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The Role of Learning Styles in the Uptake of Index Insurance: Evidence from Kenya

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Abstract: Index insurance has a huge potential to increase the income of households in developing countries by shielding them against various shocks and by facilitating technology adoption. Despite this theoretical promise, however, the uptake of insurance has turned out to be disappointingly low. One of the key barriers in the adoption of this financial technology has been learning difficulty. Index insurance can be considered a relatively complex product especially in the context of low financial literacy in developing countries. Despite the relevance of learning in the diffusion of the product, however, previous studies on the subject have been quite limited. This study attempts to address this gap by testing the effect of two learning methods, a 9min video and a computer-simulated insurance game. The study relies on experimental data from Samburu County of Kenya on the adoption of IBLI (Index-Based Index Livestock Insurance) that insures against drought for pastoral households. The two training methods, or treatments, are tested on 1743 households. The main finding of the study is that both types of interventions could enhance the uptake of index insurance. The insurance game increases the uptake of index insurance provided that it is framed as insurance for household rather than for livestock. The effect is a 3-4 percentage point (pp) increase in uptake and only appears for sales windows right after the treatment. The video intervention has opposite effects depending on the gender of the treated household head. For male-headed households, the effect is a 2-3 pp increase in uptake while for females, it is about a 6 pp decrease in uptake. In general, the results suggest that the insurance game has a stronger and consistent effect on the uptake than index insurance.

1. Introduction

Risk is a key poverty trap in developing countries. A significant number of smallholder farmers in developing countries, over 60 percent in some cases, face at least one type of shock in the form of extreme weather, pests, and volatile price, etc. (World Bank, 2013). To cope with these shocks, farmers often employ inefficient ex-ante and ex-post risk management strategies (Awel & Azomahou, 2014). Their ex-ante risk management strategies usually confine them to low-risk low-return investments effectively incurring high-risk premiums. And once a shock occurs, the farmers often have to sell their productive assets further tightening the grip of poverty. The effective risk premium of these traditional risk mitigation strategies of farmers could be as high as 35 % of annual production (Rosenzweig & Binswanger, 1993).

Index insurance has been introduced in an agrarian setting as a substitute for formal insurance. As of today, more than 10 million farmers are using the service (Greatrex et al., 2015). Index insurance has been effective in addressing the challenges of implementing formal insurance in smallholder settings in the developing world due to difficulties in acquiring necessary actuarial data, managing moral hazards, and confirming claims (Jensen, Mude, & Barrett, 2018). Index insurance employs weather or other objectively verifiable indices for which neither the insurer nor the client has exclusive access, thereby minimizing the risks of moral hazard and adverse selection. In relative terms, the actuarial data for index insurance are also easily available as it relies on weather and other aggregate level measures.

To the disappointment of many, however, the uptake of index-based insurance has been below expectations, where uptake as low as 0.5 % has been reported (Ahmed, McIntosh, & Sarris, 2020; Carter, de Janvry, Sadoulet, & Sarris, 2017; Jensen et al., 2018). The sustainable adoption of index insurance often entailed heavy subsidies

(Carter et al., 2017) and at times remained low despite subsidies (Cai & Song, 2017). Reasons for the low uptake have been attributed to several factors, including basis risk, high price elasticity of demand, liquidity constraints, and learning difficulties. Two of these factors, however, could be considered peculiar to index insurance. The first is basis risk. Basis risk is the probability that indemnity payment from index insurance is not triggered while a farmer actually incurs a substantial loss in income. Several studies have shown that the miscorrelation between indices and actual loss is quite substantial (Clarke, Mahul, Rao, & Verma, 2012), and could explain the low demand for index insurance (Jensen et al., 2018; Karlan, Osei, Osei-Akoto, & Udry, 2014).

Along with basis risk, the learning difficulty could be considered one of the most important challenges in the diffusion of index insurance. Index insurance is not just a new product in the ranks of microcredit or new seeds for rural farming and pastoral communities. Unlike prior innovations introduced in the developing world, farmers need to take several years to experience what an insurance product can actually provide. In other words, learning about index insurance requires learning a new probability distribution of gains and losses (Carter et al., 2017) that may demand real-world experience over many years than required by most technologies.

The extensive literature in technology adoption in developing countries has particularly emphasized learning for relatively complex technologies. Learning can be defined "as taking place when new information affects behavior and results in outcomes for an individual that are closer to the (private) optimum" (Foster & Rosenzweig, 2010). Therefore, acquiring and processing new information is at the core of the learning process. For relatively simple technologies, this could be quite straightforward. For example, learning about a new fertilizer may only involve explaining the link between the yield and nutrient needs of plants. However, for technologies like index insurance, the learning process often entails having a good grasp of how the probability distribution of income changes in the presence of insurance. As a result, relatively complex technologies are often strongly associated with a higher level of schooling whereas the role of experience is diminished (Foster & Rosenzweig, 2010).

Learning about index insurance may involve two formats: description-based and experience-based. The description-based choice takes place when index insurance is presented by describing how it reduces risk and how it changes the probabilities of losses and gains. This is similar to the choice format extensively studied by Tversky and Kahneman in prospect theory (Harbaugh, Krause, & Vesterlund, 2010).
The fourfold pattern from prospect theory contains some key insights that could be useful in thinking about the learning process for index insurance. According to this theory, people are risk-seeking for small probabilities of gains while being risk-averse for small probabilities of losses. This is attributed to the overweighting of small probabilities. The pattern is reversed for medium and large probabilities. In the latter case, people tend to be risk-averse for gains and risk-seeking for losses. Assuming the probability of gain from index insurance falls within the medium and large probability range, the descriptive format may indicate risk-aversion in adopting the insurance.

A relatively less-researched decision format is experience-based (feedback-based) choice. In this decision format, individuals make decisions based on a learning process that provides feedback to their proposed decisions. Examples of experience-based learning mechanisms may include role-playing and simulated computer games. Rakow and Newell (2010) extensive review of experience-based choices showed that in general for low probability choices, this decision format shows an opposite pattern to the predictions of prospect theory. Thus, for small probabilities of gains, individuals are risk-averse while being risk-seeking for small probabilities of losses. For medium and large probabilities, however, the empirical literature is still scant and inconclusive. The experience-based approach has gained more attention particularly with the rise of gamification. Gamification can be defined as the use of game design elements in non-game contexts (Deterding, Khaled, Nacke, & Dixon, 2011). Gamification allows a more realistic learning but its advantage over traditional methods is not still well established

There is a growing yet limited literature on the best ways of training potential clients for index insurance. These studies use both description- and experience-based techniques ranging from a short promotional video to computer-simulated insurance games. Their findings are often inconsistent showing positive to no relationship between training and insurance uptake. Cai and Song (2017) examined how insurance games and simple probability information influence insurance (for disaster) uptake in China. In the insurance game, participants decide whether to insure themselves or not in each of the ten rounds. In each of these rounds, a lottery system reveals whether there are disasters or not in each round and the associated income levels. Cai and Song (2017) find that playing the insurance game increases uptake by about 9.1 percentage points. The simple provision of the probability information, however, performed significantly better (30 percentage points) than the insurance game. The results of this study seem to suggest that the description-based training format has superior performance.

Patt, Suarez, and Hess (2010) corroborated the findings of Cai and Song (2017). The study examined how traditional training sessions and role-playing games influence the understanding and decision of farmers in Ethiopia and Malawi in buying an index insurance product. The study finds that both mechanisms perform well and the role-playing games do not necessarily outperform the traditional training sessions. A key result of the study is also that after both of the treatments, many farmers still had difficulty in understanding the basic concepts of the insurance.

Gaurav, Cole, and Tobacman (2010) produced similar results for descriptive training methods while finding no effect for insurance games. The experimental study took place in Gujarat, India, and examined two key mechanisms of promoting rainfall insurance: two-day financial literacy training and insurance games. The financial training which also includes a 30-minute promotional video on index insurance is strongly linked with higher uptake of the index insurance. However, the insurance games did not show any statically significant effect on uptake.

Cole et al. (2013) results contradict the preceding positive effects of an educational video where they were not able to find any statistically important effect from similar sessions on insurance demand. Cole et al. (2013) did their study in Andhra Pradesh India, but unlike Gaurav et al. (2010) their training video is much shorter than Cole et al. (2013).

The empirical literature on the role of learning in insurance uptake is still largely scant. Particularly, it is vital to understand the potentially differential performance of description- and experience-based training methods. The theoretical literature still is limited in establishing a stronger theoretical difference between the two choice formats for medium and large probabilities as discussed earlier. Yet, the stark difference for small probabilities makes the difference for medium and large probabilities quite a possibility.

In this study, we investigate the effect of a simulated insurance game and a 9-min training video on the uptake of index insurance. The study uses a randomized experiment on 1743 pastoral households in the Samburu county in north Kenya. The study investigates the effect of the two training methods on the uptake of an Index-Based Livestock Insurance (IBLI), which provides insurance against drought that may lead livestock mortality in the study area.

In the following four sections of this research paper, we will discuss data sources, empirical models and hypotheses, and finally results & discussion and conclusions, in the same order listed here.

2. Explanation of data sources

This study makes use of experimental data from the Samburu County (North Sub-county) of Kenya. A research program that investigates two major treatment arms produced the experimental data. The first is IBLI, which is the focus of this study. The research program bundles this treatment with a second treatment, REAP Asset Transfer (or Graduation) Program. REAP stands for Rural Entrepreneur Access

Project. The overarching goal of the program is to see the impact of the two treatments on the welfare of the sampled households both separately and in a complementary manner. The scope of our study is limited only to the IBLI intervention.

The experimental study focuses on two sub-populations: (i) poor households who are eligible for the REAP program; and, (ii) vulnerable, non-poor households who are not eligible for REAP but who are just barely ineligible in terms of their asset endowment and living standards. The study area comprises of 7 mentor areas (for REAP) where a total of 66 communities are included. From the selected communities, a total of 1743 households are randomly included in the study.

A private insurance company has provided subsidized IBLI contracts in the study area since January 2018. A baseline survey took place in January 2018, followed by a midline in January 2020. The endline survey will be carried out in January 2022. The experimental data used for this study primarily relies on data from 6 sales windows that took place around Jan 2018; Aug 2018; Jan 2019; Aug 2019; Jan 2020 and Aug 2020.

The insurance game is a simulated interactive computer game. The subjects played the game on tablets. The game starts by allotting certain cash and livestock assets, both virtual. During the game, players decide whether to insure their livestock and how they invest resources in livestock or schooling. There are two versions of the game treatment based on how the insurance is framed. In the first case, the index insurance is presented as insurance for livestock loss. In the second version, the game presents the insurance in general as insurance for the livelihood of the household. Each of these two framings is applied to half of the treated households. The insurance game is assigned to sampled households using both random and convenience sampling techniques. At the first stage, some Manyattas were selected which are easier to be accessed by the researchers. In the second stage, households are randomly selected from the selected Manyattas.

The video treatment (9 min) was randomly assigned to half of the sampled households just before the fifth sales window (Jan 2020). Similarly to the game treatment, the insurance game is also presented to households in two framings, as insurance for household and as insurance for livestock. The videos use a narrative approach (in the local language) to communicate the benefits of IBLI and how it works. The videos make use of cartoons, relevant pictures, and maps in the video production.

3. Hypotheses and empirical models

This study tests two hypotheses:

I. Computer-based simulation insurance games enhance the likelihood of the purchase of index insurance

II. Informational and promotional video enhances the likelihood of the purchase of index insurance

To test the preceding hypotheses, simple OLS regression models are fitted (Eq. 1):

$$Buy_i = \beta_0 + \beta_1 Game_i + \beta_2 Video_i + \beta X_i + \varepsilon_i \qquad \text{(Eq. 1)}$$

Buy_i is a binary variable for whether an individual i bought index insurance or not. For each treatment, Buy_i refers to purchase after the treatment. Since there are more than one sales windows after each treatment, separate regression models are run for different dependent variables defined for each sales window after the game treatment on a cumulative basis. For example, for the fourth sales windows, Buy_i is defined as purchases at and before the fourth sales window but after the treatment. $Game_i$ indicates whether individual i received insurance game treatment or not. Similarly, we interpret $Video_i$ for the video treatment. To account for the framings in the treatments, $Game_i$ and $Video_i$ will be split based on whether the insurance is framed as insurance for household or insurance for livestock. X_i is a vector of socioeconomic factors such as household size, age, and income. Finally, ε_i is the error term.

4. Results

4.1 Household characteristics

An average sampled household has about 5 (4.7) members; see Table 1. This is somewhat higher than the average household size in Kenya (about 4). The higher household size is, however, expected for pastoral communities who often have larger households (Githinji, Otieno, Ackello-Ogutu, Mureithi, & Bostedt, 2019). Most of the interviewees are male households (about 70 percent) and the average age is 46 years.

Most of the respondents, about 84 percent, do not have any formal schooling. The average income of the sampled pastoral households is about 36,000 KES (330 USD) but with a relatively high standard deviation of about 59,000 (550 USD). Annual income as high as 892, 000 (8300 USD) is recorded. The same high heterogeneity is also observed for livestock ownership as shown in Table 1. Almost 29 percent of the households purchased insurance at least once.

4.2 Treatment and relation to insurance uptake-descriptive statistics

Nearly half of the sampled households (51 percent) participated in the video treatment, see Table 1. The insurance game, however, is played by only 20 percent of the sample households. Figure 1 summarizes the descriptive relationship of the treatments to the uptake of insurance. Out of those who took the insurance game 18.4 percent purchased the insurance at least once, compared to 17.9 in the control group. This supports the hypothesis that the game positively affects insurance uptake. For the video treatment, similar statistics suggests the opposite, contrary to our expectation. Out of those treated with the video, about 5.7 percent purchased insurance compared to 6.7 in the control group.

Figure 2 depicts the percent of buyers for each treatment across the six sales windows. Here, we can see that the insurance game is associated with higher percent of buyers. It reversed the relatively higher number of buyers in the control group prior to the game treatment just before the second sales window. The positive effect of the game appears to persist till the 4^{th} sales window (Aug 2019) after which it is reversed. Figure 3 replicates the above diagram splitting the game treatment based on framing. The household framing suggests a stronger effect from the treatment than observed in Figure 2. For the livestock framing, however, there doesn't appear to be any positive effect on uptake. In fact, the gap in the proportion of buyers between the control and treatment groups becomes wider after the game treatment with livestock framing.

For the video treatment, the pre and post video uptake doesn't show any important change. Repeating the same graph based on the framing used in the video treatment (Figure 4) also doesn't show any important effect.

4.3 Econometric models

4.3.1 Insurance Game

We ran regression models defining the dependent variable for each sales window based on cumulative sales after the game treatment. However, it is only uptake at the second sales window, right after the game treatment, that showed some association with the game treatment, see Table 2. The fourth column shows a positive association between game treatment and uptake at just 10 percent level of significance. Adding household size and schooling, however, reduced the significance just below 10 percent. These results could be taken as marginal evidence of the positive effect of the game treatment on uptake.

Table 3 shows the results when Table 2 is replicated by splitting the game treatment into two based on the framing of the index insurance as insurance for household and insurance for livestock. As it is evident in the table, the game treatment with household framing shows a consistent and positive effect on uptake at the second sales window, i.e. right after the game treatment. The effect is 3-4 percentage point (pp) increase in uptake. We are not able to find any significant effect for latter sales windows. In Table 2, even if column (5) indicates a smaller significance than column (4), it should be noted that the significance for game (household) is almost 5 percent (p value= 0.053). Presenting the insurance, as insurance for livestock doesn't, however, seem to have any effect on uptake. In both Table 2 and 3, prepurchase and discount coupon showed significant effects. The negative sign for the former could be traced to the poorly implemented first sales window, based on subjective witnesses of researchers who took part in the survey. The most important factor that determines insurance demand is the discount coupon. Receiving a coupon increases the probability of buying an index insurance product by about 0.1.

Figure 5 depicts the coefficients of the game treatment with household framing along the 95 percent confidence intervals for column (5) of Table 3. As it is evident in the figure, the coefficients show a slight decline after the second sales window (Aug 2018) except the last window. This indicates that the effect from the games doesn't persist for long. Furthermore, the confidence intervals consistently widen from the first to the last sales window further stressing the same observation.

The OLS models showed no statistically significant relationship between insurance uptake and the video treatment when no interaction terms are included (Table 4). This holds for all sales windows after the treatment and despite splitting the video treatment into two based on framing. However, when we interact the two strongly significant variables, female and coupon, with the treatment variable, statistically significant variables emerge. Table 5 shows the results for the fourth sales window and for the fifth sales window the results remain more or less the same (Appendix 1). It appears that the video treatment positively affects uptake for males, 2-3 pp increase in uptake. Yet for females the effect turned out to be negative, about 6 pp decrease in uptake. A visual depiction of the result is provided in Figure 6. Applying the same type of analysis using interaction terms but splitting the video treatment into two based on framing also shows significant results. However, the results do not indicate differential impact as was the case for the game treatment, appendix 2.

Significant results are also observed for the prepurchase variable, with or without the interaction. The prepurchase variable for the video treatment is defined in a different way from prepurchase in Table 3 & 4 for the game treatment. In addition to the first sales window, it includes the fourth sales window and all the preceding ones. The positive sign for it therefore indicates that pastorals that bought in any of the four sales windows before the fifth window are likely to purchase insurance. This is an indication that the quality of the service delivery has showed improvement after the first sales window, which was possibly ill executed as suggested by the results in Table 3 and4.

5. Discussion and conclusion

Our main finding is that both the 9-min video and the insurance game could positively affect uptake. The insurance game enhances the uptake of index insurance provided that the insurance is framed as insurance for household. The effect is 3-4 percentage point (pp) increase in uptake. And it appears that the effect of the game is short-lived and only affects the uptake just right after the treatment. The effect of the video treatment depends on the gender of the treated household. For males, the effect is 2-3 pp increase in uptake while for females, the effect is about 6 pp decrease in uptake. The effect also persists up to a second sales window.

The framing aspect of the study is, to the best of our knowledge, the first in the literature on the topic. It is possible that framing the insurance as insurance for the household may make it appear more useful than narrowly presenting it as insurance for the livestock. Besides, the IBLI is hardly an insurance product that insures livestock mortality as much as it insures against drought that affects a broader aspect of a household’s livelihood than just its livestock. The study’s finding on framing has a crucial implication than transcends the topic of learning styles. It also indicates that the index insurance should be presented as insurance for the household in any form of communication whether in regular sales or in formal trainings.

Some studies in the past have found similar results for experience-based or experiential games. For example, Cai and Song (2017) find that playing an insurance game increases uptake in a study area in China by about 9.1 percent. A study by Janzen et al. (2021) on smallholder farmers in Kenya also found a significant and positive effect in line with ours. Patt, Suarez, and Hess (2010) also documented a similar finding based on a study in Ethiopia and Malawi. In contrast to our finding, Gaurav et al. (2010) observed that an insurance game does not affect the uptake of an index insurance in Gujarat, India.

Bearing in mind the particularly positive effect from more descriptive training methods in the literature, a strong positive effect for a video treatment is in general expected. Cai and Song (2017) found that a simple provision of probability information outperformed an insurance game by a higher margin in increasing insurance demand based on a study of disaster insurance in China. Similarly, Amh and Gaurav et al. (2010) were able to support the same line of argument where a training session did better than insurance game.

In this study, however, the effect of the video treatment is somewhat less strong than the insurance game. The treatment has a conditional effect based on the gender of the learner, which could be even negative for females. One possible reason for this could be the design of the video that does not specifically and effectively address the expectations of female clients. A more concrete interpretation requires further study. A stronger effect from the insurance could be associated with the superior performance of interactive games, or gamification in general, in learning about index insurance. It is also possible that following the fourfold pattern (Harbaugh et al., 2010), descriptive choice format may induce risk aversion assuming medium to large probabilities for the occurrence of gains from the insurance.

Our result highlighted the crucial role played by subsidies and earlier purchases. A major review by Carter et al. (2017) underscored the importance of liquidity and subsidies in the uptake of index insurance. According to the review "take-up has been disappointingly low without large and sustained subsidies". In line with this our coupon variables showed the strongest positive effect on uptake. The negative effect observed for prepurchase in the game treatment models also underscores the need for a cautious first time introduction of the product as this may have serious bearing on future sales. This is based on the subjective assessment of researchers who evaluated the quality of the index insurance delivery in the first sales window as inferior.

Index insurance is a complex new product which has been introduced in the context of limited financial literacy. Index insurance is arguably more complex even compared to the regular insurance products people are familiar with because of its use of index rather than actual loss-valuation to make payouts. Furthermore, experiencing any benefit of the product may take several years unlike many other technologies. Yet, it seems that there is quite limited research on the learning aspect of the product. Even the basis risk problem of index insurance could be related to a lack of effective communication at the beginning of the diffusion of index insurancet which ic crucial to set the expectation of clients in the right way.

Technology adoption in agriculture has demanded heavy investment in agricultural extension and communication infrastructures in the past. And for index insurance, the need for similar investment could be even more vital. The 9-min video or the insurance game that normally takes less than 30 min can be considered light interventions in view of the complexity of the product. It could be possibele to have a much larger and persistent effect by increasing the intensity and frequency of the treatments.

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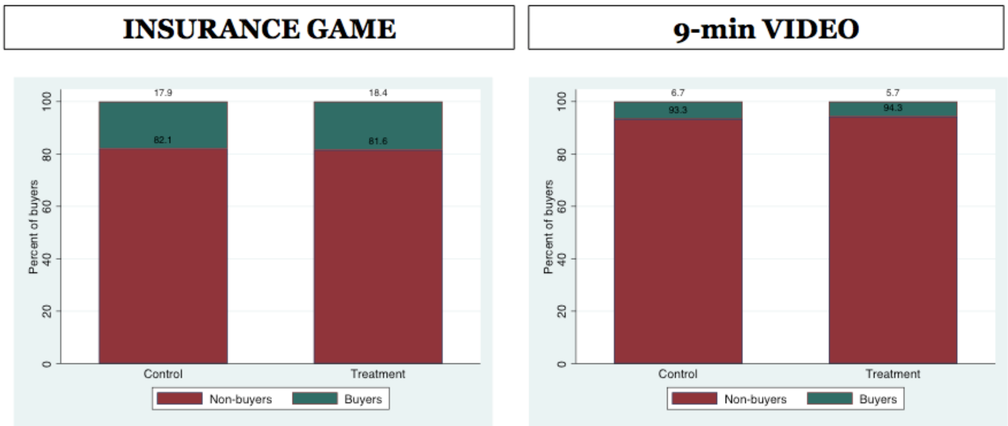

Figure 1. Percent of buyers by treatment

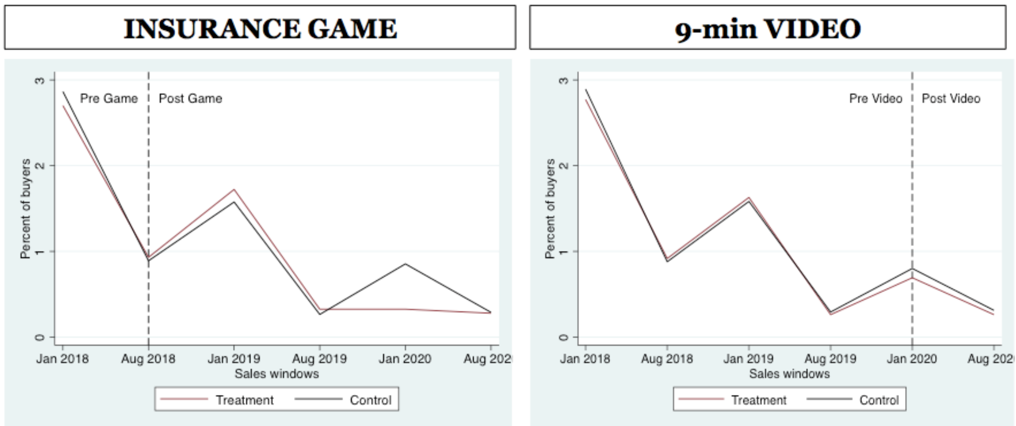

Figure 2. Percent of buyers by treatment for each sales window

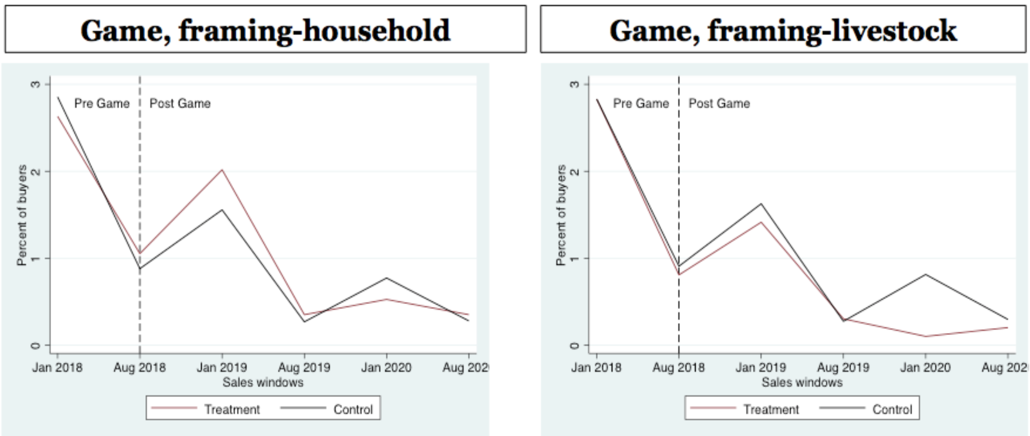

Figure 3. Percent of buyers by game treatment and framing, for each sales window

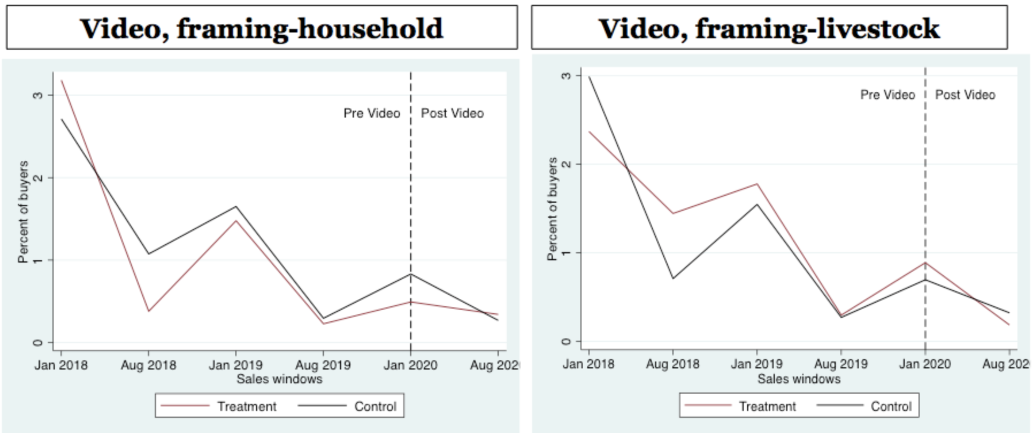

Figure 4. Percent of buyers by video treatment and framing, for each sales window

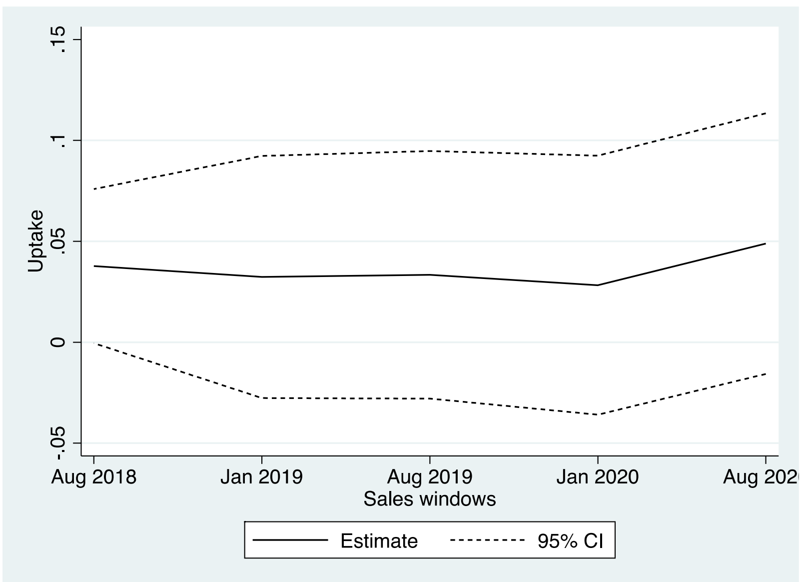

Figure 5. Coefficient estimate and CI for insurance game (household framing) for fifth column in Table 3.

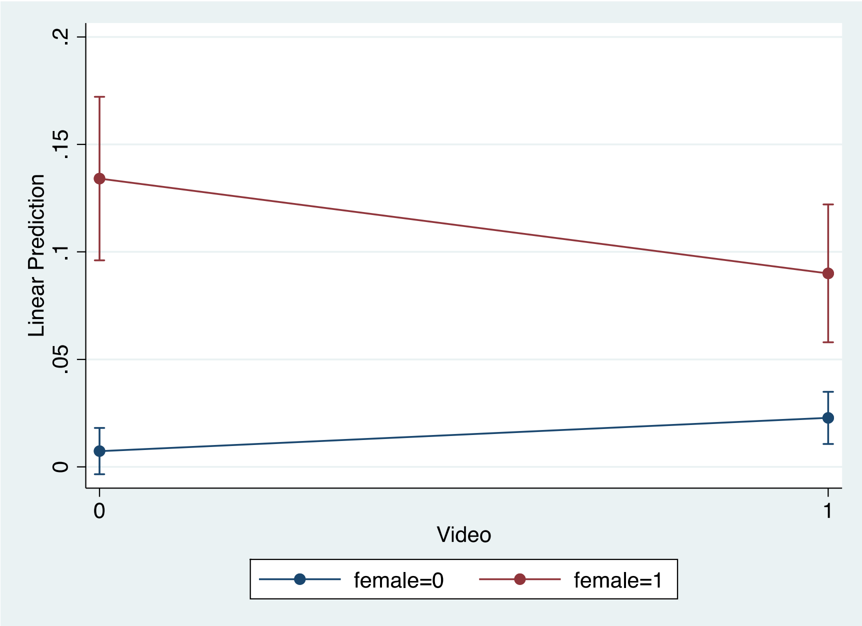

Figure 6. Predictive margins of the video treatment, based on Table 5 column 5 with 95% CI

Variable	Mean	SD	Description
Insurance uptake	.289	.453	Dummy, 1 for purchasing insurance at least once, and 0 otherwise
Insurance Game	.205	.404	Dummy, 1 for playing insurance game and 0, otherwise
9-min video	.511	.500	Dummy, 1 for taking video treatment and 0, otherwise
HH size	4.70	2.32	The number of members in a household

Table 1 Summary statistics for explanatory variables

Female	.310	.463	Dummy, 1 if the household head is female, 0 otherwise
Age	46.26	16.81	Age of the household head
Schooling	.163	.370	Dummy, 1 for any schooling and 0 otherwise
Annual income	36,065	59,097	Annual income of the household
Coupon	.512	0.500	Dummy, 1 for receiving coupon for insurance purchase, 0 otherwise
Cattle ownership	2.66	3.34	Number of cattle owned by the household
Camel ownership	.424	1.15	Number of camels owned by the household
Goat ownership	8.24	8.25	Number of goats owned by the household
Sheep ownership	4.76	5.65	Number of sheep owned by the household

Table 2 Insurance uptake **after GAME TREATMENT**
Dependent variable: 1 = Household bought index insurance at the 2nd sales window
OLS estimate, with robust standard errors

	(1)	(2)	(3)	(4)	(5)
Game	0.00244	0.00196	0.0168	0.0248*	0.0234
	(0.0136)	(0.0135)	(0.0149)	(0.0149)	(0.0149)
Prepurchase		-0.0487***	-0.00797	-0.0720***	-0.0721***
		(0.00925)	(0.00891)	(0.0123)	(0.0123)
Coupon				0.110***	0.110***
				(0.0113)	(0.0113)
Female				0.00680	0.00808
				(0.0110)	(0.0112)
HH size					0.000928
					(0.00236)
Schooling					0.0104
					(0.0183)
Manyatta fixed effect	No	No	Yes	Yes	Yes
Constant	0.0534***	0.0618***	-0.00643	-0.0577***	-0.0633***
	(0.00605)	(0.00692)	(0.00698)	(0.0129)	(0.0185)
Observations	1,743	1,743	1,737	1,735	1,734
R-squared	0.000	0.007	0.247	0.296	0.296

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3 Insurance uptake **after GAME TREATMENT with framing**
Dependent variable: 1 = Household bought index insurance at the **2nd sales window**
OLS estimate, with robust standard error

	(1)	(2)	(3)	(4)	(5)
Game (household)	0.00984	0.00918	0.0382*	0.0391**	0.0377*
	(0.0187)	(0.0186)	(0.0201)	(0.0196)	(0.0195)
Game (Livestock)	-0.00483	-0.00492	-0.00487	0.0103	0.00916
	(0.0178)	(0.0178)	(0.0212)	(0.0210)	(0.0210)
Prepurchase		-0.0486***	-0.00787	-0.0716***	-0.0716***
		(0.00925)	(0.00894)	(0.0123)	(0.0123)
Coupon				0.109***	0.109***
				(0.0113)	(0.0113)
Female				0.00686	0.00802
				(0.0110)	(0.0112)
HH size					0.000828
					(0.00236)
Schooling					0.00999
					(0.0182)
Manyatta fixed effect	No	No	Yes	Yes	Yes
Constant	0.0533***	0.0616***	-0.00572	-0.0570***	-0.0620***
	(0.00604)	(0.00691)	(0.00740)	(0.0129)	(0.0185)
Observations	1,743	1,743	1,737	1,735	1,734
R-squared	0.000	0.007	0.248	0.296	0.297

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4 Insurance uptake **after VIDEO TREATMENT**
Dependent variable: 1 = Household bought index insurance at the **5th sales window**
OLS estimate, with robust standard error
Robust standard errors in parentheses

	(1)	(2)	(3)	(4)	(5)
Video	-0.00649	-0.00590	-0.000726	-0.00323	-0.00302
	(0.00993)	(0.00970)	(0.00964)	(0.00945)	(0.00947)
Prepurchase		0.1000***	0.109***	0.0725***	0.0730***
		(0.0152)	(0.0160)	(0.0172)	(0.0172)
Coupon				0.0551***	0.0545***
				(0.00998)	(0.0100)
Female				0.0933***	0.0960***
				(0.0134)	(0.0138)
HH size					0.00306
					(0.00220)
Schooling					-0.0196
					(0.0138)
Manyatta fixed effect	No	No	Yes	Yes	Yes
Constant	0.0481***	0.0204***	0.00753	-0.0230	-0.0384
	(0.00733)	(0.00650)	(0.0286)	(0.0298)	(0.0352)
Observations	1,743	1,743	1,737	1,735	1,734
R-squared	0.000	0.047	0.098	0.149	0.151

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

Table 5 Insurance uptake **after VIDEO TREATMENT, with interaction**
Dependent variable: 1 = Household bought index insurance at the **5th sales window**
OLS estimate, with robust standard error

	(1)	(2)	(3)	(4)	(5)
Video	-0.00649	-0.00590	-0.000726	0.0224**	0.0235**
	(0.00993)	(0.00970)	(0.00964)	(0.00951)	(0.00952)
Prepurchase		0.1000***	0.109***	0.0735***	0.0741***
		(0.0152)	(0.0160)	(0.0171)	(0.0172)
1.Coupon				0.0622***	0.0619***
				(0.0145)	(0.0146)
1.Video#1.Coupon				-0.0153	-0.0158
				(0.0187)	(0.0187)
Female				0.123***	0.127***
				(0.0202)	(0.0205)
1.Video#1.Female				-0.0577**	-0.0595**
				(0.0266)	(0.0265)
HH size					0.00331
					(0.00219)
Schooling					-0.0204
					(0.0137)
Manyatta fixed effect	No	No	Yes	Yes	Yes
Constant	0.0481***	0.0204***	0.00753	-0.0351	-0.0522
	(0.00733)	(0.00650)	(0.0286)	(0.0300)	(0.0352)
Observations	1,743	1,743	1,737	1,735	1,734
R-squared	0.000	0.047	0.098	0.153	0.155

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix

Appendix 1

	(1)	(2)	(3)	(4)	(5)
Video	-0.00952	-0.00865	-0.00546	0.0255**	0.0268**
	(0.0116)	(0.0111)	(0.0110)	(0.0108)	(0.0107)
Prepurchase		0.148***	0.162***	0.116***	0.117***
		(0.0177)	(0.0185)	(0.0193)	(0.0193)
Coupon				0.0815***	0.0811***
				(0.0162)	(0.0162)
1.Video#1.Coupon				-0.0236	-0.0242
				(0.0211)	(0.0211)
Female				0.173***	0.178***
				(0.0223)	(0.0226)
1.video_all#1.Female				-0.0716**	-0.0739**
				(0.0297)	(0.0295)
HH size					0.00435*
					(0.00252)
Schooling					-0.0264*
					(0.0151)
Manyatta fixed effect	No	No	Yes	Yes	Yes
Constant	0.0668***	0.0258***	-0.00100	-0.0581*	-0.0806**
	(0.00855)	(0.00724)	(0.0289)	(0.0307)	(0.0364)
Observations	1,743	1,743	1,737	1,735	1,734
R-squared	0.000	0.076	0.132	0.213	0.216

Insurance uptake **after VIDEO TREATMENT, with interaction**
Dependent variable: 1 = Household bought index insurance at the **6th sales window**
OLS estimate, with robust standard error
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)	(5)
Video (household)	-0.0185*	-0.0165	-0.00865	0.0330**	0.0339**
	(0.0109)	(0.0108)	(0.0124)	(0.0138)	(0.0138)
Video (livestock)	0.00527	0.00449	0.00669	0.0130	0.0143
	(0.0129)	(0.0125)	(0.0143)	(0.0123)	(0.0123)
Prepurchase		0.0996***	0.109***	0.0728***	0.0733***
		(0.0151)	(0.0160)	(0.0171)	(0.0171)

Appendix 2.a

Insurance uptake **after VIDEO TREATMENT, with interaction and framing**
Dependent variable: 1 = Household bought index insurance at the **5th sales window**
OLS estimate, with robust standard error

Coupon				0.0627***	0.0624***
				(0.0145)	(0.0145)
1.Video (HH)#1.Coupon				-0.0378*	-0.0382*
				(0.0211)	(0.0211)
1.lVideo (Livestock)#1.Coupon				0.00539	0.00472
				(0.0237)	(0.0237)
Female				0.122***	0.127***
				(0.0203)	(0.0206)
1.Video (HH)#1.Female				-0.0747**	-0.0761**
				(0.0304)	(0.0303)
1.Video (Livestock)#1.Female				-0.0423	-0.0445
				(0.0330)	(0.0329)
HH size					0.00346
					(0.00220)
Schooling					-0.0190
					(0.0137)
Manyatta fixed effect	No	No	Yes	Yes	Yes
Constant	0.0481***	0.0205***	0.00349	-0.0370	-0.0551
	(0.00733)	(0.00649)	(0.0287)	(0.0298)	(0.0350)
Observations	1,743	1,743	1,737	1,735	1,734
R-squared	0.002	0.048	0.098	0.155	0.158

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 2.b

Insurance uptake **after VIDEO TREATMENT, with interaction and framing**
Dependent variable: 1 = Household bought index insurance at the **6th sales window**

	(1)	(2)	(3)	(4)	(5)
Video (household)	-0.0168	-0.0139	-0.0169	0.0217	0.0229
	(0.0135)	(0.0131)	(0.0154)	(0.0159)	(0.0158)
Video (livestock)	-0.00238	-0.00353	0.00522	0.0290**	0.0305**

	(0.0144)	(0.0137)	(0.0153)	(0.0141)	(0.0141)
Prepurchase		0.148***	0.162***	0.115***	0.116***
		(0.0177)	(0.0185)	(0.0193)	(0.0193)
Coupon				0.0818***	0.0814***
				(0.0162)	(0.0162)
1.Video (HH)#1.Coupon				-0.0311	-0.0316
				(0.0254)	(0.0253)
1.Video (livestock)#1.Coupon				-0.0168	-0.0176
				(0.0258)	(0.0257)
1.Female				0.172***	0.177***
				(0.0224)	(0.0226)
1.Video (HH)#1.Female				-0.0771**	-0.0788**
				(0.0360)	(0.0356)
1.lVideo (livestock)#1.Female				-0.0661*	-0.0689*
				(0.0356)	(0.0354)
HH size					0.00442*
					(0.00252)
Schooling					-0.0258*
Manyatta fixed effect	No	No	Yes	Yes	Yes
Constant	0.0668***	0.0258***	-0.00681	-0.0624**	-0.0853**
	(0.00856)	(0.00723)	(0.0290)	(0.0306)	(0.0364)
Observations	1,743	1,743	1,737	1,735	1,734
R-squared	0.001	0.076	0.132	0.213	0.216

OLS estimate, with robust standard error

Robust standard errors in parentheses

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