number
HH head education	Years of schooling	Number
Relation with development agents	The frequency of visiting farmers training center (1 = strong, 0 = weak)	Dummy
Wheat producing	Major product in the HH (1 = Yes, 0 = No)	Dummy
Teff producing	Major product in the HH (1 = Yes, 0 = No)	Dummy
Corn producing	Major product in the HH (1 = Yes, 0 = No)	Dummy
Barely producing	Major product in the HH (1 = Yes, 0 = No)	Dummy
Others producing	Major product in the HH (1 = Yes, 0 = No)	Dummy
Farm size	Size of land holding	Number
Irrigated cereal producing	Major irrigation product (1 = Yes, 0 = No)	Dummy
Irrigated others producing	Major irrigation product (1 = Yes, 0 = No)	Dummy
Irrigation farm size	Irrigated land holding size	Number
Cattle size	Number of cattle	Number
Sheep and goat size	Number of number of sheep and goats	Number
Transporting animals	Numbers of number of donkeys, horses, mules	Number

3. Results and Discussion

3.1. Descriptive Statistics

The descriptive statistics in Table 4 show that, on average, a farm HH has five family members, two of whom are full-time workers, two part-time workers, and the remaining one is either under working age or retired. The average age of the HH head is 45 years old and 77% of them are married. Regarding physical resources, they have an average of six cattle, three sheep and/or goats, one transporting animal, and 1.71 ha of farmland, of which 0.68 ha is irrigated.

Table 4. Descriptive statistics.

	Full	SSIMP	SSDIS	Mean Difference
HH head gender	0.1630	0.0000	0.2000	−0.2000
HH head age	45.3261	46.5882	45.0400	1.5482
Family size	4.8370	4.3529	4.9467	−0.5937
HH head marital status	0.7717	1.0000	0.7200	0.2800
Full-time workers	2.2500	2.0588	2.2933	−0.2345
Part-time workers	1.6087	1.4118	1.6533	−0.2416
Not working	0.9783	0.8824	1.0000	−0.1176
HH head education	1.6848	2.6765	1.4600	1.2165
Model farmer	0.4891	1.0000	0.3733	0.6267
Relation with development agents	0.9348	1.0000	0.9200	0.0800
Wheat producing	0.8587	0.4118	0.9600	−0.5482
Teff producing	0.0109	0.0588	0.0000	0.0588
Corn producing	0.1196	0.5294	0.0267	0.5027
Barely producing	0.0000	0.0000	0.0000	0.0000
Others producing	0.0109	0.0000	0.0133	−0.0133
Farm size	1.7161	2.3176	1.5798	0.7379
Irrigated cereal producing	0.0652	0.2353	0.0267	0.2086
Irrigated others producing	0.0000	0.0000	0.0000	0.0000
Irrigation farm size	0.6852	0.5118	0.7246	−0.2128
Cattle size	6.2500	8.3529	5.7733	2.5796
Sheep and goat size	2.9565	3.3529	2.8667	0.4863
Transporting animals	0.7500	1.1765	0.6533	0.5231

Source: Authors' calculations.

Farmers have strong connections with agricultural development agents for daily consultations and short-term training, and half of them are model farmers. They use their own agricultural production experiences and undertake short-term training and daily consultations with development agents for crop production and animal husbandry activities. The main product is wheat.

3.2. Estimation Results

To estimate the propensity scores (PS), we included covariates associated with the treatment assignment and outcome variable, as well as weights for each sample, to balance the sampling rate difference [31]. The number of people in the family classified as the working labor force and who owned farmland were the covariates included in the PS estimation. The PS was estimated with a logit model using the data from the survey design. As shown in Table 5, the weights attached to the sample groups improved the significance level of the variables.

Table 5. Logit result with and without weights.

	Without Weights		With Weights	
	Estimate (Std. Error)	**Pr(>|t|)**	**Estimate (Std. Error)**	**Pr(>|z|)**
(Intercept)	−0.1002 (0.6713)	0.8813	−1.6383 (0.6272)	0.0106 *
Working labor	−0.2972 (0.1655)	0.0726	0.2777 (0.1481)	0.0641
Land ownership	−17.7833 (1662.8510)	0.9915	−17.3596 (0.4539)	$<2.0 \times 10^{-16}$ ***

Note 1: *** and * represents 1% and 10% significance level, respectively.

Then, using the calculated PS, we minimized the dimensions of covariates into scalar variables to match the SSIMP users and SSCIS users [32]. As shown in Table 6 and Figure 4, nearest neighbor matching (NNM) with 0.25 and 0.1 calipers was found to provide better matches, as the standardized mean differences are below 5% [25] and the histograms of the two groups are similar. Likewise, before matching, the mean value of PS in the treated group was 96% higher than that of the control group, and, after matching, it was reduced to 0%. Table 7 illustrates that the mean values of the working labor force and land ownership were, respectively, 0.5 and 20% higher in the control group than in the treated groups before matching, and were both 0% after matching. Moreover, the *t*-test of the difference in means showed an improvement after matching [25,27]. Therefore, the PSM improved the balance between the two groups, which became more similar after matching.

Table 6. Nearest neighbor matching (NNM) with and without calipers.

		PS Value	Matched n
Before matching	Means Treated	0.0737	17
	Means Control	0.0486	75
	Std. Mean Diff.	0.9639	
NNM	Means Treated	0.0737	17
	Means Control	0.0716	17
	Std. Mean Diff.	0.0801	
NNM (Caliper = 0.25)	Means Treated	0.0732	15
	Means Control	0.0745	15
	Std. Mean Diff.	−0.049	
NNM (Caliper = 0.1)	Means Treated	0.0732	15
	Means Control	0.0732	15
	Std. Mean Diff.	0	

Note 2: 200 bootstrap replications were used to estimate the standard errors.

Table 7. *t*-test of difference in means.

	Before Matching				After Matching			
	Mean Treated	**Mean Control**	**Mean Diff.**	***p*-Value**	**Mean Treated**	**Mean Control**	**Mean Diff.**	***p*-Value**
PS value	0.073735	0.048600	0.0251	0.002324 ***	0.073181	0.073181	0	1
Working labor	3.470588	3.946667	−0.4761	0.2865	3.533333	3.533333	0	1
Land ownership	0.0000	0.2000	−0.2000	5.119e-05 ***	0	0	0	NA

Note 3: 200 bootstrap replications were used to estimate the standard errors. *** represents 1% significance level, respectively.

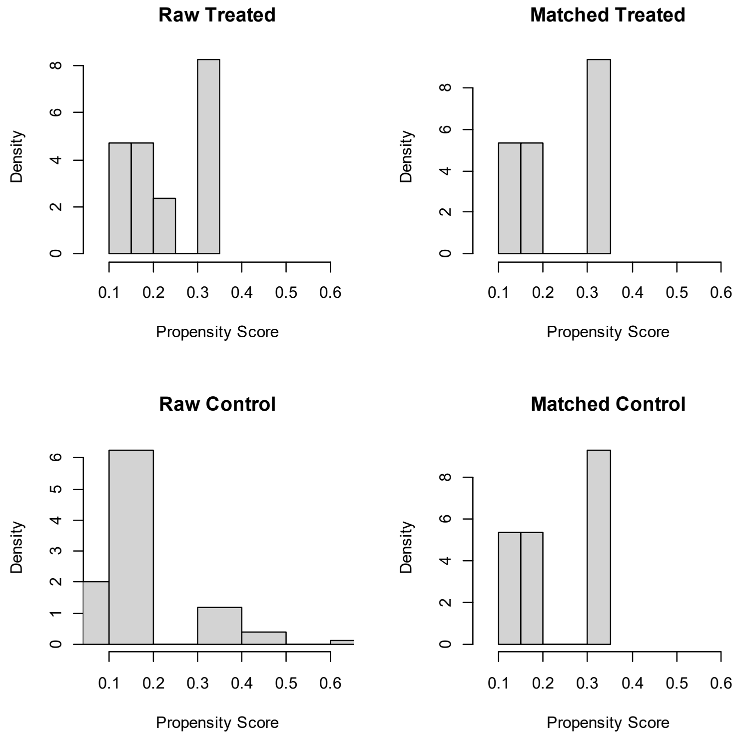


Figure 4. NNM with 0.1 caliper.

The treatment effect estimation result in Table 8 shows that, for all matching algorithms, *p* values are not significant. Therefore, we do not have sufficient support for the alternative hypothesis that the mean outcome difference in the two groups is not zero. Thus, we cannot state that the difference between the mean income of SSIMP users and SSCIS users is different from zero. Previous studies asserted that the use of irrigation technologies can improve production and productivity such that it increases HH income [14–16]. During field visits, farmers also confirmed that their income had improved due to the adoption of SSIMP and/or SSCIS. This study tried to measure the comparative advantage of using either of the irrigation technologies, considering both technologies have a positive impact on HH income compared with not using irrigation technologies. Therefore, the value of the estimation results shows only the mean income difference between the two treatment groups, but not the actual scale between irrigation users and non-users.

The objective of introducing SSIMPs is to provide irrigation access to farmers and improve their livelihoods. Therefore, HHs can adopt SSIMPs to gain a comparative advantage and improve HH income when large-scale irrigation is not applicable due to high investment costs. The size of irrigated farmland is dependent on the type of motor pumps distributed to farmers. From the descriptive statistics, the average farm size of small-scale farmers in the study area is 1.71 ha (2.36 ha after matching), which is above the national average of 0.9 ha [33,34]. Additionally, the average irrigable farm size is 0.68 ha (0.87 ha after matching), while the command area of the pump is around 10 ha.

Furthermore, the average operational cost of irrigation motor pumps is not significantly different from the average maintenance fee of canal irrigation users. Therefore, the different treatments do not show any differences in the size of irrigable land, as well as operational costs and labor. If there are any differences between them, they are random for both treatment conditions. As a result, we considered that the only difference between these two treatments is how they access irrigation water from the source. Namely, SSIMP users access the water by pumping the river to their farmland using irrigation motor pumps and SSCIS users use the irrigation canal constructed by the regional government that passes through their farmland. Both groups cultivate, on average, an area of 0.68 ha (0.87 ha after matching) using either water source. The estimation results show that the mean income difference in the two groups cannot be statistically different from zero.

Table 8. Estimation result for average treatment effect on the treated (ATT(E)).

	Before Matching	After Matching		
		NNM	NNM (Caliper = 0.25)	NNM (Caliper = 0.10)
ATT	−7547.845	−6028.5	−10,453.63	−11,608.63
p	0.3365	0.5754	0.3627	0.55
n	92	34	30	30

Irrigation promotes land-intensive agriculture that creates opportunities to use the large labor force in the sector intensively [35]. Irrigation non-users are dependent on natural rainfall and only produce once per year. These farmers adjust their cropping schedule based on the raining season. As such, any production plan that does not consider the rainy season is not expected to have a positive impact on production size and productivity unless using an alternative water source. Assuming other factors of production and activities are constant, the availability of an irrigation water source creates opportunities to use the land more intensively. Therefore, the availability of an irrigation water source allows farmers to increase production and productivity using available resources. First, by making decisions irrespective of the raining season, farmers can plan and produce independently from the natural rain cycle and other farmers' production schedules based on the market demand and home consumption. However, creating an additional production cycle demands more labor. When using the natural rainfall cycle, seasonal unemployment is a problem, as extra labor is only needed during the land preparation period. Nonetheless, because of the favorable environmental conditions in the study area, using irrigation is expected to increase work opportunities and production throughout the year. Therefore, access to irrigation promotes land-, labor-, and capital-intensive agriculture that boosts the quantity of production over a year [8,28].

An increase in production size increases subsistence farmers' HH income. As income inequality and a relatively higher poverty prevalence are current challenges in Ethiopia, an improvement in rural HH income narrows the income inequality between rural and urban HHs and also decreases the rural poverty level [16,36].

Furthermore, drought and low rainfall have been affecting the agriculture sector negatively by reducing HH production to nearly zero production in some years. In this case, small-scale farmers living on subsistence production are expected to avail the compulsory food aid. As such, access to irrigation creates a constant alternative water source, meaning that small-scale farmers can create climate-resilient agriculture with minimum environmental risks [11,37].

However, access to irrigation may create income inequality among small-scale farmers. If irrigation access does not benefit all farmers, inequality will surface in rural areas [13]. Currently, in the study area, there are many alternative types of SSITs available to all farmers to access irrigation water in each plot, namely motor pumps, pedal pumps, treadle pumps, and geomembranes. Therefore, farmers can choose the type of technology depending on the type of water source they can access. Thus, the availability of these technologies minimizes income inequality across small-scale farmers and creates a pull factor that motivates non-irrigation farmers to adopt irrigation technologies.

4. Conclusions

This study furthered the understanding of the expanded application of experimental methods using two treated groups instead of the conventionally used treated and non-treated groups. Moreover, it contributed to filling the knowledge gap on the comparative advantage of using irrigation motor pumps, which serve as alternative irrigation water sources. A quasi-experiment approach was applied to understand the impact of using SSIMP on farmers' HH incomes in cases where SSCIS is not applicable. The treatment effect estimation results show that the mean income difference between SSIMP users and SSCIS users is not statistically significantly different from zero. This means that the introduction of SSIMPs can have a positive impact by improving the livelihood of farm HHs, similar to SSCISs. Therefore, household-level alternative irrigation motor pumps can be adopted in low-income countries, where capital is binding, to invest in large-scale irrigation dams.

Additionally, irrigation promotes land-intensive agriculture that creates opportunities to use the large labor force in the sector more intensively. It enhances production quantity and labor productivity, which further improves HH income. It also helps decrease poverty and narrows down the income inequality between rural and urban HHs.

Furthermore, as the agriculture sector has been affected by drought and low rainfall, access to irrigation creates an alternative water source that small-scale farmers can use to create climate-resilient agriculture with minimal risks. However, while it creates income inequality within rural HH with non-irrigation users, it can also be a pull factor for non-irrigation users, as there are many household-level SSITs that can easily be adopted by small-scale farmers.

In summary, the findings of this study show that SSIMPs and SSCISs can be used alternatively depending on the available water sources to improve subsistence farmers' income.

However, the study considered a moderate sample size due to budget and time constraints. Future investigations with a relatively large sample size and a wide range of variables will enhance our understanding of alternative irrigation motor pumps.

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