Mekelle University

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Can Microfinance Help to Reduce Poverty?

With Reference to Tigrai, Northern Ethiopia

By:

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A Thesis Submitted in Partial Fulfillment of the Requirements for the Master of Science degree in Economics

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DECLARATION

This is to certify that this thesis entitled "Can Microfinance Help to Reduce Poverty? With Reference to Tigrai, Northen Ethiopia" submitted in partial fulfillment of the requirements for the award of the degree of MSc., in Development Policy Analysis to the College of Business and Economics, Mekelle University, through the Department of Economics, done by Mr. Hailai Abera Weldeslassie, Id.No. FBE/PR0079/00 is an authentic work carried out by him under my guidance. The matter embodied in this thesis has not been submitted earlier for award of any degree or diploma to the best of my knowledge and belief.

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ABSTRACT

Background: Microfinance has broadened rapidly since its inception in the late 1970s, but scholars have divergent views whether and how much it helps the poor. This research reports on the assessment of the impact of participation in microfinance. However, it is difficult to establish a causal relationship between participation and poverty indicators, because of unobserved heterogeneity and reverse causality. These issues were largely avoided in the present study, which used propensity score matching and FE and RE methods to examine whether microfinance helps to reduce poverty.

Methods: Using the 2009 dataset, we first estimated propensity scores for participation on several pretreatment variables. We then matched clients and non-clients on the basis of these. Next, we estimated the average treatment effect, considering participation as a treatment, and participants as the treated group. We employed different matching methods to ascertain the robustness of any effects. Besides, for the (2007 & 2009) data set, we used the FE and RE models to fully address the two major problems.

Results: We found significant impact of microfinance on household productive assets, but we did not find significant impact on fixed assets and monthly expenditures in both cases.

Conclusions: the propensity score matching and panel data analyses identified microfinance as having direct effects on household productive and no effect on fixed assets and monthly expenditures.

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List of Acronyms

AEMFI	Association of Ethiopian Microfinance Institutions
Attk	Average treatment effect on the treated kernel density matching
Attnd	Average treatment effect on the treated nearest neighbors matching
Attr	Average treatment effect on the treated radius matching
Atts	Average treatment effect on the treated stratification matching
Coff.	Coefficients
CPI	Consumer Price Index
CSA	Central Statistical Authority
DECSI	Dedebit Credit and Saving Institutions
ETB	Ethiopian Birr
FE	Fixed Effects Models
FGLS	Feasible General Least Squares
FGT	Foster, Greer and Thorbecke
FINCA	Foundation for International Community Assistance
HHs	Female Headed Households
i. e.	That means /is
LDCs	Least Developed Countries
MF	Microfinance
MFI	Microfinance Institutions
OLS	Ordinary Least Square
PASDEP	A Plan for Accelerated and Sustainable Development to End Poverty
RE	Random Effects Models

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Executive Summary

As program evaluation is sensitive to the methods used in impact assessment, we employed a quasi-experimental survey design to resolve the endogeneity of program participation for the survey and panel households to bear out the consistency of results. Relying on the 2009 survey data and panel data sets (2007 and 2009), our study looks over the impact of micro finance on poverty situations of households, in which household monthly expenditures and productive and fixed assets are employed as measures reflecting households' poverty and asset accumulations. Considering its merit, we followed the expenditure approach as a good indicator of basic household poverty indicators by adopting the poverty line computed some years back in the same areas. In so doing, necessary adjustments are done to capture inflationary effects.

For the survey data, by and large, the propensity score matching (PSM) model and the treatment-effects model, a version of the Heckman sample selection model, are employed to estimate the poverty-reducing impacts of participation in microfinance on the aforesaid impact indicators. It is strongly believed that the methodologies we executed and the models utilized would allow for taking care of the sample selection bias associated with participation.

Notwithstanding some drawbacks cropping up from the unobservable potentially essential determinant of participation; its impact on the poverty status indicators and household fixed asset (with house) is found to be insignificant or significant in one of the various ATTs. This is also confirmed by the treatment-effects model. On the other hand, impact of participation in microfinance on household non-food expenditures on (education and personal care) and household per capita productive assets is found to be significant

Nevertheless, the impact assessments are subject to assumptions and selection bias cannot fully be controlled particularly in cross-sectional based impact analysis. In order to examine whether cross-section data impact analyses are affected by individual household heterogeneity or idiosyncratic disturbances, we perform panel data analysis. The panel household survey assists to estimate the program effects by using the household FE and RE methods, removing the bias due to endogeneity of program placement or participation. Results confirm the earlier findings that impact of households' participation in microfinance on reducing poverty and accumulating fixed assets (with house) is insignificant.

In sum, even if the ultimate objectives of DECSI programs are to reduce poverty via improving the economic situation of the low income and poor people based on voluntary participation, albeit some momentary impacts, poverty is rampant in the study areas in the presence of micro-finance programs. Of course, micro-finance alone may not provide the panacea for this high incidence of poverty.

1. Introduction and Theoretical Framework

1.1. Introduction:

Microfinance(MF) engrosses the provision of a broad range of chiefly financial services such as deposits, loans, payment services, money transfers, and insurance to poor and low-income households and their micro enterprises but also non-financial (social, marketing, training, environmental and other) services to the self-employed that are excluded by the formal banking system for many reasons including collateral requirements.

It has mushroomed as a focal tool of poverty cutback during the last four decades. NGOs, bilateral donor agencies, governments, multilateral agencies, individuals and the community shore up the development of Microfinance Institutions (MFIs). Though stated differently, some brief theoretical underpinning for possible links between micro-finance and poverty in various countries are the following (Dunford, 2006):

(i) Its potential to help for the poor undertake micro economic activities: by providing financial services; the poor can take on in productive economic activities and become entrepreneurs establishing, running and expanding their petty businesses;

(ii) Take new economic activities: by offering credit as an incentive and creating possibilities to the poorest to partake in various economic activities, to engender income and stimulate the economy;

(iii) Managing (minimizing) risks and vulnerability: by providing poor families with relatively cheap credit and convenient savings services that effectively help the family to have reasonable cash to lessen shocks and unforeseen misfortunes throughout the year to trim down the impact of the annual hungry season and other major social and private expenses;

(iv) MFI helps addressing gender sensitivity, by and large, building of social capital: to shore up self-help efforts at the family and community levels and to build up the voice of women and other marginalized groups as right holders and agents of local development;

(v) It facilitates the development of micro financial institutions that primarily benefit the poorest of the poor. The five points are crucial intermediary steps towards poverty reduction.

Historically, cheap credit was widely extended to petty farmers so as to create access to credit to adopt modern agricultural technologies, inputs and selected seeds though it did not meet the envisaged objective. To the contrary, rural elites and landlord reaped the fruits of the credit scheme rather than the poor farmers. Since there was no simple and customary mechanism of charging reasonable interest rate for nonfinancial services; the credit scheme suffered from exorbitant default. In addition, inefficient performance and waiting for persistent injection of subsidy led to many prominent economists to cast serious doubt on the success of the credit scheme and heavily castigated it as counter to economic logic (Adams, 1980). These economists asserted that agricultural loans can be carried out charging an interest rate in such a way that it covers costs and poor farmers are able to pay these interest rates and a need to transform the poor farmers form loan beneficiaries to clients. Historical development of microfinance in Ethiopia followed more or less similar trend to what is discussed above.

Scholars have divergent views on the functions of microfinance scheme to lessen poverty. Champions pronounce its audacious success stories and its effectiveness to alleviate poverty and they claim that participants do better than non-participants in the credit program. Employing household level panel data in Bangladesh, Khandker (2003) confirm that microfinance schemes have a sustained effect on reducing poverty among the participants and a positive spillover effect on non-clients.

Challengers cast serious doubt on the success stories. They went on saying that microfinance does not help the poor to break the vicious circle of poverty nor make poor nations rich (Cowen and Boudreaux, 2009). Despite its fast growth and huge financial flow to this sector, there are divergences of views whether microfinance helps to reduce /end poverty. Over and above, there are relatively few studies that evaluate the effect of microfinance on poverty in northern Ethiopia. This research aims to provide empirical evidence on the relationship between microfinance and poverty employing 361, 326 households in 2007 and 2009 respectively.

1.2. Statement of the Problem

The establishment of the Grameen Bank as a micro-credit delivery model has motivated many LDCs to replicate similar and/or modified credit and saving programs. Apart from that, the promising premises drawn the attention of Governments, NGOs, financial institutions, donors and individuals entice their mind and start to believe that allocating vast resource to this sector can help to eradicate poverty and has positive impact in enhancing the living standard of the poor and a lot of attention has been given to those micro-credit borrowers. While there are evidences of success stories, the challenges are equally eye-catching.

Scholars have divergent views on the functions of microfinance scheme to lessen poverty. The champions pronounce the audacious success stories of the scheme and its effectiveness to alleviate poverty and they claim participants do better than non-participants in the credit program in per capita income, per capita expenditure, and over all wellbeing of the society Khandker (2001, 2003). Empirical findings, (e.g. Zaid, 2008; Dunford, 2006; Pitamber, 2003; Amaha, 2002) confirmed the positive contribution of microfinance.

Nonetheless, challengers cast serious doubt particularly on the type and extent of the successes. Contrary to this, they contend, microfinance does not address the economic problem of the poorest, neither does it empower women. They further claim that if it address at all, either it benefits the middle poor or it helps the poor to keep their soul in its body (Cowen and Boudreaux, 2009*; Kondo* et.al., 2008; Imai et al. 2006; Morduch, 2005; Shreiner, 2002) are some behind this proposition.

Considering these divergences of thoughts, this study analyzes if micro credit scheme helps to reduce poverty and explore its impact on household productive and fixed asset holdings of clients. Moreover, it examines its impact on some basic household poverty indicators (household food and non-food expenditures). In addition, it is believed that not only the correlation between microfinance and poverty but also the approaches to analyze impact are complex and controversial and are still open-ended questions. So, this study provides further empirical evidences on this and other relevant issues.

In sum, the sector is dynamic and appropriate refinements are expected in the theoretical, methodological, empirical and policy research methods and approaches. This study provides further empirical evidences on the poverty-reducing effects of access to microfinance and its impact on clients using data (both cross-sectional and panel) collected from four rural 'tabias' namely, Tsekanet, Rubafeleg, Arato and Siye which are located in four woredas of different zones of Tigrai Region.

1.3. Purpose of the study

The study will help to formulate pragmatic approaches in scrutinizing whether microfinance schemes help to reduce poverty. As reducing poverty is the top most agenda of the Ethiopian Government and relatively huge resource is earmarked to the microfinance sector, there is a need to continuously assess its impact. There is a room for further investigation as there are controversies on whether microfinance helps to reduce poverty or not. Given the widespread poverty, policy-interventions should be there to minimize or eliminated this deep rooted poverty and the impact of microfinance as antipoverty program should be evaluated tirelessly. Keeping these notions in mind; conducting research and suggesting ways to improve the usefulness of these institutions are timely and appropriate.

1.4. Research Hypothesis

Our main hypothesis is that participation in microfinance reduces poverty defined by some basic household poverty indicators (household monthly expenditures) and has positive impact on household productive and fixed assets.

1.5. Research Objectives

The general objective of this study is to examine if participation in microfinance helps to reduce poverty and its impact on households' productive and fixed assets holdings. The specific objectives are: (1**)** to explore if microfinance helps to alleviate poverty (2**)** to analyze if microfinance has significant impact on households productive and fixed household assets ownership.

1.6. Limitations of the study:

Despite our unreserved effort to minimize endogeneity or exogeneity program placement and participation biases by using some of the most parsimonious methodologies; still, it is cloudy to accredit success or blame failure for microfinance alone. It is so because, many development package programs are going on in the study areas and singling out its impact on the aforementioned variables is difficult. With this, the panel data set employed are only for two years and difficult to fully control the individual household heterogeneity and time effect idiosyncratic disturbances. Therefore, a general equilibrium impact analysis method that includes all package programs and helps to identify the partial effect each one and utilizes some more years' panel data is preferable.

Finally, we only used rural household and panel data for our analysis. However, it is good to consider urban and rural household panel data to address market issues and rural-urban linkage simultaneously. There is a strong bond between poverty and environmental degradation. The underfed and ravenous poor are swelling the pressure to force immediate solutions. This leads to reckless efforts to exploit natural resources and the rapid increase of agricultural production. Devastation of nature leads to a downward spiral hunger, plunder, food, negative and irreversible changes to the environment, and hunger. The root cause for this is extreme poverty. Interventions that assist to reduce poverty in turn minimize overexploitation of environmental resources. So, nexus between the two should be explored which in not treated in this paper. Finally problem of missing elements from the sampling frame is another limitation of this paper.

2. Literature Review

In this part, we briefly outline previous studies giving more emphasis to the most recent ones. Furthermore, we shed light on records pertinent to this topic.

2.1. Background

Although the development of microcredit, as we know today, is relatively a recent phenomenon; studies show that it has been practiced for more than three centuries, such as the Irish Loan Fund and FWR of Germany (CGAP, 2003*)*. It was also introduced into Asia (e.g. the People's Credit Bank) and Latin America in the 19th century (CGAP, 2003*)*.

Beginning from the 1980s the world has seen a massive movement against the subsidy- oriented provision of agricultural credit and this marked as a basis for the introduction of business like microfinance. The period 1980–1990 defined a minimalist neo-liberal role of the state that allowed for the free working of the market and a conviction that it will trickle down to the poorest. In this period, we see the emergence of mf in many countries of the world.

Microfinance service provision broadened and expanded to include other services like saving, insurance and money transfer. This period was special where many microfinance institutions flourished. Grameen Bank, BancoSol, and FINCA are the most popular of the lot. After the failure of the Green Revolution as a development program particularly in Africa; the world witnessed incessant growing enthusiasm for promoting microfinance as antipoverty intervention and some scholars ruminated it as a panacea to end poverty (CGAP, 2003).

Any discussion of microcredit will not be complete if one overlooks the innovative thought and practical contributions of Professor Muhammad Yunus. Modern-day microcredit began in 1976 when Yunus, then an economics professor at Bangladesh's Chittagong University, left academia, went to the village of Jobra and lent $27 to a group of 42 villagers to instigate soap-making and basket-weaving petty business (Lepeska, 2008).

Today, microfinance is conceived to be the principal supporter of millions where well over 100 million are believed to have access. It prevails in every quarter of the planet and is considered by many as the best program to fight poverty village by village as it touches almost all Millennium Development Goals (Dunford, 2006).

2.1. 1. Evolution of Micro Finance in Ethiopia

Since the cataclysmic drought of 1984/85, many NGOs and donors have endeavored to pump financial resources in to the village economies without actually making out and prioritizing the actual felt needs of small households. This can be taken as the origin of Micro Credit in this country albeit some studies reveal that the practice of micro credit in Ethiopia can be thought of being introduced after the failure of the subsidy-driven provision of agricultural loans during the package programs of the 1970s (Zaid, 2008).

Apart from this, the local and international NGOs activities caught up in disbursing financial resources in the remote village, increased the number of informal sectors in the country but there was no uniform lending interest rate on different parts of the society. All of the sudden, the program did not inspired the saving culture of farmers owing to the miniature interest rate the informal institutions used to pay to depositors. Even, sometimes it was not clearly specified. These messes up and the canonical argument of MFIs, (as the main tool to alleviate poverty) paved the way for their establishment.

Finally, it was also to marshal the rural unused resources to the revenue engendering activities to craft employment openings, to trim down unemployment by boosting economic growth.

After the promulgation of proclamation No.40/1996, there are about 29 MFIs legally registered in all corners of the country serving 2.2 million active borrowers with an outstanding loan portfolio of approximately 4.6 billion birr (AEMFI, 2009). DECSI is one of those institutions licensed as per this proclamation.

2.1.2. Development of Microfinance in Tigrai

Relief Society of Tigrai (REST) has been engaged in development programs principally in environmental rehabilitation, agricultural development, aid, social development, rural water supply and credit and saving services (Woldehanna et al., 2003). The pillar objectives of these programs are to improve the economic situation of the low income and poorest people in the Tigrai Region. Besides, to accomplish independence based on bona fide participation of the people. By embarking upon and surmounting the core grounds and consequences of poverty through advancing sustainable rural development.

In 1994, REST put into action Rural Credit Scheme in Tigrai, accessible and affordable micro financing services in the poor areas. When the scheme's operational coverage and client outreach was increasingly widened, institutional restructuring became indispensable. The Rural Credit Scheme was thus required to be registered under the National Bank of Ethiopia and was allowed by law to form a micro financing institution. Accordingly, the Rural Credit Scheme was changed into a new institutional form under the name Dedebit Credit and Savings Institution (DECSI) S. C. since March 1997(Woldehanna et al., 2003).

2.1.2.1. DECSI's Products

Since its establishment in 1994, DECSI has been providing the following three loan types: Regular, Agricultural Input and Agricultural Package Loans. Besides, it provides saving services such as compulsory deposit of group and center saving, voluntary deposit from loan clients and the public at large and Pension Payments. Recently, DECSI has expanded its services particularly in the area of package (mainly individual) and enterprise loans.

2.2. Synopsis of Conceptual Review

On the philosophical spectrum of microfinance; we scrutinize the thoughts of academia that have explored many aspects of the theories and practices of microfinance. It may be appropriate to start from the philosophical controversies regarding microfinance and particularly those of the poverty and the sustainability camps.

The nucleus view of the poverty camp gravitates around social business. They posed the question how do you solve the problem of poverty in this modern day and age? Yunus unearths a possible solution in a thought termed "social business," at which you run business not by profit motive but to maximize social goods the most deprived call for; the concept of businesses with social values rather than monetary aims (Yunus, 2007).

Yunus and his followers maintain that the free market is an astonishingly powerful tool to bring about opulence and provide products to consumers. Market actors, aiming primarily to maximize profits, continuously find ways to do more with less. Still, the economic prosperity brought about by the free market they claim has brought with it a worsening of social problems. The reason for this is that it is not the purpose of the capitalist economy to solve social problems and therefore the free market may exacerbate poverty, disease, pollution, corruption, crime, and inequality.

This is so since the most marginalized who face multifaceted crises are out of the game in the profit motive market mechanisms where goods and services are provided to those who can afford for the ticket. Forerunners of this thought further aver that the institutions and incentives in the market economy are inherently deficient in that they do not provide a means for solving poverty. Instead of bringing the benefits of the market to the poor, market actors seem to compete in providing more advanced and expensive products to consumers in already prosperous countries. The dominant thought is governed by a novel type of entrepreneur whose inspiration is not profit but to "do well," a motivation that will lead not to profit-maximization but to social business. The social business is a competitive enterprise restricted from making losses or paying dividends working to provide charitable rather than business goals. The social business operates as a business enterprise, with products, services, customers, markets, expenses, and revenues but with the profit-maximizing principle replaced by the social-benefit principle. It creates variety of opportunities for the poor and it brings the benefits and advantages of free-market competition to social improvement.

Besides, proponents of the poverty camp not only rely heavily on the ability of globalization and the free market to bring more benefits to the poor than any other conceivable alternative; but the concept also rely on a fundamental confidence that poor people are endowed with a latent ability to get out of poverty. Thus, what is keeping them from doing so is the lack of an enabling environment. The problem is therefore structural in the market economy, but in a way that can easily be corrected by introducing a social aspect of market action that recognizes the multi-dimensional needs of the poor.

Additionally, they vie; with microcredit, life becomes more endurable and easier to manage. If a poor family is able to keep a child in school, send someone to a clinic, be able to purchase seeds for future productions, be able to buy forage to rescue the lives of live-stocks; though its well-being does not improve, or improves only marginally the role of credit is still undeniable. This is a big part of the story why poor people are demanding greater access to microcredit loans. Other arguments pertinent to the above hinge around pronouncing the significance of microfinance in bringing women as the main engine of economic activity by enabling and empowering them.

Precursors of the sustainability camp on the other flipside firmly challenge the belief of social business and poverty camp on the ground that not only microcredit burdens the very poor with debt, but also it leads to sterilization of capital by killing incentive to invest and making it very passive (Morduch, 2000). They explicate their propositions by presenting these concepts: subsidized credit programs to benefit the poorest are inefficient and ultimately bound to fail, and most often end up in the hands of non-poor households. Whereas, financially-sustainable programs can achieve greater scale than subsidized programs and are more feasible in poverty reduction. Mobilizing savings is not likely to make sense for subsidized credit programs (Morduch, 2000). On top of that, they went on saying microfinance is merely a painkilling measure, which does nothing to bring about the large societal reforms necessary to reduce poverty and even serves to preserve the status quo, by making the lives of the poor more tolerable (Morduch, 2009; Cowen,2009).

The crux of the matter is, as businesses that can generate jobs for others are the best hope of any country trying to put a final blow to relinquish poverty but one cannot achieve this with fragile petty business. Unremitting economic growth entails companies that can make gigantic investments and building a factory and that can exploit the economy of scale that make workers more productive and ultimately ensures economic transformation. Furthermore, other exponents of this camp, on the practical side, vehemently tell off “credit is a human right” Yunus’s philosophy as ridiculous (Zeitinger and Chen, 2009).

First, credit is for the one that has an opportunity to make something productive out of it. This is in a way creating wealth, more than wiping out poverty.

Secondly, target population for this program should be the working poor people who are well nourished and have a level of well-being that allows them to slot in economic activity where microfinance is effective.

Thirdly, do away with philanthropic capital, the biggest obstacle to commercialization of the sector by garbling the market and not only by filling channels that might otherwise draw commercial investors but also by keeping unsustainable programs alive.

Fourthly, they attest that there is a big difference between undemanding capitals contributed by donors, who expect nothing in return and demanding capital which requires transparency of financial reporting and an appropriate reward for risk taking.

Fifthly, they believe that there is a role for philanthropic capital in carefully delineated areas like funding research and building infrastructure. However, building “Museum of poverty!” for our next generation is outrageous! To claim that microfinance is going to solve poverty is a myth. From ancient Greece to today, poverty has been with us and it will occupy us forever. Finally, they assert that those who are pro-poverty reduction and advocators are actually politicians more of visionaries and not reactionaries.

Therefore, instead of considering credit as a human right we must believe that it means one owes something and can get overly indebted. In response to the bunch of critics, forerunners of the poverty camp and social business thought determinedly shield their stand and went on saying- "*Microcredit is not a miracle cure that can purge poverty in one fell pounce; while combined with other innovative programs that unleash people's potential, microcredit is an essential tool in our search for a poverty-free world*" (Yunus, 2003).

Furthermore, advocators of the social business philosophy claim that poverty alleviation involves a series of tools like education, health care, environmental rehabilitation and protection, political and macroeconomic stability, good governance and state of business, zero tolerance to corruption and so forth but microfinance is just one variable in the sets of equations. To this end, we should not perceive microcredit as a transformational panacea that is going to lift people out of poverty. If there are little pockets here and there of people who are made better off by the credit scheme we should not diminish its significance even if the average effect is weak. Indeed, microfinance may make some poor better off; but it cannot make poor countries richer (Karlan, 2009; Hussain, 2008).

Other set of scholars (third group) take middle stand and claim that the reality is more complicated; microloans are often used to smoothen consumption tiding borrowers over in times of crisis. They're also often used for non-business expenses, such as a child's education. But it's also because most micro businesses aren't looking to take on more workers. The vast majorities have only one paid employee and microfinance rarely generates new jobs for others (Morduch, 2005; Boudreaux and Cowen, 2009).

These scholars (third group) appreciate the contribution of microfinance specially in serving the poor yet the reprimand is its malfunction to instigate SMEs. Microloans have achieved resounding triumphs, what (Boudreaux and Cowen, 2009) call "Micro Magic." But the excitement of their promise has made them desert the enterprises that could be real engines of macro magic. They believe that the poor could be good entrepreneurs if they have the access to microfinance; but thinking that everyone is, and should be, an entrepreneur leads us to underrate the virtues of larger businesses and of the income that a steady job can provide. They suggest there should be ranges of loans and business models from Bank to community or household loans and credit services (Boudreaux and Cowen, 2009; Chen, 2005).

To sum up, poverty is a multi-dimensional problem and hence needs multi-faceted intervention. Breaking the vicious circle of poverty demands integration of other development programs (household package, agricultural extension, selected seeds, irrigation and water source development) good infrastructure, political stability and good macroeconomic environment, sound business plan and management. In so doing, special care should be given to assess its impact as it may be impossible to disentangle the impact of each and this helps not to over or underrate the impact and to be prissy as such reduction in poverty is not due to proliferation of microcredit alone. In addition, we presume microfinance scheme is not a single orbit program but needs continuous training and follow-up and discussions to change the psychology of clients, poor culture and work ethics as it may not flinch ahead with all these restraints and close watch what happens before; during and after you give a loan to a client is mandatory.

2.3. Empirical Review

There exist a wealth of literature on microfinance scheme since its inception and we cannot be exhaustive to cover all but the most relevant to our study. We will give special emphasis to some evidences to the success stories of microfinance scheme which contend that throughout the world in serving and those that are partially or fully excluded from the formal banking; helping to reduce poverty and empowering the powerless specially women on one rift; and those who display the tremendous challenges and impediments that led them to mission drift on the other corner and emerging thoughts against the poverty camp and a paradigm shift to issues of sustainability .

Poverty reduction has been one of the major aspirations of development planning since 1950s-60s and the planning process has been sensitive to the needs of the poor. Accordingly, the development attempts have been directed in creating adequate livelihoods and provision of services for a better quality of life for the poor. It is appreciated that poverty is an outcome of multiple deprivations and it is not simply a matter of inadequate income but also a matter of low literacy, short life expectancy, lack of basic needs such as drinking water, persistent drought (famine), lack of self-esteem and social-exclusion. Since these deprivations are inter-related, a comprehensive and integrated approach may eliminate poverty and ensure optimal utilization of human resources for sustainable development.

Thus, multi-pronged and convergent approaches with proper targeting are deemed essential for elimination of poverty. Well designed poverty alleviation programs, if effectively implemented, not only supplement the poverty reducing effects of growth but also could promote pro-poor growth. Several poverty alleviation programs have been in place for a long time now and one of them is microfinance. The programs and schemes have been modified, consolidated, expanded and improved over time (Cole, et al., 2008).

The establishment of the Grameen Bank as a micro-credit delivery model motivated many LDCs to replicate similar and/or modified credit and saving programs. Apart from that, the promising premises drawn the attention of Governments, NGOs, financial institutions, donors and individuals entice their mind and start to believe that allocating vast resource to this sector can help to eradicate poverty and has positive impact in enhancing the living standard of the poor and a lot of attention has been given to those micro-credit borrowers.

There is resounding triumph in the development of MFIs and fabulous achievements in reaching the bottom poor. However, the pitfalls are equally monstrous. Empirical researches conducted in Asia (Kondo et al., 2008; Imai et al., 2006; Yoshida and Zaman, 2005; Dwivedi, 2005; and Khawari, 2004): Latin America (Cowen and Boudreaux, 2009; Morduch, 2008 and Shreiner, 2002) and Africa (Zaid, 2008; Pitamber, 2003; Amaha, 2002) have well documented the said assertion. To corroborate this let's consider current developments: very recent reports by State of (Micro credit Summit Campaign, 2009) reveals that in this year, more than 150 million of the world's poorest families received a micro loan and achievement of this goal touches the lives of an estimated half a billion.

When the United Nations designated 2005 as the International Year of Microcredit, heated controversies, whether should it be year of microfinance or microcredit, among supporters of poverty and sustainability camps reached high stage and this year can be considered as a land mark for the mf schism (Morduch, 2005).

The broader shift towards the profit model began in the nineties, when Acción International, a network of Latin-American institutions, concluded that "commercialization was the only way microfinance could serve large numbers of people, because commercial enterprises could tap the capital markets for the funds they needed to grow" (Morduch, 2005). As a result, BancoSol, an Acción affiliate, transformed itself from a nonprofit into the first private commercial bank in the world dedicated exclusively to microfinance and dozens of other institutions have followed this foot step (Morduch, 2005).

Many outstanding specialists in this sector consider the entrance of the profit motive as threats than potential sources of capital and pronounce the issue of humanity. It is inhuman and unfair to see a world where a few hundred million people enjoy access to all the resources of the planet, while over a billions struggle to survive. Yunus cites one study that concluded in the year 2000, "*the richest 1 percent owned 40 percent of the world's assets, and the richest 10 percent owned 85 percent. By contrast, the bottom half of the world's population owned barely 1 percent of the planet's assets*" (Yunus, 2007).

On the practical front, the underline reasons behind the failure stories pivot around not only the fungible nature of money (Zaid, 2008). It is observed that clients are using microcredit for consumption and not for business. Moreover, it is also a means to settle the existing debt and it eventually entails debt accumulation. It is so, since most borrowers are self-employed and work in the informal sector of the economy; their incomes are often erratic; small, unexpected expenses can make repayment impossible in any given month or year.

In the rural area, farmers have seasonal incomes and little cash for long periods of time. Recent studies have witnessed that microloans are often used to finance consumption and domestic expenses. Cowen and Boudreaux (2009) found that many borrowers use the money on personal expenses, fixing their roof, sending kids to school, purchasing a mobile phone - rather than on a small business.

Proponents of the sustainability camp defend their stand by asserting the poor are not amenable to microcredit but to other direct aids and the productive middle poor have been overlooked for centuries while the forerunners of the poverty camp try to redirect cash to the passive strata of the society. Recently, even the most celebrated success of microcredit playing hugely important role in allowing women to participate in productive economic activities is challenged and there are astonishing findings that microcredit enslaves women than to free them and women's empowerment through this scheme is dried out (Rozario, 2007). According to Rozario (2007) microcredit women clients are harassed, bitten and harmed by their husband as they consider them as source of capital in the form of dowry. Even this problem is exported to the women's family and many household were indebted while trying to fulfill this demand. .

Considering these divergences of thoughts and research findings, this study analyzes if micro credit scheme helps to reduce poverty and explore its impact on household productive and fixed asset holdings of clients after participation in microfinance. Moreover, it examines impact of microfinance on some basic household poverty indicators (household total and food expenditures) and productive and fixed asset holdings. What is more, we strongly believe that not only the correlation between microfinance and poverty but also the approaches to analyze impact are controversial and are still open-ended; so this study provides further empirical evidences on the poverty-reducing power of access to microfinance and its impact on the aforementioned interest variables.

Moreover, Ethiopia's top priority agenda of reducing/ending poverty (PASDEP, 2006) and the remarkable achievement of this sector that it reached 2.2 people directly and many more indirectly (AEMFI Report, 2009), and the challenges in the other flip- side (anti microcredit movement); not only that there is room to conduct research on this issue that many variables can be considered for analysis. On top of these divergences, there is lack of sufficient research on how microfinance scheme functions and whether they are really reducing poverty on the practical aspect in Ethiopia.

In general, the sector is dynamic and appropriate refinements are expected in the theoretical, methodological, empirical and policy research methods and approaches. This study provides further empirical evidences on the poverty-reducing effects of access to microfinance and its impact on clients using data (both cross-sectional and panel) collected from four rural 'tabias' namely, Tsekanet, Rubafeleg, Arato and Siye which are located in four woredas of different zones of the Tigrai Region. We have tried to update the most recent empirical findings, and in chapter four we make the analysis vis-à-vis the empirical researches and we furnish more evidences to explore if what works somewhere else can also work in the show case.

3. Data, Methodology and Variables

3.1. Site Selection and Description

The study is made in four tabias, namely Arato (Enderta-Woreda) in Southeastern zone, Tsenkanet (Saese-tsaeda-Emba-Woreda), Rubafeleg (Atsbi-Womberta-Woreda), both in Eastern zone, Siye (Tanqua-Abergele-Woreda) in Central zone. These sites are selected by MU-IUC (a ten year collaboration program between the Mekelle University, Ethiopia and the Flemish Inter University Council, Belgium). All tabias are located within 150 kms from the heart of the state city (Mekelle-Tigrai). Arato is located 18 km east; Rubafeleg 56kms northeast; Tsenkanet is 57km north and Siye 92km west of Mekelle. Considering climate, Arato and Tsenkanet are in the midland (weina dega) agro-ecological zone (1500-2300m), Rubafeleg has a temperate (dega) agro-ecology (2300-3200) and Siye is located in the lowland (kola) agro-ecological zone (below 1500). Their main stay is predominantly mixed farming (crop production and livestock holding. For details, (see Fredu, 2008)

3.2. Data sources and Sampling Method

The data for the study comprise household survey and Focus Group Discussion (FGD). Data analysis was based on household data collected in 2007 and 2009. For the focus group discussion (FGD), first we collected a list of households for each tabias separated by kushet from local administrators. Next, we divided each local administration (tabia) in to 4 villages with the help of the Kebelle administration and local coordinators and then we selected one village by lottery method. Finally, we selected 8 households randomly from each tabias for the FGD.

3.3. Framework: Assessing Impact of MFIs on Poverty Status Indicators and Household Productive and Fixed Asset Holding

To begin with, in order to outline the extent of poverty of the study areas we shed light on poverty measures such as (Foster, J. E., et. al., 1984)

i. Head count index: $P_0 = {}^1\!/_N \sum_{i=1}^{N} I(y_i \prec Z)$

ii. Poverty gap index: $P_1 = {}^1\!/_N \sum_{i=1}^{N} \frac{G_i}{Z}$

iii. Poverty severity: $P_2 = {}^1\!/_N (\sum_{i=1}^{N} \frac{G_i}{Z})^2$ The three equations above can be captured in one equation given by the FGT

$$P_\alpha = {}^1\!/_N (\sum_{i=1}^{N} \frac{G_i}{Z})^\alpha, \ (\partial \geq 0)$$

$G_i = Z - Y_i$, $Z =$ poverty line, $Y_i =$ household consumption expenditures

And average time taken to exit (average exit time from poverty) $W = {}^1\!/_N (\sum_{i=1}^{q} (\ln(z) - \ln(y_i)))$ this is the Watt index, dividing this by economic growth gives us average exit time from poverty.

That assessment will typically be based on a set of poverty lines (for our study, we assumed the poverty line, which aims to give the minimum "standard of living" needed to be non-poor) computed by (Fredu, 2008) in the same sites. We have undertaken all necessary price adjustments as there was alarming price soaring in Ethiopia in 2008/09 due to internal and external reasons. Based on the Cost of Basic needs approach, (Fredu, 2008) obtain 828 ETB and 1008 ETB for the food and total poverty lines.

3.4. Empirical Model and Estimation Procedures

Our main hypothesis is that participation in microfinance reduces poverty defined by some basic household poverty status indicators (household expenditures) and has positive impact on household productive and fixed assets. The principal challenge in impact appraisal is fundamentally finding a valid counterfactual against which the treatment group is compared (Kondo et al., 2008). To solve this basic appraisal problem that arises from the impossibility of observing what would have happened to a given person in both states of nature where someone receive a treatment and the state where he or she does not, we use comparison group. Nonetheless, we cannot simply statistically compare those impact indicators (household expenditures and productive and fixed assets) for microfinance clients and non-clients owing to the sample selection bias. It may arise from either the self selection where the households themselves decide whether they should participate in programs carried out by microfinance, which depend on household observable and unobservable characteristics; and the program endogeneity that may possibly emanate from those who execute the microfinance programs in selecting a group or households based on some predetermined criteria.

In the regression context, self-selection bias occurs when one or more explanatory variables are correlated with the residual term of outcome equation or selection bias arises because the "treatment" was correlated with the error term in the outcome equation. Thus, self selection bias can be thought of as a form of omitted variable bias (Heckman, 1979).

We need to employ statistical remedies to the inherent problems of causal inference. To do so, we can introduce a reduced for of model defining household expenditures equation and participation in microfinance as follows:

$Y_i^D = H^D(X_i) + \varepsilon_i^D \; \mathrm{D} = 0,1,$ --- (1)

$D_i = L(Z_i) + \eta_i$ -- (2)

where Y_i^D stands for households' i who participate in microfinance (D) expenditures on food and non-food items. Thus, Y_i^1 and Y_i^0 denote expenditures in household i for participants and non-participants respectively. Expenditure depends on vectors of observable variables X_i and and vector of unobservable variables, ε_i^D [1]

D_i binary response(=1) if household i participates in microfinance and(=0 otherwise).

---

[1] By assumption, $E\ (\varepsilon_i^{\ 1}) = 0$ and $(\varepsilon_i^{\ 0}) = 0$ for the sample households and $E(\varepsilon_i^D | X_i) = 0$

Z_i is a subset of X_i and includes observed pretreatment variables influencing participation; other unobserved household specific factors are summarized by the random variable η_i.

In a counterfactual framework, the quantity of interest is the average treatment effect on the treated, defined by Rosembaum and Rubin (1983) as

$\alpha = E\left(Y_i^1 - Y_i^0\right)$ -- (3)

A fundamental problem in estimating the causal effect equation(3) is that we observe only Y_i^1 or $\mathrm{Y_i}^0$, and not both for each household. Formally, we can write what we observe as follows:

$Y_i = D_i Y_i^1 + (1-D)Y_i^0 \quad \mathrm{D} = 0, 1.$--- (4)

Accordingly, we can rewrite the expression for α as follows:

$\alpha = p.\left[E\left(Y^1 \middle| D=1\right) - E\left(Y^0 \middle| D=1\right)\right] + (1-p)\left[E\left(Y^1 \middle| D=0\right) - E\left(Y^0 \middle| D=0\right)\right]$-------- (5)

Where p is the probability of observing a household with D=1 in the sample. Equation (5) says that the effect of participation in microfinance for the sample is the weighted average of the effect of participation in microfinance in the two groups of households, the treated group (participants) and the control group (non-participants).

To appropriately estimate the unobserved counterfactuals and make causal inference, we employ non-parametric statistical matching methods like Propensity Score Matching (PSM). The Instrumental Variable (IV) model; or the Heckman Sample Selection Models can be employed to take care of the aforementioned possible bias (for details see Zaid, 2008). In this paper, it is true that all rural dwellers are eligible for microfinance loans by definition and as practice and program endogeneity can be minimized that way. We can control or minimize only the self selection bias utilizing the PSM.

We do not use IV model as it assumes linearity and difficulty of finding a valid IV. A remedy to the drawbacks of the alternatives method of impact analysis in obtaining the counterfactual in order to address the problem of missing data is the PSM. In a seminal work, Rosembaum and Rubin (1983) proposed that PS can be used as a means of reducing the bias in the estimation of treatment effects with observational data sets. In the PSM, the first stage identifies a function matching of the proximity of one household to another in terms of observable household characteristics and then observations are grouped in order to minimize the distance between matching cases. For detail discussion of this methodology, see (Becker and Ichino, 2002; Wooldridge, 2002; Dehejia and Wahba, 2002; Smith and Todd, 2005; Todd, 2008; Zaid, 2008; Fredu, 2008 and Ravallion, 2008).

3.5. Propensity Score Matching (PSM)

PSM estimates will be reliable if the following assumptions hold: (i) participants and controls have the same distribution of unobserved characteristics, failure of this condition to hold is often referred to as the problem of "selection bias;" (ii) they have the same distribution of observed characteristics; (iii) the same questionnaire is administered to both groups; and (iv) participants and controls are from the same economic environment; (v)assumption of unit homogeneity(no unobserved heterogeneity); and (vi)assumption of conditional independence(no reverse causality[2]). This study takes into account all the given assumptions. Particularly, assumptions V and VI are taken in to account by randomization of sample households and control treatment quasi-experiment as remedies in the Cross-sectional data analysis. The propensity score is defined by Rosendaum and Rubin (1983) as the conditional probability of receiving a treatment given pre-treatment characteristics.

$$p(X) \equiv \Pr\{D = 1/X\} = E\{D/X\} \text{-------------------------------} (6)$$

Where: $D = \{0,1\}$ the indicator of exposure to treatment. In this paper, it is the binary variable whether a household participates in microfinance (participate in microfinance, 1=yes; 0=otherwise) and X is the vector of pre-treatment or time-invariant characteristics. The function $p^3(x)$ is the response probability for treatment. Rosenbaum and Rubin (1983) showed that if participation in microfinance is random within cells defined by X ; it is also random with in cells defined by the mono-dimensional variable $p(X)$. As a result, given a population of units denoted

[2] treatment depends on Y(impact indicators)

[3] $0 < p(X) < 1 \quad \forall X$, i.e. we exclude those that have no chance of being treated and treatment for certainty. In such situations the propensity score reports either dropped due to co linearity or full prediction

by i, if the propensity score $p(X_i)$ is known; the Average effect of Treatment on the Treated (ATT) or in the case of this study the policy effect of microfinance as antipoverty tool can be estimated in the same way as in Becker and Ichino (2002) as follows:

$$\tau \equiv E\{Y_{1i} - Y_{0i} / D_i = 1 \}$$

$$= E\{E\{Y_{1i} - Y_{0i} / D_i = 1, p(X_i) \}\} \text{------------------------------------} (7)$$

$$= E\{E\{Y_{1i} / D_i = 1, p(X_i) \} - E\{Y_{0i} / D_i = 0, p(X_i) \} / D_i = 1 \}$$

Where i denote the i-th household, Y_{1i} the impact indicators (vectors household per capita yearly expenditures or asset holding) over the distribution of $\left(p\left(X_i\right)/ D_i = 1\right)$ and Y_{0i} is the potential outcomes in the counterfactual situations of no participation. Thus, the first line of the equation states that the policy effect is defined as the expectation of the difference of the impact indicators (discussed above) of the *i-th* household with participation in MFI and that for the same household in the counterfactual situation where it would not have had participated in microfinance. The second line is same as the first line except that the expected policy effect is defined over the distribution of the propensity score. The last line is the policy effect as an expected difference of the expected impact and poverty status indicators for *i-th* household with participation in microfinance given the distribution of the probability of participation in microfinance and that for the same household without participation in it given the same distribution. The following two hypotheses are required to derive equations

(1) and (2)

Lemma 1 Balancing of pre-treatment variables given the propensity score

If $p(X)$ is the propensity score, then

$D \perp X \quad \left| p(X) \right.$[4]-- (8)

This implies that given a specific probability of having participation in microfinance, a vector of household characteristics, X is orthogonal to (or uncorrelated to) the participation in. Paraphrasing it differently, for a specific propensity score, the microfinance participation is randomly distributed and thus on average households who participate in microfinance and those who do not are observationally identical (given a propensity score). Otherwise, we cannot statistically match households of different categories.

Lemma2. Unconfoundedness given the propensity score:

If treatment, (or whether a household participates in microfinance) is unconfounded,

That is,

$Y_{1i,}Y_{0i} \perp D \left| X \right.$ --- (9)

Then assignment to treatment is unconfounded given the propensity score, i.e.

$Y_{1i}Y_{0i} \perp D \left| p(X) \right.$ --- (10)

The latter implies that given a propensity score the impact or poverty status indicators are uncorrelated to participation in microfinance. If the above Lemma theorems are satisfied, MFI's impact can be estimated by the procedures discussed in (Becker and Ichino, 2002); and (Smith and Todd, 2005; Imai et.al. 2006).

The propensity score reduces the dimensionality problem of matching treated and control units on the basis of the multidimensional vector X. The probit regression estimates the propensity score and tests the Balancing Hypothesis (Lemma 1) according to the following algorithm (Becker and Ichino, 2002):

Estimate the probit model:

Pr $\left\{ D_i = 1 \left| X_i \right. \right\} = \Phi(h(X_i))$ -- (11)

[4] This is called in the literature as strong ignorability-of-treatment assumption: which is basically the orthagonality assumption about $E(v_0 / X_i)$ and $E(v_1 / X_i)$ where v_0 and v_1 are unobserved error terms of the two groups (Wooldridge, 2002, pp. 616).

Where: Φ denotes the normal (logistic) c.d.f. and $h(X_i)$ is a starting specification which includes all the covariates as linear terms without interactions or higher order terms.

3.6. Estimation of Average Treatment Effects Based on Propensity Scores

What we have discussed so far is not enough to obtain the desired result. Our interest variable is ATT and estimation of the propensity scores in not the end because the probability of observing two units with exactly the same values of the propensity score is in principle zero since $p(X_i)$ is a continuous variable (Becker and Ichino, 2002). Various non-parametric methods such as (Nearest Neighbor, Radius, Kernel and Stratification Matching Methods) [5]have been proposed to overcome this problem.

To briefly discuss these matching methods, the stratification method comprises dividing the range of variation of the propensity score in intervals such that interval treated and control units have on average the same propensity score. For practical purposes the same blocks identified by the algorithm that estimates the propensity score can be used. Then, within each interval in which both treated and control units are present, the difference between the average outcomes of the treated and control units are present, the difference between the average outcomes of the treated and controls is computed. The ATT of interest is finally obtained as an average of the ATT of each block with weights by distribution of treated units across blocks.

One drawback of this method is that it discards observations in blocks where either treated or control units are absent. This observation suggests an alternative way to match treated and control units, which consists of taking each treated unit and searching for the control unit with the closest propensity score, i.e. the Nearest Neighbor. Once each treated unit is matched with a control unit, the difference between the outcomes of the treated units and the outcome of the matched control is computed. The ATT of interest is obtained by averaging these differences. The pitfall of this matching method is all treated units find matches and even for fairly poor propensity score of the control group. The Radius Matching and Kernel Matching methods furnish remedies to the

[5] Asymptotic distribution is assumed in all the propensity score matching methods.

weakness of the Nearest Neighbor. With the Radius Matching each treated unit is matched only with the control units whose propensity score falls in the predicted neighborhood of the propensity score of the treated unit. If the dimension of the neighborhood (i.e. the radius) is set to be very small, it is possible that some treated units are not matched because the neighborhood does not contain control units. On the other hand, the smaller the size of the neighborhood the better is the quality of the matches.

With Kernel Matching, all treated are matched with a weighted average of all controls with weights that are inversely proportional to the distance between the propensity score of treated and controls. We conceive that none of these matching methods is superior to the other and all should be used at once for more robust estimation of the propensity score. In line with this common support restriction is complementary with these matching methods and it helps to improve the quality. For the mathematical notation of these matching methods (see Becker and Ichino, 2002).

Finally, we use Treatment-Effect-Model which is a Heckman version with similar inference to verify the consistency of the results obtained by using propensity score matching methods by picking some variables as a case show. More explicitly, we can adopt the selection model stated in (Greene, 2002, pp.764)

$$D_i^* = \gamma' X_i + \varepsilon_i$$

And

$D_i^* = 1$ If $D_i^* = \gamma' X_i + \varepsilon_i > 0$ -- (12)

$$D_i^* = 0 \text{ Otherwise}$$

Where

$$pr\{D_i = 1 | X_i \} = \Phi\left(\frac{\gamma' X_i}{\sigma}\right)$$

$$\text{pr}\{D_i = 0 | X_i \} = 1 - \Phi\left(\frac{\gamma' X_i}{\sigma}\right)$$

D_i^* is the latent variable. In our case, D_i takes 1 if the households participate in microfinance and 0 if not; X_i is pre treatment variable that determine participation while Φ stands for the normal cumulative distribution.

The linear outcome regression model in the second stage is specified below to study the impact indicators and examine poverty determinants. It follows like this,

$Y_i = \beta' Z_i + \omega D_i + \eta_i$ -- (13)

$(\eta_i \varepsilon_i)$ ~ Bivariate normal $[0,0,1,\sigma_\eta,\rho]$

Where ω is the average benefit of participating in microfinance

Z_i is a vector of household characteristics

Manipulating the formula for joint density of bivariate normally distributed variables,

the expected impact and poverty indicator for clients is given by

$$E[Y_i \mid D_i = 1] = \beta' Z_i + D_i \omega + E[\eta_i \mid D_i = 1] = \beta' Z_i + D_i \omega + \rho\sigma_\eta \frac{\phi\left(\frac{\gamma' X}{\sigma}\right)}{\Phi\left(\frac{\gamma' X}{\sigma}\right)} \text{-----------------} (14)$$

Where ϕ is the standard normal density function, and the ratio of ϕ and Φ are called the inverse Mill's ratio (Heckman's lambda). Expected impact and poverty indicator for the non-participants of MFI:

$$E[Y_i \mid D_i = 0] = \beta' Z_i + E[\eta_i \mid D_i = 0] = \beta' Z_i - \rho\sigma_\eta \frac{\phi\left(\gamma' X_i / \sigma\right)}{1 - \Phi\left(\gamma' X_i / \sigma\right)} \text{-------------------------------} (15)$$

The expected effect of poverty reduction associated with mf is obtained as

(Greene, 2002, pp. 765)

$$E[Y_i \mid D_i = 1] - E[Y_i \mid D_i = 0] = \omega + \rho\sigma_\eta \frac{\phi\left(\gamma' X / \sigma\right)}{\Phi\left(\gamma' X / \sigma\right)\left[1 - \Phi\left(\gamma' X / \sigma\right)\right]} \text{-------------------------} (16)$$

If ρ is positive (negative), the coefficient estimate of ω using OLS is biased upward (downward) and the sample selection term will correct this. Since σ_η is positive, the sign and significance of the estimate of $\rho\sigma_\eta$ (usually denoted as β_λ) shows whether there exists any selection bias. To estimate the parameter of the model, the likelihood function given by (Madalla, 1983, pp. 260-265) is employed where the bi-variate normal function is reduced to the uni-variate function and the correlation ρ. the predicted values of (7) and (8) are derived and compared by the standard t test to examine whether the average treatment effect or poverty reducing effect is significant.

However, cautious interpretation of the results is needed because they are sensitive to the specification of the model and/or the selection of explanatory variables and distributional assumptions. What we have discussed so far are methodologies relevant for the survey data; next we briefly explain methodologies employed in the panel data**.**

3.7. Methodology for the Panel Data

The availability of two years panel data allows us to consistently estimate treatment effects without assuming ignorability of treatment (unrealistic assumption in the propensity score matching.) If the treatment is assumed to have the same effect for each unit and if the effect is constant over time, fixed effects[6] or first-differencing methods are the most logical methods that can be used in such case.

Reasons for using Repeated survey/panel data analysis (Khandker, 2000):

1. Results may otherwise be less robust, as some studies show that the measurement of program impact depends on the treatment of program endogeneity (Khandker, 2000). In dealing with unobserved heterogeneity and program reverse causality in the cross-sectional data analysis; we performed randomization of sample households and quasi-experiment Controlled treatment as way outs. However, this does not fully address the individual household heterogeneity. With

[6] The fixed-effect or the first differencing model addresses the problem of searching for an IV as well (Wooldridge, 2002, pp. 284).

panel data we can tackle one of the two major problems. In other words, the strongest assumption is that eligibility does not change over time. Nevertheless, this is unrealistic and an alternative method such as the household/individual fixed or random effects and the pooled OLS (FGLS) take care of program endogeneity and selection bias, without relying on controversial assumptions (Wooldridge, 2002, pp.287)

2. Cross-section data provides short-term program effects; however, there are cases when programs take a long period to influence outcomes such as fixed and productive household assets (Khandker, 2000). A panel survey analysis measures the long-term program effects and that why we are more interested to see the consistency of results obtained in the cross-sectional data analysis.

When we have only two time periods, fixed effects estimation and first differencing produce identical estimates and inference (Wooldridge, 2002, pp. 285). After formally testing the assumptions underlying the consistency of the FE and RE estimators, using a Hausman test: we prefer to use the robust form alternatively. In this study, we focus on two techniques use to analyze panel data for analyzing effect microfinance on some impact and poverty indicators. The counterfactual approach to causality (Rubin's model) with panel data it can be presented with panel data (within estimation) ${Y_{i,t_1}}^T - {Y_{i,t_0}}^C$. we start by specifying the equation for the fixed effects model as follows (Oscar, 2008):

$Y_{it} = \beta' X_{it} + \partial_i + U_{it}$ -- (17)

Where

- $\partial_i (i = 1...n)$ is the unknown intercept for each entity (n entity-specific intercepts)
- Y_{it} is the dependents variable (DV) where $i = entitiy$ and $t = time$
- X_{it} represents one independent variables (IV)
- β is the coefficient for that IV
- U_{it} is the error term

Panel data per se do not remedy the problem of unobserved heterogeneity and we use the following appropriate methods of analysis. By constructing a regression model that relies on the before-after comparison and disaggregating the error component in to person-specific error V_i and idiosyncratic error ε_{it}; we have $U_{it} = v_i + \varepsilon_{it}$

v_i represents person-specific time-constant unobserved heterogeneity (fixed-effects), in our case v_i could be unobserved entrepreneurial ability of individuals. To get rid of the fixed-effects, we include them as dummies in the regression. In literature, it is termed as Leas-square-dummy-variable-estimator (LSDV).

Including dummy variable representation, the FE model becomes

$$Y_{it} = X_{it}{}^{'}\beta + \sum_{i=1}^{N} \partial_i d_{it} + U_{it} \text{ -- (18)}$$

More elegantly, we undertake the within transformation to address the within variation (Bruderl, 2008). Rearranging equation 12,

$$Y_{it} = \beta^{'} X_{it} + v_i + \varepsilon_{it} \text{ -- (19)}$$

Averaging over t for each i equation (13) becomes

$$\overline{Y_i} = \beta \overline{X_i} + v_i + \overline{\varepsilon_i} \text{ -- (20)}$$

Subtracting (14) from (13) cancels out fixed-effects

$$Y_{it} - \overline{Y_i} = \beta(X_{it} - \overline{X_i}) + \varepsilon_{it} - \overline{\varepsilon_i} \text{ -- (21)}$$

For equations (12) to (16) to hold, in addition to Gauss-Markov, we need the following presumptions:

v_i (unobservable individuals-specific effects) are correlated with X -variables, $E(v_i | X_{it}) \neq 0$

ε_{it} are random errors assumed to be $IIDN(0, \delta_{\varepsilon}{}^{2})$

v_i and ε_{it} are independent among themselves and X-variables

$E(\partial_i | X_i) = g(X_i)$ Or $\mathrm{Cov}(X_{it}, \partial_i) \neq 0$ -Effects are correlated with included variables

$$E\left[(X_{it} - X_i)^{'}\left(U_{it} - \overline{U}_i\right)\right] = 0,\ \text{t= 1, 2} \text{ -- (22)}$$

This assumption shows that each element of X_{it}, (the impact of MFI) can be correlated with ∂_i and $\overline{U_i}$. what fixed-effects require for consistency is that X_{it} be uncorrelated with deviations of U_{it} from the average over the time period. Alternatively, we can consider the RE model. An advantage of the RE model is that we can include time invariant variables (e.g. gender). In the FE model such variables are absorbed by the intercept (Oscar, 2008).

The above model can remedy the problem of unobserved heterogeneity. However, with FE-regressions we cannot estimate the effects of time-constant covariates. Since they are cancelled out by the within transformation. This means the “within logic” applies only with time-varying covariates. Thus, need arias to treat the time –constant covariates and we employ the RE model as an alternative. It is specified as follows

$Y_{it} = \beta X_{it} + \partial + U_{it}$ -- (23)

Where $\quad U_{it} = v_i + \varepsilon_{it}$

Xs are independent of ε

$v_i \approx IIDN(0, \delta_v^{\ 2})$, Homoscedastic

v_i and ε_{it} are independent among themselves and X-variables

$\mathrm{Cov}(X_{it}, v_i) = 0$

Equivalent to pooled OLS after following transformation:

$(Y_{it} - \theta\overline{Y_i}) = \beta(X_{it} - \theta\overline{X_i}) + \{v_i(1-\theta) + (\varepsilon_{it} - \theta\overline{\varepsilon_i})\ \}$--- (24)

Where $\theta = 1 - \sqrt{\delta_\varepsilon^{\ 2} \Big/ T\delta_v^{\ 2} + \delta_\varepsilon^{\ 2}}$ T= time

To sum up, RE is more efficient, if $\mathrm{Cov}(X_{it}, v_i) = 0$. If this fails due to selection bias, FE provides unbiased estimates.

3.8. Description of variables

i. impact indicator variables: Several impact indicator variables are considered in the study, namely: (a) Basic household welfare measures such as per capita income, per capita food and total expenditures. The measure of consumption used in this paper is sum total of food and nonfood consumptions. The food consumption includes food items that the household purchased or produced (used for own consumption). The nonfood consumption is based on sum total of expenditures on non-food items.

Even if there is no consensus whether to take income, expenditure/consumption or some other approaches/measures as proxies to household welfare, throughout this paper we consider expenditure/consumption approach for the following good reasons; compared to income, consumption is easily monetized, ("since in Ethiopia traditionally it is easier for households to give information on their consumption than their earnings besides the arguments in economic literature,") (Yesuf, 2008). Therefore, we narrowly define poverty merely considering households per capita monthly expenditures to simplify matters though poverty goes beyond the money-metric measures. The pitfalls of this approach is failing to slot in some important aspects of individual welfare, such as consumption of public goods (for instance, schools, health services) and what have you.

(b) Household productive and fixed assets (including house value) we classified these as fixed and productive household assets. Household fixed assets such as land, gold, silver, articles, mobile, radio, tape and so on; Productive household assets: like farm equipment, livestock, poultry, and apiculture;

(c) Human capital investments (expenses) such as education and health;

(d) Other expenses such as household expenses on personal care, household utility expenses (drink water, telephone, gas etc) and social expenses. Some of these variables are continuous such as per capita income, expenditure, savings, food expenditure, health expenditure per capita, and education expenditure per attending child. Others are binary such as poor, no poor.

ii. Treatment variables: There is only one treatment variable in our data that can be used to assess the impact of microfinance on outcome and household welfare (poverty) indicators. The natural question that we asked was "Have you ever taken any loan from DECSI" to demonstrate the participation and not participation scenario. It is a binary response (1=yes, 0=otherwise); typical of limited dependent variable models and hence we used the probit regression model.

iii. Independent variables. Here two types of independent variables are used.

The pre-treatment (control) variable and other explanatory variables: Ability to correctly identify the pre-treatment (time-invariant) variables provides the basis for impact analysis as it traps the selection bias and quality of good impact evaluation rests on. Some of the independent variables used in the control functions are similar to those used in existing literature (e.g. Montgomery, 2005; Becker and Ichino, 2005; Imai et al., 2006; Zaid, 2008; Ravallion, 2008).

These include household characteristics such as age of the household; education of the household, area dummies (arato, rubafeleg, siye and tsenkane), sex of the household heads and household size which are believed to be time invariant control variables and they are common in most impact literatures.

Age and age square are expected to be factors because it is well-known that age-earning profile is not flat and age square is a signal for the non-linearity effect.

To minimize part of the selection bias in our study, we include the following variables as determinant of participation. Other sources of borrowing are also included in the control variable as they could be important sources of selection bias.

3.9. Limitation of Methodology

Draw backs of the survey household methodology include among the others, the estimated impact depends on the variables used for matching and the quantity and quality of available data. In addition, procedures to eliminate any sample selection bias depends on observable variables and if there are vital unobservable variables in the model, the estimate results are likely to be biased (Ravallion, 2008). To take care of the unobservable bias, for the survey households, we checked the robustness of results in PSM by employing the treatment-effects modes model and panel data analysis for the panel households.

Issues of incomplete, attrition, dropout bias are addressed partially and may cause serious bias of inference (see Zaid, 2008)

4. Results and Discussions

In the course of investigating whether participation in microfinance reduce poverty using the cross-section and panel data and the respective methodologies discussed in chapter three; first we succinctly describe the extent of poverty in the study areas. Next, we present and discuss the results of impact of microfinance on basic household poverty indicator using the cross-section data. Moving on, we analyze the impact using the panel data sets.

4.1. Extent of Poverty and Estimation Results of Its Measures

This part summarizes the extent of household poverty in the study area and some poverty measures. For comparison, we present the status of poverty in 2007 and 2009. Apart from that, poverty distribution of borrowers and non-borrowers for panel data sets. As mentioned in the above discussions, we made use of two years (2007 and 2009) panel data set for the poverty analysis part. The survey period is characterized by good harvest and relatively stable price in the first year (2007) and bad harvest (drought) and distorted price in the second year (2009). So as to rein in the price climb, price adjustment is made for both data sets considering 2006 price as a base year. This is also the base year price utilized by Fredu (2008) while computing the food and total poverty lines.

We used the CPI for food and non-food items from CSA, CPI report (2009). Thus, as much as possible, we have tried to minimize the impact of inflation while using poverty line computed some years back. After adjustments for price for both years (2007 and 2009)), we obtained (1192.2 ETB and 1278 ETB) and (1592 ETB and 1718.4 ETB) food and total poverty line in 2007 and 2009 respectively. We strongly believe using this poverty line more appropriate than the national poverty line as it was based in the particular study area.

As can be inferred from table 4.1below, both extreme poverty (poverty measured using the food poverty line) and moderate poverty (poverty measured using the total poverty line we adopted) remained the same in 2007 and 2009

Food poverty was much higher than compared to its total counterpart. This is economically valid and logical for the following reasons. First and foremost, this is as a result of the price soar which distorted the real purchasing power of households and very much harmed the living standard of rural households. There are claims for and against this proposition, the gist of the opposite arguments is since price scaling up is observed in cereals, farmers are not the main victim of the price rise. However, this is weak and narrow argument because many rural households are net buyers and the separability of production and profit maximizations is not often-observed in rural households.

Second point is the drought that occurred in these sites last year which resulted in loss of human capital (migration) and livestock. May impact assessment studies have well documented that when clients of MFIs face unforeseen shocks such as droughts, loan is diverted for consumption smoothening and purchase of fodder and silage. Even if there is access to credit, poverty may remain rampant and living standard goes down. A direct quote from recent study may be quite revealing: "*The reality is more complicated. Microloans are often used to "smoothen consumption"—tiding borrowers over in times of crisis. They very often use the microloan for non-business expenses, such as a child's education."* (Boudreaux and Cowen, 2009)

What we are driving here is we should not be surprised for observing poverty getting worse in the presence of good access to microfinance as drought visits Ethiopian intermittently and whenever poverty is suspected in any part of the Tigrai Region. The third point is the agricultural sector and the rural livelihoods itself where framers some foot-steps away from the poverty line are skeptical and conservative from participating in risky areas that may possibly result in higher return. From these and other possible angles, poverty (especially, extreme poverty) slightly ascended in 2009.

As can be seen in table 4.1, poverty measures such as poverty incidence remained the same in 2007 and 2009; while, the depth of poverty raised from 12 and 10.5 percent in 2007 to 19 and

14.5 percent, and finally severity of poverty from 6.9 and 3.5 percent in 2007 to 10.3 and 6.8 in extreme (food) poverty and moderate (total) poverty respectively for the total sample. So as to help us to make some economic insight about the impact of microfinance in this regard, we examine poverty situation between borrowers and non-borrowers for the pane data. Let's briefly discuss the situations considering food and total poverty between the borrowers and non-borrowers in the panel data respectively.

- The proportion of poor below the poverty line is 54 and 45 percent for borrower households; whereas 52 and 46 percents for non-borrowing household in 2007. While, it is 58 and 46 percent for borrowers and 46 and 34 percent for non-borrowers in 2009. In this regard, we do not see predictable pattern of poverty for borrowers and non-borrowers.
- The poverty gap ratio is 16 and 9.9 percent for participant households, but 18 and 12.5 percent for non-participants in 2007. However, it is 21 and 15.3 percent for borrowers and 16.2 and 12 percent for non-borrowers in 2009.
- The squared poverty gap ratio is 10.3 and 3.5 percent for client households; while 9.1and 6.2 for non-client households for in 2007. But it is 10.9 and 6.9 percent for borrowers and 9.4 and 6.8 percent for non-borrowers in 2009.

<u>Table 4.1 Estimation Results of some Poverty Measures</u>

	2009						2007					
Poverty Measure	Total Sample		Borrowers		Non-borrowers		Total Sample		Borrowers		Non-borrowers	
	Food Poverty	Total poverty	Food Poverty	Total Poverty	Food Poverty	Total poverty	Food Poverty	Total Poverty	Food poverty	Total poverty	Food poverty	Total poverty
Head Count Ratio	0.5306 (0.0276)	0.4294 (0.0278)	0.5770 (0.0320)	0.4632 (0.0324)	0.4190 (0.0527)	0.3409 (0.0508)	0.5203 (0.0294)	0.4178 (0.0273)	0.5367 (0.0310)	0.4515 (0.0309)	0.5224 (0.0615)	0.4627 (0.0614)
Poverty Gap ratio	0.1961 (0.0141)	0.1446 (0.0121)	0.2123 (0.0165)	0.1526 (0.0138)	0.1615 (0.0279)	0.1230 (0.0247)	0.1238 (0.0104)	0.1053 (0.0106)	0.1643 (0.0127)	0.099 (0.0097)	0.1822 (0.0291)	0.1341 (0.0258)
Squared Poverty Gap ratio	0.1026 (0.0102)	0.0683 (0.0053)	0.1094 (0.0115)	0.0685 (0.0082)	0.0939 (0.0235)	0.0673 (0.0204)	0.0697 (0.0073)	0.0379 (0.0046)	0.1033 (0.0091)	0.0348 (0.0048)	0.0913 (0.0185)	0.0617 (0.0180)

Results in parenthesis are standard errors!

To sum up, notwithstanding their importance in assisting for pursuing anti-poverty intervention; the first two measures do not endure the three crucial axioms[7] to any measure of poverty discussed by (Ravallion and Chen, 2001). The poverty severity accomplishes well under the focus, monotonicity and transfer axioms. Other measures such as the Watts index satisfy these three axioms are employed in many recent poverty distribution analyses (Ravallion and Chen, 2001).

Nevertheless, we do not utilize the alternative measures that satisfy the three crucial axioms as our intention is more with antipoverty intervention than with poverty distribution analysis. Finally, on average we need 205.25 ETB to lift the poor out of poverty.

4.2. Time Taken to Exit Poverty

When conferring about poverty lessening policies, it is quite valuable to show how long it would take, considering the regional or national economic growth rates, for the average poor person to exit poverty than reporting the proportion the poor or severities of poverty. A poverty statistic to handle such circumstances is derived by (Morduch, 1998); the statistic is decomposable by population sub-groups and is also sensitive to how expenditure (or income) is distributed among the poor. For the jth person below the poverty line, the expected time to exit poverty (i.e., to reach the poverty line), if consumption per capita grows at positive rate *g* per year is given by

$$t_g^{\ j} \approx \frac{(\ln z) - \ln(y_j)}{g} = W/g$$

In other words, the time take to exit is the same as the Watts index divided by the expected growth rate of income (or expenditure) of the poor. Having computed the watts Index, and manipulating this equation; we computed the time take to exit poverty for the survey area.

[7] I) the focus axiom: poverty measures should not vary if income of the non-poor varies

II) the monotonicity axiom: any income gain for the poor should reduce poverty

III) The transfer axiom: inequality-reducing income transfers among the poor should reduce poverty.

The official economic growth rate of 2009(10.1%) is taken as proxy for expenditure growth rate as there is strong (direct) economic correlation between them.
The estimated result of Watts's index manipulating the above equation is

$\left\{\left(0.423\right);\left(0.423/_{(10.1\%)}\right)\right\} = 0.0418\ \}$, the first result (in parenthesis) is the Watts Index.

Using this growth rate, it takes 4 years and 5 months on average to exit poverty.
However, if the current national/regional economic growth is tripled yearly; keeping the other things constant, on average, the poor will exit poverty in one year. Therefore, whenever we talk of money-metric poverty measures we are not engrossed with the statistical reports per se, but more with their economic implication and other intuitions behind.

In the above discussion, we have seen that poverty in the study areas is extensive and even above the national average poverty level which is 0.393 in 2004/05(PASDEP,2006). Let's see now what was the role of MFI which is presumed to be the one of best tolls to reduce poverty by gauging it temporary and permanent impact using the cross-section and panel data.

4.3. Impact of MFI: Reporting Cross-section Data Results

In this part we present, brief description and definition of Microfinance participation explanatory variables given in the appendix I. This table provides definition and descriptive statistics of the independent variables for the total sample, the sample households with access to MFIs and for those without. When we conducted this survey in March 2009, 361 households were reached, of which 264 were clients and 97 non clients. Of the total, 105 are females and 256 are males.

Appendix I demonstrate succinct description and definition of the control (pre-treatment) variables of all respondents employed in the probit repression. Considering demographic characteristics, it shows that the respondents are 50 years old on average and the average household size is 6. 29.4 percent of the survey households are female headed while 70.6 percent are male headed. Furthermore, 25.4 percent of the treatment groups are female headed whereas 59.8 percent of the control groups are male headed and this may give an interesting insight to women's participation roughly. It means women's participation in MFI is very low compared to men.

In terms of education, 65% of the treatment and 80% of the control groups' household heads are illiterate, of the children who ended school, 18.9% of the treatment group and 37.7% of the control group are elementary incomplete. While 13.9% of the former and 24.5 % of the latter groups have completed some elementary education; secondary education is negligible in both cases.

The area dummy in (area participation) in Arato and Rubafeleg is higher by 26.8 as compared to the Siye (base area) where as that of Tsenkanet is 28.3%, the highest of all. In point of fact, Siye is full of rugged terrain (not conducive for farming compared to others) and remote area and this may hinder participation. Other variables such as other sources borrowing, pre- capita land and, work force ratio) included pre-treatment in order to minimize or control selection bias are in line to our expectation. In a nutshell, considering these variables as pre-treatment (control) variable to minimize selection bias while evaluating the impact of microfinance (DECSI Credit and Saving Scheme in our case); on some of the poverty status indicators summarized in appendix2 using the cross-section data is logical and sound.

Having identified these pre-treatment variables, the next logical step is estimating the propensity score using these control variables. The propensity score estimates the propensity score of the treatment on variable lists (the control variables) using a probit (or logit) model. If the balancing property is satisfied; we proceed to measuring impact. To obtain the average treatment effect on the treated; the estimated propensity scores will be used to match observations. (For details see chapter 3)

4.4. Results of Propensity Score Matching on Participation in Microfinance Determinants: Dep Variable: Whether a household has ever taken any loan from microfinance

To commence the discussion, first, we offer the results for matching estimators to look into the effects of participation in microfinance on household non-food, food and total expenditure, household productive and fixed assets and other poverty indicators. Owing to the fundamental similarities of environment, topographical structures, household characteristics and mainstay activities of the four sites; we shall derive the estimations for all respondents at once. The results of the probit model entail what sort of characteristics are the key determinants underpinning the participation in and use of microfinance services.

Estimation results of probit model in Table 4.2 are generally insightful in the case for the entire households where dependent variable is participation in microfinance. Compared to young and old aged households, middle aged households are more likely to be participant of microfinance; save for the negative coefficient of age square suggests the non-linear effect, which is significant at 10% significance level. Households with large family size are more likely to participate in microfinance which is significant at 1% significance level. This is plausible as a family with excess labor force may decide to take credit and participate in farm or non-farm activities. In addition to this, per capita land and its log are significant at (5%level of significance) and we can infer from table 4.2 that households with lager per capita land participate more.

Table 4.2 Probit Estimates for determinants of participation in Microfinance

Participation in microfinance	Coefficients	Z	Marginal effects after probit(mfx)
Household's Demographic Characteristics			
Household head age	.072	1.93*	.0218
Household head age square	-.0007	-2.04*	-.0002
Female headed households	.2313	0.26	.067
Male headed households	.2021	0.22	.063
Household family size	.1783	3.29***	.054
Work force	.3469	0.91	.105
Education			
Household head education	-.2255	-1.15	-.062
Household member with some primary education	-.2448	-1.31	-.098
Household member with some secondary education	.2894	0.98	.088
Household ownership			
Per capita land	. 5394	2.85**	.163
per capita land(Log)	-.4913	-2.28 **	-.149
Other sources of borrowing	-.2356	-1.27	-.075
Location Dummies			
Rubafeleg	.7810	2.46**	.202
Arato	.9768	4.08***	.238
Tsenkanet	.6460	2.45**	.173
Constant	-3.360	-2.50**	-

Number of obs = 361 y = Pr (participation in mf) (predict)

LR chi2 (16) = 70.76 *** = .771

Prob > chi2 = 0.0000

Log likelihood = -174.705 Pseudo R2 = 0.1684

*** = significant at 1% level; ** = significant at 5% level; and * = significant at 10% level.

The coefficient estimates of area dummies in all the three sites, Arato, Rubafeleg and Tsenkanet are positive and highly significant. Arato is significant at 1% level of significance and the other two significant (at 5% level of significance). Their interpretation is considering Siye as a base area dummy and we can conclude from table 4.2 that residents of these areas have higher probability to participate in MFI than residents of Siye.

The other variables are insignificant and we shortly summarize the intuition behind their signs. The coefficient estimates of the borrowing from formal banks, money lenders, friends and relatives it is negative though insignificant, which reflects the fact that those who cannot obtain loans or less amount tend to utilize microfinance services whereas those with other alternatives do not participate in MFIs. Both variables on education are insignificant save for the coefficient estimates are negative in both household sex and household member with some primary education. We can infer from this that illiterate household heads and primary incomplete children who attained school in the family participate less in microfinance and vice versa. Besides, female headed households and work force ratio are part of the insignificant pretreatment variables.

Using the aforementioned pre-treatment variable in table4.2, we derived the propensity scores using probit regression. With this functional specification the balancing hypotheses are satisfied. Furthermore, it is assumed as in Becker and Ichino (2002) that 'unconfoundedness' (Lemma2 theorem) is satisfied.

4.5. Descriptive Statistics and Definitions of impact indicator Variables for the Cross-Section Data

Here, we present short definition and descriptive statistics of variables used as impact indicators. Taking an eye glance at appendix II; we see that investment on human capital (mainly on education for children who attained school) is higher for microfinance participants than non -participants and it is 172.7. Whereas, household medical expenditure is higher for non-clients compared to clients and it is 136.2 on average respectively. For the total survey, it is 141.6 and 90.9.

Considering household productive and fixed assets without house, the mean impact is slightly lower for participants as compared to non-participants for the former and higher for the latter. In view of expenditures on personal care and social occasions; however, it is higher for participants as compared to non-participants in both cases.

Referring to appendix II again, we notice that the mean results of household expenditures on food and aggregate (food and non-food) for participants, non-participants and total sample are; (2253, 2817), (2799, 3462), (2400, 2990), (6.89, 6.91) and (7.26, 7.29) respectively and it is in favor of non-clients.

In general**,** we discern small differences between microfinance participants and non-participants; yet we cannot vividly detect whether differences are statistically significant or not. Thus, more rigorous and advanced analysis is needed. To do so, we briefly introduce the propensity score matching methods.

4.6. Results of Propensity Score Matching: Effects of Microfinance on various Impact Indicators (Estimation using Bootstrapped Standard Errors)

Now, we offer estimation results of average treatment effect on the treated (ATT) of some impact indicator variables. Namely, household expenditures on medical care, education, personal care and social occasions, (otherwise in aggregate termed as log of household expenditures on non-food items) using the propensity score matching methods discussed above. Table 4.3 provides ATT for different expenditure categories estimated via matching of treated and control observations. In all matching methods, the treated group comprises 264 observations. Whereas, the number of control group for stratification and kernel is 97, but 95 and 62 for radius and nearest neighbor matching methods. Table 4.3 below shows the results which are based on whether a household has ever taken loan from DECSI. We focus on expenditure on children who attained school and expenses on medical care to the whole sample. Together, in literatures they are commonly termed as expenditures on human capital development. All the results use bootstrapped standard errors. The columns we are interested in those labeled as ‘Average treatment Effect on Impact Indicators’, and the ‘t-ratio’.

Expenditure on school attainment bears out participation in microfinance has significant effect on capacitating parents to expend more on items such as exercise books, pens and others. This is so because outcome indicators of households with access to microfinance is fairly higher than those of households with the same propensity score (estimated in table4.3 using the pre-treatment variables) in all Propensity Score Matching methods but in nearest neighbor.

This is consistent with the findings of Cowen and Boudreaux (2009) who disclosed that many borrowers in Tanzania use 60% of their loan to send children to school and to cover costs of school items (Cowen and Boudreaux, 2009).

Estimation results in table 4.3 displays that ATTS aren’t significant for expenditures on medical and personal care. Moreover, ATT does not appear to be significant on expenditures related to social occasions. We keep in mind that educational expenditure in the above analysis refers to expenditure on educational items listed. However, education in Ethiopia, particularly in the rural area is public and no education fees.

As a concluding remark, the results in the propensity score matching methods are in line with our visual inspection in the descriptive statistics where we showed reasonable difference in expenditure on education between DECSI clients and non-clients but slight differences in the other cases on average. Therefore, the average policy impact of microfinance in the above impact indicators (gain/or loss) range from -90.7, adverse effects on participants’ to 94.3 ETB substantially significant positive average effect on clients.

Table 4.3 Estimation of ATT Using Propensity Score Matching

Dep Variable: Various Investments on Human Capital and Social Occasions Indicators

Impact indicators	Matching methods	DECSI Clients	DECSI Non-Clients	ATT	t-ratio
Household medical expenditures	Atts	264	97	-61.8	-1.52
	Attr	264	95	-90.7	-1.31
	Attnd	264	62	-184.8	-1.61
	Attk	264	97	-131.1	-1.5
Expenditure on children's education	Atts	264	97	115.632	5.9***
	Attr	264	95	94.3	4.4***
	Attnd	264	62	33.3	0.93
	Attk	264	97	69.01	2.7**
Expenditures on social occasions	Atts	264	97	74.2	0.70
	Attr	264	95	44.9	0.43
	Attnd	264	62	3.03	0.14
	Attk	264	97	18.5	0.14
Expenditure on closing and personal items	Atts	264	97	40.6	0.91
	Attr	264	95	11.2	0.15
	Attnd	264	62	-17.6	-0.14
	Attk	264	97	-48. 9	-0.37

*** = significant at 1% level; ** = significant at 5% level; and * = significant at 10% level

4.7. Household Productive and Fixed Assets with and without House

This part is estimation result of ATT using the same method above and it displays microfinance's impact on per capita household productive and fixed assets with (and without) the current value of house in ETB.

Table 4.4 presents the results of matching estimators which are based on the equations (1) to (11) in Chapter three. It shows the results which are based on whether a household has ever taken loan from DECSI.

Table4. 4 Household Productive Fixed Assets with and without House

Impact indicators	Matching methods	DECSI Clients	DECSI non-Client	ATT	t-ratio
Household fixed assets(with house)	Atts	264	97	529.9	1.15
	Attr	264	95	5.09	.16
	Attnd	264	62	732.4	1.84*
	Attk	264	97	341.8	0.83
Household fixed assets(without house)	Atts	264	97	242.6	1.09
	Attr	264	95	263.2	1.5
	Attnd	264	62	288.3	1.67*
	Attk	264	97	278.7	1.27
Household productive assets	Atts	264	97	15.1	1.79*
	Attr	264	95	76.1	0.65
	Attnd	264	62	284.2	2.05**
	Attk	264	97	50.1	0.45

** = significant at 5% level; * = significant at 10% level

ATT appears significant in nearest neighbor in household productive and fixed assets with and without the current value of house (in ETB) (at 5% and 10% significance level) respectively. Moreover, ATT is significant (at 10% level of significance) in stratification matching methods for household productive assets.

All the results use bootstrapped standard errors. The columns we are interested in those labeled as ‘Average treatment Effect on Impact Indicators’ and the‘t- value’.

ATTs are not significant in the other matching methods in all cases. The numeric impact (gain/loss) of participation in microfinance on the variables mentioned above ranges 15.5 to 732 on average. Moreover, the balancing property is satisfied and the common support is imposed in all matching methods.

4.8. ATT Estimation Results of Household Food, Total expenditures and Total Poverty severity

In this part, we present the ATT estimation results demonstrating microfinance impact on the basic household welfare measures such as household food and total expenditures (including expenditures on non-food) and square poverty gap ratio. Impact on any of these variables is the best signal to judge the capacity of microfinance as anti-poverty tool. Likewise, insignificance or no impact on these variables detects the weakness of the policy to reduce poverty.

Table 4.5 displays the results of matching estimators which are based on the equations (1) and (11) discussed in chapter three. Table 4.5 also portrays the results which are based on whether a household has ever taken loan from DECSI. In the above table, we are interested in household basic welfare indicators: such as, per capita monthly expenditures on food and non food items and total poverty severity. All the results use bootstrapped standard errors. The columns we are interested in those labeled as ‘Average treatment Effect on Impact Indicators/ATT/’ and ‘t- value’. As can be seen from table 4.5, ATTs are found to be significant (at 5% level of significance) in stratification matching in all cases. However, ATTs are insignificant in all other propensity score matching methods.

Table 4.5ATT Estimation Results of household food, total expenditures and Total poverty severity

Impact indicators	Matching methods	DECSI Clients	DECSI non-Client	ATT	t-ratio
Household expenditures on food	Atts	264	97	-545.7	-2.10**
	Attr	264	95	-272.9	-1.58
	Attnd	264	62	-161.6	-0.55
	Attk	264	97	-233.6	0.82
Household total expenditures on food and non-food items	Atts	264	97	-644.8	-2.3**
	Attr	264	95	-320.3	-1.56
	Attnd	264	62	-204.4	-0.57
	Attk	264	97	-296.6	-1.21
Household square poverty gap ratio (poverty severity)	Atts	264	97	0.001	2.1**
	Attr	264	95	0.0015	1.42
	Attnd	264	62	0.0012	0.536
	Attk	264	97	0.0007	1.027

** = significant at 5% level; and * = significant at 10% level

The immediate question that naturally arises is if participation in microfinance has no significant impact in the primary household welfare indicators, does it mean that MFIs in general and DECSI Credit and Saving Microfinance Institution in particular are not hitting their target?

Pertinent to the results presented above, we dare to claim that the impacts on the basic welfare indicators are in significant both in the descriptive statistics and in the propensity score matching methods except in stratification matching. (Methodologically as well, we are prissy about any possible erroneous procedures and minimize possible errors that may emanate from measurement error; except failing to control the impact of other development programs going on in the study areas.)

To recap the above discussion, our finding is summarized starting from tables 4.2-4.5 above. And microfinance's impact on majority of poverty indicators is insignificant in most cases. Being this the case, we prefer to limit the analysis to the study area and to inform our readers to be vigilant about the findings and their implication for two basic reasons:

1. There was consecutive drought in 2008 and 2009 in all study sites and that complicates matters. For example if microfinance rescued their life just to keep the soul in its body for the destitute; though we may not see significant positive impact, it is still indispensable. Because without it, clients may lose their life, migration and lose of human capital from the area may harm its productivity in the future. Hence, we should take in to account all possible angles before running in to clumsy conclusions and the opportunity cost without it. This claim is supported by a recent research finding which substantiates our stand. "A sad reality that many microcredit loans help borrowers to survive or tread waters more than they help them get ahead" (Cowen and Boudreaux, 2009). At the same time, it is difficult to declare poverty killer is born as the microfinance gurus' claim or that microfinance is useless as those against it proclaim.
2. To heart fully single out the impact of microfinance on outcome or poverty indicators, the question of disentangling is real blockade and a model of general equilibrium that incubates all other development packages in a certain area is necessary and we do not employ that in our analysis and hence inferences do not apply out of the study area.

4.9. ATT Treatment-Effects Model Estimation Results of Household Expenditures

Table 4.6 shows the First Stage: Whether a household has ever taken any loan from DECSI in both household food and total monthly expenditures. We are particularly interested in the second column first coefficients and fourth column second coefficients (coefficients for household total and food expenditures) and their respective t-ratios.

As the final part of this chapter's discussion, tables 4.6 and 4.7 put on view the treatment-effect Model /Heckman the two-stage selection model Version/ where the first-step probit estimates of the selection equation exhibiting microfinance participation equation and the second stage the outcome equation in both household total and food monthly expenditures.

The fundamental notion in the treatment effect model is that by controlling part of the selection bias due to unobserved household specific endogeneity, it minimizes the bias that may creep into during impact analysis. However, this Hechman version model procedure relies on a very strong assumption that the unobserved determinants of household total expenditures ε and participation in microfinance η are jointly normally distributed, with zero means, constant variance and a covariance term (i.e. they jointly follow a bivariate normal distribution).

4.6. Results of Treatment -Effect model for Household Food and Total monthly Expenditures: Table 4.6 Probit regression estimates for participation in MF

Participation in microfinance	Coefficients	Z	Coefficients	Z
Household's Demographic Characteristics				
Household head age	.072	1.94*	.072	1.91
Household head age square	-.00071	-2.1*	-.00071	-2.02
Female headed households	.232	0.07	.231	0.06
Household family size	.178	3.7**	.178	3.45
Work force	.346	.79	.346	1.06
Education				
Household head education	-.212	-0.84	-.212	-1.04
Household member with some primary education	-.306	-0.96	-.306	-1.29
Household member with some secondary education	.119	0.45	.119	0.43
Household ownership				
Per capita land	.539	2.82**	.539	1.74
Log of per capita land	-.492	-2.07 **	-.491	-1.62
Other sources of borrowing	-.236	-1.27	-.236	-1.17
Location Dummies				
Rubafeleg	.789	2.38**	.789	2.2
Arato	.969	5.74***	.977	3.28
Tsenkanet	.655	2.80**	.646	2.32
Constant	-3.36	-2.25**	-3.36	-2.18

Number of obs = 361 Wald chi2 (14) = 70.58***

Log likelihood = -175.67388 Prob > chi2 = 0.0000

*** = significant at 1% level; ** = significant at 5% level; and * = significant at 10% level

Besides other independent variables, the latter equation incorporates the Inverse Mill's Ratio/IMR/ otherwise termed as Heckman's Lambda"λ" and microfinance participation dummy.

The Treatment-effect model (Heckman Sample selection Version) is presented here as an alternative way to examine impact of microfinance on household total and food expenditures and verify the reliability of the results obtained using the propensity score matching method. This model can serve the same purpose as the propensity score matching to evaluate the gain or loss of microfinance on the treated by minimizing part of the selection bias caused by unobservable variables. Hence, consistency of the signs and significance of the control variable justifies the reliability of propensity score as well and the quality of the control variable to minimize the selection bias.

Estimation results of this model in Table4.6 have by and large the expected sign and size. A household with a middle age head tends to have significant coefficient estimate with non-linear effects; which is significant (at 10% level of significance). Other participation explanatory variables are similarly significant in this case too with some differences.

The Inverse Mill's ratio is insignificant and we have no statistical reason to reject the null hypothesis (we accept it) which claims the coefficient of Heckman's lambda is zero and we conclude the mode is linear and linear regressions are sound for household per capita food and total monthly expenditures. The key interest variable participation in microfinance institutions remains in significant in both cases.

To conclude, while interpreting these variables, the reference points are those we demonstrated above; i.e. weak/insignificant poverty reducing power or insignificant impact of MFI on the mentioned variables. Since the next part using panel data set is all about exploring poverty reducing effect microfinance using the two years panel data; let's wind up this chapter by underlining the argument under table 4.5.

Table 4.7 Treatment-effects model -two-step estimates (outcome equation)

Household total and food monthly expenditures	Coefficients	Z	Coefficients	Z
Household Demographic Characteristics				
Household head age	40.62	1.65*	12.01	0.21
Household head age (log)	-706.7	-0.47	26.7	0.02
Female headed households	-505.4	-0.88	-300.2	-0.50
Household family size	-65.82	-0.83	-41.9	-0.48
Household Work force ratio	1927.5	3.1 ***	1540.2	3.4
Education				
Household head education	70.65	0.41	69.5	0.50
Household member with some primary education	-559.6	-1.7*	-348.1	-1.29
Household ownership				
Per capita land	-264.5	-1.90*	249.5	1.67*
Other sources of borrowing	-513.9	-2.9**	-420.9	-2.2**
Location Dummies				
Rubafeleg	-197.4	-1.76*	-1740.8	-1.44
Woreda	-563.4	-0.83	-553.3	-0.89
Arato	227.7	0.30	-39.8	-0.05
Siye	-1337.9	-0.58	-1275.1	-0.65
Particpmfi	**-1813.4**	**-1.09**	**-1627.7**	**-1.2**
Mill's ratio	920.9	0.99	841.7	1.06

Number of obs = 361

Wald chi2 (25) = 326.2 *** Prob > chi2 = 0.0000

*** = significant at 1% level; ** = significant at 5% level; and * = significant at 10% level

Rephrasing the pillar notion observing weak or insignificant effect for the total sample does not mean MFI are useless and considered as dissipating the meager capital of developing countries like Ethiopia; appreciating the key role in rescuing the poorest from dying of starvation and the social disorder that could have been created in its absence and its importance should not be jugged from narrow angles.

Poverty alleviation involves a series of tools like education, health care, environmental rehabilitation and protection, political and macroeconomic stability, good governance and state of business, zero tolerance to corruption and so forth but microfinance is just one variable in the sets of equations. To this end we should not perceive microcredit as a transformational panacea that is going to lift people out of poverty. If there are little pockets here and there of people who are made better off by the credit scheme we should not diminish its significance even if the average effect is weak. Indeed, microfinance may make some poor better off, and others sustain their lives at the margin; but it cannot make poor countries richer (Hussain, 2008; Karlan, 2009).

4.10. Impact of Microfinance: Reporting Panel Data Results

First, we shed light on the descriptive statistics and then we discuss the econometric results of the panel data employing various panel data estimation methods.

4.11. Summary Statistics of Outcome and Explanatory Variables

Appendix III presents the summary statistics of endogenous and exogenous variables additional to those described in appendices I and II. Looking at appendix III; it shows microfinance participants do better than non-participants in some of the exogenous variables (e.g. household per capita productive assets). The converse is true for house hold fixed assets and expenditure on food. However, the important point is how significant are the differences between microfinance clients and non-clients? For detail see appendix III. Next we present the econometric discussion part to arrive at logical and valid conclusions about the impact of MFI.

4.12. Fixed–Effect Estimation Results of MF's impact on Household Productive and Fixed Assets:

Table 4.8 Household Productive and Fixed Assets

Dep Var: household productive assets			Dep Var: household fixed assets(with house)		
Explanatory Variables	Coeff.	t-ratio	Explanatory Variables	Coeff.	t-ratio
Household head age	.003	0.15	>>	.005	0.15
Household head age square	-.81	-2.1*	>>	-.424	-0.67
Mean age of household heads	-.072	-1.8**	>>	.028	1.22
Number of adult household members	2.44	3.1***	Household members primary education incomplete	.032	0.35
Participation in microfinance	**.876**	**2.3****	>>	***.247***	***0.77***
Mean age of household members(log)	7.87	1.9*	Household members primary education complete	-.458	-2.40**
Household land ownership (per capita)	.224	1.1	>>	.106	3.51***
Non-farm activities	.697	0.88	>>	.429	2.70 **
Household family size square	-.059	-1.43	Household family size	-.308	-1.87 *
constant	9.96	2.72**	constant	10.2	2.94**

sigma_u= 1.203 n=652 sigma_u = 1.588
sigma_e=1.072 sigma_e= 1.2
rho=0.558 (fraction of variance due to u_i) rho= .613(fraction of variance due to u_i)
F(325, 304) = 1.98 Prob > F = 0.0000 F(10,300) = 3.4 Prob > F = 0.0001
F (325, 311) = 2.06 Prob > F = 0.0000 F (10,310) = 2.94 Prob > F = 0.0005
*** = significant at 1% level. ** = significant at 5% level. * = significant at 10%

Table 4.8 gives the Fixed-Estimation Results of MFI's impact on per capita household productive and fixed assets which are based on the last equations discussed in the methodology part using the panel data. The dependent variables in the table 4.8 are household productive and fixed household (including house) and the variable of interest participation in microfinance is treated as of the explanatory variables. In order to ensure robustness, we performed the following tests: (1) To investigate whether there exists idiosyncratic disturbance term with some of the explanatory variables; (2) whether to use fixed effect or random effect for the panel data.

To this end, we make use of the Breusch-Pagan Lagrangian multiplier effect to test our panel data set for individual heterogeneity/unobservable effects. The null hypothesis is the idiosyncratic disturbances are equal to zero, that is, $V\{\varepsilon_i\} = 0$ in any of the equations (12-24). The test statistic as shown in tables 4.9 and 4.10 at the end part of this topic has a chi-square distribution with one degree of freedom. The calculated test statistics of 25.07 for the former and 27.6 for the latter are reasonably enough to reject the null hypothesis of zero individual heterogeneity (at 1% level of significance for both cases). The logical conclusion then is to employ panel data estimation techniques than pooled OLS method. In other words, it affirms the superiority of the panes data estimation methods over the pooled OLS.

Having done this, what next? The next step is looking in to the potential correlation of the individual heterogeneity with the explanatory variables and deciding whether to use Random-effects (RE) or Fixed-effects (FE). Since the key consideration in choosing between a random effects and fixed effects approach is whether ε_i and X_{it} are correlated, it is important to have a method for testing this assumption. Hausman (1978) proposed a test based on the difference between the random effects and fixed effects estimates (Wooldridge, 2002, pp.289-290). Since FE is consistent when ε_i and X_{it} are correlated, but RE is inconsistent, a statistically significant difference is interpreted as evidence against the random effects assumption.

Another assumption of RE model is that the individual specific effects are uncorrelated with the independent explanatory variables. This is basically the first assumption of the Guass-Markov assumptions. In other words, the orthagonality assumption i.e. $E(\varepsilon|X_{it}) = 0$ If this is true, the estimator of the RE model is not only efficient but also consistent. However, if this assumption does not hold, it is biased and inconsistent. The FE model is unbiased and consistent in both the null and alternative hypothesis. For detail (see Verbeek, 2006, pp.352-353) and (Wooldridge, 2002, pp.298-290)

Tables 4.9 and 4.10 show the Breusch and Pagan Lagrangian multiplier test in favor of panel data estimation techniques. Besides, under the null hypothesis of zero correlation between the idiosyncratic disturbances and the explanatory variables, the test statistic is asymptotically distributed and has chi squared distribution with 11 regressors. The calculated test statistic is significant (1% significance level) for both cases and hence, rejects the null hypothesis of orthagonality. The logical conclusion is in favor of the FE model.

Table4.8 shows that participation in microfinance is significant (at 5% level of significance) for the per capita household productive asset while insignificant for the per capita household fixed assets (including house) other things remaining constant.
This is quite consistent with findings of an earlier study in the same area (see Zaid, 2008). Even after controlling the multiplicative endogeneity of the idiosyncratic disturbances with the vectors of explanatory variables; microfinance's impact is reasonably high on the productive assets and this is plausible due to the fact that loans are disbursed in terms of various packages (for instance, package loans) in either livestock's (dairy farming, fattening) and agricultural productive inputs, draught animals and other inputs like motor and riddle pumps.

Results of this study show that, participation in microfinance has positive impact on the former but insignificant on the latter. The fixed-effects estimated size of the coefficients of household productive assets can be interpreted as one percent increase participation in microfinance results in 83 percent of accumulating more productive household assets.

The insignificant impact of the credit scheme on fixed household assets accords our expectation specially, when current value of house is included. Firstly, the maximum terms of loan is four years while possessing fixed assets requires relatively longer period of time. Secondly, the mean current value of house is 8550 whereas; the maximum loan amount that one can borrow from DECSI is 5000. Therefore, it may not be easier to immediately build fixed assets.

With regard to some of the explanatory variables in productive household assets, estimated coefficients such as household head age has positive sign but insignificant. While age square and mean ages have negative sign and significant (at 10% and 5%level of significance) respectively which may be interpreted too old people do not participate in microfinance.

The only significant explanatory variable (at 5% level of significance), to both interest variables is mean age (logarithm) which has the same inference as the above case. The other significant independent variables (for fixed asset) are household off-farm activities land and family size; both significant (at 5% and10% level of significance) and the estimated coefficients have the expected sign. This implies households with infertile land and large family size cannot augment fixed assets ultimately. With the presumption that the large family size possesses low human capital (education) and hence lower marginal productivity; as it is often-observed in rural households; the above claim holds water. Finally, the estimated coefficient of non- farm activity is positive and significant at 5% level of significance. It entails that when households participate in off-farm activity, they accumulate more fixed household assets.

Table 4.9 Breusch and Pagan Lagrangian multiplier test for random effects household per capita productive assets [hhid, t] = Xb + u [hhid] + e[hhid,t]

Variables	Variance	Standard deviation= sqrt(Var)
Household per capita productive asset	.788423	.802189
E	.48574	.071716
U	.5228713	.7230984

Test: Var (u) = 0
chi2 (1) = 25.07
Prob > chi2 = 0.0000

Table 4.10 Hausman specification test between FE and RE models

variables	Coefficients		(b-B) Difference	S.E. (Standard Errors)
	B FE	B RE		
Household head age	.0306	.0322	-.0015	.0255
Household head age square(log)	-4.106	-2.864	-1.242	1.477
Mean age of household members	-.1348	-.1062	-.0286	.0431
Number of adult household members	-.663	-.3309	-.3321	.2105
Participation in microfinance	.6983	.5297	.1686	.2383
Mean age of household members(log)	7.865	5.452	2.414	2.717
Number of oxen(per capita)	2.458	4.235	-1.776	1.126
Household marital status	.6972	.1582	.5391	.3348
Household family size square	-.0590	-0.069	0.01001	.0325
Household head age	-.0815	-.0183	-.0632	.0846

chi2 (21) = 43.70**; Prob>chi2 = 0.0026
** = significant at 5% level. * = significant at 10%

Table 4.11 Fixed –Effect and OLS Estimation Results of Microfinance Impact on Household Per capita Total Expenditure

Dep Var: Household Per capita Monthly Total Expenditures

	Fixed-Effects		FGLS	
Explanatory Variables	Coeff.	t-ratio	Coeff.	z-value
Household Demographic Characteristics				
Household head age	-.0018	-0.26	.0067	1.86*
Household members mean age	-.0483	-2.17**	-.0141	-1.51
Female headed households	-1.163	-8.4***	-.0674	-0.11
Male headed households	1.21	4.8***	.0396	0.06
Tropical live stock unit current value(ETB)	.0813	2.25**	.0809	5.09***
Number of household members(size)	-1.851	-2.40**	-.6968	-1.76*
Siye	-2.59	-9.15***	-.0359	-0.38
Tsenkanet	-.192	-0.80	.1358	1.94
Household land ownership(in per capita terms)	.2073	1.79*	.0827	2.00**
Active member of household(working force ratio)	.2802	1.85*	.1366	3.01***
Household fixed assets	.0457	0.97	.0688	4.26***
Participation in microfinance	**.4486**	**1.13**	**.0436**	**0.76**
Constants	8.764	7.8***	6.513	17.3***

sigma_u = 1.168 Wald chi2 (14) = 226.83
sigma_e = .6199 Prob > F = 0.0000
rho =.7803 (fraction of variance due to u_i)
F (325, 308) = 1.23 Prob > F = 0.0783
F (14,308) = 19.9 Prob > F = 0.0000 n=652

*** = significant at 1% level. ** = significant at 5% level. * = significant at 10

Table 4.11 shows the fixed-effects and pooled OLS estimates of program impacts on a short-term outcomes indicator i.e. total per capita expenditure. We conducted similar tests as in table 4.8 above and the test statistic has a chi-square distribution with one degree of freedom. The calculated test statistics of 4.38 with (p-value=0.033) is satisfactory enough to reject the null hypothesis of zero individual heterogeneity (at 5% level of significance for both cases). The logical conclusion then is to employ the FE estimation techniques than pooled OLS. But, for comparison purpose and remedying the drawback of FE model; we present the estimation results of the two techniques (FE and pooled OLS/FGLS/) side by side.

Examining the estimation results above participation in microfinance is found to have insignificant effect on per capita total expenditure in both FE and FGLS estimation results. Shedding light on the explanatory variables: mean age, family size and per capita tropical livestock unit in the FE; age of household and land ownership in the FGLS are significant (at 5% level of significance). Moreover, female and male headed households and area dummy Siye in the FE and household fixed assets and tropical livestock units in the FGLS are significant at (1% level of significance). While the first three explanatory variables and area dummies (Siye and Tsenkanet) are negatively associated, the others are positively related. Some explanatory variables in both cases are significant at (10% level of significance) and others are insignificant.

As a concluding remark, the insignificant impact on monthly per capita total expenditure does not mean microfinance has no role in poverty reduction. For one thing, poverty is a multifaceted and too complex concept that demands such multidimensional, integrated and coordinated antipoverty-intervention programs and requires unremitting and long living stab. Thus, short term impact assessments may not give as the precise picture. In order to have power over idiosyncratic disturbances we make use of the most parsimonious technique and we notice some differences at least in the per capita total expenditures (the positive sign of the estimated coefficient). Of course, the impact of microfinance is insignificant in this robust analysis and is consistent to the cross-section data analysis. Being this the case, it is difficult to blame for microfinance as there was widespread drought in the study areas in 2009 (when the second data was collected). We rather appreciate micro-finance as one instruments among the sets of poverty reduction strategies that policymakers can pursue to eradicate poverty with some corrective measures in the practical front.

Table 4.12 shows the random-effects and OLS estimates of program impacts on a short-term outcomes indicator i.e. poverty line minus per capita expenditure over poverty line. We conducted similar tests to the above two cases and the test statistic has a chi-square distribution with one degree of freedom. The calculated test statistics of 0.6 with (p-value=0.440) is not satisfactory enough to reject the null hypothesis of zero individual heterogeneity (at 5% level of significance for both cases). The logical conclusion then is to employ the pooled OLS than FE. To provide an alternative to the pooled OLS, we present the RE result side by side for comparison purpose. Looking at the estimation results of table 4.12, participation in microfinance has insignificant effect on total poverty in both the RE and pooled OLS estimation models

4.13. Estimation Results of Microfinance Impacts on Household Poverty Indicators

In the following discussion, we present estimation results of impact of microfinance on some (house hold expenditures, poverty severity and other measure) which are deemed to represent the poverty situation of panel households.

Table 4.12 Random-Effects and OLS Estimation Results MFI Impact on Total Expenditure divided by Total poverty line

Dep Var: total poverty line minus total monthly expenditures over total poverty line

	Random-Effects		Pooled OLS	
Explanatory Variables	Coeff.	z-value	Coeff.	z-value
Household head age	. 0072	1.59	.0072	1.61
Household members mean age	-0.177	-1.35	-.0177	-1.73*
Female headed households	-.0767	-0.89	-.7665	-0.91
Male headed households	.723	0.84	.7226	0.85
Household members with some secondary education	.5154	3.67***	.5155	3.7***
Tropical live stock unit current value(ETB)	-.0795	-3.6**	-.0795	-3.6***
Number of household members(size)	-1.517	-2.73**	-1.518	-2.8**
Siye	-.381	-0.28	-.0381	-0.30
Arato	.2103	1.97*	.2103	2.0**
Household land ownership(in per capita terms)	.0582	1.02	.0593	1.03
Active member of household(working force ratio)	.3325	2.2**	.3251	2.01**
Household fixed assets	.1413	2.38**	.1181	5.7***
Participation in microfinance	**-.0359**	**-0.42**	**-.0358**	**-0.40**
Constants	1.596	3.29***	1959	3.8***

sigma_u= .0485 F (17, 633) = 9.53
sigma_e=. 7845 Prob > F = 0.0000
rho= .0038 (fraction of variance due to u_i) Adj R-squared = 0.18
Wald chi2 (17) = 245.96 Prob > chi2 = 0.0000 Root MSE = .7943 n=652

*** = significant at 1% level. ** = significant at 5% level. * = significant at 10

Considering the regressor variables: family members with some secondary education and tropical livestock unit (in both RE and OLS) are significant (at1% significance level). Besides, number of household members and working force ratio are significant at (5% level of significance).

The negative signs of large size households (assuming large household as good sources of labor supply either to the farm or off-farm and helping the household to generate high income) and secondary complete member of households is in harmony with our logical expectation that. The other explanatory variables are insignificant.

We can infer and identify the determinants of poverty from table 4.12 above. Thus, individual/household characteristics (e.g. age of the house hold, household head (male or female head); membership characteristics (family size, education level of family members); economic characteristics (number of oxen and household properties, and other per capita household productive assets) and geographical characteristics (Siye (base dummy), Arato) and other are the main determinants of poverty. This support majority of the existing set of literatures on the determinants poverty (Fredue, 2008).

Mulling over the finding in table 4.13, it summarizes the impact of microfinance on the total and food poverty. The dependant variable has discrete choice model by comparing total per capita expenditure and food expenditures with the adopted food and total poverty lines. The dummy dependent variable takes values

(i.e. 1= poor if $Y_{it} < Z$ and 0=non-poor if $Y_{it} \geq Z$ where $Y_{it} =$ is total or food per capita expenditure and Z = the respective adopted poverty lines) The live out of discrete choice models in the analysis of determinants of poverty has been trendy approach in many poverty determinant studies. This analysis then proceeds by employing binary probit model to estimate the probability of a household being poor conditional up on the commonly used explanatory variables (household/individual, demographic/community and economic characteristics.

Table 4.13Probit Estimation Results MFI Impact on Food and Total Poverty

(Probit: dummy;($1 = y_{it} < z$ $0 = y_{it} \geq z$)

Explanatory Variables	Dep Var: Food Poverty Coeff.	t-ratio	Dep Var: Total Poverty Coeff.	t-ratio
Household head age	-.0243	-1.40	-.0406	-1.908*
Number of household members	1.674	2.05**	2.775	2.39**
Female headed households	.0312	0.23	-.0761	-0.52
Household non-farm activities	-.3091	-2.73**	-.4070	-3.32**
Household land ownership9inper capita terms)	-.4718	-3.18***	-.1642	-1.67 *
Number of adults in the household	-.2853	-1.82*	-.3668	-2.18**
Tropical livestock unit current values(in ETB)	-.0917	-2.59**	-.1723	-4.99***
Per capita number of oxen	- 3.86	-2.01**	-.0665	-0.72
Household land ownership(in per capita terms)	-.3080	-2.58**	-.2256	-1.58
Arato	-.3419	-2.49**	-.3517	-2.29**
Tsenkanet	-.2988	-2.25**	-.2234	-1.58
Household members with some secondary education	-.4769	-2.13**	-.3647	-1.42
Participation in microfinance	**. 1371**	**1.03**	**-.0067**	**-0.05**
Constant	-2.56	-1.14	6.81	-1.12

Food Poverty	Total Poverty
lnsig2u = -12.9143	lnsig2u = -14.144
sigma_u = .00157	sigma_u = .00073
rho = 0.0006	rho = 5.24e-07
Wald chi2 (14) = 86.45	Wald chi2 (14) = 90.33
Prob > chi2 = 0.0000	Prob > chi2 = 0.0000

*** = significant at 1% level. ** = significant at 5% level. * = significant at 10

Table 4.13 also displays that the impact of participation in microfinance on both food and total poverty is statistically insignificant. Moreover, it demonstrates that household landownership and productive household assets are significant at 1% level of significance with food and total poverty. It is in harmony with economic theories that households with better land holding and productive assets are less affected by poverty compared with the land less and low productive asset households.

Estimation results of other regressores show that households who engage in non-farm activities, who possess fertile land, and who have secondary education level have negative signs and are significant impact (at a 5% level of significance) on food poverty particularly. Besides, family size is positively related in both cases and is significant at (5% level of significance).

Household possession of infertile land has negative sign and is significant (at 10% and 5% level of significance) respectively. Area dummies Arato and Tsenkanet are inversely related to food and total poverty and the former significant (at5% level of significance) in both cases. Whereas, the latter significant (at 5% significance level) in total poverty comparing to area dummy Siye which is base area dummy and is considered as a base for analyzing for the other sites. This is plausible owing to the geographical difference.

Table 4.14Fixed –Effects and FGLS Estimation Results of Microfinance Impact on Household square poverty gap (poverty severity)

Dep Var: Household Square poverty(Poverty Severity)

	Fixed-Effects		FGLS	
Explanatory Variables	Coeff.	z-value	Coeff.	z-value
Household Demographic Characteristics				
Household head age	.0080	0.45	.0079	0.43
Number of Household members (size)	.6684	1.71*	.6657	2.15**
Female headed households	-2.6372	-2.5**	-2.034	-2.11**
Male headed households	2.425	2.3**	3.306	0.66
Tropical live stock unit current value(ETB)	.1251	1.74*	.2519	1.78*
Average age of household heads	-.0951	-2.6**	-.6171	-1.68*
Education				
Member of households with some primary education	-0.614	-0.25	-0.694	-0.27
Members of households with some secondary education	1.592	1.96*	1.392	2.64**
Household land ownership(in per capita terms)	-.0642	0.33	.0827	2.00**
Active member of household(working force ratio)	0.276	1.87*	.367	1.69*
Household fixed assets ownership	.0257	2.7**	.0264	3.02***
Participation in microfinance	**.0734**	**0.24**	**.0746**	**0.26**
Constants	3.4	2.24***	4.623	7.35***

sigma_u = 3.34 Wald chi2 (14) = 149.8
sigma_e = 3.727 Prob > F = 0.0000
rho =. 4453(fraction of variance due to u_i)
F (325, 308) = 1.43 Prob > F = 0.0083
F (14,308) = 8.9 Prob > F = 0.0000 n=652

*** = significant at 1% level. ** = significant at 5% level. * = significant at 10

Table 4.14 displays the fixed-effects and Feasible Generalized least square estimates of program impacts on square poverty gap/poverty severity. We conducted similar tests we discussed in table 4.8 above and the test statistic has a chi-square distribution with one degree of freedom. The calculated test statistics of 7.31 with (p-value=0.026) is satisfactory enough to reject the null hypothesis of zero household specific heterogeneity (at 5% level of significance for both cases). The logical conclusion then is to employ the FE estimation techniques than pooled OLS. But, for comparison purpose and remedying the drawback of FE model; we present the estimation results of the two techniques (FE and pooled OLS/FGLS/) side by side.

Examining the estimation results above participation in microfinance is found to have insignificant effect on household square poverty gap in both FE and FGLS estimation results. To briefly discuss the explanatory variables: mean age, female and male headed households and household fixed asset ownership in the FE; household size, female headed households, and mean age of household in the FGLS are significant (at 5% level of significance). Moreover, number of household members in the FE and Tropical live stock unit current value (ETB) in both estimation models are significant (at 10% level of significance). In addition, household fixed assets ownership in the FE is significant (at 1% level of significance)

While the estimated coefficient of female headed households has negative sign, it is positive for male headed household. This is in line with our expectation and it shows that poverty severity adversely affecting female headed households as compared to male headed counterparts.

5. Conclusions and Recommendations

5.1. Conclusions of the Study:

As program evaluation is sensitive to the methods used in impact assessment, we employed a quasi-experimental survey design to resolve the endogeneity of program participation for the survey and panel households to bear out the consistency of results. Falling back on the 2009 survey data and panel data sets (2007 and 2009), our study looks over the impact of microfinance on poverty situations and asset accumulations of survey and panel households, in which household monthly expenditures and productive and fixed assets) are employed as measures reflecting these variables. Taking into account its plus good point, we followed the expenditure approach as a good indicator of basic household welfare by adopting the poverty line computed some years back in the same areas. In so doing, necessary adjustments are done to capture price inflationary effects.

For the cross-section data, by and large, the propensity score matching (PSM) model and the treatment-effects model, a version of the Heckman sample selection model, are used to estimate the poverty-reducing impacts of participation in microfinance on the aforementioned households' poverty indicators and asset measures. It is strongly believed that the methodologies we executed and the models employed would allow for the endogenous binary treatment effects or the sample selection bias associated with participation in microfinance.

Notwithstanding some drawbacks cropping up from the unobservability of potentially essential determinants of participation in microfinance; its impact on poverty status indicators (household monthly expenditures) and household productive and fixed asset is found to be insignificant save for productive asset in some matching methods in the PS. This is also confirmed by the treatment-effects model. On the other hand, impact of participation in microfinance on household monthly non-food expenditures on (education and personal care) and household productive assets is found to be significant. The latter is quite consistent with the findings of an earlier study in the same area (see Zaid, 2008)

The general comment for the above results is impact of microfinance on survey households' poverty indicators is insignificant. Although, it may help households just to survive in times of shocks and vulnerabilities or for consumption smoothening. Our finding is under the umbrella of the second view (microfinance cannot help to reduce poverty save for some differences) but implications and interpretations should be with great care as we discussed it in 4.6.

Nevertheless, the impact assessments are subject to assumptions and selection bias cannot be fully controlled particularly in cross-sectional based impact analysis. In order to examine whether cross-section data impact analysis are affected by household heterogeneity or idiosyncratic disturbances, we perform panel data analysis. The panel household survey assists to estimate the program effects by using the household FE and RE methods, removing the bias due to individual heterogeneity and endogeneity of participation. Results confirm the earlier findings that impact of households' participation in microfinance on reducing poverty and accumulating fixed assets is insignificant. It is significant in boosting households' per capita productive assets; however.

In general, even if the ultimate objectives of DECSI programs are to reduce poverty via improving the economic situation of the low income and poorest people based on voluntary participation, albeit some momentary impacts, poverty is rampant in the study areas in presence of micro-finance programs. Of course, micro-finance alone may not provide the panacea for the high incidence of poverty.

5.2. Recommendations

Research findings and focus group discussions with survey households lead us to the following recommendations:

1. The significant impact of microfinance on household per capita productive assets is heartening signal of the importance of DECSI credit greed towards improving live- stocks of the poor. Moreover, integration with other development packages aiming at ultimately reducing poverty is timely and commendable. However, feasibility study about climate, farmer’s preference, livestock species, availability of enough grazing area and harmony with other development packages going on is recommended.
2. Of course, microfinance’s effect on household fixed asset (excluding current value of house) is significant. Therefore, efforts that augment accumulation of assets that may ultimately help to reduce poverty are encouraged.
3. The insignificant impact of microfinance on the primary household poverty status indicators needs special focus. To begin with the supply side (DECSI), it ought to make sure that loans go with the need and preference of clients. Series of activities, such as training and follow up (before, during and after) loans, independent impact and process evaluation of its program, and organized data base of clients is recommended. Moreover, revising some of its policies like increasing loan amount and lengthening terms of loan, reducing the recently continuously swelling interest rates (that eats up any possible return of clients), increasing interest rate for depositors to instigate saving habit and thus capital accumulation, diversifying loan packages and ranges, specially providing loan for human capital development, encouraging participation of clients and minimizing the role of local administrators are fairly recommended.

   Instead of concentrating on the amount of loan disbursed and increasing number of clients for simple promotion, it is better DECSI introduces different loan modalities in harmony with, market penetration, development and diversification in order to smack its target. In one of our focus group discussion, we learned that the living standard of some clients is going from bad to worse owing to the loan. In Arato for instance, some clients were in jailed and some others snatched their land up to three years when clients default (due to circumstances beyond their control/drought and deaths of live stocks) and that is common in other areas as well. Thus, our findings are not far from facts on the ground and it is high time DECSI took corrective measures.

It is better to win consensus at the grass root that microfinance is among the tools that assist to reduce/wipeout poverty and the poor can escape poverty by taking credit and engrossing in productive economic activities. Another point that we learned in the focus group discussions is that many do not believe credit from DECSI can eradicate poverty. They believe that poverty can be reduced only at the will of God and neither credit nor aid can reduce it. “Poverty is part of our life; it has been here from fore fathers and will be here for the next generations.” One client at his 50 roared in one of the focus group discussions.

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Appendices: Summary Statistics and Descriptions of Variables

Appendix I. Descriptive Statistics and Definitions of the Participation Determinant Variables

Brief description of variables	MFI clients			MFI non-clients			Sample Total			
Definitions	obs	mean	S.D	obs	mean	S.D	obs	mean	S.D	t-test
Participation in mf; dummy(1=yes; 0=no)	264	1	0	97	0	0	361	.731	.443	-
Age of household head	264	49.87	13.8	97	53.04	17.02	361	50.68	14.70	1.75*
Square age of households	264	2673	1450	97	3088	1801	361	2785	1560	2.3**
Female household head (1=male head; 0=female head)	264	.254	.436	97	.402	.492	361	.294	.456	2.8**
Male household head (1=male head; 0=female head	264	.746	.434	97	.598	.493	361	.706	.455	-2.8**
Education of the household head, (1= literate, 0= illiterate)	264	.647	.478	97	.804	.397	361	.691	.463	2.9**
number of total household members	264	6.01	2.19	97	5	2.31	361	6	2	-5.3***
Education of household member(1= primary incomplete; 0=otherwise)	264	.189	.392	97	.377	.487	361	.239	.427	3.7***
Education household members(1= primary complete; 0=otherwise)	264	.139	.359	97	.245	.432	361	.168	.381	2.38**

*** = significant at 1% level; ** = significant at 5% level; and * = significant at 10% level

Brief description of variables	MFI clients			MFI non-clients			Sample total			
Variables	obs	mean	S.D	obs	mean	S.D	obs	mean	S.D	t-test
Education of household members (1=secondary complete; 0=otherwise)	264	.061	.283	97	.031	.305	361	.053	.289	-0.87
Per capita land (total land dividing by family size)	264	.844	.805	97	1.17	.943	361	.931	.855	3.2***
Whether a household has any other credit sources(1=yes; 0 otherwise)	264	.226	.419	97	.247	.434	361	.231	.422	0.41
Rural dummy**:(**1= if a household lives in Rubafeleg; 0=otherwise)	264	.268	.443	97	.204	.405	361	.251	.434	-1.4
Rural dummy**:(**1= if a household lives in Arato; 0=otherwise)	264	.268	.443	97	.173	.380	361	.242	.429	-1.85*
Rural dummy**:(**1= if a household lives in Siye; 0=otherwise)	264	.182	.386	97	.392	.491	361	.238	.427	4.3***
Rural dummy**(**1= if a household lives inTtsenkanet; 0=otherwise)	264	.283	.451	97	.235	.426	361	.269	.445	-0.83
Household members aged 15-64(working force) divided by family size	264	.489	.208	97	.462	.238	361	.482	.216	-1.02
Log of per capita land	264	-.483	.833	97	-.041	.722	361	-.365	.827	4.6***

*** = significant at 1% level; ** = significant at 5% level; and * = significant at 10% level

Appendix II. Descriptive Statistics and Definitions of the impact and poverty indicator Variables for the Cross-Section Data (2009)

Description of Variables	DECSI clients			DECSI non-clients			Sample Total			
Variables	Obs	mean	S.D	Obs	mean	S.D	Obs	Mean	S.D	t-test
Children's education expenditures	264	172.7	284.4	97	57.1	84.5	361	141.6	252.2	-3.9***
Household medical expenditures	264	74.36	252.2	97	136.2	410	361	90.9	303.5	1.72*
Social expenditure on social occasions	264	625	823.8	97	551	880	361	605.2	838.9	-0.74
Household expenditures on personal care	264	454.1	323.3	97	413.5	472	361	443.2	369.1	-0.93
Per capita household productive assets	264	1130	1255	97	1206	1287	361	1150	1262	0.52
Per capita fixed assets excluding house	264	356.1	3376	97	113.4	215	361	2286	4124	-0.71
Per capita fixed assets including house	264	2144.2	4085	97	2674	4226	361	290.8	2890	1.08
Household per capita expenditures on food	264	2253	1469	97	2799	1967	361	2400	1633	2.84**
Household total expenditure on food and non food items	264	2817	1661	97	3462	2330	361	2990	1883	2.91**
For the bottom poor (bottom 50% of those below the threshold)	264	.201	.401	97	.112	.317	361	.163	.3703	-2.21**
For the moderate poor (upper 25% of those below the threshold)	264	.167	.373	97	.175	.382	361	.169	.375	0.19

*** = significant at 1% level; ** = significant at 5% level; and * = significant at 10% level

Appendix III Summary Statistics of Endogenous and Exogenous Variables for (2007 and 2009) Data

Description of Variables	2009						2007							
	DECSI Clients			DECSI non- Clients			DECSI non- Clients			DECSI Clients				
Variables	Obs	mean	S.D	Obs	mean	S.D	Obs	Mean	S.D	Obs	Mean	S.D	t-ratio	
Household productive assets	238	852	1024	88	824	805	67	582	651	259	757	607	-0.23	-2**
Household fixed assets (with house)	238	2214	4257	88	2705	4408	67	1637.9	2234	259	1383	1994	0.92	.9
Household expenditures on food items	238	914	686	88	1187	946	67	1107	763	259	1083	655	2.9**	.26
Household total expenditures on food and non-food items(in per capita terms)	238	1214	769	88	1532	1140	67	1782	1048	259	1743	945	3**	0.3
household head marital status	238	.79	.40	88	.59	.49	67	.57	.50	259	.81	.76	-4***	-4***
Household non-farm activities	238	.45	.50	88	.26	.44	67	.43	.50	259	.47	.5	-3**	-.5
Adult households members	238	3	1	88	2	1	67	2	2	259	3	3	-4***	-4***
Work force ratio	238	1.1	1.03	88	.99	1.02	67	1.02	.90	259	1.05	.91	-0.7	-0.3
Illiteracy ratio	238	.41	.27	88	.57	.33	67	.51	.31	259	.41	.25	4***	3***
Per capita land	238	.84	.79	88	1.2	.94	67	1.1	1.2	259	.95	.93	.36	1.2
Per capita oxen	238	.18	.17	88	.18	.19	67	.14	.18	259	.190	.169	.27	-2**

*** = significant at 1% level; ** = significant at 5% level; and * = significant at 10% level

Appendix IV: Microfinance Participation Determinants Estimation Results

pscore particpmfi fmage1 agesq femhead malhead fmeduc1 fmsize hheleminc1 hhseccomp hhelemcomp1 pcland borrother rubafeleg arato tsenkanet workfratio siye lnpclnd, pscore(p1) comsup

```
**************************************************
Algorithm to estimate the propensity score
**************************************************
The treatment is participation in Microfinance
 Participn_mfi |      Freq.     Percent        Cum.
------------+----------------------------------------
         no |         97       26.87       26.87
        yes |        264       73.13      100.00
------------+-----------------------------------
      Total |        361      100.00
```

Estimation of the propensity score

note: siye dropped because of collinearity

```
Iteration 0:   log likelihood = -210.08741
Iteration 1:   log likelihood = -175.7511
Iteration 2:   log likelihood = -174.7112
Iteration 3:   log likelihood = -174.70521
Iteration 4:   log likelihood = -174.70521

Probit regression                          Number of obs   =        361
                                           LR chi2(16)     =      70.76
                                           Prob > chi2     =     0.0000
Log likelihood = -174.70521                Pseudo R2       =     0.1684
```

particpmfi	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
fmage1	.07176	.0371797	1.93	0.054	-.0011109	.144631
agesq	-.0007069	.0003471	-2.04	0.042	-.0013873	-.0000265
femhead	.2312978	.8990347	0.26	0.797	-1.530778	1.993373
malhead	.201288	.9138825	0.22	0.826	-1.589889	1.992465
fmeduc1	-.2119142	.197966	-1.07	0.284	-.5999203	.176092
fmsize	.1783375	.0541591	3.29	0.001	.0721876	.2844875
hheleminc1	-.3059075	.2812379	-1.09	0.277	-.8571237	.2453086
hhseccomp	.2894114	.2947981	0.98	0.326	-.2883822	.8672049
hhelemcomp1	.1187248	.311274	0.38	0.703	-.4913609	.7288106
pcland	.5394699	.1890141	2.85	0.004	.1690091	.9099308
borrother	-.2355601	.1861304	-1.27	0.206	-.600369	.1292488
rubafeleg	.7899589	.3208568	2.46	0.014	.1610912	1.418827
arato	.9768301	.2391474	4.08	0.000	.5081098	1.44555
tsenkanet	.6460176	.263973	2.45	0.014	.12864	1.163395
workfratio	.346906	.3811838	0.91	0.363	-.4002005	1.094013
lnpclnd	-.4913386	.2154319	-2.28	0.023	-.9135773	-.0690998
_cons	-3.360418	1.345007	-2.50	0.012	-5.996582	-.7242536

Note: the common support option has been selected

The region of common support is [.25376239, .99633034]

Description of the estimated propensity score in region of common support

Estimated propensity score

Percentiles		Smallest		
1%	.2823085	.2537624		
5%	.3448427	.2671391		
10%	.4600804	.2678269	Obs	356
25%	.6165251	.2823085	Sum of Wgt.	356
50%	.7825374		Mean	.7397761
		Largest	Std. Dev.	.1843231
75%	.8938624	.9835069		
90%	.9433565	.9846083	Variance	.033975
95%	.9629196	.987134	Skewness	-.7464121
99%	.9835069	.9963303	Kurtosis	2.678331

****

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 |      particpmfi
of pscore  |        no        yes |     Total
-----------+----------------------+----------
```

.2	13	7	20
.4	27	38	65
.6	38	63	101
.8	14	156	170
Total	92	264	356

Note: the common support option has been selected

****

End of the algorithm to estimate the pscore

****