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MICROINSURANCE AS A TOOL FOR CLIMATE CHANGE: IMPLICATION FOR PRODUCTIVITY AND ADOPTION OF TECHNOLOGY IN RURAL TIGRAY, NORTHERN ETHIOPIA

by

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Abstract

One variant of agricultural micro-insurance is being implemented in Rural Tigray, Ethiopia. The project is a weather index insurance (WII) in which if the amount of measured rainfall index is below a predefined threshold then the insurance company pays indemnity to the insurance holder (farmers). The project innovatively extends WII to technically challenging communities and use methods that allow cash constrained farmers to pay for premiums in kind (labor). Despite its relatively successful implementation for some years, no attempt has been made so far to evaluate what the project has yielded to the beneficiaries of the program. This study is thus aimed at investigating the impacts of the WII project on productivity and technology adoption decision among rural households in Northern Ethiopia. To this end a stratified random sample of 501 (insured (301) and uninsured (200)) households were surveyed. Moreover focused group discussions and key informant interviews were conducted to design and complement the information from the survey. To identify the impacts of the project in terms of productivity and technology adoption of the participants, a propensity score matching coupled with endogenous switching regression model is employed. The results, from the mean difference tests, propensity score matching and FIML endogenous switching regression estimations, show that insured households fared better in terms of average total product (24.6 percent), average compost use (8 percent) and fertilizer use (3.5kg per tsimad). On the other hand insured households utilized less pesticide/insecticide (60 percent) per tsimad[1]*. Since insured household's fared batter in most of the indicators considered, it can be said that the WII not only improved the technology adoption decision of insured households but also improved their productivity.*

Key words: microinsurance, climate change, endogenous switching regression, technology adoption, productivity, propensity score matching

[1]Tsimad is the local unit of measurement for land roughly equivalent to a quarter of a hectare

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1. BACKGROUND AND JUSTIFICATION

Risk and shocks are common in developing countries and have adverse impact on household welfare. In the presence of risk, households make decisions *a priori* to safeguard themselves from the possible negative consequences of risk (Dercon, 1996). Similarly, when shocks occur, households make decisions to cope *ex-post* with shocks. Several studies examined the effectiveness of ex-ante and risk coping strategies and the findings indicate incomplete insurance. Existing evidence clearly portray adverse impact of uninsured risk and partial insurance of existing risk management and coping strategies calling for innovations or strategies in managing or transferring risk in the agricultural sector (see for example Morduch, 1990; Dercon, 1996; Dercon & Christiaensen, 2007; Rosenzweig & Binswanger 1993; Carter & Barrett 2006). In such situations, agricultural insurance can be potentially used as a strategy that transfers risk.

One variant of agricultural weather index microinsurance has been implemented in the study area for some years now. The project is an initiative involving poor farmers. Between November 2007 and December 2009, the project partners[2] designed a climate risk management package for farmers in the village of Adi Ha, located in Ethiopia's northernmost state of Tigray. In 2010, it expanded to another additional four villages known as Genetie, Hade Alga, Awet Bikalsi, and Hadush Adi. The former two villages are from Southern zone, the third village is from Central zone and the fourth village is from Eastern zone of the region. The project has broken new ground in the field of climate change resiliency and microinsurance by addressing the needs of smallholder producers through an unusual mix of risk reduction, drought insurance, and credit. Under the project's risk management package, insurance complements disaster risk reduction and long-term, sustainable investments in agriculture (Oxfam America, 2009). In the 2013 agricultural season, the project expanded its operations to 80 villages including 79 villages in the Tigray region, and 1 village in a new region (Amhara) where a pilot is being implemented in Michael Debir village. A total of 20,365 farmers purchased insurance that year (WFP & Oxfam America, 2013).

[2] The project partners include Oxfam America, Swiss Re, the Relief Society of Tigray (REST), Columbia University's Institute of Climate and Society (IRI), Nyala Insurance, Dedebit Credit and Saving Institution (DECSI) and different agencies of the Ethiopian Government.

One innovative element of the project is that it allows cash poor farmers the option to work for their insurance premiums by engaging in community identified projects to reduce risk and build climate resilience. Under this scheme, farmers have the option of working in exchange for an insurance voucher that protects them against drought. However, due to budget implications and constraints, the insurance for work scheme has fixed quota for each insurance *tabia* depending on the availability of fund. This scheme is meant for relatively poor famers; mainly for farm households who are participating in the Safety Net program or those who recently graduated from the Safety Net program. The other scheme is the insurance for cash scheme. This scheme has no fixed quota and those who can afford to pay the premium in cash may buy insurance irrespective of their number. For a given growing season, the project pays out (in cash) if the amount of rainfall falls below a pre-defined threshold level (i.e., the trigger). The premium payment varies from village to village based on differences in local weather conditions and historical data. It also varies depending on whether the farmer purchases either early or late in the growing season. For the 2013 growing season, the premium ranged from as low as 18 to 32 percent of the indemnity payment for early coverage of insurance for long cycle crops while for late coverage the premium varies from 15.5 to 32 percent of the indemnity payment. Long cycle crops have both early and late coverage window while short cycle crops have only late coverage window. The indemnity payment ranges from as low as 800 Birr to as high as 3000 Birr for the 2013 growing season.

The literature on weather index insurance (WII) in developing world is sparse. Several studies assess the level of demand and factors that affect demand for and/or participation in index insurance (Zhang, 2008; Gine *et al.*, 2008; Heenkenda, 2011; Sakurai & Reardon, 1997; Gine *et al.*, 2010). An exception in this regard is Fuchs and Wolff (2011), who studied the *ex-post* potential spill over effects of the Mexican WII program where they have argued that the WII program has resulted in a disincentive to invest in non-insured crops and a disincentive to invest in irrigation systems as the program covers production activities in non-irrigated land. Moreover the available literature almost exclusively includes *ex-ante* analyses (Hill *et al.*, 2011; Hill and Viceisza, 2010; Heidelbach & Bokusheva, 2009; Cai *et al.*, 2009; Gine & Yang, 2009). The impact of index based insurance, even in markets where they flourished, is not yet exactly known (Hellmuth *et al.*, 2009).

Despite the good take-up rate of WII in the project *tabias* (Madajewicz *et al.*, 2011a), not much attempt has been made to evaluate what could be the impacts of the project to the beneficiaries of the project. This study investigates the impacts of the WII on the productivity and adoption of technology in Tigray, northern Ethiopia. Given that the WII program is at pilot level in many African countries and it is totally new to the region in particular and the country in general, the study of any potential impact of the program will have greater significance not only to the practitioners but also to the academics and policy makers.

In particular I investigate the factors affecting participation in the WII program, differences in technology adoption decision of participants and non-participants of the WII program, and, conditional on technology adoption, the resultant differences in their productivity.

2. METHODOLOGY OF THE STUDY

2.1 Sources of Data

The study uses both primary and secondary sources. Most of the information needed to achieve the objectives of the study was gathered using the questionnaire. The questionnaire had three major parts. The first part included questions related to the socio-economic characteristics of the respondents followed by questions related to adoption of technology, including the kind and amount of modern inputs applied by the respondent in the last growing season. The third part included questions related to crop production of the respondent. How much *tsimad/s* of land they have cultivated, crops they have grown, and harvests were among the questions asked. In the study area it is customary to grow more than one crop and thus the questionnaire was designed to accommodate this.

2.2 Sampling Procedure and Sample Size

As discussed earlier, according to WFP and Oxfam America (2013), the project expanded its operations to 80 villages including 79 villages in the Tigray region. The 79 villages include 43 villages where insurance was offered consecutively in 2011 and 2012 agricultural season, where farmers continue to have the option to buy insurance through labour (insurance for work) or with cash. In 36 remaining villages, farmers were offered insurance through a cash-only option. In Tigray, of the total 20,015 farmers who purchased insurance, 82 percent were from the villages where farmers had both options, and the remaining 18 percent of purchasers were from the villages where only the cash option was offered for purchasing insurance. Of the total farmers who enrolled in Tigray in 2013, 81 percent purchased insurance by paying 10 percent of the premium in cash, with the remaining 90 percent of the premium covered by working additional hours in the Productive Safety Net Program (PSNP). The remaining 19 percent paid fully in cash. Farmers in five villages—Adi Ha, Awet Bikalsi, Genetie, Hade Alga, and Hadush Adi—have been offered the insurance for work (IFW) option for the past four consecutive years (WFP & Oxfam America, 2013).

For this study only villages (*tabias*) in Tigray region were considered. The study followed[3] a sampling procedure that was designed and conducted by the International Research Institute for Climate and Society (IRI) at Columbia University in partnership with Mekelle University, and in close consultation with the Relief Society of Tigray (REST), who play a central role in the project.

First, a qualitative survey was done in February, 2010 through focus group discussions in four insured villages (Genetie, Hade Alga, Hadush Adi and Awet Bikalsi) that helped in designing the quantitative baseline and follow-up surveys questionnaires. Households for the survey were selected using proportional and stratified sampling. The stratification in the program *tabias* was based on the household status of insurance purchase (insured and non-insured). 15% of households that purchased insurance and 3.5% of households that did not purchase insurance in each program *tabia* were surveyed, and 2.9% of all households in each uninsured *tabia* surveyed. The households were randomly selected from the lists of households that purchased insurance and that did not purchase insurance in each program *tabia*, and randomly from the entire list of households in each uninsured *tabia*. Overall, 400 households sampled; among which 301 households from the program villages and 99 households in uninsured villages (Gebreegziabher *et al*., 2011).

The baseline survey conducted in August and September of 2010 in 5 *tabias* in which the project was implemented (treatment *tabias*) and in 3 *tabias* in which no program activities took place (uninsured *tabias*). One uninsured *tabia* chosen in each of the 3 Woredas in which the

[3] The following three paragraphs explain how the International Research Institute for Climate and Society undertake the sampling for their survey. The initial plan of this work was to use their data by complimenting it with a new survey so that the data will be a panel nature. But because of the delay in their response about the final decision of my request, it was not possible to use their data and till now no communication was received about their final decision. So the description is to show how their initial survey was planned and conducted since this work also built the sampling procedure based on that.

treatment *tabias* are located: Menji in Kola Tembien, Were Abaye in Raya Azebo, and Agazi in Saesie Tsaedaemba. In fact, the baseline survey was conducted after the farmers decided whether or not to buy insurance at the beginning of the growing season. This was done to have sufficient sampled households from insurance purchasers. Follow-up surveys were conducted to gather information about demographic characteristics, crop production, input use, outputs, networks and services, wealth status and assets of respondents.

By using a fund obtained from Mekelle University and Institute of Climate and Society of the University, I have conducted a survey for the purpose of this study from last week of March to third week of April, 2014. The sampling procedure was built based on the same procedure as the original project. The total sample size of this survey was 501 respondents of which 301 are insured while the remaining 200 are uninsured households. The main reason for using the same sampling procedure with the project's is that since I had sent a request to Oxfam America to allow me to use the data they have collected and there had been positive indications about my request. The second and the main reason is that the villages in the project's survey are the oldest in terms of the insurance intervention. Given the no or low financial literacy of farm households in rural areas of the developing world in general and that of Ethiopia in particular, it is always an advantage to make sure that farmers have a better understanding of the terms of the insurance and how it works before a genuine impact evaluation attempt. In this regard the study has built up on the project's respondents with additional respondents due to large sample size.

As a result, as is shown in table 1, three districts (Weredas) have been selected namely Kola Tembien, Saesi Tsaedamba and Raya Azebo from Central, East and South zones of the region, respectively. Three villages from each district were selected. Adi-Ha, Awet Bikalsi and Menji from Kola Tembien; the first two are insured while the latter is uninsured villages. From Saesi Tsaedamba, Villages Hadush Adi, Agazi and May Megeltae were selected. In the project's survey Hadush Adi is insured village while Agazi has been an uninsured village but for the 2012 growing season insurance has been introduced to the Agazi village. As a result an additional village, May Megelatae, has been chosen as an uninsured village. In Raya Azebo, villages Hade Alga, Genetie, and Horda have been chosen. The first two are insured while Horda is an uninsured one.

Ten enumerators and one supervisor had been selected from a large number of applicants based on previous experience, academic qualification, and knowledge of English and local language. One day training was given to the enumerators and the supervisor. The researcher was also in the field to check whether enumerators were faring as required and to give immediate correction when necessary.

2.3 Analytical Framework

Without randomized treatment, an impact evaluation is essentially a problem of missing data, because one cannot observe the outcomes of program participants had they not been beneficiaries. Without information on the counterfactual, the next best alternative is to compare outcomes of insured individuals or households with those of a comparison group that has not been insured. In doing so, one attempts to pick a comparison group that is very similar to the insured group, such that those who received treatment would have had outcomes similar to those in the comparison group in absence of treatment. For individual *i*, for *i* = 1, . . . , N, it is possible to postulate the existence of two potential outcomes, denoted by $Y_i(0)$ and $Y_i(1)$. The first, $Y_i(0)$, denotes the outcome that would be realized by individual *i* if he or she did not purchase insurance for a given growing season. Similarly, $Y_i(1)$ denotes the outcome that would be realized by individual *i* if he or she did buy insurance. Individual *i* can either participate or not participate in the program, but not both, and thus only one of these two potential outcomes can be realized. Let denote the realized outcome by Y_i, with Y the N-vector with i^{th} element equal to Y_i. This implies that

$$Y_i = Y_i(T_i) = Y_i(0) * (1 - T_i) + Y_i(1) * T_i = \begin{Bmatrix} Y_i(0)\ if\ T_i = 0 \\ Y_i(1)\ if\ T_i = 1 \end{Bmatrix} \quad (1a)$$

The impact of a treatment for an individual *i*, noted β_i, is defined as the difference between the potential outcome in case of treatment (WII purchase) and the potential outcome in absence of treatment (insurance):

$$\beta_i = Y_{1i} - Y_{0i} \quad (2a)$$

In general, an evaluation seeks to estimate the mean impact of the program (modern input use or technology adoption and productivity in this case), obtained by averaging the impact across all the individuals in the population. This parameter is known as Average Treatment Effect or ATE:

$$ATE = E(\beta) = E(Y_1 - Y_0) \qquad (3a)$$

where E(.) represents the average (or expected value). The Propensity Score Matching (PSM) works under the theoretical assumptions of conditional independence and common support. The available literature shows that comparing results across different matching methods can reveal whether the estimated program effect is robust. This study employed two matching methods to ensure the robustness of the results.

To complement the PSM techniques and to assess consistency of the results to different assumptions, endogenous switching regression techniques were applied. Following DI Falco *et al.*, (2011), the first stage is a selection model for purchase of WII where a farm household chooses to purchase WII if it generates net benefits. Let A* be the latent variable that captures the expected benefits from the insurance purchase decision with respect to not purchase. The latent variable can be specified as:

$$A_i^* = \boldsymbol{Z_i\alpha} + \eta_i \text{ with } A_i = \begin{cases} 1 & if\ A_i^* > 0 \\ 0 & otherwise, \end{cases} \qquad (1b)$$

that is farm household *i* will choose to purchase WII (A_i =1) for a given growing season of a year, if A*>0, and 0 otherwise.

The vector **Z** represents variables that affect the insurance purchase decision of the farm household. These factors can be classified in different groups. The first is the demographic characteristics of the respondents. Age is at the forefront of such considerations and despite the direction of the effect of age on participation of the insurance program, it is not expected to have a linear effect. As a result, to account such fact into consideration, age squared is introduced. The introduction of age squared is also important given the fact that most of the premium payments are done in kind (mainly labour). Gender, marital status, education is also another variable of consideration. Since education in this case refers to the education level of the respondent, it was necessary to incorporate the highest level of education achieved by a member of the household to see the possible effect of education other than head of the household. Another variable of interest was the involvement of both the respondent and other family members in off-farm activities. Given, again, that most of the premium payments are done in kind, it was necessary to see whether the hours devoted for in-kind premium payments are competing with off-farm activities.

Apart from the socioeconomic factors, the respondents were asked to state the amount of land they owned. For a farm household to participate in the WII he/she has to be cultivating a plot of land, irrespective of its size, in a given growing season. Respondents were also asked about their perception of their previous year's production level compared to the other previous two years' production levels.

Some studies (such as Smith & Chamberlain, 2010) have stated that the prevalence of *iddir* (a funeral society in which members contribute in-kind or in-cash when an adverse event, such as death or serious illness, befalls ones of the member families) and *iquub* (a rotating saving and credit association) are considered as an opportunity factors for microinsurance in Ethiopia since they show the need for risk management. Thus a question on whether the household is a member of *iddir* was asked. Since *iddir* is an informal risk management activity, the inclusion of such variable enables us to see whether the WII is competing or complementing with tradition risk management activities.

The second stage is modeling the effect of insurance purchase on adoption of modern farm inputs[4] and thereby its effect on crop yield of farm households. Farmers face two regimes: (1) to purchase WII, and (2) not to purchase defined as follows:

Regime1: $y_{1i} = \boldsymbol{X_{1i}\beta_1} + \varepsilon_{1i} if A_i = 1$ (2ba)

Regime2: $y_{2i} = \boldsymbol{X_{2i}\beta_2} + \varepsilon_{2i} if A_i = 0$ (2bb)

[4]The modern farm inputs in the study areas include chemical fertilizer, compost/manure and pesticide/insecticide among others. Each modern input is computed per unit of *tsimad*. The productivity is also computed per unit of *tsimad*.

Where y_i[5] is the quantity produced per *tsimad* in regimes 1 and 2, and $\mathbf{X_i}$ represents a vector of inputs. The inputs considered in this study include the amount of land cultivated, the amount of fertilizer applied, the amount of compost/manure utilized and the amount of insecticide/pesticide applied. While the amount of land owned could affect the decision to participate in WII, the amount of land cultivated is considered as a variable affecting the average production level of both insured and uninsured groups. In Ethiopia, farm households, even if they don't own any plot of land, can still grow crops under different land arrangements. They can either rent or enter into a sharecropping arrangement. As a result, amount of land cultivated rather than owned is considered as a factor affecting the production level of farm respondents.

A district dummy was introduced to account for differences in local conditions. Apart from the perception and expectation dummies, all other variables included in **Z** were also incorporated in **X**. Finally, the error terms in equations (1b), (2ba), and (2bb) are assumed to have a trivariate normal distribution (DI Falco *et al.*, 2011).

2.3.1 Conditional Expectations, Treatment and Heterogeneity Effects

The conditional expectations for food production and input adoption in the four cases are defined as follows:

$$E(y_{1i}|A_i = 1) = \boldsymbol{X_{1i}\beta_1} + \sigma_{1\eta}\lambda_{1i} \tag{3ba}$$

$$E(y_{2i}|A_i = 0) = \boldsymbol{X_{2i}\beta_2} + \sigma_{2\eta}\lambda_{2i} \tag{3bb}$$

$$E(y_{2i}|A_i = 1) = \boldsymbol{X_{1i}\beta_2} + \sigma_{2\eta}\lambda_{1i} \tag{3bc}$$

$$E(y_{1i}|A_i = 0) = \boldsymbol{X_{2i}\beta_1} + \sigma_{1\eta}\lambda_{2i} \tag{3bd}$$

While cases (3ba) and (3bb) represent actual expectations, cases (3bc) and (3bd) stand for the counterfactual expectations. That is, 3bc represent the counterfactual outcome of insured farmers

[5] The specification for the adoption of modern inputs is similar with that of the crop production except with some modifications on the variables to be included in X (the inputs utilized are avoided from X). In that case y_i stands for the particular input utilized in a growing season.

had they been uninsured and 3bd represents the counterfactual outcome of uninsured farmers had they been insured.

Following Heckman *et al.* (2001), we calculate the effect of the treatment (to purchase WII") on the treated (TT) as the difference between (3ba) and (3bc),

$$TT = E(y_{1i}|A_i = 1) - E(y_{2i}|A_i = 1) \tag{4b}$$

Similarly, it is possible to calculate the effect of the treatment on the uninsured (TU) for the farm households that actually did not purchase WII as the difference between (3bd) and (3bb),

$$TU = E(y_{1i}|A_i = 0) - E(y_{2i}|A_i = 0) \tag{5b}$$

Following Carter and Milon (2005), I define the effect of base heterogeneity for the group of farm households that decided to purchase WII as the difference between (3ba) and (3bd),

$$BH_1 = E(y_{1i}|A_i = 1) - E(y_{1i}|A_i = 0) \tag{6b}$$

Similarly for the group of farm households that decided not to purchase insurance, "the effect of base heterogeneity" is the difference between (3bc) and (3bb),

$$BH_2 = E(y_{2i}|A_i = 1) - E(y_{2i}|A_i = 0) \tag{7b}$$

Finally, the "transitional heterogeneity" (TH), that is whether the effect of purchasing WII is larger or smaller for farm households that actually are insured or for farm households that actually are uninsured in the counterfactual case that they were insured, is the difference between equations (4b) and (5b) (i.e., TT and TU).

3. RESULTS AND DISCUSSION

3.1 Description of the Data

Looking at the gender composition of the respondents, close to 47 percent of the respondents in the total sample are female and the same gender comprises 46.5 and around 58[6] percent in the uninsured and insured samples, respectively. Male respondents account for 53, 53.5 and 42 percent in the total, uninsured and insured samples, respectively. Married respondents account for the lions share in both groups; 73, 67 and above 65 percent in the uninsured, insured and total samples, respectively. For both groups, next to married respondents is divorced ones followed by widowed and then by single respondents. The mean age for the insured sample is 42 years while for the uninsured it is 46 years and the mean age for the total sample is slightly above 43 years. Uninsured respondents have higher mean age than insured respondents. Insured households have, more or less, similar family size.

Both groups are dominated by illiterate respondents; 56 percent for the uninsured sample and about 65 percent for insured respondents. In addition to the respondent's education level, a question was asked to elicit the highest education level (in years) achieved within the household. Accordingly, the highest education level achieved on average is 6.2 and 6.5 years for insured and uninsured households.

Given that most of the premium payments are made partly in labor and partly in cash, it was necessary to see whether the activities those households are involved in are competing the time to be devoted to off-farm employment. I found no statistically significant difference in the groups.

Uninsured respondents owned and cultivated bigger rain fed land size (3.7 and 4 *tsimads*, respectively) than insured respondents who owned an average rain fed land size of 3 *tsimads* and cultivated roughly 3.4 *tsimads*. There is no significant difference in the owned and cultivated irrigated land within the groups. Similarly, the total production from rain fed land showed a

[6] The large number of female respondents doesn't mean that more female headed households have participated in the insurance program. This can be contested by looking at the figures of married respondents which constitute larger proportion in both samples. During the survey, if male respondents could not be found on repeated visits, housewives were picked (normally on the third visit) to be interviewed. Due to the unavailability of data on the number of visits, I was not able to control for this situation though. However, as Madajewicz *et al.* (2013) reported, the program has especially targeted female-headed households who are considered to be particularly vulnerable.

statistically significant difference among the two groups while for the irrigated land the difference in total production is not significant. But if the average production functions are considered, both average functions appear to show a statistically significant difference among the two groups.

Another comparison of interest for this study was to look how insured and uninsured households fared in terms of technology adoption. The mean total usage of fertilizer, compost and pesticide/insecticide is 83kg, 307kg and one liter for uninsured households, compared to 85kg, 375kg, and one liter for insured households, respectively (table 2), mean total compost usage was statistically different. When average usages of these inputs are taken into consideration, however, both compost and pesticide usages show a statistically significant difference among insured and uninsured respondents (table 2).

Considering results of the descriptive statistics of some of the outcome variables, there seems to be a mixed outcome. While insured respondents achieved a statistically significant better outcome in terms of total and average yields from rain fed land, total and average compost use, uninsured households fared better in terms of average yield from irrigated land and pesticide use. This necessitates for the further investigation of these results with better models and verify the consistency and robustness of the outcomes. In the following section, the outcome variables are analyzed with the propensity score matching and then they are further investigated with an endogenous switching regression model.

3.2 Impact of the Weather Index Insurance: Propensity Score Matching (PSM) Approach

The first procedure in applying the PSM is to compute the propensity score for insured and uninsured households which gives the probability of participation in the WII program. Accordingly, the propensity score for insured and uninsured observations is estimated using logit model in which the dependent variable equals one if the household bought WII and zero otherwise. Next is to check the balancing properties of the propensity scores. The balancing procedure tests whether insured and uninsured observations have the same distribution of propensity scores. The common support approach is used for all PSM estimates. The quality of the match can be improved by ensuring that matches are formed only when the distribution of the density of the propensity scores overlaps for insured and uninsured observations—that is, when the propensity score densities have common support. All results presented in the following pages are based on specifications that passed the balancing tests. Insured and uninsured observations are matched by two PSM techniques: namely nearest neighbor and kernel. The standard errors of the impact estimates are calculated by bootstrap using 100 replications for each estimate.

From the estimation of the propensity score, age and age squared appear to be significantly affecting the probability of participation in the insurance program (table 3). While age affects it positively age squared affects the probability negatively. This is not surprising, however, given that the majority of premium payments are done in combination of labor and cash. As people get aged, they may not have the capacity and energy to get involved themselves in labor intensive activities in order to make their premium payments.

Among the Woreda (district) dummies, being in Saesi Tsaedamba, resulted in a significantly lower probability of participation in the WII compared to those in Kola Tembien, which is the base category. This could be due to the fact that Kola Tembien is one of the pioneer places for piloting the insurance scheme and hence this could have resulted in better awareness of the farmers in terms of understanding how the insurance works.

Only religious education has a significantly positive impact on the propensity score, implying that those individuals who have religious education have higher probability of participation in the insurance scheme against those who are illiterate respondents. Respondents were also asked to evaluate the level of their crop production in 2013 growing season compared to the production levels of two previous years. With the exception of those who said it was ‘very good’, for the others (who said good, fair and worst) it has a significantly positive effect on the propensity score against those who said it was ‘excellent’. But this shouldn’t be surprising since farmers whose production level is lower in the season immediately before the current production season, tend to be left with less stock from the production of the previous season, if any, and hence are in a position to be frustrated that the current production year may also not yield good harvest. Hence they tend to look for something which may transfer their risk in this case insurance.

The estimated results based on the two matching methods, the Kernel method (KM) and nearest neighbor (NNM), are reported in table 4. To see the impact of the WII on productivity, two parameters, average total product and the average yield from irrigation activities are considered. The analysis reveals that insured farm households have reaped a significantly higher production per *tsimad* than their uninsured counterparts. The gain in average total production for the insured households ranges from 59 to 63kg per *tsimad*. The average total production is the sum of average production from rain fed and irrigated land. Given the results from the mean difference test for average yield from irrigation activities, it was necessary to verify the consistency of the result with the PSM. The decline in average yield from irrigation activities for insured households ranges from -37.7 to -38.7 though this difference is not statistically significant under both nearest neighbor and kernel matching techniques.

Insured farm households applied more fertilizer than uninsured respondents. However, the gain is only statistically significant with the kernel matching approach and hence to check the robustness of this result, it was further investigated with stratification matching approach. The gain in average fertilizer use also appeared to be statistically significant under the stratification matching. Thus it can be said that the increase in fertilizer use ranges from about 3.2 to 3.3kg per *tsimad*.

The PSM results show that insured households applied more compost than uninsured households (statistically significant at 1 percent level of significance under both matching techniques). The gain in average compost use ranges from 40 to 44kg. In terms of pesticide/insecticide use, uninsured households applied more of it than the insured ones. The decline in average pesticide use ranges from -0.2 to -.1 liter though the decline is significant under the nearest neighbor matching technique alone. The number of farm households who applied pesticide/insecticide appeared to be very small in the entire sample (21.8, 20.5 and 22.6 percent in the total, uninsured and insured samples, respectively) and hence it was not possible to further investigate the robustness of this result with other matching approaches.

Similar to the mean difference tests, the results for the impact of WII on productivity and adoption of technology appeared to be mixed. The PSM results showed that even if uninsured households fared better in terms of average yield from irrigation activities and average pesticide/insecticide use, they do not, however, show strong evidence on these variables. This could be due to the fact that insured households applied more compost than uninsured households and normally farm households prefer to apply more fertilizer to irrigated land than rain fed one. But it may be also because PSM cannot provide consistent estimation of causal effects in the presence of hidden bias. This again necessitates for the further investigation of these results with an endogenous switching regression method for consistency and robustness.

4.3 Impact Estimation of Weather Index Insurance: FIML Endogenous Switching Regression Approach

Finally, the data is estimated with an endogenous switching regression that can control for unobservable selection bias. The full information maximum likelihood estimates of the endogenous switching regression[7] model is run and reported for average total production (table 5). The second column presents the estimated coefficients of selection equation (1b) on purchasing or not purchasing WII, while the third and fourth columns present the estimated coefficients of average food production functions (2ba) and (2bb) for insured and uninsured farm households, respectively.

The results of the estimation of equation (1b) (column 2 of table 5) suggest that gender is one of the determinants of WII purchasing decision; women are more likely to participate. Again, age and age squared significantly affect the decision of WII purchase by farm households in the same manner as in PSM. Respondents who have primary education are less likely to participate than illiterate respondents. All the perception dummies significantly affect the likelihood of participating in the WII program and with the exception of the "very good" dummy the other results are similar to the results under PSM.

The results of equation (2ba) (column two) show the average total product function and the factors that affect it for uninsured farm households. Family size negatively and significantly affects the average production function for uninsured households. As family size gets bigger, the productivity declines. This could be as a result of the family heads spending more time in caring their siblings at home. Having primary education resulted in a positive and significant increment in the average

[7] The "movestay" command of STATA has been used to estimate the endogenous switching regression by full information maximum likelihood (FIML) (Lokshin and Sajaia, 2004)

production level of uninsured households compared to the illiterate respondents. The secondary school dummy was dropped due to collinearity.

Only average compost use has a positive and significant effect on the productivity function of the uninsured households. The average fertilizer use, even if it has the expected positive sign, is not statistically significant. This could be because of the fact that in order to apply fertilizer and thereby benefit effectively from it, the amount of rainfall in a growing season has to be adequate enough. Otherwise, the effect of fertilizer use could be counterproductive. Thus given the recent fluctuation on the amount of rainfall due to climate change and other factors, and due to the limited availability of irrigation facilities in the study cites, the farmers may tend to prefer the use of compost than fertilizer. Among the district dummies, being in district Saesi Tsaedamba results in a significantly lower productivity level of the households compared to those living in Kola Tembien. As stated before Saesi Tsaedamba is less productive and hence this result is not unexpected.

The results of the equation (2bb), which appear at column 3 of table 5, show the yield function of insured households and factors that affect it. Insured respondents who have primary education achieved a significantly higher productivity level, as measured by their average total product function, compared to those who are illiterate. Another variable that affect the productivity function of insured households is the application of compost which has a positive and significant effect on their productivity.

From the above discussion, it is clear that there is a difference in the coefficients of the productivity functions of insured and uninsured households and this illustrates the presence of heterogeneity in the sample. Moreover, the estimated coefficients of correlation terms ρ_j for the productivity functions of both insured and uninsured households (table 5, bottom row) are not significantly different from zero. As has been stated by Di Falco *et al.* (2011), this implies that I cannot reject the hypothesis of no sample selectivity bias.

Table 6 presents the expected quantity produced per *tsimad* and the expected fertilizer, compost and pesticide use per *tsimad* under the actual and counterfactual conditions. Cells (a) and (b) represent the expected quantities of the respective variables produced or applied per *tsimad* in the sample. Looking at productivity differences between the two groups, the expected average production level for insured households is 288.6kg while the same figure for the uninsured respondents is 240.7kg. However, this simple comparison could be misleading and is tempting to conclude that insured households achieved about 20 percent gain in productivity compared to the uninsured households.

The treatment effect of the insurance program is shown in the last column of table 6 for the respective variables of interest. Cell (c) presents the counterfactual case for the insured households. It predicts that insured households would have produced 57kg (24.6 percent) less had they not participated in the WII program. Similarly, the counterfactual case for the uninsured households (d) shows that farm households who didn't buy insurance for the growing season would have produced more, 30kg (12.7 percent) per *tsimad*, had they participated in the WII program.

The transitional heterogeneity is positive and significant implying that the effect of the WII program on insured households (TT_1) is higher than its effect on uninsured respondents (TU_1). Thus, it can be said that, consistent with the results from the mean difference tests and the propensity score matching approach, the results under the endogenous switching regression confirm the positive and significant gain in the productivity of insured households. This result is consistent with Madajewcz *et al.* (2013) who reported that households in Kola Tembien that bought insurance in 2010 and 2012 had achieved higher average yield of Teff while similar result have been reported for Sorghum in Raya Azebo and Wheat in Saesi Tsaedamba over the period of time.

Moreover, the potential heterogeneity in the sample is accounted under this approach and is reported in the row labeled 'heterogeneity effects' in table 6. Uninsured farm households, in the counterfactual case (d), would have produced less had they participated in the WII program than insured households (BH_{11}). Similarly, in the counterfactual case (c), insured households would have produced less in the absence of the WII than uninsured respondents (BH_{12}). This implies that while the WII program has increased the productivity of both insured and uninsured households, its effect is higher for the insured households. However, in the absence of the WII, the uninsured households achieve higher productivity than the insured respondents. Once more, because of the small sample size of households who had access to irrigation facilities in the entire sample, it was not possible to estimate the impact of the program on yields from irrigation activities.

Looking at the technology adoption indicators, both groups have applied more or less same amount of fertilizer, on average, under their actual expectations 27.7 kg (a) and 27.4kg (b), respectively. In case of compost, insured and uninsured households have applied 135kg and 102.7 kg under their actual expectations, respectively; while for compost these figures are 0.285 and 0.442 liters, respectively. However, when the counterfactual expectations are considered, (c) for insured and (d) for uninsured respondents, the insured households applied about 21kg and 10kg more fertilizer and compost per *tsimad*, respectively. Similar results have been shown by Madajewicz *et al.* (2013). They have reported higher, on average, application of fertilizer in Kola Tembien for Teff and Maize while only very few farmers used fertilizer in Raya Azebo before the project starts its operation there. These same authors have reported two times and six times higher application of compost by insured households in Kola Tembien and Raya Azebo, respectively, than uninsured households. The uninsured households would have applied around 3.5kg and 74 kg more fertilizer and compost per *tsimad*, respectively, had they participated in the WII program. Similar to the average product results, the WII program has positive and significant effect for both insured and uninsured households in their application of compost and fertilizer when both are treated. But the treatment results for the application of pesticide/insecticide are negative for both groups when their counterfactual expectations are taken into consideration. Precisely, insured households applied 60 percent more pesticide/insecticide and uninsured households applied 26.7 percent more of the same input under their counterfactual expectations leading the treatment effect to be negative.

The transitional heterogeneity results, in the last column of table 6, shows that the treatment effects of average fertilizer and average pesticide/insecticide use are higher for insured households while the opposite is true in the case of compost use. That is the treatment effect on the compost use of uninsured households is higher (by about 64 kg) than its effect on the insured households.

When potential heterogeneity in the samples are considered (base heterogeneities), uninsured respondents would have applied, on average, higher amount of fertilizer, compost, and pesticide/insecticide in the presence of the WII treatment than insured respondents. That is, in the counterfactual case (d), uninsured households would have applied more fertilizer, compost, and pesticide/insecticide per *tsimad*, had they participated in the insurance program, than insured respondents (BH_{21}, BH_{31}, and BH_{41}). In the absence of treatment (if both groups are untreated), insured households would have achieved higher average compost and pesticide/insecticide use than uninsured respondents.

The results from the mean difference tests, the propensity score matching and the FIML endogenous switching regression showed that insured households not only achieved higher productivity, since the findings confirm that they have achieved higher average productivity, but also fared better in term of technology adoption. With the exception of the application of pesticide/insecticide of which uninsured households applied more of it, the insured households applied more of both compost and fertilizer.

5. CONCLUSIONS AND POLICY IMPLICATIONS

The objective of this study was to investigate the impact of the WII project on the productivity and technology adoption decision of the participants in the project area. The data was analyzed using mean difference tests, propensity score matching (PSM) and then finally with FIML endogenous switching regression approaches. Since FIML endogenous switching regression model takes into account the simultaneity in insurance purchase decision and crop production, it is the preferred model for this study. The mean difference test and the PSM were useful to check the consistency and robustness of the results.

Looking at the factors identified to indicate impact, all results; that is, the results from mean difference tests, propensity score matching (PSM) and FIML endogenous switching regression estimations, confirmed that insured households achieved 24.6 percent higher productivity levels as manifested in high average production levels. Similarly, from the technology adoption indicators, the 8 percent gain for insured households in their application of compost per *tsimad* is not only significantly higher but also is consistently confirmed by all the methods employed. The only variable that uninsured households fared, on an average basis, from the technology adoption indicators, is the application of pesticide/insecticide and it has been also consistently confirmed under all the methods employed. In terms of fertilizer application, unlike the mean difference test, the PSM approach and endogenous switching regression results shown that the insured households applied 3.5kg more fertilizer, on average, than uninsured respondents.

Generally, it can be said that the weather index insurance program not only improved the technology adoption decision of the participant farm households but also it increased the participants' productivity, on average. The increase in productivity and adoption of modern farm inputs among participant farm households necessitates the need to look for mechanisms to streamline WII with agricultural policies and programs that are meant to achieve these objectives. While aid from donors and climate change funds as a result of future climate change negotiations could be one source for the continuation of the WII program, streamlining the WII with government's policies and programs will reduce the potential shortage in cash which is the main threat for the continuation of such programs. The experience of the government in other sectors, say in community health insurance, could be an asset for how to deal with micro-insurance programs in the agricultural sector including the WII.

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Table 1: List of districts and villages selected for the survey

Name of District	Selected insured villages	Selected uninsured villages
Kola Tembien	Adi-Ha and Awet Bikalsi	Menji
Saesi Tsaedamba	Hadush Adi and Agazi (Hadnet)	My Megeltae
Raya Azebo	Genetie and Hade Alga	Horda

Table 2: Descriptive statistics of the data

Total Sample			Uninsured Farm Households		Insured Farm Households		t-stat
Variable	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***	
gender	1.533	.4994	1.465	.5	1.578	.4947	**
age	43.60	13.73	46.09	15.17	41.95	12.44	***
Marital status	2.449	.8099	2.365	.7379	2.505	.851	*
Education	2.058	1.424	2.21	1.462	1.957	1.391	*
Family size	5.261	1.881	5.385	1.888	5.179	1.875	
Off-farm employment	.9034	.7691	.895	.7726	.9091	.7679	
Highest education	6.35	3.263	6.55	3.283	6.215	3.248	
Total owned land	3.446	2.334	3.755	2.902	3.24	1.836	**
Owned rain-fed land	3.312	2.284	3.741	2.891	3.029	1.724	***
Owned irrigated land	.6966	.648	.6916	.5599	.6982	.6757	
Production in 2013	2.996	1.102	2.765	1.05	3.148	1.111	***
Cultivated rain-fed land	3.667	2.818	4.098	3.388	3.384	2.334	***
Cultivated irrigated land	.7462	.6887	.6604	.5959	.778	.7202	
Total yield – rain-fed	896.6	693.9	845.1	667.4	930.7	710	*
Total yield - irrigated	309.0	276.5	342.2	305.7	294.4	63.3	
Total fertilizer	84.65	44.87	83.12	42.63	85.53	46.16	
Total compost	350.7	175.7	306.8	161.7	375.6	178.7	***
Total pesticide	1.019	.5611	1.038	.5034	1.008	.5966	
Average yield – rain-fed	255.2	95.39	222.4	92.81	276.9	90.89	***
Average yield - irrigated	463.9	195.7	523.4	187.8	437.8	194.4	**

Average total yield	261.2	98.43	232.7	98.67	270	93.8	***
Average fertilizer	28.05	14.9	27.59	15.31	28.31	4.69	
Average compost	121.7	80.5	100.9	71.69	133.4	82.94	***
Average pesticide	.308	.2714	.3718	.3795	.2695	.1695	*
Sample size		**501**		**200**		**301**	

***significant at the 1% level of significance; ** significant at 5% level of significance; *significant at 10% level of significance

Table 3: Logistic Regression Estimation of the Propensity Score

Treatment status (1/0)	Coef.	Std. Err.
Gender	.1516	.2956
Age	.1475	.0560***
Age2	-.0018	.0006***
Family size	-.0709	.0712
Off-farm employment	-.0055	.1364
Raya Azebo	-.2231	.2981
Saesi Tsaedamba	-1.579	.3302***
Married	-.2702	.7973
Widowed	-.9764	.8762
Divorced	-.0074	.8410
Religious	.9174	.5268*
Informal	-.6588	.4595
Primary	-.3554	.2772
Secondary	-.4693	.6157
V.good	.7567	.5950
Good	1.859	.6535***
Fair	1.996	.6265***
Worst	3.166	.7523***
Highest education	.0023	.0367
Community particip.	-.0751	.1327
Iddir membership	-.2117	.2584
Constant	-2.169	1.756
No. of observations		485

LR chi2(21)	84.52
Prob > chi2	0.0000
Pseudo R2	0.1292
Log likelihood	-284.94305

***significant at the 1% level of significance; ** significant at 5% level of significance; *significant at 10% level of significance

Table 4: Impact of WII: PSM Approach

Matching method	Number of insured respondents	Number of uninsured respondents	Average Treatment Effect on the Treated (ATT)	t-stat
1. Average total yield				
Nearest neighbor	289	106	59.249	4.246***
kernel	289	182	62.934	6.384***
2. Average yield from irrigation				
Nearest neighbor	289	18	-37.667	-0.469
kernel	289	182	-38.727	-0.796
3. Average fertilizer				
Nearest neighbor	289	88	0.859	0.377
kernel	289	182	3.330	2.639**
Stratification	282	189	3.160	1.834*
4. Average compost				
Nearest neighbor	289	84	44.083	3.904***
kernel	289	182	40.427	4.535***
5. Average pesticide				
Nearest neighbor	289	24	-0.209	-2.026**
kernel	289	182	-0.137	-1.602

***significant at the 1% level of significance; ** significant at 5% level of significance; *significant at 10% level of significance

Table 5: FIML Estimation of Endogenous Switching Regression

Dependent variable: average yield

Variables	FIML Endogenous Switching Regression		
	(1) ***WII purchase (1/0)***	*(2)* ***Uninsured households***	*(3)* ***Insured households***
Gender	.3749*	29.96	-10.71
	(.2239)	(25.09)	(17.71)
Age	.0960**	.7308	-3.0704
	(.0449)	(4.562)	(3.839)
Age squared	-.0012***	.0006	.0328
	(.0005)	(.0455)	(.0423)
Family size	-.0671	12.98***	-.7621
	(.0521)	(5.063)	(4.276)
Off-farm employment	.1419	5.746	-1.648
	(.1016)	(9.371)	(8.589)
Education dummies (base=illiterate)			
(religious	.5260	27.24	9.749
	(.3902)	(37.76)	(30.67)
informal	-.5412	12.02	2.861
	(.3336)	(30.91)	(31.34)
primary	-.3638*	60.17***	29.56*
	(.1946)	(19.55)	(17.18)
Secondary)	-.1028	dropped	-17.73
	(.5546)		(36.49)
Marital dummies (base=single)			
(married	.5259	-50.71	35.23
	(.5418)	(53.03)	(39.12)
widowed	.2939	-7.842	53.74
	(.6074)	(65.7)	(42.53)
Divorced)	.6860	-39.93	46.89
	(.5735)	(62.15)	(40.67)
Total cultivated land		-3.288	-4.111
		(3.377)	(3.982)
Average fertilizer		.6960	-.5960
		(.7443)	(.4897)

Table 5 cont'd

variables	(1) **WII purchase (1/0)**	(2) **WWI purchase=0 (uninsured)**	(3) **WII purchase=1 (insured)**
Average compost		.2674**	.1838**
		(.1253)	(.0889)
District dummies (base=Kola Tembien)			
(Raya Azebo		-23.51	-5.689
		(27.2)	(14.85)
Saesi Tsaedamba)		-43.79**	-4.961
		(18.31)	(16.64)
Total owned land	.0608		
	(.0383)		
Perception dummies (base=excellent)			
(V.good	1.191**		
	(.5660)		
good	1.690***		
	(.6297)		
bad	1.783***		
	(.5526)		
Worse)	2.374***		
	(.6088)		
Buy WII next year	-1.276***		
	(.1980)		
Iddir membership	.1941		
	(.1843)		
Constant	-2.479*	85.28	328.0***
	(1.407)	(124.1)	(104.7)
σ_i		81.11***	88.39***
		(5.165)	(4.774)
ρ_j		-.1189	.1391
		(.2384)	(.5780)

Note: standard errors in parenthesis.

σ_i denotes the square root of the variance of the error terms ε_{ji} in the outcome equations (2ba) and (2bb), respectively; ρ_j denotes the correlation between the error term η_i of the selection equation (1b) and the error term ε_{ji} the outcome equations (2ba) and (2bb), respectively.

***significant at the 1% level of significance; ** significant at 5% level of significance; *significant at 10% level of significance

Table 6: Impact of WII – using FIML endogenous switching regression

Sub samples	**Decision stage**		**Treatment effects**
	To buy WII	**Not to buy WII**	
1. Average total yield			
Insured farm households	(a) 288.6	(c) 231.6	TT_1=57.0***
			(3.404)
Uninsured farm households	(d) 271.3	(b) 240.7	TU_1=30.6***
			(5.029)
Heterogeneity effects	BH_{11}=17.3***	BH_{12}=-9.12*	TH_1=26.4***
	(2.84)	(5.239)	(4.372)
2. Average fertilizer			
Insured farm households	(a) 27.7	(c) 6.90	TT_2=20.8***
			(.7742)
Uninsured farm households	(d) 30.9	(b) 27.4	TU_2=3.5***
			(1.319)
Heterogeneity effects	$BH_{21=}$-3.2***	$BH_{22=}$-20.5***	TH_2=17.3***
	(.9499)	(1.068)	(.8723)
3. Average compost			
Insured farm households	(a) 135.1	(c) 125.1	TT_3=10.0***
			(3.806)
Uninsured farm households	(d) 176.8	(b) 102.7	TU_3=74.1***
			(6.687)
Heterogeneity effects	$BH_{31=}$-41.7***	$BH_{32=}$22.4***	TH_3=-64.1***
	(6.258)	(3.479)	(4.786)
4. Average pesticide/insecticide			
Insured farm households	(a) .285	(c) .711	TT_4=-.426***
			(.0191)
Uninsured farm households	(d) .324	(b) .442	TU_4=-.118***
			(.025)
Heterogeneity effects	$BH_{41=}$-.039***	$BH_{42=}$.269***	TH_4=-.308***
	(.0129)	(.0282)	(.0278)

***significant at the 1% level of significance; ** significant at 5% level of significance; *significant at 10% level of significance