Agricultural Technology Adoption and Rural Poverty: A Study on Smallholders in Amhara Regional State, Ethiopia

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Abstract

Poverty has remained to be the major development and policy challenge in Ethiopia. Studies indicate that poverty is higher in rural areas in all its measures. Since smallholder agriculture is the mainstay of rural dwellers, policies of the country intended to give priority to increasing the productivity of agriculture to challenge rural poverty. Consequently, different strategies were put in place since the 1994 reform period. Under the growth and transformation plan, whose tenure has just come to an end, intensification (through adoption of agricultural technologies) and structural change were sought to bring about smallholder 'productivity revolution' for a transformative growth in the sector and poverty reduction. Agricultural technology adoption is however limited in the country with greater geographical differences. We analyze smallholders' propensity to and intensity of agricultural technology adoption in Amhara Regional State using Double-Hurdle Model to identify the relative importance of the factors that explain the underlying choice. A modest attempt is also made to link technology adoption to household welfare using matching techniques of impact evaluation. The study is based on the Ethiopian Socioeconomic Survey (ESS, 2013/14) data of the Living Standards Measurement Study. The results corroborate the importance of policy support schemes, input market and physical infrastructure, poverty [capacity] to explain agricultural technology adoption. Considerable evidence on the positive welfare impact of technology adoption is documented which entails a tenable link between technology

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adoption and poverty reduction. However, a comprehensive policy framework is needed to tackle the capacity and physical access constraints to promote agricultural technology adoption.

Key words: technology adoption, poverty, double hurdle, PSM.
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1. Introduction

Food insecurity and poverty remain to be the major development and policy challenges in Ethiopia. The country is found at the tail of both the hunger index (76th out of 79 countries) of the International Food Policy Research Institute (IFPRI) and human development index (173th out of 187 countries with a score 0.396 in 2012) of the United Nation Development Program(Oxfam. 2012. UNDP. 2013). An interim report by the government indicates that the proportion of people below the poverty line stood at 29.6percent. The Disaggregated results show that those proportions in rural and urban areas for the year 2010/11 are 30.4 percent and 25.7 percent respectively (FDRE. 2012). Although it is recognizable that there is a substantial decline in poverty incidence (from 38.7 percent in 2004) and depth (from 0.083 in 2004 to 0.078 in 2010/11), the size and impact of the problem is still considerably worrisome. It is also indicated in the interim report that rural poverty is higher than urban poverty in all periods. More so, much of the decline in country level poverty is arguably attributed to the decline in urban poverty albeit poverty (measured in incidence and depth) has shown a declining trend both in rural and urban areas. The report associated the observed improvement to the pro-poor programs implemented by the government both in rural and urban areas. However, the distribution of income among the poor showed no improvement.

On the other hand, some studies showed that rural poverty is on an increasing trend since 2004. Studies based on the Ethiopian Rural Household Survey data, a unique longitudinal data over 15 years (1994-2009), found that rural poverty has shown a tremendous decline up to 2004 (Dercon *et al.* 2007) and then started to rise (Dercon *et al.*, 2011). Yet, movement into and out of the state of poverty – poverty dynamics – is high during all periods. These studies suggested that transition into and out of (chronic) poverty are related to the growth handicaps faced by the poor while the increase in rural poverty during 2004–2009 is closely related to local factors and high inflationary pressure. Although most of the growth stimulants (including agricultural extension packages and infrastructure) have fundamentally the same effect for the chronic-poor and the rest, the former face considerably severe growth handicap compared to the rest, leaving them permanently behind.

The agricultural sector is believed to be the key sector both for poverty alleviation and to materialize a transformative growth in Ethiopia. This, together with its major contribution to rural livelihood in the country where poverty is the highest, has placed the sector at the center of development and policy interventions (FDRE, 2012; FDRE, 2010). More than 80percent of the population lives in rural Ethiopia where its livelihood is tied to traditional agriculture which in turn is hinged to sporadic rainfall. As a result, agricultural growth and sustainability has become a priority in policy making in the country (Asfaw and Shiferaw, 2010; Pycroft, 2008; FDRE, 2010). Under the broader Agricultural Development Led Industrialization (ADLI) development strategy and pursuant to the prevailing structure of the economy, the policy environment has long been giving priority to the structural change and productivity of the pervasive peasant agriculture. Pushing the prevailing agricultural technologies to the frontier is argued in the ADLI framework to bring about productivity growth, inter alia, application of improved seeds, increased adoption of inputs (fertilizer. pesticide…) and expanding irrigation and infrastructure (Dercon and Zeitlin, 2009). However, the rate of technology adoption and its intensity in the country is very low even by sub-Saharan standard. For instance, the average adoption rate of modern fertilizer is estimated to be less than 33% of the total cultivated land and the average level of use of modern fertilizer is only 11kg per hectare which is very low compared to 48kg per hectare in Kenya. In addition, the loss of soil nutrients due to land degradation and improper use of animal dung is the highest in sub-Saharan Africa (Yesuf and Köhlin, FDRE, 2010).

Moreover, technology adoption in the country followed a clear spatial pattern as well as greater variations by crops. Amhara region is among those which are characterized by low technology adoption which is mostly attributed to fragmented land, environmental degradation, population and livestock pressure, and relatively low productivity. North Gondar zone can be recited in here for it is one of the least adopters in the country which is corroborated by a recent study that argued for a limited application of chemical fertilizer in all crops except *Teff* (Yu *et al*. 2011).

In response to the observed insufficient agricultural technology adoption and to promote intensification, several attempts have been made to identify the relative importance of factors that determine smallholders' technology adoption in Ethiopia and developing countries, at large. However, previous research generally focused on a mere characterization of farm households in terms of adoption in which the socioeconomic characteristics of farmers are used to explain adoption level. The more fundamental process in which farm households make choices regarding the adoption of the available technology based on the specific features of the technology (inter alia. suitability and linkage with farmers' indigenous knowledge and experience) has long been sidelined.

For a complete understanding of agricultural technology adoption and its effectiveness, research needs to equally focus on how smallholders' adoption choices and its intensity are explained by the peculiar features of the technology in point in relation to pre-existing farm knowledge. These factors are of vital importance not only for adoption decision but also for the effectiveness of the adopted technology. On the supply side, agricultural technologies are often introduced in a package program although most adopters use part of the package. And, the determinants and welfare impact of such variation in adoption is not well investigated in the study area and Ethiopia, in general.

The relationship between technology adoption and poverty reduction is yet ambiguous. The extant literature seemed to have focused on the contribution of technology adoption in poverty alleviation in which a positive impact of technology adoption on household wellbeing appeared to be a general consensus. Among the contributions that corroborate such a relationship, the EEA/EEPRI (2006) report documented that the introduction of improved seed and chemical fertilizer in a package program has generally a positive impact on productivity for although its impact on *Teff* production was found ambiguous (cited in (Brown and Teshome, 2008)). Most other studies also commend that technology adoption has a direct role on improving rural household welfare through increasing agricultural productivity (Asfaw and Shiferaw, 2010).

On the other hand, some studies argue that agricultural technology adoption depends on poverty status of households. Although agricultural technology adoptions have identical impact on the poor and non-poor, the poor have more capacity constraints to adopt. Moreover, Agricultural technology adoption is a high risk and high return choice. The farmers need to invest more to get the technology. Since the poor cannot insure their consumption against shocks like crop failure, they will generally limit themselves to low risk low return choices (Dercon *et al.*, 2007). Hence, poor people may not choose to adopt agricultural intensification schemes. This is very important yet an overlooked issue both in the literature and policy debates. The implication of this line of argument is that the poor smallholders refrain from adopting productivity enhancing technologies and face a type of vicious circle of poverty under the backdrop of no planned systematic intervention. However, this theoretical possibility shall be supported by empirical evidence which is argued missing in this particular study.

Against this backdrop, the objectives of this paper are twofold. First, it analyses the propensity to and intensity of agricultural technology adoption by smallholders to identify the relative importance of the factors that explain the underlying economic process. It then evaluates the impact, through increased productivity, of technology adoption on household welfare (poverty). With an overarching framework of the technology adoption–farm productivity–poverty reduction nexus, the study provides empirical evidence on the relationship between agricultural technology adoption and rural poverty in Amhara Region. For empirical focus, the study concentrates on adoption of chemical (inorganic) fertilizer. And analysis is made for three major crops.

2. Model and Estimation

2.1 Understanding Smallholders' Technology Adoption

Informed by microeconomic theories of the firm [farm], smallholders are modeled as producing agents which decide on the use of certain technology products based on its profitability. For instance, a smallholder chooses to apply chemical fertilizer on its farm if the productivity gain outweighs all the costs associated with the use of the fertilizer. Basically, observed level of adoption is an outcome of two distinct processes. The first stage involves the adoption decision of farmers and is commonly called participation decision. In the second stage, farmers decide on the intensity of use of the fertilizer. The standard Tobit model can be good candidates in modeling the adoption behavior of smallholders under no (capacity and information) constraints. However, two major drawbacks of Tobit can be considered here, especially from the perspective of our study. First, Tobit model assumes that decision to adopt a given technology and intensity of adoption are governed by fundamentally the same stochastic process. The same vector of parameters are assumed to determine the first and the second stages of decision. These rules out the possibility that a given variable has different marginal effects on the probability of adoption and intensity of adoption. It is also impossible to have different vectors of parameters for the two stages of decision under Tobit setting (Burke, 2009; Eakins, 2014).

Second, the Tobit model assumes that zero value is observed when the dependent variable is censored at zero. However, as explained in Cragg (1971), zero values may be observed due to other factors too. In the context of our study, there are varieties of demand and supply side constraints which can be fairly associated with the general low rate of agricultural technology adoption. The demand side constraints are reasonably related to income levels, access to credit and (most importantly. information. Farmers do not have complete information to decide on the profitability of the technology product. The supply-side constraints can be related either to low access to information, insufficient (incomplete) information or improper use of information. Above all, access to a given farm technology is not guaranteed. So, ruling out constraints does not seem appealing.

Farm households' choice to and level of technology adoption in the presence of constraints gave rise to three distinct subsamples (Amare *et al*., 2012). The first groups of farmers are well aware, have demand and adopt technology. The second groups do not want to adopt agricultural technologies for it is not profitable at current prices. The third groups want to adopt the available agricultural technology but cannot get it due to supply side constraints. Therefore, farmers' choice is observed after passing two hurdles. Based on this classification, our model is developed to consider three aspects of the fundamental choice process: decision to adopt (desired demand for) a given technology, access to the technology and intensity of adoption of the technology in question. It is under this backdrop that the use the Double-hurdle model to estimate the propensity to and intensity of technology adoption is justified appropriate.

A parametric Double-Hurdle Model is argued appropriate in modeling empirical studies in evolving sequential decisions in two stages. It was first proposed by Cragg (1971) and used in variety of empirical literature including health economics(Jones, 1989; Labeaga, 1999; Tauras, 2005), estimating expenditure(Yen and Jensen, 1996; Lin and Milon, 1993), labor economics. valuation studies (Saz-Salazar and Rausell-Koster, 2008; Oseni, 2015) and technology adoption(Islam *et al*., 2015; Akpan *et al*., 2012;

Hazarika *et al.*, 2015; Asfaw *et al.*, 2011; Gebremichael and Gebremedhin, 2014). The Double-Hurdle model is a generalization of the Tobit model designed to deal with survey data in which the decisions can be modeled as dependent. independent or sequential to each other(Gao *et al.,* 1995).

Following (Amare *et al.,* 2012; Asfaw *et al.*, 2011), we specify the double hurdle model as in what follows. Suppose now that for any individual farm household *i.* the desired demand for fertilizer is given by:

$$D^{*} = \;{}^{'}X_{i} + «_{i}\ldots \qquad \textbf{(1)}$$

Where *Xi* is a vector of determinants of demand. β is a vector of parameters. μ is Gauss-Markov's error term, and 'D^*' *is* latent desired demand. In addition, assume that the farm household's access to fertilizer is given by

$$A^{*} = \ddot{}\,{}^{'}Z_{i} + £_{i}.. \qquad \textbf{(2)}$$

where *A** is latent variable denoting farm household's possibility of access to fertilizer supply; Z is vector of determinants of access to fertilizer; φ is vector of parameters and ε is Gauss-Markov's error term. These two equations are assumed to be independent of each other and divide the total sample in to three sub-samples.

1. Those households who adopt fertilizer ($D^*>0$ *and* $A^*>0$).
2. Those households who do not want fertilizer regardless of access for it ($D^*<0$).
3. Those households who have positive desired demand to fertilizer but do not adopt due to lack of access ($D^*>0$ *and* $A^*<0$).

Hence, adoption of fertilizer is observed after it passes two thresholds: positive desired demand and access thresholds. Yet, an important decision of farm households is intensity of adoption, i.e.

$$Y_i = Y^* \text{ if } D_i > 0, A_i > 0 \tag{3}$$
$$Y_i = 0, otherwise$$
$$Y^* = \text{©}' H_i + ¦_i .$$

Where, H is a vector of variables; κ is vector of parameters and η is Gauss-Markov's error term (Beshir *et al.*, 2012). On the basis of this setting, the likelihood function for the observed demand is given by:

$$\ln(L) = \sum_{G1=1} \ln\left[\Phi\left(¥' Z_i / ¢_«\right) * ¤\left(\left(D_i - X_i\right) / ¢_«\right)\right] + \sum_{G2=1} \ln\left[1 - \Phi\left({}' X_i / ¢_«\right)\right] + \sum_{G3=1} \ln\left[\Phi\left({}' X_i / ¢_«\right) * \left(1 - \Phi\left(¥' Z_i\right)\right)\right] ... \tag{4}$$

Where, ϕ and Φ are (resp.) probability density function (pdf) and cumulative distribution function (cdf) of standard normal variable (Asfaw *et al.*, 2011).

Double hurdle models with continuous response variable in the second stage are mostly estimated by specifying binary choice for the first hurdle and ordinary least square (OLS) regression for the second hurdle, assuming that the distribution of the error terms is bivariate normal. However, in our case, the distribution of the response variable for the second hurdle was highly skewed. Thus, normality assumption doesn't seem to hold. The first natural choice would be logarithmic transformation of the response variable. However, such transformation may lead to bias in estimating elasticities as discussed in Tauras (2005). More so, retransformation is not easy in the case of heteroscedastic errors (Ornelas-Almaraz. 2012. Tauras. 2005).

Whenever such distributional issues arise, GLM with log-link relationship and appropriate distribution family is preferred (Tauras. 2005. Ornelas-Almaraz. 2012. Manning and Mullahy. 2001). GLM provides a flexible option to relax the normality assumption with no need for retransformation as predictions are based on raw scale (Salmon and Tanguy, 2015; Jones, 2010;. Tauras, 2005). However, it is worth mentioning that GLM estimators may be less precise especially for data with heavier tails in log scale (Baser, 2007; Manning *et al.,* 2002). Our study uses GLM with log link and Gaussian distribution in the second hurdle.

2.2. Welfare/Poverty Impact of Agricultural Technology Adoption

Evaluation of the welfare [poverty] impact for agricultural technology adoption has something to do with the determination of ex-post measured outcomes of welfare indicators for technology adopting smallholders in comparison to the counterfactual [outcomes of welfare indicators had the smallholders not adopted the technology product] (Heckman and Vytlacil, 2005). In effect, technology adoption is considered as a treatment [intervention] which is however subject to non-random assignment to smallholders and self-selection.

More so, the outcome variables of welfare indicators are not observable in both treated and untreated states. This necessitate the statistical construction of a suitable counterfactual in the untreated state conditional on receiving treatment (Diaz and Handa, 2004). For our study of exploring the welfare impact of agricultural technology adoption is based on observational data than in an experimental setting. the most widely employed technique of Propensity Score Matching is used to settle the counterfactual problem (Austin, 2011; Steiner and Cook 2013). Apparently, the validity of matching technique relies on certain assumptions. The first basic (identification) assumption is the conditional independence assumption. The assumption states that outcomes in the untreated state are independent of program participation conditional on a particular set of observable characteristics (Diaz and Handa, 2004; Khandker *et al*., 2010). Suppose X denotes a set of observable characteristics, and T is a dummy variable for treatment. If the parameter of interest is average treatment effect (ATE), the identification assumption is given by:

$$\left(Y^t, Y^c\right) \perp T \mid P(X). \qquad \textbf{(5)}$$

Where the symbol $\perp$ indicates independence and $P(X)$ is the propensity score. Y^t and Y^c indicate the outcome of interest for treated and untreated groups respectively. For estimation of the treatment effect on the treated (TOT), the assumption can be relaxed to

$$Y^c \perp T \mid P(X).. \qquad \textbf{(6)}$$

The second assumption of PSM is the common support condition which requires that the treatment observations have comparison observations nearby in the distribution of the propensity scores. It is given by.

$$0 < P(T = 1 \mid X) < 1.. \qquad \textbf{(7)}$$

For estimation of TOT. the common support condition can be relaxed as

$$P(T = 1 \mid X) < 1.. \qquad \textbf{(8)}$$

Imposing conditional mean independence assumption, our parameter of interest, average treatment effect on the treated (ATT), is evaluated as:

$$ATT(x) = E\left(Y_1^t \mid T = 1, P(X)\right) - E\left(Y_0^t \mid T = 1, P(X)\right) \qquad \textbf{(9)}$$

The second term in equation (9) is the average welfare outcome of treated individuals had they not been treated. However, this is not observable in cross-sectional studies like ours. Instead, corresponding outcomes for untreated observation is estimated as

$$ATT(x) = E\left(Y^t \mid T = 1, P(X)\right) - E\left(Y^c \mid T = 0, P(X)\right).. \qquad \textbf{(10)}$$

The difference between (9) and (10) is attributed to selection bias. In our study, balancing scores are estimated from logit model and the common support condition was imposed. Matching estimators, based on (Diaz and Handa, 2004; Khandker *et al.*, 2010), have the general form as:

$$ATT = \frac{1}{N_t}\left[\sum_{i \in T} Y_i^{tT} - \sum_{j \in C} \mu(i, j) Y_j^c\right] \ldots \quad \textbf{(11)}$$

Where *N is* the number of participants and; $\mu(i, j)$ represents a weighting function that depends on the specific matching estimator. Thus, the choice of the matching technique is crucial. While it is possible to select a matching technique based on its performance in minimizing bias, we prefer to use three commonly used matching criteria that, we believe, complement each other. Nearest Neighbor Matching (NNM), Radius Matching (RM) and Kernel Matching (KM) are used to make sure that our results are robust. As discussed in Khandker *et al.* (2010). NNM matches each treatment unit to a comparison unit with the nearest propensity score. However, the difference in propensity score between the closest treatment and control units may still be high. This may be avoided by specifying the maximum propensity score distance (caliper) which justifies the use of Radius Method. On the other hand, Kernel Method is a nonparametric matching estimator which uses weighted average of all nonparticipants to construct the counterfactual match for each participant. Major advantage of this method over the other two is that more information is used (Khandker *et al.*, 2010, Caliendo and Kopeinig, 2005). Estimation was done using STATA 12 software.

The Foster-Greer-Thorbecke (FGT) index (Foster *et al.*, 1983), which is defined as in what follows, is used to measure the poverty status of smallholders.

$$P_a = \frac{1}{N}\sum_{i=1}^{q}\left(\frac{z - yi}{z}\right)^a . \quad \textbf{(12)}$$

Where, '*z*' is the poverty line; y is real Percapita consumption expenditure and '*a*' is the poverty aversion parameter. The poverty incidence, depth and severity are measured by changing the values of 'a' in the formula. The

2010/11 national poverty line estimate, adjusted for price changes is used to compute the FGT indices (FDRE, 2012).

3. Data and Descriptive Statistics

The study is based on data from the Ethiopian Socioeconomic Survey (ESS. 2013/14). The ESS is a collaborative project between the Central Statistics Agency of Ethiopia (CSA) and the World Bank Living Standards Measurement Study- Integrated Surveys of Agriculture (LSMS-ISA) team. It primarily targets on developing and implementing a multi-topic survey that meets Ethiopia's data demand and gaps and is believed to be of high quality, accessible to the public and aligned with the National Strategy for the Development of Statistics (NSDS).

The survey covers rural areas, large towns and small towns in all regions except some exceptional zones of Afar and Somali region. Sample units were selected using stratified two stage sampling procedure and the sampling frame for rural areas was based on 2013/14 Agricultural sample survey of the CSA. A total of 5.262 sample households were selected for the whole country of which 20.5 percent (1080) are drawn from Amhara Region. The data is argued to be representative for regional estimation in the most populous regions (Amhara, Oromiya, SNNP and Tigray) (CSA, 2011/12). As such, the survey covered 61 rural, 15 medium and large urban and 10 small urban enumeration areas in Amhara regional state. The data for all rural households in Amhara region is used in the study. And. the analyses on the pattern of technology adoption and its implied impact on rural poverty are made based on three crops, namely *Teff*, Wheat and Maize.

3.1 Distribution of Plot Size, Technology Adoption and Intensity

A simple exploration of the data offer important insights on adoption of agricultural technologies and intensity of use. It is apparent from Table 1 that about 65% of the samples adopt chemical fertilizer with a small variation across crop type. This is consistent with previous results in other parts of the country and sub-saran Africa (Terefe *et al.,* 2013; Endale, 2011). On the other hand, the adoption of improved seed appeared small when compared to chemical fertilizer.

Table 1: Distribution of plot size and technology adoption by crop category (%)

Crop Code	Improved Seed (percentage of plots)	Fertilizer Use (percentage of plots)		
		Chemical Fertilizer	Manure	Compost
MAIZE	34.75	66.15	46.79	18.0
TEFF	3.68	66.58	9.50	8.0
WHEAT	9.80	63.91	17.40	15.86
Total	16.74	65.77	25.31	13.62

On average, only 16.74% of the plots use improved seeds with a large variation between crop types. The adoption of improved seeds is larger for maize followed by wheat. The application of organic fertilizers (manure and compost), as indicators of pre-existing knowledge and technological practices, is way below the application of chemical fertilizers with considerable variation across crops. The data entails a significant variation in the intensity of improved seeds and fertilizer application, as well, from Table 2, the average use of urea and dap in kilogram per hectare of fertilized (for the three crops) land is 74.28 and 89.91 respectively. And. the intensity of chemical fertilizer use is generally larger for maize followed by wheat.

Table 2: Distribution Fertilizer use by crop category (kg/ha)

Fertilizer Type	Crop Type			
	Maize	***Teff***	**Wheat**	**Total**
Urea	99.15	52.85	68.89	74.28
Dap	115.62	66.36	86.68	89.91
Total (Urea + Dap)	215.16	119.35	155.21	164.29

4.2 Average Productivity and Technology Adoption

An important issue worth exploring is the relationship between land productivity (yield) and application of chemical fertilizer in comparison to pre-existing technological practices. An insightful result on average yield under different technology regimes is presented in Table 3. The average yield is about 1461kg/ha with significant variation across crop types. Maize gives highest yield per hectare followed by wheat. Another important feature in the table is the impact of fertilizer use on productivity. There is a negative differential in productivity between adopters and non-adopters of both organic and inorganic fertilizer.

An exception in this respect is Maize for which all types of fertilizers except compost have negative effect. This is not surprising for many variables which affect the relationship are not controlled. A typical example is crop damage. Crop damage is reported on about 22% of the total plots taken in the sample, and maize plots experience the largest damage both in terms of the number of plots with reported damage (30%) and the perceived share of damage from the total crop in the plots (40%). The three major causes of the damage have been insects (21%), shortage of rain (20%) and hail (13%) [see Appendix 2]. More so, Maize is grown in arid and semi-arid parts of the region that makes the crop yield vulnerable to weather related and other shocks, as a result of which, the productivity impact of fertilizer is so unpredictable.

Table 3: Average Yield of Crops (in kg/ha) under Different Fertilizer Regimes

Crop Code	Fertilizer Regimes									Total
	Chemical Fertilizer			Manure use			Compost			
	No	Yes	Diff	No	Yes	Diff	No	Yes	diff	
Maize	1990.9	1887.6	103.3	2163.2	1673.7	489.7	1842.7	2166.8	-324.1	1921.7
Teff	971.8	1153.8	-181.9	1073.2	1081.2	-8	1215.5	1337.6	-122.1	1092.8
Wheat	1161.0	1423.9	-262.9	1256.5	1497.9	-241.4	1454.7	1457.7	-3	1329.8
Total	1393.6	1495.6	-101.9	1585.0	1568.3	16.7	1529.1	1780.3	-179.2	1461.1

Generally, further exploration of the summary statistics for the study variable and its covariates offered appealing results in view of the process underpinning the observed technology adoption and intensity of use [See Appendix 1]. A simple mean comparison test between adopters and non-adopters of fertilizer indicates that a set of household characteristics, including education and livestock wealth (in TLU), are significantly larger for adopters. The mean distance from markets, all weather road and urban centers is significantly larger for non-adopters indicating that non-adopters have lesser access to market and technology information which in turn results in slow diffusion of farm technology as well as high transportation cost. There is also a significant variation in the characteristics of plots with and without chemical fertilizer use. More so, adopters have significantly higher mean values in terms of microclimate indicators like potential wetness index and elevation, and lower mean values in terms of plot slope and distance from homestead.

Other factors such as extension contact, advisory service, the use of manure and compost and credit have also statistically significant association with adoption of fertilizer. The first two are related with farmers' access to information on fertilizer and its profitability while access to credit indicates farmers' ability to finance their purchase of modern technology under cash constraints. The institutional support system has long been a major factor for modern technology adoption and productivity of smallholders. However, such support has remained low. The use of manure and compost (organic fertilizer) has negative association with adoption of chemical fertilizer with a possible explanation that the pre-existing technology practices are preferred substitutes to inorganic chemical fertilizers.

4. Estimation Results and Discussion

4.1 The Probability and Intensity of Agricultural Technology Adoption

The estimation of the probability equation for farm household's technology adoption, application of fertilizer on the farm, and the level of technology adoption is performed under the double-hurdle model assumptions. The estimated model relates smallholder farm households' adoption decision and the intensity of technology use to a long list of socio-economic factors in Amhara Region. For the interest of interpretation and discussion, we grouped such factors into household characteristics, plot characteristics and micro-climate factors, institutional factors and policy support. The double-hurdle model estimation result is presented and discussed in this section.

4.1.1 Explaining Technology Adoption in Amhara Region

Understanding technology adoption goes beyond the simple characterization of factors as determinants of the technology use to evaluating the relative importance of competing theoretical explanations. Evidence from the estimated relationship on the widely discussed socio-economic factors and technological practices and smallholders' technology adoption entails more on this (Table 4). From among the household characteristics, formal education and sex have the expected sign but in significant. Off farm employment of the household head significantly increase the probability of adoption, suggesting that smallholders diversifying into the off-farm economy and credit constrained finance chemical fertilizer through off farm earnings. About two-third of the participants in off farm activities have no credit access and this strengthens the argument. Similarly, land area has significant positive impact on propensity to adopt inorganic fertilizer. Land and off farm employment are poverty related variables. Especially land is the major component of wealth of rural households. A simple mean comparison test indicates that the land holding of the poor[4] is significantly lower than the non-poor [See Appendix 5]. Our estimation result shows that the probability of adoption increases with an increase in size of farm land owned.

[4]Poverty is calculated based on the national poverty line after the households' annual Percapita expenditures are adjusted for inflation. See FDRE 2012, Ethiopia's Progress Towards Eradicating Poverty: An Interim Report on Poverty Analysis Study In: Directorate, D.P.A.R. (ed.). Addis Ababa: Ministry of Finance and Economic Development.

Agricultural market (input and output) and physical infrastructure constitutes another important set of factors that influence smallholder's technology adoption. Accordingly, distance from the nearest all weather road, nearest market and zonal town have also negative and significant impact on the probability of adoption.

The marginal effects (for the total sample) indicate that at average an increase in distance from the nearest all weather road and nearest market by 1 kilometer results in a decrease in the likelihood of chemical fertilizer adoption by 0.013 and 0.0016, respectively [see Appendix 4]. Therefore, in comparison road infrastructure has the strongest impact. Lack of road infrastructure is one of the major bottle necks which affect farmers' adoption decision in different ways. First, lower road infrastructure increases the transportation cost for chemical fertilizers and thus creates a large difference between the actual price and the price farmers' face in the input market. It also reduces competition between input suppliers resulting in little choice available for farmers. Second, poor infrastructure reduces the profitability of a given technology. In the output market, it increases the difference between farm-gate price and the actual market price and creates geographic barrier restricting local demand to depend only on local supply. If there is information asymmetry, it is possible for middlemen with better information to expropriate information rent from farmers. Poor road infrastructure is also associated with slow diffusion of agricultural technology. Distance from the nearest market and proximity to urban center also have similar effect.

Institutional support factors are considered equally important to understand smallholders' technology adoption. And, this is supported by the empirical evidence. Credit and extension appeared important determinants of adoption. Around 40% non-adopters cite lack of financial capital as their major reason for not adopting chemical fertilizer. The two major reasons for inability to access credit, as reported by respondents in the study area, are inability to pay previous loans (48.05%) and inadequate service (13%), implying pervasive credit constraint for smallholders [See Appendix 6].

Table 4: Estimation Results of Smallholders' Propensity to Technology Adoption

Variables	Probit model. Dependent variable: adoption			
	Maize	***Teff***	**Wheat**	**Total sample**
Household characteristics				
Sex	-0.0233	-0.303	-0.0743	-0.0858
	(0.213)	(0.287)	(0.265)	(0.131)
Age	-0.0124*	-0.00630	-0.0106	-0.00901**
	(0.00527)	(0.00597)	(0.00570)	(0.00295)
Education	-0.0150	0.0512	0.0592	0.0376
	(0.0471)	(0.0538)	(0.0452)	(0.0252)
Land area (hectare)	2.504***	1.352	-0.0397	0.796**
	(0.685)	(0.739)	(0.420)	(0.276)
Off farm employment	0.155	0.331	1.183***	0.647***
	(0.316)	(0.400)	(0.357)	(0.185)
Input market and infrastructure				
Distance from road all weather road	-0.0193*	0.00509	-0.0205**	-0.00699*
	(0.00836)	(0.00620)	(0.00682)	(0.00324)
Distance from market	0.00186	-0.0153***	-0.00878**	-0.00906***
	(0.00384)	(0.00377)	(0.00331)	(0.00172)
Distance from zonal town	-0.00687***	0.00761***	-0.00410**	-0.000880
	(0.00157)	(0.00184)	(0.00144)	(0.000751)
Institutional support				
Extension	1.743***	2.460***	2.103***	1.987***
	(0.184)	(0.250)	(0.187)	(0.0997)
Credit	0.212	0.526**	0.487**	0.341***
	(0.165)	(0.202)	(0.186)	(0.0935)
Use of organic inputs				
Manure use	-1.077***	-0.651*	-0.858***	-0.981***
	(0.168)	(0.254)	(0.260)	(0.106)
Compost use	-0.148	-1.276***	-0.622*	-0.572***
	(0.198)	(0.293)	(0.277)	(0.123)
Plot characteristics				
Plot distance from home	-0.0541	-0.0880	-0.0252	-0.0264
	(0.0610)	(0.0714)	(0.0438)	(0.0285)
Soil quality (poor=1)	0.165	-0.376**	-0.0816	-0.149*
	(0.123)	(0.130)	(0.117)	(0.0620)
Plot slope	-0.0464***	-0.0284***	-0.0115	-0.0285***
	(0.0128)	(0.00837)	(0.00774)	(0.00470)
Plot potential wetness index	0.0531	-0.00738	-0.0586	-0.0264
	(0.0597)	(0.0621)	(0.0310)	(0.0209)
Altitude	0.00123***	0.000800**	0.000272	0.000596***
	(0.000342)	(0.000269)	(0.000238)	(0.000112)
Agroecology	-0.914**	-0.278	-0.297	-0.361**
	(0.333)	(0.257)	(0.200)	(0.131)
_cons	-1.503	-1.677	2.091*	0.271
	(1.111)	(1.259)	(0.970)	(0.463)

Akin, plots under extension are more likely to adopt chemical fertilizer in the region. Agricultural extension is the major instrument for dissemination of outputs of agricultural research. In Ethiopia, though agricultural extension has a long history, the dissemination of technology has been less than expected. Agricultural extension affects technology adoption decision in many ways. First, extension workers give training and advisory service to farmers which increase human capital and information access. Second, agricultural extension is mostly coupled with input distribution and farm credit. Third, it is the major channel through which agricultural research and development outputs are transferred to smallholders.

Plot characteristics and microclimate variables are another set of factors considered in explaining smallholders' technology adoption, mainly to account for varying plot quality and unobserved differences between agro-ecological zones. The three crops are grown in two major agro-ecological zones of the region: Semi-arid and sub-humid. The result shows that the likelihood of adoption in semi-arid areas is higher and significant for maize. On the other hand, plot slope and altitude have negative and significant effect on adoption. The probability of adoption decreases with deteriorating soil fertility indicating that framers are less likely to adopt inorganic fertilizer on poor quality plots. Another important implication of the result is the relationship between adoption of inorganic and organic fertilizers [See Appendix 7]. The use of manure and compost has strong negative impact on the adoption of inorganic fertilizer corroborating the result of possible substitutability in the descriptive analysis.

4.1.2. Explain the Intensity of Technology Adoption in Amhara Region

Study of agricultural technology in relation to smallholder productivity and implied impacts on poverty reduction will be fairly complete when analysis of farm households' propensity to technology adoption is substantiated to analysis of the intensity of technology use. In line with this strand of thinking, intensity equation is estimated for fertilizer use, the result of which is presented in Table 5. Household characteristics such as age and livestock ownership have negative and significant effect while education has positive and significant effect. The negative effect of livestock ownership on intensity of use may be due to that livestock ownership increases households access to manure which they use as a substitute for chemical fertilizer. Given the transportation cost, poor infrastructure and other constraints, farmers may prefer to use manure though livestock ownership also relaxes their cash constraint. Similar results were found by other studies(Hailu *et al.*, 2014; Kassie *et al.*, 2009). The effect of off farm employment is mixed.

Off-farm employment has positive and significant effect for *Teff* and wheat but negative effect for maize. On the other hand, access to all weather roads and other market related variable has mixed effects by crop type but are not significant for the total sample. Access to extension has a positive and significant effect on intensity of adoption which, as discussed in the adoption decision part above, may be due to that access to extension is the major way through which farmers get technology information and other services important for. Plot size has a negative and significant effect on intensity of fertilizer use. With regard to plot characteristics that are related with microclimate, the results indicate positive and significant effects of potential wetness index of soil, altitude and agro-ecology.

Table 5: Estimation Results of Smallholders' Intensity of Technology Adoption

GLM	Dependent Variable: Intensity of Adoption (amount of fertilizer in kilogram per hectare of land under chemical fertilizer). logarithm link and Gaussian distribution			
	Maize	*Teff*	Wheat	Total sample
Household characteristics				
sex	0.302*	-0.0145	-0.421	0.472*
	(0.130)	(0.199)	(0.526)	(0.200)
age	-0.00773**	-0.0156**	-0.111***	-0.0122**
	(0.00290)	(0.00510)	(0.0254)	(0.00429)
Education	-0.0126	0.0642**	0.288***	0.164***
	(0.0235)	(0.0224)	(0.0490)	(0.0138)
Household size	0.00203	0.0765*	0.444**	-0.0964**
	(0.0258)	(0.0304)	(0.136)	(0.0309)
Off farm employment	-0.217	0.406*	1.134**	-0.836**
	(0.145)	(0.198)	(0.440)	(0.318)
Livestock ownership (tlu)	-0.0390*	-0.00209	-0.850***	-0.153***
	(0.0174)	(0.0243)	(0.183)	(0.0312)
Input market and infrastructure related				
Distance from road all	-0.0111	-0.00132	-0.179***	-0.00914
weather road	(0.00664)	(0.00469)	(0.0477)	(0.00468)
Distance from market	-0.00384	-0.00439	0.0273***	0.00215
	(0.00222)	(0.00262)	(0.00757)	(0.00175)
Distance from zonal town	-0.000834	0.00348*	0.0115**	0.00206
	(0.00120)	(0.00156)	(0.00382)	(0.00126)
Institutional support				
Extension	0.378*	0.823***	1.203**	0.848***
	(0.156)	(0.196)	(0.401)	(0.174)
credit	-0.0446	0.144	-0.454	-0.00174
	(0.0877)	(0.134)	(0.296)	(0.106)
				Plot characteristics
Agro- ecology	0.555	0.370	3.580***	0.490*
	(0.303)	(0.248)	(0.905)	(0.249)
Plot size	-0.853**	-2.812***	-24.78***	-7.780***
	(0.325)	(0.596)	(3.043)	(0.836)
Plot slop	-0.00904	-0.0285**	0.00957	0.00619
	(0.0100)	(0.00944)	(0.0144)	(0.00439)
Plot wetness index	0.00587	0.00964	0.147*	0.0876**
	(0.0277)	(0.0335)	(0.0681)	(0.0288)
Altitude	0.000456*	0.0000351	0.00184***	0.000712***
	(0.000208)	(0.000174)	(0.000315)	(0.000128)
Constant	4.583***	4.772***	0.301	2.770***
	(0.678)	(0.814)	(1.603)	(0.606)
N	661	415	653	1729
Standard errors in parentheses	*** p<0.05. ** p<0.01. *** p<0.001**			

4.2 Welfare/Poverty Reduction Impact of Technology Adoption

Rural poverty reduction and food security has long remained to be the priority of poor agricultural economies, of which Ethiopia is an excellent case in point, in introducing agricultural innovations. Evidence-based policy choices can be motivated in this particular area with the analysis of welfare/poverty impacts, through productivity growth, of technology adoption. This section presents a modest attempt in this direction in which the impact of fertilizer use on household welfare is analyzed and discussions of the results ensue. To fix ideas, we use (1) propensity score matching technique and (2) simple comparison of poverty incidence, depth and severity between adopters and non-adopters of fertilizer. Logit model is used to compute the propensity scores in the first method and FGT curves are fit letting the poverty line to vary in the interval [0.7562] to ensure robust comparison in the later[5].

4.2.1 Comparison of Poverty Indices by Technology Adoption

The poverty rate for the region is estimated at 28.8%. only slightly less than the 2010/11 estimated poverty rate for the rural Amhara which was estimated at 30.7%(FDRE. 2012). This indicates that no significant improvement has been made in reducing rural poverty in the region for the last three years until 2013/14. On the other hand, it is evident from Table 6 that adopters have lower outcomes in terms of headcount, depth and severity of poverty. The poverty headcount for adopters is 20.8% while the same for non-adopters is 38.6%. The poverty curves are also fitted to make the comparison independent of the choice of poverty line [See Appendix 8]. The poverty incidence, depth and severity curves show a clear dominance for non-adopters in that adopters have lower incidence, depth and severity at all possible poverty lines in the range [0. 7526].

[5]The upper limit is selected to be twice the poverty line considered in our analysis.

Table 6: Poverty Headcount. Depth and Severity of for Adopters and Non-Adopters

Index	Adopter	Non-adopter	Total
Head count [6]	0.208281 (0.023613)	0.386223 (0.031795)	0.287942 (0.019529)
Depth	0.096318 (0.012774)	0.174695 (0.017320)	0.131406 (0.010550)
Severity	0.057345 (0.008879)	0.104598 (0.012231)	0.078499 (0.007383)

This gives a clue on the positive welfare (poverty reduction) impact of technology adoption. However, it is worth mentioning that such comparison doesn't account for problems of confounding which necessitates' impact evaluation proper' for it will single out the impact of adoption. Simple comparison of poverty by adoption status may correctly reflect the effect of technology adoption as poverty its self may the factor for not adopting agricultural technology. Therefore, we use propensity score matching technique to evaluate the impact of technology adoption under statistically controlled environment.

4.2.2 Estimation of Average Treatment Effects for Technology Adoption

The ATT impact of agricultural technology adoption on poverty reduction (welfare) was estimated using Kernel Matching. Nearest Neighborhood Matching and Radius Matching Methods. Estimated average treatment effects from the three matching methods are presented for purposes of comparison and robustness check [Table 7]. For the interest of clarity, the covariate balancing test procedure is performed to check whether the distributions of relevant covariates of adoption are balanced before and after matching, once the assumptions of the model are satisfied [Table 8].

[6]Standard errors in parenthesis

Table 7: Summary of Covariate Balancing Test

Algorithm	Psedo R^2		LR ¡ ^{2} (p-values)		Mean bias		Total % |bias| reduction
	Before matching	After matching	Before matching	After matching	Before matching	After matching	
NNM	0.160	0.013	117.88 (0.000)	11.11 (0.196)	30.9	6.6	78.6
Kernel	0.160	0.006	117.88 (0.000)	5.33 (0.722)	30.9	6.0	80.58
Radius	0.160	0.005	117.88 (0.000)	4.66 (0.793)	30.9	5.5	82.2

The likelihood ratio test for joint significance of the covariates is strongly significant before balancing and insignificant after balancing for all matching algorithms. In addition, the pseudo R^2 is very small after balancing indicating that the model balances the covariates between adopters and non-adopters. On the other hand, the bias minimizing matching algorithm is found to be the radius matching. Caliper size is another important point to be noted. In our case, (for NNM and Radius matching algorithms) caliper size of 0.056, determined based on the recommended way as $1/4^{th}$ of the standard deviation of the propensity score. is used (Rosenbaum and Rubin, 1985).

It is evident from the result in Table 8 that technology adoption significantly improves household welfare (reduce poverty) as measured by Percapita consumption expenditure. Per capita consumption expenditure has increased by about 16.9% and 23.9% with the KM and RM techniques, respectively. The estimated positive impact of agricultural technologies supports the theoretical explanations argued.

Table 8: Estimation of Average Treatment Effect on the Treated

Matching Method	N		ATT	Std error	t-value
	Treated	Control			
Kernel matching (KM)	306	232	0.169	0.081	2.098
Nearest neighbour (NNM)	306	105	0.154	0.109	1.407
Radius matching (RM)	306	232	0.239	0.078	3.084

Sensitivity of the average treatment effect in the presence of unobserved heterogeneity between the treatment and control groups is tested using Rosenbaum bounds test [See Appendix 9]. The results show that the upper and lower bound estimates of significance levels for changes in gamma values at 0.05 intervals between 1 and 2 are zero, ensuring the robustness of the estimated ATT.

5. Conclusion and Policy Implication

The governments in developing countries, where structural transformation is yet to take place, have long been through agriculture led growth to address development challenges of poverty and food security. Agricultural innovation through enhanced technological capabilities has is emerging as a consensus paradigm in which systems of agricultural research and development, technology transfer and adoption are seriously considered to go about. Under the growth and transformation plan recently concluded. intensification (through adoption of agricultural technologies) and structural change were sought to bring about smallholder 'productivity revolution' for a transformative growth in the sector and poverty reduction. Agricultural technology adoption is however limited in the country with greater geographical differences. In view of this, we analyze smallholders' propensity to and intensity of agricultural technology adoption in Amhara Regional State using Double-Hurdle Model. The Ethiopian Rural Socioeconomic Survey (ESS. 2013/14) data of the Living Standards Measurement Study is used to estimate key relationships. The results corroborate the importance of policy support schemes. input market and physical infrastructure, poverty [capacity] to explain agricultural technology adoption. Considerable evidence on the positive welfare impact of technology adoption is also documented which entails a tenable link between technology adoption and poverty reduction policy endeavors. On the basis of this findings, the study urges for comprehensive policy frameworks to tackle the capacity and physical access factors which deter farmers from adopting agricultural technology..

References

Akpan, S. B., Nkanta, V. S. & Essien, U. A. (2012). A Double-Hurdle Model of Fertilizer Adoption and Optimum use among Farmers in Southern Nigeria, *Tropicultura*, 30, 249-253.

Amare, M., Asfaw, S. & Shiferaw, B. (2012). Welfare Impacts of Maize–pigeonpea Intensification in Tanzania. *Agricultural Economics,* 1-17.

______. (2010). Agricultural Technology Adoption and Rural Poverty: Application of an Endogenous Switching Regression for Selected East African Countries. Poster Presented at the Joint 3rd African Association of Agricultural Economists (AAAE) and 48th Agricultural Economists Association of South Africa (AEASA) Conference, Cape Town. South Africa

Asfaw, S., Shiferaw. B., Simtowe, F. & Haile, M. G. (2011). Agricultural Technology Adoption, Seed Access Constraints and Commercialization in Ethiopia. *Journal of Development and Agricultural Economics.* 3, 436-447.

Austin, P. C. (2011). An Introduction to Propensity Score Methods for Reducing the Effects of Confounding in Observational Studies. University of Toronto: Institute for Clinical Evaluative Sciences Department of Health Management, Policy and Evaluation.

Baser, O. (2007). Modeling Transformed Health Care Cost with Unknown Heteroskedasticity. *Applied Economic Research* 1-6.

Beshir, H., Emana, B., Kassa, B. & Haji, J. (2012). Determinants of Chemical Fertilizer Technology Adoption in North Eastern Highlands of Ethiopia: The Double Hurdle Approach. *Journal of Research in Economics and International Finance (JREIF).* 1, 39-49.

Brown, T. & Teshome, A. (2008). Implementing Policies for Chronic Poverty in Ethiopia. *Background Paper for the Chronic Poverty Report.* Chronic Poverty Research Center.

Burke, W. J. (2009). Fitting and Interpreting Cragg's Tobit Alternative using Stata. *The Stata Journal*. 9, 584-592.

Caliendo, M. & Kopeinig, S. (2005). Some Practical Guidance for the Implementation of Propensity Score Matching. IZA Discussion Paper

Cragg, J. G. (1971). Some Statistical Models for Limited Dependent Variables with Application to the Demand for Durable Goods. *Econometrica* 39, 829-844.

Dercon, S., Hoddinott, J. & Woldehanna, T. (2007). Growth and Poverty in Rural Ethiopia: Evidence from 15 Communities 1994-2004. Background Paper for the Chronic Poverty Report Chronic Poverty Research Center.

_______. (2011). Growth and Chronic Poverty: Evidence from Rural Communities in Ethiopia. CSAE Working Paper WPS. 18.

Dercon, S. & Zeitlin, A. (2009). Rethinking Agriculture and Growth in Ethiopia: A Conceptual Discussion. Paper Prepared as part of a study on Agriculture and Growth in Ethiopia.

Diaz, J. J. & Handa, S. (2004). An Assessment of Propensity Score Matching as a Non Experimental Impact Estimator: Evidence from a Mexican Poverty Program.

Eakins, J. (2014). An Application of the Double Hurdle Model to Petrol and Diesel Household Expenditures in Ireland. Survey Energy Economics Discussion Paper Series.

Endale, K. (2011). Fertilizer Consumption and Agricultural Productivity in Ethiopia. EDRI Working Paper 003.

FDRE. (2010). Ethiopia's Agricultural Sector Policy and Investment Framework (PIF) 2010-2020. Ministry of Agriculture and Rural Development.

______. (2012). Ethiopia's Progress Towards Eradicating Poverty: An Interim Report on Poverty Analysis Study*:* Directorate, D.P.A.R. (ed.), Addis Ababa: Ministry of Finance and Economic Development.

Foster, J., Greer, J. & Thorbecke, E. (1983). Notes and Comments: a Class of Decomposable Poverty Measures. *Econometrica.* 52, 761-766.

Gao, X. M., Wailes, E. J. & Cramer, G. L. (1995). Double-hurdle Model with Bivariate Normal Errors: An Application to U.S. Rice Demand. J*ournal of Agriculture and Applied Economics.* 27**,** 363-376.

Gebremichael, B. & Gebremedhin, B. (2014). Adoption of Improved Box Hive Technology: Analysis of Smallholder Farmers in Northern Ethiopia. *International Journal of Agricultural Economics and Extension* 2, 077-082.

Hailu, B. K., Abrha, B. K. & Weldegiorgis, K. A. (2014). Adoption and Impact of Agricultural Technologies on Farm Income: Evidence from Southern Tigray. *International Journal of Foodand Agricultural Economics.* 2**,** 91-106.

Hazarika, B., Bezbaruah, M. P. & Goswami, K. (2015). Adoption of Modern Weaving Technology in the Handloom Micro-Enterprises In Assam: A Double Hurdle Approach. Technological Forecasting & Social Change

Heckman, J. J. & Vytlacil, E. (2005). Structural Equations, Treatment Effects and Econometric Policy Evaluation 1. *Econometrica.* 73, 669-738.

Islam, A. H. M. S., Barman, B. K. & Murshed-E-Jahan, K. (2015). Adoption and Impact of Integrated Rice–Fish Farming System in Bangladesh. *Aquaculture* 447**,** 76-85.

Jones, A. M. (1989). A Double-Hurdle Model of Cigarette Consumption. *Journal of Applied Econometrics.* 4**,** 23-39.

Jones, A. M. (2010). Models For Health Care. HEDG Working Paper 10/01.

Kassie, M., Yesuf. M. & Köhlin, G. (2009). The Role of Production Risk in Sustainable Land-Management Technology Adoption in the Ethiopian Highlands. *Gothenburg University Working Papers in Economics*, 407.

Khandker, S. R,. Koolwal, G. B. & Samad, H. A. (2010). *Handbook on Impact Evaluation: Quantitative Methods and Practices.* Washington D. C.. The World Bank.

Labeaga, J. M. (1999). A Double-Hurdle Rational Addiction Model with Heterogeneity: Estimating the Demand for Tobacco. *Journal of Econometrics* 93, 49-72.

Lin, C.T. J. & Milon, J. W. (1993). Attribute and Safety Perceptions in a Double-Hurdle Model of Shellfish Consumption. *American Journal of Agricultural Economics.* 75, 724-729.

Manning, W. G., Basu, A. & Mullahy, J. (2002). *Modeling Costs with Generalized Gamma Regression.*

Manning, W. G. & Mullahy, J. (2001). Estimating log models: to transform or not to transform? *Journal of Health Economics* 20.

Ornelas Almaraz G. A. (2012). Patterns of Tobacco Consumption in Mexico – Current Perspective. PhD thesis. The University of East Anglia.

Oseni, M. O. (2015). Assessing the Consumers' Willingness to Adopt a Prepayment Metering System In Nigeria. *Energy Policy.* 86**.** 154-165.

OXFAM. (2012). Country profile of Ethiopia, Canada.

Pycroft, J. (2008). The Adoption and Productivity of Modern Agricultural Technologies in the Ethiopian Highlands: A cross-sectional analysis of maize production in the West Gojam zone. *Prepared for presentation at the Centre for the Study of African Economies (CSAE) Conference. Economic Development in Africa. 15th-17th March 2008.* University of Sussex.

Rosenbaum, P. R. & Rubin, D. B. (1985). Constructing a Control Group using Multivariate Matched Sampling Methods that Incorporate the Propensity Score. *The American Statistician.* 39, 33-38.

Salmon, C. & Tanguy, J. (2015). Rural Electrification and Household Labor Supply: Evidence from Nigeria. Institute for Labor Studies and Public Policies.

Saz-Salazar, S. D. and Rausell-Koster, P. (2008). A Double-Hurdle Model of Urban Green Areas Valuation: Dealing with Zero Responses. *Landscape and Urban Planning* 84**.** 241-251.

Steiner, P. M. & Cook, D. 2013. *Matching and Propensity Scores. The Oxford Handbook of Quantitative Methods.* New York: Oxford University Press.

Tauras, J. A. (2005). An Empirical Analysis of Adult Cigarette Demand. *Eastern Economic Journal.* 31

Terefe, A. T., Ahmed. M. H. & Gebremariam, G. G. (2013). Adoption and Extent of use of Organic Fertilizer in Arsi Negelle District. Oromia Regional State of Ethiopia: What are the Sources? *Advanced Journal of Agricultural Research.* 1**.** 061-071.

UNDP. (2013). Human Development Report 2013. *The Rise of the South: Human Progress in a Diverse World.* New York.

Yen, S. T. & Jensen, H. H. (1996). Determinants of Household Expenditures on Alcohol. *The Journal of Consumer Affairs.* 30**.** 48-67.

Yesuf, M. & Köhlin, G. (2009). Market Imperfections and Farm Technology Adoption Decisions: Case Study from the Highlands of Ethiopia. Department of Economics Göteborg University.

Yu, B., Nin-Pratt, A., Funes, J. & Gemessa, S. A. (2011). Cereal Production and Technology Adoption in Ethiopia. *The Ethiopia Strategy Support Program II (ESSP II) Working Paper*, 31.

Appendices

Appendix 1

Variable	Chemical fertilizer adoption			
	No	Yes	Total	T-value
		Household Characteristics		
Age	50.13	46.85	48.68	5.2
Household size	**5.16**	**5.20**	**5.18**	**-0.51**
Education	**.43**	**.82**	**.69**	**-4.78**
Number of oxen	**1.13**	**1.52**	**1.38**	**-8.6**
Livestock (TLU)	**3.50**	**3.9**	**3.8**	**-3.1**
		Market Access and technology diffusion		
Distance from woreda town (km)	**26.54**	**18.41**	**21.22**	**11.22**
Distance from the nearest asphalt (km)	**37.00**	**34.51**	**35.36**	**1.34**
Distance from the nearest weekly market	**13.2**	**8.7**	**9.78**	**8.70**
Distance from major urban	**92.40**	**70.60**	**78.10**	**7.37**
		Plot Characteristics		
Distance from homestead	**1.00**	**.833**	**.926**	**1.71**
Plot Slope (percent)	**20.33**	**11.37**	**14.47**	**16.12**
Plot potential wetness index	**12.24**	**12.95**	**12.7**	**-6.80**
Plot size (hectare)	**.137**	**.198**	**.164**	**-9.13**
Plot elevation	**2085**	**2206.6**	**2164**	**-5.97**
		Average crop yield in kilogram per hectare		
Crop yield (total sample. KG)	**1393.6**	**1495.58**	**1461**	**-0.71**
Crop yield (Maize)	**1990.9**	**1887.6**	**1921.70**	**0.4**
Crop yield (*Teff*)	**971.8**	**1153.75**	**1092.76**	**-0.6**
Crop yield (Wheat)	**1160.97**	**1423.9**	**1329.79**	**-1.8**

For categorical variables (percent)

Variable		Adopt		Total	χ^2 (P-value)
		No	Yes		
Extension		13.67	75.71	41.26	867.9(0.000)
Manure		78.49	16.53	38.56	568.1(0.000)
Compost		42.39	12.65	23.28	173.35(0.000)
Certified		75.9	80.2	77.79	5.21(0.023)
	Good	31	38	34	
Soil quality	Fair	47	44.7	46. 06	14.1 (0.001)
	Poor	21.73	17.21	19.72	
Sex(male=1)		87.91	89.37	88.55	1.1405(0.286)
Literate		35.92	38.95	37.26	2.1439(0.143)
Credit		20.39	50.00	33.53	215.80(0.000)
Advisory service		74.52	95.64	83.89	181.08(0.000)
Offarm Employment		7.1	4.53	5.67	6.7653(0.009)

Appendix 2

What is the cause of damage of [Crop]?

	Freq.	**Percent**	**Cum.**
Too Much Rain |	40	9.41	9.41
Too Little Rain |	77	18.12	27.53
Insects |	75	17.65	45.18
Crop Disease |	30	7.06	52.24
Weeds |	51	12.00	64.24
Hail |	47	11.06	75.29
Frost |	1	0.24	75.53
Floods |	22	5.18	80.71
Wild Animals |	9	2.12	82.82
Birds |	1	0.24	83.06
Depletion of Soil |	30	7.06	90.12
Bad Seeds |	10	2.35	92.47
Other Specify |	32	7.53	100.00
Total |	**425**	**100.00**	

Appendix 3: Combined average Marginal effects from the double hurdle model (for the total sample)

Variable	dy/dx	Std. Err.	z	P>|z|
sex*	9.944333	4.77832	2.08	0.037
age	-.5473838	.15157	-3.61	0.000
educat~n	5.493141	1.1088	4.95	0.000
agroec~y*	5.974511	6.95786	0.86	0.391
area_h~e	-203.391	30.456	-6.68	0.000
dist_r~d	-.4154768	.14552	-2.86	0.004
dist_m~t	-.1405554	.06623	-2.12	0.034
dist_a~r	.0389304	.03852	1.01	0.312
offfarm*	-10.25094	5.97141	-1.72	0.086
extens~n*	67.35615	10.433	6.46	0.000
soil_q~y	-3.312054	1.50679	-2.20	0.028
dist_h~d	-.5872526	.64412	-0.91	0.362
credit*	7.481162	4.12205	1.81	0.070
manure*	-20.58218	4.23779	-4.86	0.000
compost*	-12.36074	3.37167	-3.67	0.000
plot_s~p	-.4574314	.18483	-2.47	0.013
plot_twi	1.901591	.98503	1.93	0.054
plot_s~m	.033503	.00577	5.81	0.000
hh_size	-2.73941	.90317	-3.03	0.002
livest~u	-4.337814	.99638	-4.35	0.000

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Appendix 4: Average Marginal Effects after Probit (the first hurdle)

| Delta-method						
|	dy/dx	Std. Err.	z	P>|z|	[95% Conf. Interval]	
sex |	-.0151799	.0245047	-0.62	0.536	-.0632082	.0328484
age | -.	-.0017325	.000548	-3.16	0.002	-.0028066	0006584
education |	.0069655	.004698	1.48	0.138	-.0022425	.0161735
land_area |	.1537459	.0511316	3.01	0.003	.0535298	.2539621
offfarm |	.1222236	.0342035	3.57	0.000	.0551861	.1892611
dist_road |	-.001349	.0006016	-2.24	0.025	-.0025281	-.0001699
dist_market |	-.0016522	.0003157	-5.23	0.000	-.0022709	-.0010335
dist_admctr |	-.0001936	.0001401	-1.38	0.167	-.0004681	.0000809
extension |	.3687343	.011474	32.14	0.000	.3462458	.3912229
credit |	.063195	.01729	3.66	0.000	.0293073	.0970827
manure |	-.1838001	.0188956	-9.73	0.000	-.2208347	-.1467655
compost |	-.1064715	.0227273	-4.68	0.000	-.1510161	-.0619269
dist_household |	-.0047485	.0051995	-0.91	0.361	-.0149394	.0054424
soilquality_poor|	-.0616316	.021049	-2.93	0.003	-.1028869	-.0203763
plot_srtmslp |	-.0054123	.0008594	-6.30	0.000	-.0070968	-.0037278
plot_twi |	-.0048808	.0038969	-1.25	0.210	-.0125185	.0027569
plot_srtm |	.0001111	.0000205	5.41	0.000	.0000708	.0001513
agroecology |	-.0659415	.0243254	-2.71	0.007	-.1136184	-.0182647

Appendix 5

Poverty	Average land holding in hectare	Std. err.	t-value
Non-poor	.17701466	.0045877	3.9394
poor	.14111327	.0064037	
Total	.1687934	.0038446	
Difference	.0359014	.0091134	

Appendix 6

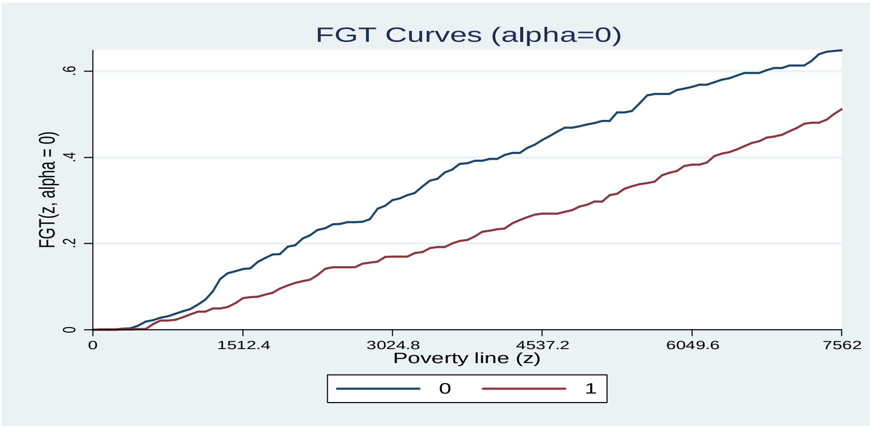
What is the reason for not using chemical fertilizers?	Freq.	Percent	Cum.
Ignorance	57	8.74	8.74
High Price	84	12.88	21.63
Lack of Money	267	40.95	62.58
Non-Availability of Supply	17	2.61	65.18
Skeptical of the Outcome	98	15.03	80.37
Other Specify	128	19.63	100.00
Total	652	100.00	

Why did you not get credit Services?	Freq.	Percent	Cum
Non-Availability of the Service	14	1.14	1.14
Unable to Pay the Loan	597	48.50	49.63
Inadequate Service Provided	164	13.32	62.96
Ignorance	27	2.19	65.15
Does Not Yield Any Results	102	8.29	73.44
Other Specify	327	26.56	100.00
Total	1.231	100.00	

Appendix 7

Do you use any manure on [Field]?	Summary of livestock tlu		t-value(diff=0)
	Mean	Std. Dev.	
No	3.7212931	2.4692197	-1.8406
Yes	3.9677777	2.5839421	
Total	3.784363	2.5006767	

Appendix 8


FGT Curves (alpha=0)
FGT(z, alpha = 0)
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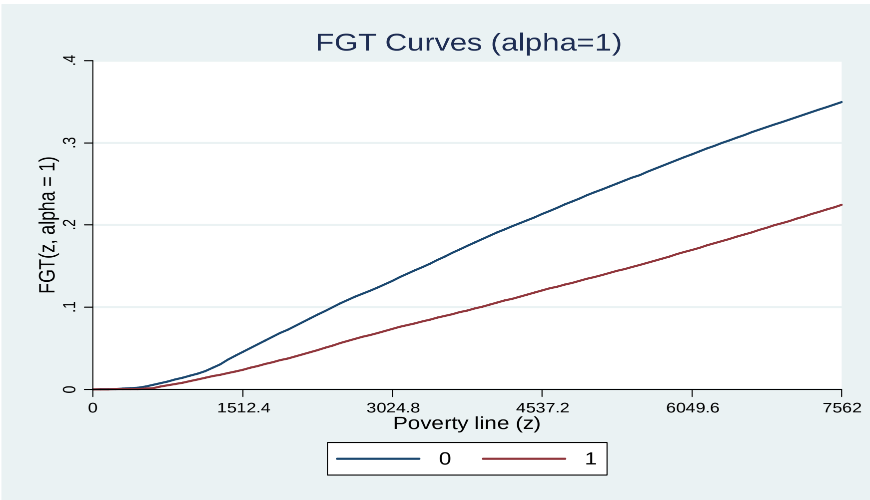
.4
.6
0
1512.4
3024.8
4537.2
6049.6
7562
Poverty line (z)
0
1


FGT Curves (alpha=1)
FGT(z, alpha = 1)
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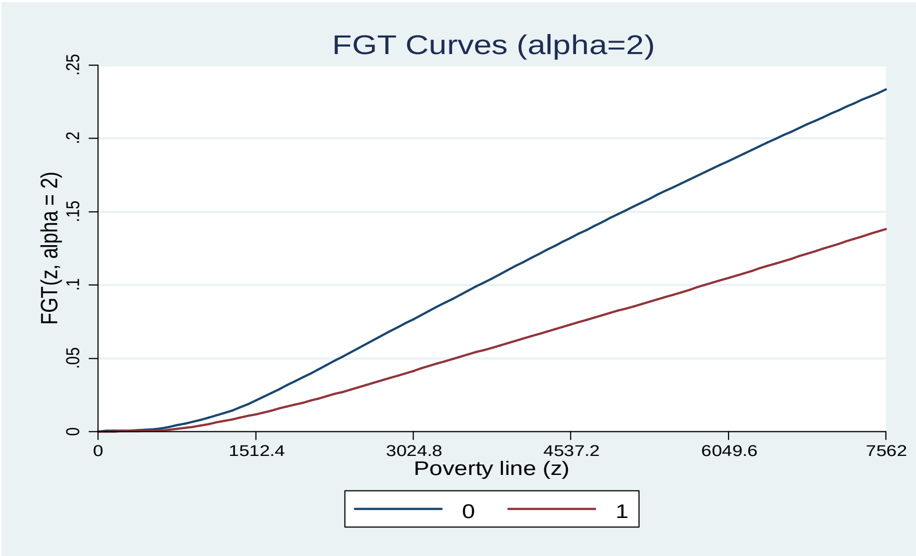
.1
.2
.3
.4
0
1512.4
3024.8
4537.2
6049.6
7562
Poverty line (z)
0
1



Appendix 9

Propensity score matching: logistic regression

Logistic regression Number of obs = 540

LR chi2(8) = 118.65

Prob> chi2 = 0.0000

Log likelihood = -310.16063 Pseudo R2 = 0.1606

chemical_f~r	**Coef.**	**z**	**Std. Err.**	**P>|z|**	**[95% Conf. Interval]**	
sex |	.1003654	.2817922	0.36	0.722	-.4519371	.6526679
age |	-.0108202	.006532	-1.66	0.098	-.0236227	.0019822
education |	.1993076	.0660882	3.02	0.003	.0697771	.3288382
livestock_~u |	-.0408566	.0317039	-1.29	0.198	-.102995	.0212819
area_hectar |	1.067947	.2348623	4.55	0.000	.6076256	1.528269
credit |	1.521178	.2361859	6.44	0.000	1.058262	1.984094
compost |	.4280458	.2353659	1.82	0.069	-.0332629	.8893546
manure |	.0458289	.2005118	0.23	0.819	-.3471669	.4388248
_cons |	-.3791707	.4374617	-0.87	0.386	-1.23658	.4782385

Sensitivity Analysis

rboundslnpcce. Gamma (1 (0.05) 2)

Rosenbaum bounds for lnpcce (N = 595 matched pairs)

Gamma	sig+	sig-	t-hat+	t-hat-	CI+	CI-
1	0	0	7.08643	7.08643	7.01145	7.15925
1.05	0	0	7.06713	7.10584	6.9914	7.17745
1.1	0	0	7.04853	7.12411	6.97123	7.195
1.15	0	0	7.03028	7.14136	6.9519	7.21052
1.2	0	0	7.01306	7.15818	6.93323	7.22543
1.25	0	0	6.99624	7.17346	6.91512	7.2398
1.3	0	0	6.97969	7.18745	6.89762	7.25359
1.35	0	0	6.96398	7.20129	6.88146	7.26701
1.4	0	0	6.94776	7.21384	6.86476	7.27995
1.45	0	0	6.93285	7.22579	6.84903	7.29193
1.5	0	0	6.91806	7.23743	6.83403	7.30382
1.55	0	0	6.90375	7.24874	6.81924	7.31487
1.6	0	0	6.88995	7.25992	6.80499	7.32503
1.65	0	0	6.87711	7.27006	6.79132	7.33522
1.7	0	0	6.86367	7.28074	6.77795	7.3452
1.75	0	0	6.85126	7.29039	6.76542	7.35447
1.8	0	0	6.83905	7.30011	6.75295	7.3633
1.85	0	0	6.82658	7.30933	6.74073	7.37206
1.9	0	0	6.81536	7.31782	6.72948	7.38112
1.95	0	0	6.80412	7.32571	6.71739	7.38967
2	0	0	6.79309	7.33376	6.70646	7.3977

*** gamma - log odds of differential assignment due to unobserved factors**

sig+ - upper bound significance level

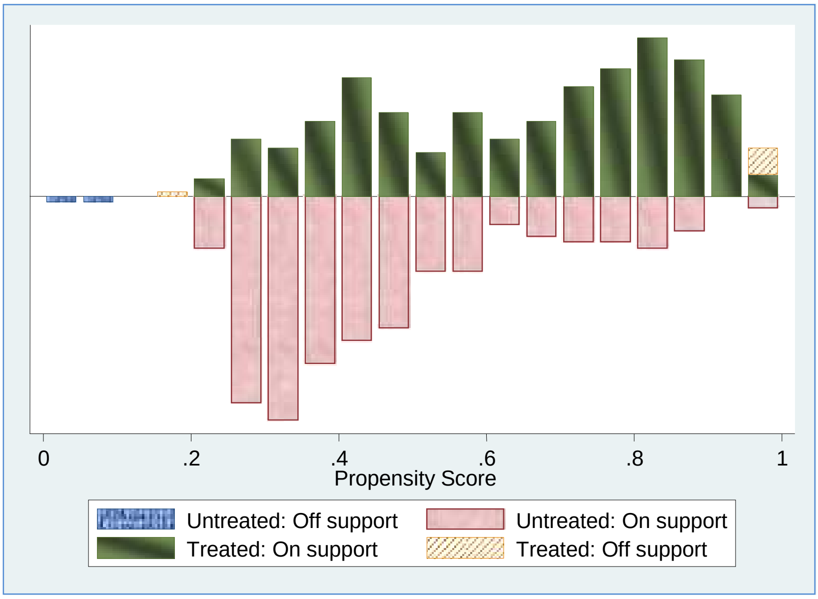
sig- - lower bound significance level

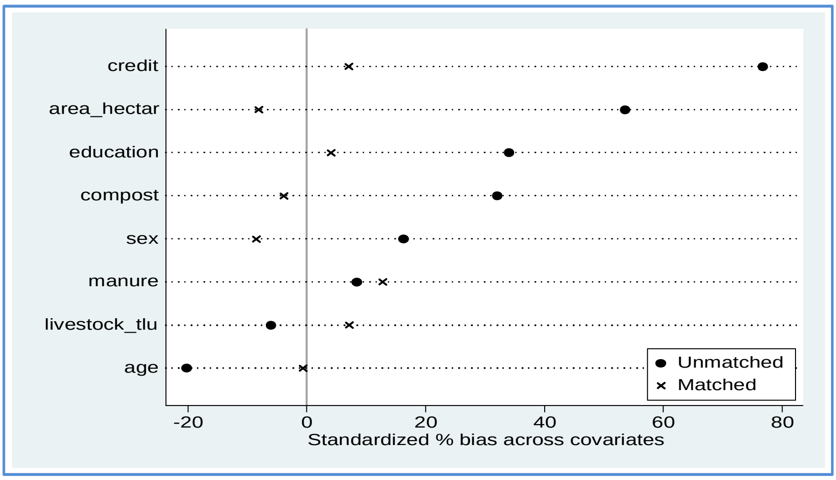
t-hat+ - upper bound Hodges-Lehmann point estimate

t-hat- - lower bound Hodges-Lehmann point estimate

CI+ - upper bound confidence interval (a= .95)

CI- - lower bound confidence interval (a= .95)


0
.2
.4
.6
.8
1
Propensity Score
Untreated: Off support
Untreated: On support
Treated: On support
Treated: Off support


credit
area_hectar
education
compost
sex
manure
livestock_tlu
age
Unmatched
Matched
-20
0
20
40
60
80
Standardized % bias across covariates