Productivity and welfare effects of weather index insurance: Quasi-experimental evidence*

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PRELIMINARY DRAFT, PLEASE DO NOT CITE! Comments Welcome!

Abstract

We evaluate the impact of large commercially traded index-insurance on technology adoption, productivity and welfare. We use a unique cross-section of household data collected from both insurance purchasers and non-purchasers. Relying on propensity score matching (PSM), inverse probability weighted regression adjustment (IPWRA) and instrument variable (IV) techniques, we find that insurance improves adoption of technology, which is consistent across different estimations. The result from IPWRA indicates positive and significant effect of insurance on farm productivity; however, our results from PSM and IV suggest an otherwise insignificant effect. Consistently, we find no evidence on welfare improvements due to insurance. This study confirms only the positive benefit of insurance in terms of altering farmers behavior in risk-taking.

JEL Classification: C21; G22; O16; Q12

Key Words: Technology adoption; agricultural productivity; welfare; impact evaluation; weather index insurance; Ethiopia

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1 Introduction

The substantial rise in incidence of natural disaster (like drought and flood), food price shock and risk of climate change in the past few decades is of significant concern for the developing world (World Bank, 2013). The 2014 World development report documents that households that faced at least one shock range from 16 to 66 percent in sample of developing countries. The impacts are acute on the poor in the developing countries, since they have rarely access to formal insurance mechanisms.

In the presence of risk and absence of formal insurance, households make decisions apriori to safeguard themselves from possible negative consequences of risk. These risk management decisions or ex-ante strategies have implications both in the short and long-term outcomes of households. Households decide to forgo valuable technologies and profitable opportunities in fear of risk (Morduch, 1999). For instance, asset poor households devote a larger share of land to safer traditional varieties than to riskier but higher-return varieties (Morduch, 1995). There is further evidence of limited modern input use due to consumption risk (Dercon and Christiaensen, 2011) and production risk (Kassie et al., 2009). The implication of these ex-ante risk management strategies translate into reduced household welfare and results in poverty and poverty persistence (Carter and Barrett, 2006; Rosenzweig and Binswanger, 1993).

Similarly, when shocks occur, households make decisions to cope ex-post. These decisions or coping strategies have pernicious effects on household welfare. Households use their accumulated productive assets to smooth consumption or involve in informal risk sharing groups like funeral societies and informal credit arrangements (Carter et al., 2007; Morduch, 1999; Townsend, 1995; Rosenzweig and Wolpin, 1993). Households may also resort to adverse actions such as reducing the number and quality of meals, postponing health-related expenditure, engaging in child labor and informal employment. According to Carter et al. (2007), households that slipped into poverty due to shocks find it difficult to recover and restart the long-term process of accumulating assets.

Several studies examined the effectiveness of informal risk management strategies. Findings indicate incomplete insurance, translating into partial protection against risk and shocks. Firstly, some strategies like informal risk sharing groups are ineffective due to spatially covariate shocks. Secondly, other strategies like sale of livestock may not be effective due to loss of value during shocks. This is possible, for instance, due to weight loss of livestocks and oversupply in the market that dampens price. Thirdly, the implied risk premium of risk mitigation strategies may be high. For instance, the risk premium estimated to be at about 35 percent for farmers in rural India (Rosenzweig and Binswanger, 1993) and at about 25 percent in the case of farmers in rural Tanzania (Dercon, 1996). Existing evidence clearly portrays the adverse impact of uninsured risk and incomplete insurance through informal risk management and coping strategies, calling for innovations and enhanced strategies in managing risk in the agricultural sector.

Formal insurance presents a strategy to pool and transfer risk. Farmers hesitantly invest in lucrative activities, lest they lose their investment due to weather risk. With provision of insurance, we can install sense of security that could influence their risk-taking behavior. Hence, they may invest in risky but remunerative activities. Additionally, when weather shocks realize farmers lose their harvest. To cope with the weather shocks, farmers engage in inefficient coping strategies like depleting their productive assets. Insured farmers get payouts that could enable them cope with the shock without depleting their productive assets. Thus, insurance has a potential to address welfare losses due to weather risk and complement the existing informal risk management strategies. Nevertheless, the insurance market is missing or thin in most developing countries. Commonly offered explanations that bedeviled formal insurance schemes are, among others, information asymmetries and transaction costs (Clarke and Dercon, 2009; Skees, 2008; Hazell et al., 1986).

An innovation that could address these problems is index-based insurance. Index-based insurance is a product in which insurance payouts are based on values obtained from an index without calculating actual losses of a policy holder. Often, the index is objectively measured, highly correlated with losses and hard to be manipulated by both the insurer or policy holder. For instance, Weather Index Insurance (WII) measures a specific weather variable (for example, rainfall or temperature) for a specific locality and a particular product based on historical weather data. It then specifies a threshold and a limit for making payouts. Payouts are made for policy holders if the amount of rainfall is below or above a certain threshold. Although weather based insurance scheme reduce moral hazard, adverse selection and transaction costs, it involves basis risk due to imperfect index use.

Recently, there is a wide excitement among both the academia and practitioners on introducing index-based insurance schemes in the developing world. In less than a decade, more than 20 index insurance programs are under experimentation (Hazell and Hess, 2010). Nevertheless, the impact of index based insurance, even in markets they flourish, is still widely unknown (Radermacher et al., 2012; Hellmuth et al., 2009). There are only few studies, among others, Karlan et al. (2014); Vickery et al. (2013); Giné and Yang (2009) that evaluate the impact of WII on production decisions. These studies are based on pilot trials and the insurance is not commercially marketed. Unlike these studies, we evaluate the impact of WII on farmers' production decision, productivity and welfare for the case of a large commercially traded WII in Sub-Saharan Africa.

We use a unique rural household data from Ethiopia collected in 2013. The data gathered detailed information on both WII purchasers and non-purchasers in order to rigorously evaluate the impact of WII on farmers' production decision, productivity and welfare to contribute to the nascent microinsurance literature. The novelties in our study are: First, this study evaluates the impact of WII on a range of outcome indicators. We evaluate whether WII changes risk-taking behavior, especially in terms of farm investment. We also assess, whether WII results in productivity increase. Ultimately, we investigate whether WII leads in to welfare improvement. Second, the WII program we evaluate is unique. It is largely commercially marketed and farmers are free to subscribe an insurance or not. Further, they can pay the premiums either in cash or in-kind (through labor work for the safety net program-insurance for work).[1]

To preview the main results: Consistently, we find positive and significant effect of insurance on enhancing risk-taking behavior of households in terms of raising use of chemical fertilizer. We do also find significant effect of being insured on productivity improvements in one of the specifications. Nevertheless, we find no significant impact of insurance on welfare.

The structure of our paper is as follows. Section 2 review the impact evaluation literature on WII with a focus on agricultural insurance in developing countries. In Section 3, we present the data and provide descriptive statistics; we discuss our empirical strategy in Section 4. Section 5 presents the estimation results and we conclude in Section 6.

[1]The IFW arrangement allows farmers to work extra days in the productive safety net program (PSNP) and make payments for premium through contribution from their remuneration from PSNP. The arrangement relaxes financial constraint. PSNP is an innovative social protection scheme that covers more than 7 million households in Ethiopia.

2 Impact of WII on technology adoption, productivity and welfare: A review

In this section, we review previous studies that examined the impact of WII focusing on agricultural insurance. Several channels through which insurance could impact are discussed in Radermacher et al. (2009). Insurance will have an effect on both the ex-ante and ex-post risk management strategies used by households. Insurance is hoped to alter farmers risk-taking behavior through increasing technology adoption, higher input use and overall farm investment in the face of risk. It is also expected to improve the financial protection of the insured. Insurance is likely to reduce the perverse effect of risk coping strategies such as sell of productive assets. There are growing efforts to demonstrate the possible benefits associated with insurance at theoretical level. We review the recent literature focusing on index insurance.

Carriquiry and Osgood (2012) formalize the relationship between input choice under uncertainty and index insurance. They show that farmers increase their level of input use when insured. Similar works that examine the relation between index insurance and input usage is found in Chambers and Quiggin (2002) and Mahul (2001).

In a two period model, Cai (2012) examines the possible effect of providing insurance on household's investment, financial decisions and welfare. She shows that farmers invest more when insured and increase their first period consumption. In terms of saving, she evidences that saving decreases when the household is insured. The effect of providing insurance on borrowing is ambiguous. In a dynamic stochastic optimization model, de Nicola (2010) investigates the effect of insurance on household investment and welfare. She shows that weather insurance enhances the adoption of riskier but more productive improved seeds. She also finds welfare enhancing gains from insurance, which is almost equivalent to 17% of improvements in permanent consumption. Vickery et al. (2013) derive similar result in regard to farm investment. They show that a risk averse farmer invests more in risky production when provided with insurance against production risk.

The impact of insurance on risk-taking could be ambiguous, when one factors in financial constraint. On the one hand, in the presence of weather risk farmers may involve in ex-ante risk management that include investment in low-risk and low-return options. Provision of insurance could reverse this course into high risk but remunerative activities. On the other hand, insurance requires payments in advance that competes for the few financial resources at the farmers disposal, hence reduced investment on production investment.

Karlan et al. (2014) provide a framework to motivate their evaluation of investment decisions after relaxing credit and risk constraints. First, they show that farm investments are lower if both credit and insurance markets are missing. Second, when credit constraint is binding, relaxing liquidity constraints enhance farm investment but provision of insurance grant discourage investment. Third, when the insurance market is incomplete, relaxing liquidity constraint has little impact on farm investment while provision of insurance positively increases farm investments.

Although a number of pilot insurance programs are underway, there are only few impact evaluation of index insurance schemes. An early test of insurance impact on technology adoption is Giné and Yang (2009). Surprisingly, in their randomized control trials, they find that farmers are less likely to demand insured loans for purchasing high-yielding seeds compared to uninsured loan for the same purchase. In contrast, Hill and Viceisza (2010) in a framed field experiment in Ethiopia find a positive effect of insurance on technology adoption (purchase of fertilizer).

In a three year multi-stage randomized control trials in Ghana, Karlan et al. (2014) evaluate the impact of relaxing both credit and risk constraints on agricultural decisions. They find that relaxing liquidity constraint alone have no significant effect on production investments, rather relaxing risk constraint through provision of weather insurance leads to more risky production investment. Similarly, Vickery et al. (2013) using a randomized control trials in India report an increase in both investment on inputs for high yielding cash crops and land allocated for these crops. Complement to these results, Mobarak and Rosenzweig (2012) find that insured Indian farmers taking less risk mitigating activities against weather shocks. They find insured households favoring high yielding rice varieties.

Cai (2012) finds positive impact of insurance on raising the production inputs used among tobacco farmers in China. She finds that farmers increased the land allocated for insured crop by almost 20% and raised their loan demand by about 25%. Looking at livestock insurance, Liu et al. (2013) find that insured Chinese farmers bought more piglets for fattening and cross-breeds. This indicates that insurance has an inducing effect on farmers to invest on risky but remunerative breeding activity.

The aforementioned evidence suggest that insurance enhances risk-taking behavior of the households that may result in high returns. Hence, insurance may help households break the poverty trap reverting in to high-risk high-return activities as demonstrated in theoretical literature. Reviewing the impact of insurance on farmers risk coping strategies, Janzen and Carter (2013) show that insured households are less likely to sell their livestock following weather shock in Kenya. There are only a count of studies that evaluate the impact of WII.

Our understanding of the impact of WII on production decision, productivity and welfare is far from being complete and more systematic studies are required to deepen our understanding of its worth. Hence, in this study we contribute an impact assessment of WII for the case of large commercially traded insurance scheme in Africa. Furthermore, the evidence thus far skewed on evaluating the impact on farm investment improvements. This seems based on hope and assumption that the rise in investment translates in to higher production and better welfare. However, in this study we extend the impact assessment and evaluate the effect of WII on adoption of technology and whether the insured has improved productivity and their welfare.

3 Data and descriptive statistics

3.1 The Sample

The focus of this study is on the microinsurance product designed to address weather shock in Tigray, Northern Ethiopia. It was piloted in 2009 in village Adiha and later scaled to 5 more villages in 2010. Now, the WII scheme covers around 79 villages insuring about 20,015 households in Tigray and a pilot roll-out village in Amhara insuring 350 households (Oxfam America, 2013b). Currently, two local insurance companies (Nyala Insurance Company and Africa Insurance Company) underwrite the policies. According to Oxfam America (2013a), the product insures different crops (Teff, Wheat, Barley and others) in two windows, early index and late index. The early index addresses deficit or delay of onset rainfall, while the late index targets deficit or early end of rainfall. Both windows pay once every four or five years. Farmers has an option of purchasing insurance with cash or with labor (Insurance for Work-IFW). The average premium paid in 2010 was about 270 Birr ($19) per household.

The study is based on a unique cross-sectional data collected from 364 rural households in Northern Ethiopia. We chose the northern region due to the introduction of large commercial weather index insurance in the area. The data was collected during May-June, 2013. We filled standard household socio-economic questionnaire with focus on household experience on risk and insurance. The questionnaire includes modules on household demographics, household assets and wealth, details on agricultural production and consumption expenditure. It also includes modules on risk and time preference, financial and insurance literacy, risk and risk coping mechanisms. Details of insurance participation, insurance premium and related questions are also incorporated. The survey took approximately up to two hours per household. We interviewed household heads.[2] To address concern of possible variation in outcome measures due to survey design difference (see Heckman et al., 1999; Diaz and Handa, 2006), we used the same survey instrument to collect the data from both purchasers and non-purchasers.

The sampling procedure followed was proportional stratified random sampling. First, households are stratified by their purchase decision of insurance. Households that purchased weather index insurance starting 2010 and households that did not purchase the WII. Second, households are randomly drawn systematically from the sample frames of both the purchasers and non-purchasers. In order to ensure sampling of enough observations of households that purchased insurance, about 13 percent of those that purchased (169) are included in our sample. Further, we sampled around 3 percent of the households (195) that did not buy WII. The sample was drawn from eight tabias (villages). In five of the sampled villages, WII was marketed by local insurance company in collaboration with local NGO, an international NGO and other partners. There was no formal insurance marketed in the remaining three villages in our sample. This three villages were selected to draw a comparison group for further impact analysis. Overall, we sampled and administered the interviews on 364 households distributed across eight villages. Table 1 describes the sample size drawn from purchasers and non purchasers in each village. However, in this paper, we preliminarily assess the impact on the sample households drawn from the treatment villages only. Specifically, we use 169 purchasers and 106 non-purchasers of WII in 2012 harvest season to estimate the impacts.

Insert Table 1

[2]The interview was handled by experienced enumerators with undergraduate degree in Economics and Business. Detailed training sessions were given, where each question is discussed and elaborated to get them in to a similar picture. The enumerators were closely supervised by the research fellow and recruited supervisor with rich experience on socio-economic surveys. The enumerators and the field supervisors were fluent in local language of the interview.

3.2 Descriptive statistics

In this study, we aim to evaluate the impact of WII on three major outcomes (technology adoption, productivity and welfare) at household level. The WII is designed to insure crop production and our outcome measures focus on the relevant agricultural technology and outcomes. As discussed above, we expect that purchase of WII enhances technology adoption and other farm investments. Two common agricultural technologies in Ethiopia are chemical fertilizer use and adoption of high yielding seed varieties. Relatively, fertilizer is less supply constrained than improved seeds. Thus, first, we use fertilizer adoption as our technology adoption outcome indicator. We measure fertilizer adoption as the amount of fertilizer used in kilograms (kg).

Second, the rise in technology adoption and increase in other farm investment translates in to higher crop productivity. Further, farmers produce different crops depending on their soil type and market incentives, among others. Hence, we use productivity as our second outcome indicator. We measure overall crop productivity in value of yield per timad (in Birr).[3] This eases the aggregation of different crop production and accounts for the market incentives in production.

The ultimate goal of insurance intervention is to improve welfare. The first and second outcome indicators can be considered as intermediate mechanisms through which insurance influences welfare. Moreover, insurance also affects welfare through its effects on other risk management strategies that affect welfare. For instance, an insured household may not stock food in expectation of drought in next period; since the household expects insurance payouts in case of drought leading to higher food consumption than uninsured household. Thus, we use household welfare as our third outcome indicator. Specifically, we measure household welfare using food and total consumption expenditure per capita (in Birr).

Table 3 presents the descriptive statistics of the key variables used in our analysis disaggregated by insurance status of the sample. The average fertilizer use in our sample is 59 kg. Insurance purchasers use more fertilizer compared to non-purchasers (63.9 and 51.8 kg respectively). In terms of yield value, purchasers have higher yield value per timad (1605.8 Birr) than non-purchasers (1114.3 Birr). We measure household welfare using both food consumption expenditure per capita and total consumption expenditure per capita. The average per capita food and total expenditure,

[3]Timad is a local measure approximately 0.25 hectare. Birr is the Ethiopian currency.

respectively, are 2682.4 and 3249.8 Birr. Comparing the insurance purchasers and non-purchasers, purchasers have slightly higher mean food and total consumption expenditures.

Insert Tables 2 and 3

Table 4 presents the mean difference test in the outcome variables. We find statistically significant difference in both the amount of fertilizer applied and yield value per timad between the insurance purchasers and non-purchasers. There are no significant differences in both the annual food expenditure per capita and overall consumption expenditure per capita between the two groups.

Insert Table 4

The average age of the household head is 45 years. About 40% and 71%, respectively, are female and married household heads. The average household size is about 5 persons, of which about 3 are adults. In terms of literacy, 6.5% of the household heads have some secondary level education, 28% have some elementary level education while the rest are illiterate.

In regard to preference and financial literacy, the mean estimate of risk preference is 0.38, denoting average households to be risk averse.[4] This is close to estimates based on comparable method in South Africa, which is 0.393 (Brick et al., 2012); but lower than estimates in Harrison et al. (2010) for Ethiopia, which is 0.54. Nearly, 55% of the household heads have a discount rate above 30% making the majority present biased. This result is close to monthly discount rate in Indonesia (Cole et al., 2011). The elicited monthly discount rate could be exaggerated since previous studies (Holden, 2013; Hill et al., 2011; Harrison and Rutström, 2008) claim an overestimation of the discount rate using hypothetical question.

About 49% and 37% of the questions used to measure basic financial literacy and insurance knowledge are correctly answered by respondents. The result is comparable to financial literacy findings in Indonesia (52%) and India (34%) reported in Cole et al. (2011). About 67% of the sampled households reported that they understand the WII well and nearly 80% of the household heads attended the training/marketing sessions.

[4]Our risk preference parameter is estimated based on responses elicited from binary lottery games with the farm households for real monetary prize (see Awel and Azomahou, 2014).

In regard to use of other risk management strategies, 7% and 16% of the respondents participate in *eqqub* and *iddir*.[5] 63% of the respondents participate in the productive safety net program (PSNP) and about 12% received remittances. Credit participation is around 43%. Average ownership of livestock is about 2.6 total livestock units (TLU). Nearly 26% of the households have house with roof from corrugated iron sheet and 20% of the households own radio.

4 Empirical strategy

In the absence of randomization, we address the evaluation challenges using quasi-experimental design. The WII scheme in our case is a commercially marketed insurance product, in which any farmer could purchase the product by paying the premium. The insurance is not randomly assigned and there is a possibility of self-selection to purchase or not purchase the insurance. This design only partially address the selection problems. Hence, we employ different alternative approaches that address the selection bias differently. First, we use matching technique assuming the selectivity bias due to observables. Second, we use instrument variable (IV) approach assuming selection problem due to unobservables.

4.1 Matching: Propensity score and doubly robust approach

We are interested in evaluating the impact of insurance on those that purchased insurance compared to those that did not purchase during an observational period (i.e., the average treatment effect on the treated, ATET). This treatment effect parameter is defined as the difference between the mean outcome of all insured households and the mean outcome of the same group had they not been insured. Formally, ATET is:

$$ATET = E[Y(1) - Y(0)|I = 1] = E[Y(1)|I = 1] - E[Y(0)|I = 1] \tag{1}$$

where $Y(1)$ and $Y(0)$ are the potential outcomes if insured and uninsured respectively. I is treatment indicator that takes value 1 if insured and 0 otherwise. $E[Y(1)|I = 1]$ is the expected

[5] *eqqub* is an Ethiopian form of rotating saving and credit association (ROSCA) and *iddir* is an Ethiopian form of funeral society.

insured outcome conditional on being insured and $E[Y(0)|I = 1]$ is expected uninsured outcome conditional on being insured. A challenge in causal inference is that the quantity $E[Y(0)|I = 1]$ is unobservable. That is, we can not observe the outcomes of the insured households had they not been insured once they did. Taking the mean outcome value of all unisured households is inappropriate, since factors that lead to insurance purchase most likely also influence the outcome. Thus, the outcomes of the households from treatment and comparison group would differ even in the absence of treatment leading to 'self-selection bias'. Formally,

$$E[Y(1)|I = 1] - E[Y(0)|I = 0] = ATET + E[Y(0)|I = 1] - E[Y(0)|I = 0] \tag{2}$$

The difference between left hand side of Eq.(2) and ATET is the so called 'self-selection bias'. Several methods proposed to address the bias based on different assumptions in the selection process, which we discuss and apply two of them below.

4.1.1 Propensity score matching

Assuming the selection bias is due to observables, we use matching technique. In matching, we attempt to mimic the randomized experimental setting by statistically creating treatment and comparison groups that are similar in observed covariates. Our identification strategy is to assume that given a set of observable covariates, $\mathbf{x}$, which are not affected by treatment, potential outcomes $(Y(1), Y(0))$ are independent of treatment assignment (I).

Matching on propensity score, we statistically construct the treatment and comparison groups and compute the treatment effects of our interest.[6] Given the conditional independence assumption and the overlap conditions, the average treatment effect on the treated ($ATET_{psm}$) can be written as in Eq. (3):

$$ATET_{psm} = E[Y(1)|I = 1, p(\mathbf{x})] - E[Y(0)|I = 0, p(\mathbf{x})] \tag{3}$$

$ATET_{psm}$ is propensity score weighted mean difference in outcomes over the common support.

[6] we estimate the treatment effects using $STATA^{®}$ command *teffects* in which the standard errors are based on Abadie and Imbens (2012) that take in to account the estimated nature of the propensity score.

However, misspecification in the propensity score model could lead in to bias (Robins et al., 2007). Thus, we also estimate inverse probability weighted regression-adjustment to reduce the possible model misspecification bias if any.

4.1.2 Doubly robust approach: Inverse probability weighted regression-adjustment (IPWRA)

IPWRA enables to consistently estimate the treatment effect parameters as far as we correctly specify only one of the two models (either the outcome or treatment). This property is known as "doubly robust property"(Robins and Rotnitzky, 1995; Wooldridge, 2007). For technical details on IPWRA, see Wooldridge (2007) and Wooldridge (2010).

According to Wooldridge (2010), combining the propensity score method with regression adjustments could achieve some robustness to misspecification in the parametric models (propensity score or regression adjustment model). Hence, one could better identify the causal effects using the IPWRA developed in Robins and Rotnitzky (1995) and van der Laan and Robins (2003). Following Wooldridge (2010), we first estimate the propensity score model and obtain the estimated propensity scores $p(\mathbf{x}_i, \hat{\gamma})$. Then, we use regression in which we weight by the inverse probability. In our case, we use linear outcome functions and estimate (α_I, β_I) using inverse probability weighted least squares. Formally, it is written as in Eq. (4) and (5) below:

$$\min_{\alpha_1,\beta_1} \sum_{i=1}^{N} (y_i - \alpha_1 - \beta_1 \mathbf{x}_i)/p(\mathbf{x}_i, \hat{\gamma}) \quad \text{if} \quad I_i = 1 \tag{4}$$

$$\min_{\alpha_0,\beta_0} \sum_{i=1}^{N} (y_i - \alpha_0 - \beta_0 \mathbf{x}_i)/(1 - p(\mathbf{x}_i, \hat{\gamma})) \quad \text{if} \quad I_i = 0 \tag{5}$$

Then, we estimate the average treatment effect on the treated, $ATET_{ipwra}$, as in Eq. (6) taking the mean difference in predicted values over the treated sample.[7]

$$ATET_{ipwra} = N_T^{-1} \sum_{i=1}^{N_T} [(\hat{\alpha_1} - \hat{\beta}_1 \mathbf{x}_i) - (\hat{\alpha_0} - \hat{\beta}_0 \mathbf{x}_i)] \tag{6}$$

[7] Another doubly robust treatment effect estimator is augmented inverse probability weight (AIPW). For details, see Tsiatis (2007); Rubin and van der Laan (2008) and Tan (2010).

where $\hat{\alpha}_I$, $\hat{\beta}_I$ are respectively estimated inverse probability weighted parameters for $I = 0$ and $I = 1$. N_T is the number of treated individuals in our sample.

Remark (Estimating the propensity score model): In both the PSM and IPWRA, we estimate the propensity score following the implementation procedure discussed in Caliendo and Kopeinig (2008). We have first to choose the model to estimate and the variables to include. In the case of binary treatment variable, often the choice is between logit or probit models. We estimate a logit model since both logit and probit models yield closely similar result. Then, we have to decide the covariates to include in the model. We choose variables that influence both the treatment decision and outcomes. Also, the variables should not be influenced by the treatment. Our choice of the covariates is guided based on economic theory (Karlan et al., 2014; Dercon et al., 2012; Clarke, 2011; Giné et al., 2008), our prior empirical evidence on index insurance demand (Awel and Azomahou, 2014) and other empirical literatures on insurance demand (Cole et al., 2013; Hill et al., 2011).

4.2 Instrument variable (IV) approach

Obviously, one can hardly measure all the relevant variables that influence treatment participation as well as outcome. In such cases, the estimated treatment effect after matching the purchasers and non-purchasers based on PSM or doubly robust approach may not be attributed to the program (WII). Rather the farmers may have purposely self-selected to purchase or not the WII due to unobservables to us, hence our treatment effect estimates may be biased due to selection on unobservables. Further, the two types of selection bias (due to observables and unobservables) need not have same sign. So, reducing one of the bias need not reduce the other (Ravallion, 2007). Therefore, we apply econometric technique that allows us estimate the treatment effects under the selection on unobservables, the IV approach. The use of IV approach requires availability of at least one variable $\mathbf{z}$, called "instrument variable". The instrument should satisfy the following two conditions (Angrist and Pischke, 2008): $\mathbf{z}$ should be correlated with the treatment indicator I and it should not be correlated with the outcome variable $\mathbf{y}$.

Moreover, there is possibility of heterogeneous treatment bias (Heckman et al., 2006). This relates to the fact that individuals may benefit differently depending on their idiosyncratic characteristics. For instance, individuals with better financial literacy know better about financial product and may also have better ability to understand benefit and costs of insurance. Hence, they strive to get the most benefit out of the product. A risk averse farmer also may benefit better than less risk averse, since more risk averse one is less likely to adopt technology (Dercon and Christiaensen, 2011). But with availability of insurance, those with high risk aversion improve their adoption. Thus, we allow the impact of WII to vary across farmers depending on their level of financial literacy and risk preference in the fertilizer and productivity models. This accounts for ex-post heterogeneity. Formally, we include the interaction term of the treatment indicator and the two covariates $(I * (\mathbf{x}^h - mean(\mathbf{x}^h)))$.

In order to investigate the impact of endogenous insurance purchase on range of outcome indicators, we specify the following equations (7)-(9):

$$y_i = \alpha_0 + \alpha_1 I_i + \mathbf{x}_i\beta + \gamma I_i * (\mathbf{x}^h - mean(\mathbf{x}^h)) + u_i \tag{7}$$

$$I_i^* = \kappa_0 + \mathbf{x}_i\varphi + \mathbf{z}_i\delta + \varepsilon_i \tag{8}$$

$$I_i = \begin{cases} 1 & \text{if} \quad I_i^* \geq 0 \\ 0 & \text{if} \quad I_i^* \leq 0 \end{cases} \tag{9}$$

where $\mathbf{x}^h$ is vector of covariates that differentiate impacts across farmers. Given the non-zero condition of the covariance between u_i and ε_i, $Cov(u_i;\varepsilon_i) \neq 0$, and the endogenous treatment variable I, we cannot consistently estimate average treatment effect (ATE) using OLS. Hence, we use *probit two-stage least square (probit-2SLS)* to consistently and efficiently estimate the treatment effect parameters. Our identification strategy is to impose an exclusion restriction, the IVs, that influence only the selection process but not the outcome. This means the selection in to the treatment depends on the same factors that affect the outcome plus the instruments $\mathbf{z}$, which do not affect directly the outcome but indirectly through their effect on I. After estimating the model, we can compute wide range of treatment effects.

In our case, we exploit the binary nature of the treatment variable I_i and first run a probit of I_i on $\mathbf{x}_i$ and $\mathbf{z}_i$ to get the predicted probability of I_i. We use the predicted probability of I_i as instrument for the treatment I_i in the two-stage least square. This is more efficient than using direct 2SLS (Wooldridge, 2010; Cerulli, 2012). The optimal instrument for I_i is its orthogonal projection in the vector space generated by $(\mathbf{x}_i, \mathbf{z}_i)$ that produces the "smallest error". This orthogonal projection is $E(I_i|\mathbf{x}_i, \mathbf{z}_i)$, which is also the probability of getting treatment $[P(I_i|\mathbf{x}_i, \mathbf{z}_i)]$. Thus, the probability of getting treatment $[P(I_i|\mathbf{x}_i, \mathbf{z}_i)]$ estimated from the treatment equation in Eq.(9) is an optimal instrument for I_i. Practically, we implement probit-2SLS as follows: First, we estimate a probit model of I_i on $\mathbf{x}_i$ and $\mathbf{z}_i$ to get the predicted probability of I_i, p_I. Then, run an OLS of I_i on $\mathbf{x}_i$ and p_I to get the fitted values of $I_{2fv,i}$. Last, run an OLS of the outcome variable y_i on $\mathbf{x}_i$ and $I_{2fv,i}$. In the class of linear instruments for I_i, the coefficient for $I_{2fv,i}$ is the most efficient estimator of ATE (Wooldridge, 2010; Cerulli, 2012). Moreover, the consistency of the coefficient does not require the treatment equation to be correctly specified.

5 Estimation results

5.1 Matching results

Table 5 presents the treatment effects based on propensity score matching and doubly robust estimation results. We matched households based on nearest neighbor matching in the PSM. The regressions are wighted using the inverse propensity scores to obtain the doubly robust results. Column 2 reports the average treatment effect on the treated (ATET) based on PSM, while column 3 reports IPWRA results. We find positive and statistically significant impacts of WII on technology adoption in terms of fertilizer use in both the PSM and IPWRA estimations. We find a mixed impacts of WII on productivity measured in terms of value of yield per timad. Positive and insignificant effects are found in the case of PSM, while the impact on productivity is positive and statistically significant in the case of IPWRA. However, we find no significant effect of WII purchase on the household welfare both in terms of food per capita expenditure as well as overall consumption expenditure per capita.

Insert Table 5

Purchase of WII significantly increases application of fertilizer use among the insured by about 16 kilograms (kg) in the PSM estimates, while it is estimated to a rise of about 13 kg in the IPWRA estimates. Said differently, being insured raises fertilizer use by about 25% compared to being not insured. The ATET for productivity is estimated to be 167 Birr/timad though insignificant in the

PSM. In the IPWRA, the corresponding ATET is higher and significant. Being insured results in farm productivity rise of 662 Birr/timad. Thus, the ATET estimates on productivity are mixed. ATET estimates on household welfare are statistically insignificant in both estimations.

Discussing the results from the first stage logit regressions (see Table A.1), we find a quadratic effect of age on participation in to WII. Insurance purchase increases up to a point and declines there after. Education and membership in informal risk sharing groups positively correlate with insurance purchase. Similarly, we find positive relationship between participation in safety net program (PSNP) and insurance purchase. Financial literacy also significantly affect the purchase of insurance. The treatment equation model results are almost similar in both the PSM and IPWRA approaches. These results are closely similar to earlier findings on index-insurance demand, for instance, Awel and Azomahou (2014); Cole et al. (2013) and Giné et al. (2008).

Insert Table A.1

We check for the quality of matching using different tests. We find a considerable overlap in both those who purchased WII and those who do not. This satisfies the common support condition. Figures (1)-(3) show the distribution of both purchasers and non-purchasers. Visually, we can see a significant overlap in the distribution of the purchasers and non-purchasers.

Insert Figures 1-3

Table A.2 reports summary of the covariate balancing tests pre and post matching. The standardized mean difference for all covariates used in the PSM is reduced from 25.1% pre-matching to 7.3% post-matching. In net, matching leads to a bias reduction of about 70%. The p-values of the likelihood ratio tests indicate that the joint significance of covariates was always rejected post-matching. Pre-matching, however, the joint significance of covariates never rejected. The pseudo-R^2 also dropped from 20.9% pre-matching to 5.8% post-matching. Overall, the low mean standardized bias, joint insignificance of the covariates and low pseudo-R^2 are indicative of successfully balancing the distribution of covariates between purchasers and non-purchaser through matching.

Insert Table A.2

5.2 IV estimation results

We present the IV estimation results for the impact of WII on technology adoption, productivity and welfare in Tables 6, 7 and 8 respectively. We used two IVs: attendance in the insurance training/marketing sessions and insurance knowledge index. These two variables are correlated with the insurance purchase decision (Awel and Azomahou, 2014). They are not likely to affect the outcomes (fertilizer use, productivity and welfare). The training sessions were arranged before the farming season in the slack period. The trainings were organized and delivered by the non-government organizations. Insurance knowledge index is an index constructed to measures the household head's level of knowledge about insurance collected through series of 5 questions based on Madajewicz et al. (2010).

Insert Tables 6, 7 and 8

Turning to results based on IV approach, we find statistically significant impact of WII on technology adoption. In contrast, we fail to find significant impact of WII on both productivity and household welfare. Table 6 reports the IV results of impact of WII on fertilizer application. The coefficient for WII is 1.84 and statistically significant at 10%. Other factors that influence the application of fertilizer are financial literacy, wealth and distance to the input markets. Financial literacy has significant u-shape effect on the application of fertilizer. After a certain threshold, rise in the level of financial literacy lead to application of more fertilizer. Wealth (measured whether the household owns house with corrugated iron roof and the total amount of livestock given in TLU) has positive and significant effect on the use of fertilizer. The farthest the input market, the lower the application of fertilizer by the household. We can also see the distribution of treatment effects for the treated, untreated and overall in Figure 4. The figure shows a bi-modal distribution with an overall positive impact of insurance on fertilizer use. It also confirms the heterogeneity in the treatment effect. A particular note follows observing the high value of ATENT(x) compared to ATET(x) as we move towards right on the panel. This indicates that those non-purchasers of the insurance could have used more fertilizer had they been insured.

Insert Figure 4

The IV estimates for the impact of WII on farmers' productivity is given in Table 7. The results suggest a positive but insignificant impact of being insured. In the case of impacts of being insured on household welfare measured in annual food expenditure per capita, we find no significant effect (Table 8). These results suggest that the impact of insurance on productivity and welfare is insignificant once accounted for selection on unobservables. Tentatively, we offer the following explanations for the insignificant impacts observed. The rise in fertilizer use may be not sufficient enough to translate in to increased productivity and better welfare. Another possible explanation is though the insured have used more fertilizer, the deficit in rainfall registered during 2012 harvest season had an adverse impact largely on the insured, since chemical fertilizer use is risk enhancing in a rainfall deficit environment (Dercon and Christiaensen, 2011; Kassie et al., 2009). Specific to the insignificant impacts on the welfare, the insured may have improved their consumption, however, there may be a possibility of spillover effects given the already existing informal insurance mechanism. In developing countries and specifically in Ethiopia, households involve in informal risk sharing where friends, family or relatives support each other during hardships (Dercon, 2002). Thus, those that received insurance payout or those that produced more may have shared their output or payouts with the non-purchasers due to the already existing informal insurance arrangements.

Looking at the overall model results, the IV models are statistically significant with high R^2 in all the four estimation results. The IVs also pass the joint significance test with χ^2-values of 14.28, 12.3 and 14.7 for the fertilizer application, productivity and welfare models respectively, which are significant at 1%.[8]

6 Conclusion

Relaxing the risk constraints is considered to be an effective avenue to break the poverty trap in agrarian societies. In response, there is a wide excitement among both the academia and practitioners on introducing the index-based insurance schemes in the developing world. The hope is based on predictions of economic models that demonstrate improvement in farm investment, productivity and welfare (See Hazell and Hess, 2010; Clarke and Dercon, 2009 and Barrett et al., 2008, among others). Nevertheless, there is dearth of impact assessments to support or refute the hope. We

[8]The first stage regression results are not reported here but will be available up on request.

contribute to the impact evaluation literature on index-based insurance providing evidence from commercially traded large index-insurance scheme in Africa.

We use a unique observational data collected from index-insurance purchasers and non-purchasers in Ethiopia. We apply recent advances in quasi-experimental technique to credibly estimate the impact of WII on farmers technology adoption, productivity and welfare. Specifically, we use propensity score matching, inverse probability weighted regression adjustment and IV techniques. We find a consistent evidence that insurance has a positive and significant impact on technology adoption. Farmers that are insured apply more inorganic fertilizers than those not insured. Though, we find significant impact of insurance on farm productivity using IPWRA, we could not confirm the results using PSM and IV. In contrast, we find no evidence supporting welfare gains due to insurance.

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Table 1: Sampled households by district (Woreda) and village (Tabia)

Woreda	Village	Insurance Status		Total	Village Status
		Purchasers	*Non-purchasers*		
Raya Azebo	Genetie	16	31	47	Treatment village
	Hadealga	24	29	53	Treatment village
	Werebaye	0	21	21	Control village
Kola Tembien	Adiha	46	11	57	Treatment village
	Awet bikalsi	30	18	48	Treatment village
	Menji	0	26	26	Control village
Sase'a Tsa'adaemba	Hadush Adi	53	17	70	Treatment village
	Agazi	0	42	42	Control village
Total		169	195	364	

Table 2: Summary statistics of variables

	Mean	Sd	Min	Max
Outcome indicators				
Fertilizer amount used (in kg)	58.6	75.3	0	800
Yield value per timad (in Birr)	1386.8	2515.4	0	37275
Food expenditure per capita (in Birr)	2757.3	1236.6	692.7	10364.2
Total consumption expenditure per capita (in Birr)	3332.0	1468.4	1079.4	12006.2
Treatment indicator				
Weather Index Insurance	0.61	0.49	0	1
Demographic characteristics				
Age of household head	44.8	12.9	20	85
Sex of household head (1=female)	0.40	0.49	0	1
Married (1=yes)	0.71	0.46	0	1
Religiosity (1=attend daily)	0.17	0.38	0	1
Head some elementary education (1=yes)	0.28	0.45	0	1
Head some secondary education (1=yes)	0.065	0.25	0	1
Highest educational level in the household	5.50	3.68	0	16
Household size	5.28	2.03	1	12
Number of adults in the household	2.76	1.45	0	9
Informal risk management strategies				
Iddir participation (1=yes)	0.16	0.36	0	1
Eqqub participation (1=yes)	0.062	0.24	0	1
PSNP participation (1=yes)	0.63	0.48	0	1
Credit (1=accessed)	0.43	0.50	0	1
Remittance and other gifts received	0.12	0.33	0	1
Preference				
Risk aversion parameter	0.38	0.19	-0.22	0.80
Time preference (1 if discount rate $\geq$ 30 percent)	0.55	0.50	0	1
Financial literacy				
Basic financial literacy index	0.49	0.22	0	0.90
Understand WII	0.67	0.47	0	1
Instrument variables				
Insurance knowledge index	0.37	0.24	0	1
Attended WII training/marketing session	0.81	0.40	0	1
Farm inputs				
Total land owned in timad	2.61	2.51	0	12
Family labor used in days	21.5	16.9	0	100
Hired labor used in days	10.3	16.7	0	100
Own oxen used in days	8.04	9.03	0	50
Wealth				
Total livestock unit	2.58	2.56	0	16.4
Korkorobet(corrugated iron sheet roof)	0.26	0.44	0	1
Information sources				
Extension contact (wet season)	2.52	1.63	0	10
Extension contact (dry season)	1.85	1.64	0	9
Household own radio (1=yes)	0.21	0.41	0	1
Location dummies				
Adiha (1=yes)	0.21	0.41	0	1
Awetbikalsi (1=yes)	0.17	0.38	0	1
Genetie (1=yes)	0.17	0.38	0	1
Hadealga (1=yes)	0.19	0.40	0	1
Hadushadi (1=yes)	0.25	0.44	0	1
# of observations	275			

Table 3: Descriptive statistics by insurance status

	Non-purchasers		Purchasers		Full sample	
	Mean	Sd	Mean	Sd	Mean	Sd
Outcome indicators						
Fertilizer amount used (in kg)	51.8	75.8	63.9	77.1	59.3	76.7
Yield value per timad (in Birr)	1114.3	1037.8	1605.8	3165.3	1419.8	2583.7
Food expenditure per capita (in Birr)	2652.5	1031.4	2700.6	1140.6	2682.4	1098.8
Total consumption expenditure per capita (in Birr)	3158.8	1164.9	3305.2	1423.2	3249.8	1330.9
Treatment indicators						
Weather Index Insurance	0	0	1	0	0.62	0.49
Demographic characteristics						
Age of household head	46.1	13.5	43.0	11.8	44.2	12.5
Sex of household head	0.34	0.48	0.41	0.49	0.38	0.49
Married (1=yes)	0.72	0.45	0.73	0.44	0.73	0.44
Religiosity (1=attend daily)	0.21	0.41	0.15	0.36	0.17	0.38
Head some elementary education (1=yes)	0.22	0.42	0.33	0.47	0.29	0.45
Head some secondary education (1=yes)	0.031	0.17	0.093	0.29	0.069	0.25
Highest educational level in the household	5.10	3.83	5.73	3.60	5.49	3.70
Household size	5.60	2.10	5.34	1.81	5.44	1.92
Number of adults in the household	2.98	1.57	2.73	1.32	2.82	1.42
Informal risk management strategies						
Iddir participation (1=yes)	0.10	0.30	0.18	0.39	0.15	0.36
Eqqub participation (1=yes)	0.031	0.17	0.081	0.27	0.062	0.24
PSNP participation (1=yes)	0.53	0.50	0.70	0.46	0.63	0.48
Credit (1=accessed)	0.44	0.50	0.42	0.50	0.43	0.50
Remittance and other gifts received	0.17	0.38	0.099	0.30	0.13	0.33
Preference						
Risk aversion parameter	0.44	0.18	0.34	0.19	0.38	0.19
Time preference (1 if discount rate $\geq$ 30 percent)	0.53	0.50	0.57	0.50	0.55	0.50
Financial literacy						
Basic financial literacy index	0.46	0.24	0.52	0.20	0.49	0.22
Understand WII	0.63	0.48	0.70	0.46	0.67	0.47
Instrument variables						
Insurance knowledge index	0.30	0.23	0.42	0.23	0.37	0.24
Attended WII training/marketing session	0.66	0.48	0.91	0.28	0.82	0.39
Farm inputs						
Total land owned in timad	3.18	3.00	2.37	2.11	2.68	2.51
Family labor used in days	23.6	16.0	21.2	17.4	22.1	16.9
Hired labor used in days	12.4	19.1	9.34	15.4	10.5	16.9
Own oxen used in days	9.27	9.31	7.80	8.96	8.35	9.11
Wealth						
Total livestock unit	2.73	2.58	2.64	2.61	2.67	2.59
Korkorobet(corrugated iron sheet roof)	0.28	0.45	0.25	0.44	0.26	0.44
Information sources						
Extension contact (wet season)	2.68	1.67	2.45	1.62	2.54	1.64
Extension contact (dry season)	2.16	1.77	1.70	1.57	1.88	1.66
Household own radio (1=yes)	0.16	0.37	0.24	0.43	0.21	0.41
Location dummies						
Adiha (1=yes)	0.11	0.32	0.27	0.44	0.21	0.41
Awetbikalsi (1=yes)	0.17	0.38	0.17	0.38	0.17	0.38
Genetie (1=yes)	0.29	0.45	0.099	0.30	0.17	0.38
Hadealga (1=yes)	0.27	0.44	0.14	0.35	0.19	0.39
Hadushadi (1=yes)	0.16	0.37	0.32	0.47	0.26	0.44

Table 4: Mean difference test by Insurance status

	Mean Difference (NP vs P)	
Fertilizer amount used (in kg)	-15.69*	(-1.69)
Yield value per timad (in Birr)	-517.9*	(-1.67)
Food expenditure per capita (in Birr)	32.16	(0.21)
Total consumption expenditure per capita (in Birr)	-54.26	(-0.30)
# of observations	275	

NP stands for non-purchasers, WII=0 and P stands for purchasers, WII=1

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: ATET-PSM, IPWRA and IV estimation results

	(1) PSM	(2) IPWRA	(3) IV
Fertilizer amount used (in kg)	16.55***	13.71*	1.61*
	(5.92)	(7.99)	(0.98)
Yield value per timad (in Birr)	167.62	662.65*	1395.96
	(266.41)	(378.13)	(3497.95)
Food expenditure per capita (in Birr)	-49.22	65.51	-66.34
	(179.12)	(125.70)	(625.06)
Consumption expenditure per capita (in Birr)	-159.09	-27.88	257.11
	(172.07)	(166.20)	(791.51)

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In the IV estimation, the outcome variable, fertilizer amount used is in log value. Standard errors are bootstrapped for the IV estimation results.

Table 6: Fertilizer use model: IV-outcome equation estimates

Dependent variable: Log fertilizer use (in kg)	Coef.	Std. Err.
Treatment indicator		
Weather Index Insurance	1.876*	(1.033)
Heterogeneity indicators		
$WII * (fli - mean(fli))$	1.411	(2.673)
$WII * (r_{crra} - mean(r_{crra}))$	6.949*	(3.611)
Financial literacy		
Basic financial literacy index	-5.770**	(2.827)
Squared basic financial literacy index	4.869*	(2.877)
Risk preference		
Risk aversion parameter	-5.573	(4.422)
Squared risk aversion parameter	3.644	(4.202)
Demographic characteristics		
Log age of household head	-0.150	(0.461)
Sex of household head	-0.523	(0.339)
Married (1=yes)	0.187	(0.385)
Head some elementary education (1=yes)	-0.399	(0.353)
Head some secondary education (1=yes)	-0.790	(0.584)
Log household size	0.490	(0.307)
Informal risk management strategies		
Eqqub participation (1=yes)	-0.588	(0.620)
PSNP participation (1=yes)	-0.216	(0.306)
Credit (1=accessed)	-0.366	(0.252)
Wealth		
Total land owned in timad	0.010	(0.071)
Total livestock unit	0.155***	(0.059)
Korkorobet (corrugated iron sheet roof)	0.686**	(0.325)
Input market		
Input market distance(travel hours)	-0.084*	(0.043)
Information sources		
Household own radio (1=yes)	-0.086	(0.316)
Extension contact (wet season)	0.008	(0.090)
Extension contact (dry season)	-0.028	(0.107)
Location dummies		
Adiha (1=yes)	0.920**	(0.435)
Awetbikalsi (1=yes)	1.016**	(0.414)
Genetie (1=yes)	-0.691	(0.609)
Hadealga (1=yes)	-1.816***	(0.553)
Constant	5.134*	(2.730)
	R-squared = 0.229	F(27,237)= 4.85
# of observations	265	

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Productivity model: IV-outcome equation estimates

Dep. Variable: Yield value per timad (in '000 Birr)	Coef.	Std. Err.
Treatment indicator		
Weather Index Insurance	1.315	(1.548)
Heterogeneity indicator		
$WII * (fli - mean(fli))$	-0.332	(3.051)
$WII * (r_{crra} - mean(r_{crra}))$	-2.326	(4.361)
Farm inputs		
Total land owned in timad	-0.046	(0.102)
Family labor used in days	0.002	(0.018)
Hired labor used in days	0.008	(0.019)
Own oxen used in days	-0.057	(0.044)
Fertilizer amount used (in kg)	0.003	(0.002)
Number of adults in the household	0.335*	(0.178)
Highest level of education in the household	-0.031	(0.062)
Wealth		
Total livestock unit	0.024	(0.088)
Information sources		
Extension contact (wet season)	0.217*	(0.128)
Extension contact (dry season)	-0.189	(0.168)
Household own radio (1=yes)	-0.079	(0.468)
Demographic characteristics		
Sex of household head	-0.152	(0.507)
Age of household head	-0.004	(0.018)
Married (1=yes)	0.538	(0.581)
Head some elementary education (1=yes)	0.602	(0.490)
Head some secondary education (1=yes)	-0.488	(0.801)
Household size	-0.175	(0.138)
Informal risk management strategies		
Credit (1=accessed)	0.462	(0.356)
Eqqub participation (1=yes)	-0.721	(0.865)
PSNP participation (1=yes)	-0.734*	(0.438)
Financial literacy		
Basic financial literacy index	0.598	(1.892)
Risk preference		
Risk aversion parameter	1.978	(3.668)
Location dummies		
Adiha (1=yes)	1.704***	(0.632)
Awetbekalsi (1=yes)	1.421**	(0.580)
Genetie (1=yes)	0.788	(1.005)
Hadealga (1=yes)	0.071	(0.816)
Constant	-0.975	(2.508)
	R-squared=0.17	F(29,229)=1.88
# of observations	259	

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Welfare model: IV-outcome equation estimates

Dependent variable:	Food expenditure per capita		Consumption exp. per capita	
	Coef.	Std. Err.	Coef.	Std.Err.
Treatment indicator				
Weather Index Insurance	-0.092	(0.651)	0.243	(0.776)
Heterogeneity indicator				
$WII * (Landowned - mean(Landowned))$	-0.089	(0.170)	-0.048	(0.202)
Demographic characteristics				
Age of household head	0.029^{***}	(0.007)	0.036^{***}	(0.008)
Sex of household head	0.185	(0.207)	0.173	(0.246)
Married (1=yes)	-0.123	(0.238)	-0.163	(0.284)
Head some elementary education (1=yes)	0.212	(0.180)	0.243	(0.215)
Head some secondary education (1=yes)	0.966^{***}	(0.302)	1.054^{***}	(0.359)
Number of adults in the household	-0.264^{***}	(0.057)	-0.313^{***}	(0.068)
Informal risk management strategies				
Credit (1=accessed)	0.166	(0.148)	0.198	(0.177)
Iddir participation (1=yes)	-0.333	(0.223)	-0.323	(0.266)
Eqqub participation (1=yes)	0.382	(0.377)	0.395	(0.449)
PSNP participation (1=yes)	-0.213	(0.175)	-0.294	(0.209)
Remittance and other gifts received	0.070	(0.229)	0.037	(0.272)
Wealth				
Total livestock unit	0.045	(0.035)	0.059	(0.041)
Total land owned in timad	-0.008	(0.074)	-0.035	(0.089)
Location dummies				
Adiha (1=yes)	0.865^{***}	(0.228)	0.885^{***}	(0.272)
Awetbekalsi (1=yes)	0.697^{***}	(0.225)	0.722^{***}	(0.268)
Genetie (1=yes)	0.644^{**}	(0.323)	0.546	(0.385)
Hadealga (1=yes)	0.392	(0.288)	0.196	(0.343)
Constant	1.634^{***}	(0.589)	1.942^{***}	(0.702)
	R-squared=0.259	F(19,255)=4.93	R-squared=0.254	F(19,255)=4.75
# of observations	275		275	

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Food and consumption expenditure per capita are in '000 Birr

Fig. 1: Kernel densities of the probability of getting the treatment-PSM

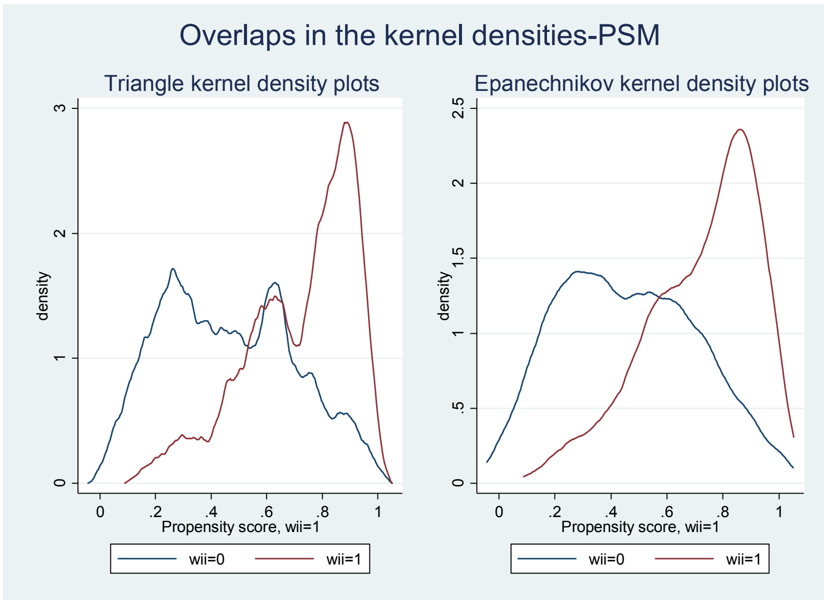


Fig. 2: Kernel densities of the probability of getting the treatment-IPWRA

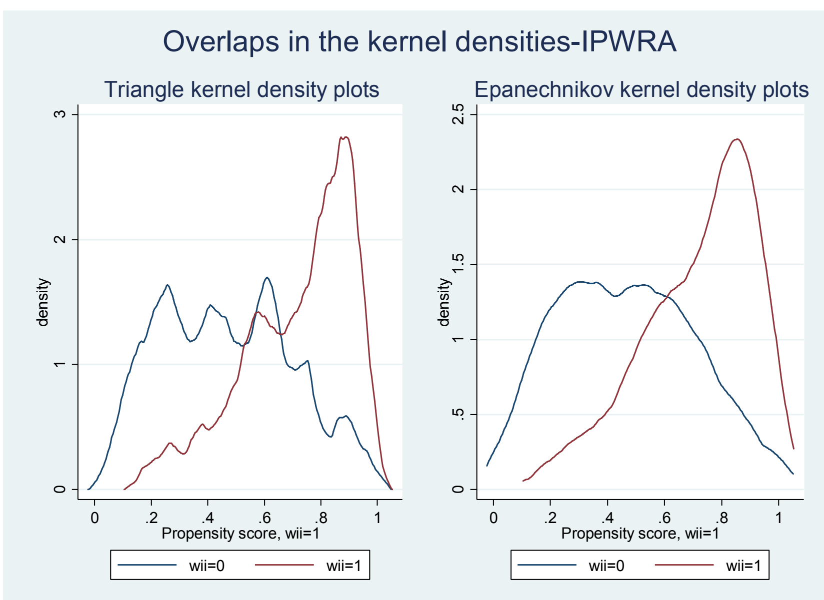


Fig. 3: Propensity score distribution and Common support for propensity score estimation

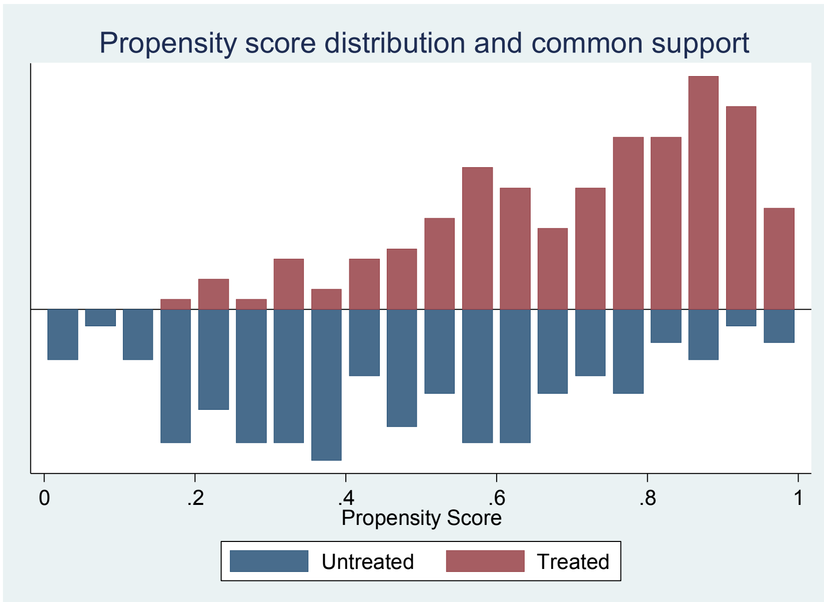
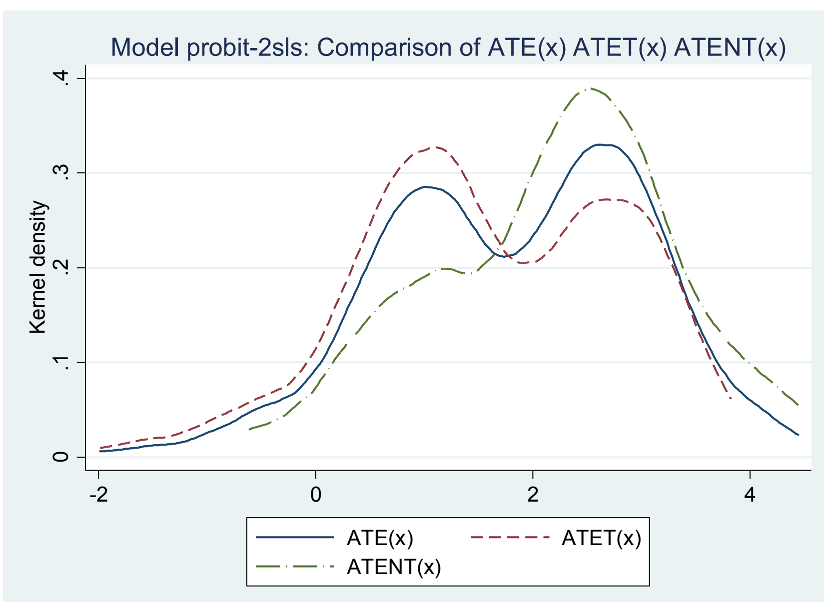


Fig. 4: Comparison of Treatment Effect Results-*Fertilizer use model*



A Appendix

Table A.1: Propensity score model results

	(1) WII	(2) WII	(3) WII	(4) WII	(5) WII
Age of household head	0.156	0.158*	0.158*	0.158*	0.158
	(0.095)	(0.095)	(0.095)	(0.095)	(0.100)
Squared age	-0.002**	-0.002**	-0.002**	-0.002**	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Married (1=yes)	0.625	0.610	0.721	0.721	0.721
	(0.483)	(0.482)	(0.474)	(0.474)	(0.451)
Religiosity (1=attend daily)	0.006	0.025	0.039	0.039	0.039
	(0.442)	(0.436)	(0.433)	(0.433)	(0.437)
Head some elementary education (1=yes)	0.461	0.461	0.458	0.458	0.458
	(0.405)	(0.406)	(0.409)	(0.409)	(0.405)
Head some secondary education (1=yes)	1.037	1.036	1.020	1.020	1.020
	(0.920)	(0.925)	(0.936)	(0.936)	(0.796)
Log household size	-1.022*	-1.006	-0.983	-0.983	-0.983*
	(0.618)	(0.616)	(0.610)	(0.610)	(0.578)
Highest educational level in the household	0.106**	0.105**	0.114**	0.114**	0.114**
	(0.053)	(0.053)	(0.053)	(0.053)	(0.054)
Log total land owned	0.060	0.058	-0.030	-0.030	-0.030
	(0.318)	(0.319)	(0.310)	(0.310)	(0.296)
Iddir participation (1=yes)	0.887	0.913*	0.788	0.788	0.788
	(0.549)	(0.545)	(0.514)	(0.514)	(0.495)
Eqqub participation (1=yes)	1.807***	1.820***	1.787***	1.787***	1.787**
	(0.599)	(0.600)	(0.599)	(0.599)	(0.829)
PSNP participation (1=yes)	0.699**	0.702**	0.658*	0.658*	0.658*
	(0.349)	(0.350)	(0.346)	(0.346)	(0.352)
Credit (1=accessed)	-0.112	-0.105	-0.159	-0.159	-0.159
	(0.331)	(0.331)	(0.330)	(0.330)	(0.337)
Remittance and other gifts received	-0.212	-0.220	-0.245	-0.245	-0.245
	(0.475)	(0.476)	(0.486)	(0.486)	(0.530)
Risk aversion parameter	-3.617	-3.656	-3.601	-3.601	-3.601
	(2.971)	(2.974)	(2.954)	(2.954)	(3.548)
Squared risk aversion	3.448	3.434	3.489	3.489	3.489
	(4.550)	(4.558)	(4.533)	(4.533)	(5.008)
Time preference (1 if discount rate $\geq$ 30 percent)	0.299	0.306	0.350	0.350	0.350
	(0.348)	(0.348)	(0.342)	(0.342)	(0.334)
Basic financial literacy index	5.945**	5.923**	5.609*	5.609*	5.609*
	(3.018)	(3.000)	(2.870)	(2.870)	(3.247)
Squared financial literacy index	-6.554**	-6.554**	-6.298**	-6.298**	-6.298**
	(2.874)	(2.859)	(2.765)	(2.765)	(3.137)
Insurance knowledge index	0.832	0.843	0.915	0.915	0.915
	(0.835)	(0.832)	(0.844)	(0.844)	(0.829)
Understand WII	0.418	0.421	0.451	0.451	0.451
	(0.337)	(0.338)	(0.337)	(0.337)	(0.363)
Adiha (1=yes)	0.047	0.036	-0.008	-0.008	-0.008
	(0.610)	(0.611)	(0.618)	(0.618)	(0.634)
Awetbikalsi (1=yes)	-0.189	-0.204	-0.183	-0.183	-0.183
	(0.558)	(0.558)	(0.563)	(0.563)	(0.572)
Genetie (1=yes)	-1.602**	-1.610**	-1.696***	-1.696***	-1.696***
	(0.632)	(0.634)	(0.642)	(0.642)	(0.649)
Hadealga (1=yes)	-0.903	-0.911	-0.901	-0.901	-0.901
	(0.712)	(0.714)	(0.717)	(0.717)	(0.692)
Constant	-3.095	-3.115	-3.073	-3.073	-3.073
	(2.340)	(2.333)	(2.332)	(2.332)	(2.422)
# of observations	257	259	265	265	265

Standard errors in parentheses.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

(1)-(4) are treatment equations estimated in the IPWRA for the four outcome models (fertilizer, yield, food expenditure per capita and consumption expenditure per capita) respectively. (5) is the treatment equation or propensity score model estimated in the PSM.

Table A.2: Matching quality test

	(1) Pseudo R^2	(2) LR χ^2	(3) p-value	(4) Mean bias
Pre-matching	0.209	73.28	0.000	25.1
Post-matching	0.058	26.6	0.376	5.1