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THE EFFECT OF WEATHER INDEX BASED MICRO-INSURANCE ON FOOD SECURITY STATUS OF SMALLHOLDERS

Research has demonstrated that the use of weather index insurance is one of the most effective ways of cushioning smallholders against the vagaries of nature like excess rains and drought hence improving smallholders' food insecurity status. We use cross sectional data from 401 farm households in Embu County, eastern Kenya and a propensity score matching technique. We model the effects of adoption of weather index based insurance decision on food security of the smallholder farmers. We find that a positive impact on food security is associated with the uptake of index insurance. This suggests that index insurance technology can benefit farmers more through up-scaled use of index based insurance in the context of their socio-economic conditions and institutional arrangements.

Key words: *weather index insurance, food security, propensity score matching.*

Introduction and review of literature. Agriculture is an important source of livelihood among the rural households in the developing countries around the world [1]. These households comprise majority of the small scale farmers who contribute up to 70 % of the global food [2] hence playing a vital role in contributing to food security. According to [3] food security is a situation when all people have physical and economic access to sufficient, safe and nutritious food that meets dietary needs and food preference for an active healthy life at all times. However, bout 805 million people are estimated to be chronically undernourished with Sub-Saharan Africa having the highest prevalence [4].

Among the causes of undernourishment is the perpetual crop failure and loss of livestock that result from adverse weather like drought and floods. The corollary is that agriculture has been rendered an uncertain business [5], [6] where the farming households are the most susceptible to inevitable weather risks. In Kenya food insecurity occurs as either chronic or transitory [7] and food shortage affects poor households living under extreme poverty level, thus pushing them to be at a higher risk of starvation [8]. As an effort to overcome such stark challenges, government as well as other development partners has been developing strategies of ensuring food security and enhancing smallholder farm incomes. Their efforts include a spectrum of policies to promote innovative agricultural practices, use of high yielding inputs, and developing modern agribusiness models and markets, agricultural financing, launching and enhancing of agricultural insurance [9]. The success of such measures among small-scale producers who are low resource users requires sound financial base. Mostly, financial institutions shun giving credit to smallholders because the high risk involved and lack of collaterals [10]. It is widely held that such farmers are more likely to default on their commitments to successfully service their loans in the event of crop failure or livestock mortality. Agricultural insurance aim is to compensate smallholder farmers in the event of loss, enhance financial or credit access and enhance use of modern technologies that yield economic benefits [11] and ultimately transform the archaic subsistence farming to high value commercial farming. This would encourage higher investments in agriculture, improved incomes and also bolster food security among the farming households. In addition, [12] affirms that insurance programs in developing countries target to provide farmers with an alternative risk hedging tool, improve farmers' access to credit and up-take of high-value crops in order to smooth production.

A study by Larochelle & Alwang (2013) points out that in an environment where formal insurance is rare and vulnerability on climatic risk is high, households will most likely choose self-insurance mechanisms. Similarly, households with small incomes and limited wealth express unwillingness to adopt risky, but high yielding agricultural inputs [14] or investment in improved agricultural technology and market opportunities thus promoting precautionary strategies over activities that are of more economic value [15], [16]. Generally, agricultural producers are incapable of managing less frequent risks which precipitate severe losses thus necessitating transferring them for insurance (World Bank, 2010). In-fact, large or repeated shocks in a series can push households to sell-off assets to an extent of getting into an acute poverty trap [17]. Thus farmers can use crop insurance to mitigate their risks [18] however uptake of insurance services in the agricultural sector are low.

One such crop insurance is *Kilimo salama* (Safe Agriculture in Kiswahili) insurance which protects farmers' investment in farm inputs such as seed, fertilizer and chemicals and against extreme weather risk of drought or excess rainfall. This index crop insurance scheme was established in the year 2008 and it was designed for maize and wheat farmers. The scheme uses solar powered weather stations to monitor rainfall and mobile phone payment technology to collect premiums and make payouts respectively. Whenever farmers purchase inputs (seeds, fertilizer or chemicals) from authorized dealers/stockiest, they pay an extra 5% in addition to price as premium. They are then registered by the dealer/stockiest using a camera-phone to scan a bar code on every input. Then a text message that confirms the policy is instantly sent to the farmer. In addition, automated weather stations have been set up to aid in monitoring the insurance. If a station reports insufficient rainfall early or late in the crop growing season all farmers in affected area receive an automatic payout in part or full depending on how extreme the weather was via a Safaricom M-PESA money transfer service. Every farmer who buys insurance is linked to the nearest weather station that is within 20 kilometers. Index based insurance technology, thus provides a safety net against weather-related risks to the smallholder farmers hence it can improve food security and attenuate the vulnerability of rural households to the weather shocks.

The purpose of the article. Cole et al. (2012) demonstrates that little has been done to assess the ultimate impacts of index insurance such as in the contribution to food security and income. Thus, against this backdrop, the study models the effect of index insurance adoption on small-scale producers' food security status using household data by following the propensity score matching. Primarily the study implemented the Household Dietary Diversity Scores approach measure of the social economic level and household economic access to food [20] and complement it with the Food Insecurity perception [21] to analyse the impact of the weather index insurance. Therefore, this study contributes to the growing literature on weather index insurance while the survey data from smallholder farmers are also assessed to provide policy implications for nurturing weather index based micro-insurance.

Results and discussion. The study was carried out in Embu County, Eastern territory of Kenya. A sample of 401 smallholder farmers was obtained following Multi-stage sampling technique. Smallholder farmers are defined on the basis of land cultivation that is less than 5 acres. Embu County was purposively selected following the implementation of weather index insurance programme. Secondly, purposive sampling was also used to select maize farmers around the five weather stations including; (Embu town – Embu Divisional Agricultural office, Ishiara region- Ishiara Agriculture farm; Runyenjes –Runyenjes Agricultural Office; Siakago area – Siakago Rural Technology development Unit and Gachoka DO station) because *Kilimo Salama* insurance targeted maize farmers. Maize is the most important cereal crop in Kenya (Embu County included) as the main staple food which provide more than one-third of the caloric intake and it accounts for about 56% of cultivated land [22].

In Kenya food security is mainly dependent on the availability and affordability of maize, although structural deficits limit its production [23]. Maize production has decreased due to recurrent droughts and floods. For example [24] observed a declining trend in maize yields from 2.7 million tonnes in 1995 to 2.1 million tonnes in 2007 and 30% reduction in annual yields over the same period of time due to extreme weather. Mostly, this results to price increase that leads to severe consequences on household food security. Thirdly, systematic random sampling was done to identify the farmers who participated in the weather index insurance. Finally selection of the non-participant farmers in index insurance was done following the simple random sampling. Cross sectional data were collected by administering a pre-tested interview schedule to the smallholder farmers. The interview schedule captured information pertaining to the farm characteristics, social-economic, institutional factors and weather index technology characteristics. In addition, data on perception and food security status were collected.

The Average Treatment Effect (ATE)

The average treatment approach was used in the study to analyse the effect of the weather index based insurance on food security among smallholders. According to Wooldridge (2002) Average Treatment Effect (ATE) refers to the average partial effect for a binary variable. The central challenge in evaluation that often arises is how to deal with self-selection and the counterfactual setting [26]. If the impact of treatment on individual *i* is denoted by δi, then the equation can be written as:

$$\partial_i = Y_{1i} - Y_{0i} \qquad (1)$$

where Y_{1i} is the outcome in case of treatment and Y_{0i} is the outcome in the absence of treatment. Hence this is the basic formula for ATE. But then it averages the impact across individuals and therefore the equation becomes [26]:

$$ATE = E\,(\partial) = E\,(\mathrm{Y}_1 - \mathrm{Y}_0) \qquad (2)$$

where *E* denotes the average or expected value.

The study assessed the effect of weather index insurance on food security of the small-scale producers in this case is the Average Treatment Effect on the Treated (ATT). According to Dugoff, Schuler, & Stuart (2014) the ATE compares the mean outcome the entire treated population to the mean outcome if entire population had not received treatment. On the other hand ATT compares mean effects on the individuals who in reality received treatment to the mean outcomes if these same individuals had instead not received treatment [27]. The study was thus interested in the impact of index insurance on the adopters of index insurance rather than the population smallholders. Nonetheless, Heckman (1997) asserts that the ATE may not be relevant to policy makers because it takes in the effect on persons for whom the program was never intended for. If D denotes the value if treated (adopter) or not such that D=1 if treated and D=0 if not (non-adopter), then:

$$ATT = \mathrm{E}\,(\mathrm{Y}_1 - \mathrm{Y}_0 | \mathrm{D} = 1) \qquad (3)$$

Since the average of the differences is the difference of averages, then ATT can be written as:

$$ATT = \mathrm{E}\,[(\mathrm{Y}_1|\mathrm{D} = 1) - (\mathrm{Y}_0|\mathrm{D} = 1)] \qquad (4)$$

However, we cannot observe the second term in equation 4 this is because it is a counterfactual of the outcome of the smallholder farmers who adopted index insurance if they had not adopted. But we can observe the term $\mathrm{E}\,(\mathrm{Y}_0|\mathrm{D} = 0)$, which is the value of Y_0 for the non-adopters of index insurance and thus we get the difference as:

$$\Delta = \mathrm{E}\,(\mathrm{Y}_1|\mathrm{D} = 1) - \mathrm{E}\,(\mathrm{Y}_0|\mathrm{D} = 0) \qquad (5)$$

The difference in equation 5 therefore is the selection bias. It gives the difference between the counterfactual for adopters of weather index insurance and the observed outcome for the non-adopters. This can be demonstrated by addition and subtraction of the term $E(Y_0|D = 1)$ in equation 4 as shown below:

$$\Delta = \mathrm{E}\,(\mathrm{Y}_1|\mathrm{D} = 1) - \mathrm{E}\,(\mathrm{Y}_0|\mathrm{D} = 1) + \mathrm{E}\,(\mathrm{Y}_0|\mathrm{D} = 1) - \mathrm{E}\,(\mathrm{Y}_0|\mathrm{D} = 0)$$

$$\Delta = \mathrm{ATT} + \mathrm{E}\,(\mathrm{Y}_0|\mathrm{D} = 1) - \mathrm{E}\,(\mathrm{Y}_0|\mathrm{D} = 0)$$

If $\lambda = \mathrm{E}\,(\mathrm{Y}_0|\mathrm{D} = 1) - \mathrm{E}\,(\mathrm{Y}_0|\mathrm{D} = 0)$, then

$$\Delta = \text{ATT} + \lambda \tag{6}$$

the symbol λ represents the selection bias and where λ is zero, then ATE provides an unbiased estimator of ATT:

$$ATE = \text{E}\,(\text{Y}_1|\text{D} = 1) - \text{E}\,(\text{Y}_0|\text{D} = 0) \tag{7}$$

The term λ is often not equal to zero, because normally smallholders may self-select themselves in a program. This makes it challenging in evaluation while trying to make the selection bias be equal to zero. According to [29] this is done through random assignment which ensures that the treatment status (D) is not correlated with other observable or variables and thus the outcomes are statistically independent of the treatment category. In essence, this ensures that the characteristics of the treated (adopters of index insurance) and the untreated (non-adopters of index insurance) are the same i.e statistically equivalent [26], hence the groups will be identical except for the treatment category:

$$E(Y_0|D = 1) = E(Y_0|D = 0) \tag{8}$$

This makes it possible to replace the unobservable term $E(Y_0|D = 1)$ with the observable term $E(Y_0|D = 0)$ so as to estimate ATT by ensuring the selection bias is equal to zero.

Propensity-Score Matching (PSM)

The propensity score matching model is a method used to evaluate the average effect of a programme on participants' outcome, conditional on the pre-participation characteristics of such participants [30]. The PSM technique has been applied widely in a variety of fields in the program evaluation [26].The model is appropriate for addressing the problem of selection bias [25] in determining the difference between the participant's outcome with (in this case adoption of weather index insurance) and without (non-adoption of the weather index insurance) programme [31]. Pufahl & Weiss also note that participants and non-participants ordinarily differ even in the absence of the programme. Studies on program evaluation show that where the survey design, sample selection and econometric analysis are correctly conducted to solve for endogeneity of participation in programmes, then the estimated coefficients should appropriately measure average impact of the programme on participants' outcome [32], [33].

The PSM model's main purpose is to enable the identification of non-participants who are similar to the participants in all relevant pre-participation characteristics [26]. The group of non-participant individuals thus identified serves as a control group in evaluating the effects of a program. PSM is ideal compared to standard regression methods for two reasons. Firstly, the matching estimators highlight the problem of common support, because treatment effects can only be estimated within the common support region [30] and secondly, matching does not necessarily require functional form assumptions for the outcome equation. In retrospect, PSM is a non-experimental method [26] hence it was appropriate for this study because the weather index insurance programme did not have experimental farmers to act as a control group. Consequently, the difference-in-difference method was not appropriate for the study because it would require baseline data or repeat cross-section data for calculating the propensity score on a baseline year [26], [30] in this case about the farmers' food security status before and after the adoption of weather index. Instrumental variables and design approach, though suitable raises difficulties in finding a suitable instrument because, in identifying the treatment effect, one needs at least one regressor which determines participation, but is not itself determined by the factors which affect outcomes [34], [35].

The regression discontinuity method on the other hand needs a large number of farmers next to the discontinuity to draw meaningful decision. However, this is difficult because the further one moves from the discontinuity line the more the variable characteristics vary [29]. PSM assumes that farmers who receive treatment and those who do not, differ not only in treatment, but also in characteristics that affect participation and the outcome [26]. It thus seeks untreated (in our case non-adopters of weather index) farmers who have the same characteristics of the treated (adopters of weather index) farmers and matching them using propensity scores and thus creating a quasi-experiment [29]. The propensity score was therefore used to estimate the probability of receiving treatment (adoption of weather index insurance) (P_i = 1) given observed characteristics (X):

$$\Pr(P_i) = \Pr(P_i = 1|X) \tag{9}$$

Since 0 < P_i< 1, the conditional probability of participation in the weather index insurance scheme was estimated using a probit model where the dependent variable is a dummy variable equal to one if the farmer participates and zero otherwise [25]. The independent variables are the characteristics that determined participation in index insurance thus replicating the selection process. Following Rosenbaum & Rubin (1983), PSM was used to match the scores of participants and non-participant in the index insurance programme. The result of the treated and untreated group and the difference between the two provide the measure of the impact attributable to index insurance. Hence, taking the mean of these individual impacts thus yields the estimated ATE [37]:

$$ATE = E[Y_1(t = 1, D = 1) - Y_0(t = 1, D = 0)] \tag{10}$$

Where $Y_1$is the outcome for the treated (adopters), Y_0 is the outcome for the non-treated or (non-adopters), $t=1$ represents the period post-treatment, $D=1$ represents participation and $D=0$ represents non-participation.

Descriptive statistics

Overall, there were more female headed (56.18%) than male headed households (43.82%) among the adopters of index insurance in the study (Table 1). On the contrary the male headed households (59.01%) were more in the non-adopter category of farmers leaving their female counterparts with (40.99%). Results show that more than half of the entire smallholder farmers (68%) participated in groups or associations. Among the adopters of index insurance (77.8 %) of farmers were members in both formal and informal groups/associations while (53.21%) of non-adopters are the ones who participated in groups. Such membership was observed in organizations like women's groups, self-help groups and youth groups. These organizations or associations probably enhanced adoption of weather index insurance since information is easily disseminated or shared by members during group meetings. In addition, many development interventions by the government and non-governmental organizations mostly prefer/target organized groups for implementation rather than individuals. The group networks are also vital in the rural set up because of the role they play in providing a platform for information flow through extension services, farmer trainings, marketing activities, purchase of farm inputs all of which enhance farmers to carry out more valuable agricultural activities including uptake of technology index based insurance, unlike their counterparts who are not in organized groups.

Access to extension services variable was significant thus suggesting that it was an important variable through which smallholders possibly engaged to participate in weather index insurance. Access to extension, however is limited because on average the farmer-extension officer contact is 2.2930 times in a year hence indicating that access to extension may be facing inadequacies. The study reveals a significant difference in credit access among the adopters and non-adopters where 35.37% of the adopters and 20.58% of the non-adopters of index insurance scheme had access to credit respectively. Access to financial services is important in providing funds for farm investments, improving post-harvest methods, smooth household cash flow, enabling better access to markets and promoting better management of risks (through uptake of such measures as weather index insurance). It can also play a role in climate adaptation by increasing resilience of agriculture, hence contributing to longer term food security [38]. However, according to International Financial Corporation (IFC), access to a comprehensive range of financial services remains a major challenge for smallholders. Research also shows that farmers struggle to pay for their seasonal inputs, and invest in agricultural technology and their expansion is even more difficult because the lack of finance often leads to a low agricultural productivity particularly in sub-Saharan Africa [39].

Land holding of *less than 1*= 21.50%, 1-1.9 = 30.67%, 2-3.9= 34.33%, 4 and above acres = 13.54% for adopters and *less than 1*= 28.66%, 1-1.9 = 34.00 %, 2-3.9 = 17.33%, 4 and above acres = 20.00 % for non-adopters show that most households own land that is less than two acres. Normally, ownership of large parcels of land provides for on-farm trial of a new agricultural technology without compromising conventional farming among smallholders. However this technology of weather index insurance does not necessarily require large tracts of land as it is a financial product that aims at cushioning smallholder farmers against losses resulting from adverse weather variations. Contrary, a study by Sadati et al. (2010) found that the amount of adoption had a positive correlation with the amount of agricultural land. Nonetheless, land is a sign of wealth such that ownership of large parcels of land may indicate the financial ability to take up new technology. Similarly [40] argue that households with large farms have a wider range of financial services in both the formal and informal sectors, hence there financial capacity to purchase farm inputs.

The findings further reveal that adopters of index based weather insurance were more elderly with a mean age of 51.14 years thus indicating that most of the youthful households are possibly engaging in other non-agricultural activities. It is worth noting that the average off-farm income for the non-adopters of index insurance KES 27,094.38 is higher compared to that of the adopters KES 26,101.55. Although this is not significant, the difference can suggest or be explained by the age variation among the adopters and non-adopters as earlier explained.

Table 1

Descriptive statistics of selected variables of adopters and non-adopters of weather index insurance

Variable	Pooled mean	Adopters mean	Per %	Non-adopters mean	Per %	χ^2	t-value
Sex of household head (*male=1*)	0.4865(0.0833)	0.4382(0.0313)	43.82	0.5901(0.0447)	59.016	7.6428**	
Extension(*Yes=1*)	0.6443(0.0258)	0.7231(0.0288)	72.31	0.4554(0.0498)	45.54	22.282***	
Group member *(Yes=1)*	0.68(0.0243)	0.7786(0.0266)	77.86	0.5321(0.0480)	53.21	21.921***	
Credit Access *(Yes=1)*	0.3693(0.0521)	0.3537 (0.0727)	35.37	0.2058(0.0402)	20.58	8.418**	
Log of off-farm Income	26429.08 (2936.45)	26101.55 (3265.11)		27094.38 (6017.82)			0.1582
Age of house hold head	49.4119(0.6531)	51.1451(0.7325)		45.8595(1.2526)			-3.8708**
Household size	3.5192(0.1000)	3.5502(0.1266)		3.4563(0.1613)			-0.4408
Extension contact	2.2930(0.1257)	2.4606(0.1531)		1.7674(0.1935)			-2.1919**
Distance fertilizer dealer	5.5244(0.3802)	5.15(0.412)		6.39(0.889)			-1.446**
Distance to market	4.7032(0.2666)	4.66(0.359)		4.65(0.411)			0.008
Distance agro-vet seeds	4.7880(0.4621)	4.56(0.302)		5.24(0.578)			-1.150*
Distance extension provider	6.0078(0.4082)	5.98(0.503)		5.92(0.785)			0.075
Years of farming	22.68(0.6242)	23.85(0.7452)		20.28(1.12)			0.466***
Distance Weather station	12.2590(0.6528)	11.6706(0.6895)		15.526(1.8414)			34.627***
Land size (*1= <1*)	2.4974(0.1192)	2.5996(0.1798)	21.50	2.2796(0.0998)	28.66	13.823*	
(*2=1-1.9*)			30.67		34.00		
(*3=2-3.9*)			34.33		17.33		
(*4=4 andabove*)			13.54		20.00		

Source: authors' Survey data, 2015.

Note ***, **, * means significant at 1 %, 5 % and 10 % probability levels, respectively and Numbers in parenthesis denote standard errors.

The study also established that distance to the nearest fertilizer dealer 5.5244 kilometers, distance to the nearest agro-vet seeds dealer 4.7880 kilometers and the distance to the nearest market 4.7032 kilometers were significant. This suggests that accessibility to markets and farm input outlets are important in enhancing the uptake of new technologies such as weather index insurance products. Similarly, distance to the nearest weather station was, on average 12.2590 kilometers with that of the adopters of index insurance being a mean distance of 11.6706 kilometers, while for the non-adopters it was 15.526 kilometers on average from the weather station respectively. Eligibility for participation in index insurance requires cultivating land that within a radius of 20 kilometers from a given weather station. However, it is not clear whether there are measures put in place to confirm the exact locality of the farmers' farming land since the concept of weather index insurance does not require physical inspection or evaluation of loss for the farmers to be indemnified but rather by the weather station data threshold that triggers payout. As such this may create an opportunity for unscrupulous farmers to procure insurance policy with reference to a given weather station where they do not own or have not rented land for cultivation. In effect they can speculate for payouts hence creating a burden of payment to the insurer.

Determination of Average Treatment effect

The Average Treatment Effect of adoption of weather index based insurance was determined following probit estimation to establish how the explanatory variables influence participation probability. The probit model was used where the treatment variable (adoption of weather index insurance) was regressed against selected variables as shown in Table 2. After predicting the propensity score, the matching algorithm was considered where the stratification matching approach was used. According to Austin (2011) the stratification approach partitions the common support of the propensity score into strata and the effect of treatment on outcomes can be estimated by comparing outcomes directly between treated (adopters of weather index) and untreated (non-adopters of weather index). In addition the stratum-specific estimates of treatment effect can be pooled across stratum to estimate an overall treatment effect [42]. Again, this approach was chosen over radius, kernel and nearest neighbor methods because by comparing respondents in the same strata, the difference is made more precise since the difference in the observable characteristics other than treatment is minimized [42]. This was followed by assessing the quality of the match, estimation of the average effect and its standard error.

The study applied variables that influence the likelihood of participation in the weather index insurance. The underlying rationale is that, where a variable influences participation, but not the outcome then, there is no need of controlling for differences with respect to that particular variable. Therefore, only those variables that have an effect on both the treatment (adoption of weather index) and the outcome are requisite for matching. Thus, they were included in the model. The results in (Table 2) show estimated coefficients from the probit model. The R^2 value indicates that about 12.2 % variation in the dependent variable was due to the independent variables included in the model. The LR χ^2 was significant at 1 % level of significance, thus indicating the goodness of fit measures of the model.

Out of the nine explanatory variables, results indicate that the probability of participation in weather index insurance is significantly influenced by six explanatory variables. These variables include age of household head, education level, household size, access to extension, distance to the nearest market and group membership. The age of household head squared and the type of road connecting the farmers' homes to the nearest market also influence participation negatively unlike the size of land owned which has a positive influence.

Table 2

Probit regression for estimation of propensity scores

Variable	Coef.	Std. Err.	z	P>z
Age of household head	0.0966	0.0491	1.970	0.009***
Age of household head squared	-0.0007	0.0002	-1.430	0.151
Education level	0.0193	0.0592	0.330	0.000***
Household size	-0.0284	0.0506	-0.560	0.075*
Land Size	0.0029	0.0388	0.070	0.941
Access to extension	0.7316	0.1921	3.810	0.000***
Distance to nearest market	-0.0086	0.0152	-0.560	0.003***
Type of road connecting market	-0.1247	0.1019	-1.220	0.221
Group membership	-0.2748	0.2011	1.370	0.002***
_cons	-2.6014	1.2310	-2.110	0.035
Number of observations	= 401			
LR Chi2(9)	= 35.92			
Prob>Chi2	=0.000			
Pseudo R^2	=0.1222			
Log Likelihood	=-128.9808			
Region of support	*[0.261991, 0.938312]*			

Source: authors' Survey data, 2015.

Note ***, **, * means significant at 1 %, 5 % and 10 % probability levels, respectively.

The age of the household head implies whether a farmer is more likely to be a risk taker or risk averse. Thus, indicating the extent of willingness to adopt index insurance so as to avoid or cushion their farming activities against weather risks. Age of the household head also suggests that older farmers are likely to have accumulated more capital that would lessen the risk effects associated with the adoption of new technology. In addition, it represents the experience and exposure to farming technologies. This is consistent with Staal et al. (2006) who found that investment level and experience are highly correlated with age. Younger household heads may also equally participate in adoption of agricultural technologies like weather index insurance for purposes of avoiding circumstances that would subject them to vulnerability as shown by [18].

Education level is an important variable that is included in the model because it is expected that if farmers are more educated then they would be better placed to understand the issues and interpret the express benefits of weather index insurance such as the contribution to food security. Thus, regarding these results education level influences participation of smallholders in index insurance negatively thereby implying that better educated farmers possibly consider alternative economic activities hence find minimal or no reason to adopt index insurance. The size of household is significant at 10 % level with a positive influence on the adoption of index insurance among the smallholders. Having a big household size has been associated with adoption of agricultural technologies due to provision of labour [44, 45].

As expected the access to extension services variable is positive and significant at 1 % level. This means that farmers who accessed extension services from the relevant agricultural officers were more likely to adopt index insurance. Another variable is the distance from the homestead to the nearest market, which shows that an increase in distance is likely to discourage the up-take of index insurance. Markets are important outlets for the farm produce and sources for farm inputs among the rural community. Therefore, a farmer's proximity to market would influence the decision to participate in a new technology. Group membership reveals a likelihood of influencing adoption of weather index insurance. Social networks are observed when farmers are involved in various formal and informal group activities. Through such membership and active participation in the groups, farmers can benefit from access to vital information such as agricultural innovations like weather index insurance, which in turn influence the decision to participate in the same.

Assessment of the index insurance effect on food security

This study used the household dietary diversity (HDD) which refers to the number of different groups of food consumed over a given reference period [46] and food insecurity perception to determine the food security of the smallholders. The HDD is an attractive proxy indicator because a more diversified diet is an important outcome associated with a number of improved outcomes in areas such as birth weight, child anthropometric status, and improved hemoglobin concentrations [20]. In addition, a diversified diet is highly correlated with factors such as caloric and protein adequacy, percentage of protein from animal sources and household income [47]. Firstly, the dietary diversity questionnaire [48] was administered among smallholders to collect data. The questionnaire comprises of sixteen questions. Following Swindale & Bilinsky (2006), the questions were aggregated into twelve food groups so as to create the household dietary diversity score (HDDS). Normally the individual dietary scores (IDDS) is used as a proxy to reflect or measure the nutritional quality of an individual's diet while the HDDS is used as a proxy measure of the social economic level [20] and it also indicates the household economic access to food [46]. The twelve food groups are presented in Table 3.

Table 3

Combination of food groups from the Questionnaire to generate HDDS

Question Number(s)	Food Group
1	Cereals
2	White tubers and roots
3,4,5	Vegetables
6,7	Fruits
8,9	Meat
10	Eggs
11	Fish and other seafood
12	Legumes, nuts and seeds
13	Milk and milk products
14	Oils and fats
15	Sweets
16	Spices, condiments and beverages

Source: Food and Agriculture Organization (FAO), 2011.

The food groups on (Table 3) were given a value of one thus giving a range of 0–12 for all the scores. Fundamentally, given that there is no established cut-off point to indicate adequacy or inadequate dietary diversity, the distribution of scores was used for further analytical purposes following guidelines for measuring household and individual dietary diversity [48]. The HDDS scores were input into the propensity score matching model so as to determine the effect of the index insurance on the smallholders' food security. The average treatment effect on the Treated (ATT) was computed using stratified matching. The adopters of index insurance were matched with 150 non-adopters. The t-statistic of 4.237 which is greater than two shows a good match because of the insignificant difference between the adopters and non-adopters after matching (Table 4). This implies that the significant covariates were conditioned to be insignificant hence indicating that the balance was made in terms of the covariates between participants and non-participants of the weather index insurance.

The results in (Table 4) also show that the participants in the index insurance have a higher dietary diversity score of 1.217. This further implies that smallholder farmers who adopted index insurance had a more diverse diet compared to the farmers who did not participate. It also shows an increase in food access for the adopters over the non-adopters because the dietary diversity score similarly measures a household's ability to access food which is consistent with the findings of [46]. As noted earlier, there is no static level of adequate or inadequate dietary diversity level therefore the food insecurity perception was also incorporated in the analysis to determine the food security level of the farmers. The aim was to elaborate the household dietary diversity scores findings.

Table 4

HDDS Average Treatment Effects on the Treated - Stratification Matching

Adopters	Non-adopters	ATT	Std. Err.	T
251	150	1.217	0.6780	4.237

Source: authors' Survey data, 2013.

Food insecurity perception has been used in the past as a measurement scale of food security in many countries including developing countries [49]. It is a low cost and easy to use method that represents a highly reliable and consistent indicator that entails asking respondents 15 questions which determine the food security status of a household. According to Corrêa (2007), the use of the scale is anchored on the basis of the number of questions answered. The scale has four levels: food security, light food insecurity, moderate food insecurity, severe food insecurity.

In order to implement the analysis, the food insecurity perception responses were used to generate the food security scores with a range of 0–15 because the propensity score matching technique uses continuous data. Following Corrêa (2007), if respondents obtain a score of 15, they are food secure, if they have a score of 10 to 15, they will be at the light food insecurity level. Corrêa also notes that if the score ranges between 5 and 9, they are on moderate food insecurity level and ultimately if the score lies between 0 and 4 the respondents are at the serious food insecurity level.

Table 5 shows the results of the food security levels between the adopters and non-adopters of the weather index insurance programme. The findings reveal that there was a significant difference between the adopters and non-adopters of the index insurance at 5 % level with respect to the food security levels. On the other hand, there should be no significant difference so as to determine the actual effect of index insurance on the food security.

Table 5

Estimating the food security levels using food insecurity perception

Level of Food Security	Food security score	Frequency		Fisher's Exact Test
		Adopters	Non adopters	
Food secure	15	97	39	0.038**
Light food Insecurity	10–14	51	33	
Moderate food insecurity	5–9	82	46	
Serious Food Insecurity	0–4	21	32	

Source: authors' Survey data, 2015.

Note ***, **, * means significant at 1%, 5% and 10% probability levels, respectively.

Table 6 shows the use of food security scores in propensity score matching method to match the adopters and non-adopters of weather index insurance. The conditioned results indicate there is no significant difference which intern implies that a good match was attained. Also the results reveal that the smallholders who participated in the index based insurance had a higher food security score of 5.769 compared to farmers that did not adopt the index insurance. The average treatment on the treated score of 5.769 is positive which means that the index insurance enhanced the food security level of the small scale producers who adopted it. The results of the household dietary diversity scores and the food insecurity perception are in concurrence following the stratification matching. This further suggests that weather index based insurance had a positive effect on improving the food security level of the participating smallholders.

Table 6

Food security score average Treatment Effects on the Treated with Stratification Matching

Adopters	Non-adopters	ATT	Std. Err.	T
251	150	5.769	0.328	7.537

Source: authors' Survey data, 2015.

Conclusions. This study sought to establish the effect of weather index insurance on food security of the small-scale producers. A propensity score approach was used to compare participants in the index insurance programme with non-participants in terms of their food security status following the household dietary diversity score (HDD) and the food insecurity perception approaches. The results show that the index insurance had a positive effect on food security status. Similarly the results reveal that factors such as age of household head, education level, household size, access to extension and distance to nearest market are important variables that influence farmer's propensity to adopt the weather index insurance.

The results therefore suggest that weather index based insurance technology can contribute to a more resilient rural agricultural society with respect to food security status among small-scale producers. The study recommends for promotion of education, financial literacy and index based insurance in bringing about understanding of insurance as well as up-scaling the weather index insurance among farmers.

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