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Risk Management for Smallholder Farmers: An Empirical Study on the Adoption of Weather-Index Crop Insurance in Rural Kenya

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Abstract

This study examines the determinants of smallholder farmers' adoption of weather-index crop insurance, which is considered to be a promising means of mitigating the negative welfare impacts of crop loss caused by drought or excess rainfall. The study utilizes household survey data covering 495 smallholder farmers in rural Kenya. It finds that a better understanding of insurance, together with a significant positive effect of years of education, considerably increases insurance uptake. The evidence suggests that it is important to provide educational programs on new financial products when introducing such products to smallholder farmers. However, it also shows the limitations of this study by revealing how important proper study design is to draw reliable methodological impact evaluations.

Keywords: agriculture, weather risk, weather-index insurance, rural households, Kenya.

JEL (O12, O13, O33, G22)

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1. Introduction

Farmers are vulnerable to various risks. Production instability due to climate risks has been a major source of income fluctuations. Climatic vulnerability challenges the welfare and livelihoods of low-income farmers who make up the majority of rural populations in developing countries. Income fluctuations would not be directly translated into consumption fluctuations if farmers had access to effective risk-coping mechanisms. In developing countries, however, insurance and credit markets are typically incomplete or altogether absent, hence, negative income shocks often cause serious damage to the wellbeing of smallholder farmers.

Agricultural microinsurance products offer one strategy to manage weather risks by transferring the risks to insurers. In recent years, weather index insurance has drawn considerable attention because (i) it causes less adverse selection and moral hazard than traditional insurance, (ii) lowers transaction costs and thus insurance premiums, and (iii) enables quicker and simpler insurance payouts. With the use of reliable historical weather and crop yield data, adverse selection of clients due to asymmetric information about farmers' real risk exposure is reduced. Moral hazard, which is the issue that individuals consciously increase their risk in expectation of insurance payouts, is also avoided by the objective and tamper-proof index (Coning and Udry 2005; Dowd 1992; Ghosh et al. 2000; Hellmuth et al. 2009).

Additionally, as the index falls to a certain level, agricultural households automatically receive a payment without the need for a costly inspection of their potential yield losses. Based on historical weather and crop-loss data, these index-based risk transfer products can, in theory, keep their insurance premiums lower for poor clients. Moreover, the introduction of new technologies such as mobile payment further promotes the provision of such insurance services and enables even smallholder farmers to have access to them. For these reasons, index insurance has the potential to become a viable risk mitigation tool for small-scale farmers (Barrett et al. 2008; Cai et al. 2020; Hellmuth et al. 2009).

While the use of weather index insurance holds much promise, the practical realization of sustainable and scalable products in the context of developing countries is an ongoing challenge. Although index insurance on a small scale has been provided in a number of countries (Casaburi and Willis 2018; Cole et al. 2013; Giné and Yang 2007; Hess and Hazell 2009; McIntosh et al. 2013; Meherette 2009; Takahashi et al. 2016), its full scale and extensive provision is yet to be tested. The key determinants of farmers selecting index insurance need to be explored further.[1] This study contributes to index insurance studies by addressing the following question: what are the key determinants of insurance adoption by low-income farmers? It should be noted that after this paper was first drafted, a discussion emerged within behavioral economic analysis that states that simple demand for insurance may be a misleading element in considerations of its welfare impacts (Harrison et al. 2021 and 2020; Harrison and Ng 2017). The intention of this paper is not to advocate setting higher insurance uptake as an optimal goal. Rather, the paper aims to contribute to the development of a better system for sharing the risks of weather shocks for low-income agricultural households by identifying important factors influencing insurance take up.[2]

This study examines the determinants of the take up of weather index insurance by smallholder farmers using data collected through a rural household survey conducted in 2011, which covered 495 households in 22 rural communities in the western part of Kenya. The weather index insurance targeted in this study is a crop insurance product that was introduced in some parts of Kenya as a pilot project in 2009. It can be taken up when farmers buy agricultural inputs at local input retailers by paying an additional 5% input cost as the insurance premiums and then covers the input cost. This means that the input cost will be fully or partially returned via mobile

[1] Also, see Cai et al. 2020; Cai 2012; Cole 2013; Giné and Yang 2009; Karlan et al. 2014; McIntosh et al. 2014.

[2] There is also a need to re-examine index insurances quality as a number of recent review papers have worried about it and suggested that rainfall indices such as the one used by the product discussed in this paper may not be very reliable (see Benami and Carter 2021; Benami et al. 2020; Carter et al. 2017; and Jenson and Barrett 2017). While the scientific evaluation of these indices is beyond the scope of this paper, the authors acknowledge here that the right structures of insurance products are the basis of our future discussion and that without those foundations, the products may not be able to generate welfare benefits to the recipients.

money[3] depending on whether the rainfall level is above or below a certain threshold in the coming cropping season. The insurance payout will be done automatically via mobile money transfer without the need for processing of an insurance claim made by the insured. In February 2011, a workshop on the use of weather index insurance and agricultural input use was held by a local input dealer in 11 out of the 22 survey communities in two counties. The Japan International Cooperation Agency Research Institute (JICA-RI) conducted the household survey in November 2011, not only in those 11 villages but also in their neighboring villages in order to evaluate the impact of the new insurance commodity on the farming practices of smallholder farmers and their welfare. This paper focuses on the determinants of the take up of the new insurance product by smallholder farmers by utilizing unique data.

Our empirical results are consistent with those of preceding research. Indi- viduals who participated in the workshop are more likely than non-participants to correctly understand the insurance concept and have a greater tendency to adopt insurance. This suggests that once people understand insurance and how it works, they have a much higher probability of accepting it. This result confirms the need for insurance education when introducing weather index insurance as a new financial product. Moreover, this study examines which additional factors determine insurance adaption. It finds that travel time to the input dealer who handles the insurance, negatively influences the demand for index insurance. Also, the level of education of the farmers, which is often thought important for the demand for financial products (for example, Cai et al. 2020; Chirwa 2005; Cole 2013; Giné and Yang 2009; Hill et al. 2013), has a significant impact on insurance uptake. By clarifying the reasons behind insurance purchases, our study contributes to the extensive literature on the financial system's role in risk-sharing. It also contributes to research on household financial market participation and risk management (e.g., Lusardi and

[3] Mobile money is a money transaction service often provided by mobile network service providers, which is commonly used in Kenya and enables its users to make a peer-to-peermoney transfer via mobile phones. See Jack and Suri (2015) and Mnyegera and Matsumoto(2016) for more details about mobile money services in Africa and their impacts.

Mitchell 2007; Cai et al. 2010; Cole et al. 2011). The remainder of this paper is organized as follows: Section 2 describes the Kenyan context and the insurance design studied. The study design, the survey data, and its descriptive statistics are presented in Section 3. Section 4 interprets and discusses the empirical results on the determinants of insurance take-up, and section 5 presents the conclusions of the study.

2. The Kenyan context: study area and insurancedesign

In Kenya, as in many African developing countries, most households dependon agriculture for their livelihoods. The income of farmers is particularly at risk from natural calamities caused by droughts or excessive rainfall. Weather perils lead to reduced agricultural productivity and, occasionally, serious famines. The secondary effect of this is decreased investment in the agricultural sector, which further threatens food security and livelihoods. Historically, Kenya is known for having frequent droughts with a high number of victims. Irrigation development usually takes a long time, and until it is established, farmers must rely on rain-fed agriculture. What is worse is that a large proportion (5.4%) of the arable land in Kenya is not suitable for irrigation development (JICA 2012). Kenyan farmers diversify income sources by engaging in non-farm earning activities and planting different types of crops to reduce the risks associated with income fluctuation. However, such efforts are not sufficient to solve the unfortunate situation that Kenya faces from repeated droughts.[4]

Against this background, weather index insurance has attracted special attention in Kenya due to the theoretically low transaction costs for insurance providers and consumers. The Kenyan market has an advantage for the prevalence of weather index insurance because the country has widespread mobilemoney services such as M-Pesa, Airtel Money, Yu Cash, and Orange Money.[5] By

[4] Wineman et al. (2017) reported droughts severely reduce crop income and total household income of farmers in Kenya.

[5] Safaricom's M-Pesa, the oldest mobile money service, was started in 2007. It has a dominant market share and is currently used by over 13 million Kenyans (IFC 2015).

utilizing the mobile money system, all money exchanges can be performed using a mobile phone, which reduces the procedural and time costs for both providers and purchasers.

Despite the advantages of and expectations towards weather index insurance, FinAccess (2009) data shows that in 2009, only 7% of Kenyan adults used an insurance product, a slight increase from 6% in 2006. As with other insurance types, the use of conventional agricultural insurance products is very limited in Kenya. Crop insurance has been considered too expensive for smallholder farmers. Effective management of the moral hazard associated with conventional crop insurance requires individualized farm visits for valuation and loss adjustments (based on yield losses at harvest time) when a claim arises. The result is significantly high transaction costs, which render them unviable as inexpensive policies required by smallholder farmers. Agricultural microinsurance is now emerging as a strategy for effectively reducing the impact of severe weather and supporting increased investment in farm productivity (Dick 2009). Under these circumstances, a weather index insurance, *Kilimo Salama*, was introduced in some parts of Kenya in 2009 as a pilot project.

Kilimo Salama, which literally means "safe agriculture" in Swahili, is an index-based insurance product that covers farmers' inputs in the event of drought or excessive rainfall. It was developed by the Syngenta Foundation for Sustainable Agriculture (SFSA) and launched in partnership with Safaricom (the largest mobile network operator in Kenya) and UAP (a large insurance company based in Kenya). During the planting season, actual rainfall levels are measured at a solar-powered weather station installed at each of the project sites. If the rainfall is determined to be too little or too much, then the insurees will receive a payout based on the deviation from the rainfall index. Key details of the policies offered are briefly described below. As an insurance premium, people pay an extra 5% of the purchased input cost to insure a bag of maize seeds (Ksh 180-189/kg), fertilizer (Ksh 2,000- 2100/50kg), or other agricultural chemicals (Ksh 1,055-1108/lt.) against crop failure (JICA 2012). Local input dealers, who are the sales agents for the insurance product, register a policy with UAP by using a mobile phone to scan a barcode on each bag of seed or chemicals sold. A text message confirming the policy is then sent to the farmer's handset. Individuals are registered at their nearest weather station, which transmits data over the mobile network. If weatherconditions deteriorate, an investigation is carried out by a panelof experts referring to an index system and payouts are then made accordingly. Cash transfers are made directly to the handsets of farmers in the affected areas using Safaricom's mobile banking system (Tantia and Tyler 2015).

In November 2011, JICA-RI carried out a survey in two study sites in the Western part of Kenya (see Appendix Figure 1 for the location of the study area) where the new insurance product had been introduced in the year before the survey. The first study site covers the Rachuonyo North and Rachuonyo South Districts in Nyanza Province (see Appendix Figure 2A) and the second covers the Bungoma Central, Bungoma South, Bungoma East, and Kimilili-Bungoma Districts in Western Province(see Appendix Figure 2B).

The districts in Bungoma experience a relatively moderate rainfall pattern and benefit from rather well-maintained roads. Similar to other parts of Kenya, farming is the major economic activity in the two study areas. It contributes to over 70% of the district's gross domestic product. Livestock production is a major economic activity complementing crop production with the predominant type of livestock kept being zebu cattle, sheep, goats, poultry, and dairy cattle. The features of the two provinces described in the JICA survey are as follows:

A high majority of the arable land in Rachuonyo districts is farmed by small-scale holdings of sizes ranging from 1.2 hectares to 3.0 hectares. The main food crops grown are maize, beans, finger millet, sweet potatoes, cassava, and sorghum, while the main cash crops include tea, coffee, cotton, pineapples, and other horticultural crops. Small-scale irrigation for horticultural crops is also used within the study area. In Bungoma, the main crops grown are maize, beans, sweet potatoes, cassava, sunflower, tobacco, coffee, and sugarcane. The land holdings in Bungoma vary with both small- and large-scale holdings (JICA 2012).

3. Study design and descriptive statistics

The study sample was composed of 495 farmers from 22 sub-locations (the smallest administrative unit in Kenya, hereinafter referred to as "villages") in the areas described in the previous section. Half of the villages were selected because their villagers had been exposed to detailed information on the new insurance product through a workshop organized by a local agricultural input dealer. These agents had also been the sales agents for thepromotion of *Kilimo Salama* in February 2011.[6] The other half of the villages were randomly selected for comparison purposes and each satisfied the following criteria (JICA 2012): (i) rare communication with the villages holding the workshop (e.g., if the village is approximately 30-minutes drive away), (ii) same agro-ecological zone, (iii) similar elevation and landslope, (iv) similar distance from Lake Victoria, and (v) similar accessibility to major roads as the villages holding the workshop.

Although the sampling design or the choice of villages was not that of a randomized control trial, the JICA-RI researchers consider the workshops held by the local private agricultural dealers as a treatment in a natural experiment. The 11 villages where the workshops were held were considered as "treatment villages" andtheir comparable households were collected from 11 "control villages." Since the workshop is different from a "treatment" in a randomized control trial, we call those villages "W villages" and "NW villages," respectively.

At the workshop, the local private agricultural dealers gave the participants both a lecture on *Kilimo Salama* and an opportunity to purchase the insurance policies on-site.[7] In conducting the household survey in November 2011, the researchers randomly selected a total of 30 households from each W village - 15 from the list of households who attended the workshop (hereinafter

[6] The owner of an agricultural input shop in Oyugis Town in Nyanza visited the 6 Rachounyo villages and organized the workshops for the promotion in the area. while An experienced employee of an agricultural input shop in Bungoma Town in Western visited the 5 Bungoma villages and organized the workshops there. The workshops were held independently of the JICA-RI survey.

[7] The dealers sold several types and brands of agricultural inputs popular in the area, including seeds, fertilizers, and chemicals, at the same price as their shop price without charging transportation costs. The participants had the option of buying such inputs with or without the insurance of their choice. If they chose to purchase inputs with insurance, they paid the cost of the input plus the insurance premium.

referred to as "participants") and 15 from the list of households who did not attend the workshop (hereinafter referred to as "non-participants"). Additionally, they randomly selected 15 households from the household population in each of the 11 NW villages. In both W villages and NW villages, simple random sampling was used to make the selections based on random numbers generated from a computer.[8]

Table 1 presents several household-level variables by household type covering almost all the target farmers. Where information was missing, these farmers could not be used for the following regression analyses.[9]

[8] The total number of households in a survey village (or sub-location) varies between 345 and 4352, with a mean of 1422 and a standard deviation of 1085, based on the 2009 Kenya Population and Housing Census (2010). About 30 households participated in the workshop in each of the W villages. Thus, the proportion of households attending the workshop varies from 0.7 to 5.5%.

[9] The numbers of households dropped from the analyses are 4, 6, and 4 for the workshop participants and non-participants in the W villages and those in the NW villages, respec-tively. The simple regression for the attrition analysis shows that the attrition probability seems uncorrelated with the 'treatment' or participation status for the workshop and for other observed household characteristics. Thus, we expect that attrition would not cause any serious biases in the following regression analyses. The results of the attrition analysis will be available upon request.

Table 1: Summary statistics by village type and workshop participation status

	W (Workshop) villages (11 villages)				NW (Non-Workshop) villages (11 villages)		t-test for difference in means		
	Workshop participants		Workshop non-participants				(1) vs. (2)	(1) vs. (3)	(2) vs. (3)
Variable	(1)		(2)		(3)		(4)	(5)	(6)
	mean	(s.d.)	mean	(s.d.)	mean	(s.d.)	p-value	p-value	p-value
1 if ever bought weather index crop insurance (WICI)	0.478	(0.50)	0.013	(0.11)	0.000	(0.00)	0.000	0.000	0.158
1 if participated in any WICI workshop held in the last 12 months	1	(0.00)	0.10	(0.30)	0.07	(0.26)	0.000	0.000	0.324
1 if correctly understands the concept of "insurance"	0.845	(0.36)	0.553	(0.50)	0.553	(0.50)	0.000	0.000	0.960
1 if ever bought medical insurance	0.193	(0.40)	0.094	(0.29)	0.149	(0.36)	0.011	0.290	0.130
1 if ever bought any agricultural insurance other than WICI	0.068	(0.25)	0.000	(0.00)	0.006	(0.08)	0.000	0.000	0.560
Number of household members	7.57	(2.66)	6.09	(2.42)	6.43	(2.79)	0.000	0.000	0.196
1 if is a female-headed household	0.14	(0.35)	0.24	(0.43)	0.24	(0.43)	0.017	0.025	0.873
Age of household head	54.14	(11.3)	48.99	(14.4)	49.92	(14.7)	0.001	0.006	0.573
Years of schooling of household head	4.65	(1.97)	4.98	(2.50)	5.12	(2.83)	0.149	0.061	0.624
Size of farmland (acres)	3.69	(3.16)	2.74	(2.75)	2.62	(2.28)	0.003	0.001	0.774
Value of household assets in 1000 Ksh	143.30	(154.3)	110.60	(209.9)	87.04	(90.2)	0.106	0.000	0.193
1 if participating in self-help groups	0.22	(0.41)	0.18	(0.38)	0.10	(0.30)	0.404	0.003	0.035
1 if is the most risk averse	0.28	(0.45)	0.36	(0.48)	0.39	(0.49)	0.121	0.037	0.596
1 if is the most risk loving	0.37	(0.48)	0.30	(0.46)	0.17	(0.38)	0.156	0.000	0.011
1 if answers on risk preference questions being irrational	0.13	(0.34)	0.11	(0.31)	0.17	(0.38)	0.491	0.361	0.110
1 if did not answer the cognitive ability questions	0.09	(0.29)	0.14	(0.35)	0.14	(0.35)	0.223	0.174	0.890
Score of cognitive ability quiz conditional on answering the questions	3.54	(0.79)	3.27	(0.89)	3.25	(0.87)	0.004	0.002	0.849
Score of financial literacy quiz	2.50	(1.12)	2.59	(1.08)	2.41	(1.01)	0.480	0.421	0.117
Travel time to the nearest WICI sales agent (minutes)	97.89	(60.84)	103.00	(63.38)	90.90	(56.22)	0.463	0.285	0.072
Number of households	161		159		161				

Source: Authors.

There is a substantial difference in the adoption of weather index crop insurance (WICI) between the three groups in 2011. Most of those who adopted the WICI were participants at the workshop held by the local agricultural input dealers in each of the two districts in February 2011 (and 48 percent of the workshop participants bought it). In contrast, only 1 percent of non-participants (or 2 people) at the workshop in the W villages and nobody in the NW villages bought insurance. Although there are a few cases where the non-participants and the NW villagers had attended WICI workshops held by someone other than the above-mentioned dealers, ordinary farmers in the region had very limited access to information on the WICI and few opportunities to purchase it. As expected, the proportion of those who understand the concept of the insurance is substantially higher among the participants than among the others. There is no difference in the levels of understanding of insurance concepts between the non-participants in the W villages and the NW villagers.[10] This indicates that there is no knowledge spillover from participants to the non-participants in the W villages, which may be the reason why only participants adopt the new insurance product. Thus, workshop participation seems to be a crucially important factor in farmers' adoption of insurance. If the participation in the WICI workshop was random, we can interpret the difference in insurance knowledge and the WICI purchase between the participants and non-participants as the causal effects of participation in the workshop. However, because the workshop participation was not random but voluntary, we may not be able to argue that enlightenment on the new insurance product through the workshop is the only factor that affects the participants' awareness

[10] The JICA-RI researchers trained enumerators to gauge the respondents' awareness of the insurance concept so that they could determine if the respondents have a good understanding of it. More precisely, the enumerators asked respondents whether they knew about insurance and if yes, what it is that they know. If they could correctly describe the relationship between insurance premiums and payouts, the researchers judged that the respondents understood it.
However, we admit that this measurement of understanding of insurance might be too naive considering the complexity of index insurance. For example, we did not know respondents' level of understanding of the payout dependency on the rain measurement at the nearest rainfall station, the exact location of the nearest station, and possible basis risk in the insurance contract. In addition, recent studies measure insurance understanding in more detail (e.g., Cai et al. 2020). Therefore, we may have to interpret our regression estimate on the awareness variable with caution.

and adoption of it. The participants may be systematically different from those who did not participate in the WICI workshops in 2011. Indeed, their characteristics appear to be largely different from the non-participants and NW villagers. We confirm from the comparison between the groups that they are also statistically significantly different in some of their observed characteristics. The workshop participants have larger households with bigger family sizes (measured by the number of household members, the size of their owned farmland, and the value of their asset holdings), they are less likely to have a female head, and their heads are older than those of the non-participants or the NW villagers. The participants may be socially in a better position to gather useful information through their connections to local elites and, may therefore be able to obtain information about upcoming workshops and attend them. In addition, theparticipants may have considerably more interest in the new insurance crop than non-participants and therefore attend the workshop. It is also possible that the participants may be heavier users of agricultural inputs than the non-participants and attend the workshop as they see it as an opportunity to buy inputs close to their homes without paying delivery costs input shops in town. Since they may be more serious about farming, they might show a higher interest in the new crop insurance. Such possible scenarios can be a source of systematic differences between workshop participants and non- participants and, hence, self-selection biases in estimating the workshop effects.

In the interviews, the JICA-RI researchers also tried to elicit respondents' risk preference, cognitive ability, and level of financial literacy.[11] With regardto these variables, there again seems to be a significant difference between the types of households. The NW villagers are less risk-loving than the others.The participants show a significantly better score in the cognitive ability test than the others, whereas there is no statistically significant difference in the financial literacy score.

In sum, the different types of households show a statistically significant difference in many of their observed attributes. In particular, the workshop participants seem different from the non-participants in the W villages as well as from the NW villagers. Thus, the significantly higher

[11] See Appendix for details of how to collect information on these variables.

levels of understanding of the concept of insurance and the adoption of WICI among the workshop participants are not purely caused by the promotional and educational content of the workshop program but are also affected by the selection bias. We expect a positive selection of both the level of knowledge and the adoption of WICI among the workshop participants in consideration of the differences in some of their observed attributes and behaviors such as family size, land size, and value of asset holdings. Since the selection might be attributed to some unobserved factors, it is quite difficult to cleanly estimate the average effect of workshop participation on enhancement of knowledge about insurance and the adoption of WICI. In the following section, we use matching estimation methods to try to reduce the influence of the selection bias and estimate the average effects.

Table 2 presents the summary statistics of the same variables shown in Table 1 by the status of WICI adoption among the workshop participants in 2011. While there was no difference in their understanding of the insurance concept and their experience in purchasing medical insurance, there was still a significant difference in their past experience of purchasing agricultural insurance other than the WICI. In addition, in comparison to non-adopters, WICI adopters are less likely to have a female head of household, and are more likely to have a larger farm, be more risk-loving, and to live closer to the WICI sales agent.

Table 2: Summary statistics of workshop participants by their purchase status of WICI

	Weather Index Crop Insurance (WICI) workshop participants				
	Those who did not buy WICI		Those who bought WICI		t-test for difference in means
Variable	(1)		(2)		(3)
	mean	(s.d.)	mean	(s.d.)	p-value
1 if correctly understands the concept of "insurance"	0.83	(0.38)	0.86	(0.35)	0.68
1 if ever bought medical insurance	0.17	(0.38)	0.22	(0.42)	0.39
1 if ever bought any agricultural insurance other than WICI	0.01	(0.11)	0.13	(0.34)	0.00***
Number of household members	7.25	(2.65)	7.92	(2.65)	0.11
1 if is a female-headed household	0.19	(0.40)	0.09	(0.29)	0.07*
Age of household head	55.24	(11.10)	52.94	(11.47)	0.20
Years of schooling of household head	4.49	(1.75)	4.83	(2.18)	0.28
Size of farmland (acres)	3.00	(2.19)	4.43	(3.84)	0.01***
Value of household assets in 1000 Ksh	127.81	(134.89)	160.22	(172.41)	0.19
1 if participating in self-help groups	0.20	(0.40)	0.23	(0.43)	0.63
1 if is the most risk averse	0.35	(0.48)	0.21	(0.41)	0.05**
1 if is the most risk loving	0.30	(0.46)	0.44	(0.50)	0.06*
1 if answers on risk preference questions being irrational	0.14	(0.35)	0.12	(0.32)	0.63
1 if did not answer the cognitive ability questions	0.10	(0.30)	0.09	(0.29)	0.93
Score of cognitive ability quiz	3.50	(0.82)	3.59	(0.77)	0.46
Score of financial literacy quiz	2.41	(1.10)	2.61	(1.15)	0.25
Travel time to the nearest WICI sales agent (minutes)	111.29	(64.51)	83.28	(53.22)	0.00***
1 if Nyanza and 0 if Bungoma district	0.66	(0.48)	0.62	(0.49)	0.68
Number of households	84		77		

Source: Authors.

4. Empirical results and discussions

We examine the determinants of smallholder farmers' adoption of weather-index crop insurance. Firstly, we focus on the effect of participation in the WICI workshop run by the local agricultural input dealers on the decision to adopt WICI. As shown in the previous section, self-selection of participation in the workshop may cause serious estimation bias. In order to reduce the bias of selection on observables, we use several matching methods to estimate the average "treatment" effects of participation in the workshops on both the awareness of insurance and the adoption of WICI.

Secondly, we estimate the influence of other individual-level factors on their adoption decisions by simple regressions using the workshop participant samples.

Effect of participation in the WICI workshop

We ran two types of matching methods: propensity score matching (PSM)and covariate matching (CVM) with Mahalanobis distance.[12] To describe the statistical model, we use the potential outcomes framework and denote the potential outcomes of the individual (or household in our study) i as y_{wi}, where the subscript w corresponds to a variable representing i's participation status taking 1 if i participates in the workshop and 0 otherwise. We denote y_i as the realized outcome. Thus, the relationship between the realized outcome and the potential outcomes is given as follows:

$$
\begin{aligned}
y_i &= (1 - w_i)y_{0i} + w_i y_{1_i} \\
&= y_{0i} + (y_{1i} - y_{0i})w_i.
\end{aligned}
$$

It is worth noting that the term $(y_{1i}-y_{0i})$ on the right-hand side in the second equation above indicates the causal effect of the workshop for the individual i. We are interested in estimating its

[12] It is known that the CVM with many covariates shows poor performance because of the so-called small cell (or empty cell) problem when the sample size is small. Although the PSM can overcome the curse of dimensionality, it is known that it does not perform well compared with the CVM when the sample size is small. In general, especially in finite sample settings, we do not know which matching method is superior a priori. Thus, we use both methods. Zhao (2004) discusses more about the differences between PSM and CVM.

average over the target population orthe average treatment effect (ATE): $ATE = E[y_{i1} - y_{i0}]$. However, we can only observe one of the potential outcomes, either y_1 or y_0 for each individual. The observed difference in the average of the outcome variables between the treated and the untreated may be biased due to the selection.[13] Underthe assumption of the independence of the potential outcomes (y_{0i}, y_{1i}) from the participation status w_i conditioning on a set of confounders X_i, i.e., $w_i \perp (y_{0i}, y_{1i}) | X_i$, the average treatment effect conditional on $X_i = X$ can be derived by $ATE(X) = E[y_{i1} | X_i = X] - E[y_{i0} | X_i = X]$.

Averaging this conditional ATE over the distribution of X_i yields the average treatment effect. However, the dimension of X_i may be large, and it becomes difficult to find a pair of individuals who have X_i equivalent or close to X. To avoid the issue of the curse of dimensionality, Rosenbaum and Rubin (1983) propose the PSM method by noting that if $p(X_i)$, denoting the conditional probability that an individual receives a treatment given all measured confounders X, is between 0 and 1, then $w_i \perp (y_{0i}, y_{1i}) | p(X_i)$ under the assumption of $w_i \perp (y_{0i}, y_{1i}) | X_i$.

$$E[y_{1i} | p(X_i), w_i = 1] - E[y_{0i} | p(X_i), w_i = 0] = E[y_{1i} | p(X_i)] - E[y_{0i} | p(X_i)].^{14}$$

For the PSM method, we ran a probit regression of workshop participation using only samples from the W villages where the local input dealers held the WICI workshop in February 2011 because no residents in the NW villages were informed or had access to the WICI workshop. Next, we calculate the propensity score of workshop participation for all the samples based on the probit

[13] The observed difference is expressed as follows:

$$\begin{aligned} E[y_i | w_i = 1] - E[y_i | w_i = 0] &= E[y_{i1} | w_i = 1] - E[y_{i0} | w_i = 0] \\ &= E[y_{i1} | w_i = 1] - E[y_{i0} | w_i = 1] + E[y_{i0} | w_i = 1] - E[y_{i0} | w_i = 0] \\ &= E[y_{i1} - y_{i0} | w_i = 1] + E[y_{i0} | w_i = 1] - E[y_{i0} | w_i = 0], \end{aligned}$$

where the first term on the right-hand side of the last equality is the average treatment effect among the participants. The difference between the second and third terms indicates the selection bias caused by the difference in the untreated outcome between the participants and non-participants. If the participation status is determined at random, the selection bias will be zero.
We are also interested in the average effect of the workshop among the non- participants, that is, the average treatment effect on the untreated ($ATU = E[y_{i1} - y_{i0} | w_i = 0]$). It is also interesting to estimate the average effect of the residents in the NW villages.

[14] Averaging the conditional ATE over the distribution of X_i among a subgroup (e.g., the non-participants or the residents in NW villages) yields the average treatment effect of the subgroup.

regression estimates with the following covariates: the number of family members, a dummy variable indicating a female-headed household, age and years of schooling completed by the household head, a set of dummy variables indicating the risk preference of the household head, scores of the cognitive ability and financial literacy quizzes, the size of farm land, the total value of household assets, a dummy indicating whether the household is a member of a local community group, distance to the nearest agricultural input shop which deals with the WICI, and the location dummies. The probit regression results are given in Table 3. The second (Column 2) specification includes the village dummies as covariates, while the first specification (Column 1) does not.

Table 3: WICI workshop participation among W village residents

Dependent variable	1 if WICI workshop participant	
Variable	Probit	Probit
	(1)	(2)
Number of household members	0.0818**	0.0838**
	(0.034)	(0.035)
1 if is a female-headed household	-0.178	-0.201
	(0.210)	(0.217)
Age of household head	0.0248***	0.0271***
	(0.007)	(0.007)
Years of schooling of household head	-0.033	-0.034
	(0.037)	(0.038)
1 if is the most risk averse	-0.244	-0.277
	(0.224)	(0.234)
1 if is the most risk loving	-0.0169	-0.0651
	(0.220)	(0.234)
1 if answers on risk preference questions being irrational	-0.229	-0.23
	(0.300)	(0.313)
Score of cognitive ability quiz	0.277***	0.285***
	(0.095)	(0.096)
Score of financial literacy quiz	-0.0471	-0.0591
	(0.077)	(0.078)
Size of farmland (acres)	0.0275	0.0245
	(0.027)	(0.028)
Value of household assets in 1 million Ksh	-0.115	-0.186
	(0.429)	(0.449)
1 if participating in self-help groups	0.0734	0.0793
	(0.215)	(0.222)
Travel time to the nearest WICI sales agent (hours)	-0.0132	-0.05082
	(0.076)	(0.158)
Constant	-2.379***	
	(0.618)	
Village fixed effects	No	Yes
Observations	283	283

Source: Authors.

The WICI workshop participants tend to have larger household sizes, are older, show better performance in the cognitive ability quiz (which was completed by the interview respondent, typically household head, at the JICA survey) than the non-participants in the W villages. We calculate the propensity scores based on the coefficient estimates from the first (Column 1) specification since the two specifications generate similar estimates, and we adopt the parsimonious model.

The average "treatment" effects of the workshop on awareness of the insurance concept (i.e., whether the respondent understands the insurance concept) and the adoption of WICI are estimated using the matched samples based on their propensity scores. The same effects are also estimated by the CVM method where matching is done based on the Mahalanobis distance of the same co-variates as those used to calculate the propensity score for the PSM. The estimations of the average "treatment" effects are given in Table 4.[15]

[15] Given the possible difference in the treatment effect between the workshop participants and the non-participants, the over-representation of the participants could cause upward bias (downward) in the PSM and CVM estimates of the average effect if the average effectof the participants is larger (smaller) than that of the non-participants. We also estimated the average effect on the untreated, that is, $ATU = E[y_{i1} - y_{i0} | w_i = 0]$. Since the non- participants in the W and NW villages were randomly selected from the resident list of each village, they are supposed to be representative of the village population. The results are similar to those in Table 4 and presented in Appendix 2.

Table 4: Estimations of average treatment effects of WICI workshop participation

Dependent variable	1 if understand insurance concept		1 if purchasing WICI	
	PSM	CVM	PSM	CVM
	(1)	(2)	(3)	(4)
ATE of WICI workshop participant	0.250***	0.270***	0.463***	0.469***
	(0.040)	(0.049)	(0.041)	(0.043)
Observations	422	422	422	422

Source: Authors.

Standard errors obtained by bootstrap with 50 replicates are given in parentheses. The PSM uses 1 to many matching with Epanechnikov kernel weights and 0.06 of bandwidth based on propensity scores calculated by the coefficient estimates in Column 1 in Table 3. The CVM uses Mahalanobis distance of the same covariate with thePSM for matching. All the specifications pass the balanced test of the matched sample.

We obtain similar estimation results of the average effects of the WICI workshop regardless of the different estimation methods. The first two columns show that the WICI workshop enhances participants' level of understanding of the insurance concept. The point estimate by the PSM (CVM) indicates that the proportion of those who understand the concept increases by 25 (27) percentage points because of the workshop.

Similarly, the last two columns show the positive effect of the WICI workshop on the decision whether to purchase WICI products. The PSM and the CVM obtain almost similar point estimates of the average effect, which indicates that the workshop increases the proportion of farmers who buy the WICI products by 46 percentage points. Although selection by unobserved characteristics of the samples is not controlled, it seems that the WICI workshops run by local agricultural input dealers were crucial factors in farmers' decision to purchase new insurance products that did not previously exist and were new to them.

Determinants of the WICI adoption among the workshop participants

In this subsection, we focus on individual factors other than awareness of or curiosity about the WICI, that affect farmers' decision to adopt the insurance. As seen in Table 2, among the participants there is no difference in level of understanding of the concept of insurance between those who buy the WICI products and those who do not. Table 5 presents the regression coefficients of the WICIpurchase decision among the workshop participants. The first column reports the result of the ordinary least squares (OLS) regression on the adoption of the individual characteristics with a region (Nyanza) dummy. Moreover, the second column reports the result of the OLS regression with almost the same regressors but with village fixed effects instead of the region dummy.

Table 5: Determinants of WICI purchase among the WICI workshop participants

	Dependent variable: 1 if purchasing WICI	
Variable	OLS	OLS
	(1)	(2)
Number of household members	0.010	0.007
	(0.018)	(0.019)
1 if is a female-headed household	-0.194	-0.161
	(0.111)	(0.121)
Age of household head	-0.0066**	-0.006
	(0.003)	(0.004)
Years of schooling of household head	0.0421**	0.0384*
	(0.018)	(0.018)
1 if is the most risk averse	-0.216*	-0.192
	(0.106)	(0.112)
1 if is the most risk loving	-0.025	0.028
	(0.055)	(0.070)
1 if answers on risk preference questions being irrational	-0.185	-0.142
	(0.158)	(0.179)
Score of cognitive ability quiz	0.026	0.019
	(0.060)	(0.064)
Score of financial literacy quiz	0.035	0.039
	(0.040)	(0.049)
Size of farmland (acres)	0.0285**	0.0286**
	(0.013)	(0.013)
Value of household assets in 1 million Ksh	0.297	0.432
	(0.430)	(0.501)
1 if participating in self-help groups	0.004	-0.010
	(0.118)	-0.138
Travel time to the nearest WICI sales agent (hours)	-0.0899***	-0.062
	(0.022)	(0.084)
Constant	0.510*	
	(0.252)	
Village fixed effects	No	Yes
Number of observations	161	161
R-squared	0.182	0.224

Source: Authors.
Clustered standard errors at village level are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5 shows several interesting findings. Firstly, it appears that farmers'education is positively correlated with demand for WICI, which is consistent with previous literature (for example, Carter et al. 2021; Cole et al. 2013; Giné and Yang 2009; Hill et al. 2013; Jiang et al. 2014; Landry and Jahan-Parvar 2011 and Rampini and Viswanathan 2010). Even though the effect of education may depend on how education changes the farmers' perception of the prior probability of the insurance (Cole et al. 2013), as this result implies, it is likely that people need to have a certain level of cognitive ability to purchase insurance. A recent study from Cai et al. (2020) considers the different roles of educational interventions and subsidies that allow skeptical people to try out insurance and learn about its value from their own experiences. While the result of this study cannot speak to the breadth of the interventions that Cai et al. evaluate, it supports their suggestion if the goal is to maximize insurance uptake over the longer term. Secondly, farmland size is an important determinant of the purchase decision. Since the WICI is bundled with agricultural inputs, it is plausible that the higher demand for WICI is accompanied by a higher demand for inputs due to the larger farm size. Moreover, it is thought that individuals who own larger agricultural land and thus could be exposed to larger rainfall risks seek out insurance more often. Thirdly, the cost related to travel time to access the input shop dealing with WICI products appears to be influential in the demand for insurance; travel time costs did not, however, attract much attention in the previous literature. The coefficient estimate indicates that if it takes 1 hour more for individuals to reach their nearest WICI agent, they are 9 percentage points less likely to take up insurance. This significance disappears when the village fixed effects are included since the variation of the travel time variable becomes much smaller within a village. Here, the regression uses only the samples, which were the workshop participants and, therefore, had an opportunity to purchase the WICI products on-site during the workshop. Hence, the negative coefficient should not reflect the effect of travel cost to purchase WICI products itself but reflect something else, such as the trust of the input dealers. Fourthly, risk-averse people are less likely to buy the WICI products, although the demand for insurance is theoretically associated with risk aversity. By contradicting to the theory, it is possible that risk-averse people are hesitant to purchase the WICI products since the WICI products are new and can be considered as risky investments for some individuals, whose future returns are uncertain. Moreover, farmers do not know whether insurance providers are trustworthy or not. Thus, risk-averse people tend to buy the WICI products less. This is consistent with findings from the existing studies that examine the relationship between risk preference and insurance take up and explain it by applying the model of technology adoption (for example, Carlan et al. 2013; Duflo, Kremer and Robinson 2011; Giné and Yang 2009; Hill 2009). Additionally, one could expect that participation in self-help groups, such as rotating savings and credit associations (ROSCAs), may decrease insurance demand because they can act as informal social security networks and work as risk management tools, thereby substituting the role of insurances. However, we do not find such evidence that enforces this motivation for the adoption of formal insurance in this research. This is possible because the ROSCAs' informal insurance mitigates damage from idiosyncratic risks, whereas the WICI covers covariate weather shocks. The types of risks that they can cover may be very different and, hence, they are not substitutes. Similarly, one could also expect that financial literacy enhances insurance purchases. It is logical that individuals with higher financial literacy have higher take up of insurance because they are more likely to be capable of examining the benefit of insurance and making a decision whether to purchase new financial products. However, there is no such evidence from this analysis.

5. Conclusions

In recent years, a myriad of index-based insurances have emerged as a means to improve household risk management. The newly developed products are designed to diversify key sources of risk and have the feature that payouts are based on observable and exogenous events, thereby eliminating adverse selection and moral hazard as sources of market failure. The weather index insurance discussed in this paper deals with the risk caused by rainfall, which is one of the most significant risks in western Kenya. We targeted nearly 500 smallholder farmers and collected their knowledge on insurance and willingness to purchase the insurance product using information from our household survey uniquely designed to examine their decision on insurance take up. Even though insurance takeup should be price sensitive, our study results suggest that several non-price factors further change farmers' behavior toward demand for insurance.

To summarize our key findings: (i) insurance acknowledgment and its correct understanding, (ii) years of education, and (iii) travel time to the nearest input dealer selling WICI are all crucial factors determining demand for WICI. The workshop designed to promote a better understanding of insurance among farmers contributes to the correct understanding of the insurance and significantly increases the demand for insurance. This result shows that the recognition and understanding of the utility of index insurance have a great impact on the take up of insurance. The evidence also suggests that it is important to provide some educational programs on new financial products when introducing them to agricultural households, especially without a high level of financial literacy. Consistent with other studies, our research outcomes also suggest that school education has a significant effect on demand for risk-mitigating products. In addition, it is found that there is a significant negative relation between travel time to the insurance sales point and tendencies to take up insurance. Ensuring convenience for consumers to purchase insurance, such as improving transportation access and increasing sales points, may also be important for the widespread adoption of insurance.

While presenting some interesting results, there are several drawbacks to this research. First, as mentioned earlier, the data set we assessed was collected from a study where the sampling design was not that of a randomized control trial. Thus, although we tried to reduce estimation bias by utilizing several methodologies, it may still remain. While we did not have control over the study design, this is the major limitation of this research, which shows the importance of study planning in order to draw reliable methodological impact evaluations.

In addition, it is worth noting that the adaption analysis in this study is static, based on a one-time decision by rural small holder farmers to make a first purchase of an index insurance product. Thus, we must acknowledge that this study lacks the ability to see the dynamic aspect of respondents' behavior, namely whether they repurchased this new novel insurance in the following seasons. Cai et al. (2020) note that demand in the second year falls if insured farmers do not observe an insurance payoff in the first year. They mention that farmers learning from their own experience significantly affects their take-up decisions in subsequent periods. Therefore, it should be noted that one-off demand for a novel product like that examined in this study could be easier to stimulate than sustained demand. Moreover, as the weather index insurance market matures and product familiarity increases among the population, the effect of non-price barriers to insurance adoption may wane. In this sense, lower prices today could have dynamic effects by accelerating the process of learning and product diffusion. However, a full analysis of this question is outside the scope of this paper. In addition to insurance familiarity, improvements in insurance contract design may also help mitigate the impact of non-price factors. Comparison analysis between the insurance products in the market remains an interesting are for future study. It would also be interesting to explore the influence of insurance providers and their educational program contents. Familiarity and the relationship of the purchaser to the providers may also have significant effects on the take up of insurance.

This paper does not directly analyze how basis risk affects insurance demand. None of the randomized "treatments" is specifically designed to measure the importance of basis risk for insurance demand; instead, the focus is on within-village variation amongst farmers, each facing a similar level of index basis risk. However, further analysis with a focus on basis risk would be an important and interesting topic for future research. Specifically, as Harrison et al. (2020 and 2021) have pointed out, "nudging" farmers to buy insurance, which is what the workshops examined in this study tried to do, can make people worse off, especially when inherent basis risk on insurance is high. We recognize, therefore, that the weather index insurance adopted in this study may have a quality issue and higher basis risks due to its simple design. Educational programs that enhance farmers' knowledge and understanding of insurance and the new insurance product should positively benefit farmers. However, if farmers are nudged to purchase insurance at those workshops without a correct understanding of the product's mechanisms, it may put them in a less fortunate position. Together with what Harrison et al. have pointed out about nudging efforts from the insurance providers (2020 and 2021), the overall quality of insurance should also be examined further.[16]

[16] This point was also discussed by numerous authors in recent studies. See for example, Benami and Carter 2021; Carter et al.2017; Harrison et al. 2020; and Jenson and Barrett 2017)

Lastly, other household characteristics that are out of the scope of our research are household religion, time preference, the experience of weather-related shocks such as drought or flood, and access to other financial services. These factors may affect farmers' behavior towards insurance. In addition, alternative models of selling insurance, such as selling it alongside other financial services (e.g. Giné et al. 2009) or marketing insurance in a group setting (e.g. Cole2007), could also be a promising way to improve insurance adoption rates among farmers. Not only weather index insurance but also the microinsurance market as a whole, are still at the incipient stage of development. Therefore, drawing practical implications from the empirical study results will further develop these products and their usage.

Given the limitations of the indications in this study as listed above, fundamental discussions on index insurance quality and the relationship between insurance demand and welfare impacts are still underway. Further research on index-based insurances and their dynamics in relation to structure and uptake is expected to contribute to the future development of risk-transferring products for low-income farmers.

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Appendices

Appendix 1: Definition of Variables

VARIABLES	Definition of variable
Household size	Number of individuals (of any age) in the household
1 if female-headed household	Dummy variable equal to 1 if household head is female
Age of household head	Age of household head in years
Years of schooling of household head	Years of schooling of the household head
Risk preference	Answers to the question whether he/she wants to play a set of 7 hypothetical lotteries estimating the individual's risk preference (0 = risk averse < 7 = risk loving)
Financial literacy	Number of correct answers to a set of 4 hypothetical questions (see APPENDIX B) to check financial literacy (0 <= financial literacy <= 4)
Land size for farming	Amount of total land size for cultivation
Total assets (1000Ksh)	Total value of all assets including financial assets, household assets and livestock inventory (value in 1000 Ksh)
1 if participating in self-help groups	Dummy variable equal to 1 if any member of the household is participating in a local self-help group (e.g. ROSCA)
Travel time to the nearest WICI sales agent (minutes)	Travel time (in minutes) to the nearest agrovet where the household can buy the WICI

Source: Authors.

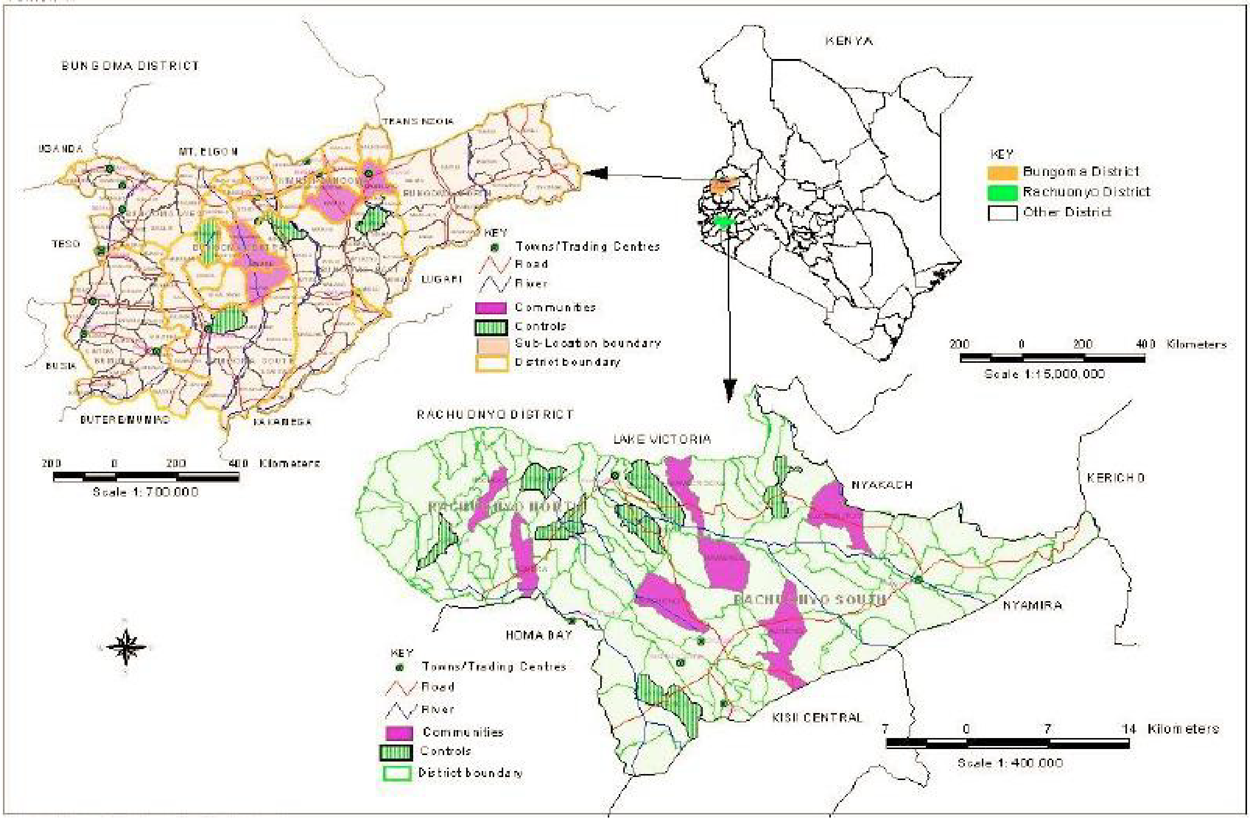
Appendix 2: Estimations of average treatment effects of WICI workshop participation among the non-participants

Dependent variable	1 if understand insurance concept		1 if purchasing WICI	
	PSM	CVM	PSM	CVM
	(1)	(2)	(3)	(4)
ATU of WICI workshop participant	0.269***	0.319***	0.461***	0.467***
	(0.059)	(0.039)	(0.040)	(0.058)
Observations	422	422	422	422

Source: Authors.

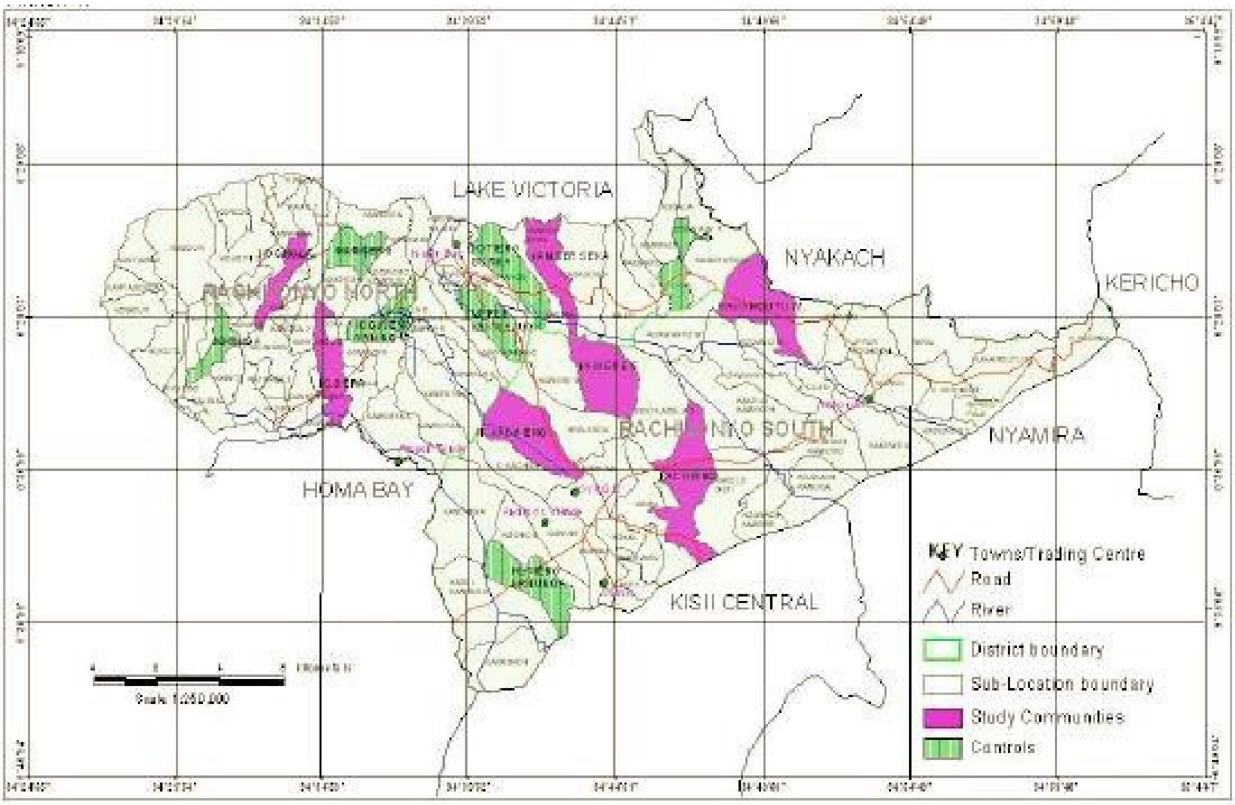
Standard errors obtained by bootstrap with 50 replicates are given in parentheses. The PSM uses 1 to many matching with Epanechnikov kernel weights and 0.06 of bandwidth based on propensity scores calculated by the coefficient estimates in Column 1 in Table 3. The CVM uses Mahalanobis distance of the same covariate with thePSM for matching. All the specifications pass the balanced test of the matched samples.

Figure 1: Location of Study



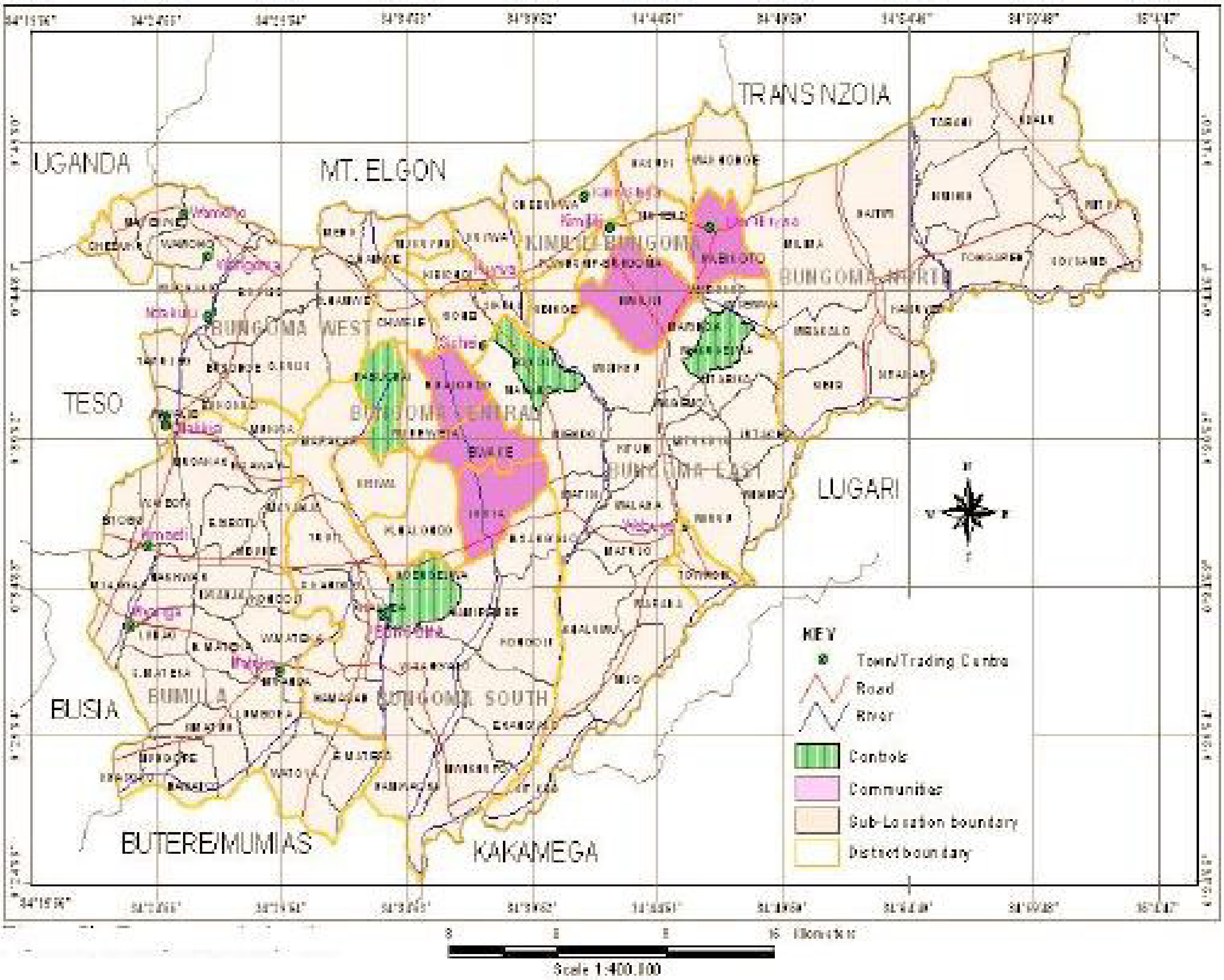
Source: JICA (2012)

Figure 2A: Rachuonyo Study Sites



Source: JICA (2012)

Figure 2B: Bungoma Study Sites



Source: JICA (2012)

Abstract (in Japanese)

要約

旱魃や過剰降雨に起因する農作物の収量減がもたらす負の厚生効果を和らげる手段として農村地域では天候インデックス型保険が有望視されているが、本稿ではケニア農村部の小規模農家 495 世帯を対象とした調査データを活用して小規模農家の天候インデックス型保険の加入要因を分析している。本研究では教育年数が保険加入に有意に影響を及ぼすことに加えて、保険商品のより良い理解が保険需要を増加させることが明らかとなった。分析結果からは、新しい金融商品を小規模農村世帯に導入する際には保険商品理解のための教育プログラムをあわせて提供することの重要性が示唆されている。一方、そもそも信頼性の高いインパクト評価を実施するには調査デザインが肝要であり、その点における本分析の限界に留意した上で、本稿が農業保険発展の一助となり小規模農家の厚生向上に役立つことを願っている。

キーワード: 農業、天候リスク、天候インデックス型保険、農村世帯、ケニア