MEKELLE UNIVERSITY
COLLEGE OF BUSINESS AND ECONOMICS

IMPACT OF SMALL SCALE IRRIGATION ON HOUSEHOLD WELFARE: CASE OF LAELAY DAYU IRRIGATION SCHEME, ALAMATA DISTRICT, TIGRAY

BY
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A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR
MASTER OF SCIENCE IN ECONOMICS
SPECIALIZATION: DEVELOPMENT POLICY ANALYSIS

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JUNE, 2014
MEKELLE, ETHIOPIA

MEKELLE UNIVERSITY
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DECLARATION

I hereby declare that this thesis is my own work and has not been submitted for any other degree. All sources of materials used for this thesis have been duly acknowledged.

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CERTIFICATION

This is to certify that this thesis entitled: **<u>Impact of Small Scale Irrigation on Household Welfare: Case of Laelay Dayu Irrigation Scheme</u>** is an authentic work of ______________________________ ID.No.______________who carried out the research under my guidance. I certify that, to the best of my knowledge, the work reported here does not form part of any project report or thesis on the basis of which a degree or award was conferred on an earlier occasion on this or any candidate.

Principal Advisor:_______________________Signature:_________________ Date:______________

Internal Examiner:_______________________ Signature:_________________Date:______________

ACKNOWLEDGMENTS

First, I praise ALLAH, the CHERISHER and SUSTAINER of the worlds. It is because of YOU that I am where I am today. YOU are the GREATEST!

Then, my sincere gratitude goes to my principal advisor Dr. Gebrehaweria Gebregziabher. I remain grateful for the encouragement, supervision, professional guidance and close collaboration during the course of the study. Thank you very much for your desire to see me succeed in this research.

I am also indebted to my co-advisor Achamyeleh Tamiru for his unreserved efforts and constructive comments that helped me to come up with this document. Besides, I would like to appreciate his kindness and collaboration in providing me different materials to facilitate my work.

It would be unfair if I failed to express my appreciation to Dilla University for granting me a study leave to pursue my graduate studies. I would also extend my gratitude to Mekelle University in general and the staff in department of economics in particular.

Finally, I reserve my most gratitude to my family. Thank you for very much!!!

Anwar A.

June, 2014

Mekelle, Ethiopia

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TABLES

ACRONYMS

ADOARD	Alamata District Office of Agriculture and Rural Development
ADOPF	Alamata District Office of Planning and Finance
AE	Adult Equivalent
ATT	Average Treatment Effect on Treated
CIA	Conditional Independence Assumption
CSA	Central Statistical Authority
ETB	Ethiopian Birr
FDRE	Federal Republic of Ethiopia
GDP	Gross Domestic Product
GTP	Growth and Transformation Plan
GW-MATE	Ground Water Management Advisory Team
IPMS	Alamata Pilot Learning Site
IWMI	International Water Management Institute
LDCs	Least Developed Countries
LSI	Large Scale Irrigation
MSI	Medium Scale Irrigation
MoA NRMD	Ministry of Agriculture Natural Resources Management Directorate
MoFED	Ministry of Finance and Economic Development
MoWR	Ministry of Water Resources
NGOs	Non Governmental Organizations
OECD	Organization for Economic Cooperation and Development
PC	Per Capita
PSM	Propensity Score Matching
REST	Relief Society of Tigray
RWH	Rain Water Harvesting
SNNPR	South Nations Nationalities and Peoples Region
SSI	Small Scale Irrigation
TAMPA	Tigray Agricultural Marketing Promotion Agency
TRBPF	Tigray Region Bureau of Planning and Finance
UNDP	United Nations Development Program
WHO	World Health Organization
WUA	Water Users Associations

ABSTRACT

This paper evaluates the impact of small scale irrigation on household welfare measured by household income and consumption expenditure. The study is based on cross-sectional data collected from a sample of 180 households [80 adopters and 100 non adopters] using two stage random sampling. The analysis was performed applying propensity score matching and poverty analysis. These results suggest that access to irrigation has profound impact on improving household welfare and reducing rural poverty.

Key words: *Impact, propensity score matching, small scale irrigation, welfare, poverty.*

CHAPTER-1
INTRODUCTION

1.1 BACKGROUND

Ethiopia is a poor country in the Horn of Africa where around 80% of the population depends on agriculture for their livelihood [Van Koppen et al., 2009]. The sector contributes 43% to the GDP and over 80% of export value [Awulachew, 2010]. Agriculture is primarily rain fed and the country has experienced chronic food insecurity due to degradation of natural resources, poverty, weak institutions, low functioning markets and inconsistent policies [Yami and Snyder, 2012].

According to IWMI [2005], Ethiopia covers 12 river basins with an annual runoff volume of 122 billion m3 of surface water and an estimated 2.6 billion m3 of ground water potential. This amounts to 1707 cubic meters of water per person per year. Currently, surface water resources are mainly used for irrigation systems, although groundwater is widely available in Ethiopia [GW-MATE, 2011]. So far, only 10- 12% of the total irrigation potential is developed in both traditional and modern schemes [MoA-NRMD, 2011]. Given the water potential, promoting water related technologies, especially irrigation at different scales makes sense [IWMI, 2005].

To this end, the government has been engaged in irrigation development endeavors to change the traditional agrarian system into a widespread irrigated agriculture and gradually into food secure economy [Hagos, 2005]. Similarly, nongovernmental organizations such as REST, UNDP, Oxfam and Water Action have been engaged in funding and implementing irrigation dams and river diversion structures. After constructed, these irrigation infrastructures are handed over to water users associations on the principle that local farmers will have a comparative advantage over the government through collective action [Meinzen-Dick et al., 2000 and IWMI, 2005].

However, irrigation is not a simple silver bullet [Awulachew, 2010]. It brings positive returns only if it is complemented by other components of the agricultural system. Unfortunately, the country’s agricultural sector is characterized by traditional technologies and poor systems.

Specifically, there are different production constraints impeding performance of the irrigation sector. These gaps are technical, agronomic, financial, infrastructural and institutional. Hence, quantifying the explicit impact of irrigation schemes deems essential.

1.2 PROBLEM STATEMENT

Agriculture in Ethiopia is mostly small- scale, rain dependent, traditional and subsistence with limited access to technology and institutional support services [Desta, 2004]. Consequently, rain-fall variability and moisture stress is constraining development of the rural sector. For example, in Tigray, low agricultural productivity and lack of alternative income sources accompanied by high population growth have been among the main causes of food insecurity in the region [REST, 2007]. Consistent with this notion, the government and NGO's of both international and local origin have been exerting bolder efforts in funding and implementing small scale irrigation schemes in many arid and semi-arid parts of the country.

However, the impact of irrigation water is not always promising. While many studies like Huang et al., 2005 in China; Kuwornu and Owusu, 2012 in Ghana; Sekhri, 2013 in India; Haji and Aman, 2013 in Ethiopia found positive welfare impacts of adopting irrigation water, other studies failed to show significant positive results. For example, Pender et al. [2002] indicated that in Tigray irrigation has less impact in agricultural yields than expected. A similar study Hagos et al [2006] in Northern Ethiopia indicated that households with ponds and wells were not significantly better off compared to households without, even though they were comparable in essential household characteristics. Another study made in rural Tigray [Haile, 2008] has indicated that irrigation through pond water had not significant effect in increasing the welfare of beneficiary households. These findings call for further research on the topic.

In Tigray, to the best of my knowledge, the welfare impact of river diversion irrigation schemes is not well documented. Besides, no attempt has been made to analyze the impact of Laelay Dayu irrigation scheme on the welfare of irrigation adopters so far. Given these facts, my study tries to provide explicit empirical evidences about the impact of small scale irrigation on the welfare of irrigating households.

1.2 OBJECTIVE OF THE STUDY

The overall objective of the study is to examine the impact of small scale irrigation interventions on improving the welfare of small holder farmers in the study area. Hence, the specific objectives are:

- To examine the impact of irrigation on consumption expenditure.
- To compute the impact of irrigation on household income.
- To assess poverty situation of irrigation adopters and non adopters.
- To analyze problems associated with the performance and management of small scale irrigation.

1.4 SIGNIFICANCE OF THE STUDY

This paper contributes to irrigation literature by providing a micro perspective on the impact of small scale irrigation on rural households. Specifically, it tries to justify whether the policy driven investment on small scale irrigation infrastructures in general and river diversion projects in particular is a viable poverty reducing strategy. In addition, it is believed to be of some significance to Oxfam and REST who directly finance and implement the Laelay Dayu irrigation scheme. Besides, the paper tries to unveil the opportunities and constrains brought about by the irrigation scheme to the local government and stakeholders in the study area.

1.5 SCOPE OF THE STUDY

Even though there are several ways of diverting, conveying and applying irrigation water on farms ranging from traditional gravity methods to pumped modern trickle and sprinkler systems, this study confined itself to the modern surface/gravity irrigation systems. To compare poverty status of irrigating and non irrigating households, the study adopted the uni-dimensional instead of the multidimensional poverty. Financial appraisal and technical analysis are beyond the scope of the study.

1.6 THESIS ORGANIZATION

In this thesis there will be six chapters. The first chapter presents background of the study in relation to national and regional contexts. It also precisely discusses statement of the problem and objectives of the study.

The second chapter tries to review recent literatures on the subject. To this end, both theoretical and empirical literatures are reviewed. In the theoretical part, an attempt was made to clarify the irrigation-poverty linkage by offering a review of recent researches on the subject. In the empirical part, some findings about the impact of small scale irrigation on poverty and household welfare are discussed.

The third chapter is devoted to review irrigation development and policy environment in Ethiopia. Accordingly, Ethiopian government water resource development policies and strategies in general and irrigation policy in particular were extensively reviewed. This will give context information about the need for small scale intervention in the country.

The fourth chapter elaborates on the methodology used for this research, including a description of the sampling process, data collection and analysis methods. Besides the procedures used in econometric modeling and poverty analysis are explained. In addition, a brief description about the study area is included.

The fifth chapter is fully devoted to empirical analysis. It presents results and discussion in relation to major objectives of the thesis. The sixth chapter ends the research by concluding the main findings. It will also suggest policy intervention based on lessons derived from the study.

CHAPTER-2
LITERATURE REVIEW

2.1 IRRIGATION-POVERTY LINKAGE: ANALYTICAL FRAMEWORK

Poverty is intricate and multidimensional and it is the consequence of multitude interactions between resources, technologies and institutions and that there is no unique solution to this problem [Hussain and Wijerathna, 2004]. It is now acknowledged that poverty is caused by deprivation of resources, opportunities, information, technologies, socioeconomic and demographic factors, and that it is also deep-rooted in other important factors, such as global-level policies and actions, national level historical factors and government policies, institutions and actions at various levels, and community-level power structures and informal institutions [Ibid].

The irrigation-poverty linkages are distinguished as direct and indirect effects. The direct effects of irrigation on yields and farm income are well understood. However, the indirect effects that link irrigation and poverty, as well as the effects of irrigation on inequality, are less clear, even though these effects may be more important in terms of poverty reduction [Bhattarai et al, 2002].

The direct linkages operate through localized and household-level effects, and indirect linkages work through aggregate or sub national and national level impacts. Irrigation benefits the poor though higher production, higher yield, lesser risk of crop failure, and higher year-round farm and nonfarm employment [Hussain and Hanjra, 2004]. There are also direct benefits for non-irrigators. Food accessibility and affordability usually boost up when irrigated agriculture expands and more reliable production helps to stabilize food prices. New employment opportunities arise in farming, and also in the wider rural economy as increased farm income leads to greater demand for both agricultural inputs and nonfarm goods and services [Bhattarai et al, 2002; Delgado et al, 1997]. Irrigation can thus cushion both irrigators and non-irrigators against risks in their income and preventing or reducing the need for last-resort coping strategies such as sale of belongings or high-cost borrowing [Lipton et al, 2003].

The indirect linkages operate by means of regional, national, and economy-wide effects. Irrigation investments act as production and supply shifters, and have a significant positive effect on growth, benefiting the poor in the long run. In addition, irrigation benefits also accrue to the poor and landless in the long run, even if in the short run relative benefits to the landless and land-poor may be small, as the distribution of water often tends to be land-based [Hussain and Hanjra, 2004]. Despite that, the poor and landless benefit, in both absolute and relative terms, from irrigation investments. More advanced systems in irrigation technologies, such as micro-irrigation systems, have strong poverty reduction potential [Ibid].

Hussain and Hanjira [2004] pointed out that antipoverty impacts of irrigation can be strengthened by creating situations or enabling environments that could attain effective inclusion of the poor. These include: (1) fair access to land; (2) integrated water resource administration; (3) access to and adequacy of quality surface and groundwater; (4) modern production technology, (5) shift to high-value market-oriented production; and (6) opportunities for the sale of farm outputs at low transaction costs. The benefits of irrigation to the poor can be augmented by introducing broader level and targeted interventions simultaneously.

2.1.1 DIRECT IMPACTS

The first direct impact is on output. Irrigation enhances farm output and thus, with prices remaining constant, raises farm incomes. Output levels may increase for any of at least three reasons. Firstly irrigation boosts yields by mitigating crop loss due to unpredictable, unreliable or inadequate rainwater supply. Secondly, irrigation permits the possibility of multiple-cropping and a boost in total output. Thirdly, irrigation enables a greater area of land to be used for crops in times where rain-fed production is not possible or insignificant. Consequently, irrigation is expected to increase output and income levels [Lipton et. al, 2003].

The second major impact of irrigation is in the employment generated both on and off the farm, offering entitlement or purchasing power for the poor. For landless laborers, increased cropping intensity has the maximum impact on employment. Irrigation means extra work in more days of the year. The employment impact is felt not only in irrigated areas but also in rain-fed areas.

Sometimes, landless workers in rain-fed villages migrate long distances to take advantage of employment opportunities in the irrigated areas [Barker et al, 2000].

According to Lipton et al. [2003], there are two sources of extra demand for labour created by irrigation projects. Firstly, irrigation projects need labour for construction and on-going maintenance of canals, wells and pumps etc. This is expected to be a vital sector of employment for the poor, particularly the landless rural poor or rural households with extra labour or seasonal excess labour. Secondly, higher farm outputs as a result of irrigation will stimulate more demand for farm labour. Thus, rural poverty could be reduced by the increased employment opportunities associated with the adoption of irrigation schemes.

The third direct effect on poverty is by means of food prices. If irrigation boosts the level of output then this may result in lower prices of foods [Lipton et. al, 2003]. Lower food prices have reduced vulnerability associated with distribution of food and its access among poor and marginal communities [Bhattarai et al, 2002]. Therefore, both rural net purchasers and urban consumers will gain from cheaper food prices. Thus, a fall in the staple price as a result of more outputs from irrigated plots is expected to be poverty reducing.

2.1.2 INDIRECT IMPACTS

There are a number of irrigation induced linkages that affect the economy of rural households. Bhattarai et al [2002] analyzed linkage effects such as forward linkages [in farm output market], backward linkages [in farm factors market] and adjustments for the shadow prices of the factors and products in the economy [feedback effects from foreign exchange rates].

Lipton et al. [2003] argued that access to irrigation also has second round impacts through output, employment and prices on poverty. In the longer run with a dynamic general equilibrium scenario and farm outputs, irrigated land in general initiate farmers to adopt fertilizers, pesticides, improved seeds and other agricultural factors of production. This also has a positive effect in poverty reduction.

2.2 IMPACT OF IRRIGATION ON WELFARE: EMPIRICAL FINDINGS

Irrigation accounts for the greatest investment in the agricultural and rural development sectors in developing countries [World Bank, 2003].Over the past few years; many research works have been carried out to comprehend the effect of irrigation on poverty reduction in developing countries. Although irrigation infrastructure is believed to be the main catalyst to boosting overall growth in the agricultural sector, the plausibility to which this is true has not been extensively rectified [Tong et al, 2011].

The existing literature in relation to the impact of irrigation on poverty is mixed. Some studies indicate the impact of irrigation on agricultural productivity and rural livelihood is not significant. But others have confirmed a strong link between irrigation and poverty reduction in developing countries.

For example Pender et al. [2002] indicated that in Tigray irrigation has less impact in agricultural yields than expected. Another study by Lire et al. [2005] has indicated that small scale irrigation technology introduced in Tigray was associated with significant health side effects. A similar study [Hagos et al, 2006] in Northern Ethiopian on the impact of water harvesting on household welfare indicated that households with ponds and wells were not significantly better off compared to households without, even though they were comparable in essential household characteristics. This study has also found no significant difference in fertilizer use between households owning a well and those who do not have access to a well.

Another study by Hanjra et al. [2009] in SNNPR found that although irrigation contributes to poverty reduction, smallholders remain poor due to small land holdings, large family size, high dependence on agriculture, illiteracy, low education, poor health, poor access to infrastructure and markets, and low use of modern inputs such as fertilizer.

There are also similar studies from other countries which established a weak or negative impact of irrigation on agricultural productivity. For example, Rosegrant and Everson [1992] found a negative relationship between irrigation investment and productivity in India.

Similarly, Fan et al. [2000] has made a comparative analysis of the impact of public expenditure in irrigation, research and development and rural infrastructure where investment in irrigation was found to have the least impact on both production and poverty. Moreover, Jin et al. [2002] were not able to establish any correlation between irrigation and total factor productivity growth of any major grain crop in China.

On the other hand, many studies have indicated irrigation is positively correlated with household income and expenditure and negatively correlated with poverty. These studies have confirmed that the probability of households with access to irrigation water being poor was significantly less than those with no access to irrigation water.

Some of the studies undertaken in Ethiopia in relation to the role of small scale irrigation in poverty reduction are summarized below. Another study by Gebregziabher et al, [2009] in Tigray indicated that farming income was more important to irrigating households than to non-irrigating households, while off-farm income was negatively related with access to irrigation. They also found that irrigating households' average income was above the regional average, while non-irrigating households' average income was 50 % less than the average income of irrigating households.

Similarly, Haile [2008] studied the impact of irrigation development on poverty reduction and he concluded that households' access to deep well or shallow well irrigation has a significant impact on poverty reduction through increasing household incomes and consumption and overall family employment. The study also showed access to deep well or shallow well irrigation has a significant effect in increasing the welfare of beneficiary households. However, the study has indicated that irrigation through pond water had not significant effect in increasing the welfare of beneficiary households.

A recent study by Haji and Aman [2013] revealed that access to small-scale irrigation scheme have significantly reduced the incidence, the depth and the severity of households' poverty in Gorogutu District of Eastern Hararghe. Their empirical model revealed that access to irrigation scheme has significantly influenced households' consumption expenditure level. They indicated that the per capita consumption expenditure of irrigation users is 25% more than non-users of irrigation. In general their study concluded access to small-scale irrigation scheme improved the livelihood of households in the study district.

Similarly, literature from other parts of the world show mixed results. In India, for example, Bhattari et al. [2002] discovered that access to irrigation infrastructure along with the availability and access to new technologies, high yielding varieties and fertilizers were the principal factors for the success of the green revolution in the country. They noted that better access to irrigation has facilitated better cropping practices and contributed to modernization of the agricultural sector. Huang et al [2005], a study from China which showed that irrigation increased income and reduced poverty and inequality in the country.

Bhandari and Pandey [2006] using farm level data from Nepal also indicated that irrigation has generated a significant positive effect in increasing rice yields and overall farmers' incomes. On an average, the yield of shallow tube well irrigation owners was increased by 86% when compared to that of rainfed farmers. Oni and Malik [2011] indicated that poverty incidence, depth and severity were found to be higher among non-irrigation household than among irrigation households in Limpopo Province of South Africa.

CHAPTER-3
IRRIGATION DEVELOPMENT AND POLICY ENVIRONMENT

3.1 THE WATER RESOURCES MANAGEMENT POLICY

The overall goal of 1999 Ethiopian Water Resource Management Policy is: *"to enhance and promote all national efforts towards the efficient, equitable and optimum utilization of the available Water Resources of Ethiopia for significant socioeconomic development on sustainable basis"* [MoWR, 1999].

The objectives of the water resources management policy include: development of the water resources of the country for economic and social benefits of the people on an equitable and sustainable basis; allocation and apportionment of water based on comprehensive and integrated plans and optimum allocation principles that incorporate efficiency of use, equity of access, and sustainability of the resource; managing and combating drought through, *inter alia*, efficient allocation, redistribution, transfer, storage and efficient use of water resources; combating and regulating floods through sustainable mitigation, prevention, rehabilitation and other practical measures; conserving, protecting and enhancing water resources and the overall aquatic environment on a sustainable basis.

The need for participation of different stakeholders is emphasized by the policy. Accordingly, when projects are designed, there should be a room for the identification and recognition of all relevant stakeholders to consult with each other and discuss issues regarding water systems. The government is also supposed to pay attention for a legal basis to ensure an active and meaningful participation of all stakeholders [MoWR, 1999].

3.2 THE WATER SECTOR STRATEGY

To put the Water Resource Management Policy into action, the Ethiopian Water Sector Strategy was developed in 2001 by the Ministry of Water Resources. The main guiding principle of the strategy is that water resource development will be rural-centered, decentralized managed and developed from a participatory approach [MoWR, 2001].

More specifically, the Ethiopian Water Sector Strategy sets the road map as how to make meaningful contributions towards: improving the living standard and general socio-economic well being of the Ethiopian people; realizing food self-sufficiency and food security in the country; extending water supply and sanitation coverage to large segments of the society, thus achieving improved environmental health conditions; generating additional hydro-power; enhancing the contribution of water resources in attaining national development priorities; and promoting the principles of integrated water resources management. Hence, the strategy will be able to make significant contributions towards assuring broader national objectives of poverty alleviation and sustainable human resources development.

3.3 THE NATIONAL IRRIGATION POLICY

The National Irrigation Policy aims to develop new and to enhance existing small, medium, and large scale irrigated agricultural schemes that are economically viable, socially equitable, technically efficient and environmentally sound.

The overall objective of irrigation policy is to develop the huge irrigated agriculture potential for the production of food crops and raw materials needed for agro industries on efficient and sustainable basis and without degrading the fertility of the production fields and water resources base.

The main objectives of the irrigation policy part of the Ethiopian Water Resource Management Policy [MoWR, 1999] are: development and enhancement of small scale irrigated agriculture and grazing lands for food self-sufficiency at the household and national levels; promotion of irrigation study, planning and implementation on economically viable, socially equitable, technically efficient, environmentally sound basis as well as development of sustainable, productive and affordable irrigation farms; promotion of water use efficiency, control of wastage, protection of irrigation structures and appropriate drainage systems; and ensuring that small-, medium- and large-scale irrigation potential projects are studied and designed to a stage ready for immediate implementation by private and/or the government at any time.

3.4 THE IRRIGATION DEVELOPMENT STRATEGY

The irrigation development strategy is one of the sub-sectors dealt in the water sector strategy. The principal objective of the irrigation development strategy is to exploit the agricultural production potential of the country to achieve food self sufficiency at the national level, including export earnings, and to satisfy the raw material demand of local industries, but without degrading the fertility and productivity of country's land and water resources base.

3.5 THE GROWTH AND TRANSFORMATION PLAN

Currently, the government of Ethiopia is trying to improve the existing water supply and irrigation situation by promoting water centered development; an approach where water resource development is being integrated with economic development and land-use planning [GW-MATE, 2011]. Accordingly, bolder goals have been set for the agriculture-based industrialization of the country. These goals are part of the Growth and Transformation Programme [GTP], a five-year development plan for broad-based accelerated and sustained economic growth [MoFED, 2010].

The plan pointed out that the protection and development of natural resources, improving the use of water resources, and expansion of the irrigation sector as the main driving forces to achieve accelerated and sustainable agricultural growth. Therefore during the next five years, developing underground and surface water, improving water use, and expanding irrigation interventions will be among the priority areas of the plan. Moreover, soil and water conservation, protection and utilization of forest resources will be implemented through community participation [MoFED 2010].

With regard to the targets of the irrigation sector, the development of medium and large scale irrigation systems [from 2.6% in 2009/10 to 15.6% in 2014/15] is planned. The target for small scale irrigation is to develop 1850 million hectares irrigated land by 2014/15 using small scale systems [the baseline is 853 million hectares in 2009/10] [MoFED, 2010].

3.6 SMALL SCALE IRRIGATION CATEGORIES AND FEATURES

Irrigation schemes differ considerably in size and structure. In the Ethiopian context, irrigation schemes are categorized in to three classes. They are small, medium and large-scale irrigation schemes. Small-scale irrigation [SSI] schemes are those which have less than 200 hectares of area. Medium- scale [MSI] schemes cover an area of 200-3000 hectares while large-scale irrigation [LSI] schemes cover an area greater than 3000 hectares [MoWR, 2001]. SSI schemes are the responsibility of the MoARD and regions, while MSI and LSI are the responsibility of the MoWR [Awulachew, 2010].

Small scale irrigation projects can be classified as traditional and/ or improved schemes. Traditional irrigation schemes are usually initiated, implemented and managed by the community, while modern schemes of various categories are usually initiated and assisted by the government, NGOs and other donors [MoA-NRMD, 2011]. Some features of the different categories of SSI are described as follows.

3.6.1 TRADITIONAL SCHEMES

Traditional schemes of small-scale irrigation are reconstructed after every flood season and they are managed by beneficiary farmers through their own water users' associations. The farm size of such irrigated plots is usually in the range of 0.25 ha - 0.5 ha per household [MoA-NRMD, 2011]. The traditional water users' associations in the form of water committees are well organized and successfully operated by farmers who know each other and are devoted to cooperate closely to achieve common goals.

A typical association comprises up to 200 users who share a common main canal or its branches may be grouped into several teams of 20 to 30 farmers each [Ibid]. These water associations handle construction, water allocation, and operation and maintenance functions of irrigation systems.

3.6.2 MODERN DIVERSION SCHEMES

Modern diversion schemes are usually built on permanent rivers and/ or springs with sufficient base flow. Due to the fact that these structures do not have storage on the stream, they are not capable of regulating the flow [MoA-NRMD, 2011]. These diversion structures help in efficient and sustainable diversion of the flow and stabilizing banks. Usually, rivers with large width and deep alluvial material are costly to be handled by SSI. Consequently, intakes on the banks are used instead of complete barrier across the river [Ibid].

3.6.3 MICRO/MEDIUM DAMS

In response to erratic nature of the rainfall, flow regulation is very important for complementary irrigation and increased intensity of irrigation. The construction of small- to medium-scale dams is undertaken in the mid- and highlands of the country where there is high population pressure and sever food security problems [MoA-NRMD, 2011]. The construction of such dams and irrigation infrastructures is undertaken in response to controlling seasonal flows and storing more water in areas with insufficient base flows [Ibid].

3.6.4 PUMPED SCHEMES

These are schemes with pumping plants implemented when water must be lifted from the water source and / or when sufficient head or pressure is not available to operate the farm irrigation system. The adoption, operation and maintenance of such plants is relatively costly and sometimes credit arrangements deem essential to finance such schemes [MoA-NRMD, 2011]. Due to the high financial requirements, pumped systems are successful in areas with good market access, better service delivery and more demand for high value crops. Depending on the size of the pump, such schemes can be privately owned or communal [Ibid].

3.6.5 MICRO-IRRIGATION

Relatively speaking, micro irrigations are recent developments in the area of SSI. Micro-irrigation refers to individual small-scale irrigation technologies for lifting, conveying and applying irrigation water on farms. These micro irrigations use treadle and small- power pumps to lift water and irrigation application systems such as smallholder drip irrigation, micro-sprinklers and trickle systems [MoA-NRMD, 2011]. In terms of financial requirements, micro irrigation technologies are more reasonably priced to be used by smallholder farmers.

Nowadays, low-pressure drip irrigation systems such as bucket, family drip and family nutrition kits are being used in areas where there is acute water shortage. The development of low-head emitters and simple filtration system has reduced a large amount of the initial capital investment which makes low-pressure drip systems less expensive for the smallholder farmers [Ibid].

3.6.6 SHALLOW GROUND WATER HARVESTING

Shallow ground water is usually used for household water supply. Nevertheless, in areas where large volume of shallow ground water is accessible, it is promising to use suitable water lifting technologies to broaden its use for irrigation. These are appropriate for individual holding due to access to low-cost drip irrigation technologies [MoA-NRMD, 2011].

CHAPTER-4
RESEARCH METHODOLOGY

4.1 DESCRIPTION OF THE STUDY AREA

Laelay Dayu irrigation scheme is one of the small-scale irrigation projects implemented in Tigray region by REST with the support of Oxfam America. The project is found in Alamata district in the southern zone of Tigray region. The sub district of Laelay Dayu is about 170 km far from Mekelle, the capital of Tigray region. According to ADOARD [2012], there are 2035 households in the village. The major soil type of the area is eutric vertisols. Average annual rainfall ranges between 600 and700 millimeters and its mean temperature is 20-21^0 Celsius [IPMS ATLAS, 2008]. The total area of Laelay Dayu sub district is 4582 ha [ADOARD, 2012].

The Laelay Dayu irrigation scheme is situated across Dayu River that originates from highlands of Korem and marches in the defiles of Girat Kahsu Mountain until it reaches the lowland plain area. The off-taking canal bifurcates into two main canals feeding the command areas of Gerjelle 35 hectares and Dayu 89 hectares [Negash et al., 2013]. Uncontrolled flooding and furrow irrigation methods are used to apply irrigation water at field level. Initially the project was implemented to serve 70 ha of land and benefit 433 households. However, both the area served by the scheme and number of beneficiaries have increased in the course of the years [Ibid].

4.2 SAMPLE AND SAMPLING DESIGN

The study adopted a multi stage sampling technique of purposively selecting the Laelay Dayu sub district due its implementation of small-scale irrigation scheme, followed by a two-stage random sampling.

In the first stage, the sampling frame was identified and then it was stratified into two strata. The first stratum consist households that participate in irrigation farming hereafter referred as the treatment group and the second stratum consists households that do not participate in irrigation farming hereafter referred as the control group.

In the second stage, a total sample of 180 households has been selected applying the random sampling technique in each stratum. A total of 80 households from the treatment group and 100 households from the control group were surveyed in the study.

4.3 DATA TYPE AND SOURCE

The research was undertaken using both primary and secondary data. Due to the nature of household studies, the main data source used was primary data. Accordingly, a well designed questionnaire was deployed to collect relevant information from sample respondents. Besides, data on the socio economic aspects of the sub district was collected from secondary sources.

With regard to the nature of data collected, both quantitative and qualitative questions were considered. Doing so provides richer pool of data and greater analytical power than would have been available with either of these methods. The target sources of data for the research were sample households, agricultural development agents and relevant local administrative offices. Furthermore, a transect walk visit to the irrigated command area was undertaken.

4.4 DATA ANALYSIS

To achieve its objective, the study used descriptive statistics, econometric modeling and poverty analysis. The descriptive analysis was performed using averages and mean difference tests to compare socio economic characteristics of treated and control households. To estimate the impact of the small-scale irrigation scheme on household welfare, the propensity score matching [PSM] econometric model was applied. In addition, a poverty line for the sample households was calculated and the two groups were compared in relation to the incidence, depth and severity of poverty.

4.5 ECONOMETRIC FRAMEWORK

4.5.1 ESTIMATING PARTICIPATION DECISION

The first step in evaluating the impact of a program through matching approach calls for identifying factors that make a beneficiary participate in the treatment. Therefore, the probability of a household to participant in irrigation was estimated to generate propensity scores for the matching algorithm.

4.5.1.1 MODEL SPECIFICATION

To estimate the household's probability of participation in the irrigation scheme [Y=1decision to participate, Y=0 otherwise], the logit model was deployed. In the binary logit model the predictor variables X_1, X_2....X_3 are related to the dependent variable Y by the following equation:

$$\text{Logit } [P] = \ln\left[\frac{p}{1-p}\right] = B_0 + B_1X_1 + B_2X_2 + ... + B_8X_8$$

Where B_i = regression coefficient

P =probability[Y=1]

The value of P can be calculated by taking the inverse of the logit [P] as shown in the following equation:

$$P = \frac{e^{B_0+B_1X_1+B_2X_2+B_3X_3+B_4X_4+B_5X_5+B_6X_6+B_7X_7+B_8X_8}}{1+e^{B_0+B_1X_1+B_2X_2+B_3X_3+B_4X_4+B_5X_5+B_6X_6+B_7X_7+B_8X_8}}$$

4.5.1.2 DESCRIPTION OF VARIABLES

In estimating propensity score, only variables that influence the participation decision and the outcome variable simultaneously and are unaffected by participation [or the anticipation of it] should be included in the model [Caliendo & Kopeinig, 2005]. In the subsequent sections, the variables selected in the logit model are discussed in detail.

Sex of the household head [hhsex**]:** This is a dummy variable and its value is 1 if the household head is male and 0 otherwise. In rural economies like Ethiopia, men often have better control to household resources and decisions regarding adoption of agricultural technologies and inputs. Due to this uneven access to resources and decision making powers, male headed households are more likely to participate in the irrigation scheme.

Age of the household head [hhage]**:** This is a continuous variable measured in years. The relationship between age and adoption of agricultural technologies is of mixed nature. On the one hand, it is assumed that younger farmers are more innovative and hence more willing to adopt agricultural technologies than old farmers. On the other hand, it is argued that older farmers have more agricultural experience and more tendencies to apply for agricultural technologies. Therefore, this study did not hypothesize explicit relationship between age of the household head and participation in irrigation scheme.

Education level of the household head [hhedu]**:** This is a continuous variable measuring the formal school years completed by the household head. In many adoption studies [Ramji et al., 2002; Tassew, 2004], it was indicated that more educated farmers show higher tendencies to adopt new agricultural technologies than less educated farmers. Accordingly, this variable is expected to positively influence participation in the irrigation scheme.

Household size [hhsiz]**:** This is a continuous variable measuring the total number of the household members. The study argues the impact of household size on irrigation adoption to be mixed and hence no prior sign is assigned to the variable under consideration.

The logic is that the effect of household size on participation decision depends on the demographic composition of the given household. If the household is composed from working labor force, the effect will be positive and if the household is composed from dependants, the effect will be negative.

Land size [landsiz]**:** This is a continuous variable measured in tsimdi [1 tsimdi is equivalent to 0.25 hectare] and it refers to the total cultivated land of the household. As most of the households in the study area are smallholders, one of the possible ways to increase their output is by intensive farming. Hence, this variable is hypothesized to have a positive effect on participation in the irrigation scheme.

Adult labour [adultlab]**:** This is a continuous variable and it refers to the number of adult labour of the household. Due to the intensive labour requirements of irrigation farming, this variable is expected to positively affect the participation decision.

Access to extension services [ext]: This is a dummy variable and its value is 1 if the household has access to extension services and 0 otherwise. Due to the role of extension services in increasing productivity and efficiency, the study expected a positive coefficient for this variable.

Table 4.1 Description of Variables Used in the Logit Model

Variable	Type	Description	Expected Sign
hhsex	Dummy [male=1]	Sex of the household head	+
hhage	Continuous	Age of the household head	?
hhage_2	Continuous	Age of the household head squared	?
hhedu	Continuous	Formal schooling of the household head	+
hhsiz	Continuous	Household size	?
landsiz	Continuous	Size of cultivated land	+
adultlab	Continuous	Number of adult labour	+
ext	Dummy[yes=1]	Access to agricultural extension services	+

4.5.2 THE IMPACT EVALUATION PROBLEM

Propensity score matching estimators were developed by Rosenbaum and Rubin [1983]. The PSM technique has been applied in a very wide variety of fields in the program evaluation literature. For example, Heckman, Ichimura and Todd [1997], Dehejia and Wahba [2002], and Smith & Todd [2005] have used PSM techniques to estimate the impact of labor market and training programs on income.

In non-experimental studies, the most common approach evaluate a program effect is to calculate the average effect of the treatment on the treated [ATT]. The standard representation of the impact evaluation problem is discussed as follows:

Let Y_i^T = outcome variable for the *i*th household in the treatment group

Y_i^C = outcome variable for the *i*th household in the control group

$D \in \{0,1\}$ = treatment indicator [D = 0 for control group and D = 1 for treated group]

$Y = \begin{cases} Y_i^C if D = 0 \\ Y_i^T if D = 1 \end{cases}$ = observed outcomes

X = set of observed household characteristics

Hence, $\Delta_i = Y_i^T - Y_i^C$ = treatment effect……………………………………………………...[1]

Following Ravallion [2005], the average treatment effect [ATE] of the *i*th household can be written as:

$ATE = E(Y_i^T \mid D = 1) - E(Y_i^C \mid D = 0)$ ……………………………………………………….......[2]

If participation in irrigation scheme were allocated randomly to households then the average difference in outcome between households with and those without would be an unbiased estimate of the ATE.

In the absence of random treatment allocation, this naïve estimator will yield biased results if treatment and control populations have systematic differences, as we would expect them to have in this case, especially since self-selection plays a large role to participate in the irrigation scheme [Mitra, 2012]. This requires us to adjust the sample of households with and without access to irrigation suitably so as to make them comparable.

The greatest challenge in evaluating any intervention or program is obtaining a credible estimate of the counterfactual $E(Y_i^C \mid D=1)$: what would have happened to participating units if they had not participated? Without a credible answer to this question, it is not possible to determine whether the intervention actually influenced participant outcomes or is merely associated with successes [or failures] that would have occurred anyway. This problem is often referred to as the "*fundamental problem of causal inference*''.

Thus, simple mean comparison between the treated and non treated can be misleading, yet taking the mean outcome of non participants as an approximation is not advisable, since participants and non participants usually differ even in the absence of treatment [See Holland,1986; Macro and Sabine 2008].

With matching methods, one can develop a counterfactual or control group that is similar to the treatment group in terms of observed characteristics. The idea is to find, from a large group of nonparticipants, individuals who are observationally similar to participants in terms of characteristics not affected by the program [Khandker et al., 2010]. Hence, each participant is matched with an observationally similar nonparticipant and then the mean difference in outcomes is compared to get the program treatment effect. If one assumes that differences in participation are based solely on differences in observed characteristics, and if enough nonparticipants are available to match with participants, the corresponding treatment effect can be measured even if treatment is not random [Ibid].

The problem is to credibly identify groups that look alike. Identification is a problem because even if households are matched along a vector, X, one would rarely find two households that are exactly similar to each other in terms of many characteristics [Khandker et al., 2010].

Rosenbaum and Rubin [1983] showed that under certain assumptions, matching on *X* was equivalent to matching on the propensity score $P(X_i) = \Pr(D_i = 1 | X_i)$, the probability of a household receiving the treatment given its vector of covariates X, thus reducing a multidimensional matching problem to a single dimension, the propensity score. Since the true propensity score is not known, this is usually estimated by a logit or probit model, leading thus to a semi parametric matching process [Mitra, 2012]. According to Rosenbaum and Rubin [1983] the necessary assumptions for identification of the program effect are [a] conditional independence and [b] presence of a common support.

The first assumption is the *conditional independence assumption* [CIA]: it states that given a set of observable covariates *X* that are not affected by treatment; potential outcomes *Y* are independent of treatment assignment *D*. This is the key assumption on which all impact evaluation rests.

$$\left(Y_i^T, Y_i^C\right) \perp D_i \mid X_i$$

In other words, we need to assume that the treatments are not assigned in a way that is systematically related to the outcome variable, once we have controlled for the effects of the *X* covariates. The conditional independence is a strong assumption and is not a directly testable criterion; it depends on specific features of the program itself. If unobserved characteristics determine program participation, conditional independence will be violated, and PSM is not an appropriate method.

Now, the interest is in the average treatment effect for those households which had access to irrigation, i.e. the average treatment effect for the treated. The ATT can be driven from the ATE as follows:

$$ATE = E(Y_i^T | D = 1) - E(Y_i^C | D = 0) \text{ ....} [2]$$

$$E\left(Y_i^T \mid D = 1, X\right) - E\left(Y_i^C \mid D = 0, X\right) \text{ ....} [3]$$

Now adding and subtracting $E(Y_i^C | D=1)$ from [3] we have,

$$\{E(Y_i^T \mid D=1, X) - E(Y_i^C \mid D=1, X)\} + \{E(Y_i^C \mid D=1, X) - E(Y_i^C \mid D=0, X)\} \ldots\ldots[4]$$

But, by the assumption of independence, $E(Y_i^C \mid D=1, X) = E(Y_i^C \mid D=0, X)$.

Therefore, $E(Y_i^C \mid D=1, X)$ can be taken as a counterfactual to the treatment.

Hence, the average treatment effect on the treated can be written as:

$$ATT = E(Y_i^T - Y_i^C | D=1) = E(Y_i^T | D=1) - E(Y_i^C | D=1) \ldots\ldots\ldots\ldots\ldots\ldots[5]$$

This expression highlights the counter-factual nature of a causal effect. The first term is the average value of the outcome variable for the treatment group, a potentially observable quantity. The second term is the average value of the outcome variable for the treatment group had they not been participated in irrigation. This cannot be observed, though we may have a control group or econometric modeling strategy that provides a consistent estimate.

The second assumption is the *common support or overlap condition*: $0 < P(D_i = 1 \mid X_i) < 1$. This condition ensures that treatment observations have comparison observations “nearby” in the propensity score distribution [Heckman, LaLonde, and Smith 1999]. Specifically, the effectiveness of PSM also depends on having a large and roughly equal number of participant and nonparticipant observations so that a substantial region of common support can be found [Khandker et al, 2010].

Treatment units will therefore have to be similar to non treatment units in terms of observed characteristics unaffected by participation; thus, some non treatment units may have to be dropped to ensure comparability. However, sometimes a nonrandom subset of the treatment sample may have to be dropped if similar comparison units do not exist [Ravallion 2008].

4.5.3 SENSITIVITY ANALYSES FOR SELECTION ON UNOBSERVABLES

The CIA is a basic assumption to identify the true treatment effect in the ATT estimation strategy. While the validity of the CIA cannot be tested using non-experimental data, there are some methods that help to assess the sensitivity of the baseline estimates to violations of the CIA [Crinò, 2011]. In this paper, the approach designed by Ichino et al. [2008] is adopted to assess violations of the CIA. The approach relies on the hypothesis that assignment to treatment may be confounded given the set of observable variables but it is unconfounded given observed and an unobservable variable, U.

$$\Pr[D=1 \mid Y_i^T, Y_i^C, X, U] = \Pr[D=1 \mid X, U] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [1]$$

This approach assumes the CIA to be violated by the incidence of an unobserved binary variable U ϵ {0, 1}. The approach tries to assess the sensitivity of the point estimate of the ATT to changes in a small set of parameters that characterize the relationship of U with treatment and outcome.

More formally, the distribution of the unobserved binary confounding variable U can be derived by specifying the parameters

$$\Pr[U=1 \mid D=i, Y=j, X] = \Pr[U=1 \mid D=i, Y=j] \equiv pij \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [2]$$

with i, j ϵ {0, 1}, which correspond to the probability that U=1 in each of the four[1] groups defined by treatment status D_i and outcome Y_j [Millamaci & Sciulli, 2011]. In order to simulate a "dangerous" confounder [i.e., a confounder that represent a real threat for the baseline estimate], Ichino, Mealli and Nannicini [2007] argue the following implications should hold:

$$p_{01} > p_{00} \Rightarrow \Pr[Y_i^C = 1 | D=0, U=1, X] > \Pr[Y_i^C = 1 | D=0, U=0, X] \ldots\ldots\ldots\ldots\ldots\ldots [3]$$

$$p_{1}. > p_{0}. \Rightarrow \Pr[D=1 | U=1, X] > \Pr[D=1 | U=0, X] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [4]$$

[1]For a detail discussion, see Ichino et al. [2008].

As a result, assuming $p_{01} > p_{00}$ a confounding factor that has a positive effect on the untreated outcome Y_i^C (conditioning on X) can be simulated. Likewise, by assuming $p_{1\cdot} > p_{0\cdot}$ a confounding factor that has a positive effect on treatment assignment D (conditioning on X) can also be simulated.

Finally easily interpretable measures of association [outcome effect and selection effect] are given by the average odds ratios as follows:

$$\Gamma \equiv \sum_{r=1}^{R} \frac{1}{R} \left[\frac{\Pr(Y=1|D=0,U=1,X)/\Pr(Y=0|D=0,U=1,X)}{\Pr(Y=1|D=0,U=0,X)/\Pr(Y=0|D=0,U=0,X)} \right] \ldots\ldots\ldots\ldots [5]$$

$$\Lambda \equiv \sum_{r=1}^{R} \frac{1}{R} \left[\frac{\Pr(D=1|U=1,X)/\Pr(D=0|U=1,X)}{\Pr(D=1|U=0,X)/\Pr(D=0|U=0,X)} \right] \ldots\ldots\ldots\ldots [6]$$

where R indicates the number of replications, Γ represents the outcome effect and Λ stands for the selection effect.

Ichino et al [2008] argued that if U is simulated by setting $p_{01} > p_{00}$ and $p_{1\cdot} > p_{0\cdot}$, both the outcome and selection effects must be greater than unity [i.e., Γ > 1 and Λ> 1).Therefore, they concluded if only “implausible” confounders either drove the ATT to zero or far away from the baseline estimate that the sensitivity analysis would support the robustness of estimated results.

4.6 POVERTY ANALYSIS

Three ingredients are required in computing a poverty measure [Ravallion, 1998]. First, one has to choose the relevant dimension and indicator of well-being. Second, one has to select a poverty line, that is, a threshold below which a given household or individual will be classified as poor. Finally, one has to select a poverty measure to be used for the population as a whole or for a population subgroup only.

4.6.1 CHOOSING INDICATOR OF WELFARE

Most less-developed countries [LDCs] use consumption to reflect well-being, while prosperous countries typically use income [Haughton and Haughton, 2011]. A possible explanation is that income is relatively simple to measure in a rich society where most people earn wages and salaries, but is difficult to measure in poorer countries where income is largely derived from agriculture or from self-employment. On the contrary, consumption may be relatively easier to measure when people are poor, and spend on a narrow range of goods and services, but increasingly complicated to measure as people become more prosperous. Another reasonable justification is that for most households in LDCs, income may vary considerably more than consumption, making the latter a better guide to lifetime well-being [Haughton and Haughton, 2011].

Following Haji and Aman [2013] and MOFED [2013], this study used consumption expenditure as the metric to measure poverty. Consumption is a better measure of longer-term household welfare because it is subject to less temporal variation than income. Also, in Ethiopia as elsewhere in LDCs, consumption is likely to be measured more accurately than income. While consumption per capita is the most commonly used measure of welfare, some analysts use consumption per adult equivalent, in order to capture differences in need by age, and economies of scale in consumption. This study adopted both per capita and adult equivalent scales to compare consumption expenditures between irrigating and non irrigating households in the study area.

4.6.2 POVERTY LINE SETTING

The poverty line may be defined as the minimum expenditure required by an individual to fulfill his or her basic food and nonfood needs. Once we have computed a household’s consumption, we need to determine whether that amount places the household in poverty, or defines the household as poor. The threshold used for this is the poverty line.

The construction of a poverty line is the most difficult step in the practical measurement of poverty. There are three methods of setting poverty lines that use caloric requirement: direct caloric intake, food energy intake, and cost of basic need methods.

These days, the cost of basic needs approach has become the most commonly used method of setting poverty lines. In determining the cost of basic needs, the commonest approach is first to stipulate a consumption bundle, including both food and nonfood, and then to estimate the cost required to acquire this bundle [Haughton and Haughton, 2011].

Following [MoFED, 2013], the cost of basic needs approach developed by [Ravallion and Bidani, 1994] is adopted to construct the poverty line. This approach is currently widely used for poverty assessment in Ethiopia [Hagos and Holden, 2003; and Haji and Aman 2013].This approach of poverty line determination was used due to its ability to accommodate estimate of cost of food and other basic non-food requirements. Accordingly, a food poverty line was constructed by valuing a basket of food items that meet the minimum energy requirement 2200 Kcal per day per adult equivalent. This is the minimum per day energy requirement for a person to keep up its normal activities [WHO, 1985]. Then, the share of non-food items was added to determine the consumption based total poverty line.

4.6.3 SELECTING MEASURE OF POVERTY

Even though there are different indices of measuring poverty such as the watts index, the Sen index and others, the FGT index has become the most widely used class of poverty measurement in empirical work. The attractiveness of the FGT measures stems largely from their simple structure, their ease of interpretation, and their sound axiomatic properties. Therefore, in this study the additively decomposable poverty index, developed by [Foster et al., 1984] is used to measure the number of households below and above the poverty line.

The FGT poverty index is based on the following equation:

$$P_{\alpha} = \frac{1}{N}\sum_{i=1}^{M}\left[\frac{(Z - Y_i)}{Z}\right]^{\alpha}$$

Where: Z is the poverty line

$Y\ i$ is the per capita consumption expenditure of the *ith* household,

N is the number of households in the sample/ sub sample,

M is the number of poor households in the sample/ sub sample, and

α[1] is a parameter reflecting the weight placed on the very poorest individuals.

The headcount index [P0] measures the proportion of the population that is poor. It is popular because it is easy to understand and measure. But it does not indicate how poor the poor are. The poverty gap index [P1] measures the extent to which individuals fall below the poverty line as a proportion of the poverty line. The sum of these poverty gaps gives the minimum cost of eliminating poverty, if transfers were perfectly targeted. It can be thought of as the amount of income that an average person in the economy would have to contribute for poverty to be eliminated. This measure does not reflect changes in inequality among the poor.

The squared poverty gap index [P2] averages the squares of the poverty gaps relative to the poverty line. This measure applies an increasing weight to distances below the poverty line, which makes it particularly sensitive to the severity of poverty. Although difficult to interpret, it is useful in poverty comparisons.

There are two ways of comparing poverty indices across groups. The first way to compare poverty indices between the treatment and control groups is to conduct a statistical test or means separation test. If the poverty measures are estimated from unit record data [i.e., on the basis of sample observations], it is possible to test whether the observed differences in their values are statistically significant [MoFED, 2013].

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[1] α =0, incidence of poverty]; α =1, depth of poverty and α =2, severity of poverty.

The hypothesis test developed by Kakwani [1993][1] can be used to test whether poverty indices [Pα] differ significantly between the two groups. The second way to compare poverty indices is to use the stochastic dominance test and checking the robustness of poverty comparisons between groups. In this study the mean separation test was adopted.

[1]For a detail discussion see Kawkani [1993] and MoFED [2013].

CHAPTER-5
RESULTS AND DISCUSSION

5.1 DESCRIPTIVE ANALYSIS

To estimate the impact of small-scale irrigation on the outcome variables of interest, descriptive analysis of selected demographic and socioeconomic characteristics of sample household is vital as it would help to frame the econometric analysis.

5.1.1 DEMOGRAPHIC CHARACTERISTICS

In this section, demographic characteristics of sample households such as age, sex, marital status level of education of household heads as well as number of adult labor and dependency ratio will are analyzed.

Table 5.1 Gender Composition of Household Heads

Treatment Status	Gender of Household Head		Total
	Male	Female	
Yes	61	19	80
No	77	23	100
Total	138	42	180

Source: Own Survey, 2014.

The sample under consideration is composed of 80 treated households [45%] and 100 control households [55%]. With regard to gender of household heads, female headed households accounted for approximately 25% in both treatment and control groups. Therefore, about three-quarters of the treatment households were male-headed and hence there is a significant difference in the distribution of the gender of household heads between adopters and non-adopters.

Table 5.2 Demographic Characteristics of Sample Households

Variable	Control Group [N=100]		Treatment Group [N=80]		Difference	
	Mean	SE	Mean	SE	Mean	t-value
Age of Household Head	44.89	[1.18]	46.93	[1.44]	-2.04	-1.10
Household Size [Persons]	5.8	[0.22]	4.86	[0.20]	0.94	3.11***
Household Size [AE][1]	3.76	[0.13]	3.31	[0.12]	0.46	2.54**
Adult Labor	3.17	[0.17]	3.05	[0.16]	0.12	0.52
Education of Head	1.03	[0.21]	1.8	[0.36]	-0.77	-1.94*
Dependency Ratio	1.06	[0.08]	0.75	[0.07]	0.31	2.79***

*** Significant at 1%, **5% significant and *significant at 10%.

The age of the household head has an influence on household decision because of experience and risk taking differences between old and young farmers. The results [Table 5.2] show that the average age of household heads of the control group is nearly 45 years while that of the treatment group is approximately 47 years. The mean comparison test shows there is no significant difference in the distribution of household head age between control and treatment group household heads.

In the study area, the average household size of the control group was 5.8 and of the treatment group was found to be 4.8 [Table 5.2]. The t-test shows that there is significant difference in household size between the control and treatment groups at 1% level of significance. But, there is no significant difference observed in the number of adult labors between the two groups.

It is widely believed that education level of household heads is a decisive factor in affecting the adoption of irrigation technologies and improving agricultural productivity. The education level of household heads was found to be higher for irrigating the treated households and the mean difference in education level is significant at 10% significance level. This indicates the more farmers are educated the more easily they adopt and utilize agricultural technologies.

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[1]The OECD adult equivalent scale was used, AE= [1+0.7 (Nadults-1) +0.5 Nchildren].

The dependency ratio adopted in this paper refers to the proportion of a population which is composed of dependants, people who are too young or too old to work. Hence, by the dependency ratio it is meant the number of individuals in the household aged below 15 or above 65 divided by the number of individuals aged 15 to 65, expressed as a percentage.

Accordingly, the mean dependency ratio for the control group is 1.06 and the corresponding figure for the treatment group is 0.75 [Table 5.2]. This means that the number of dependants and economically active household members of the control group is roughly equal while for the treatment group it means every 100 economically active household members had 75 dependants to feed, cloth, educate and medicate. The mean difference is significant at 1% level.

5.1.2 ECONOMIC CHARACTERISTICS

In this section, socio-economic characteristics of sample households such as oxen holding, live stock holding [excluding oxen], cultivated land size in per capita and in per adult equivalent scales are discussed with particular difference to the mean difference between the control and treated groups. This helps to set the ground for the econometric analysis.

Table 5.3 Asset Holding: Mean Comparison Results

Variable	Control Group [N=100]		Treatment Group [N=80]		Difference	
	Mean	SE	Mean	SE	Mean	t-value
Oxen in TLU	1.32	0.12	1.5	0.13	-0.18	1.03
Livestock in TLU	5.07	0.56	5.81	0.61	-0.74	-0.89
Land Size Per Adult	1.13	0.07	1.15	0.09	-0.02	-0.15
Land Size Per Capita	0.76	0.05	0.79	0.06	-0.04	-0.56

Source: Own Survey, 2014.

In agrarian economies like Ethiopia, livestock holding is the most important form of productive assets for rural households. Specifically, oxen holding serve a dual purpose [source of income and draft power] in traditional farming which is a common place in the study area. As it is indicated in [Table 5.3], the mean oxen holding of the treated group is higher than the control group but the mean difference is not statistically different.

In a broader sense, livestock ownership is an important indicator of wealth and tendency of farmers to spend on utility generating goods and services. Furthermore, it consolidates social, religious and cultural links among the society and serves as source of prestige. However, the mean difference in livestock holding between the two groups was not statistically significant.

The other productive asset is cultivable land which is considered as the most important factor of production in rural settings. The average land holding size for the sampled households in per capita and per adult scales is 0.78 and 1.14 *tsimdis* respectively [See Appendix 8]. From the mean difference test, there is no significant difference between irrigating and non-irrigating households in average per capita and per adult land holding. Thus, treated and control households are similar in their land holding indicating the control group can serve as a good counterfactual for the matching analysis as land is the most important asset in determining welfare of rural households.

5.1.3 CONSUMPTION AND INCOME EVALUATION

In this section, an attempt is made to compare consumption and income of the unmatched sample. To this end, household data on total annual consumption expenditure and total annual income was collected. Finally, the per capita and per adult equivalent scale were used to make a reasonable analysis.

The results obtained from the survey [Table 5.4], indicated the mean annual food, non food and total expenditure differences in per capita and in per adult scales were found to be statistically significant at 1% level of significance.

Table 5.4 Household Expenditure: Mean Comparison Results

Variable	Control Group [N=100]		Treatment Group [N=80]		Difference	
	Mean	SE	Mean	SE	Mean	t-value
Food Expenditure [PC]	4997.13	192.80	6517.14	251.00	-1520.01	-4.8843***
Food Expenditure [AE]	7436.41	234.58	9349.43	327.94	-1913.02	-4.8626***
Non Food Expenditure[PC]	1673.67	70.99	2107.21	89.81	-433.55	-3.8395***
Non Food Expenditure [AE]	2498.58	98.05	3025.27	121.31	-526.68	-3.415***
Total Expenditure [PC]	6670.80	251.53	8631.46	310.11	-1960.67	-4.9642***
Total Expenditure [AE]	9934.99	311.88	12386.01	399.89	-2451.02	-4.9072***

*** Significant at 1%.

Specifically, the per capita food expenditure of the control group was found to be approximately 77% that of the treatment group and the corresponding figure in per adult scale was calculated to be nearly 80%. Given the results from the mean separation test, these results show that treated households have higher marginal propensities to consume than their counterparts. This shows treated households have better welfare status given the similar food items consumed by the sample households under consideration.

Likewise, the per capita non food expenditure of the treated group was 433.55 ETB higher than that of the control group and the non food expenditure in per adult equivalents gives similar result as the control group spends 526.68 ETB less as compared to the treated group. The differences are statistically significant. The overall findings from the consumption analysis suggest that the treated households enjoy a higher standard of living and better quality of life than the control households.

Table 5.5 Household Income: Mean Comparison Results

Variable	Control Group [N=100]		Treatment Group [N=80]		Difference	
	Mean	SE	Mean	SE	Mean	t-value
Farm Income [PC]	5400.88	353.29	8548.07	524.67	-3147.19	-5.13***
Farm Income [AE]	8147.90	541.99	12269.68	738.56	-4121.78	-4.60***
Off-farm Income [PC]	916.33	125.30	771.93	121.73	144.40	0.81
Off-farm Income [AE]	1398.48	190.53	1125.32	179.20	273.17	1.02
Total Income [PC]	6317.21	365.83	9320	536.45	-3002.79	-4.76***
Total Income [AE]	9546.38	564.11	13394.99	760.68	-3848.62	-4.15***

*** Significant at 1%.

With regard to income evaluation, income from cultivated plots and off-farm income were measured and analyzed to see whether there is significant difference in income between irrigating and non irrigating households. The details of the income evaluation are given in [Table 5.5] above.

Accordingly, the survey result indicated farm income for the treated group was higher than the farm income of the control and the difference was found to be statistically significant at 1% level of significance. On the other hand, the control group reported more off-farm income than the treated group. Although the off farm income gain is not statistically significant, the results show control households have to earn more off farm income than their counter parts in order to bridge the income gap with the treated group as the later earn more farm income due to year round intensive cultivation.

To sum up, the total income evaluation indicated the treated households earn more income than the treated group and the mean separation test confirmed the difference is statistically significant. Hence, the descriptive analysis suggests the treated households have more income on average and can enjoy a higher standard of living and better quality of life than the control households assuming other variables remaining constant.

5.2 ECONOMETRIC ANALYSIS

5.2.1 PROPENSITY SCORE ESTIMATION

As explained in the methodology section, the first step of the econometric approach is to estimate the propensity score, i.e. the probability to participate in irrigation conditional on observable variables. To generate the propensity scores for the matching process, the probability of a household to adopt irrigation was estimated using the logit model. The variables included in the model are gender of the household head, age of the household head, size of the household, cultivated land size, size of adult labor, education level of the household head, and access to agricultural extension services. The estimation results are presented in [Table 5.6] below.

Table 5.6 Propensity Score Estimation Results

Variable	Coefficient	Standard Error	z	P>|z|
hhsex	.4900903	.4901677	1.00	0.317
hhage	.0898559	.1020118	0.88	0.378
hhage_2	-.0006921	.0009837	-0.70	0.482
hhsiz	-.4090389	.1500817	-2.73	0.006***
hheduc	.1422118	.071359	1.99	0.046**
landsiz	-.0551328	.0699314	-0.79	0.430
adultlab	.1865374	.1868073	1.00	0.318
ext	1.085526	.3910521	2.78	0.006***
_cons	-2.318141	2.372489	-0.98	0.329
Logistic Regression		Number of obs=		180
		LR chi2(8)=		31.02
		Prob > chi2=		0.0001
Log likelihood= -108.1415		Pseudo R2=		0.1254

Note: *** significant at P<0.01, ** significant at P<0.05.

The logit estimation provides information about some of the driving forces behind farmers' decisions to participate in irrigation farming. The pseudo R-squared is about 13%. This low pseudo R-squared suggests that the proposed specification of the propensity score is fairly successful in terms of balancing the distribution of covariates between the two groups. The likelihood ratio chi-square value at 8 degrees of freedom is significant at 1%. This confirms the overall fitness of the model.

The logit regression revealed that variables such us size of the household, education of the household head and access to extension services affect the probability of participation in irrigation farming significantly. Moreover, the signs of significant variables are in line with the prior expectations.

The number of years of formal schooling of the household head returned a positive and significant coefficient. This is consistent with prior expectation as more educated farmers have better knowledge on the importance of adopting new technologies. Also consistent with prior expectations, access to extension services returned an expected positive and significant coefficient, suggesting that farmers who have access to extension services get better consultancy and encouragement in adopting irrigation farming. The coefficient of household size is negative and significant at 1% suggesting that the probability of irrigation adoption diminishes with large household size. This negative effect can be interpreted in terms of the high dependency ratio [0.92] of sample households which reduces their willingness to adopt as irrigation farming is usually a labor intensive activity.

On the contrary, variables such us age of the household head, sex of the household head size of adult labour and cultivated land size did not provide strong evidence in relation to the probability of participation decision in the irrigation scheme. But their signs are similar to previous findings made on related studies [Haile 2008; Gebregziabher et al., 2009; and Haji & Aman, 2013].

5.2.2 ESTIMATION OF TREATMENT EFFECT: MATCHING ALGORITHMS

The second step of the econometric analysis is matching treated households with households from the control group on the basis of their propensity scores. To assess the causal effect of irrigation adoption on household welfare, four outcome variables were employed: annual total expenditure in adult equivalent, annual food expenditure in adult equivalent, annual per capita total income and annual per capita farm income. Accordingly, the ATT was estimated using nearest neighbor, radius, kernel and stratification matching algorithms. The subsequent sections present the impact of irrigation on outcome variables of interest.

5.2.2.1 IMPACT OF IRRIGATION ADOPTION ON EXPENDITURE

To estimate the impact of access to irrigation on consumption expenditure, the average treatment effect on the treated was determined using the four matching algorithms: nearest neighbor, radius, kernel and stratification. For this purpose, the program pscore.ado was employed to estimate the propensity scores and to test the balancing property. The empirical evidence of the impact of irrigation on consumption expenditure is presented in [Table 5.7]. The t- statistics are based on bootstrapped standard errors with 200 replications.

The results obtained indicate there is a positive and significant difference in the mean annual per adult expenditure of the treated and control groups in all matching algorithms. The mean per adult annual expenditure difference between the two groups ranges from 1800 to 2400 ETB depending on the matching algorithm adopted.

The nearest neighbor algorithm estimated the average per adult household expenditure of the matched treated to be 12386.01 ETB and of the matched control to be 9992.286 ETB. Therefore, the ATT as a result of access to irrigation is 2393.725 ETB. This difference is found to be statistically significant at 1% significance level. In a common framework, the radius matching estimated the ATT to be 2101.284 ETB which was also found to be significant at 1% significance level.

Table 5.7 ATT Estimation Results: Impact of Irrigation on Total Expenditure

Matching Algorithm	Number of Treated	Number of Control	Mean Per Adult Expenditure			Standard Error	t-stat
			Matched Treated	Matched Control	ATT		
Nearest Neighbor	80	43	12386.01	9992.286	2393.725	779.272	3.072***
Radius Matching	80	93	12386.01	10284.73	2101.284	483.147	4.349***
Kernel Matching	80	93	12386.01	10579.221	1806.790	607.910	2.972***
Stratification	80	93			2024.703	542.019	3.735***

*** Significant at 1%.

Similarly, the estimate obtained from the kernel matching indicated the matched treated households had 1806.79 ETB additional per adult total expenditure than the matched control households, and this difference was found to be statistically significant at 1% significance level. A similar finding was found using the stratification algorithm.

The kernel matching algorithm yields the least mean per adult total expenditure. In relation to the matched pairs, the nearest neighbor matching algorithm is somewhat conservative as only 43% of the control households were judged to be comparable to the treatment households. Conversely, the radius, kernel and stratification algorithms found to be less restrictive as 93% of control households are matched with the treated households.

In conclusion, the empirical findings suggest that access to irrigation has improved the welfare status of treated households [estimated by per adult consumption expenditure] in a significant way. These results are in line with the findings of Haji and Aman [2013].

Alternatively, an attempt was also made to estimate the impact of irrigation on per adult food expenditure. The results obtained [Table 5.8] show that there is a significant difference in the per adult food expenditure using the radius, kernel and stratification algorithms. The t- statistics are based on bootstrapped standard errors with 200 replications.

The results from [Table 5.8] show that the average treatment effect on the treated is positive for all matching algorithms. The t-values generated by bootstrapping the standard errors show the ATT for food expenditure is statistically significant in all matching algorithms. These results could substantiate the aforementioned evidences from the descriptive analysis.

Table 5.8 ATT Estimation Results: Impact of Irrigation on Food Expenditure

Matching Algorithm	Number of Treated	Number of control	ATT	Std. Err.	t-stat
Nearest Neighbor	80	43	1846.100	725.48	2.545**
Radius Matching	80	93	1648.536	356.227	4.628***
Kernel Matching	80	93	1433.846	500.059	2.867***
Stratification	80	93	1593.491	423.268	3.765***

*** Significant at 1%, **significant at 5%.

5.2.2.2 IMPACT OF IRRIGATION ADOPTION ON INCOME

While consumption expenditure is the common measure of welfare in developing countries, some analysts use income as an alternative measure of household welfare. In this section, an attempt is made to measure household welfare by looking at household income.

The results in [Table 5.9] confirmed the above findings in that the ATT from the four matching algorithms were also found to be statistically significant. The mean difference of income in per capita between the matched treated and control groups ranges from 500 to 900 ETB depending on the matching algorithm under consideration.

Table 5.9 ATT Estimation Results: Impact of Irrigation on Total Income

Matching Algorithm	Number of Treated	Number of Control	Mean Per Capita Income			Standard Error	t-stat
			Matched Treated	Matched Control	ATT		
Nearest Neighbor	80	43	9320	6803.51	2516.490	899.404	2.798***
Radius Matching	65	93	9320	6588.176	2731.824	509.219	5.365***
Kernel Matching	80	93	9320	6518.0181	2801.982	716.617	3.910***
Stratification	80	93			2987.993	686.975	4.349***

*** Significant at 1%.

The nearest neighbor algorithm estimated the average per capita income of the matched treated to be 9320 ETB and of the matched control to be 6803.51 ETB. Therefore, the average treatment effect as a result of access to irrigation is 2516.49 ETB. This difference is statistically significant. In a common fashion, the radius matching algorithm estimated the average treatment effect on the treated to be 9320 ETB which was found to be significant at 1% significance level. With regard to the kernel and stratification algorithms, both methods result in a significant [at 1% level of significance] and a higher ATT than the nearest neighbor matching.

A narrower comparison was also made by taking the mean difference of farm income. This approach is more powerful in explaining the pure income difference between the treatment and control groups. In this regard, significant ATT scores were found in the four matching algorithms.

More specifically, the mean per capita farm income of the matched treated is higher than the mean of the matched control group by 39.6%, 51.2% and 51.2% using the nearest neighbor, radius and kernel matching respectively. The results of this specification are presented in [Table 5.10] below. The t- statistics are based on bootstrapped standard errors with 200 replications.

Table 5.10 ATT Estimation Results: Impact of Irrigation on Farm Income

Matching Algorithm	Number of Treated	Number of control	ATT	Std. Err.	t-stat
Nearest Neighbor	80	43	2425.555	769.64	3.152***
Radius Matching	80	93	2893.685	531.419	5.445***
Kernel Matching	80	93	2893.651	636.100	4.549***
Stratification	80	93	3036.930	538.178	5.643***

*** Significant at 1%.

5.2.3 SENSITIVITY ANALYSIS

The third and final step of the PSM analysis is testing the robustness of the estimated results to possible failures of the CIA. The sensitivity analysis proposed by Ichino et al, [2008] and the Stata program written by Nannicini [2007] were deployed to check robustness of the estimates.

To be precise, an unobserved confounder was simulated using reasonable values for pij. The matching estimation was repeated 50 times and the simulated average estimate of the ATT was retrieved. The comparison between the simulated and the baseline estimates gives an idea of the robustness of ATT estimation results to possible failures of the CIA.

As it is shown in [Table 5.11], even though U is associated with a large selection and outcome effects [Λ >1 and Γ >1], the simulated ATTs are still very close to the baseline ATTs. This implies it is only when U is simulated to provide implausibly large outcome effect, that the ATT can be driven closer to zero. Thus, it can be concluded the results estimated support robustness of the matching analysis.

Table 5.11 Results of Simulation Based Sensitivity Analysis

Matching Algorithm	Outcome Variable	Baseline ATT [1]	Λ	Γ	Simulated ATT [2]	Absolute Difference [1-2]	Percentage Difference [1-2]/[1]
Nearest Neighbor	Tot. Exp	2393.725	1.685	1.114	2248.620	145.105	6.1
	Food Exp	1846.100	1.719	1.943	1743.977	102.123	5.5
	Tot. Income	2516.490	2.310	10.191	2689.804	-173.314	6.9
	Farm Income	2425.555	1.025	4.693	2681.911	-256.356	10.6
Radius	Tot. Exp	2101.284	1.290	1.647	2072.343	28.941	1.4
	Food Exp	1648.536	1.714	1.970	1628.597	19.939	1.2
	Tot. Income	2731.824	2.108	1.121	2725.365	6.459	0.2
	Farm Income	2893.685	1.450	2.987	2887.582	6.103	0.2
Kernel	Tot. Exp	1806.790	1.641	1.339	1805.917	0.873	0.0
	Food Exp	1433.846	1.894	1.495	1431.443	2.403	0.2
	Tot. Income	2801.982	1.687	8.873	2795.045	6.937	0.2
	Farm Income	2893.651	1.540	2.326	2891.189	2.462	0.1

Notes* Γ refers to the outcome effect which measures the estimated effect of the simulated confounder on the relative probability to have a positive outcome in case of no treatment.

** Λ refers to the selection effect which measures the estimated effect of the simulated confounder on the relative probability to be assigned to the treatment controlling for the set of covariates X.

5.3 IMPACT OF IRRIGATION ON HOUSEHOLD POVERTY

Although propensity score matching is considered as a powerful method of impact assessment, a combination of PSM with other methods would be an appropriate strategy in strengthening the finding. To this end, a poverty analysis is undertaken to compare poverty status between the treatment and control households.

5.3.1 POVERTY LINE ESTIMATION

In estimating the poverty line, the cost of basic needs approach was adopted. The CBN method stipulates a consumption bundle deemed to be adequate for basic consumption needs and then estimates what this bundle costs in reference prices. Accordingly, two poverty lines [absolute and moderate] were calculated based on different calorie requirements per day per adult person. The absolute poverty line was estimated based on the cost of fulfilling the minimum calorie requirements for maintaining a healthy life 2,200 calories, while the moderate poverty line was derived based on a calorie requirement of 2,750 calories which is commonly used for welfare monitoring by the Ethiopian Central Statistics Agency [Haile, 2008]. The estimation of poverty line [food and non food] used in this paper is explained in [Appendix 4] in detail.

Table 5.12 Results of Poverty Line Estimation

Poverty Line	Kcal per adult per day	Food Poverty Line [1] [Birr/adult/year]	Non Food Poverty Line [2] [Birr/adult/year]	Total Poverty Line [1+2] [Birr/adult/year]
Absolute	2200	3731.2	1159.6	4890.9
Moderate	2750	4664	1388.5	6052.5

Source: Own Survey, 2014.

As it is indicated in [Table 5.12], using the absolute poverty line definition, the food and non food poverty lines are 3731.2 and 1159.6 ETB respectively. Hence, the poverty line is approximately 4890.8 ETB per adult per year. This poverty line would not be as such different from the national poverty line 3781 ETB [MoFED, 2011] given the differences in rate of inflation, time of survey, and the methodologies adopted by the two studies. Similarly, the moderate poverty line is calculated to 6052.5 ETB.

For the purpose of this study, the absolute poverty line 4280.6 ETB and the moderate poverty line 5285.4 ETB are taken as a bench mark to compare poverty profiles between the treated and control groups under consideration.

5.3.2 POVERTY PROFILE COMPARISON

In this section, poverty profile comparison between treatment and control households will be undertaken. This analysis is helpful because it sheds light on the welfare difference between the two groups. Hence, the poverty indices for the treatment and control groups are given in [Table 5.13] below.

Table 5.13 Decomposition of Poverty Indices

Index	Absolute Poverty		Moderate Poverty	
	Treated	Control	Treated	Control
Poverty Incidence [P_0]	0.063	0.260	0.150	0.500
Poverty Depth [P_1]	0.011	0.031	0.028	0.096
Poverty Severity [P_2]	0.003	0.006	0.008	0.026

Source: Own Survey, 2014.

As far as the absolute poverty line is concerned, 26 % of control households are poor while this figure is only 6.3% for treated households. The poverty depth was found to be 3.1% for the control group and 1.1% for the treatment group. Similarly, poverty severity for the control group was found to be twice that of the treatment group.

In the case of the moderate poverty, the results show about 50% of the control group lived below the poverty line. The corresponding figure for the treatment group is only 15%. Hence, the incidence of poverty was found to be almost 30% less for the treated group as compared to their counterparts. Likewise, the poverty depth for the control group was estimated to be 9.6% while the corresponding figure for the treatment group is 2.8%. In a similar fashion, the severity of poverty for the control group was found to be twice that of the treatment group. These findings might be due to the higher and relatively stable income generated by the treatment group as a result of access to irrigation.

As explained in the methodology section, there are two ways of comparing poverty indices across groups. The first way to compare poverty indices is to conduct a statistical test or means separation test and the second is to undertake the stochastic dominance test. The results from the mean separation test are presented in [Table 5.14].

Table 5.14 Mean Separation Results Based on Moderate Poverty

Index	Control Group [N=100]			Treatment Group [N=80]			Difference	
	Value	SE	t-stat	Value	SE	t-stat	Value	t-stat
P_0	0.260	0.044	5.898	0.050	0.022	2.283	-0.210	-4.396***
P_1	0.031	0.007	4.298	0.009	0.004	1.940	-0.022	-2.757***
P_2	0.006	0.002	3.493	0.002	0.001	1.447	-0.004	-1.879*

*** Significant at 1%, *significant at 10%.

The mean separation test carried out verified that the incidence, depth and severity of poverty indices show the difference in poverty status among the two groups are statistically significant. These results indicate access to reliable irrigation water has tremendous potential to poverty reduction and hence to improve the welfare of beneficiary households.

5.4 PROBLEMS OF IRRIGATION MANAGEMENT AND PERFORMANCE

The impact of irrigation on improving the livelihoods is affected by a multiple factors. Some of the packages of successful irrigation systems include existence of effective water user associations, availability of agricultural inputs [quantity and quality], access to markets and dependable information, availability of socio-economic infrastructures, and access to full-fledged extension services. In this section major constraints that impede irrigation management and performance are discussed.

5.4.1 CANAL RELATED PROBLEMS

In the Laelay Dayu irrigation scheme water is conveyed from the water source to the command area via canals. The design and construction of river diversion and canal structures were constructed five years ago. Now, the canals are cracked and causing serious water seepage problems. Besides, the canal covers only small distance and hence water would flow in traditional furrow until it reaches farmers' plots. In the meantime, considerable amount of water will be lost due to evaporation and infiltration. This decreases water efficiency and hence productivity of the land than otherwise.

5.4.2 WATER ALLOCATION AND CONFLICTS

The task of water allocation is undertaken by the WUAs. Due to water shortage, this process is repeatedly marked by rivalry between and within communities. In this regard, there are some conflicts and troubles in water usage among farmers in the command area. The sources of conflict were related to lack of enough water, shortage of land and water theft.

Another issue regarding the sustainability of the project is the conflict between upstream and downstream water users. This is due to the two river diversions implemented in the upstream before the water reaches to Laelay Dayu village. When there is high demand by upstream users, conflicts are inevitable due to water shortage and this has a negative impact on the overall performance of the irrigation scheme.

5.4.3 MARKETING PROBLEMS

One of the main factors that affect the success of irrigation performance is the existence of effective and competitive marketing systems. Nevertheless, farmers in the study area blame the poor functioning of markets in the locality. Farmers feel they are not paid reasonable prices for their produce. They argued prices are determined by retailers and wholesalers as the farmers have no bargaining power and access to nearby alternative markets.

Due to the high risk associated with horticultural production, the more complex the marketing channel the more reluctant farmers are to produce high value marketable products. The severity of the marketing problem would be more pronounced when the issue of asymmetric information and lack of storage facilities are taken into account. These factors are observed affecting the overall returns from irrigated plots in the study area.

5.4.4 POOR EXTENSION SERVICES

In the study area, different gaps are identified in relation to extension services and infrastructures. The extension worker in the village serves more than 250 farm households which is too big to administer properly given the absence of transportation facilities and other logistics.

The major constraints and challenges reported by the extension worker and farmers include improper crop rotation cycle; inappropriate cropping pattern and cropping intensity; poor soil fertility management; crop-water requirement imbalance; and inadequate crop pest management practices. This coupled with poor education background of farmers and absence of modern farming equipments, the productivity of the plots is likely to be affected negatively.

CHAPTER-6
CONCLUSIONS AND RECOMMENDATIONS

6.1CONCLUSIONS

The overall motive of this study was to evaluate the impact of small-scale irrigation scheme on improving the welfare of rural households. To this end, a household income and consumption survey was undertaken on 180 rural households [80 treated and 100 controls] in village of Laelay Dayu, a sub district in Tigaray National Regional State. The study had an implicit working hypothesis that access to irrigation water has a positive impact on household welfare. In this regard, both income and consumption expenditure were used as a proxy for measuring household welfare. To analyze the impact of irrigation on household welfare, descriptive and econometric analyses were deployed. Besides poverty status comparison was also undertaken.

This chapter presents a summary of major findings of the impact evaluation. It starts by drawing main conclusions from the study, and then it makes appropriate recommendations in relation to improving the performance and management of small scale irrigation schemes.

Generally speaking, this study has concluded access to small-scale irrigation has a profound impact on improving the livelihoods of smallholder farmers in the study area. The specific conclusions drawn from the study are presented below.

From the descriptive analysis no significance difference observed between the two groups in relation to the variables age of household head, size of cultivated land, number of adult labor and oxen holding. In the same way, there was no significant difference in the number of adult labor between irrigating and non irrigating households, but it was found that irrigating households had less off farm income than their counter parts. By this, it can be generalized that irrigated farms have more labor absorbing tendency than non irrigated farms.

The PSM model results for the outcome variable per adult consumption expenditure indicated the average treatment effect on the treated was in the range of 1800-2400 ETB depending on the matching algorithm under consideration. The corresponding figure using the unmatched sample was calculated to be 2451 ETB. Assuming consumption expenditure as good proxy for welfare measurement, the study concludes the standard of living of irrigating households is better than non irrigating households. Likewise, the mean difference for the outcome variable food expenditure in per adult was found to be in the range 1400-1900 ETB using the matched sample and 1913 ETB using the unmatched sample. This shows the PSM avoids over estimation attributed to the selection bias associated with the full sample analysis. Based on these results, it can be generalized that irrigating households are consuming more calories and hence have healthier standard of living than non irrigating households.

Similarly, a positive and significant ATT was reported in relation to the outcome variable per capita farm income. To be precise, while the mean per capita farm income for irrigating households was found 8548 ETB the corresponding figure for the non irrigating households was found in the range 5600-6150 ETB. Thus, it can be concluded that access to water has enabled irrigating households to diversify cropping, to increase farming intensity, to minimize crop failure and hence to enhance productivity and farm income.

From the poverty analysis based on the absolute poverty line, 26% of non irrigating households were below the poverty line while the corresponding number for irrigating households was only 6%. Similarly, the depth and severity of poverty were significantly higher for the non irrigation households. These results suggest that access to irrigation has a profound impact on reducing rural poverty.

A part from the positive contributions of the irrigation scheme, the study has distinguished some problems that affect the performance of small scale irrigation. The chief problems identified include lack of enough surface water, loss of water through seepage, water conflicts and weak market links and poor extension services. Therefore, irrigation infrastructures have to be complemented by other components of the agricultural system to achieve the desired target of poverty alleviation.

6.2 RECOMMENDATIONS

This study has indicated access to irrigation water enabled farmers to increase household income and consumption expenditure and reduces poverty at household level. However, from the key informant interview and informal discussions with the farmers, a number of factors were found inhibiting the performance of small scale irrigation in the study area. To sustain the positive impacts of the project and to enable beneficiary households make an optimum use of the irrigation scheme, the following recommendations are suggested.

6.2.1 STRENGTHEN EDUCATION AND TRAINING

Education is believed to have a positive impact on improving welfare and reducing poverty over time. Although education level of household heads was found to be positively correlated with participation decision into irrigation, the average education level of irrigating household heads was estimated to be 1.8 years. This low level of education would affect farmers to communicate with extension workers and to make sound economic decisions regarding crop production management, and cost benefit analysis. Therefore, the local education and agricultural offices should bridge this gap by introducing need based education and training programs for farmers in the study area.

6.2.2 ADDRESSING CANAL PROBLEMS

The quality of water conveying canals has a great role in improving water efficiency in river diversion systems. Due to the cracks created in the canals, there is a substantial loss of water in the command area. Maintenance of the cracks and extending the main canal over wider distance can minimize seepage and improve conveyance efficiencies. In this regard, concerned bodies such as the WUAs, Oxfam America and REST are expected to allocate funds and to provide technical supports.

6.2.3 MANAGING WATER CONFLICTS

In some villages which are located upstream there are two river diversions implemented before the Laelay Dayu irrigation project. This has been a source of conflict between upstream and upstream water users. Therefore, some interventions should be made by authorized bodies to ensure equity in water allocate water among different users and to minimize potential sources of conflicts.

6.2.4 SOIL AND WATER CONSERVATION

By its very nature, the project area is bordered by mountains which are almost bare. Consequently, heavy runoffs and floods are causing scouring and sliding of the irrigated land and damaging irrigation structures. This would reduce the productivity of the land and decrease the size of the command area overtime as the river bed area is expanding at the expense of irrigated area. Therefore, local government and community leaders should undertake soil and water conservation practices in the area.

6.2.5 ADDRESSING MARKETING PROBLEMS

The returns to irrigation are affected by the existence of effective markets and post harvest facilities. However, in the study area farmers reported marketing related problems such as poor bargaining power and asymmetric information were affecting their incomes. Therefore, to maximize the welfare and poverty impacts of irrigation, linking farmers with markets and post harvest technologies deems essential.

In line to this, stakeholders in the irrigation project such as the regional bureau of agriculture and rural development, TAMPA, Oxfam America, REST and related local institutions should enable farmers to have dependable and quality information in relation to high value cash crops, product demand, marketing channels and price signals. This would enable farmers to increase their earnings and to expand improve their standard of living.

6.2.6 CONSIDERING GENDER EQUITY

The gender dimension of access to irrigation is not uniform. Form the descriptive analysis it was reported about 75% of adopter households were male headed. This could be due the uneven access to resources and decision making powers between males and females which is a common problem in developing countries like Ethiopia. Therefore, interventions that ensure gender equity and empowerment should be introduced to enable female headed households benefit from fruits of the irrigation scheme.

6.3 LIMITATIONS AND PROPOSALS FOR FUTURE RESEARCH

This study focuses on the impact of small scale irrigation on the welfare of rural households. However, the study has some limitations that require further in-depth analysis o the topic. For example, the comparison of income between irrigation adopters and non adopters was based on gross income. This could not indicate the true impact of adopting irrigation as the cost dimension was not included. Therefore, a cost-benefit analysis should be undertaken in order to value the net effect of the irrigation scheme on the welfare of beneficiary households.

Another issue that needs further research is the case of social and environmental effect. The study focused only on the ‘good’ of small scale irrigation. Yet, there are also some ‘bad’ effects on the environment and the local communities such as waterborne diseases, water logging, salinity and so forth. As a result, the ‘bad’ effect of the irrigation scheme should be investigated.

The study was conducted at one village and for a relatively short period of time. Hence, it becomes difficult to generalize about the impact of irrigation elsewhere in Ethiopia and in other developing countries. Therefore, a detail study that considers different agro ecological zones and the actual impact of irrigation adoption on nutrition, education and other indicators of household well-being should be undertaken.

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APPENDIX 1: STATA OUTPUT FOR PROPENSITY SCORE MATCHING

```
****************************************************
Algorithm to estimate the propensity score
****************************************************


The treatment is treat

      treat |      Freq.     Percent        Cum.
------------+-----------------------------------
          0 |        100       55.56       55.56
          1 |         80       44.44      100.00
------------+-----------------------------------
      Total |        180      100.00


Estimation of the propensity score

Iteration 0:   log likelihood = -123.65308
Iteration 1:   log likelihood = -108.51564
Iteration 2:   log likelihood = -108.14352
Iteration 3:   log likelihood =  -108.1415

Logistic regression                               Number of obs   =        180
                                                  LR chi2(8)      =      31.02
                                                  Prob > chi2     =     0.0001
Log likelihood =  -108.1415                       Pseudo R2       =     0.1254

------------------------------------------------------------------------------
       treat |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       hhsex |   .4900903   .4901677     1.00   0.317    -.4706207    1.450801
       hhage |   .0898559   .1020118     0.88   0.378    -.1100834    .2897953
     hhage_2 |  -.0006921   .0009837    -0.70   0.482    -.0026202     .001236
       hhsiz |  -.4090389   .1500817    -2.73   0.006    -.7031937   -.1148842
      hheduc |   .1422118    .071359     1.99   0.046     .0023507    .2820729
     landsiz |  -.0551328   .0699314    -0.79   0.430    -.1921958    .0819301
    adultlab |   .1865374   .1868073     1.00   0.318    -.1795983    .5526731
         ext |   1.085526   .3910521     2.78   0.006     .3190778    1.851974
       _cons |  -2.318141   2.372489    -0.98   0.329    -6.968135    2.331852
------------------------------------------------------------------------------


Note: the common support option has been selected
The region of common support is [.11270925, .91437923]
```

Description of the estimated propensity score
in region of common support

Estimated propensity score

	Percentiles	Smallest		
1%	.1131865	.1127092		
5%	.1359309	.1131865		
10%	.194987	.1138658	Obs	173
25%	.3170879	.117138	Sum of Wgt.	173
50%	.4487367		Mean	.4587612
		Largest	Std. Dev.	.1897932
75%	.601957	.8349327		
90%	.7089682	.8459806	Variance	.0360215
95%	.7782727	.8505702	Skewness	.0835916
99%	.8505702	.9143792	Kurtosis	2.27466

****
Step 1: Identification of the optimal number of blocks
Use option detail if you want more detailed output
****

The final number of blocks is 5

This number of blocks ensures that the mean propensity score
is not different for treated and controls in each blocks

****
Step 2: Test of balancing property of the propensity score
Use option detail if you want more detailed output
****

The balancing property is satisfied

This table shows the inferior bound, the number of treated
and the number of controls for each block

Inferior of block of pscore	treat 0	1	Total
.1127092	16	3	19
.2	34	13	47
.4	30	31	61
.6	10	30	40
.8	3	3	6
Total	93	80	173

Note: the common support option has been selected

****
End of the algorithm to estimate the pscore
****

A. OUTCOME VARIABLE: TOTAL EXPENDITURE PER ADULT EQUIVALENT

```
****************************************************************
Estimation of the ATT with the nearest neighbor matching method
Random draw version
****************************************************************


 The outcome is paexp

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
       paexp |       173    11140.91    3539.199   3970.323    20776.3


****************************************************
Display of final results
****************************************************


Average outcome of the matched treated

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
       paexp |        80    12386.01    3576.744   3970.323    20776.3


Average outcome of the matched controls

    Variable |     Obs      Weight        Mean   Std. Dev.       Min        Max
-------------+-----------------------------------------------------------------
       paexp |      43          80    9992.286   2741.564   4964.138   15154.67



Bootstrapping of standard errors

command:      attnd paexp treat hhsex hhage hhage_2 hhsiz hheduc landsiz adultlab ext , pscore() logit comsup
statistic:    attnd      = r(attnd)
....................................................................................................

note: label truncated to 80 characters

Bootstrap statistics                              Number of obs    =       180
                                                  Replications     =       100

------------------------------------------------------------------------------
Variable     |  Reps  Observed      Bias  Std. Err. [95% Conf. Interval]
-------------+----------------------------------------------------------------
       attnd |   100  2393.725 -740.8271  779.2721   847.4802    3939.97   (N)
             |                                       114.8913   3172.617   (P)
             |                                       1882.858   3325.398  (BC)
------------------------------------------------------------------------------
Note:  N   = normal
       P   = percentile
       BC  = bias-corrected


ATT estimation with Nearest Neighbor Matching method
(random draw version)
Bootstrapped standard errors

---------------------------------------------------------
n. treat.   n. contr.         ATT   Std. Err.           t
---------------------------------------------------------

       80          43    2393.725     779.272       3.072

---------------------------------------------------------
Note: the numbers of treated and controls refer to actual
nearest neighbour matches



******************************************************************************
End of the estimation with the nearest neighbor matching (random draw) method
******************************************************************************
```

****

Estimation of the ATT with the radius matching method

****

The outcome is paexp

Variable	Obs	Mean	Std. Dev.	Min	Max
paexp	173	11140.91	3539.199	3970.323	20776.3

Average outcome of the matched treated

Variable	Obs	Mean	Std. Dev.	Min	Max
paexp	80	12386.01	3576.744	3970.323	20776.3

Average outcome of the matched controls

Variable	Obs	Weight	Mean	Std. Dev.	Min	Max
paexp	93	80.0000003	10284.73	2937.667	4964.138	20517.65

Bootstrapping of standard errors

```
command:      attr paexp treat hhsex hhage hhage_2 hhsiz hheduc landsiz adultlab ext , pscore() logit comsup radius(.1)
statistic:    attr       = r(attr)
....................................................................................................
```

note: label truncated to 80 characters

```
Bootstrap statistics                              Number of obs    =       180
                                                  Replications     =       100
```

Variable	Reps	Observed	Bias	Std. Err.	[95% Conf.	Interval]	
attr	100	2101.284	-70.38746	483.1467	1142.616	3059.952	(N)
					1042.936	2877.325	(P)
					1282.561	3269.958	(BC)

```
Note:  N   = normal
       P   = percentile
       BC  = bias-corrected
```

ATT estimation with the Radius Matching method
Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
80	93	2101.284	483.147	4.349

Note: the numbers of treated and controls refer to actual
matches within radius

****

End of the estimation with the radius matching method

****

****

Estimation of the ATT with the kernel matching method

****

The outcome is paexp

Variable	Obs	Mean	Std. Dev.	Min	Max
paexp	173	11140.91	3539.199	3970.323	20776.3

****

Display of final results

****

Mean paexp of matched treated = 12386.011

Mean paexp of matched controls = 10579.221

Effect of treatment = 1806.7897

Bootstrapping of standard errors

```
command:      attk paexp treat hhsex hhage hhage_2 hhsiz hheduc landsiz adultlab ext , pscore() logit comsup bwidth(.06)
statistic:    attk       = r(attk)
....................................................................................................
```

note: label truncated to 80 characters

Bootstrap statistics — Number of obs = 180; Replications = 100

Variable	Reps	Observed	Bias	Std. Err.	[95% Conf.	Interval]	
attk	100	1806.79	-249.0677	607.9103	600.5638	3013.016	(N)
					37.4004	2494.87	(P)
					969.9175	3053.523	(BC)

Note: N = normal
P = percentile
BC = bias-corrected

ATT estimation with the Kernel Matching method
Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
80	93	1806.790	607.910	2.972

****

End of the estimation with the kernel matching method

****

```
****************************************************
Estimation of the ATT with the stratification method
****************************************************


 The outcome is paexp

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
       paexp |       173    11140.91    3539.199   3970.323    20776.3



****************************************************
Display of final results
****************************************************


Bootstrapping of standard errors

command:      atts paexp treat , pscore(_mypscore) blockid(_myblock) comsup
statistic:    atts       = r(atts)
....................................................................................................

Bootstrap statistics                              Number of obs    =       180
                                                  Replications     =       100

------------------------------------------------------------------------------
Variable     |  Reps  Observed      Bias  Std. Err. [95% Conf. Interval]
-------------+----------------------------------------------------------------
        atts |   100  2024.703  42.12411  542.0192   949.2199   3100.187   (N)
             |                                       945.9825    3069.48   (P)
             |                                       902.1367   3060.236  (BC)
------------------------------------------------------------------------------
Note:  N   = normal
       P   = percentile
       BC  = bias-corrected


ATT estimation with the Stratification method
Bootstrapped standard errors

---------------------------------------------------------
n. treat.   n. contr.         ATT   Std. Err.           t
---------------------------------------------------------

       80          93    2024.703     542.019       3.735

---------------------------------------------------------


****************************************************
End of the estimation with the stratification method
****************************************************
```

B. OUTCOME VARIABLE: FOOD EXPENDITURE PER ADULT EQUIVALENT

```
****************************************************************
Estimation of the ATT with the nearest neighbor matching method
Random draw version
****************************************************************
```

The outcome is pafoodexp

Variable	Obs	Mean	Std. Dev.	Min	Max
pafoodexp	173	8372.613	2787.251	2705.807	17493.75

```
****************************************************
Display of final results
****************************************************
```

Average outcome of the matched treated

Variable	Obs	Mean	Std. Dev.	Min	Max
pafoodexp	80	9349.426	2933.187	2705.807	17493.75

Average outcome of the matched controls

Variable	Obs	Weight	Mean	Std. Dev.	Min	Max
pafoodexp	43	80	7503.326	2205.35	2846.896	11711.59

```
Bootstrapping of standard errors

command:      attnd pafoodexp treat hhsex hhage hhage_2 hhsiz hheduc landsiz adultlab ext , pscore() logit comsup
statistic:    attnd      = r(attnd)
....................................................................................................

note: label truncated to 80 characters

Bootstrap statistics                              Number of obs    =       180
                                                  Replications     =       100
```

Variable	Reps	Observed	Bias	Std. Err.	[95% Conf.	Interval]	
attnd	100	1846.1	-501.2476	725.4796	406.5909	3285.609	(N)
					-275.5417	2537.668	(P)
					1065.757	2576.438	(BC)

```
Note:  N   = normal
       P   = percentile
       BC  = bias-corrected
```

ATT estimation with Nearest Neighbor Matching method
(random draw version)
Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
80	43	1846.100	725.480	2.545

Note: the numbers of treated and controls refer to actual nearest neighbour matches

```
*****************************************************************************
End of the estimation with the nearest neighbor matching (random draw) method
*****************************************************************************
```

****

Estimation of the ATT with the radius matching method

****

The outcome is pafoodexp

Variable	Obs	Mean	Std. Dev.	Min	Max
pafoodexp	173	8372.613	2787.251	2705.807	17493.75

Average outcome of the matched treated

Variable	Obs	Mean	Std. Dev.	Min	Max
pafoodexp	80	9349.426	2933.187	2705.807	17493.75

Average outcome of the matched controls

Variable	Obs	Weight	Mean	Std. Dev.	Min	Max
pafoodexp	93	80.0000003	7700.89	2208.834	2846.896	16094.12

Bootstrapping of standard errors

```
command:      attr pafoodexp treat hhsex hhage hhage_2 hhsiz hheduc landsiz adultlab ext , pscore() logit comsup radius(.1)
statistic:    attr       = r(attr)
....................................................................................................
```

note: label truncated to 80 characters

```
Bootstrap statistics                              Number of obs    =        180
                                                  Replications     =        100
```

Variable	Reps	Observed	Bias	Std. Err.	[95% Conf.	Interval]	
attr	100	1648.536	-65.80193	356.2266	941.7052	2355.367	(N)
					888.3406	2241.757	(P)
					1054.952	2292.299	(BC)

```
Note:  N   = normal
       P   = percentile
       BC  = bias-corrected
```

ATT estimation with the Radius Matching method
Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
80	93	1648.536	356.227	4.628

Note: the numbers of treated and controls refer to actual matches within radius

****

End of the estimation with the radius matching method

****

```
*******************************************************
Estimation of the ATT with the kernel matching method
******************************************************


 The outcome is pafoodexp

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
   pafoodexp |       173    8372.613    2787.251   2705.807   17493.75


****************************************************
Display of final results
****************************************************


   Mean pafoodexp of matched treated  = 9349.4256

   Mean pafoodexp of matched controls = 7915.5794

   Effect of treatment  = 1433.8462


Bootstrapping of standard errors

command:      attk pafoodexp treat hhsex hhage hhage_2 hhsiz hheduc landsiz adultlab ext , pscore() logit comsup bwidth(.06)
statistic:    attk       = r(attk)
....................................................................................................

note: label truncated to 80 characters

Bootstrap statistics                              Number of obs    =       180
                                                  Replications     =       100

------------------------------------------------------------------------------
Variable     |  Reps  Observed      Bias  Std. Err. [95% Conf. Interval]
-------------+----------------------------------------------------------------
        attk |   100  1433.846 -216.2013  500.0587   441.6213   2426.071   (N)
             |                                       224.8288   2265.085   (P)
             |                                       521.9681   2442.153  (BC)
------------------------------------------------------------------------------
Note:  N   = normal
       P   = percentile
       BC  = bias-corrected


ATT estimation with the Kernel Matching method
Bootstrapped standard errors

---------------------------------------------------------
n. treat.   n. contr.         ATT   Std. Err.           t
---------------------------------------------------------

       80          93    1433.846     500.059       2.867

---------------------------------------------------------


******************************************************
End of the estimation with the kernel matching method
******************************************************
```

```
****************************************************
Estimation of the ATT with the stratification method
****************************************************

 The outcome is pafoodexp

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
   pafoodexp |       173    8372.613    2787.251   2705.807   17493.75

****************************************************
Display of final results
****************************************************



Bootstrapping of standard errors

command:      atts pafoodexp treat , pscore(_mypscore) blockid(_myblock) comsup
statistic:    atts       = r(atts)
....................................................................................................

Bootstrap statistics                              Number of obs    =       180
                                                  Replications     =       100

------------------------------------------------------------------------------
Variable     |  Reps  Observed      Bias  Std. Err. [95% Conf. Interval]
-------------+----------------------------------------------------------------
        atts |   100  1593.491  6.276857  423.2678   753.6357   2433.346   (N)
             |                                       788.6417   2440.582   (P)
             |                                        735.265   2304.406  (BC)
------------------------------------------------------------------------------
Note:  N   = normal
       P   = percentile
       BC  = bias-corrected


ATT estimation with the Stratification method
Bootstrapped standard errors

---------------------------------------------------------
n. treat.   n. contr.         ATT   Std. Err.           t
---------------------------------------------------------

       80          93    1593.491     423.268       3.765

---------------------------------------------------------


****************************************************
End of the estimation with the stratification method
****************************************************
```

C. OUTCOME VARIABLE: PER CAPITA TOTAL INCOME

```
*****************************************************************
Estimation of the ATT with the nearest neighbor matching method
Random draw version
*****************************************************************


 The outcome is pcincome

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
    pcincome |       173    7793.288    4464.073   1166.667      27275



****************************************************
Display of final results
****************************************************


Average outcome of the matched treated

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
    pcincome |        80        9320    4798.196   1733.333      27275


Average outcome of the matched controls

    Variable |     Obs      Weight        Mean   Std. Dev.       Min        Max
-------------+-----------------------------------------------------------------
    pcincome |      43          80     6803.51   3541.843       1550      18075


Bootstrapping of standard errors

command:      attnd pcincome treat hhsex hhage hhage_2 hhsiz hheduc landsiz adultlab ext , pscore() logit comsup
statistic:    attnd      = r(attnd)
....................................................................................................

note: label truncated to 80 characters

Bootstrap statistics                              Number of obs    =       180
                                                  Replications     =       100

------------------------------------------------------------------------------
Variable     |  Reps  Observed      Bias  Std. Err. [95% Conf. Interval]
-------------+----------------------------------------------------------------
       attnd |   100   2516.49 -11.45008  899.4038   731.8777   4301.102   (N)
             |                                       620.5909   3967.332   (P)
             |                                       620.5909   3967.332  (BC)
------------------------------------------------------------------------------
Note:  N   = normal
       P   = percentile
       BC  = bias-corrected


ATT estimation with Nearest Neighbor Matching method
(random draw version)
Bootstrapped standard errors

---------------------------------------------------------
n. treat.   n. contr.         ATT   Std. Err.           t
---------------------------------------------------------

       80          43    2516.490     899.404       2.798

---------------------------------------------------------
Note: the numbers of treated and controls refer to actual
nearest neighbour matches


*****************************************************************************
End of the estimation with the nearest neighbor matching (random draw) method
*****************************************************************************
```

****

Estimation of the ATT with the radius matching method

****

The outcome is pcincome

Variable	Obs	Mean	Std. Dev.	Min	Max
pcincome	173	7793.288	4464.073	1166.667	27275

Average outcome of the matched treated

Variable	Obs	Mean	Std. Dev.	Min	Max
pcincome	80	9320	4798.196	1733.333	27275

Average outcome of the matched controls

Variable	Obs	Weight	Mean	Std. Dev.	Min	Max
pcincome	93	80.0000003	6588.176	3520.503	1166.667	20500

```
Bootstrapping of standard errors

command:      attr pcincome treat hhsex hhage hhage_2 hhsiz hheduc landsiz adultlab ext , pscore() logit comsup radius(.1)
statistic:    attr       = r(attr)
....................................................................................................

note: label truncated to 80 characters

Bootstrap statistics                              Number of obs    =        180
                                                  Replications     =        100
```

Variable	Reps	Observed	Bias	Std. Err.	[95% Conf.	Interval]	
attr	100	2731.824	-42.27443	509.2186	1721.424	3742.224	(N)
					1686.393	3594.926	(P)
					1760.11	3772.404	(BC)

```
Note:  N   = normal
       P   = percentile
       BC  = bias-corrected
```

ATT estimation with the Radius Matching method
Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
80	93	2731.824	509.219	5.365

Note: the numbers of treated and controls refer to actual
matches within radius

****

End of the estimation with the radius matching method

****

```
*****************************************************
Estimation of the ATT with the kernel matching method
*****************************************************
```

The outcome is pcincome

Variable	Obs	Mean	Std. Dev.	Min	Max
pcincome	173	7793.288	4464.073	1166.667	27275

```
****************************************************
Display of final results
****************************************************
```

Mean pcincome of matched treated = 9319.9997

Mean pcincome of matched controls = 6518.0181

Effect of treatment = 2801.9816

```
Bootstrapping of standard errors

command:      attk pcincome treat hhsex hhage hhage_2 hhsiz hheduc landsiz adultlab ext , pscore() logit comsup bwidth(.06)
statistic:    attk       = r(attk)
....................................................................................................

note: label truncated to 80 characters

Bootstrap statistics                              Number of obs    =       180
                                                  Replications     =       100
```

Variable	Reps	Observed	Bias	Std. Err.	[95% Conf.	Interval]	
attk	100	2801.982	-184.7781	716.6172	1380.058	4223.906	(N)
					1557.815	4447.501	(P)
					1936.959	5768.508	(BC)

```
Note:  N   = normal
       P   = percentile
       BC  = bias-corrected
```

ATT estimation with the Kernel Matching method
Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
80	93	2801.982	716.617	3.910

```
******************************************************
End of the estimation with the kernel matching method
******************************************************
```

****
Estimation of the ATT with the stratification method
****

The outcome is pcincome

Variable	Obs	Mean	Std. Dev.	Min	Max
pcincome	173	7793.288	4464.073	1166.667	27275

****
Display of final results
****

```
Bootstrapping of standard errors

command:      atts pcincome treat , pscore(_mypscore) blockid(_myblock) comsup
statistic:    atts       = r(atts)
....................................................................................................

Bootstrap statistics                              Number of obs    =       180
                                                  Replications     =       100
```

Variable	Reps	Observed	Bias	Std. Err.	[95% Conf.	Interval]	
atts	100	2987.993	5.800771	686.9754	1624.884	4351.101	(N)
					1539.139	4251.07	(P)
					1530.12	4132.565	(BC)

```
Note:  N   = normal
       P   = percentile
       BC  = bias-corrected
```

ATT estimation with the Stratification method
Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
80	93	2987.993	686.975	4.349

****
End of the estimation with the stratification method
****

D. OUTCOME VARIABLE: PER CAPITA FARM INCOME

```
*******************************************************************
Estimation of the ATT with the nearest neighbor matching method
Random draw version
*******************************************************************
```

The outcome is pcplotincom

Variable	Obs	Mean	Std. Dev.	Min	Max
pcplotincom	173	6928.878	4388.641	450	27275

```
*******************************************************
Display of final results
*******************************************************
```

Average outcome of the matched treated

Variable	Obs	Mean	Std. Dev.	Min	Max
pcplotincom	80	8548.07	4692.835	1266.667	27275

Average outcome of the matched controls

Variable	Obs	Weight	Mean	Std. Dev.	Min	Max
pcplotincom	43	80	6122.516	3720.076	450	18075

```
Bootstrapping of standard errors

command:      attnd pcplotincom treat hhsex hhage hhage_2 hhsiz hheduc landsiz adultlab ext , pscore() logit comsup
statistic:    attnd      = r(attnd)
....................................................................................................

note: label truncated to 80 characters

Bootstrap statistics                              Number of obs    =       180
                                                  Replications     =       100
```

Variable	Reps	Observed	Bias	Std. Err.	[95% Conf.	Interval]	
attnd	100	2425.555	430.8956	769.6402	898.4216	3952.688	(N)
					1134.785	4282.907	(P)
					780.8881	3524.68	(BC)

```
Note:  N   = normal
       P   = percentile
       BC  = bias-corrected
```

ATT estimation with Nearest Neighbor Matching method
(random draw version)
Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
80	43	2425.555	769.640	3.152

Note: the numbers of treated and controls refer to actual
nearest neighbour matches

```
*******************************************************************************
End of the estimation with the nearest neighbor matching (random draw) method
*******************************************************************************
```

****
Estimation of the ATT with the radius matching method
****

The outcome is pcplotincom

Variable	Obs	Mean	Std. Dev.	Min	Max
pcplotincom	173	6928.878	4388.641	450	27275

Average outcome of the matched treated

Variable	Obs	Mean	Std. Dev.	Min	Max
pcplotincom	80	8548.07	4692.835	1266.667	27275

Average outcome of the matched controls

Variable	Obs	Weight	Mean	Std. Dev.	Min	Max
pcplotincom	93	80.0000003	5654.386	3376.609	450	19333.33

Bootstrapping of standard errors

```
command:      attr pcplotincom treat hhsex hhage hhage_2 hhsiz hheduc landsiz adultlab ext , pscore() logit comsup radius(.1)
statistic:    attr       = r(attr)
....................................................................................................
```

note: label truncated to 80 characters

```
Bootstrap statistics                              Number of obs    =       180
                                                  Replications     =       100
```

Variable	Reps	Observed	Bias	Std. Err.	[95% Conf.	Interval]	
attr	100	2893.685	-14.73597	531.4191	1839.234	3948.135	(N)
					1844.858	3951.733	(P)
					1984.58	4301.494	(BC)

```
Note:  N   = normal
       P   = percentile
       BC  = bias-corrected
```

ATT estimation with the Radius Matching method
Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
80	93	2893.685	531.419	5.445

Note: the numbers of treated and controls refer to actual
matches within radius

****
End of the estimation with the radius matching method
****

```
******************************************************
Estimation of the ATT with the kernel matching method
*****************************************************
```

The outcome is pcplotincom

Variable	Obs	Mean	Std. Dev.	Min	Max
pcplotincom	173	6928.878	4388.641	450	27275

```
****************************************************
Display of final results
****************************************************
```

Mean pcplotincom of matched treated = 8548.0704

Mean pcplotincom of matched controls = 5654.4199

Effect of treatment = 2893.6505

Bootstrapping of standard errors

```
command:      attk pcplotincom treat hhsex hhage hhage_2 hhsiz hheduc landsiz adultlab ext , pscore() logit comsup bwidth(.06)
statistic:    attk       = r(attk)
....................................................................................................
```

note: label truncated to 80 characters

```
Bootstrap statistics                              Number of obs    =       180
                                                  Replications     =       100
```

Variable	Reps	Observed	Bias	Std. Err.	[95% Conf.	Interval]	
attk	100	2893.651	-132.5194	636.0997	1631.491	4155.811	(N)
					1357.382	3811.264	(P)
					1678.999	3849.407	(BC)

```
Note:  N   = normal
       P   = percentile
       BC  = bias-corrected
```

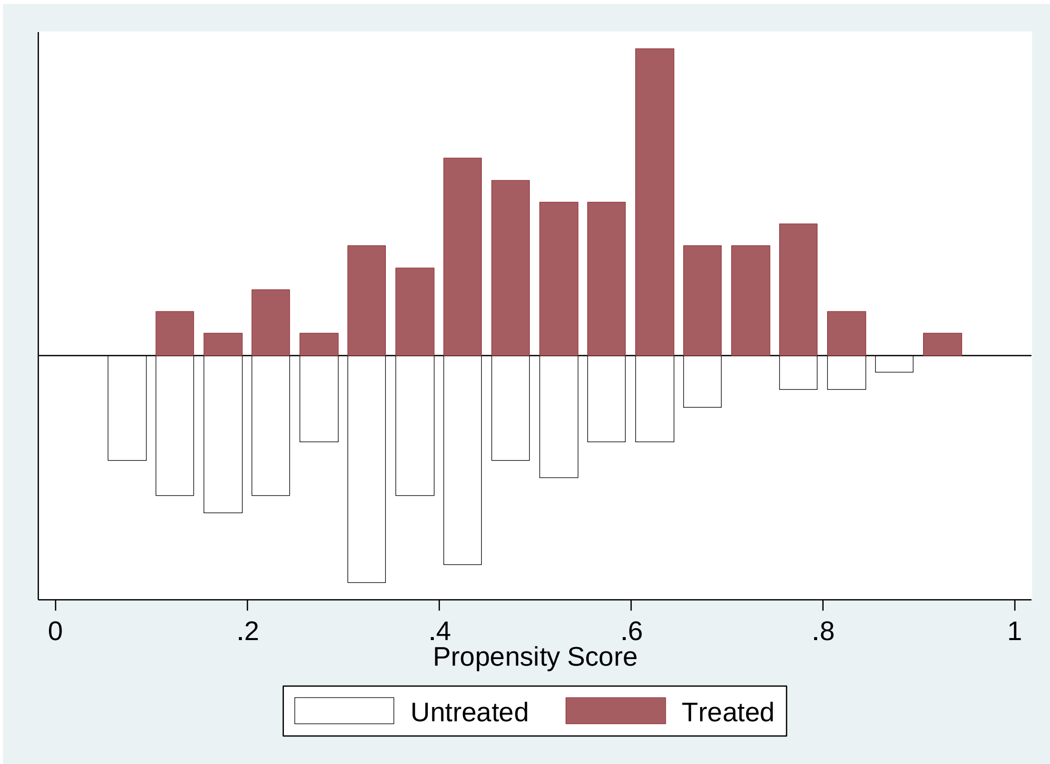
ATT estimation with the Kernel Matching method
Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
80	93	2893.651	636.100	4.549

```
******************************************************
End of the estimation with the kernel matching method
******************************************************
```

```
****************************************************
Estimation of the ATT with the stratification method
****************************************************

 The outcome is pcplotincom

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
 pcplotincom |       173    6928.878    4388.641        450      27275


****************************************************
Display of final results
****************************************************


Bootstrapping of standard errors

command:      atts pcplotincom treat , pscore(_mypscore) blockid(_myblock) comsup
statistic:    atts       = r(atts)
....................................................................................................

Bootstrap statistics                              Number of obs    =       180
                                                  Replications     =       100

------------------------------------------------------------------------------
Variable     |  Reps  Observed      Bias  Std. Err. [95% Conf. Interval]
-------------+----------------------------------------------------------------
        atts |   100   3036.93  31.86868  538.1782   1969.068   4104.793   (N)
             |                                      1982.748   4096.881   (P)
             |                                      1897.759   4087.012  (BC)
------------------------------------------------------------------------------
Note:  N   = normal
       P   = percentile
       BC  = bias-corrected


ATT estimation with the Stratification method
Bootstrapped standard errors

---------------------------------------------------------
n. treat.   n. contr.         ATT   Std. Err.           t
---------------------------------------------------------

       80          93    3036.930     538.178       5.643

---------------------------------------------------------


****************************************************
End of the estimation with the stratification method
****************************************************
```

APPENDIX 2: CHECKING COMMOMN SUPPORT



APPENDIX 3: SIMULATION BASED ESNSITIVITY ANALYSIS

A. OUTCOME VARIABLE: TOTAL EXPENDITURE PER ADULT EQUIVALENT

```
*** THIS IS THE BASELINE ATT ESTIMATION (WITH NO SIMULATED CONFOUNDER).

 The program is searching the nearest neighbor of each treated unit.
 This operation may take a while.

ATT estimation with Nearest Neighbor Matching method
(random draw version)
Analytical standard errors
```

n. treat.	n. contr.	ATT	Std. Err.	t
80	43	2393.725	706.911	3.386

Note: the numbers of treated and controls refer to actual nearest neighbour matches

```
*** THIS IS THE SIMULATED ATT ESTIMATION (WITH THE CONFOUNDER U).

The probability of having U=1 if T=1 and Y=1 (p11) is equal to:     0.99
The probability of having U=1 if T=1 and Y=0 (p10) is equal to:     0.99
The probability of having U=1 if T=0 and Y=1 (p01) is equal to:     0.99
The probability of having U=1 if T=0 and Y=0 (p00) is equal to:     0.97

The probability of having U=1 if T=1 (p1.) is equal to:     0.99
The probability of having U=1 if T=0 (p0.) is equal to:     0.98

ATT estimation with simulated confounder
Between-imputation standard errors
```

ATT	Std. Err.	Out. Eff.	Sel. Eff.
2248.620	298.107	1.114	1.685

Note: Both the outcome and the selection effect are odds ratios from logit estimations.

```
*** THIS IS THE BASELINE ATT ESTIMATION (WITH NO SIMULATED CONFOUNDER).


 The program is searching for matches of treated units within radius.
 This operation may take a while.



ATT estimation with the Radius Matching method
Analytical standard errors

---------------------------------------------------------
n. treat.   n. contr.         ATT   Std. Err.           t
---------------------------------------------------------

       80          93    2101.284     545.654       3.851

---------------------------------------------------------
Note: the numbers of treated and controls refer to actual
matches within radius



*** THIS IS THE SIMULATED ATT ESTIMATION (WITH THE CONFOUNDER U).

The probability of having U=1 if T=1 and Y=1 (p11) is equal to:     0.99
The probability of having U=1 if T=1 and Y=0 (p10) is equal to:     0.99
The probability of having U=1 if T=0 and Y=1 (p01) is equal to:     0.99
The probability of having U=1 if T=0 and Y=0 (p00) is equal to:     0.97

The probability of having U=1 if T=1 (p1.) is equal to:     0.99
The probability of having U=1 if T=0 (p0.) is equal to:     0.98


ATT estimation with simulated confounder
Between-imputation standard errors

-----------------------------------------------
      ATT    Std. Err.    Out. Eff.   Sel. Eff.
-----------------------------------------------

 2072.343     29.606        1.647       1.290

-----------------------------------------------
Note: Both the outcome and the selection effect
are odds ratios from logit estimations.
```

*** THIS IS THE BASELINE ATT ESTIMATION (WITH NO SIMULATED CONFOUNDER).

The program is searching for matches of each treated unit.
This operation may take a while.

ATT estimation with the Kernel Matching method

n. treat.	n. contr.	ATT	Std. Err.	t
80	93	1806.790	.	.

Note: Analytical standard errors cannot be computed. Use
the bootstrap option to get bootstrapped standard errors.

*** THIS IS THE SIMULATED ATT ESTIMATION (WITH THE CONFOUNDER U).

The probability of having U=1 if T=1 and Y=1 (p11) is equal to: 0.99
The probability of having U=1 if T=1 and Y=0 (p10) is equal to: 0.99
The probability of having U=1 if T=0 and Y=1 (p01) is equal to: 0.99
The probability of having U=1 if T=0 and Y=0 (p00) is equal to: 0.97

The probability of having U=1 if T=1 (p1.) is equal to: 0.99
The probability of having U=1 if T=0 (p0.) is equal to: 0.98

ATT estimation with simulated confounder
Between-imputation standard errors

ATT	Std. Err.	Out. Eff.	Sel. Eff.
1805.917	59.945	1.339	1.641

Note: Both the outcome and the selection effect
are odds ratios from logit estimations.

B. OUTCOME VARIABLE: FOOD EXPENDITURE PER ADULT EQUIVALENT

```
*** THIS IS THE BASELINE ATT ESTIMATION (WITH NO SIMULATED CONFOUNDER).

 The program is searching the nearest neighbor of each treated unit.
 This operation may take a while.


ATT estimation with Nearest Neighbor Matching method
(random draw version)
Analytical standard errors

---------------------------------------------------------
n. treat.   n. contr.       ATT    Std. Err.          t
---------------------------------------------------------

       80          43   1846.100     564.449      3.271

---------------------------------------------------------
Note: the numbers of treated and controls refer to actual
nearest neighbour matches



*** THIS IS THE SIMULATED ATT ESTIMATION (WITH THE CONFOUNDER U).

The probability of having U=1 if T=1 and Y=1 (p11) is equal to:     0.99
The probability of having U=1 if T=1 and Y=0 (p10) is equal to:     0.99
The probability of having U=1 if T=0 and Y=1 (p01) is equal to:     0.99
The probability of having U=1 if T=0 and Y=0 (p00) is equal to:     0.97

The probability of having U=1 if T=1 (p1.) is equal to:     0.99
The probability of having U=1 if T=0 (p0.) is equal to:     0.98



ATT estimation with simulated confounder
Between-imputation standard errors

-----------------------------------------------
      ATT    Std. Err.    Out. Eff.   Sel. Eff.
-----------------------------------------------

 1743.977     216.031        1.943       1.719

-----------------------------------------------
Note: Both the outcome and the selection effect
are odds ratios from logit estimations.
```

*** THIS IS THE BASELINE ATT ESTIMATION (WITH NO SIMULATED CONFOUNDER).

The program is searching for matches of treated units within radius.
This operation may take a while.

ATT estimation with the Radius Matching method
Analytical standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
80	93	1648.536	430.362	3.831

Note: the numbers of treated and controls refer to actual
matches within radius

*** THIS IS THE SIMULATED ATT ESTIMATION (WITH THE CONFOUNDER U).

The probability of having U=1 if T=1 and Y=1 (p11) is equal to: 0.99
The probability of having U=1 if T=1 and Y=0 (p10) is equal to: 0.99
The probability of having U=1 if T=0 and Y=1 (p01) is equal to: 0.99
The probability of having U=1 if T=0 and Y=0 (p00) is equal to: 0.97

The probability of having U=1 if T=1 (p1.) is equal to: 0.99
The probability of having U=1 if T=0 (p0.) is equal to: 0.98

ATT estimation with simulated confounder
Between-imputation standard errors

ATT	Std. Err.	Out. Eff.	Sel. Eff.
1628.597	27.052	1.970	1.714

Note: Both the outcome and the selection effect
are odds ratios from logit estimations.

*** THIS IS THE BASELINE ATT ESTIMATION (WITH NO SIMULATED CONFOUNDER).

The program is searching for matches of each treated unit.
This operation may take a while.

ATT estimation with the Kernel Matching method

n. treat.	n. contr.	ATT	Std. Err.	t
80	93	1433.846	.	.

Note: Analytical standard errors cannot be computed. Use the bootstrap option to get bootstrapped standard errors.

*** THIS IS THE SIMULATED ATT ESTIMATION (WITH THE CONFOUNDER U).

The probability of having U=1 if T=1 and Y=1 (p11) is equal to: 0.99
The probability of having U=1 if T=1 and Y=0 (p10) is equal to: 0.99
The probability of having U=1 if T=0 and Y=1 (p01) is equal to: 0.99
The probability of having U=1 if T=0 and Y=0 (p00) is equal to: 0.97

The probability of having U=1 if T=1 (p1.) is equal to: 0.99
The probability of having U=1 if T=0 (p0.) is equal to: 0.98

ATT estimation with simulated confounder
Between-imputation standard errors

ATT	Std. Err.	Out. Eff.	Sel. Eff.
1431.443	48.681	1.495	1.894

Note: Both the outcome and the selection effect are odds ratios from logit estimations.

C. OUTCOME VARIABLE: PER CAPITA TOTAL INCOME

```
*** THIS IS THE BASELINE ATT ESTIMATION (WITH NO SIMULATED CONFOUNDER).

 The program is searching the nearest neighbor of each treated unit.
 This operation may take a while.


ATT estimation with Nearest Neighbor Matching method
(random draw version)
Analytical standard errors
```

n. treat.	n. contr.	ATT	Std. Err.	t
80	43	2516.490	927.947	2.712

```
Note: the numbers of treated and controls refer to actual
nearest neighbour matches


*** THIS IS THE SIMULATED ATT ESTIMATION (WITH THE CONFOUNDER U).

The probability of having U=1 if T=1 and Y=1 (p11) is equal to:     0.99
The probability of having U=1 if T=1 and Y=0 (p10) is equal to:     0.99
The probability of having U=1 if T=0 and Y=1 (p01) is equal to:     0.99
The probability of having U=1 if T=0 and Y=0 (p00) is equal to:     0.97

The probability of having U=1 if T=1 (p1.) is equal to:     0.99
The probability of having U=1 if T=0 (p0.) is equal to:     0.98


ATT estimation with simulated confounder
Between-imputation standard errors
```

ATT	Std. Err.	Out. Eff.	Sel. Eff.
2689.804	276.204	10.191	2.310

```
Note: Both the outcome and the selection effect
are odds ratios from logit estimations.
```

*** THIS IS THE BASELINE ATT ESTIMATION (WITH NO SIMULATED CONFOUNDER).

The program is searching for matches of treated units within radius.
This operation may take a while.

ATT estimation with the Radius Matching method
Analytical standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
80	93	2731.824	691.566	3.950

Note: the numbers of treated and controls refer to actual matches within radius

*** THIS IS THE SIMULATED ATT ESTIMATION (WITH THE CONFOUNDER U).

The probability of having U=1 if T=1 and Y=1 (p11) is equal to: 0.99
The probability of having U=1 if T=1 and Y=0 (p10) is equal to: 0.99
The probability of having U=1 if T=0 and Y=1 (p01) is equal to: 0.99
The probability of having U=1 if T=0 and Y=0 (p00) is equal to: 0.97

The probability of having U=1 if T=1 (p1.) is equal to: 0.99
The probability of having U=1 if T=0 (p0.) is equal to: 0.98

ATT estimation with simulated confounder
Between-imputation standard errors

ATT	Std. Err.	Out. Eff.	Sel. Eff.
2725.365	43.004	1.121	2.108

Note: Both the outcome and the selection effect are odds ratios from logit estimations.

*** THIS IS THE BASELINE ATT ESTIMATION (WITH NO SIMULATED CONFOUNDER).

The program is searching for matches of each treated unit.
This operation may take a while.

ATT estimation with the Kernel Matching method

n. treat.	n. contr.	ATT	Std. Err.	t
80	93	2801.982	.	.

Note: Analytical standard errors cannot be computed. Use
the bootstrap option to get bootstrapped standard errors.

*** THIS IS THE SIMULATED ATT ESTIMATION (WITH THE CONFOUNDER U).

The probability of having U=1 if T=1 and Y=1 (p11) is equal to: 0.99
The probability of having U=1 if T=1 and Y=0 (p10) is equal to: 0.99
The probability of having U=1 if T=0 and Y=1 (p01) is equal to: 0.99
The probability of having U=1 if T=0 and Y=0 (p00) is equal to: 0.97

The probability of having U=1 if T=1 (p1.) is equal to: 0.99
The probability of having U=1 if T=0 (p0.) is equal to: 0.98

ATT estimation with simulated confounder
Between-imputation standard errors

ATT	Std. Err.	Out. Eff.	Sel. Eff.
2795.045	38.243	8.873	1.687

Note: Both the outcome and the selection effect
are odds ratios from logit estimations.

D. OUTCOME VARIABLE: PER CAPITA FARM INCOME

*** THIS IS THE BASELINE ATT ESTIMATION (WITH NO SIMULATED CONFOUNDER).

The program is searching the nearest neighbor of each treated unit.
This operation may take a while.

ATT estimation with Nearest Neighbor Matching method
(random draw version)
Analytical standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
80	43	2425.555	943.497	2.571

Note: the numbers of treated and controls refer to actual
nearest neighbour matches

*** THIS IS THE SIMULATED ATT ESTIMATION (WITH THE CONFOUNDER U).

The probability of having U=1 if T=1 and Y=1 (p11) is equal to: 0.99
The probability of having U=1 if T=1 and Y=0 (p10) is equal to: 0.99
The probability of having U=1 if T=0 and Y=1 (p01) is equal to: 0.99
The probability of having U=1 if T=0 and Y=0 (p00) is equal to: 0.97

The probability of having U=1 if T=1 (p1.) is equal to: 0.99
The probability of having U=1 if T=0 (p0.) is equal to: 0.98

ATT estimation with simulated confounder
Between-imputation standard errors

ATT	Std. Err.	Out. Eff.	Sel. Eff.
2681.911	293.755	4.693	1.025

Note: Both the outcome and the selection effect
are odds ratios from logit estimations.

*** THIS IS THE BASELINE ATT ESTIMATION (WITH NO SIMULATED CONFOUNDER).

The program is searching for matches of treated units within radius.
This operation may take a while.

ATT estimation with the Radius Matching method
Analytical standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
80	93	2893.685	673.659	4.295

Note: the numbers of treated and controls refer to actual matches within radius

*** THIS IS THE SIMULATED ATT ESTIMATION (WITH THE CONFOUNDER U).

The probability of having U=1 if T=1 and Y=1 (p11) is equal to: 0.99
The probability of having U=1 if T=1 and Y=0 (p10) is equal to: 0.99
The probability of having U=1 if T=0 and Y=1 (p01) is equal to: 0.99
The probability of having U=1 if T=0 and Y=0 (p00) is equal to: 0.97

The probability of having U=1 if T=1 (p1.) is equal to: 0.99
The probability of having U=1 if T=0 (p0.) is equal to: 0.98

ATT estimation with simulated confounder
Between-imputation standard errors

ATT	Std. Err.	Out. Eff.	Sel. Eff.
2887.582	35.861	2.987	1.450

Note: Both the outcome and the selection effect are odds ratios from logit estimations.

*** THIS IS THE BASELINE ATT ESTIMATION (WITH NO SIMULATED CONFOUNDER).

The program is searching for matches of each treated unit.
This operation may take a while.

ATT estimation with the Kernel Matching method

n. treat.	n. contr.	ATT	Std. Err.	t
80	93	2893.651	.	.

Note: Analytical standard errors cannot be computed. Use the bootstrap option to get bootstrapped standard errors.

*** THIS IS THE SIMULATED ATT ESTIMATION (WITH THE CONFOUNDER U).

The probability of having U=1 if T=1 and Y=1 (p11) is equal to: 0.99
The probability of having U=1 if T=1 and Y=0 (p10) is equal to: 0.99
The probability of having U=1 if T=0 and Y=1 (p01) is equal to: 0.99
The probability of having U=1 if T=0 and Y=0 (p00) is equal to: 0.97

The probability of having U=1 if T=1 (p1.) is equal to: 0.99
The probability of having U=1 if T=0 (p0.) is equal to: 0.98

ATT estimation with simulated confounder
Between-imputation standard errors

ATT	Std. Err.	Out. Eff.	Sel. Eff.
2891.189	37.278	2.326	1.540

Note: Both the outcome and the selection effect are odds ratios from logit estimations.

APPENDIX 4: COMPUTATION OF THE FOOD AND NON-FOOD POVERTY LINES*

Choice of the "Cost of Basic Needs" Method

The objective of a poverty line is to capture the basic needs necessary to meet minimum living standards. The cost-of-basic-needs [CBN] method addresses this objective through defining a consumption bundle – incorporating food and non-food items – that is adequate to meet the nutritional requirements, and estimates the cost of purchasing that consumption bundle. The important question related to this method is that of how to estimate the non-food component of the poverty line, in a way such that it captures the basic non-food requirements.

A standard approach, recommended by a number of researchers, has been to estimate the non-food component from the expenditure composition of households whose food expenditures are close to what is required to achieve the nutritional anchor. The standard approach for poverty line estimation using the CBN method is to first find a food consumption bundle of the population likely to be poor [called henceforth the "reference group"], and then estimate the cost of consuming this bundle using the prices faced by the reference group. The food expenditure thus derived constitutes what is referred to as the food poverty line. This method is described in detail below.

Defining the Food Poverty Line

In this paper, the method outlined above is implemented to derive the food poverty line in the following way:

[i] the households in the bottom 50% ranked by real per-capita total consumption expenditure are chosen as the reference group;

[ii] all food items for which information on expenditure, quantity and estimated calorie value are available are selected;

[iii] the aggregates of food expenditures and calorie intakes in the reference group are calculated;

[iv] the cost per calorie is derived by dividing the former with the latter;

[v] the food poverty line is defined at ETB 3731.2 per adult equivalent per year by multiplying the per calorie cost with the nutritional anchor per year [2200*365 Kcal]

Variable	Obs	Mean	Std. Dev.	Min	Max
cost_cal	90	.0046466	.0008211	.0021568	.0072547

The food poverty line, therefore, is calculated as:

Food Poverty Line= [Cost Per Calorie]*Nutritional Anchor Per Year]

= [.0046466]*[2200*365]

= 3731.2 ETB

---

* *Adopted from Department of Census and Statistics – Sri Lanka – 2004 June*

Defining the Non-Food Poverty Line

Deriving the non-food component of the poverty line is less straightforward than deriving the food poverty line, since it is not clear what level of non-food expenditures should be defined as basic needs. Important literature in this area proposes a range of seemingly appropriate nonfood poverty lines by linking non-food expenditures to food expenditures.

The lower bound of the non-food poverty line is defined as the ***average per capita non-food expenditure of households whose per capita total expenditure is close to the food poverty line***. The logic behind this definition is as follows. Such households' non-food expenditure should be considered as absolutely necessary for sustaining the minimum living standards, simply because any amount of spending on non-food items for such households necessarily reduces their food expenditure below what is required to attain the minimum calorie requirement.

The upper bound is defined as the ***average per-capita non-food expenditure of households whose per-capita food expenditure is close to the food poverty line***. The rationale for such an "upper bound" is as follows. The average non-food expenditures among households whose food expenditure is around the food poverty line is applicable to households that no longer need to sacrifice food expenditures necessary to meet the minimum calorie requirement in order to consume nonfood items. As long as the non-food poverty line is chosen from the range between the above lower and upper bounds, such an approach is justifiable. The total poverty line is then calculated by adding up the food poverty line and the non-food poverty line.

The Total Poverty Line

We avoid the two extremes for the non-food line– the upper and lower bounds – and instead select the average. Taking the average of the upper and lower bounds is a simple and straightforward selection, and acceptable as a practical solution. To estimate the upper and lower bounds, we use a simple non-parametric approach. For estimating the upper bound, the reference group is selected as households whose real per capita food expenditures are within an interval of plus or minus 10 percent around the food poverty line [i.e., between 3358.08 and 4104.32]. The median per-capita nonfood expenditure of this reference group is taken as the upper bound.

Estimating the lower bound differs only in terms of the definition of the reference group. This group now consists of households whose real per-capita total expenditures are in the interval of plus or minus 10 percent around the food poverty line.

Accordingly, the results from the non-parametric estimates [allowances] for the upper and lower boundaries for the non-food expenditure are:

1. Upper Boundary: 1346.7 ETB
2. Lower Boundary: 972.5 ETB

Summary of Poverty Lines @2014 Local Prices

Poverty Line	ETB/Year
Food Poverty Line	3731.2
Non-Food Poverty Line*	1159.6
Absolute Poverty Line	4890.8

*Non-Food Poverty Line= $\left[\frac{UpperBoundary + LowerBoundary}{2}\right]$

APPENDIX 5: FGT POVERTY INDICES

BASED ON ABSOLUTE POVERTY LINE

****

```
. ifgt pcexp_0 pcexp_1, alpha(0) pline(4890.8)

    Poverty index   :  FGT index
    Parameter alpha :  0.00
```

Variable	Estimate	STE	LB	UB	Pov. line
pcexp_0	0.260000	0.044084	0.172527	0.347473	4890.80
pcexp_1	0.062500	0.027234	0.008292	0.116708	4890.80

```
. ifgt pcexp_0 pcexp_1, alpha(1) pline(4890.8)

    Poverty index   :  FGT index
    Parameter alpha :  1.00
```

Variable	Estimate	STE	LB	UB	Pov. line
pcexp_0	0.031159	0.007249	0.016775	0.045542	4890.80
pcexp_1	0.010884	0.005591	-0.000244	0.022012	4890.80

```
. ifgt pcexp_0 pcexp_1, alpha(2) pline(4890.8)

    Poverty index   :  FGT index
    Parameter alpha :  2.00
```

Variable	Estimate	STE	LB	UB	Pov. line
pcexp_0	0.006173	0.001767	0.002666	0.009679	4890.80
pcexp_1	0.002588	0.001786	-0.000968	0.006144	4890.80

****

```
. difgt pcexp_0 pcexp_1, alpha(0) pline1(4890.8) pline2(4890.8)
```

Variable	Estimate	Std. Err.	t	P>|t|	[95% Conf.	interval]	Pov. line
pcexp_0	.26	.0440844	5.89778	0.0000	.172527	.347473	4890.8
pcexp_1	.05	.0219043	2.28266	0.0246	.0065371	.0934629	4890.8
diff.	-.21	.0477684	-4.39621	0.0000	-.3047829	-.1152171	---

```
. difgt pcexp_0 pcexp_1, alpha(1) pline1(4890.8) pline2(4890.8)
```

Variable	Estimate	Std. Err.	t	P>|t|	[95% Conf.	interval]	Pov. line
pcexp_0	.0311588	.0072489	4.29842	0.0000	.0167754	.0455422	4890.8
pcexp_1	.0087072	.0044884	1.93993	0.0552	-.0001988	.0176132	4890.8
diff.	-.0224516	.0081442	-2.75676	0.0070	-.0386115	-.0062917	---

```
. difgt pcexp_0 pcexp_1, alpha(2) pline1(4890.8) pline2(4890.8)
```

Variable	Estimate	Std. Err.	t	P>|t|	[95% Conf.	interval]	Pov. line
pcexp_0	.006173	.0017672	3.4931	0.0007	.0026665	.0096795	4890.8
pcexp_1	.0020703	.0014311	1.44665	0.1512	-.0007693	.0049099	4890.8
diff.	-.0041027	.0021831	-1.8793	0.0631	-.0084344	.000229	---

BASED ON MODERATE POVERTY LINE

****

```
. ifgt pcexp_0 pcexp_1, alpha(0) pline(6052.5)

    Poverty index   :  FGT index
    Parameter alpha :  0.00
```

Variable	Estimate	STE	LB	UB	Pov. line
pcexp_0	0.500000	0.050252	0.400289	0.599711	6052.50
pcexp_1	0.150000	0.040174	0.070036	0.229964	6052.50

```
. ifgt pcexp_0 pcexp_1, alpha(1) pline(6052.5)

    Poverty index   :  FGT index
    Parameter alpha :  1.00
```

Variable	Estimate	STE	LB	UB	Pov. line
pcexp_0	0.096257	0.012926	0.070609	0.121904	6052.50
pcexp_1	0.027893	0.009559	0.008867	0.046918	6052.50

```
. ifgt pcexp_0 pcexp_1, alpha(2) pline(6052.5)

    Poverty index   :  FGT index
    Parameter alpha :  2.00
```

Variable	Estimate	STE	LB	UB	Pov. line
pcexp_0	0.025806	0.004558	0.016761	0.034850	6052.50
pcexp_1	0.007996	0.003683	0.000665	0.015327	6052.50

****

```
. difgt pcexp_0 pcexp_1, alpha(0) pline1(6052.5) pline2(6052.5)
```

Variable	Estimate	Std. Err.	t	P>|t|	[95% Conf.	interval]	Pov. line
pcexp_0	.5	.0502519	9.94987	0.0000	.4002893	.5997107	6052.5
pcexp_1	.12	.0326599	3.67423	0.0004	.0551957	.1848043	6052.5
diff.	-.38	.0599326	-6.34046	0.0000	-.4989193	-.2610807	---

```
. difgt pcexp_0 pcexp_1, alpha(1) pline1(6052.5) pline2(6052.5)
```

Variable	Estimate	Std. Err.	t	P>|t|	[95% Conf.	interval]	Pov. line
pcexp_0	.0962567	.0129258	7.44687	0.0000	.0706091	.1219043	6052.5
pcexp_1	.0223141	.0077191	2.89076	0.0047	.0069977	.0376305	6052.5
diff.	-.0739426	.0148304	-4.98588	0.0000	-.1033693	-.0445159	---

```
. difgt pcexp_0 pcexp_1, alpha(2) pline1(6052.5) pline2(6052.5)
```

Variable	Estimate	Std. Err.	t	P>|t|	[95% Conf.	interval]	Pov. line
pcexp_0	.0258059	.0045582	5.66142	0.0000	.0167614	.0348504	6052.5
pcexp_1	.0063967	.0029603	2.16083	0.0331	.0005228	.0122706	6052.5
diff.	-.0194091	.005226	-3.71395	0.0003	-.0297786	-.0090396	---

APPENDIX 6: FOOD ITEMS AND CALORIC CONTENT

SN	Food Item	Kcal per kg	SN	Food Item	Kcal per kg
1	Maize	3620	12	Chick Peas	3570
2	Barley	3540	13	Fresh Milk	780
3	Sorghum	3470	14	Tomato	700
4	Wheat	3510	15	Potato	870
5	Horse Bean	3440	16	Garlic	1490
6	Edible Oil	9000	17	Cabbage	250
7	Cow Peas	3380	18	Onion	420
8	Teff	3450	19	Beef	2350
9	Berbere	3180	20	Coffee	20
10	Lentils	3700	21	Salt	0
11	Sugar	4000	22	Butter	7450

Source: Own Compilation

APPENDIX 7: CONVERSION FACTOR FOR TROPICAL LIVESTOCK UNIT [TLU]

SN	Livestock Type	TLU	SN	Livestock Type	TLU
1	Ox	1.0	7	Donkey [Adult]	0.7
2	Cow	1.0	8	Donkey [Young]	0.35
3	Bull	0.75	9	Horse	1.1
4	Heifer	0.75	10	Mule	1.1
5	Sheep & Goat [Adult]	0.13	11	Poultry	0.013
6	Sheep & Goat [Young]	0.06	12	Camel	1.25

Source: Yilma, 2005.

APPENDIX 8: DESCRIPTIVE SUMMARY OF SOME VARIABLES

Variable	Obs	Mean	Std. Dev.	Min	Max
hhage	180	45.79444	12.2992	25	80
hhsiz	180	5.383333	2.055854	1	14
pahhsiz	180	3.56	1.215615	1	8.9
adultlab	180	3.116667	1.547299	1	11
depratio	180	.9202652	.7443827	0	3
hheduc	180	1.372222	2.663703	0	13
oxhol	180	1.4	1.165615	0	6
livstock	180	5.398111	5.538902	0	24.645
pclivstock	180	.9920546	.9553969	0	4.929
landsiz	180	4.041667	2.828859	.5	13
landsizpc	180	.7753272	.5102053	.125	3
landsizpa	180	1.140651	.7231412	.1724138	3.703704
pcexp	180	7542.204	2801.588	3077	17842
paexp	180	11024.33	3538.008	3970.323	20776.3
pcfoodexp	180	5672.69	2203.178	2064	14208
pafoodexp	180	8286.638	2783.741	2705.807	17493.75
pcnonfoodexp	180	1866.352	781.1408	666	4174
panonfoodexp	180	2732.666	1058.365	1040.625	6531.818
pcincome	180	7651.782	4449.89	1166.667	27275
paincome	180	11256.87	6458.169	1891.892	40407.41
pcfarmincom	180	6799.631	4368.277	450	27275
pafarmincom	180	9979.798	6302.723	720	40407.41
pcoffarmin~e	180	852.1511	1181.825	0	7200
paoffarmin~e	180	1277.075	1777.665	0	10746.27