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## The Economic Impact of a New Rural Extension Approach in Northern Ethiopia

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### Abstract

In this paper we analyze the impact of the Integrated Household Extension Program (IHEP) in the Tigray region in northern Ethiopia. The government of Ethiopia – in contrast to the majority of countries in Sub-Saharan Africa – invests heavily in agricultural extension but very little empirical evidence is available on the impact of public extension services on farm performance and household welfare that could justify these investments. The IHEP program is a particularly interesting case as it is an example for how agricultural extension systems in developing countries changed during the past two decades, from centralized top-down technology-transfer-orientated approaches to decentralized, participatory and more integrated approaches. We empirically assess the impact of participation in the IHEP program on household income, investment and income diversification. We use household survey data from 730 farm-households in the Tigray region and propensity score matching methods to estimate the impact. We find that the extension program had a large positive impact on household welfare – increasing income with about 10 percent – and on investment and income diversification.

**Key words:** Agricultural extension**,** farm-household welfare, income diversification, propensity score matching, Ethiopia

**JEL classification:** Q12, Q16, O12

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**The Economic Impact of a New Rural Extension Approach in Northern Ethiopia**

## 1. Introduction

Developing countries' agricultural extension[2] systems have undergone major changes over the past two decades. During the second half of the 20th century, after independence from colonial power, most developing countries had public extension systems that were funded by the central government, often with very limited resources, and organized top-down (Swanson, 2008). The main focus of agricultural extension was on the transfer of technologies from central research units and experimentation stations to farmers, with the ultimate aim of increasing agricultural production in the interest of national food security and foreign exchange earnings through commodity export. Resource-poor and food insecure farmers were often neglected because they were less likely to innovate and adopt the promoted technologies as compared to resource-richer farmers.

During this period, Green Revolution Technologies became available and top-down technology-transfer-oriented extension services have played a major role in making these new technologies available to farmers in some regions and countries, especially in Asia. This has resulted in a positive impact on agricultural output growth, farm income and food security (Feder and Zilberman, 1986; Birkhaeuser et al., 1991). However, in other countries and regions, especially in Sub-Saharan Africa, top-down agricultural extension systems have largely failed to foster agricultural growth (Rivera, 1997, 2001). The early empirical literature on the economic impact of extension services in the post-independence era mostly points to positive effects on farm productivity, agricultural growth and rural income but much of this literature suffers from methodological weaknesses in identifying the causal impact of extension services[3] (Evenson, 2001).

The extension system changed importantly during recent decades. First, there has been a tendency towards decentralized and demand-driven public extension systems (Umali-Deininger, 1997; Rivera, 2001). This has been driven by the need for technologies that are adapted to specific agro-ecological and socio-economic conditions and the recognition that not only technologies but also markets are main drivers of agricultural development

[2] The term 'advisory services' is sometimes used instead of 'extension services'. These terms might mean slightly different things but many authors use them interchangeably. In this paper, we stick to the older but still more common terminology and use the term extension services.
[3] For a review of this literature and a discussion on identifying causality in measuring the impact of extensions services, see Evenson (2001) in the Handbook of Agricultural Economics.

(Swanson, 2008). Bottom-up and participatory approaches to agricultural extension are emerging, such as farmer-to-farmer extension and farmer field schools.

Second, there has been a tendency towards privatization (Umali-Deininger, 1997). Extension services are increasingly provided by input suppliers or food processing and distribution companies, often as part of contract-farming arrangements (Dinar, 1996; Swinnen and Maertens, 2007). Also producer cooperatives and civil society organizations have started to play a role in the provision of extension services to poor farmers, sometimes in cooperation with other private actors or public institutions. This has resulted in the existence of pluralistic extension systems that are based on public-private partnerships. Such private or pluralistic forms of agricultural extension are not yet widespread and in many countries, especially the poorest ones, public extension systems remain central (Anderson and Feder, 2004).

Third, the focus of agricultural extension services is gradually changing from a narrow focus on technology transfer towards a wider focus on human and social capital formation (Leeuwis, 2003, Swanson, 2008). Rather than merely transferring information on new technologies and improved management practices, extension services increasingly focus on expanding the skills and knowledge of farmers in general and on organizing them in producer groups.

Fourth, the objectives of agricultural extension expanded from agricultural productivity and output growth as a main goal to wider and more comprehensive aims such as sustainable natural resource management (Leeuwis, 2003; Swanson, 2008). In recent years, extension services have engaged in promoting technologies such as integrated pest management, conservation agriculture and integrated soil fertility management that aim at both output growth and sustainable use of natural resources. These broader aims of extension have shifted extension approaches further from technology-transfer-oriented and crop-specific approaches to more integrated approaches that promote several agricultural and sometimes even non-agricultural activities. With the liberalization of input markets at the end of the 20$^{th}$ century, extension systems have sometimes also taken on the provision of inputs and credit to poor farmers.

Fifth, while traditional agricultural extension systems have often specifically targeted resource-richer farmers because of their larger capacity and willingness to innovate, new extension approaches are more inclusive. The insights that not only food availability at the national level is important for food security but that also individual household access to food matters, increased the attention to poverty outreach in public extension programs (Swanson, 2008). Most extension systems are no longer biased to resource-richer farmers and poverty targeting has become an important additional objective.

These changes have provoked a renewed interest from researchers and academics in agricultural extension programs and their impact on farm performance and household welfare. Recent empirical impact studies have come up with diverse results and conclusions on the impact of extension programs. Some recent studies point to the failure of contemporary extension systems to bring about agricultural productivity growth and income gains (e.g. Binam et al., 2004; Feder et al., 2004; Haji, 2006). Others show positive effects of participation in extension programs on agricultural productivity, rural incomes and poverty reduction (e.g. Cunguara and Moder, 2011; Benin et al., 2011; Solis et al., 2008). Dercon et al. (2009) specifically analyzed the impact of agricultural extension in the early 1990s in Southern and Central Ethiopia and found that public extension visits reduced the poverty headcount ratio with 9.8 percent and increased consumption levels with 7.1 percent.

In this paper we analyze the impact of the current Integrated Household Extension Program (IHEP), which is claimed to be moving towards a decentralized, participatory and integrated extension program in the Tigray region in Northern Ethiopia. First, apart from the above mentioned study by Dercon et al. (2009), very few evidence is available on the impact of rural extension in Ethiopia in general, and on the impact of contemporary extension approaches in Northern Ethiopia in specific. The government of Ethiopia – in contrast to the majority of countries in Sub-Saharan Africa – invests heavily in agricultural extension. It is estimated that more than 2 percent of agricultural GDP is invested in public extension services (Spielman et al., 2010). This calls for appropriate impact studies that address the causal impact of public investment in extension programs on farm-household welfare.

The agricultural extension system in Ethiopia changed dramatically during the past decade (Belay, 2003), which makes it a particularly interesting case. There has been a shift from a centralized and top-down agricultural extension system a move towards to a decentralized approach, financed and organized by regional governments, and implemented in a participatory way. The system has changed from a narrow focus on technology transfer for cereal and export crop production towards an integrated system focusing on different agricultural as well as non-agricultural activities, on production as well as marketing, and on human capital formation as well as on relaxing cash and input constraints. The new system has become more inclusive and aims at a large (or even complete) outreach among smallholder farmers while the old system mainly focused on large-scale state and collective farms. It is important to understand the impact of this new approach and with this article we aim at contributing to this understanding.

To empirically assess the causal impact of the IHEP extension program in the Tigray region, we use primary data from a self-implemented survey among 734 farm-households in four districts. We consider different welfare and performance measures, including household income, investments and income diversification, and analyze the causal effect of household participation in the extension program on these indicators. Given the cross-sectional nature of our data and the difficulty with finding relevant and exogenous instruments for extension participation and using an instrumental variable model, we use propensity score matching to deal with potential selection bias problems and address causality.

The paper is organized as follows. In a next section we give a very brief historical overview of the agricultural extension system in Ethiopia, with a specific focus on Tigray. In section three we describe our research area and the data collection procedure. In section four we discuss household participation in the extension program and describe the differences in household characteristics and welfare across participating and non-participating households. In section five we describe our approach for estimating the causal impact of participation in the extension program on different outcome variables and discuss the results. We conclude in section six.

## 2. Agricultural extension in Ethiopia and Tigray[4]

Ethiopia has had a public agricultural extension service (excluding the 1930s Ambo Agricultural School's and later IECAMA's outreach programs), since the 1950s. Accordingly, various public extension programs have been implemented in Ethiopia. From the 1950s to the early 1990s, extension services in Ethiopia were organized by the central government and implemented in a top-down approach. Extension was mainly meant to improve agricultural output in cereal and export crop production through a transfer of improved agricultural technologies. The services were completely supply-driven and not at all tailored to the potential and constraints of different agro-ecological zones or to the needs of farmers. The focus was largely on large-scale state and cooperative farms, and on high-potential areas (Gebremedhin et al., 2006). Smallholder farmers, who were responsible for over 90 percent of cereal production, were completely neglected (Aredo, 1990). Little is known about the impact of these programs but it is generally believed that the impact has not been very impressive

[4] For a more detailed historical overview of the agricultural extension system in Ethiopia we refer to Belay (2003), Gebremedhin et al.(2006) and Abate (2007)

(Aredo, 1990; Belay, 2003; Gebremedhin et al., 2006). Some increases were observed in the use of mineral fertilizer, farm yard manure, optimal time of planting, improved seeds and improved animal breeds but agricultural productivity and household welfare did not improve substantially (Belay, 2003, Abate, 2007). Agricultural output growth could not keep pace with population growth and during the 1960s Ethiopia become a net food importer (Aredo, 1990). During the Mengistu era, from 1974 until 1991, civil war severely disrupted all economic activities and also agricultural extension services were severely disorganized during that period.

After the overthrow of the military government by the Ethiopian People Revolutionary Democratic Front (EPRDF) in 1991, agricultural extension regained importance in Ethiopia. In 1995, a new agricultural extension program was launched by the national government: the Participatory Agricultural Demonstration Extension and Training System (PADETES). PADETES for the first time applied a more participatory approach, called Extension Management and Training Plots (EMTP). This involved the establishment of on-farm demonstration plots that were managed by farmers themselves and the use of these plots for training and demonstration purposes. Besides receiving technical training, farmers also received complementary credit services in the form of provision of inputs on credit. The main focus, however, was still on technology transfer and on cereal production in high potential areas. The program had a quite limited coverage and the Tigray region in northern Ethiopia was for example not a main target area of the program (Gebremedhin et al., 2006). The PADETES program has known limited success in diffusing modern input use, which can at least partially be explained by simultaneous further liberalization of fertilizer markets and related increases in fertilizer prices (Diao, 2010).

In 2003 the extension system was decentralized to some extent and the regional governments received more autonomy to formulate, manage and implement extension programs. This decentralization policy was based on the observed need for local solutions adapted to existing agro-ecological and socio-economic conditions of specific areas. Within the general framework of PADETES, regional governments were allowed to adapt the approach to fit the specific needs in their regions. Accordingly, the Tigray regional state developed the Integrated Household Extension Program (IHEP) in 2003 (Gebremedhin et al., 2006; Abate, 2007; Belay, 2003). The IHEP program focuses on two main objectives: increasing rural incomes and diversifying household incomes. The focus on income diversification stems from the need to diversify rural incomes away from cropping and thereby reduce pressure on land and other natural resources. With increasingly fragmented landholdings and decreasing farm sizes[5], an important share of income growth will have to come from diversification out of agriculture. The IHEP program applies an integrated package approach focusing on different economic activities, including crop production, livestock rearing, and non-farm activities. Rural households receive information on service packages from extension workers and can choose which components of the extension packages they take up. Farmers Training Centers are put up to demonstrate technologies and train farmers for the implementation of specific technologies and practices. When farmers are trained, they receive inputs and credits from the extension program to apply the technologies and practices in their own farm or non-farm businesses. This approach is more demand-driven and participatory than previous extension program in Ethiopia. In addition, the IHEP program aims at a complete outreach, serving all interested rural households in the region.

## 3. Research area and data

Our study focuses on the area of the Geba catchment in the Tigray Region in northern Ethiopia. This catchment area covers 10 districts and 168 sub-districts – the smallest administrative units in Ethiopia – and is part of a large collaborative and multi-disciplinary research project. The area stretches over three different agro-climatic zones: lowlands below 1500 m.a.s.l. (*kolla*), mid-highlands between 1500 and 2300 m.a.s.l. (*woina dega*), and upper highlands between 2300 and 3200 m.a.s.l. (*douga*).

The Geba catchment is predominantly a rural area and the large majority of people are smallholder farmers. The typical farming system is that of mixed farming in which cereal cropping is combined with livestock rearing mainly cattle. Farm sizes are very small – 0.65 ha on average in the region (TBoANRD, 2003) – and decrease with the altitude. Productivity in cereal cropping is low with average yields below one ton per ha (Pender et al., 2006). As a result, many farmers are subsistence farmers who face difficulties supporting their families, with on average 5 to 6 members, from their farm. In drought years people become fully dependent on food aid. It is against this rationale that the regional government continues to invest in extension services in order to increase and diversify household income.

To analyze the impact of the integrated and collaborative extension approach in the Geba catchment area, we implemented a household survey in the period May - June 2009. A three-stage stratified random sampling design was chosen to ensure representativeness of the sample and to cluster observations per district and sub-district. First, districts were stratified

[5] Landholdings per household in the Tigray region have declined from 3.8 hectares to 0.65 hectares over the last 30 years (TBoANRD, 2003).

according to the agro-climatic zone. One district was randomly selected from the lowland and from the upper highland zones and two from the mid-highland zone. Second, in each selected district, two sub-districts were randomly selected. Third, in each selected sub-district, households were selected proportional to the sub-district population size and stratified according to whether or not they received extension services from the IHEP program. The final sample includes 734 households, of which 363 received extension services and 371 did not.

A self-designed quantitative questionnaire was used for the survey. The questionnaire was composed of different modules on different topics, including modules on household demographic characteristics, on landholdings (including recall data), on farming systems, on livestock holdings (including recall data), on extension services (including recall data), on consumption, expenditures and investments, and on off-farm activities and income.

## 4. Household participation in extension services and welfare

### *4.1. Participation in the IHEP program*

An estimated 20,053 rural households live in the Geba catchment area, out of which, during the survey period more than 80 percent were participating in the IHEP extension program (CSA, 2011; CSA, 2007b; TBoANRD, 2003). Our sample includes 363 households who received extension services under the new IHEP program – we call those the treated households – and 371 households who were not part of the IHEP extension program – we call those the control households. Table 1 includes household and farm characteristics for treated and control households and reveals some important differences across the two groups. Treated households have significantly older household-heads, larger household sizes, more adult labor, and a higher probability of being male-headed. No significant differences are observed in the level of education of the household head. Treated households seem to be better off in terms of productive capital with larger land and livestock holdings. Treated households initially, before the IHEP extension program started in 2003, already had significantly larger land and livestock holdings. Also, social capital, measured by membership in an Iddir organization[6], is significantly higher among treated households. Moreover, treated households are located further from markets, both district markets and the main urban market in Mekelle, than control households.

[6] Iddir is an association in which people are united through living in the same neighborhood , other criteria with the aim of the association is to provide mutual aid and financial assistance when faced with shocks.

**Table 1: Household and farm characteristics for treated and control households**

| Variables | Description | Treated households (n=363) Mean | SE | Control Households (n=371) Mean | SE | Ttest (treated-control) t-value |
|---|---|---|---|---|---|---|
| **Household characteristics** | | | | | | |
| AgeHHH | Age of the household head (years) | 45.185 | *0.674* | 42.785 | *0.835* | -2.229 ** |
| HHHedu | Education of the household head (years) | 0.897 | *0.071* | 0.837 | *0.072* | -0.593 |
| Gender | =1 if for male-headed household | 0.806 | *0.021* | 0.669 | *0.024* | -4.241 *** |
| Fsize | Family size of the households | 6.047 | *0.111* | 4.747 | *0.115* | -8.109 *** |
| Adult | Adult labor force in the household | 3.061 | *0.076* | 2.463 | *0.069* | -5.823 *** |
| **Farm characteristics** | | | | | | |
| Landsize lag | Land size before treatment, 2003 (tsemad[1]) | 5.019 | *0.182* | 3.792 | *0.165* | -4.999 *** |
| Landsize | Land size survey year, 2009 (tsemad[1]) | 4.317 | *0.169* | 3.067 | *0.161* | -5.360 *** |
| Livestock | Value of livestock holdings, 2009 (Birr) | 7344 | *464* | 5447 | *379* | -3.167 *** |
| Oxen | Number of oxen, 2009 | 1.423 | *0.058* | 1.246 | *0.060* | -2.110 ** |
| Oxen lag | Number of oxen, 2003 | 1.088 | *0.041* | 0.844 | *0.044* | -4.069 *** |
| TLU | Tropical livestock units, 2009 (TLU[2]) | 3.745 | *0.147* | 2.789 | *0.166* | -4.299 *** |
| TLU lag | Tropical livestock units, 2003 (TLU[2]) | 2.622 | *0.107* | 1.992 | *0.097* | -4.372 *** |
| **Social capital and distance to markets** | | | | | | |
| Iddir | = 1if the hh is a member of Iddir | 0.296 | *0.024* | 0.168 | *0.019* | -4.154 *** |
| DistanceM | Sub-district distance to Mekelle market (km) | 72.884 | *1.635* | 67.729 | *1.463* | -2.352 *** |
| DistanceD | Sub-district distance to District market (km) | 13.434 | *0.481* | 11.202 | *0.458* | -3.365 *** |

Significant differences are indicated with * p<0.1; ** p <0.05; *** p<0.01

[1] Tsemad=1/4 hectare

[2] TLU= Tropical Livestock Unit (equals 1 for camel, cattle 0.7, sheep and goats 0.1, horses 0.8, mules 0.7 , donkey 0.5, and chickens 0.01)

*Source: Author's calculation from survey data*

In summary, treated households who received extension services under the IHEP program are better off in terms of human and social capital, and productive asset ownership. This indicates that participation in the extension program is not randomly distributed over households and strongly correlated with observable household and farm characteristics.

### *4.2. Household income*

The first aim of the IHEP extension program is increasing rural incomes. When comparing total household income and income from different sources for treated and control households in table 2, it is clear that participation in the IHEP program is associated with sharp differences in households income. A simple comparison of means reveals a large difference in total household income: 8,101 Birr for treated households compared to 6,344 Birr for control households. This is a difference of 28 percent, which is large and significant. Treated households have larger incomes than control households but given the non-random distribution of the program this does not say anything about the impact of the IHEP extension program. Further in-depth econometric analysis is needed to address causality.

**Table 2: Income and income sources for treated and control households**

| | Treated households (n=363) | | Control households (n=371) | | ttest (treated-control) |
|---|---|---|---|---|---|
| | Mean | *SE* | Mean | *SE* | t-value |
| **Total average income** | | | | | |
| Total household income | 8,101 | *420* | 6,344 | *323* | -3.327*** |
| **Average income from different sources[1]** | | | | | |
| Farm income | 5,546 | *305* | 4,306 | *305* | -2.872*** |
| Income from cropping | 4,659 | *299* | 3,752 | *301* | -2.139** |
| Income from livestock-rearing | 887 | *78* | 554 | *47* | -3.646*** |
| Non-farm income | 2,375 | *287* | 1,455 | *98* | -3.058*** |
| Income from wages | 1,725 | *156* | 1,115 | *67* | -3.612*** |
| Income from non-farm businesses | 650 | *169* | 340 | *70* | -1.710** |
| Non-labor income | 180 | *41* | 583 | *99* | 3.724*** |
| Transfer income[2] | 37 | *11* | 215 | *58* | 2.989*** |
| Migration income[3] | 142 | *40* | 368 | *78* | 2.573*** |
| **Average share of income from different sources** | | | | | |
| Farm income | 68.5 | | 67.9 | | |
| Non-farm income | 29.3 | | 22.9 | | |
| Non-labor income | 2.2 | | 9.2 | | |
| **Income diversification** | | | | | |
| Income diversification index (SID)[4] | 0.428 | *0.011* | 0.419 | *0.011* | -0.551 |

Significant differences are indicated with * p<0.1; ** p <0.05; *** p<0.01

[1] Income from all different sources are calculated for the 12 months period prior to the survey.

[2] Transfer income refers to public transfers from governmental and non-governmental programs (in cash or in kind).

[3] Migration income refers to remittances sent by migrated household and family members.

[4] The Simpson index of diversity (SID) is defined as $SID = 1 - \sum V_i^2$; Where $V_i$ is the proportion of income coming from source $i$

*Source: Author's calculation from survey data*

Farming is the most important activity in the region, and both treated and control households obtain on average about 70 percent of their total household income from farming (table 2). Crop income is the most important part of farm income and is significantly higher for treated households (4,659 Birr) than for control households (3,752 Birr). Also the difference in livestock income between treated and control households are significant: 887 Birr and 554 Birr for treated and control households respectively. Non-farm income, including income from wages[7] as well as income from non-farm businesses, accounts for about 25 percent of total income for both groups and is again significantly higher for treated households (2,375 Birr) than for control households (1,455 Birr). The superior performance of treated households in terms of farm and non-farm income is in line with what one would expect given the better capital and asset position of these households. From the presented descriptive statistics it remains unclear whether the observed differences in income are attributable to the impact of the extension program or to differences in the underlying characteristics of treated versus control households.

Non-labor income is more important in the income portfolio of control households, where it amounts to 9.2 percent of total household income (compared to 2.2 percent for treated households). The largest share of non-labor income comes from public transfers in the form of food aid. This could indicate that control households are poorer and more often need to rely on government and charity aid.

### *4.3. Income diversification*

The second aim of the IHEP extension program is to diversify rural incomes away from agriculture and cropping. To compare the degree of income diversification between treated and control households the Simpson Index of Diversification (SID) was calculated. This index is calculated as follows:

$$SID = 1 - \sum V_i^2 \qquad (1)$$

with $V_i$ the proportion of income from source $i$. The value of SID is low when households have few different income sources and becomes 0 when the household depends on only one income source. The value increases with the number of different income sources and approaches one if the number of income sources becomes very large (Minot et al, 2006). The index is in line with a definition of income diversification referring to an increase in the number of income sources and the balance among them[8] (Joshi et al., 2003; Minot et al.,

[7] An important part of wage income comes from employment in public safety net employment programs, designed to provide households with enough income (cash/food) to meet their food gap and protect their assets during crises periods.

[8] This is the most common used definition of income diversification. Others have used other notions of income diversification: e.g. as a switch from subsistence food production to commercial agriculture (Delgado and Siamwalla, 1997); as expansion in the importance of non-crop or non-farm income (Reardon, 1997); or as a switch from low-value crop production to high-value crops, livestock and non-farm activities (Minot et al., 2006).

2006; Dercon, 1998). To calculate the index, we took into account six income sources: cropping, livestock rearing, wages, non-farm business, public transfers and private transfers. This diversification index is reported in table 2. The index is slightly higher for treated households (0.428) than for control households (0.419) but the difference is very small and statistically not significant. This indicates there is no difference in the degree of income portfolio diversification between households receiving extension services and households not receiving those services.

**Table 3: Income and income sources across income diversification quintiles**

| | Income diversification (SID) quintiles, from lowest (1) to highest (5) diversification | | | | |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| Total income | 9,910 | 6,528 | 6,147 | 6,678 | 6,846 |
| Farm income | 8,772 | 4,866 | 3,726 | 3,882 | 3,408 |
| Income from cropping | 8,546 | 4,418 | 3,121 | 2,983 | 1,997 |
| Income from livestock- rearing | 226 | 448 | 605 | 899 | 1,411 |
| Non-farm income | 1,115 | 1,328 | 2,000 | 2,327 | 2,770 |
| Income from wages | 769 | 917 | 1,609 | 1,929 | 1,853 |
| Income from non-farm businesses | 346 | 411 | 392 | 398 | 917 |
| Non-labor income | 23 | 334 | 420 | 469 | 667 |
| Transfer income[2] | 19 | 87 | 153 | 75 | 301 |
| Migration income[3] | 4 | 247 | 266 | 394 | 367 |

[1] The Simpson index of diversity (SID) is defined as $SID = 1 - \sum V_i^2$; Where $V_i$ is the proportion of income coming from source $i$

[2] Transfer income refers to public transfers from governmental and non-governmental programs (in cash or in kind).

[3] Migration income refers to remittances sent by migrated household and family members.

*Source: Authors 'calculation from survey data*

In the literature, there is a debate on the relation between income levels and income diversification. Some authors argue that diversification of incomes away from farm activities lead to higher income levels but that households face constraints to enter such new non-farm income-generating activities (Dercon, 1998; Woldenhanna and Oskam, 2001; Barrett et al., 2001a). Others argue that income diversification is associated with lower incomes because households choose to diversify their activities at a cost of lower return as a risk coping mechanism (Barrett et al., 2001b; Ellis, 1998). To shed more light on the relation between income and income diversification in our case study, we classified our sampled households in income diversification quintiles and compare incomes across the quintiles (table 3). This reveals that households with the least diversified incomes have the highest total incomes and are specialized in cropping. The lowest average income is found among households in the middle income diversification quintile. The households in the highest income diversification quintiles have the lowest cropping incomes but the highest incomes from livestock rearing, wage employment, non-farm business activities, and transfers. This indicates that income and income diversification are negatively correlated at lower levels of income diversification and positively correlated at higher levels of income diversification.

### *4.4. Investment and expenditures*

In addition to income measures of welfare, we also consider investment and expenditures measures and compare them across treated and control households in table 4. We find that treated households invested more in livestock (2,640 Birr) than control households (1,336 Birr) but that their overall asset formation is not significantly different from that of control households. This could be expected, as some packages of the IHEP extension program specifically focus on livestock rearing (dairy, poultry, sheep and goats) and improved animal breeds.

**Table 4: Investment and expenditures for treated and control households**

| | Treated households (n= 363) | | Control households (n=371) | | ttest (treated-control) |
|---|---|---|---|---|---|
| | Mean | *SE* | Mean | *SE* | t-value |
| Fixed asset formation [a] | 12,765 | *1,110* | 10,556 | *1,541* | -1.159 |
| Livestock investment [b] | 2,640 | *203* | 1,336 | *136* | -5.339*** |

Significant differences are indicated with * p<0.1; ** p <0.05; *** p<0.01

[a] Fixed asset formation includes households' investment during the 12 months prior the survey in houses, agricultural equipment, consumer durables (furniture, electronic appliances, etc), valued at the survey year price level.

[b] Livestock investment includes households' investment in the different livestock units (cattle, beehives, poultry, etc) during 12 months prior to the survey, valued at the survey year price level.

*Source: Author's calculation from survey data*

## 5. Econometric analysis of welfare effects

The descriptive analysis presented in the previous section shows that there are substantial differences in the underlying characteristics of treated versus control households as well as in their incomes and investment. However, based on a simple comparison of means it is impossible to identify causality and to attribute the observed differences in welfare outcomes to the impact of the extension program. In this section we present an econometric analysis to estimate the causal impact of participation in the IHEP extension program on household income, income diversification, and investment.

### *5.1. Estimation approach*

Participation in the IHEP extension service is not random and strongly correlated with observable household and farm characteristics. This complicates the estimation of the causal impact of the program and gives rise to selection bias. This may arise from households' self-selection into the extension program or from endogenous program placement. Households may decide, based on their access to productive resources, to participate in the extension services and self-select into the program. In addition, program administrators and extension agents may target certain villages and select households with specific characteristics.

We address the potential selection problem using propensity score matching and regression techniques. These are state-of-the-art methods proposed in program evaluation (Imbens, 2004; Wooldridge, 2008) and increasingly applied in the empirical agricultural economics literature (e.g. Maertens and Swinnen, 2009; Imai et al., 2010; Becerril and Abdulai, 2009; Faltermeier and Abdulai, 2009). First, we use a regression model – referred to as *regression on covariates* – in which we control for selection bias by including a large set of observable covariates. The model is specified as follows:

$$Y = \beta_0 + \beta_1 T + \beta_2 X_1 + \mu \tag{2}$$

The variable $T$ is the treatment variable, a dummy variable specifying whether or not the household has participated in the IHEP extension program. The causal effect of the extension program, or the treatment effect, is estimated by the coefficient $\beta_1$. Different outcome variables $Y$ are considered: 1/ total household income; 2/ livestock investments; 3/ fixed asset formation; and 4/ income diversification (SID). The outcome variables are measured and calculated as explained in section 4 and are, except for the diversification index, specified in logarithmic terms. The vector $X_1$ is a vector of control variables, including the age of the household head (ageHHH), household head education (HHHedu), household head gender (Gender), adult labor force (Adult), initial 2003 landholdings (Landsize_lag), initial 2003 livestock holdings (TLU_lag), initial 2003 number of oxen owned (Oxen_lag), Iddir membership (Iddir), distance to main market (DistanceM) and distance to local market (DistanceD). The lagged variables for 2003 refer to a base year, before the IHEP program started. By including a large set of control variables, we account for the observed heterogeneity across treated and control households.

Second, we estimate a propensity score and use this as an additional control variables in the regression model. We refer to this model as *regression on the propensity score*. The model is specified as follows:

$$Y = \beta_0 + \beta_1 T + \beta_2 X_1 + \beta_3 PS + \mu \qquad (3)$$

with $T$, $X_1$ and $Y$ as defined above in equation (3.2) and the coefficient $\beta_1$ being the treatment effect of interest. The variable $PS$ is the propensity score or the estimated conditional probability of being treated. Adding the propensity score as an additional control variable in the regression further reduces the potential bias created by selection on observable characteristics (Imbens, 2004). The propensity score is estimated as the probability of receiving extension services using a probit model:

$$PS = p(T = 1|X_2) = \gamma_0 + \gamma_1 X_1 + \varepsilon \qquad (4)$$

Third, we estimate the treatment effect using different propensity-score matching techniques, which we refer to as *matching on the propensity score*. This method involves matching treated households with control households that are similar in terms of observable characteristics (Imbens, 2004; Imbens and Angrist; 1995; Caliendo and Kopeinig, 2008). As matching directly on observable characteristics is difficult if the set of potentially relevant characteristics is large, matching on propensity scores has been proposed as a valid method (Rosenbaum and Rubin, 1983). We match every treated household in our sample with one or several control households with a similar propensity score, using the propensity score as estimated in equation (3.4) and using different matching methods. We first use stratification matching, which involves the identification of strata with different ranges of the propensity score. We then apply single-nearest neighbor matching, in which every treated household is matched to the control household with the closest propensity score. According to Imbens (2004) this leads to the most credible inferences with the least bias. This can however result in poor matches if the difference in the propensity score between the treated and the closest control unit is still large. We therefore additionally apply radius matching with a caliper distance of 0.1 as threshold tolerance level of propensity score distance between treated and matched controls. We finally apply kernel matching, using the default Gaussian kernel. This involves matching every treated unit to a construct that is a weighted average of all control units with weights depending on the propensity score distance between the treated and controls. The advantage of kernel matching is that all information from all control units is used. Since the sub-sample of control observations is relatively small, matching is always done with replacement. As propensity score matching methods are sensitive to the exact specification and matching method, the use of different matching techniques serves as a robustness check.

After matching treated households with control households on the propensity score, the average treatment effect of the treated (ATT) is calculated as a weighted difference between treated and matched controls. The ATT measures the impact of the extension program for households participating in the program and is calculated as follows:

$$ATT = E(Y^T - Y^C | T = 1) = = \frac{1}{N_T}\left[\sum_{i \in T} Y_i^T - \sum_{j \in C} \omega(i, j) Y_i^C\right] \tag{5}$$

with $N_T$ the number of treated observations, $Y^T$ outcome with treatment, $Y^C$ outcome without treatment, and $\omega(i,j)$ the weight factor used in matching. The latter factor is 1 in case of single nearest neighbor matching and smaller than 1 in case of radius and kernel matching. We estimate the ATT using propensity score matching for all four outcome variables of interest: 1/ total household income; 2/ livestock investments; 3/ fixed asset formation; and 4/ income diversification.

The reliability of propensity score matching estimators depends on two crucial assumptions. First, the conditional independence assumption requires that given observable variables, potential outcomes are independent of treatment assignment (Imbens, 2004)[9]. This implies that selection into treatment is based entirely on observable covariates, which is a strong assumption. Second, the common support or overlap condition requires that treatment observations have comparison control observations nearby in the propensity score distribution (Caliendo and Kopeinig, 2008). As proposed by Heckman et al. (1997) only observations in the common support region – where the propensity score of the control units is not smaller than the minimum propensity score of the treated units and the propensity score of the treated units not larger than the maximum propensity score of the control units – are used in the

[9] This assumption is also referred to as unconfoundedness (Rosenbaum and Rubin, 1983), selection on observables (Heckman and Robb, 1985)

analysis. This comes down to dropping ten control observations for which the estimated propensity score is higher than the maximum propensity score of the treated units. The two assumptions are further addressed in section 5.3 after the discussion of the results.

### *5.2. Results and discussion*

The estimation results are presented in tables 5, 6 and 7. First, the main results, the estimated treatment effects, are summarized in table 5. The estimated treatment effects are positive and significant in all models for income and investment measures (both livestock and fixed assets). The estimated effect on income diversification is positive and significant in all but one of the models. The results from the different estimation techniques are qualitatively identical and quantitatively very similar. This is an indication of the robustness of the results to changes in the estimation approach.

**Table 5: Estimated treatment effects using different methods**

| Outcome indicators | Regression on covariates | Regression on propensity score | Matching on propensity score | | | |
|---|---|---|---|---|---|---|
| | | | Stratification matching | Radius matching | Kernel matching | Nearest neighbor matching |
| Total income (log) | 0.076 *<br>(0.059) | 0.077*<br>(0.059) | 0.100**<br>(0.058) | 0.127 **<br>(0.060) | 0.079*<br>(0.058) | 0.138 *<br>(0.097) |
| SID | 0.024 *<br>(0.015) | 0.025*<br>(0.015) | 0.027**<br>(0.016) | 0.013<br>(0.015) | 0.026*<br>(0.017) | 0.051 ***<br>(0.021) |
| Livestock investment (log) | 1.683 ***<br>(0.283) | 1.349***<br>(0.230) | 1.468***<br>(0.380) | 1.622***<br>(0.265) | 1.521***<br>(0.285) | 1.873 ***<br>(0.411) |
| Fixed asset formation (log) | 0.196 **<br>(0.084) | 0.197**<br>(0.84) | 0.200**<br>(0.091) | 0.311***<br>(0.102) | 0.182**<br>(0.098) | 0.179 *<br>(0.134) |

Significant effects are indicated with * p<0.1; ** p <0.05; *** p<0.01
Figures in bracket are standard errors

*Source: Author's calculation from survey data*

The estimation results confirm that participation in the IHEP extension program has a positive impact on household income and investments in livestock and other productive assets. The estimated coefficients on income varies from 0.076 to 0.138 depending on the estimation approach. Since income is specified in logarithmic terms, this means that the IHEP extension program has increased household income with 7.6 to 13.8 percent. This effect might seem not overwhelmingly high. Yet, in areas where the large majority of households live close to the poverty line, an income increase of about 10 percent might make an important difference in household welfare.

The estimated effect on investment is much higher. For investment in livestock the estimated coefficients ranges from 1.87 to 1.34 depending on the estimation approach, and for overall asset investment from 0.19 to 0.31. Given the logarithmic specification, this indicates that the IHEP extension program more than doubled investment in livestock and increased overall asset investment with 20 to 30 percent. These are very large and important effects. In view of the nature of the program with a large focus on dairy, sheep and goats, the high effects on livestock investment are not surprising. The high impact of the program on productive investment might create additional long term benefits in terms of future growth in income and improved household resilience to risk and shocks.

We find a positive effect of the extension program on income diversification. This effect is not significant in the radius matching estimation but is significant at the 10% or 5% level for the other estimations. Given that the SID index ranges from 0 to 0.73 in the sample and that the average is 0.42, the estimated effect is relatively small, ranging from 0.013 to 0.051. We can take this as an indication that het program had a positive but small effect on income diversification. The IHEP program also focused on non-cropping and non-farm activities and income diversification was a specific goal of the program. In this respect, the small effect is somewhat surprising and might indicate that non-farm activities received less attention in the program, either from the extension agents or from the beneficiary households themselves. Our findings corroborate the scarce empirical evidence in the literature on the impact of contemporary extension programs in Ethiopia. Our results are in line with the results of Dercon et al. (2009) who showed that public extension programs reduced poverty with 9.8 percent and increased household consumption with 7.1 percent.

Second, the results of the full regression models are presented in table 6. These results reveal that apart from participation in the IHEP extension program, other variables determine household income, investment and income diversification. Older households are found to have lower levels of income and income diversification. Male-headed households have incomes that are 29 percentage points higher than female-headed households, have more diversified incomes and make larger investments in livestock. As could be expected, access to productive resources increases household income. More labor, larger initial landholdings and larger initial livestock holdings have a significant positive impact on income. Households with initially more land invest less in livestock and have less diversified income portfolios while households with initially larger livestock holdings invest even more in livestock and other assets. Social capital, measured by membership of an Iddir organization, has a positive and significant impact on income and investment. Distance to the main market has a negative impact on income, investment and income diversification.

**Table 6: Regression results for different outcome indicators**

| Covariates | Outcome indicators<br>Total income (log) | SID | Livestock investment (log) | Fixed asset formation (log) |
|---|---|---|---|---|
| Treatment | 0.076* | .024* | 1.8683*** | 0.196** |
| | (0.059) | (0.015) | (0.283) | (0.084) |
| AgeHHH | -0.010*** | -.003*** | -0.006 | 0.001 |
| | (0.002) | (0.001) | (0.011) | (0.003) |
| HHHedu | 0.020 | -.005 | 0.215** | 0.018 |
| | (0.023) | (0.006) | (0.011) | (0.033) |
| Gender | 0.292*** | 0.030* | 0.939*** | 0.044 |
| | (0.074) | (0.020) | (0.354) | (0.105) |
| Adult | 0.104*** | 0.015*** | 0.146* | 0.107*** |
| | (0.023) | (0.006) | (0.110) | (0.032) |
| Landsize_lag | 0.036*** | -0.011*** | -0.176*** | 0.038** |
| | (0.012) | (0.003) | (0.057) | (0.018) |
| TLU_lag | 0.070*** | -0.009** | 0.350*** | 0.109*** |
| | (0.017) | (0.004) | (0.083) | (0.024) |
| Oxen_lag | 0.151*** | 0.033*** | -0.050 | 0.215*** |
| | (0.041) | (0.010) | (0.195) | (0.058) |
| Iddir | 0.206*** | 0.019 | 0.916*** | 0.173* |
| | (0.076) | (0.020) | (0.364) | (0.108) |
| DistanceM | -0.004*** | -0.000 | -0.021*** | -0.009*** |
| | (0.001) | (0.000) | (0.006) | (0.001) |
| DistanceD | 0.006** | -0.005*** | -0.041*** | -0.007 |
| | (0.003) | (0.001) | (0.018) | (0.005) |
| Constant | 8.194*** | 0.589*** | 3.674*** | 8.191*** |
| | (0.168) | (0.044) | (0.805) | (0.240) |
| # of observations | 730 | 730 | 730 | 730 |
| $R^2$ | 0.28 | 0.10 | 0.17 | 0.21 |
| Adj R2 | 0.27 | 0.09 | 0.16 | 0.20 |
| F(11,718) | 25.00 | 7.19 | 13.35 | 17.66 |
| Prob>F | 0.000 | 0.000 | 0.000 | 0.000 |

Significant effects are indicated with * p<0.1; ** p <0.05; *** p<0.01
Figures in bracket are standard errors

*Source: Author's calculation from survey data*

Third, table 7 gives the results of the probit model estimating the propensity score. The model is statistically significant at the 1 percent level and correctly predicts 64 percent of the observations. We observe that farmers' education and household labor resources positively affect participation in the extension program. This is in line with previous studies on extension services (e.g. Chianu and Tsujii, 2004; D'Souza et al., 1993). This indicates that labor constraints might exist for participating in extension services that promote new technologies and activities that might be labor and skill intensive. The results indicate that initial landholdings have a positive impact on the probability of participating in the extension program but initial livestock holdings have no effect. This is not completely in line with the IHEP program strategy to target poorer and less-endowed households and might indicate there is still a bias towards households with larger farms in program placement.

**Tables 7: Estimation of the propensity score**

| Covariates | Marginal effects | SE |
|---|---|---|
| AgeHHH | 0 .001 | .001 |
| HHHedu | 0 .028** | .016 |
| Gender | 0 .034 | .050 |
| Adult | 0 .065*** | .015 |
| Landsize_lag | 0 .014** | .008 |
| TLU_lag | 0 .004 | .012 |
| Oxen_lag | 0 .006 | .027 |
| Iddir | 0 .184*** | .049 |
| DistanceM | 0 .002*** | .001 |
| DistanceD | 0 .006** | .002 |
| Log Likelihood | -461.84 | |
| LR Chi2 (11) | 88.22 | |
| Prob > chi2 | 0.000 | |
| Pseudo R2 | 0.09 | |
| % correctly predicted | 63.84 | |

Significant effects are indicated with * p<0.1; ** p <0.05; *** p<0.01

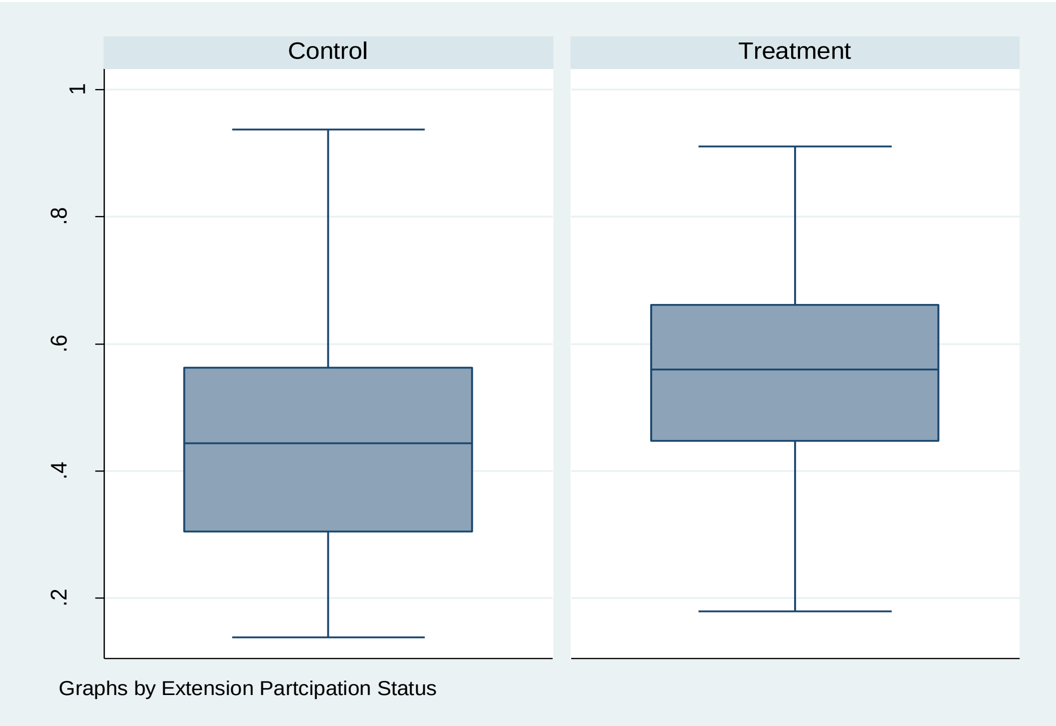
*Source: Authors 'calculation from survey data*

Distance to markets, both local and urban markets, is found to positively affect participation in the extension program. This contradicts most findings from previous studies (e.g. Mendola, 2007; Gebremedhin et al., 2009), but similar results were found by Genius et al. (2006). This finding might be related to the fact that the IHEP program aims at a poverty outreach and specifically targets remote areas where poverty headcount ratios are higher. Further, we find that membership in an Iddir, a measure of social capital, has a positive effect on the likelihood of participating in an extension program. This result indicates that social capital is important for access to programs and is in line with other studies (e.g. Tiwari et al., 2008; Zepeda, 1990).

### *5.3. Assumptions*

First, the conditional independence (CI) assumption is intrinsically not testable because the data are completely uninformative about the distribution of the treated outcome for untreated observations and vice versa (Imbens, 2004; Becker and Ichino and, 2002). Yet, we can check the sensitivity of our estimations to deviations from the CI assumption. We do so by using an approach first proposed by Rosenbaum (2002) and discussed in detail by Becker and Caliendo (2007). We perform this test using the rbounds command in stata (Becker and Caliendo, 2007) and report the results in appendix 3.1 to 3.4. The sensitivity analysis indicates that for all outcome variables (income, income diversification, livestock investment and fixed asset formation) the estimated ATTs are insensitive to a bias that would eightfold the odds of treatment due to unobserved effects. This implies that our matching estimates are free of bias caused by unobserved factors.

**Figure 1: Distribution of the estimated propensity scores over treated and control households**




*Source: Author's estimation from survey data*

Second, we verify the common support condition by comparing the propensity score distribution of the treated and control observations. This is done in figure 3.1. The figure shows that the propensity scores are strictly between 0 and 1, which is a first requirement (Imbens, 2004), and that there is sufficient overlap in the propensity scores of treated and control units with a large region of common support.

Third, we test the balancing properties for all covariates in the identified strata of propensity score ranges. These balancing properties are reported in appendix 3.5. The results indicate that all covariates are balanced in all strata at the 1% level. From this, we can conclude that the there is sufficient balance in the covariate distribution between treated the treated and matched control group.

## 6. Conclusion

This study examined the impact the IHEP extension program in the Tigray region in Ethiopia. Since this program concerns a new extension approach that is moving towards a more decentralized, integrated and participatory system, understanding the impact on local farm households is important. We find that the program importantly contributed to rising household income and investment in the region. Effects on income diversification were small. We can conclude that the IHEP program had an important positive welfare impact and extending the program further to reach the majority of rural households in the Tigray region will likely benefit the welfare of rural households further.

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## Appendix 1: Rosenbaum rbounds for ln household income

| Gamma | sig+ | sig- | t-hat+ | t-hat- | CI+ | CI- |
|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 8.587 | 8.587 | 8.527 | 8.647 |
| 1.5 | 0 | 0 | 8.439 | 8.730 | 8.374 | 8.789 |
| 2 | 0 | 0 | 8.331 | 8.826 | 8.259 | 8.886 |
| 2.5 | 0 | 0 | 8.243 | 8.898 | 8.168 | 8.959 |
| 3 | 0 | 0 | 8.173 | 8.955 | 8.091 | 9.018 |
| 3.5 | 0 | 0 | 8.111 | 9.003 | 8.026 | 9.067 |
| 4 | 0 | 0 | 8.057 | 9.043 | 7.967 | 9.109 |
| 4.5 | 0 | 0 | 8.011 | 9.078 | 7.915 | 9.145 |
| 5 | 0 | 0 | 7.968 | 9.109 | 7.869 | 9.178 |
| 5.5 | 0 | 0 | 7.928 | 9.136 | 7.828 | 9.208 |
| 6 | 0 | 0 | 7.893 | 9.160 | 7.788 | 9.235 |
| 6.5 | 0 | 0 | 7.862 | 9.183 | 7.750 | 9.259 |
| 7 | 0 | 0 | 7.832 | 9.205 | 7.718 | 9.282 |
| 7.5 | 0 | 0 | 7.805 | 9.224 | 7.687 | 9.303 |
| 8 | 1.1e-16 | 0 | 7.777 | 9.242 | 7.659 | 9.323 |

Gamma - log odds of differential assignment due to unobserved factors
sig+ - upper bound significance level
sig- - lower bound significance level
t-hat+ - upper bound Hodges-Lehmann point estimate
t-hat- - lower bound Hodges-Lehmann point estimate
CI+ - upper bound confidence interval (a= .95)
CI- - lower bound confidence interval (a= .95)

*Source: Authors 'calculation from survey data*

**Appendix 2: Rosenbaum rbounds for income diversification index (SID)**

| Gamma | sig+ | sig- | t-hat+ | t-hat- | CI+ | CI- |
|---|---|---|---|---|---|---|
| 1 | 0 | 0 | .436 | .436 | .418 | .453 |
| 1.5 | 0 | 0 | .392 | .477 | .374 | .494 |
| 2 | 0 | 0 | .362 | .504 | .343 | .520 |
| 2.5 | 0 | 0 | .340 | .523 | .322 | .538 |
| 3 | 0 | 0 | .323 | .537 | .304 | .553 |
| 3.5 | 0 | 0 | .309 | .549 | .289 | .564 |
| 4 | 0 | 0 | .296 | .559 | .275 | .573 |
| 4.5 | 0 | 0 | .285 | .566 | .264 | .580 |
| 5 | 0 | 0 | .275 | .573 | .254 | .587 |
| 5.5 | 0 | 0 | .267 | .578 | .247 | .593 |
| 6 | 0 | 0 | .259 | .584 | .239 | .599 |
| 6.5 | 0 | 0 | .253 | .588 | .231 | .603 |
| 7 | 0 | 0 | .247 | .593 | .224 | .608 |
| 7.5 | 0 | 0 | .242 | .596 | .216 | .612 |
| 8 | 1.1e-16 | 0 | .237 | .600 | .210 | .615 |

Gamma - log odds of differential assignment due to unobserved factors
sig+ - upper bound significance level
sig- - lower bound significance level
t-hat+ - upper bound Hodges-Lehmann point estimate
t-hat- - lower bound Hodges-Lehmann point estimate
CI+ - upper bound confidence interval (a= .95)
CI- - lower bound confidence interval (a= .95)

*Source: Authors 'calculation from survey data*

## Appendix 3: Rosenbaum rbounds ln livestock investment

| Gamma | sig+ | sig- | t-hat+ | t-hat- | CI+ | CI- |
|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 4.005 | 4.005 | 3.928 | 4.143 |
| 1.5 | 0 | 0 | 3.813 | 4.294 | 3.739 | 4.486 |
| 2 | 0 | 0 | 3.661 | 4.647 | 3.545 | 6.978 |
| 2.5 | 0 | 0 | 3.504 | 7.061 | 3.373 | 7.334 |
| 3 | 0 | 0 | 3.379 | 7.322 | 3.239 | 7.520 |
| 3.5 | 0 | 0 | 3.276 | 7.478 | -0.000 | 7.649 |
| 4 | 0 | 0 | 3.155 | 7.589 | -0.000 | 7.747 |
| 4.5 | 0 | 0 | -0.000 | 7.675 | -0.000 | 7.827 |
| 5 | 0 | 0 | -0.000 | 7.747 | -0.000 | 7.894 |
| 5.5 | 0 | 0 | -0.000 | 7.805 | -0.000 | 7.949 |
| 6 | 3.3e-16 | 0 | -0.000 | 7.858 | -0.000 | 8.001 |
| 6.5 | 4.3e-15 | 0 | -0.000 | 7.903 | -0.000 | 8.047 |
| 7 | 3.9e-14 | 0 | -0.000 | 7.942 | -0.000 | 8.086 |
| 7.5 | 2.6e-13 | 0 | -0.000 | 7.979 | -0.000 | 8.122 |
| 8 | 1.4e-12 | 0 | -0.000 | 8.013 | -0.000 | 8.155 |

Gamma - log odds of differential assignment due to unobserved factors
sig+ - upper bound significance level
sig- - lower bound significance level
t-hat+ - upper bound Hodges-Lehmann point estimate
t-hat- - lower bound Hodges-Lehmann point estimate
CI+ - upper bound confidence interval (a= .95)
CI- - lower bound confidence interval (a= .95)

*Source: Authors 'calculation from survey data*

**Appendix 4: Rosenbaum rbounds ln fixed asset formation**

| Gamma | sig+ | sig- | t-hat+ | t-hat- | CI+ | CI- |
|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 8.617 | 8.617 | 8.534 | 8.697 |
| 1.5 | 0 | 0 | 8.422 | 8.813 | 8.338 | 8.896 |
| 2 | 0 | 0 | 8.285 | 8.950 | 8.200 | 9.041 |
| 2.5 | 0 | 0 | 8.181 | 9.060 | 8.090 | 9.151 |
| 3 | 0 | 0 | 8.096 | 9.146 | 8.002 | 9.244 |
| 3.5 | 0 | 0 | 8.025 | 9.219 | 7.925 | 9.318 |
| 4 | 0 | 0 | 7.963 | 9.282 | 7.858 | 9.385 |
| 4.5 | 0 | 0 | 7.906 | 9.335 | 7.800 | 9.444 |
| 5 | 0 | 0 | 7.858 | 9.385 | 7.747 | 9.497 |
| 5.5 | 0 | 0 | 7.815 | 9.429 | 7.699 | 9.545 |
| 6 | 0 | 0 | 7.776 | 9.469 | 7.653 | 9.589 |
| 6.5 | 0 | 0 | 7.738 | 9.506 | 7.611 | 9.630 |
| 7 | 0 | 0 | 7.705 | 9.539 | 7.572 | 9.669 |
| 7.5 | 0 | 0 | 7.673 | 9.571 | 7.536 | 9.704 |
| 8 | 1.1e-16 | 0 | 7.642 | 9.600 | 7.500 | 9.736 |

Gamma - log odds of differential assignment due to unobserved factors
sig+ - upper bound significance level
sig- - lower bound significance level
t-hat+ - upper bound Hodges-Lehmann point estimate
t-hat- - lower bound Hodges-Lehmann point estimate
CI+ - upper bound confidence interval (a= .95)
CI- - lower bound confidence interval (a= .95)

*Source: Authors 'calculation from survey data*

## Appendix 5: Balancing properties of covariates by strata

| | Block 2 | | | | | Block 3 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Strata | Treated | (n=64) | Control (n=146) | | t-values | Treated | (n=162) | Control (n=139) | | t-values |
| | Mean | SE | Mean | SE | | Mean | SE | Mean | SE | |
| AgeHHH | 44.14 | 1.871 | 40.30 | 1.41 | -1.554 | 42.728 | 0.952 | 42.712 | 1.278 | -0.010 |
| HHHedu | 0.593 | 0.140 | 0.760 | 0.109 | 0.879 | 1.018 | 0.113 | 1 | 0.129 | -0.107 |
| Gender | 0.484 | 0.063 | 0.486 | 0.041 | 0.025 | 0.802 | 0.031 | 0.820 | 0.032 | 0.389 |
| Adult | 2.078 | 0.109 | 1.883 | 0.064 | -1.595 | 2.722 | 0.881 | 2.733 | 0.108 | 0.083 |
| Landsize_lag | 1.978 | 0.192 | 1.566 | 0.124 | -1.812 | 3.765 | 0.199 | 3.357 | 0.226 | -1.358 |
| TLU_lag | 1.547 | 0.174 | 1.269 | 0.121 | -1.275 | 2.458 | 0.133 | 2.183 | 0.127 | -1.478 |
| Oxen_lag | 0.732 | 0.0874 | 0.556 | 0.056 | -1.722 | 0.985 | 0.057 | 0.881 | 0.064 | -1.207 |
| Iddir | 0.031 | 0.021 | 0.013 | 009 | -0.853 | 0.234 | 0.033 | 0.215 | 0.035 | -0.386 |
| DistanceM | 58.859 | 2.084 | 59.959 | 1.606 | 0.393 | 73.506 | 2.464 | 74.323 | 2.681 | 0.224 |
| DistanceD | 8.781 | 0.680 | 9.119 | 0.540 | 0.363 | 12.608 | 0.649 | 11.550 | 0.710 | -1.100 |

| | Block 4 | | | | | Block 5 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Strata | Treated | (n=122) | Control (n=57) | | t-values | Treated (n=15) | | Control (n=8) | | t-values |
| | Mean | SE | Mean | SE | | Mean | SE | Mean | SE | |
| AgeHHH | 47.672 | 1.111 | 49.543 | 1.867 | 0.905 | 54.4 | 1.554 | 54.375 | 1.772 | -0.010 |
| HHHedu | 1.008 | 0.125 | 1 | 0.190 | -0.036 | 0.266 | 0.153 | 0.625 | 0.375 | 1.048 |
| Gender | 0.959 | 0.018 | 0.894 | 0.041 | -1.672 | 0.933 | 0.066 | 1 | 0 | 0.722 |
| Adult | 3.680 | 0.128 | 3.210 | 0.169 | -2.125 | 5.666 | 0.333 | 6.125 | 0.548 | 0.756 |
| Landsize_lag | 5.647 | 0.306 | 6.425 | 0.542 | 1.337 | 9.066 | 1.024 | 6.781 | 0.934 | -1.457 |
| TLU_lag | 3.056 | 0.186 | 3.647 | 0.285 | 1.763 | 5.19 | 0.951 | 3.913 | 1.029 | -0.845 |
| Oxen_lag | 1.285 | 0.065 | 57 | 1.559 | 2.187 | 2.053 | 0.210 | 2.012 | 0.308 | -0.111 |
| Iddir | 0.483 | 0.045 | 0.421 | 0.065 | -0.778 | 0.533 | 0.133 | 0.75 | 0.163 | 0.991 |
| DistanceM | 77.909 | 3.053 | 77.877 | 4.401 | -0.006 | 83.4 | 9.107 | 68.75 | 11.226 | -0.980 |
| DistanceD | 16.286 | 0.932 | 16.429 | 1.541 | 0.082 | 18.1 | 2.834 | 20.5 | 4.183 | 0.486 |

*Source: Authors 'calculation from survey data*