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Weather index insurance, agricultural input use, and crop productivity in Kenya

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Abstract
Weather risk is a serious issue in the African small farm sector that will further increase due to climate change. Farmers typically react by using low amounts of agricultural inputs. Low input use can help to minimize financial loss in bad years, but is also associated with low average yield and income. Increasing small farm productivity and income is an important prerequisite for rural poverty reduction and food security. Crop insurance could incentivize farmers to increase their input use, but indemnity-based crop insurance programs are plagued by market failures. This article contributes to the emerging literature on the role of weather index insurance (WII). We use data from a survey of farmers in Kenya, where a commercial WII scheme has been operating for several years. Regression models with instrumental variables are used to analyze WII uptake and effects on input use and crop productivity. Results show that WII uptake is positively and significantly associated with the use of chemical fertilizer and improved seeds, and also with crop yield. We conclude that upscaling WII programs may help to spur agricultural development in the small farm sector.

Keywords Weather risk · Crop insurance · Fertilizer · Small farms · Impact evaluation · Africa

1 Introduction

Growth in agricultural productivity remains a key mechanism for poverty reduction and food security, especially when this growth happens in the small farm sector of developing countries (World Bank 2008; Onyutha 2018). Agricultural growth requires the use of modern inputs and technologies (Minten and Barrett 2008; Otsuka and Larson 2013; Shiferaw et al. 2014; Theriault et al. 2018). However, in the African small farm sector, use of modern inputs and technologies is often low and hampered by significant weather risk (Evenson and Gollin 2003; Morris et al. 2007; Duflo et al. 2008; Alem et al. 2010; Jayne et al. 2014; Kathage et al. 2016). Due to climate change, weather risk will further increase. African governments have tried to increase the use of fertilizer and other inputs through various policy approaches, including input market reforms and subsidies (Jayne et al. 2003; Jayne and Rashid 2013; Mason et al. 2017). Another approach is providing insurance against weather risk, but the availability of agricultural insurance in developing countries remains limited.

Smallholder farmers often use low amounts of external inputs as a risk-management strategy (Feder et al. 1985). Keeping expenditures for purchased inputs low helps to minimize financial loss in years with bad weather conditions when crop yields are low anyway. But low input use also constrains yields in good years and thus hampers growth in average farm productivity and income. Crop insurance that compensates farmers for low yields in bad years could provide incentives for higher input use (Horowitz and Lichtenberg 1993; Mishra et al. 2005). Yet, due to high transaction costs, traditional indemnity-based crop insurance hardly exists in developing countries. Weather index insurance (WII) may be a suitable alternative involving lower transaction costs. Unlike indemnity-based insurance, WII makes payouts to farmers not according to actual crop damage but based on an objectively measurable weather variable, such as rainfall (IFAD 2010). Thus, WII helps to reduce problems of moral hazard and adverse selection that are common in traditional insurance schemes (Barnett and Mahul 2007). WII could incentivize higher input use by reducing risk and easing liquidity constraints (Boucher et al. 2008; Farrin and Miranda 2015). But empirical evidence about the actual effects is limited (Farrin and Murray 2014; Carter et al. 2016).

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WII products have not yet been adopted widely among smallholder farmers (Binswanger-Mkhize 2012; Cole et al. 2013; Sibiko et al. 2018). Impact analyses based on observational data hardly exist. A few studies have used experimental approaches to evaluate the effects of WII. Giné and Yang (2009) conducted a randomized controlled trial with farmers in Malawi and, somewhat surprisingly, found a negative influence of WII on credit uptake for technology adoption. Other studies, building on field experiments with smallholders in Ghana, Ethiopia, and Mali, reported positive effects on input use and other types of farm investments (e.g., Karlan et al. 2014; Berhane et al. 2015; Elabed and Carter 2015). These studies are very useful to better understand farmers' behavior, but the controlled experimental setup does not allow reliable predictions about the effects of commercial WII schemes, where insurance terms may be different. We contribute to this literature by using observational data collected in Kenya, where a commercial WII scheme has been operating for several years.

In particular, we look at effects of *Kilimo Salama*, a commercial WII scheme selling insurance contracts to maize farmers in Kenya (Greatrex et al. 2015; Sibiko et al. 2018). WII uptake is still limited among smallholders. For our survey, we used a stratified random sampling procedure to cover a sufficient number of insured and non-insured farmers. The first objective of our research is to analyze determinants of WII uptake. The second objective is to evaluate the effects of WII uptake on input use and crop productivity. We use treatment-effect models with instrumental variables to reduce possible problems of endogeneity. Results can help policymakers to better understand the potential of WII to contribute to agricultural development.

2 Weather index insurance in Kenya

Kenya is an interesting country to study index insurance, because commercial initiatives in the crop and livestock sector have been implemented already since 2009 (FSD 2013; Jensen et al. 2016). One of the WII initiatives in Kenya is the *Kilimo Salama* Program of the Syngenta Foundation for Sustainable Agriculture (IFC 2015). *Kilimo Salama* offers rainfall index insurance contracts against the risks of drought and excess rain. Insurance contracts are tied to the purchase of inputs and provided to farmers through local input dealers. These dealers sell inputs with and without insurance option. The insurance option is not available for all inputs, but for maize seeds, fertilizers, and other agro-chemicals from specified companies. These inputs are available with and without insurance option. If farmers decide to purchase insurance, they pay for the contract as part of the input cost. While the WII contracts differ somewhat for different products, the insurance fee is typically in a range of 10–20% of the input price (Sibiko et al. 2018), that is, products with insurance cost 10–20% more than products without insurance. The local input dealer can register insured farmers on behalf of the insurance provider. Alternatively, farmers can register themselves by sending a text message to the insurance provider with a unique code that is found in the input package. The mobile-phone-based registration is done at the farm, just before the input is applied, marking the location of the farm as well as the contract start.

Rainfall at the weather station closest to the individual farm is monitored for a certain period of time, usually 21 days. If during this period rainfall remains below (or for excess rain exceeds) a certain threshold, payout is triggered and sent to farmers automatically through mobile money networks. *Kilimo Salama* covers the full cost of the insured inputs. The quick payout well before the end of the growing season allows insured farmers to replant in cases of drought or excess rain (Greatrex et al. 2015). This should act as a strong incentive for farmers to use more inputs. For uninsured farmers, fears of financial loss and liquidity constraints in unfavorable years are important factors explaining low input intensities.

3 Materials and methods

3.1 Farm survey

This research builds on data from a survey of maize farmers in Embu County in the eastern region of Kenya. Embu is one of the areas where WII interventions were first launched back in 2009 (Sina and Jacobi 2012). The weather in Embu is characterized by erratic rainfall and frequent droughts (Ngetich et al. 2014).

The survey was carried out in mid-2014, with questions referring to the 2013 agricultural year. We used a multi-stage stratified sampling procedure to select households to be included. First, we purposively selected Embu-East, which has a larger number of farmers insured through *Kilimo Salama* than other sub-counties. Embu-East has two administrative divisions, Kyeni and Runyenjes. In both divisions, we randomly selected three sub-locations (smallest administrative units). In each of the six sub-locations, we selected all farmers that had purchased a WII contract any time between 2009 and 2013, using lists provided by *Kilimo Salama* field officers. This resulted in a sub-sample of 152 farmers, 87 of which were insured in 2013.[1] In addition, we collected data from 234 randomly selected farmers

[1] The other 65 (out of the 152) farmers were insured in any of the previous years but not in 2013. Farmers decide for every season anew whether or not they purchase inputs with insurance, so purchase dynamics are observed (Sibiko et al. 2018).

that had never purchased insurance in the same six sub-locations, resulting in a total sample of 386 farmers.[2]

The two sub-samples of farmers who had purchased and not purchased WII are representative for this region of Kenya, even though the stratified sampling procedure leads to an over-representation of insured farmers in the sample (i.e., the share of insured farmers in the sample is larger than the share of insured farmers in the population). Our sample includes about 23% farmers that were insured in 2013, whereas actual insurance uptake in that year was below 10% in Embu-East, and even much lower in other regions of Kenya.

Primary data from the 386 farmers in our sample were collected through face-to-face interviews with the household heads. The interviews were carried out by a small team of local enumerators, whom we hired specifically for this survey, trained, and supervised during the field work. The survey questionnaire was carefully designed and pretested. It captured information on farm production, weather shocks, farmers' risk preferences,[3] and experiences with WII. A broad range of socioeconomic household and contextual variables was also captured.

3.2 Modeling WII uptake

The first objective of this research is to analyze determinants of WII uptake. This is done with a probit model of the following type:

$$C_i = \alpha_0 + \alpha_1{}'\mathbf{Z}_i + u_i \tag{1}$$

where C_i is a dummy variable that takes a value of one if farmer i had purchased a WII contract in 2013 and zero otherwise, $\mathbf{Z}_i$ is a vector of explanatory variables, and $u_i$is a random error term. We expect that farm and farmer characteristics, such as farm size, sex, age, and education of the decision-maker, as well as individual risk preferences and weather shocks experienced during the recent past could influence insurance uptake (Giné et al. 2008; Hill et al. 2013). Furthermore, we include variables to describe the institutional context, such as access to credit, agricultural extension, and transport as elements in the vector $\mathbf{Z}_i$.

3.3 Modeling effects of WII uptake

The second research objective is to evaluate the effects of WII uptake. In general, insurance uptake can affect farm performance through a number of pathways, resulting from the multiple effects of risk on agricultural systems. Insurance can influence short-term and long-term farm investments, the types of crop and livestock species produced, the choice of marketing channels, and many other types of decisions (Wu 1999; Goodwin et al. 2004; Karlan et al. 2014). Here, we are particularly interested in possible effects on the use of agricultural inputs and productivity in maize farming. We hypothesize that insurance uptake leads to higher input intensity and thus also to higher productivity per unit of land. On the input side, we focus on chemical fertilizer and improved seeds, as these are the most commonly purchased inputs that farmers in Kenya use for maize production.

It should be mentioned that for this analysis of the effects of WII uptake we only consider the 87 farmers that had purchased insurance in 2013 as "treated" (farmers with insurance). The 65 farmers that had purchased WII in previous years but had decided not to purchase insurance in 2013 are included in the control group. This is justified, because the insurance contract only refers to one specific season and is therefore unlikely to have any effect in subsequent years. In a robustness check we test whether previous insurance uptake has any effect on input use in 2013.

As explained, WII in the *Kilimo Salama* Program is tied to the purchase of inputs and covers the cost of the inputs in case of drought or excess rain. In other words, the decisions of which inputs to use and whether or not to buy insurance are not completely independent; farmers who do not use any purchased inputs do not have the chance to buy insurance. Hence, in this particular context it would not make sense to model the effect of WII uptake on the binary decision of whether or not to use purchased inputs. However, in Embu-East this binary decision is of lesser relevance, because most farmers use some purchased inputs anyway, regardless of whether or not they are insured. For instance, 98% of the farmers in our sample use chemical fertilizer in maize production (see details below). Against this background, the more relevant decision is how much fertilizer to use. This decision on input intensity is not predetermined by the WII contract. While the insurance fee is proportional to the quantity of input purchased, the input quantity is chosen by the farmer himself/herself. It is realistic to assume that the farmer first decides whether or not to choose the WII option and then decides how much input to buy.[4]

[2] We had targeted a total sample size of 400, but were unable to locate 14 of the randomly selected non-insured farmers.

[3] Risk preferences were captured through farmers' self-assessment, using a range from 1 (extremely risk averse) to 10 (extremely risk taking). This is a common and accepted alternative to more time-consuming experimental approaches of evaluating risk preferences (Dohmen et al. 2011).

[4] We cannot rule out completely that the sequence of decision-making is reversed, namely that farmers first decide how much input to use and then choose whether or not to buy insurance afterwards. This would lead to issues of reverse causality that we try to address with an instrumental variable approach, as explained below. However, not all input types and brands are available with and without insurance option, so it is more likely that the decision to buy insurance is made before the decision on input quantity. This assumed sequence is also in line with experimental evidence on the impact of WII on input use (Karlan et al. 2014; Berhane et al. 2015; Elabed and Carter 2015).

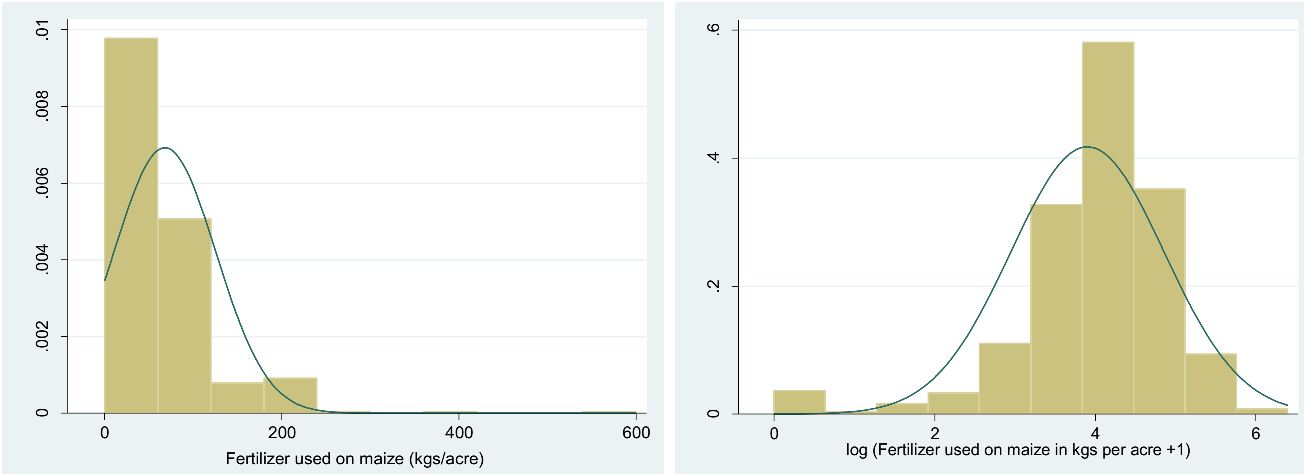

Fig. 1 Distribution of fertilizer use in linear and logarithmic terms

We model the effect of WII uptake as follows:

$$Y_i = \beta_0 + \beta_1{}'\mathbf{X}_i + \delta C_i + \varepsilon_i \qquad (2)$$

where Y_i is the quantity of input used by farmer i in the 2013 agricultural season, $\mathbf{X}_i$is a vector of covariates, $C_i$is the dummy for WII purchase, as defined before, and $\varepsilon_i$is a random error term. $\mathbf{X}_i$ includes similar farm, household, and contextual variables as those used in Eq. (1), plus a few others that may influence input demand, such as input price.

We estimate separate models for the use of chemical fertilizer and improved seeds. Fertilizer use is measured in kg per acre. Seed use is measured in monetary terms, namely in thousand Kenyan shillings (Ksh) per acre, to reflect seed quality differences. Different types of maize varieties and hybrids are available at different prices. Higher-priced seeds tend to be of higher quality and have superior agronomic properties than lower-priced seeds. Farm-saved seeds are valued at the mean market price of grain to reflect the opportunity cost. As the distribution of both input variables is highly skewed, we use log-transformations to get more symmetrical distributions (Figs. 1 and 2 in the Appendix).[5] As the logarithm of zero is not defined, we added one for all observations before taking logs, thus avoiding missing values through variable transformation. The hypothesis that WII uptake leads to higher input intensity is tested through the parameter δ. A positive and significant estimate would confirm the hypothesis.

In addition to input use decisions, we are also interested in the effect of WII on maize productivity. This is estimated with the same type of model as the one shown in Eq. (2), only using maize yield per acre as dependent variable. We start with a model that only includes general socioeconomic variables plus the WII dummy, C_i. In subsequent specifications, we add the different inputs used, so that the model becomes a regular production function. Maize yield and input quantities used are expressed in logarithmic terms, leading to a Cobb-Douglas functional form. Following Battese (1997), dummy variables are included to account for zero observations for particular inputs. We expect that WII uptake affects maize yield primarily through its effect on the use of fertilizer, seeds, and possibly other inputs. In a series of models, we therefore add the different inputs in a stepwise manner. If it is true that WII contributes to productivity increases through its effect on input intensity, δ should be positive and significant in the specification without inputs included, and should then shrink in magnitude and turn insignificant as the relevant inputs are gradually controlled for.

3.4 Addressing endogeneity

If the variable C_i (WII uptake) in Eq. (2) is exogenous, estimation with ordinary least squares (OLS) would provide unbiased estimates of the WII effect, δ. However, it is possible that C_i is endogenous, which would lead to correlation with the error term and biased impact estimates. One possible reason for endogeneity could be reverse causality, as mentioned above. Another reason could be unobserved heterogeneity, meaning that WII uptake is influenced by unobserved characteristics that are also correlated with input quantity or productivity. A common way to reduce endogeneity bias is to use instrumental variable (IV) estimators (Angrist et al. 1996).

We estimate the models in Eq. (2) with treatment-effect IV estimators (Greene 2012, p. 931). This requires identification of at least one instrument that is correlated with the treatment variable (WII uptake) but uncorrelated with any of the outcome variables (input use and maize yield). We tried various instruments and were able to find one that fulfills all

[5] Other variable transformations would have been possible, but the log-transformation has the advantage of easy interpretation in percentage terms. The log-transformation also leads to a better empirical fit than some of the tested alternatives.

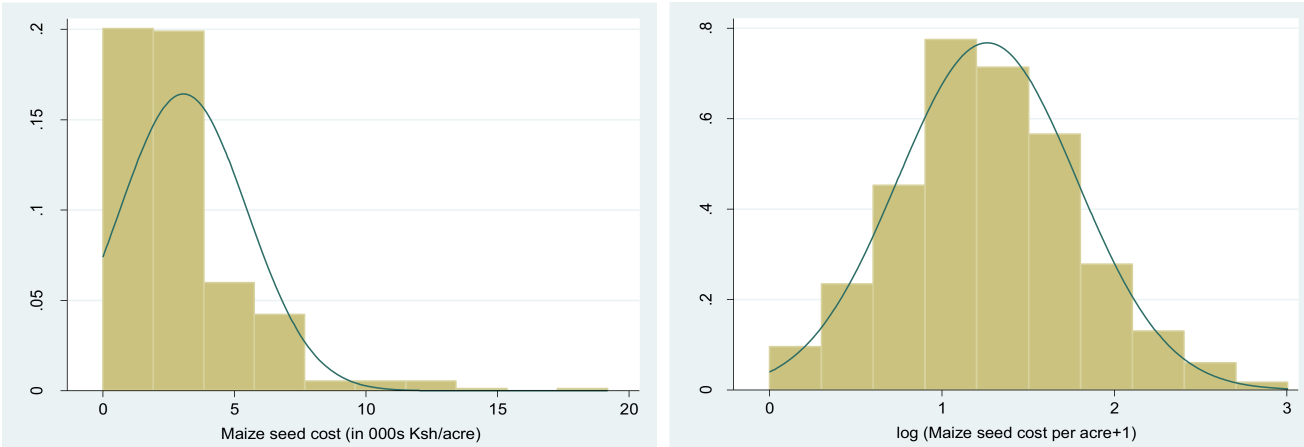

Fig. 2 Distribution of maize seed costs in linear and logarithmic terms

requirements for instrument validity. The instrument used here is a dummy indicating whether the farmer received information or training on WII during the year 2013. The WII training sessions are publicly announced and held for larger groups of farmers, usually in the market centers. These training sessions are organized and conducted by *Kilimo Salama* field officers that only focus on the WII program, that is, the field officers are different from the public agricultural extension agents.

As expected, having participated in at least one such training session significantly increases the probability of WII uptake, which is the precondition for instrument relevance. However, it is possible that training participation is endogenous itself. For instance, it could be that farmers who are using more inputs anyway, or who are planning to use more inputs, would be more likely to attend the WII training sessions. In that case, the instrument would be directly correlated with input use quantities, not only through the mechanism of WII uptake. Following Di Falco et al. (2011) and Kabunga et al. (2014), we tested for this possibility and found no direct correlation between WII training participation and input quantities, neither for the subsample of non-insured farmers nor for the total sample (Table 6 in the Appendix).[6] Yet it is still possible that there are factors that jointly influence training participation and input use or yield. Such other factors could be related to farmer characteristics – such as gender, age, education, and off-farm activities – or household characteristics – such as income and asset ownership. We tested this possibility by correlating training participation with various farmer and household variables, as shown in Table 7 in the Appendix. None of the correlation coefficients is statistically significant. We therefore cautiously conclude that the instrument is valid.

[6] The instrument is a dummy variable. We used Spearman's correlation analysis, which is suitable for variables that are not normally distributed. The statistical independence between the variables was also verified by using Pearson's chi-squared tests.

Of course, we can only test for correlation between the instrument and observed characteristics. But the fact that WII training participation is neither significantly correlated with the outcome variables nor with any of the observed characteristics makes it unlikely that there is significant correlation with important unobserved factors. In any case, rigorously proving instrument validity is hardly possible, especially not with cross-sectional data, so that causal inference should be drawn only with caution.

The treatment-effect model that we estimate is specified as follows:

Selection equation:

$$C_i = \alpha_0 + \alpha_1 \mathbf{X}_i + \alpha_2 T_i + u_i \tag{3}$$

Outcome equation:

$$Y_i = \beta_0 + \beta_1 \mathbf{X}_i + \delta C_i + \varepsilon_i \tag{4}$$

where T_i is the WII training dummy that we use as the instrument for WII uptake. The other variables are as defined above. The two error terms (u_i,ε_i) are assumed to be jointly normally distributed with mean zero and covariance matrix equal to:

$$\begin{bmatrix} \sigma^2 & \rho\sigma \\ \rho\sigma & 1 \end{bmatrix} \tag{5}$$

This implies that the error term correlation (ρ) is controlled for within the model, solving the endogeneity problem in WII uptake. We estimate eqs. (3) and (4) simultaneously, using the full information maximum likelihood estimator in STATA that also properly adjusts the standard errors to account for the fact that C_i is a generated variable in eq. (4).

4 Results

4.1 Descriptive statistics

Table 1 shows descriptive statistics of key variables for the total sample, and also separately for insured and non-insured farmers. Farmers in the sample are typical smallholders with an average farm size of 2.2 acres. Many of the differences between insured and non-insured farmers are statistically significant. For instance, insured farmers own more land and other assets, are more likely to be members of a farmer group, less likely to be male, and derive a larger share of their total income from farming, as opposed to off-farm income sources. According to farmers' recall, drought (severe rainfall shortages) occurred 2.5 times during the five years prior to the survey, interestingly without a significant difference between insured and non-insured farmers.

Table 2 provides descriptive statistics for maize output and relevant inputs used. Four farmers in our sample did not cultivate maize in 2013; these observations were excluded for this part of the analysis. The average maize yield in our sample is 1.1 t/acre, which is comparable to the 1.3 t/acre

Table 1 Descriptive statistics

Variables	Total ($n = 386$)		Insured ($n = 87$)		Non-insured ($n = 299$)	
Household and farm characteristics						
Total land owned (acres)	2.20	(2.47)	3.08***	(3.44)	1.95	(2.05)
Cultivated area (acres)	2.09	(1.92)	2.71***	(2.73)	1.91	(1.57)
Total annual income (000 Ksh)	192.92	(368.99)	185.04	(244.61)	195.22	(398.26)
Share of off-farm income	0.33	(0.33)	0.26**	(0.31)	0.35	(0.33)
Off-farm occupation (dummy)	33.42	(47.23)	29.89	(46.04)	34.45	(47.60)
Crop diversification (crop count)	2.80	(1.06)	2.74	(1.17)	2.82	(1.03)
Value of livestock owned (000 Ksh)	63.01	(116.90)	65.43	(53.63)	62.31	(129.70)
Frequency of drought in past 5 years	2.52	(1.54)	2.62	(1.50)	2.49	(1.55)
Own irrigation equipment (dummy)	7.51	(26.39)	9.20	(29.06)	7.02	(25.60)
Risk averse (dummy)	19.95	(40.01)	21.84	(41.55)	19.40	(39.61)
Risk neutral (dummy)	22.54	(41.84)	18.39	(38.97)	23.75	(42.62)
Risk taking (dummy)	57.51	(49.50)	59.77	(49.32)	56.86	(49.61)
Male household head (dummy)	67.88	(46.76)	59.77*	(49.32)	70.23	(45.80)
Age of farmer (years)	52.11	(14.56)	55.73***	(12.94)	51.06	(14.85)
Education of farmer (years)	8.18	(4.01)	8.05	(4.48)	8.22	(3.87)
Male labor endowment (adult males/acre)	1.03	(1.35)	0.80*	(0.77)	1.10	(1.47)
Female labor endowment (adult females/acre)	1.09	(1.19)	0.76***	(0.83)	1.19	(1.26)
Own transportation (dummy)	59.33	(49.19)	68.97**	(46.53)	56.52	(49.66)
Institutional characteristics						
Group membership (dummy)	88.08	(32.44)	93.10*	(25.49)	86.62	(34.10)
Access to credit (dummy)	38.60	(48.75)	40.23	(49.32)	38.13	(48.65)
Agricultural extension in 2013 (contacts)	1.51	(3.54)	1.26	(1.69)	1.60	(3.99)
Time to input market (minutes)	32.51	(25.30)	30.48	(24.14)	33.11	(25.64)
Fertilizer price (Ksh/kg)	65.53	(4.65)	65.33	(2.88)	65.59	(5.05)
WII-related characteristics						
Purchased WII before 2013 (dummy)	28.24	(45.07)	67.82***	(46.99)	16.72	(37.38)
Received WII training (dummy)	41.19	(49.28)	66.67***	(47.41)	33.78	(47.38)
Knows location of weather station (dummy)	53.37	(49.95)	77.01***	(42.32)	46.49	(49.96)

Notes: Sample mean values are shown with standard deviations in parentheses. Insured and non-insured refer to WII uptake in 2013. Risk attitudes were captured based on farmers' own subjective rating on a scale from 0 (extremely risk averse) to 10 (extremely risk taking). We classify 0–4 responses as "risk averse", 5–6 responses as "risk neutral", and 7–10 responses as "risk taking". Ksh, Kenyan shillings. * Mean difference between insured and non-insured significant at 10% level. ** Mean difference between insured and non-insured significant at 5% level. *** Mean difference between insured and non-insured significant at 1% level

Table 2 Maize production and input use

Variables	Total ($n = 382$)		Insured ($n = 86$)		Non-insured ($n = 296$)	
Maize yield (kg/acre)	1119.78	(905.64)	1118.65	(841.71)	1120.11	(924.74)
Seed cost (000 Ksh/acre)	3.07	(2.43)	3.03	(2.18)	3.08	(2.50)
Fertilizer (kg/acre)	67.91	(57.64)	63.32	(45.37)	69.25	(60.74)
Used fertilizer (dummy)	97.64	(15.19)	97.67	(15.16)	97.64	(15.22)
Pesticide (000 Ksh/acre)	0.75	(1.20)	0.76	(1.09)	0.75	(1.23)
Used pesticides (dummy)	69.11	(46.26)	72.09	(45.12)	68.24	(46.63)
Manure (t/acre)	4.99	(18.29)	3.46*	(4.73)	5.44	(20.61)
Used manure (dummy)	56.02	(49.70)	56.98	(49.80)	55.74	(49.75)
Labor (days/acre)	82.12	(64.06)	75.25	(55.51)	84.11	(66.30)
Maize area (acres)	1.01	(0.92)	1.32***	(1.35)	0.91	(0.72)

Notes: Sample mean values are shown with standard deviations in parentheses. Insured and non-insured refer to WII uptake in 2013. Ksh, Kenyan shillings. * Mean difference between insured and non-insured significant at 10% level. *** Mean difference between insured and non-insured significant at 1% level

reported by Ariga et al. (2008) in a Kenya-wide panel study. As mentioned, almost all farmers in the sample used chemical fertilizer. The average fertilizer intensity of 68 kg/acre is relatively high if compared to African smallholder conditions in general, but lower than the 100 kg/acre that are recommended by the Kenyan Ministry of Agriculture (Mason et al. 2017). The national average fertilizer use in maize is 60 kg/acre, varying between 75 kg/acre in high-potential areas to below 10 kg/acre in the drier lowlands (Ariga et al. 2008). More than 50% of the farmers in our sample also used animal manure in addition to chemical fertilizer.

Interestingly, in Table 2 we do not observe significant difference in maize yield between insured and non-insured farmers. Nor do we see significant differences in the use of chemical fertilizer and most other inputs, except for manure where the use is somewhat lower among insured farmers. These patterns are against our expectations. However, these are only descriptive comparisons, based on which we cannot draw conclusions about the effects of WII uptake.

As mentioned above, the group of non-insured includes farmers that had never purchased insurance and also farmers that had purchased insurance previously, but not in 2013. Table 8 in the Appendix shows selected socioeconomic and input use variables for both types of non-insured farmers. No significant differences are observed, suggesting that it is permissible to club both types of farmers into one group.

4.2 Determinants of WII uptake

Table 3 presents results of the probit model used to explain WII uptake, as described in eq. (1). WII training has a significantly positive effect, as we would expect. The marginal effect indicates that participation in at least one training session increases the likelihood of WII uptake by 15.8 percentage points. As explained, WII training is the instrument that we use for WII uptake in the treatment-effect models.

The results in Table 3 further show that knowing where the reference weather station for the farm is located, and previous own experience with the insurance program also increase the probability of WII uptake significantly. These results suggest that farmers' familiarity with WII and the underlying principles is still limited, meaning that additional training would be important for encouraging wider adoption. This is consistent with recent evidence on the drivers of demand for WII in Kenya and other African countries (Takahashi et al. 2016; Sibiko et al. 2018).

The other estimates in Table 3 indicate that the farmer's age has a positive influence on WII uptake; each additional year increases the probability of purchasing WII by 0.3 percentage points. Older and more experienced farmers often have a higher willingness to pay for crop insurance (Sherrick et al. 2004). Furthermore, risk aversion seems to be correlated with the likelihood of WII uptake. As one would expect, risk-neutral farmers are less likely to purchase insurance than risk-averse farmers that constitute the reference group in this model specification.

A few previous studies found a negative relationship between risk aversion and WII demand (e.g., Giné et al. 2008; Hill et al. 2013). This can especially occur in situations where understanding of the functioning of WII is low. In such cases, WII is sometimes seen as a risky type of institutional innovation. As discussed, also in our sample familiarity with the details of WII is still limited. This is reflected by farm size and other asset ownership variables (e.g., means of transportation) having a positive effect on insurance uptake. In principle, WII could be attractive especially for small and marginalized farms. But limited knowledge and familiarity with an innovation add to the subjectively felt risk, so that better-off

Table 3 Probit model results: WII uptake decision

Variables	Coefficients		Marginal effects	
WII training (dummy)	0.798***	(0.182)	0.158***	(0.034)
Knows location of weather station (dummy)	0.558***	(0.208)	0.110***	(0.040)
Purchased WII before 2013 (dummy)	1.233***	(0.203)	0.244***	(0.034)
Male household head (dummy)	−0.215	(0.195)	−0.042	(0.038)
Age of farmer (years)	0.015**	(0.007)	0.003**	(0.001)
Education of farmer (years)	0.016	(0.026)	0.003	(0.005)
Risk neutral (dummy)	−0.586**	(0.278)	−0.116**	(0.054)
Risk taking (dummy)	−0.256	(0.222)	−0.051	(0.044)
Total land owned (acres)	0.054*	(0.030)	0.011*	(0.006)
Frequency of drought in past 5 years	−0.035	(0.057)	−0.007	(0.011)
Share of off-farm income	−0.540*	(0.285)	−0.107*	(0.057)
Crop diversification (crop count)	−0.081	(0.096)	−0.016	(0.019)
Agricultural extension in 2013 (contacts)	−0.090*	(0.050)	−0.018*	(0.010)
Group membership (dummy)	0.525**	(0.257)	0.104**	(0.051)
Credit access (dummy)	−0.113	(0.196)	−0.022	(0.039)
Own transportation (dummy)	0.335*	(0.194)	0.066*	(0.038)
Constant	−2.714***	(0.603)		
Location dummies included	Yes			
Log likelihood	−137.784			
Chi-squared	114.09***			
Pseudo R^2	0.331			

Notes: The number of observations is 386. Coefficients and marginal effects are shown with robust standard errors in parentheses. * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

farmers are often more willing to adopt during the early stages (Sherrick et al. 2004; Kabunga et al. 2014).

Membership in farmer groups increases the likelihood of WII uptake by about 10 percentage points. Farmer groups can facilitate access to information and provide important platforms for learning about technical and institutional innovations (Shiferaw et al. 2009; Fischer and Qaim 2012). Somewhat surprising in this connection is the fact that agricultural extension is negatively associated with WII uptake. However, the public extension agents in Kenya do not promote WII and are themselves not very knowledgeable about the *Kilimo Salama* insurance products. This alone would not explain a negative effect on WII uptake, but it is possible that farmers with better access to the public extension service are less receptive to advice by private input dealers and insurance officers. Finally, Table 3 shows that the share of off-farm income has a negative effect on WII uptake. This may be explained by farmers with more off-farm income having better capacity to self-insure against agricultural production risks.

4.3 Effects on input use

Results of the treatment-effect models for the use of fertilizer and improved maize seeds are shown in Table 4, including estimates for the outcome and selection equations. The parameter *athrho*, which is shown in the lower part of Table 4, is an indicator of the correlation between the outcome and selection equations. This correlation is statistically significant in both models, suggesting that endogeneity bias would be an issue if not controlled for. The negative sign of this correlation means that there would be negative bias (Kabunga et al. 2014). In other words, farmers that purchased WII are those that otherwise would have used lower-priced seeds and smaller quantities of fertilizer. This is plausible and a first indication that the availability and uptake of WII may indeed affect farmers' input use decisions significantly.

This is confirmed by the other estimation results in Table 4. Controlling for other factors, WII uptake is positively and significantly associated with the intensity of fertilizer and improved maize seed use. Given the log-linear functional form in the outcome equation, the coefficient estimate of 0.409 implies that WII uptake is associated with a 51% higher fertilizer quantity used.[7]

[7] The percentage effect in a log-linear specification is calculated as [100 (exp(δ)-1)].

Table 4 Effect of WII uptake on the use of chemical fertilizer and improved seeds

Variables	Fertilizer (log, kg/acre)	WII uptake	Maize seeds (log, 000 Ksh/acre)	WII uptake
WII uptake (dummy)	0.409**		0.500**	
	(0.205)		(0.228)	
Age of farmer (years)	−0.010***	0.021***	−0.005*	0.021***
	(0.004)	(0.007)	(0.002)	(0.007)
Age squared	0.0003*	−0.0007*	0.0002*	−0.0007**
	(0.0001)	(0.0003)	(0.0001)	(0.0004)
Education of farmer (years)	0.001	0.014	0.011	0.012
	(0.016)	(0.022)	(0.008)	(0.023)
Cultivated area (acres)	−0.048**	0.053	−0.031	0.047
	(0.022)	(0.040)	(0.020)	(0.046)
Male labor endowment	0.106***	−0.042	0.060***	−0.079
(adult males/acre)	(0.030)	(0.101)	(0.020)	(0.104)
Female labor endowment	0.030	−0.244**	0.022	−0.192
(adult females/acre)	(0.040)	(0.114)	(0.028)	(0.118)
Livestock value (log, 000 Ksh)	0.157***	0.029	0.051**	0.025
	(0.044)	(0.073)	(0.020)	(0.070)
Risk neutral (dummy)	0.225	−0.700***	0.146	−0.666***
	(0.153)	(0.255)	(0.092)	(0.247)
Risk taking (dummy)	0.274**	−0.460**	0.146**	−0.446**
	(0.130)	(0.213)	(0.067)	(0.208)
Crop diversification (crop count)	0.064	−0.072	0.064**	−0.050
	(0.046)	(0.092)	(0.028)	(0.091)
Share of off-farm income	0.089	−0.407	0.098	−0.344
	(0.146)	(0.264)	(0.092)	(0.262)
Access to credit (dummy)	−0.011	0.091	0.011	0.119
	(0.092)	(0.171)	(0.058)	(0.166)
Agricultural extension (contacts)	0.026***	−0.052*	0.005	−0.042
	(0.007)	(0.030)	(0.007)	(0.029)
Own transportation (dummy)	0.097	0.300	−0.044	0.312*
	(0.099)	(0.193)	(0.065)	(0.188)
Time to input market (log, minutes)	−0.218***	−0.091	−0.069**	−0.062
	(0.064)	(0.109)	(0.035)	(0.110)
Fertilizer price (log, Ksh/kg)	−1.114**	0.015	0.282	0.170
	(0.538)	(1.150)	(0.380)	(1.143)
WII training (dummy)		0.837***		0.804***
		(0.168)		(0.160)
Village dummies included	Yes	Yes	Yes	Yes
Constant	8.084***	−0.195	−0.463	−0.971
	(2.283)	(4.842)	(1.600)	(4.861)
ath(rho)	−0.257*		−0.597*	
	(0.132)		(0.313)	
ln(sigma)	−0.155**		−0.674***	
	(0.0636)		(0.069)	
Wald test of independent equations	3.79*		3.63*	

Notes: Number of observations is 382 (only farmers growing maize). Coefficients are shown with standard errors in parentheses. Second-stage outcome equations are shown first, followed by first-stage selection equations (see eqs. 3 and 4). * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

Similarly, WII uptake is associated with a 65% higher investment in maize seeds. These are quite large estimates that we cautiously interpret as effects of WII. The estimates suggest that farmers' input use is strongly influenced by weather risk, which is line with economic theory. Hence, access to insurance tends to increase farmers' input use.

In Table 2, we saw that insured farmers do not spend more on fertilizer or seeds than non-insured farmers. Not accounting for confounding factors and negative bias could easily lead to the false conclusion that WII has no effect on input use. In reality, without the insurance option those farmers that purchased WII would have had a significantly lower input intensity. These results are consistent with recent WII impact evaluations building on experimental approaches (Karlan et al. 2014; Berhane et al. 2015).

There are also several other variables that influence input intensity, such as farmer's age, livestock assets, and farm size. Controlling for other factors, farms with smaller areas use larger amounts of fertilizer per acre, probably because they suffer more from land constraints. Family labor availability also affects input use; farmers with more male family labor use more fertilizer and also invest more in seeds. On the one hand, higher intensity in the use of these inputs is associated with higher labor requirements because all farm operations are carried out manually. On the other hand, more family labor means that less has to be spent on hired labor, so that more financial resources can be allocated to the purchase of productivity-enhancing inputs (Abdulai and Huffman 2014).

The results in Table 4 also show that risk-taking farmers spend significantly more on fertilizer and improved seeds than their risk-averse counterparts. This is consistent with the literature (e.g., Feder et al. 1985; Alem et al. 2010), and also with the finding that crop insurance can lead to higher input use. Beyond insurance, farmers also use other strategies to cope with risk, such as diversifying the types of crops produced on their farms. We use a simple count of the different crop species produced as a proxy for farm diversification. This crop count has a positive and significant coefficient in the outcome equation for maize seeds, which might point at a certain substitution of on-farm risk management strategies: the risk reduction due to a more diverse crop portfolio may permit the purchase of more expensive seeds that are associated with a higher level of financial risk.

In terms of institutional factors, the intensity of fertilizer use increases with better access to agricultural extension. The public extension service in Kenya promotes the use of fertilizer in maize to improve food security (Mason et al. 2017). The effect of extension on maize seed investments is not statistically significant. Market distance affects the use of both types of inputs negatively. In remoter locations, farmers have worse access to information and higher transportation and transaction costs (Alene et al. 2008). Finally, fertilizer price has a negative effect on fertilizer intensity, as expected. An increase in the price by 1% results in a decrease in fertilizer use by more than 1%, implying that fertilizer demand is price-elastic. Both models include village dummies to control for unobserved village-level differences, such as infrastructure or agro-climatic conditions.

In a robustness check we re-estimated the input use models and also included previous insurance uptake (before 2013) as an additional control variable. While previous insurance uptake affects uptake in 2013 in the selection equations, it has no significant effect on input use in the outcome equations. Hence, including previously insured farmers that had not purchased WII in 2013 in the control group, as we do, seems appropriate.

WII contracts in the *Kilimo Salama* Program are tied to the use of purchased inputs. Nevertheless, we saw in Table 2 that insured farmers use significantly less animal manure than non-insured farmers. To test whether this difference is possibly caused by WII uptake, we ran two other treatment-effect models with manure use as the outcome variable, one for the whole sample and the second confined to the sub-sample of manure users. Estimation results of these additional models are shown in Table 9 in the Appendix. They confirm that WII uptake significantly reduces manure use, possibly because chemical fertilizer is seen as a substitute. This effect is undesirable, because – in addition to providing nutrients – manure applications enhance soil organic matter and thus contribute to fertility and conservation (Holden and Lunduka 2012; Wainaina et al. 2016). Possibly, farmers that purchased WII use more manure on crops other than maize, which we cannot analyze with our data. In follow-up research it could be interesting to analyze effects of WII uptake on farm management practices more broadly, beyond the focus on one particular crop.

4.4 Effects on maize productivity

We now estimate the association of WII uptake and maize productivity, as explained above. Estimation results are shown in Table 5 (first-stage equations are shown in Table 10 in the Appendix). In column (1) of Table 5 we do not control for any of the agricultural inputs used, because we expect the main effect of WII uptake to be channeled through input use. WII uptake has a positive and significant coefficient. The coefficient

Table 5 Effect of WII uptake on maize yield

Variables	(1)	(2)	(3)	(4)	(5)	(6)
WII uptake (dummy)	0.485**	0.433*	0.453**	0.423*	−0.538	−0.605
	(0.246)	(0.245)	(0.210)	(0.228)	(1.037)	(0.584)
Seed (log, 000 Ksh/acre)						0.172**
						(0.072)
Fertilizer (log, kg/acre)					0.492***	0.442***
					(0.099)	(0.081)
Fertilizer not used (dummy)					−1.012***	−1.017***
					(0.370)	(0.380)
Pesticide (log, 000 Ksh/acre)				0.019	−0.014	−0.012
				(0.050)	(0.052)	(0.048)
Pesticide not used (dummy)				−0.180*	−0.076	−0.060
				(0.097)	(0.092)	(0.094)
Manure (log, t/acre)			0.168***	0.158***	0.133**	0.106*
			(0.058)	(0.058)	(0.057)	(0.056)
Manure not used (dummy)			−0.074	−0.063	0.022	0.026
			(0.083)	(0.083)	(0.079)	(0.078)
Labor (log, days/acre)		0.320***	0.299***	0.299***	0.176**	0.140*
		(0.073)	(0.070)	(0.070)	(0.073)	(0.076)
Maize area (log, acres)	−0.470***	−0.290***	−0.231***	−0.227***	−0.005	0.019
	(0.066)	(0.073)	(0.073)	(0.077)	(0.171)	(0.121)
Male household head (dummy)	−0.020	−0.004	0.010	−0.003	−0.136	−0.133
	(0.097)	(0.095)	(0.092)	(0.092)	(0.124)	(0.101)
Education of farmer (years)	0.030**	0.027*	0.024*	0.021	0.026**	0.024*
	(0.015)	(0.015)	(0.014)	(0.014)	(0.013)	(0.013)
Age of farmer (years)	−0.0002	−0.0001	0.0003	0.0004	0.007	0.008*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.004)
Off-farm occupation (dummy)	0.196**	0.209**	0.199**	0.195**	0.208**	0.219**
	(0.090)	(0.087)	(0.086)	(0.085)	(0.088)	(0.088)
Livestock value (000 Ksh)	0.005***	0.004***	0.004***	0.003***	0.003***	0.003***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0007)	(0.0007)
Frequency of droughts in past 5 years	−0.028	−0.037	−0.040	−0.043*	−0.051**	−0.047*
	(0.026)	(0.025)	(0.025)	(0.025)	(0.026)	(0.025)
Owns irrigation equipment (dummy)	0.603***	0.587***	0.526***	0.524***	0.553***	0.533***
	(0.122)	(0.110)	(0.115)	(0.116)	(0.162)	(0.151)
Agricultural extension (contacts)	−0.005	−0.006	−0.005	−0.007	−0.016	−0.015
	(0.011)	(0.011)	(0.012)	(0.012)	(0.013)	(0.013)
Time to input market (log, minutes)	−0.106*	−0.112*	−0.100*	−0.099*	−0.035	−0.025
	(0.059)	(0.058)	(0.057)	(0.058)	(0.055)	(0.055)
Village dummies included	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.704**	−0.506*	−0.501*	−0.404	−0.500*	−0.495*
	(0.279)	(0.282)	(0.279)	(0.285)	(0.297)	(0.282)
ath(rho)	*−0.231*	*−0.200*	*−0.223*	*−0.206*	*0.619*	*0.679*
	(0.182)	(0.189)	(0.159)	(0.172)	(1.063)	(0.613)
ln(sigma)	−0.250***	−0.280***	−0.290***	−0.297***	−0.327	−0.325**
	(0.051)	(0.049)	(0.049)	(0.050)	(0.216)	(0.140)
Wald test of independent equations	1.61	1.12	1.97	1.43	0.34	1.23

Notes: Number of observations is 382 (only farmers growing maize). Coefficients of treatment-effect models are shown with standard errors in parentheses. The dependent variable in all models is the logarithm of maize yield measured in kg/acre. First-stage equations are shown in Table 10 (Appendix). * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

of 0.485 implies that WII uptake is associated with 62% higher maize yields.

In Columns (2) to (6) of Table 5, we add inputs as explanatory variables in a stepwise manner. Labor and manure both have significantly positive effects on maize yield, whereas the effect of pesticide use is insignificant. Inclusion of these three inputs in columns (2), (3), and (4) leads to a decrease in the WII coefficient, but the change is small and the WII effect remains positive and significant. Once we include fertilizer and seeds in columns (5) and (6), the coefficient for WII uptake decreases drastically and turns statistically insignificant. This underlines that WII uptake affects crop productivity mainly through a higher use of chemical fertilizer and improved seeds. As expected, the production elasticities of fertilizer and seeds themselves are positive and significant. Increasing fertilizer use by 1% leads to a maize yield increase of 0.49%, whereas increasing seed expenditures by 1% contributes to maize yield gains in a magnitude of 0.17%. The results suggest that these inputs are underused in Kenya, so policies aimed at increasing input intensity can contribute to agricultural growth.

5 Discussion and conclusion

Agricultural intensification is necessary for achieving productivity growth, rural development, and food security in Africa. However, due to various factors, smallholder farmers in Africa tend to underuse modern inputs and technologies. One important factor limiting higher input use is weather risk. Crop insurance, which reduces financial risks in bad years, could possibly help. In this article, we have analyzed the role of weather index insurance (WII) with observational data from maize farmers in Kenya. In particular, we have looked at *Kilimo Salama*, a commercial WII scheme that has been operating in Kenya for several years. We have examined determinants of WII uptake and associations with input use and crop productivity. IV treatment-effect models were developed and estimated for cautious causal inference.

The estimation results have shown that WII uptake is positively and significantly associated with higher use of chemical fertilizer and improved seeds. Controlling for other factors, WII uptake is associated with 50% higher fertilizer intensity and 65% higher expenditures for seeds. WII uptake is also associated with higher maize yields in a magnitude of 60%.

If the chosen instrument for WII uptake is valid, the estimates can be interpreted in a causal sense, which would mean that access to WII causally increases input use and yield. This would be consistent with economic theory and also with the evidence available from experimental studies (Karlan et al. 2014; Berhane et al. 2015; Elabed and Carter 2015). We have carried out various tests for instrument validity, but irrefutably proving causality is difficult with cross-section data alone. Nevertheless, even when not interpreting in a causal way, the sizable and significant positive associations between WII uptake, input use, and crop yield are interesting and add to the literature on weather index insurance in a smallholder context. The findings suggest that WII can be an important ingredient in strategies for agricultural growth and rural development against the background of rising climate uncertainties.

However, WII uptake is still very limited in Kenya and other countries of Africa, which is partly due to farmers finding it difficult to fully understand the functioning of WII schemes (Sibiko et al. 2018). Our data show that farmers with more experience and higher resource endowments are more likely to purchase insurance, pointing at perceived uncertainties that should be addressed through better training and provision of relevant information. So far, information about WII is primarily provided by *Kilimo Salama* field officers and input dealers. Also using other channels, such as the public agricultural extension service, could improve information flows and farmers' trust in the insurance products. Given that the Kenyan Ministry of Agriculture has ongoing initiatives that are aimed at raising farmers' input intensity, promoting WII would be a complementary policy. Our data suggest that providing WII training to existing farmer groups could be a useful approach, because groups facilitate collective learning and farmer-to-farmer exchange of knowledge.

A few limitations of our study need to be pointed out. First, as mentioned, causal inference needs to be done with caution. We can only be certain of positive associations. Second, the concrete effects of WII will always depend on the particular program design. *Kilimo Salama* ties insurance contracts to the purchase of farm inputs. With other types of contracts, effects may possibly differ. Hence, the concrete results should not be generalized. Third, we have analyzed WII in a region where most farmers have reasonable access to input markets. In other settings, where input markets are less well developed (e.g., due to more severe infrastructure constraints), associations between WII and input intensity will likely be smaller. Crop insurance can help reduce production risk but should not be seen as a magic bullet to overcome other types of market failures. Fourth, our results have shown that *Kilimo Salama* is positively associated with the use of external inputs, such as fertilizer and improved seeds, but negatively associated with the use of organic manure. Moreover, we have only focused on one particular crop, namely maize. Follow-up research is needed to analyze possible effects of WII uptake on sustainable farming practices more broadly.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Appendix

Table 6 Correlations between instrument and outcome variables

Outcome variables	Non-insured farmers ($n = 299$)	Total sample ($n = 386$)
Maize seed (000 Ksh/acre) (log)	−0.03 (0.63)	0.03 (0.56)
Fertilizer (kg/acre) (log)	−0.06 (0.28)	−0.02 (0.69)
Pesticide (000 Ksh/acre) (log)	−0.07 (0.20)	−0.04 (0.45)
Manure (t/acre) (log)	−0.05 (0.40)	−0.02 (0.76)
Labor (days/acre) (log)	−0.01 (0.81)	0.07 (0.19)
Maize yield (kg/acre) (log)	−0.09 (0.10)	−0.04 (0.40)
Maize revenue (000 Ksh/acre) (log)	0.01 (0.80)	0.08 (0.13)

Notes: Spearman's correlation coefficients are shown with *p*-values in parentheses. The instrument used is a dummy indicating whether or not the farmer received WII training in 2013

Table 7 Correlations between instrument and household characteristics

Variable	Correlation coefficient	*p*-values
Male household head (dummy)	−0.03	0.52
Age of farmer (years)	−0.00	0.94
Education of farmer (years)	0.07	0.19
Off-farm occupation (dummy)	−0.03	0.58
Value of land owned (000 Ksh)	0.03	0.59
Value of other assets owned (000 Ksh)	0.02	0.72
Total household income (000 Ksh)	−0.08	0.13

Notes: Spearman's correlation coefficients are shown. The instrument used is a dummy indicating whether or not the farmer received WII training in 2013

Table 8 Selected characteristics of non-insured farmers by previous insurance status

Variables	Previously insured ($n = 65$)		Not previously insured ($n = 234$)	
Total land owned (acres)	2.07	(2.09)	1.92	(2.05)
Education of farmer (years)	8.12	(3.63)	8.24	(3.92)
Fertilizer use (kg/acre)	63.04	(55.95)	69.66	(61.81)
Pesticide cost (000 Ksh/acre)	0.72	(0.88)	0.76	(1.29)

Notes: Sample mean values are shown with standard deviations in parentheses. Non-insured refers to WII uptake in 2013

Table 9 Effect of WII uptake on the use of animal manure

Variables	All maize farmers		Only manure users	
	Manure (log, t/acre)	WII uptake	Manure (log, MT/acre)	WII uptake
WII uptake (dummy)	−0.656*		−1.001***	
	(0.397)		(0.353)	
Age of farmer (years)	−0.004	0.022***	−0.002	0.020**
	(0.004)	(0.007)	(0.005)	(0.010)
Age squared	−0.0003*	−0.0006*	−0.0002	−0.0007
	(0.0002)	(0.0003)	(0.0003)	(0.0006)
Education of farmer (years)	0.010	0.019	0.038*	0.071**
	(0.016)	(0.023)	(0.022)	(0.032)
Cultivated area (acres)	−0.065**	0.058	−0.076**	0.078
	(0.029)	(0.039)	(0.037)	(0.050)
Male labor endowment	0.017	0.005	0.121	0.194
(adult males/area)	(0.052)	(0.100)	(0.096)	(0.147)
Female labor endowment	−0.016	−0.266**	−0.034	−0.426***
(adult females/area)	(0.068)	(0.116)	(0.090)	(0.156)
Livestock value (log, 000 Ksh)	0.222***	0.042	0.213***	0.242*
	(0.039)	(0.070)	(0.069)	(0.131)
Risk neutral (dummy)	0.090	−0.662**	−0.342*	−0.450
	(0.169)	(0.257)	(0.204)	(0.343)
Risk taking (dummy)	−0.020	−0.396*	−0.225	−0.194
	(0.138)	(0.217)	(0.172)	(0.290)
Crop diversification (crop count)	0.022	−0.053	0.033	−0.130
	(0.051)	(0.095)	(0.070)	(0.120)
Share of off-farm income	−0.171	−0.430	0.201	−0.489
	(0.181)	(0.264)	(0.236)	(0.367)
Access to credit (dummy)	0.022	0.104	0.132	−0.047
	(0.115)	(0.169)	(0.144)	(0.234)
Agricultural extension (contacts)	0.006	−0.051**	−0.013	−0.064
	(0.023)	(0.023)	(0.020)	(0.053)
Own transportation (dummy)	0.007	0.222	−0.210	−0.080
	(0.127)	(0.190)	(0.153)	(0.266)
Time to input market (log, minutes)	−0.092	−0.101	−0.237**	−0.196
	(0.072)	(0.110)	(0.092)	(0.154)
Fertilizer price (log, Ksh/kg)	0.172	−0.015	0.481	−1.537
	(0.878)	(0.996)	(0.824)	(1.731)
WII training (dummy)		0.797***		0.748***
		(0.166)		(0.210)
Constant	0.022	−0.200	−0.052	5.595
	(3.737)	(4.178)	(3.493)	(7.186)
Village dummies included	Yes	Yes	Yes	Yes
ath(rho)	0.364 (0.226)		0.711*** (0.239)	
ln(sigma)	0.043 (0.056)		−0.066 (0.084)	
Wald test of independent equations	2.58		8.83***	
Number of observations	382		214	

Notes: Coefficients are shown with standard errors in parentheses. * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

Table 10 First-stage equations for maize yield regressions

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Seed (log, 000 Ksh/acre)						0.122
						(0.121)
Fertilizer (log, kg/acre)					0.170	0.140
					(0.203)	(0.164)
Fertilizer not used (dummy)					−0.465	−0.514
					(0.894)	(0.674)
Pesticide (log, 000 Ksh/acre)				0.122	0.120	0.118
				(0.112)	(0.101)	(0.097)
Pesticide not used (dummy)				−0.128	−0.018	0.002
				(0.185)	(0.209)	(0.191)
Manure (log, t/acre)			0.109	0.091	0.117	0.097
			(0.112)	(0.115)	(0.117)	(0.117)
Manure not used (dummy)			0.080	0.080	0.007	0.006
			(0.167)	(0.168)	(0.172)	(0.164)
Labor (log, days/acre)		0.028	0.017	0.015	−0.044	−0.073
		(0.130)	(0.131)	(0.131)	(0.145)	(0.142)
Maize area (log, acres)	0.330***	0.347**	0.390***	0.437***	0.484***	0.498***
	(0.119)	(0.140)	(0.149)	(0.152)	(0.148)	(0.147)
Male household head (dummy)	−0.266	−0.262	−0.255	−0.247	−0.227	−0.219
	(0.185)	(0.184)	(0.185)	(0.187)	(0.177)	(0.176)
Education of farmer (years)	0.019	0.019	0.017	0.013	0.013	0.011
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Age of farmer (years)	0.020***	0.020***	0.020***	0.020***	0.022***	0.021***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Off-farm occupation (dummy)	0.098	0.098	0.093	0.069	0.021	0.029
	(0.197)	(0.197)	(0.196)	(0.194)	(0.182)	(0.182)
Livestock value (000 Ksh)	0.0009	0.0009	0.0008	0.0007	0.0002	0.0001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Frequency of droughts	0.032	0.030	0.024	0.018	−0.007	−0.008
	(0.052)	(0.051)	(0.052)	(0.051)	(0.076)	(0.059)
Owns irrigation equipment	0.359	0.351	0.333	0.311	0.251	0.230
(dummy)	(0.304)	(0.306)	(0.311)	(0.321)	(0.314)	(0.303)
Agricultural extension (contacts)	−0.052*	−0.051*	−0.046*	−0.048**	−0.043	−0.042
	(0.029)	(0.029)	(0.024)	(0.024)	(0.029)	(0.029)
Time to input market	−0.118	−0.119	−0.110	−0.119	−0.082	−0.072
(log, minutes)	(0.102)	(0.102)	(0.103)	(0.104)	(0.119)	(0.114)
WII training (dummy)	0.769***	0.763***	0.785***	0.787***	0.582	0.557*
	(0.163)	(0.164)	(0.164)	(0.166)	(0.524)	(0.322)
Village dummies included	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−1.729***	−1.732***	−1.775***	−1.621***	−1.573**	−1.554***
	(0.556)	(0.559)	(0.569)	(0.571)	(0.709)	(0.593)

Notes: Coefficients are shown with standard errors in parentheses. * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level

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