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Socioeconomic Factors and Crop Index Insurance Adoption Among Maize Farmers in Trans Nzoia County Kenya

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ABSTRACT: This study examined socioeconomic characteristics associated with actual adoption, premiums paid by insured farmers, and stated willingness to pay among interested nonadopters in Trans Nzoia County, Kenya. A descriptive cross-sectional survey used multistage sampling and structured household questionnaires. Descriptive statistics, a binary logistic model, conditional ordinary least squares regressions, and an awareness contingency table were examined. Actual adoption remained limited despite widespread reported awareness. Education, farming experience, gender, income source, and association membership were associated with adoption in the main reported model. Farm size was positively associated with premiums paid, whereas experience and production costs were positively associated with stated willingness to pay. Several demographic characteristics showed weak or uncertain relationships with the conditional monetary outcomes. The awareness table concerned consideration of purchase rather than completed adoption and was affected by questionnaire routing. The findings support differentiated interventions combining understandable contracts, accessible payment arrangements, and credible protection against locally relevant risks. They also indicate that actual payments and hypothetical willingness should be analyzed separately. The study concludes that increasing insurance participation requires attention to affordability, product quality, and household circumstances alongside information provision.

KEYWORDS: crop index insurance, maize farmers, adoption, premiums, willingness to pay, socioeconomic factors, Trans Nzoia, Kenya

1. INTRODUCTION

Maize producers make expenditure decisions before knowing the rainfall, temperature, yields, and prices that will determine their returns. Weather shocks can therefore damage both current consumption and the capital available for subsequent seasons. Evidence on global production links climatic trends and extreme weather to crop losses, while synthesis of drought experiments identifies maize as particularly sensitive to water stress (Daryanto et al., 2016; Lesk et al., 2016; Lobell et al., 2011; Zhao et al., 2017). Kenyan rainfall research also shows why seasonal totals alone may inadequately describe agricultural exposure: rainfall onset, cessation, and distribution within the growing period affect planting and production decisions (Ngetich et al., 2014; Rao et al., 2011).

The consequences of agricultural uncertainty extend beyond a single harvest. Households may reduce investment, diversify into less profitable activities, borrow, or sell productive assets when informal support cannot absorb a common shock. Research on rural risk sharing, consumption smoothing, and asset based poverty dynamics explains how these responses can preserve immediate survival while weakening future earning capacity (Carter & Barrett, 2006; Fafchamps, 1999; Kazianga & Udry, 2006; Townsend, 1994). Climate related disruptions also interact with food prices and wider food security, connecting farm level losses to household purchasing power (Brown & Kshirsagar, 2015; Vermeulen et al., 2012; Wheeler & von Braun, 2013). Formal insurance is thus potentially valuable as one component of a broader resilience strategy.

Index insurance pays according to a predefined indicator, such as rainfall or area yield, rather than an individual assessment of every insured farm. This structure can reduce loss verification costs and some opportunities for adverse selection or manipulation, making contracts feasible where conventional insurance is expensive to administer (Barnett & Mahul, 2007; Miranda, 1991; Miranda & Farrin, 2012; Rao, 2010). However, the indicator may diverge from a household's realized loss. This divergence, termed basis risk, means a farmer can suffer damage without receiving compensation or receive a payment without comparable damage.

Product evaluations and demand theory show that this limitation can weaken protection and discourage purchase even among risk averse households (Clarke, 2016; Elabed et al., 2013; Jensen et al., 2016; Norton et al., 2013).

International evidence identifies several interacting barriers to insurance participation. Liquidity shortages, limited understanding, distrust, unfamiliarity, and incomplete protection can each reduce demand, and their relative importance varies across settings (Ali et al., 2020; Cole et al., 2013; Giné et al., 2008; Marr et al., 2016). African reviews likewise caution that affordability, design, education, and institutional credibility must be considered together (Binswanger-Mkhize, 2012; Nshakira-Rukundo et al., 2021; Ntukamazina et al., 2017). These mechanisms imply that knowing insurance exists is different from understanding its payout rule, believing the provider will honor it, and possessing funds at enrollment.

Kenyan studies provide relevant evidence but do not remove the need for local analysis. Farmers' preferences for weather index contracts reflect attributes such as payout timing and access to information, while observed insurance participation has been linked to differences in input use and productivity (Sibiko et al., 2018; Sibiko & Qaim, 2020). Research in Laikipia distinguishes participation from the extent of insured input purchases, emphasizing the importance of distribution channels and extension access (Wairimu et al., 2016). Experimental work in Kenya also shows that the timing of premium collection can materially change demand (Casaburi & Willis, 2018). Their findings motivate examination of maize farmers in Trans Nzoia, rather than supplying coefficients that can be transferred directly to this county.

The present study investigates socioeconomic characteristics associated with crop index insurance among maize farmers in Trans Nzoia County. It addresses actual adoption, reported premiums paid by adopters, and stated willingness to pay among aware, interested nonadopters. These outcomes describe different decisions and should not be combined into one measure of insurance intensity. A further objective examines the relationship between awareness and the purchase consideration recorded in the questionnaire. By separating realized behavior from stated intentions and interpreting the available statistical evidence conservatively, the study provides practical guidance for insurers, extension services, farmer organizations, and county agricultural planning.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1 Expected Utility Information Asymmetry and Insurance Demand

Expected utility theory explains insurance purchase as a comparison between uncertain wealth with and without a contract. A risk averse decision maker may accept a certain premium to reduce exposure to unfavorable outcomes, although demand also depends on price, wealth, and the completeness of coverage (Cohen & Einav, 2007; Mossin, 1968; Pratt, 1964; Rothschild & Stiglitz, 1970). In agriculture, preferences must be evaluated alongside the distribution of possible losses, available savings, and alternative coping mechanisms.

Information asymmetry provides a complementary explanation. Markets can function poorly when buyers cannot judge quality or sellers cannot observe relevant differences among customers (Akerlof, 1970; Rothschild & Stiglitz, 1976). Index contracts reduce dependence on individual loss reporting, but they leave information problems concerning the indicator, payout thresholds, exclusions, and provider reliability. Evidence of adverse selection in crop insurance and moral hazard under conventional insurance illustrates why contract architecture matters (Makki & Somwaru, 2001; Smith & Goodwin, 1996). For farmers, clear information about how the index behaves during locally important losses is more useful than a general assurance that insurance reduces agricultural risk.

Behavioral evidence further qualifies a purely actuarial account of demand. Decisions can depend on reference points, the framing of losses, ambiguity, and the difficulty of evaluating infrequent events (Elabed & Carter, 2015; Kahneman & Tversky, 1979; Kunreuther & Pauly, 2005). Poverty can also affect attention and decision making through demanding circumstances, although these effects cannot be diagnosed from a household income category alone (Haushofer & Fehr, 2014). Farmers may reasonably hesitate when premiums are certain but benefits are uncertain and difficult to observe. The study therefore treats socioeconomic variables as indicators of circumstances associated with participation, rather than as proof of irrationality.

Insurance also interacts with self protection and informal support. Market insurance, savings, and prevention can substitute for or complement one another depending on their costs and effectiveness (Ehrlich & Becker, 1972). Rural households frequently share risks through transfers and reciprocal obligations, but common weather shocks and limited commitment restrict the protection these arrangements provide (Ligon et al., 2002; Townsend, 1995). Formal index insurance may strengthen or reshape existing networks rather than simply replace them (Mobarak & Rosenzweig, 2013; Trærup, 2012). This interaction is important when interpreting farmer association membership. A member may have better information about insurance yet less immediate demand because the group offers credit, savings, or mutual assistance. Alternatively, networks can distribute trustworthy information and facilitate coordinated purchasing.

2.2 Education Experience Gender and Household Characteristics

Education can improve comprehension of probabilities, premium schedules, and payout conditions, potentially reducing the effort required to assess a contract. Financial literacy research emphasizes that the ability to interpret financial products is distinct from merely having access to them (Lusardi & Mitchell, 2014). Agricultural learning studies similarly show that farmers acquire information through their own experience and through observation of others (Conley & Udry, 2010; Foster & Rosenzweig, 1995; Foster & Rosenzweig, 2010). Schooling is nevertheless an imperfect measure of insurance understanding. Farmers with limited formal education can possess extensive production knowledge, while highly educated respondents may misunderstand basis risk. For this study, primary and secondary education are compared with the postsecondary category rather than treated as a continuous measure of literacy.

Farming experience can influence adoption through greater exposure to weather variability, accumulated resources, and knowledge of agricultural services. It can also support alternative coping practices that reduce demand for a new product. Technology adoption theory highlights selection and heterogeneous returns, explaining why experienced farmers need not adopt identical innovations (Suri, 2011). Experimental insurance learning research indicates that experience with contract outcomes and practical teaching can influence subsequent decisions (Norton et al., 2014; Osiemo et al., 2026; Takahashi et al., 2016). Years spent farming are not equivalent to years holding insurance or receiving payouts. Accordingly, an experience coefficient can indicate accumulated agricultural familiarity without identifying which learning mechanism operates. This distinction matters for extension design: practical demonstrations of payout and nonpayout scenarios can target contract understanding more directly than age based segmentation.

Gender and household composition may influence access to resources, information, financial decision authority, and responsibility for managing shocks. Reviews and experiments identify differences in measured preferences across populations, while also demonstrating that social context affects those differences (Booth et al., 2014; Croson & Gneezy, 2009; Dohmen et al., 2011). Agricultural insurance choice research further shows that gender interacts with product design rather than yielding a single universal demand pattern (Akter et al., 2016). The household head's recorded sex should therefore not be interpreted as an intrinsic ranking of risk tolerance. Household size can represent labor availability, dependents, consumption needs, and competing expenditure demands at the same time.

2.3 Land Income Costs and Farmer Organizations

Farm size can influence the value exposed to weather shocks and the amount of cover a household seeks. Larger farms may pay higher total premiums even when premium rates and the proportion of production insured remain unchanged. Studies of crop insurance demand and farmers' coverage decisions support examining farm characteristics separately from simple enrollment (Carrer et al., 2020; Sherrick et al., 2004; Smith & Baquet, 1996). Land tenure may also affect investment incentives or documentation required by particular providers. However, insurance of seasonal inputs can remain relevant to tenants as well as owners. The present study therefore distinguishes registered owners, owners without title, and lessees. A nonsignificant tenure coefficient would not demonstrate that land rights are economically unimportant; it would indicate limited evidence for the specified contrast within this sample and model.

Income source may influence insurance through both liquidity and diversification. Nonfarm earnings can finance premiums before harvest, but they may also reduce dependence on crop income and the value of additional protection. Evidence on agricultural investment under risk constraints and on credit market risk rationing explains why resources and exposure jointly shape demand (Boucher et al., 2008; Karlan et al., 2014; Rosenzweig & Binswanger, 1993). Kenyan experiments on payment timing and insurance embedded credit provide concrete reasons to distinguish annual income from funds available when enrollment occurs (Casaburi & Willis, 2018; Ndegwa et al., 2020).

Production costs represent resources placed at risk before output is known. Farmers with greater expenditure may attach greater value to protection, yet high costs can simultaneously restrict the cash available for premiums. Research on insurance and production decisions demonstrates that risk reduction can alter investment choices, making the relationship potentially reciprocal (Cai, 2016; Cole et al., 2017; Hill et al., 2019). Studies examining willingness to pay also show that monetary valuation depends on the attributes and conditions of the offered product (Adjabui et al., 2019; Castellani et al., 2014; Liesivaara & Myyrä, 2014). Cost associations must therefore be interpreted relative to the outcome measured. A positive relationship with hypothetical willingness to pay does not show that higher costs generate actual policy purchases. It may indicate greater perceived exposure, a different valuation scale, or shared dependence on farm expenditure.

Farmer organizations can lower search and transaction costs, support collective learning, and provide trusted channels for insurance distribution. Experimental social network research documents the importance of information transmission, while collective action studies emphasize variation in the intensity and purpose of group participation (Cai et al., 2015; Fischer & Qaim,

2014). Group based rainfall insurance research also shows that formal contracts can be offered through existing informal institutions (Dercon et al., 2014). Membership alone, however, does not measure whether a group actively promotes insurance or offers substitutes for it. Organizations differ in savings services, marketing functions, governance, and member composition. A negative membership coefficient should therefore lead to investigation of those differences rather than a recommendation to discourage associations. The size and composition of the nonmember comparison group are especially important for evaluating such a result.

2.4 Awareness Product Quality and Study Hypotheses

Awareness is a necessary practical step toward voluntary enrollment, but it is an incomplete indicator of demand. Farmers may recognize a product's name without understanding the relationship between their losses and the index. Research on communicating insurance and evaluating farmers' preferences supports explanations that make both protection and residual risk visible (Patt et al., 2009; Patt et al., 2010; Sibiko et al., 2018). Technical studies of risk reduction also show why objective quality cannot be replaced by promotional information (Breustedt et al., 2008; Jensen et al., 2016; Musshoff et al., 2011). Education that ignores basis risk can generate unrealistic expectations and subsequent distrust. For Trans Nzoia, awareness should be considered alongside actual purchase and consideration of purchase, with the questionnaire's routing rules taken into account.

The first null hypothesis states that the included socioeconomic characteristics are not associated with actual crop index insurance adoption. The second states that the included characteristics are not associated with the conditional monetary outcomes, distinguishing premiums paid from stated willingness to pay. The third states that awareness is not associated with insurance adoption; the available contingency table instead permits a narrower examination of awareness and purchase consideration. These hypotheses are assessed as observational associations. International reassessments caution that the development value of insurance depends on credible protection, appropriate delivery, and sustained market performance (Carter et al., 2017; Hazell, 1992; Jensen & Barrett, 2017; Skees, 2008). Accordingly, the manuscript evaluates statistical patterns without assuming that increasing any single characteristic would cause higher participation or improved household welfare.

3. RESEARCH METHODOLOGY

A descriptive cross-sectional survey examined maize farming households in Trans Nzoia County. The study population comprised 60,936 farmers across Kwanza, Cherangany, Kiminini, Endebess, and Saboti subcounties. Multistage sampling combined subcounty stratification, proportional allocation, and random selection of farmers, including smaller and larger farms. Household heads completed structured questionnaires during household visits. The target sample was determined using the finite population, with a nominal precision parameter of .05. Equation 1 gives the resulting planning calculation.

$$n = \frac{N}{1 + Ne^2} = \frac{60{,}936}{1 + 60{,}936(.05)^2} = 398 \quad (1)$$

Of the 398 targeted questionnaires, 303 were returned for analysis. Data covered household characteristics, farm size, farming experience, tenure, principal income source, production expenditure, association membership, awareness, purchase consideration, insurance adoption, premiums paid, and stated willingness to pay. Table 1 summarizes the operational definitions used here. Three outcomes were retained: a binary adoption indicator for the full sample, positive premiums reported by insured farmers, and positive stated payments reported by aware, willing nonadopters. These distinctions follow the participation logic of limited dependent variable models while avoiding an assumption that zeros and positive values share an identical process (Cragg, 1971; Madden, 2008; Tobin, 1958).

Table 1: Operational Definitions and Analytical Roles

Variable	Role	Recorded measure
Actual adoption	Outcome	Currently subscribed to crop index insurance; yes = 1, no = 0
Premium paid	Outcome	Positive KES payment among insured respondents; analyzed in natural logs
Stated willingness to pay	Outcome	Positive KES valuation among aware willing nonadopters; analyzed in natural logs
Gender and education	Predictors	Male indicator; primary and secondary or vocational indicators relative to postsecondary
Experience and farm size	Predictors	Years of farming and acreage
Land tenure	Predictor	Ownership without title and registered ownership relative to leasing
Principal income source	Predictor	Nonfarm principal income relative to farming
Association membership	Predictor	Member = 1, nonmember = 0
Costs and household size	Predictors	Reported production costs in natural logs and number of household members
Awareness and consideration	Descriptive test	Awareness and consideration of purchase; the latter question follows an awareness screen

Source: Researcher (2026)

3.1 Model Specification

The adoption model used a logistic probability function, shown in Equation 2. Here A_i indicates adoption by household i, X_i denotes the included covariates, and β contains the corresponding parameters. The reported explanatory variables were gender, education categories, farming experience, tenure categories, acreage, nonfarm income, and association membership. The source table labels the adoption estimates as average marginal effects, but the narrative describes evaluation at sample means. These are different calculations, so the manuscript reports them simply as marginal effects. Logit effects concern changes in predicted probability rather than changes in odds; comparisons across models require attention to scale and specification (Ai & Norton, 2003; Mood, 2010).

$$\Pr(A_i = 1 \mid X_i) = \frac{\exp(X_i'\beta)}{1 + \exp(X_i'\beta)} \quad (2)$$

Conditional ordinary least squares models related the natural logarithm of premiums paid to the insured farmers' covariates and the natural logarithm of stated willingness to pay to the interested nonadopters' covariates. Equations 3 and 4 summarize these separate specifications. P_i is the positive reported premium, W_i the positive stated payment, Z_i and Q_i the respective covariate vectors, and the error terms capture unexplained variation. Both equations included education, experience, tenure, acreage, logged production costs, and household size. Coefficients on logged costs are elasticities; coefficients on variables in their original units describe proportional differences in the logged outcome. For a unit change, Equation 5 converts a coefficient into an exact percentage difference, subject to the model's interpretation and covariate adjustment.

$$\ln(P_i) = \alpha_0 + Z_i'\alpha + \varepsilon_i, \quad A_i = 1 \quad (3)$$

$$\ln(W_i) = \delta_0 + Q_i'\delta + \nu_i, \quad A_i = 0 \quad (4)$$

$$\Delta\% = 100[\exp(b\Delta x) - 1] \quad (5)$$

Separate conditional models require consideration of selection into each observed group. Sample selection corrections can address some forms of nonrandom observation, but depend on distributional assumptions and credible identification (Heckman, 1979; Puhani, 2000; Vella, 1998). The article examined Heckman specifications before presenting conditional ordinary least squares results. The manuscript retains those reported models and treats selection diagnostics as qualifications rather than proof of unbiasedness. Likewise, willingness to pay is a stated preference outcome whose relationship with realized expenditure can be affected by hypothetical bias and survey design (Johnston et al., 2017; List & Gallet, 2001; Murphy et al., 2005).

The source reports heteroskedasticity and robust standard errors for the main models. Such covariance estimators adjust inference for unequal error variance, while dependence within sampling clusters requires separate attention (Cameron & Miller, 2015; White, 1980). Variance inflation factors were reported below five, although individual values were unavailable; a threshold alone cannot establish that estimates are stable or correctly specified (O'Brien, 2007). Pearson's chi square statistic described the awareness contingency table. Bootstrap and instrumental variable checks were reviewed alongside the main estimates. Statistical interpretation follows the principle that significance labels do not establish effect importance or causal validity (Wasserstein &

Lazar, 2016). Reported coefficients and standard errors are preserved, while inconsistent labels and unresolved specification details are identified rather than replaced with invented corrections.

4. DATA ANALYSIS AND PRESENTATION

4.1 Response Rate and Sample Profile

The achieved response rate was 76.1%, calculated from 303 returned questionnaires and the target of 398. Table 2 summarizes the categorical characteristics. Men represented 75.3% of household heads, and the largest age category was 41–50 years. Postsecondary education was reported by 47.5% of respondents, while 29.7% reported secondary or vocational education and 22.8% primary education. Registered owners accounted for 46.5%, lessees for 42.6%, and owners without title for 10.9%. Farming was the principal income source for 90.8%. Nonresponse research shows that response rates alone are insufficient to determine the presence or absence of bias (Groves & Peytcheva, 2008).

Table 2: Categorical Characteristics of Responding Households

Characteristic and category	*n*	%
Gender Male	228	75.3
Gender Female	75	24.7
Age Under 30 years	60	19.8
Age 30–40 years	70	23.1
Age 41–50 years	97	32.0
Age Over 50 years	76	25.1
Education Primary	69	22.8
Education Secondary or vocational	90	29.7
Education Postsecondary	144	47.5
Tenure Registered owner	141	46.5
Tenure Owner without title	33	10.9
Tenure Lessee	129	42.6
Principal income Farming	275	90.8
Principal income Nonfarm	28	9.2
Association Member	284	93.7
Association Nonmember	19	6.3
Aware of insurance Yes	281	92.7
Aware of insurance No	22	7.3
Actual adoption Yes	62	20.5
Actual adoption No	241	79.5
Considered purchase Yes	201	71.5
Considered purchase No	80	28.5

Source: Researcher (2026).

Association membership was widespread, with 284 members and only 19 nonmembers. This imbalance constrains interpretation of a membership contrast because the comparison category is small and potentially unusual. Insurance awareness was also widespread: 281 respondents reported awareness, compared with 22 who did not. Actual adoption was reported by 62

households, equivalent to 20.5% of respondents. Among the aware group, 201 respondents had considered purchase, while 80 had not. The much larger consideration count than adoption count illustrates a participation gap, but it does not identify a single reason for that gap. Awareness, consideration, and adoption measure successive but imperfectly observed states, and their numerical relationship should not be read as a verified transition rate over time.

4.2 Continuous Variables and Monetary Outcomes

Table 3 presents the continuous summaries. Mean household size was 3.76 persons, and mean farming experience was 16.57 years. The mean farm size was 12.51 acres, with a range from 1 to 66 acres, indicating substantial variation in the scale of recorded farms. Reported production expenditure averaged KES 70,884. The variable definition describes expenditure per acre, whereas the questionnaire asks about total production expenditure; the monetary unit is therefore retained without asserting a verified acreage denominator. This distinction matters when discussing cost elasticities and comparing farmers. The source also contains conflicting experience summaries, so the descriptive table values are used consistently.

Table 3: Continuous Characteristics and Reported Monetary Summaries

Variable	*M*	*SD*	Minimum	Maximum
Household size	3.76	0.98	2	6
Farming experience years	16.57	8.15	3	38
Farm size acres	12.51	8.03	1	66
Production costs KES	70,884	20,333	30,000	200,000
Premium paid KES	77,732.15	—	3,750	750,000
Stated willingness KES	5,652.52	1,343.60	2,000	11,000

Source: Researcher (2026)

The reported mean premium paid was KES 77,732.15, with a recorded range of KES 3,750–750,000. The supplied standard deviation exceeded the entire reported range and was incompatible with these observations; it is omitted pending verification. Stated willingness to pay averaged KES 5,652.52, with a reported standard deviation of KES 1,343.60 and range of KES 2,000–11,000. These monetary summaries concern different respondent groups and potentially different amounts of insured exposure. Their difference cannot be interpreted as a uniform affordability shortfall or as evidence that interested nonadopters value the same contract less. Preference studies emphasize that contract attributes and coverage definitions influence stated valuations (Adjabui et al., 2019; Castellani et al., 2014; Liesivaara & Myyrä, 2014). Comparable assessment would require premiums and willingness for an explicitly identical product and insured amount.

4.3 Socioeconomic Characteristics and Actual Adoption

Table 4 reports the adoption marginal effects. Male headed households had a reported marginal effect of −.126 relative to female headed households, with *SE* = 0.063 and a source significance label below .05. Primary education was associated with a marginal effect of −.133 relative to postsecondary education, with *SE* = 0.053. Secondary or vocational education had a smaller negative estimate of −.051, with *SE* = 0.063, without a significance marker. These results suggest differences across the recorded gender and schooling categories after adjustment for included covariates. They do not establish that sex or education independently causes insurance purchase. The joint education test reported in the source was not significant at .05, despite the significant primary category contrast, so these two inferential statements must remain distinct.

Table 4: Reported Marginal Effects for Actual Crop Index Insurance Adoption

Predictor	Marginal effect	*SE*
Male household head	−.126**	0.063
Primary education	−.133**	0.053
Secondary or vocational education	−.051	0.063
Farming experience years	.007**	0.003
Owner without title	.021	0.103
Registered owner	−.016	0.053
Farm size acres	.002	0.002
Nonfarm principal income	.266†	0.110
Association member	−.242**	0.110

Source: Researcher (2026)

Farming experience had a positive reported marginal effect of .007, with *SE* = 0.003. Interpreted on the stated probability scale, an additional year was associated with approximately 0.7 percentage points higher predicted adoption under the reported calculation. This pattern is compatible with greater familiarity with production risk or agricultural services, although those mechanisms were not directly tested. Both tenure contrasts were small and statistically inconclusive: .021 for ownership without title and −.016 for registered ownership, relative to leasing. Acreage had an estimate of .002, with *SE* = 0.002, and no significance marker. The results therefore distinguish experience from farm scale at the adoption stage. A weak acreage association with enrollment can coexist with higher premiums among those who already insure.

The nonfarm principal income category had a positive marginal effect of .266, with *SE* = 0.110. The source marked this estimate at the one percent level, although the rounded coefficient and standard error do not support that label under an ordinary normal approximation. The manuscript retains the estimate while identifying the inconsistent significance marker. Association membership had a negative marginal effect of −.242, with *SE* = 0.110, in the main model. Given the very small nonmember group and weaker bootstrap evidence, this result warrants caution. These findings support considering household resources and group context, but they cannot establish that nonfarm employment increases adoption or that joining a farmer organization suppresses it.

4.4 Premiums Paid and Stated Willingness to Pay

The premiums model used the 62 adopters and explained a reported 68.6% of variation in logged premiums. Table 5 shows a positive acreage coefficient of .0808, with *SE* = 0.0116 and a source significance label below .01. Using Equation 5, one additional acre corresponds to approximately 8.4% higher premiums, conditional on the model and observed adopter group. This relationship plausibly reflects greater insured exposure among larger farms. It is not evidence that a larger acreage causes a higher premium rate or greater protection per acre. Education, experience, tenure, logged costs, and household size lacked significance markers in this conditional model. Their estimates should therefore be described as inconclusive rather than as proof that these characteristics have no relationship with insured expenditure.

Table 5: Conditional Regression for Natural Logarithm of Premiums Paid

Predictor	*B*	*SE*
Primary education	0.273	0.259
Secondary or vocational education	−0.116	0.324
Farming experience years	0.0201	0.0160
Owner without title	−0.102	0.452
Registered owner	−0.0529	0.264
Farm size acres	0.0808***	0.0116
Natural logarithm of production costs	−0.663	0.644
Household size	−0.00663	0.125
Constant	16.48**	6.809

Note. n = 62 adopters; R^2 = .686. **p < .05. ***p < .01

Source, Researcher (2026)

The willingness to pay model included 139 aware, interested nonadopters and had a reported R^2 of .894. Table 6 shows a positive farming experience coefficient of .00744, with *SE* = 0.00221. This implies an approximate 0.75% increase in stated payment per additional year under the log specification. Logged production costs had a coefficient of 1.285, with *SE* = 0.120, indicating that a one percent increase in recorded costs was associated with approximately 1.285% higher stated willingness to pay. The cost relationship was statistically strong in the reported model, but its interpretation remains dependent on the unresolved total versus per acre measurement. A high explained variance does not resolve that measurement issue or show that these stated amounts would be paid during enrollment.

Table 6: Conditional Regression for Natural Logarithm of Stated Willingness to Pay

Predictor	*B*	*SE*
Primary education	−0.0238	0.0255
Secondary or vocational education	−0.0431*	0.0223
Farming experience years	0.00744***	0.00221
Owner without title	0.0710*	0.0413
Registered owner	0.0124	0.0218
Farm size acres	−0.00662	0.00433
Natural logarithm of production costs	1.285***	0.120
Household size	0.0197*	0.0114
Constant	−5.883***	1.321

R^2 = .894. *p < .10. ***p < .01.

Source, Researcher (2026)

Secondary education, ownership without title, and household size received source markers at the ten percent level in the willingness model. Their coefficients were −.0431, .0710, and .0197, respectively. These associations were weaker than those for experience and production costs and did not meet a five percent threshold under the supplied labeling. Farm size was negative but inconclusive, while registered ownership and primary education also lacked significance markers. This pattern further demonstrates why actual premiums and stated willingness must remain separate outcomes. Acreage was strongly associated with paid premiums among adopters but not with stated payments among interested nonadopters. Different coefficients can arise

from different populations, coverage expectations, and monetary questions, rather than from a contradiction in farmers' preferences.

4.5 Awareness Diagnostics and Hypothesis Assessment

Table 7 presents the awareness cross tabulation. Among 281 aware respondents, 201 had considered purchasing insurance and 80 had not. All 22 respondents coded as unaware were recorded as not considering purchase. The Pearson statistic was $\chi^2(1, N = 303) = 46.75$, $p < .001$. This is a strong association in the recorded table, but its outcome is consideration rather than actual adoption. In addition, the questionnaire asks about consideration only after a positive awareness response. The table cannot directly test the original awareness and actual adoption hypothesis, and it should not be presented as evidence that awareness caused purchase.

Table 7: Awareness and Recorded Consideration of Purchasing Insurance

Aware of insurance	Not considered	Considered	Total
No	22	0	22
Yes	80	201	281
Total	102	201	303

$\chi^2(1, N = 303) = 46.75$, $p < .05$.

Source, Researcher (2026)

Table 8 consolidates the analytical checks. The main actual premium selection model reported a two step correction term of .205, with *SE* = 0.319, and an alternative maximum likelihood dependence parameter of .249, with *SE* = 0.406. These estimates did not provide strong evidence of selection dependence in those particular specifications. A separate appendix specification, however, reported a significant correction term of .086, with *SE* = 0.030, so a universal claim that selection bias was absent is unwarranted. A pooled comparison yielded $F(4, 185) = 17.13$, $p < .05$, but compared conditional groups with different outcomes. It therefore supports specification differences without making premiums paid and willingness to pay interchangeable. Selection theory requires identification and coherent outcome definitions as well as a significance test (Heckman, 1979; Puhani, 2000; Vella, 1998).

Table 8: Reported Diagnostic and Robustness Checks

Check	Reported result	Interpretive limit
Variance inflation factors	Below 5	Individual values unavailable; threshold does not establish stability
Heteroskedasticity	Detected; robust *SE* reported	Test statistic unavailable; cluster adjustment unspecified
Premium selection Two step	$\lambda = .205$; *SE* = 0.319	Limited evidence of selection dependence in this specification
Premium selection Maximum likelihood	athrho = .249; *SE* = 0.406	Transformed dependence parameter; distinct from λ
Other appendix selection model	$\lambda = .086$; *SE* = 0.030	Significant correction in another specification; outcome comparability unresolved
Pooled group comparison	$F(4, 185) = 17.13$; $p < .001$	Different conditional groups and monetary outcomes
Bootstrap Membership	−.242; *SE* = 0.302; 500 replications	Weaker inference than the main adoption table; duplicated appendix label
Instrumental variable first stage	$F(2, 52) = .09$; $p = .912$	Weak instruments; no reliable causal identification

Source: Researcher (2026)

Bootstrap checks used 500 replications, but the appendix contained a duplicated predictor label and weaker membership inference. In that appendix, the membership estimate remained −.242 but had *SE* = 0.302 and no significance marker, weakening confidence in the main table's membership result. An instrumental variable attempt using age and subsidy access produced a first stage $F(2, 52) = .09$, $p = .912$. This weak first stage cannot supply persuasive causal identification or demonstrate that endogeneity is harmless. Weak instrument research explains why apparently plausible instruments can fail to support reliable estimation when their relationship with the endogenous regressor is insufficient (Staiger & Stock, 1997; Stock et al., 2002). The principal findings consequently remain conditional associations from the reported main models, with robustness limitations explicitly retained.

For the first null hypothesis, the main model provides evidence of association for selected socioeconomic characteristics, although a verified joint test of every included characteristic is unavailable. For the second, acreage was associated with actual premiums, and experience and logged costs were associated with stated willingness to pay. These findings support rejecting specific no association statements rather than making a blanket claim that all characteristics determine insurance intensity. The third hypothesis, concerning awareness and actual adoption, cannot be resolved by the available purchase consideration table. Statistical significance should be interpreted alongside uncertainty, sample composition, and measurement quality rather than converted into a universal policy ranking (von Elm et al., 2007; Wasserstein & Lazar, 2016).

4.6 Discussion of Findings

The education and experience patterns suggest that understanding insurance and interpreting production risk deserve attention, but the evidence does not identify a single information mechanism. Agricultural learning research describes how experience and neighbors' observations affect technology assessment (Conley & Udry, 2010; Foster & Rosenzweig, 1995; Foster & Rosenzweig, 2010). Kenyan insurance preferences and learning experiments further motivate practical explanations of payout conditions and residual risk (Osiemo et al., 2026; Sibiko et al., 2018). The relevant extension response is therefore to check comprehension of the specific contract, rather than assume that a farmer's schooling category determines capability. The contrast with Laikipia, where reported experience and group relationships differed, reinforces the importance of local institutions and product conditions (Wairimu et al., 2016).

The positive nonfarm income association is compatible with liquidity enabling purchase, while the distinct acreage relationship with premiums points toward variation in insured exposure. Experimental evidence from India, Ghana, and Malawi shows that risk and credit constraints can alter agricultural decisions, but also that those constraints operate jointly rather than as one interchangeable barrier (Cole et al., 2013; Cole et al., 2017; Giné & Yang, 2009; Karlan et al., 2014). Timing evidence from Kenya makes harvest aligned premium collection a credible candidate for further evaluation (Casaburi & Willis, 2018). The Trans Nzoia study itself did not randomize payment schedules, measure available cash at enrollment, or observe contract specific insured values. Recommendations on affordability should therefore be framed as testable delivery improvements supported by wider evidence, rather than as causal conclusions derived from the nonfarm income coefficient alone.

The negative association membership estimate deserves particular restraint. It contrasts with evidence that networks and organized delivery can support insurance information and participation (Cai et al., 2015; Dercon et al., 2014; Trærup, 2012). Several explanations remain possible: members may rely on group support, face different risk exposures, participate in organizations unrelated to insurance, or differ systematically from the small nonmember group. None was directly established in the questionnaire. Farmer organizations remain potentially useful partners for explaining contracts, aggregating demand, and gathering complaints. Program design should examine group activities and governance before assuming that membership either facilitates or discourages purchase. Differentiating organizations by actual services would be more informative than repeating a binary membership measure.

The strong cost association with stated willingness to pay indicates that perceived resources at risk may matter to prospective buyers. However, valuations cannot establish the demand curve for a standardized policy because the study did not document a uniform insured amount or experimentally vary prices. Stated preference guidance emphasizes careful description of the good, payment conditions, and respondents' budget constraints (Johnston et al., 2017; List & Gallet, 2001; Murphy et al., 2005). The substantial premium range among actual adopters reinforces this need for comparability. Future pricing analysis should ask what each payment would insure, which losses trigger payouts, and when the money must be paid. These steps would connect expressed interest with financially meaningful demand while preserving the distinction between valuation and realized behavior.

Product quality remains a central explanation that the socioeconomic models cannot directly adjudicate. A farmer who understands a poorly matched index may rationally decline coverage, and increasing publicity would not eliminate that residual risk (Breustedt et al., 2008; Clarke, 2016; Elabed et al., 2013; Jensen et al., 2016). Multiscale design, local data evaluation, and transparent communication offer possible routes to stronger protection, but each requires validation against actual losses. Reviews of insurance for development and dryland food security similarly emphasize that coverage must fit livelihood exposure

and complement broader risk management (Adetoro et al., 2022; Carter et al., 2017; Hazell & Hess, 2010; Jensen & Barrett, 2017). In Trans Nzoia, the observed awareness and adoption gap justifies examining price, trust, payout experience, and basis risk together.

5. CONCLUSION AND RECOMMENDATIONS

Crop index insurance adoption among the responding maize farmers was limited despite widespread awareness. The main model associated actual adoption with selected demographic and socioeconomic characteristics, while the conditional models revealed different monetary patterns: acreage was associated with premiums paid, and experience and production costs with stated willingness to pay. These outcomes should guide distinct questions about enrollment, insured exposure, and potential demand. The awareness contingency table documented purchase consideration rather than actual adoption and was constrained by questionnaire routing. The conclusion is that information alone is unlikely to explain participation. Household resources, learning, organizational context, and the credibility of protection should be considered together, while the observational estimates remain subject to reporting and measurement limitations.

Insurers and extension services should provide short, practical explanations of premium timing, coverage, payout thresholds, and circumstances in which a loss may receive no compensation. Training should use locally recognizable scenarios and verify understanding rather than simply record attendance or awareness. Farmer organizations can provide trusted venues, but their existing credit, savings, and support activities should be understood before designing group distribution. Providers should also evaluate payment schedules that fit seasonal cash flows for maize producers and make costs comparable across insured amounts. Such initiatives should be piloted and assessed through actual enrollment and renewal. The broader literature supports these mechanisms while cautioning against assuming that subsidies or education automatically produce sustainable participation (Ali et al., 2020; Binswanger-Mkhize, 2012; Nshakira-Rukundo et al., 2021; Skees, 2008).

County agricultural planners should treat insurance as part of a wider risk management strategy that includes reliable agronomic information, water management, savings, and accessible financial services. Mobile financial access may reduce transaction barriers, but it cannot correct an unsuitable payout rule (Kikulwe et al., 2014; Miranda & Farrin, 2012). Monitoring should therefore include claim timeliness, complaints, renewal, and losses without payouts alongside policy counts. Evidence that insurance can protect assets after drought or facilitate agricultural decisions provides a reason to evaluate these outcomes directly (Chantarat et al., 2013; Hill et al., 2019; Janzen & Carter, 2019). The present study does not measure welfare impacts, so neither household resilience nor productivity gains should be inferred from adoption alone. Evaluation should establish whether coverage preserves consumption and productive capacity during the shocks farmers seek to insure.

Further research should reconcile the subcounty labels, expenditure units, premium dispersion, significance markers, and appendix specifications using the original records. It should measure insured acreage or value, premium rates, payout histories, product understanding, liquidity, and organizational services. A prospective design could follow awareness, consideration, purchase, claims, and renewal across seasons, while a randomized delivery intervention could test specific explanations for the observed participation gap. Larger adopter samples and verified selection assumptions would strengthen conditional expenditure analysis. Standardized choice or purchase tasks could also assess willingness to pay for clearly defined coverage. These improvements would preserve the study's local contribution while generating stronger evidence for decisions about product quality, distribution, affordability, and sustained agricultural protection.

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