Paying Agents to Promote Consumer Welfare from Catastrophic Drought Insurance*

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Abstract

Personalized, data-driven financial advice is increasingly feasible at scale, but whether it improves consumer welfare depends on an underexplored condition: the incentive structure of the intermediaries who deliver it. We study this in a cluster-randomized trial with 2,416 households and 80 commissioned insurance agents in Ethiopia. We cross-randomize the provision of individualized welfare-based recommendations with an alternative agent compensation scheme that rewards alignment with those recommendations rather than sales volume. We develop a structural model to compute household-specific expected consumer surplus (ECS) from index-based drought insurance in real time and use it to generate tailored purchase advice. Despite 85% of households having positive expected welfare gains from insurance, only 8purchase. Personalized advice alone has no detectable effect on take-up or ECS under standard revenue-based agent incentives. When advice is paired with welfare-aligned incentives, insurance take-up declines by 12%, welfare-reducing purchases fall by 25%, and expected consumer surplus rises by 45% among those advised not to purchase. Effects are concentrated among households with low baseline product knowledge — those most susceptible to agent overselling. Technological advances in personalized prediction do not, by themselves, expand the welfare frontier: realizing their potential requires complementary reforms to the incentive structures governing financial intermediation.

Keywords: agent incentives, financial advice, index insurance, overselling, risk

1 Introduction

Personalized, data-driven financial advice is now technologically feasible at scale. Advances in data availability and predictive modeling make it possible to compute consumer-specific optimal financial decisions in real time (Handel et al., 2020; Harrison, Morsink, and Schneider, 2023; Ghili et al., 2024) and deliver individualized recommendations to millions of people at low cost. Yet whether such advice actually improves consumer welfare remains an open question – and we argue that the answer depends critically on the incentive structure of the intermediaries who deliver financial products. Financial products are rarely chosen in isolation. They are marketed and sold by agents, brokers, and digital platforms whose compensation is typically tied to sales volume rather than consumer welfare (Anagol, Cole, and Sarkar, 2017; Hoechle et al., 2018; Egan, 2019; Chalmers and Reuter, 2020). If intermediaries actively counteract welfare-improving advice – through persuasion, selective emphasis, or sheer sales pressure – then the mere availability of personalized guidance may not translate into better decisions, regardless of its quality. Understanding when personalized advice works therefore requires understanding the institutional environment in which it operates.

We test this argument in a large-scale field experiment in the market for index-based catastrophic drought insurance in Ethiopia. The setting is well-suited to the question. The product – Index-Based Livestock Insurance (IBLI) – is commercially priced, sold through commissioned local agents, and carries basis risk that makes its expected welfare consequences genuinely household-specific. This heterogeneity means that a single recommendation cannot serve all consumers well, that agents have both the opportunity and the incentive to oversell, and that the gap between what an agent recommends and what maximizes consumer welfare can be large and systematically self-serving. We develop a structural model to compute each household's expected consumer surplus (ECS) from insurance purchase in real time, using individually elicited risk preferences, herd characteristics, and subjective beliefs about drought risk and index performance. This allows us to generate tailored, welfare-maximizing recommendations for each household and to measure precisely whether observed purchase decisions are welfare-improving or welfare-reducing.

We cross-randomize two interventions across 240 villages and 2,416 households served by 80 agents. In the first, households receive individualized advice under standard revenue-based agent incentives – the prevailing institutional environment. In the second, households receive the same advice but agents are compensated based on the degree to which consumer purchase decisions align with the recommendations, rather than on sales volume. This design allows us to hold the information environment constant while varying only the agent incentive structure, isolating its role in determining whether advice translates into welfare-improving behavior. Three findings

emerge. First, personalized advice alone has no detectable effect on take-up or expected consumer surplus when agents retain standard sales incentives. Second, when advice is paired with welfare-aligned agent incentives, welfare-reducing purchases decline by 25 percent and expected consumer surplus rises substantially among those advised not to purchase, with gains concentrated among households with low baseline product knowledge – precisely those most susceptible to agent over-selling. Third, and strikingly, this effect is entirely one-sided: the same combination of advice and incentive alignment has no effect whatsoever on the much larger population of households who stand to gain from insurance but do not buy. Over-purchase and under-purchase are thus distinct failures requiring distinct solutions, and fixing intermediary incentives addresses only one of them. Together, these results establish that the effectiveness of personalized financial advice depends not on the quality of the advice itself, but on whether the institutional incentive environment allows it to reach consumers undistorted.

The financial product we study – Index-Based Livestock Insurance (IBLI) – is designed to protect pastoralists in the arid and semi-arid lands (ASALs) of Sub-Saharan Africa against catastrophic drought. Coverage is triggered by deviations in satellite-based measures of vegetation quality relative to historical averages, with indemnity payments scaled to insured herd size.[1] As a commercial index product, IBLI carries two-sided basis risk: payouts depend on the index rather than realized individual losses. Downside basis risk arises when the pastoralist suffers a loss but the index is not triggered, and upside basis risk arises when the pastoralist does not suffer a loss but the index is triggered so that a payout is made.[2] Combined with heterogeneity in consumer risk preferences and in subjective expectations of a drought event during the contract period, the expected consumer welfare impact of purchasing coverage varies among households (Clarke, 2016b; Jensen, Mude, and Barrett, 2018; Harrison, Morsink, and Schneider, 2023). These features make the product both economically consequential and difficult to evaluate without a model of expected consumer welfare of this insurance product.

The stakes are substantial. In 2023, our data reveal that 77 percent of livestock losses in the study region were attributable to drought-related causes and more than 3 million pastoralists now purchase IBLI coverage in the region. Yet product understanding is limited: at baseline, the average household answers only 2 out of 9 basic questions about the product correctly. Among purchasers this is only 6 out of 9. The expected consumer welfare estimates from our model imply large scope for improvemed consumer decision-making. The vast majority, 85%, of respondents

[1] For details, see Chantarat et al. (2013) or Jensen et al. (2024).

[2] This basis risk is *not* a performance risk: the index insurance contract is performing statistically as the contract specified. Of course, if pastoralists do not understand the basis risk, or are only told about the upside basis risk, they may subjectively view these basis risks as contract "non-performance," with predictable consequences for take-up and expected welfare (Doherty and Schlesinger, 1983; Clarke, 2016b; Harrison and Ng, 2016).

would maximize their expected welfare if they purchased IBLI coverage. But only 8.2% actually do. Conversely, 9% of those who we estimate should not buy IBLI do. Thus, more than three-quarters of the population makes sub-optimal IBLI purchase decisions at baseline: 88% of those not purchasing and 9% of those who do buy IBLI can improve their welfare by changing their decision.

To implement the tailored advice, we collect from each household real-time data on herd size, subjective expectations about losses and payouts, and risk preferences elicited through incentivized choice tasks. We then compute the respondent-specific expected consumer surplus (ECS) associated with alternative insurance coverage choices, including non-purchase, and recommend the coverage level that maximizes the household's ECS. To promote transparency and address ethical concerns, we communicate the logic of the recommendation using short, pictorial videos that explain how household characteristics map into welfare outcomes and advice.

To study the role of intermediary incentives, we partnered with the insurance company to implement both the standard revenue-based agent incentives scheme and a novel scheme where agent incentives are tied to consumer welfare. This allows us to experimentally vary, across villages and within each agent's portfolio the extent to which agents' financial incentives are aligned or misaligned with personalized advice. Under the non-standard scheme, agents receive the highest payment when a household's final coverage choice coincides with the ECS-maximizing recommendation communicated to the respondent, with payments declining as consumer choices deviate, in either direction, from that benchmark. This agent incentive design expressly discourages overselling of insurance. Payouts under this design are calibrated to be equal in expectation under either scheme.

We implement a cluster-randomized design in which villages are assigned to one of three arms. In the control arm, households receive no tailored advice and agents operate under standard sales incentives. In the first treatment arm, households receive tailored advice while agents retain standard sales incentives. In the second treatment arm, households receive tailored advice and agents are compensated based on consumer-welfare incentives.[3] We combine administrative data from the insurance company on insurance purchases, agent effort and agent incentives, with four rounds of household surveys and lab-in-the-field experiments with prospective consumers and agents.

We find that tailored advice alone has no detectable effect on household behavior or expected consumer welfare when agents are compensated with standard sales incentives. In contrast, when tailored advice is paired with consumer-welfare incentives for agents, on average it reduces insur-

[3]Note that it is infeasible to offer a treatment that aligns agent incentives with consumer welfare without informing consumers of the recommendations that would maximize both their welfare and agents' incentive payments.

ance take-up, increases adherence to advice not to purchase, and raises expected consumer surplus. Specifically, consumer-welfare incentives for agents combined with tailored advice reduce insurance uptake by 12 percent, and lead to a 25 percent reduction in individuals who buy when our advice suggests they should not. This, in turn, raises expected consumer welfare for those advised not to purchase by 46 percent, relative to those in the control group who would have received advice not to purchase had they been assigned to receive tailored advice and consumer-welfare aligned incentives for agents. This highlights that a key source of inefficiency is over-purchase driven by misaligned intermediary incentives. Notably, neither tailored advice nor consumer-welfare aligned incentives for agents increase welfare-enhancing insurance purchase among those advised to purchase IBLI. This asymmetry suggests that intermediary misalignment primarily distorts decisions through insurance agents over-selling rather than promoting welfare-enhancing purchase decisions.

We explore the mechanisms through which tailored advice and agent incentives affect consumer behavior. Tailored advice could improve outcomes by increasing household understanding of product features and expected welfare. We find, however, little evidence that our interventions meaningfully changed knowledge or perceived product value. We do observe that tailored advice reduced trust in agents, but this reduction occurs under both incentive schemes and cannot rationalize the main findings. Consumer-welfare incentives for agents might have altered agent effort, particularly because non-purchase advice generated potential rewards in this arm, but we find no differences in observed effort.

Instead, the effects appear to operate through the interaction between tailored advice and agent incentives. Results from an incentivized lab-in-field experiment with agents purchasing on behalf of respondents under varying conditions and agent incentives shows that agents display a strong baseline tendency to promote insurance, and standard sales incentives reinforce this behavior. Consumer-welfare incentives slightly reduce agents' push to sell, consistent with what we see in the administrative data on actual IBLI purchases.

The gains are concentrated among households with below-median baseline understanding of product attributes, contract performance, and procedures. These consumers are most responsive to tailored advice when it is delivered under the consumer-welfare incentive scheme for agents, reducing welfare-lowering insurance purchases and increasing ECS. High-knowledge households show little change. These patterns suggest that the main mechanism is not improved comprehension *per se*, but the combination of tailored advice and incentive-compatible intermediation, consistent with low-knowledge households being more susceptible to persuasion by agents who act in their own self-interest.

Our research connects to a literature that explores interventions intended to improve the quality

of financial decisions (Carpenter et al., 2021; Allcott and Knittel, 2019; Ambuehl, Bernheim, and Lusardi, 2022; Harrison, Morsink, and Schneider, 2023). Building on a recent literature that estimates consumer welfare from financial decisions at individual-level (Harrison and Ng, 2016; Bernheim, 2021; Harrison, Morsink, and Schneider, 2021; Butera et al., 2022; Harrison et al., n.d.) we test a fundamentally different intervention to improve financial decision quality. We provide personalized, data-driven and model-based advice at scale, also finding that information yields no gains under prevailing agent compensation schemes but, importantly, showing that effectiveness depends critically on intermediary incentives.

That conditional insight directly leads to our second contribution, to a literature that uses personal and administrative data to predict optimal choices (Currie and MacLeod, 2020; Abaluck et al., 2021; Mullainathan and Obermeyer, 2022; Ghili et al., 2024). Although these tools can greatly improve decision quality in some cases (Harris and Yellen, 2024), in other contexts they do not lead to better decisions because the recipients of the advice choose not to adopt it (Stevenson and Doleac, 2022; Angelova, Dobbie, and Yang, 2023; Agarwal et al., 2023). We also find that most consumers would benefit in expectation from insurance purchase but those individuals are not induced to purchase by the provision of individually tailored advice on their optimal choice. We add to this literature by showing that tailored advice using real-time consumer data can improve consumer welfare from a commercial financial product if the agents who promote the product are also incentivized to enhance consumer choice quality.

This conditional insight links to our third contribution, to the literature that studies financial intermediation and misalignment of incentives (Hackethal, Haliassos, and Jappelli, 2012; Mullainathan, Noeth, and Schoar, 2012; Anagol, Cole, and Sarkar, 2017; Foerster et al., 2017; Hoechle et al., 2018; Egan, 2019; Chalmers and Reuter, 2020). This literature shows that agent incentives rather than optimal choices for consumers typically predict consumer choice in contexts where financial intermediaries operate. We demonstrate that aligning intermediary incentives with consumers' ECS from financial product purchase decisions can effectively discourage product overselling that harms consumers but benefits agents. Although these gains are concentrated among a small minority of the target population, the resulting ECS gains are relatively large. The combination of tailored individual advice and welfare-aligned agent incentives can safeguard consumers against unintended harm from a complex financial product that benefits most, but not all consumers within a market.

More broadly, our findings have practical relevance for the design and regulation of financial advice systems. As digital financial services expand, hundreds of millions of consumers are being offered complex financial products via agents or mobile platforms whose incentives are often opaque and unregulated. Our results show that personalized advice may be insufficient to improve

consumer decision-making, and thus welfare, if delivered through intermediaries whose incentives are not aligned with prospective purchasers' interests. Successful scale-up of such tools requires institutional arrangements that align agent incentives, protect consumer interests, and preserve the credibility of delegated financial guidance.

2 Index-based Livestock Insurance in Ethiopia's Borena Zone

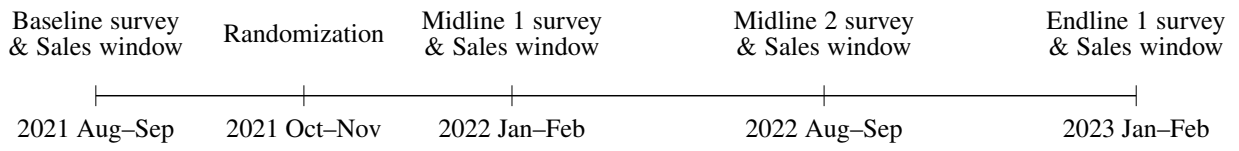
Our study takes place in 240 villages in the Borena zone of the Oromia region of southern Ethiopia, an arid and semi-arid area where pastoralism, the extensive grazing of livestock, is the predominant livelihood. In our sample, 79 percent of households report livestock herding as their primary source of income. Household welfare in this region is highly exposed to drought risk. In 2023, drought-related starvation and dehydration accounted for 77 percent of livestock losses. Because drought is spatially covariate, informal risk-sharing arrangements offer limited protection.

IBLI is a commercial insurance contract that indemnifies pastoralists against catastrophic drought losses. Payouts are triggered by deviations from historical averages of satellite-based measures of the Normalized Difference in Vegetation Index (NDVI) rather than by verified individual losses.[4] Several studies have documented positive short-term and long-term effects of IBLI on household outcomes such as increased livestock investment, reduced distress livestock sales, greater food security during drought years, increased educational attainment, reduced violent conflict, and greater subjective well-being (Jensen, Barrett, and Mude, 2017; Janzen and Carter, 2019; Tafere, Barrett, and Lentz, 2019; Barrett et al., 2026; Jensen et al., 2025; Gehring and Schaudt, 2026). The basis risk inherent in index insurance, combined with heterogeneity in herd composition, drought exposure, subjective expectations, and risk preferences, implies that the expected welfare consequences of purchasing coverage vary substantially across households. Moreover, because IBLI is commercially priced to generate profits in expectation, it cannot be welfare-improving for all potential buyers, even if they are risk averse. In this setting, the optimal insurance decision is inherently household-specific and not transparent from contract terms alone.

IBLI is marketed and sold through local insurance agents who are compensated under a standard revenue-based sales incentive scheme based on premium revenue. Households typically rely on these agents for product information and purchase decisions; there are no independent advisory channels. The incentive structure therefore creates a potential misalignment between agents' financial incentives and consumers' expected welfare, particularly in a context where basis risk and

[4]NDVI offers a reliable signal of rangeland conditions and forage availability (Tucker et al., 1985; Prince, 1991; Meroni et al., 2014; Soto et al., 2024) and is strongly correlated with livestock mortality in this region (Chantarat et al., 2013). Pastoralists may or may not internalize these objective facts about the actuarial properties of the index.

Figure 1: Experimental and Survey Timeline



heterogeneous exposure make over-purchase possible. While IBLI adoption rates have been high relative to most index-based insurance products in low-income settings, with cumulative adoption within study samples at 45% (Jensen et al., 2024), attrition in adoption has also been high, at 30% (Jensen, Barrett, and Mude, 2017; Jensen et al., 2024), consistent with the possibility that some purchases do not align with *ex ante* welfare gains.

Product understanding is limited. At baseline, households answer on average 1.7 out of 9 basic questions about IBLI correctly. Even agents score only 2.3 out of 9 on the same knowledge test. In such a low-information environment, consumers may find it difficult to evaluate whether insurance purchase is welfare-enhancing and to distinguish welfare-based recommendations from sales-driven persuasion. These features – heterogeneous expected returns, commercial pricing, reliance on commissioned intermediaries, and limited product knowledge – make this market a natural setting to study whether tailored, welfare-based advice can improve decision quality, and whether its effectiveness depends on intermediary agent incentives.

3 Experimental design

We conducted a cluster-randomized controlled trial spanning 80 kebeles and 240 villages (3 per kebele) served by 80 insurance agents over four semi-annual IBLI sales seasons between 2021 and 2023. The project chronology is summarized in Figure 1. Each agent served one kebele and three villages, and we randomly assigned villages to treatment arms at the kebele level. Each agent thus served three villages, one (and only one) from each treatment arm, so treatment effects are not confounded by differences in agent characteristics.

The experiment cross-randomized the provision of tailored advice to households and the incentive scheme for agents. In control villages, households received standard IBLI marketing and agents were paid under the prevailing revenue-based sales incentive scheme. In Treatment 1 (Advice + Sales), households received standard IBLI marketing *and* individually tailored advice, while agents continued to receive revenue-based sales incentives. In Treatment 2 (Advice + Welfare), households also received tailored advice, but agents were compensated under a consumer-

welfare–aligned incentive scheme that maximized agent incentive payments when household purchase decisions matched the tailored advice they were given.

Villages were randomly assigned to treatments after the baseline survey, and treatments were provided during three subsequent sales seasons. In all villages and in all three intervention rounds, agents first conducted a standardized information session describing IBLI contract terms. This session covered premium rates, index design, registration and claim payment procedures, and historical claim payments within the village's index unit.[5] In treatment villages, households then viewed a short video explaining the welfare framework and received tailored advice. Agents subsequently conducted sales visits, and households made purchase decisions during the sales window.

We combine administrative data from the insurance company on household-level purchases and agent effort and incentives with four rounds of household surveys and agent surveys. We conducted two types of insurance agent surveys, one that collected information on their demographic characteristics, agent experiences and product knowledge, and one that focused on their specific interactions and beliefs about respondents in each specific village. Household surveys measured demographic and production characteristics, respondent knowledge, and trust in agents. At baseline, we elicited household risk preferences through incentivized lottery-choice tasks.

To isolate the informational content of the video explaining the tailored advice from the individual-specific tailored advice itself, in the final sales season we further randomized households in control villages into three groups: pure control, video-only, and advice-only. This design allows us to distinguish the effects of the information contained in the video explaining the welfare model from the individualized recommendation.

Our primary outcomes are insurance take-up, coverage levels, and expected consumer surplus. Secondary outcomes include product knowledge, trust in agents, and agent behavior measured through administrative data and lab-in-the-field experiments.

To measure agent effort independently of sales and alignment of consumer choice with tailored advice, we implemented a raffle system. In these remote ASALs, one of the biggest components of agent effort is whether the agents travel to all villages and speak with all respondents. Therefore, each surveyed household received a uniquely numbered ticket. If agents visited the community and respondents during the sales season, they were instructed to collect these tickets from respondents and then return them to the insurance company because these tickets entered a lottery managed by the insurer, with prizes four times the maximum incentives agents could earn. Because the

[5]Borena zone is divided into eight distinct, non-overlapping geographic units each with its own NDVI-based index describing that unit's entire area. IBLI purchases are registered in the specific index unit within which they are sold. Thus payouts are invariant to where herders ultimately graze their animals. For more details, see Jensen et al. (2024).

probability of winning the raffle increased with the number of households visited and thus tickets collected, the number of tickets collected by an agent provides a direct measure of sales effort independent of sales volume.

4 Intervention

4.1 The model of expected consumer surplus of IBLI

Whether a given household benefits from insurance coverage depends on its herd size, risk preferences, and subjective beliefs about both the likelihood of losses and the probability that the index will be triggered. These parameters vary substantially across households in our setting. Generating household-specific advice requires a model that maps individual characteristics – herd size, risk preferences, and subjective beliefs about losses and payouts – into an expected welfare estimate for each possible coverage choice. We adapt the model of expected consumer surplus (ECS) of index insurance developed in Harrison, Morsink, and Schneider (2023) to the specific features of IBLI. Full details are provided in Appendix A. Here we describe the core structure and the key parameters.

A pastoral household with livestock herd value H faces the risk of losing livestock with probability p. The household pays premium R to purchase insurance. When the satellite-based index is triggered – with probability q – the household receives payout I. Because the index is an imperfect proxy for individual losses, the household also faces basis risk. Following Clarke, 2016a, with probability r the index is not triggered even though a herd loss occurs (downside basis risk), and with probability $q + r - p$, the index is triggered even though no loss occurs (upside basis risk).

This basis risk structure is central to why the insurance decision is household-specific. Without insurance, a pastoralist faces two states of the world: no loss, or a loss. Purchasing insurance expands this to four states, defined by whether a herd loss occurs and whether the index is triggered. The payoffs in each state, and their associated probabilities, are summarized in Table A1. The key insight is that in states where the index and realized losses diverge – the basis risk states – the household either pays a premium and experiences losses but does not receive a payout (downside basis risk), or receives a payout after paying a premium, even though they did not experience a loss (upside basis risk). Whether insurance is welfare-improving therefore depends on the relative likelihood of these states, which varies across households according to their subjective beliefs, and on how much the household dislikes bearing uninsured risk, which varies with risk preferences. Assuming expected utility maximization with a constant relative risk aversion (CRRA) utility func-

tion, we compute the certainty equivalent of purchasing insurance (CE_{buy}) and of not purchasing (CE_{nobuy}) for each household. The expected consumer surplus of purchasing insurance is then:

$$ECS = CE_{buy} - CE_{nobuy} \tag{1}$$

A positive ECS implies the household would benefit in expectation from purchasing coverage; a negative ECS implies the opposite. Because ECS depends on H, p, q, r and the household's risk aversion parameter θ, it varies across households and, for a given household, across coverage levels, since insuring a larger share of the herd increases both the premium paid and the potential payout received. We therefore compute ECS for each feasible coverage level and identify the level that maximizes each household's ECS from IBLI purchase. This is the basis for the tailored advice we provide. When the ECS-maximizing coverage level is strictly positive, we advise the household to purchase insurance for that share of their herd; when it equals zero, we advise against purchase. In cases where the difference between CE_{buy} and CE_{nobuy} is small – less than 20 percent of the mean ECS – we inform the household that our calculations are inconclusive.

4.2 Data for estimating welfare

The five inputs to the ECS model — herd size H, the probability of herd loss p, the probability of the index being triggered q, the basis risk parameter r, and the risk aversion parameter θ – are either elicited directly from each household or taken from external sources. We describe each in turn.

IBLI is sold twice per year, ahead of each of two seasons. A single contract provides coverage for both. A household that purchases coverage may therefore receive payouts in either or both seasons within the contract period. This two-season structure means that p and q must be elicited separately for each season. We do so immediately prior to the household's purchase decision, asking respondents to report their subjective probability that their animals will survive to the end of each season, and their subjective probability that the IBLI index will be triggered in their index unit during each season. Eliciting these beliefs in real time, rather than using historical averages, ensures that the advice reflects each household's current expectations at the moment of decision. This is especially important because such perceptions evolve with observable biophysical conditions (Jensen, Mude, and Barrett, 2018). Herd size H is likewise measured at the time of the sales visit.

Risk preferences θ were elicited from each respondent at baseline through an incentivized lottery choice task in which each respondent makes choices over 30 pairs of lotteries drawn from a

battery of 100. Risk aversion parameters are estimated following Harrison, Rutström, et al., 2008. We assume risk preferences are stable over the period of our experiment and use the baseline estimates for all subsequent rounds of advice.

The insurance premium R and payout I are taken directly from the contract terms provided by the insurance company. For the basis risk parameter r we use the externally estimated value from (Jensen, Barrett, and Mude, 2017).

Since herders make separate insurance purchase decisions for each of four animal species – camels, cattle, goats, and sheep – and their beliefs about loss probabilities differ across species, we elicit p and H separately for each species and compute ECS and the resulting advice at the species level. This is also the unit of observation in our empirical analysis.

Because real-time computation of ECS during survey administration was infeasible in the offline communities we study, we pre-computed ECS for every possible combination of input values and stored the results in species-specific look-up tables. Beliefs about p and q were restricted to bins of 10 percentage points. For each combination, the look-up table records the coverage level — expressed as a share of the herd — that maximizes ECS.

Table 1: Sources of Explained Variation in Expected Consumer Surplus and Advice Provision

	Pre-computed Expected Consumer Surplus	Advice to Purchase Insurance	Advised Number of Animals to Insure	Expected Consumer Surplus
	(1)	(2)	(3)	(4)
Risk Aversion	0.166	0.0220	0.000804	0.143
Herd Size	0.246	0.00473	0.985	0.266
Index Trigger Belief	0.574	0.947	0.0126	0.576
Herd Loss Belief – First Season	0.00313	0.0197	0.000774	0.00322
Herd Loss Belief – Second Season	0.0102	0.00695	0.000825	0.0117

Notes: Values in cells represent the relative Shapley decomposition of R^2. Each cell shows the share of explained variance in the outcome variable, attributable to each input variable. Column (1) refers to the pre-calculated Expected Consumer Surplus that was used to generate the look-up tables for the tailored advice; The outcome variable in Column (2) captures whether the respondent was advised to purchase or not purchase IBLI; Column (3) refers to the number of animals that the pastoralist was advised to insure, conditional on purchase advise; Column (4) presents the Expected Consumer Surplus calculated after all the input information from the pastoralist was received. Columns (1), (3), and (4) use OLS; Column (2) uses the McFadden pseudo-R^2 from probit.

To understand the extent to which each of the individual-specific inputs influence the tailored advice, we regressed the dependent variable on each of the five variables used to compute ECS. Since variation in ECS and the advice stemming from the potential ECS estimates is jointly determined by the resulting regression coefficient estimates and variation in the five variables, we then do a Shapley decomposition of the explained variation in the (pre-computed) potential ECS from IBLI purchase (Table 1, Column 1), Advice to Purchase Insurance (Column 2), and the Advised Number of Animals to Insure, conditional on being advised to purchase (Column 3). The Index trigger belief accounts for the largest share of variation in the ECS used to calculate the advice (57.4%) and therefore also on the actual advice to purchase (94.7%). This is intuitive; prospective purchasers should be more likely to pay for a policy they expect to pay out, holding the premium level constant. Meanwhile, herd size dominates variation in the advised number of animals to insure (98.5%), reflecting that conditional on IBLI purchase being advised, the main determinant of the scale of insurance purchase should be the volume of assets at risk.

4.3 Delivery of tailored advice

Delivering model-based financial advice to a population with low literacy – roughly 20 percent of respondents in our sample is literate – and limited familiarity with formal insurance products required a carefully designed communication strategy. We developed a 15-minute video, recorded in the local language (Oromifa), that explains the ECS framework and the logic behind the tailored advice in accessible, visual terms. The video features three fictional pastoralists who differ in herd size, risk attitudes, and subjective beliefs about losses and index triggering, and who receive different advice. By walking through these contrasting cases, the video communicates the key insight that the welfare-maximizing insurance decision is household-specific, and that the advice each respondent receives reflects their own reported characteristics. Example screenshots from the video are provided in Appendix Figure B1, illustrating the pictorial format used to convey probabilities and payoffs without relying on numerical literacy.

To address ethical concerns about the validity of the welfare framework, the video also explicitly addresses the conditions under which the advice may not be reliable. Respondents are told that if their answers to the input questions do not accurately reflect their situation, or if they believe the model omits dimensions relevant to their assessment of IBLI's value, the advice may not be applicable to them. This disclaimer was included both for ethical reasons – to ensure respondents understood the basis and limitations of the recommendation they were receiving – and to preserve the credibility of the advice by making its assumptions transparent. The individualized recommendation was delivered to each household immediately after the video, so that the framework for

interpreting it was fresh at the moment of decision.

4.4 Agent incentives aligned with consumer welfare

A central premise of this paper is that standard revenue-based agent incentives create a tension between agents' financial interests and consumers' welfare. To study whether realigning these incentives can improve consumer outcomes, we partnered with the insurance company to implement an alternative compensation scheme in Advice+Welfare villages, while retaining the standard scheme in Control and Advice+Sales villages.

Under the standard scheme, agents received a commission of 8 percent of premium revenue, up to a seasonal cap. Under the consumer-welfare aligned scheme, agents received the highest payment when a household's insurance purchase decision matched the ECS-maximizing recommendation that had been communicated to that household, with payments declining linearly as the actual purchase deviated from the recommended amount in either direction. This design expressly discourages both overselling – pushing households to purchase when the advice recommends against it – and underselling – discouraging purchase when the advice recommends it. The scheme was calibrated to equalize expected earnings per village across the two incentive schemes. This equalization serves two purposes: it ensures agents have no financial reason to exert differential effort across their assigned villages, and it allows us to attribute any behavioral differences across arms to the incentive structure rather than to differences in agent compensation levels.

Agents were trained on both incentive schemes prior to each sales season. After each season, household purchase decisions were reported to the insurance company, which verified compliance with the tailored advice and disbursed incentive payments to agents accordingly.

5 Balance and Estimation strategy

5.1 Sample summary statistics and balance

The study includes 240 villages (three per kebele) across 80 kebeles in Borena zone. Kebeles were selected from those with primary cooperatives capable of selling IBLI. Of these, 55 were actively marketing IBLI and 25 had expressed interest in doing so. Kebeles facing security concerns, extreme remoteness, or weak agent capacity were excluded *ex ante*.

In each village, household rosters were compiled with kebele development offices. From each

roster, 40 households were randomly drawn. The first ten households on that list that herded livestock and agreed to participate were included in the sample, yielding 2,416 households per survey round. Minor variation in village sample sizes reflects differences in eligibility and consent.

Each of the 80 insurance agents was assigned to one kebele and served its three study villages, one per treatment arm. The relevant unit for agent-level analysis is therefore the agent–village pair (240 total). Because each agent operated under all three experimental conditions, comparisons across incentive schemes are within-agent, and not confounded by unobserved agent characteristics.

Randomization occurred at the village level. All regressions cluster standard errors at that level.

Table 2 reports baseline characteristics of herders and balance checks for the randomization. Columns (1)-(3) display summary statistics of key variables for the control group, Advice+Sales group, and Advice+Welfare group, respectively. Respondents average 43 years of age; 38 percent are female and 87 percent married. Educational attainment is low (approximately 20 percent is literate), and average schooling is 1.3 years. Mean herd size is approximately 13 tropical livestock units (TLUs), where TLUs integrate cattle, camels, sheep, and goats into a single unit based on average weight by species. One TLU is equivalent to 0.7 camels, 1 cow, or 10 sheep or goats. Nearly 2 TLUs were lost on average in the previous 12 months. Experience with IBLI is limited. Roughly one-third of households had heard of the product at baseline, average knowledge is 1.7 correct answers out of 9 comprehension questions, and fewer than 10 percent had previously purchased coverage.

Herder characteristics are well balanced across treatment arms. Columns (4) to (6) of Table 2 show tests of differences in means between the treatment arms. The joint F-test for overall balance across all covariates fails to reject the null hypothesis that baseline characteristics are equal across groups, with p-values of 0.44, 0.46, and 0.46 for control vs. Advice+Sales incentive villages and Advice+Welfare incentive villages, and between the treatment villages, respectively. Normalized differences are below the 0.25 threshold in all cases. Of the 42 differences examined, four are statistically significant: three at the ten percent level, and one at the five percent level.

To verify that treatment assignment did not mechanically alter the distribution of tailored advice, we also generated advice for control households using baseline data. The share that would have been advised to purchase insurance (82 percent) and the recommended coverage levels are statistically indistinguishable from those in treatment villages (Appendix Table B1).

All 2,416 households were re-interviewed in each of the four survey rounds. Changes in the identity of the household respondent were rare and not systematically related to treatment status.

Table 2: Baseline Herder Variables and Balance Across Treatment Groups

	Summary statistics			Balance		
	Control	Advice + Sales	Advice + Welfare	Advice + Sales vs. Control	Advice + Welfare vs. Control	Advice + Sales vs. Advice + Welfare
	(1)	(2)	(3)	(4)	(5)	(6)
Respondent age in years	43.3	43.7	43.4	0.363	-0.002	-0.370
	[16.0]	[16.4]	[16.4]	(0.755)	(0.702)	(0.632)
				{0.023}	{0.004}	{-0.019}
Female respondent	0.378	0.376	0.385	-0.002	0.008	0.010
	[0.485]	[0.485]	[0.487]	(0.022)	(0.021)	(0.019)
				{-0.004}	{0.016}	{0.019}
Married respondent(=1)	0.870	0.879	0.874	0.009	0.005	-0.004
	[0.337]	[0.326]	[0.332]	(0.014)	(0.015)	(0.012)
				{0.028}	{0.013}	{-0.015}
N of household members	5.78	5.81	5.82	0.040	0.058	0.017
	[2.30]	[2.31]	[2.20]	(0.094)	(0.092)	(0.073)
				{0.017}	{0.022}	{0.005}
Literate in any language (=1)	0.194	0.222	0.215	0.029	0.023	-0.006
	[0.396]	[0.416]	[0.411]	(0.020)	(0.019)	(0.017)
				{0.069}	{0.051}	{-0.018}
Years of education	1.32	1.39	1.45	0.077	0.139	0.060
	[3.20]	[3.21]	[3.27]	(0.162)	(0.155)	(0.128)
				{0.024}	{0.041}	{0.017}
Traditional religion (=1)	0.655	0.658	0.664	0.003	0.008	0.004
	[0.476]	[0.475]	[0.473]	(0.017)	(0.018)	(0.016)
				{0.007}	{0.020}	{0.013}
Livestock owned or herded (TLU)	13.5	12.7	13.3	-0.855	-0.189	0.664
	[20.8]	[15.2]	[21.8]	(0.779)	(0.890)	(0.743)
				{-0.048}	{-0.010}	{0.034}
Annual livestock loss (TLU)	1.91	1.94	1.75	0.037	-0.166	-0.193
	[5.02]	[4.43]	[3.29]	(0.221)	(0.219)	(0.171)
				{0.008}	{-0.038}	{-0.051}
Annual livestock input expenditure (ETB)	5618.3	5235.0	5427.8	-387.9	-205.4	189.4
	[10287.6]	[8558.1]	[10665.8]	(395.7)	(403.4)	(353.4)
				{-0.041}	{-0.018}	{0.020}
Has land cultivation right (=1)	0.474	0.494	0.505	0.022	0.035*	0.013
	[0.500]	[0.500]	[0.500]	(0.021)	(0.021)	(0.019)
				{0.041}	{0.063}	{0.021}
Heard of IBLI (=1)	0.338	0.342	0.307	0.004	-0.032*	-0.035**
	[0.473]	[0.475]	[0.462]	(0.018)	(0.019)	(0.015)
				{0.009}	{-0.065}	{-0.074}
IBLI knowledge score (1-9, 9 Highest)	1.68	1.75	1.57	0.069	-0.109	-0.176*
	[2.90]	[2.98]	[2.81]	(0.127)	(0.119)	(0.098)
				{0.022}	{-0.038}	{-0.060}
Ever purchased IBLI (=1)	0.086	0.100	0.091	0.014	0.006	-0.008
	[0.280]	[0.300]	[0.288]	(0.015)	(0.015)	(0.012)
				{0.049}	{0.020}	{-0.029}
P-value of Joint F-test:				0.471	0.460	0.402

Standard deviations are in brackets, and standard errors, clustered at the village level, are in parentheses, and the normalized differences are in curly brackets. Columns (1) to (3) report the average of the baseline characteristics of pastoralists in control villages, Advice+Sales incentive villages, and Advice+Welfare incentive villages, respectively. Columns (4) to (6) report mean and normalized differences between the Advice+Sales villages and the control villages, between the Advice+Welfare villages and the control villages, and between the Advice+Sales villages and Advice+Welfare incentive villages respectively. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include kebele fixed effects. Tradi2tional religion equals 1 if the household's main religion is "Wakefata," a local traditional religion. Livestock owned or herded is the sum of the animals owned or herded by the household at baseline, aggregated using TLUs. Annual livestock loss is the sum of animals lost in the past 12 months aggregated using TLU. Annual Livestock input expenditure includes expenditures on water for animals, animal feed or fodder, veterinarian services, transportation costs, livestock tax, salary/wage for labor.

Table 3 reports baseline characteristics of agent–village pairs using midline 1 data, which serve as the pre-treatment baseline for agent outcomes. Agents average 3.4 years of experience, and most had previously visited their assigned villages. Social and economic ties between agents and villages are common. Agent and village characteristics are balanced across treatment arms. Joint tests fail to reject equality of means, normalized differences are small, and none of the 21 pairwise comparisons are statistically significant.

Table 3: Balance of Baseline Variables of Sales Agents – Village Pairs Across Treatment Groups

	Summary statistics			Balance		
	Control	Advice + Sales	Advice + Welfare	Advice + Sales vs. Control	Advice + Welfare vs. Control	Advice + Sales vs. Advice + Welfare
	(1)	(2)	(3)	(4)	(5)	(6)
Agents' impression on herders' IBLI knowledge	6.02	6.08	5.81	0.053	-0.211	-0.264
	[2.15]	[2.01]	[2.09]	(0.162)	(0.178)	(0.166)
				{0.025}	{-0.100}	{-0.129}
Agent's expectations about the index triggered	5.40	5.29	5.44	-0.112	0.038	0.150
	[3.33]	[3.27]	[3.01]	(0.304)	(0.278)	(0.292)
				{-0.034}	{0.012}	{0.048}
Years worked as insurance agent in the village	3.35	3.39	3.36	0.037	0.012	-0.025
	[3.10]	[3.08]	[3.14]	(0.095)	(0.128)	(0.135)
				{0.012}	{0.004}	{-0.008}
Never visited this village before (=1)	0.150	0.150	0.125	0.000	-0.025	-0.025
	[0.359]	[0.359]	[0.333]	(0.028)	(0.022)	(0.025)
				{0}	{-0.072}	{-0.072}
Have a family member in this village (=1)	0.380	0.375	0.412	-0.006	0.031	0.038
	[0.488]	[0.487]	[0.495]	(0.063)	(0.066)	(0.066)
				{-0.010}	{0.067}	{0.076}
Received transfer/gift from respondents (=1)	0.100	0.100	0.125	0.000	0.025	0.025
	[0.302]	[0.302]	[0.333]	(0.040)	(0.045)	(0.045)
				{0}	{0.079}	{0.079}
Gave something to respondents (=1)	0.188	0.188	0.150	-0.000	-0.037	-0.037
	[0.393]	[0.393]	[0.359]	(0.046)	(0.047)	(0.044)
				{0}	{-0.100}	{-0.100}
P-value of Joint F-test:				0.999	0.169	0.207

Standard deviations are in brackets, and standard errors, clustered at the village level, are in parentheses. The normalized differences are in curly brackets. Columns (1) to (3) report the average of the baseline characteristics of sales agents in control villages, Advice+Sales incentive villages, and Advice+Welfare incentive villages, respectively. Columns (4) to (6) report mean and normalized differences between the Advice+Sales group, Advice+Welfare group and the control group, and between the Advice+Sales villages and Advice+Welfare incentive villages respectively. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include kebele fixed effects. Agents' impression of herders' IBLI knowledge is the average of the agents' belief about the share of herders who correctly answered each IBLI knowledge question. Agents answered on a scale of 10: 0 is the least likely (0-10%), 10 being the most likely (91-100%). Agent expectations about the index triggered are the agents' subjective beliefs about the overall probability of the index being triggered in the village. Agents answered on a scale of 10: 0 is the least likely (0-10%), 10 being the most likely (91-100%).

5.2 Estimation strategy

We estimate treatment effects using the following specification:

$$y_{(a)izkt} = \beta_0 + \beta_1 T1_{zk} + \beta_2 T2_{zk} + \delta_{kt} + \varepsilon_{(a)izkt} \tag{2}$$

where $y_{(a)izkt}$ is the outcome of interest for herder i (or insurance agent) in village z of kebele k in survey round t. $T1_{zk}$ and $T2_{zk}$ indicate assignment to Advice+Sales and Advice+Welfare villages, respectively, with Control villages omitted. As pre-specified, we use a logit model for the extensive margin of the insurance purchase, as well as for the binary dependent variable that captures whether the advice was followed. We use an OLS specification for expected consumer surplus, the number of animals or TLU insured, and the extent to which the actual number of animals insured deviated from the advised number of animals.

Since randomization occurred at the village level within kebeles, we include kebele × survey-round fixed effects, δ_{kt}. Identification therefore comes from comparisons between villages within the same kebele and round. This absorbs time-varying kebele-level shocks, such as droughts, and ensures that estimates exploit only within-kebele, and thus within-agent treatment variation. Standard errors, $\varepsilon_{(a)ikzt}$, are clustered at the village level, which is the level of randomization, following Abadie et al. (2023), to account for within-village correlation in outcomes. We also report p-values from randomization inference, following Athey and Imbens (2017).

The coefficient β_1 identifies the causal effect of providing tailored advice under standard sales incentives for agents relative to the status quo. The coefficient β_2 identifies the effect of tailored advice combined with consumer welfare-aligned incentives for agents relative to the status quo. We test the null hypothesis $\beta_1 = \beta_2$ to assess whether aligning agent incentives with consumer welfare rather than having standard revenue-based sales incentives alters the impact of tailored advice.

In some specifications outcomes are defined at the herder × animal-species level a because the inputs to the tailored advice were measured at the animal-species level, tailored advice was generated at this level, and respondents also made insurance purchase decisions at the animal-species level.

In the final survey round, households in Control villages were individually randomized into three groups: pure control, Video Only, and Advice Only. To distinguish the effects of the informational video about the tailored advice from those of the individual-specific tailored advice, we estimate:

$$y_{(a)izkt} = \alpha_0 + \alpha_1 \text{VideoOnly}_{izk} + \alpha_2 \text{AdviceOnly}_{izk} + \eta_{zt} + \varepsilon_{(a)izkt} \quad (3)$$

where VideoOnly_{izk} and AdviceOnly_{izk} are the indicator variables equal to one if household i in village z in kebele k is assigned to each treatment arm, video-only and advice-only group. We include village $\times$ survey round fixed effects, η_{zt}, instead of the kebele $\times$ survey round fixed effects used in other specifications, because in this exercise individual households are randomized within village. We cluster standard errors at the individual household level, which is the unit of randomization. Thus α_1 and α_2 are the estimated coefficients for the treatment arm dummies. All other parameters are the same as in equation (2).

6 Results

We examine the impact of tailored advice and the agent incentive scheme on (i) insurance take-up, (ii) adherence to individualized recommendations, and (iii) ECS. Throughout, we distinguish between the provision of tailored advice under standard revenue-based sales incentives ("Advice+Sales") and tailored advice combined with consumer-welfare incentives for agents ("Advice+Welfare").

6.1 IBLI purchase

Table 4 reports estimates of equation (2) for insurance take-up at the extensive and intensive margins. Tailored advice alone has no detectable effect on insurance purchase. In contrast, when advice is paired with consumer-welfare incentives for agents, insurance take-up *declines* by 1 percentage point relative to the control mean of 8 percent, a 12 percent reduction. We reject equality of the two treatment effects at conventional levels (p-value = 0.06). Thus, personalized advice affects take-up only when agent incentives are aligned with the recommendation.

At the intensive margin, effects are small. The number of animals insured (unconditional on purchase) declines modestly in both treatment arms, though estimates are imprecise. Conditional on purchase, coverage levels increase slightly in the Advice+Welfare arm (0.354 TLUs, approximately 9 percent of the control mean of 3.8), but the estimate is statistically insignificant (p-value=0.15).

Taken together, the primary behavioral effect of incentive alignment is a reduction in the number of purchasers rather than a substantial change in coverage conditional on purchase. This pattern is

consistent with the presence of over-selling under standard revenue-based sales incentives. However, reduced take-up need not imply improved decision-making. We therefore examine whether changes in purchase behavior reflect greater alignment with individualized welfare-maximizing recommendations.

Table 4: Treatment Effects on Insurance Purchase

	IBLI Purchase		Number of animals insured	Number of animals insured |Purchase=1
	(1)	(2)	(3)	(4)
Advice+Sales vs. Control	-0.007	-0.003	-0.012	0.002
	(0.466)	(0.439)	(0.640)	(0.992)
	[0.549]	[0.511]	[0.696]	[0.993]
Advice+Welfare vs. Control	-0.021**	-0.010**	-0.022	0.354
	(0.0199)	(0.0277)	(0.409)	(0.156)
	[0.0700]	[0.0700]	[0.548]	[0.316]
Advice+Sales vs. Advice+Welfare	-0.015*	-0.006*	-0.009	0.352
	(0.0559)	(0.0617)	(0.649)	(0.140)
	[0.0550]	[0.0700]	[0.593]	[0.173]
Model	Logit	OLS	OLS	OLS
N	26744	26744	26744	1909
Control Mean	0.0818	0.0818	0.312	3.812

Column 1 presents average marginal effects from logit regressions and Columns 2-4 present marginal effects from OLs regressions. All columns present p-values calculated with standard errors clustered at the village level (in parentheses), and randomization inference p-values [in bracket]. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include kebele $\times$ round fixed effects. Column (1) presents the impact on the insurance take-up at the extensive margin, denoted as 1 if a pastoralist purchased insurance in each sales season, and 0 otherwise. Columns (2) and (3) depict the impact at the intensive margin of insurance take-up. The intensive margin refers to the number of animals insured in each sales season. In Column (2) the number of insured animals is recorded, with the count treated as 0 if a pastoralist did not purchase insurance. Column (3) presents the number of animals insured, conditional on a pastoralist purchasing insurance. The number of observations in Columns (1) and (2) is 26,744, calculated as (2,416 x 4 animal species x 3 rounds) - 562 (control households randomized to additional treatment at endline). In Column (3) the number of insured animals, conditional on purchasing insurance, is estimated with 1,909 households, since 1,915 households purchased insurance, and 6 singleton observations were dropped to avoid biases in the standard error.

6.2 Adherence to tailored advice

We begin by documenting the scope for improvement in welfare. In the control group, only 26 percent of households made purchase decisions consistent with the individualized recommendation they would have received under treatment. As shown in Appendix Table B2, for 85 percent of households, the ECS-maximizing recommendation was to purchase insurance while only 8 percent

did. Among those who were advised to purchase, only 12 percent did; the overwhelming majority of the population would benefit from IBLI purchase yet did not. Meanwhile, among the 15% of the sample who were advised not to purchase, 91.5% did not purchase, while 8.5% nevertheless did. These patterns reveal substantial under-purchase relative to the model's recommendation, alongside a smaller but nontrivial margin of over-purchase.

In Table 4 we evaluate two measures of adherence: (i) an indicator for whether the household's purchase decision matches the categorical advice (buy vs. not buy), and (ii) the absolute deviation between the advised and actual number of animals insured. We report results overall and separately by advice type (purchase vs. non-purchase).

When pooling across advice types, neither treatment significantly increases adherence (Table 5, columns (1)–(2)). Similarly, among households advised to purchase insurance, neither Advice+Sales nor Advice+Welfare increases the likelihood of buying or reduces the gap between advised and actual coverage (Table 5, columns (3)–(4)). Tailored advice does not induce households to make welfare-enhancing purchases, regardless of agent incentives.

The effects differ sharply for households advised not to purchase insurance. In the Advice+Welfare arm, adherence to non-purchase advice increases by 2.1 percentage points relative to control. Given that 8.5 percent of control households purchased when the model would have advised against it, this represents a 25 percent reduction in welfare-reducing purchases. No comparable effect appears in the Advice+Sales arm. Thus, personalized advice reduces over-purchase only when agent incentives are aligned with consumer welfare. Absent such alignment, advice does not alter adherence patterns.

This asymmetry is one of the paper's central findings and warrants emphasis. The intervention successfully reduces welfare-harming purchases among the minority advised not to buy, but leaves entirely untouched the far larger problem of under-purchase among the 85 percent of households who stand to benefit from insurance. This is not simply a power problem – the estimates for the advised-to-purchase group are precise enough to rule out meaningful effects. The asymmetry suggests that over-purchase and under-purchase reflect qualitatively different failures: the former is driven by agent sales pressure that welfare-aligned incentives can attenuate, while the latter appears to reflect deeper barriers – perhaps liquidity constraints, distrust of formal institutions, or inertia – that neither advice nor incentive realignment addresses. We return to the mechanisms underlying this asymmetry in Section 7

Table 5: Treatment Effects on Adherence to the Advice

	Any advice		Advised to purchase		Advised not to purchase	
	Adhere to Advice	|Purchase - Advice|	Adhere to Advice	|Purchase - Advice|	Adhere to Advice	|Purchase - Advice|
	(1)	(2)	(3)	(4)	(5)	(6)
Advice+Sales vs. Control	-0.007	-0.009	-0.016	0.018	0.017	0.011
	(0.434)	(0.967)	(0.277)	(0.942)	(0.405)	(0.816)
	[0.550]	[0.972]	[0.370]	[0.955]	[0.493]	[0.842]
Advice+Welfare vs. Control	0.001	-0.043	-0.022	0.043	0.058**	-0.048
	(0.896)	(0.840)	(0.119)	(0.862)	(0.0137)	(0.264)
	[0.903]	[0.870]	[0.229]	[0.878]	[0.0610]	[0.394]
Advice+Sales vs. Advice+Welfare	0.008	-0.035	-0.007	0.025	0.041*	-0.059
	(0.303)	(0.851)	(0.579)	(0.909)	(0.0653)	(0.137)
	[0.451]	[0.787]	[0.525]	[0.862]	[0.0460]	[0.238]
Model	Logit	OLS	Logit	OLS	Logit	OLS
N	17064	17064	14123	14123	2914	2914
Control Mean	0.263	5.307	0.125	6.391	0.915	0.209

All columns present coefficient estimates, p-values calculated with standard errors clustered at the village level (in parentheses), and randomization inference p-value [in bracket]. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include kebele $\times$ round fixed effects. Columns (1) and (2) compare the adherence to advice across treatment arms, irrespective of whether the advice pertains to purchasing insurance or refraining from it. Column (1) represents adherence to the advice, while Column (2) indicates the absolute difference in the number of insured animals. Columns (3) and (4) display estimates for advice recommending the purchase of insurance, while Columns (5) and (6) show estimates for advice advising against purchasing insurance. The number of observations in Columns (1) and (2) is 17,064, which is the number of herders received any tailored advice across midline 1, 2 and endline. The number of observations in Columns (3) and (4) is 14,539, which is the number of herders who received advice to buy insurance across midline 1, 2 and endline. The number of observations in Columns (5) and (6) is 2,499, which is the number of herders who received advice not to buy insurance across midline 1, 2 and endline (2,525) after dropping 26 singleton observations.

6.3 Expected Consumer Surplus

We next examine whether these behavioral changes translate into welfare gains. For each household, we compute the gap between realized ECS under the observed insurance decision and the maximum attainable ECS given estimated risk preferences, herd characteristics, and subjective beliefs about the index being triggered in the upcoming season, and their own livestock survival probability.

For normative purposes, risk preferences were estimated assuming Expected Utility Theory (EUT). The parametric model assumes a CRRA utility function $U(x) = \frac{x^{(1-r)}}{(1-r)}$ defined over the lottery prize x, and where r is the coefficient of Relative Risk Aversion (RRA). The estimates of r are produced using maximum likelihood on pooled and individual-level data. In principle, individual level estimates are used, and if needed because of convergence issues, predicted estimates from a pooled model over all individuals were used.[6] The distribution of estimated risk preferences is provided in Appendix Table B3.

In terms of welfare gains, pooling across advice types, neither treatment generates statistically significant average welfare gains (Table 6, column (1)). The magnitude of the coefficient estimate is larger in the Advice+Welfare group (13.5, $p = 0.143$) and the estimated difference between the two treatment groups is 13.4 ($p = 0.13$), but neither is statistically significant.

Disaggregating by advice type reveals the source of this pattern. Among households advised *to purchase* insurance, neither treatment increases ECS (Table 6, column (2)), consistent with the absence of increased purchase among this group. Among households advised *not to purchase* insurance, however, the Advice+Welfare treatment yields statistically significant welfare gains (Table 6, column (3)). Relative to the mean in Control this is a 40 percent increase in consumer welfare. By contrast, the Advice+Sales effect is negative and statistically insignificant. If we compare across the arms, we observe a 56 percent higher consumer surplus in the Advice+Welfare arm than in the Advice+Sales arm, taking the mean consumer welfare in Control as a reference. This implies that welfare gains arise exclusively from reductions in over-purchases that lower expected surplus.[7]

In sum, tailored advice improves expected consumer welfare only when agent incentives are aligned with the recommendation, and only by correcting over-purchase. Personalized prediction and recommendation alone are insufficient to improve outcomes in the presence of revenue-based sales incentives for intermediaries.

[6] The pooled model controls for some basic demographics, so the prediction for an individual is conditional on the value of those demographics for that individual.

[7] These results are robust when the unit of analysis is changed to the household level (Appendix Table D4.3).

Table 6: Treatment Effects on Expected Consumer Surplus

	Any Advice	Advice: Purchase insurance	Advice: Do not purchase insurance
	(1)	(2)	(3)
Advice+Sales vs. Control	0.082	-1.527	-3.689
	(0.993)	(0.886)	(0.409)
	[0.995]	[0.896]	[0.526]
Advice+Welfare vs. Control	13.511	10.165	8.564**
	(0.143)	(0.347)	(0.0358)
	[0.252]	[0.479]	[0.0810]
Advice+Sales vs. Advice+Welfare	13.429	11.692	12.253***
	(0.132)	(0.253)	(0.00668)
	[0.168]	[0.264]	[0.0690]
N	16630	13726	2878
Control Mean	-243.1	-291.5	-21.22

All columns present coefficient estimates, p-values calculated with standard errors clustered at the village level (in parentheses), and randomization inference p-value [in bracket]. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include kebele $\times$ round fixed effects. Column (1) uses the full sample of household $\times$ animal species which ECS can be generated. Column (2) and (3) uses the sample who received advice to insure animal and advice not to insure animal, respectively. Column (1) uses 16,630 observations, the number of herders for whom maximum ECS was calculated across midline 1, 2 and endline. Column (2) uses 13,726 observations, the number of herders who received advice to buy insurance across midline 1, 2 and endline. Column (3) uses 2,878 observations, the number of herders who received advice not to buy insurance across midline 1, 2 and endline.

6.4 Robustness

All our results presented in Tables 4-6 are robust to adding control variables (Supplementary Appendix Tables D1.1 to D1.3), adding only kebele fixed effects (Supplementary Appendix Tables D2.1 to D2.3), adding kebele and survey-round fixed effects separately (Supplementary Appendix Tables D3.1 to D3.3), conducting the analysis at the household-level (Supplementary Appendix Tables D4.1 to D4.3), and multi-way clustering at the village and survey round levels (Supplementary Appendix Tables D5.1 to D5.3).Furthermore the ECS results presented in Table 6 are robust to winsorizing ECS at the 1%, 5%, and 10%,-level (Supplementary Appendix Table D7.1), and using the mean risk aversion parameter for all respondents (Supplementary Appendix Table D8.1).

7 Mechanisms

The main results establish that tailored advice improves consumer welfare only when paired with welfare-aligned agent incentives, and only by reducing welfare-harming over-purchase rather than stimulating welfare-enhancing demand. This asymmetry is the central fact that any mechanism account must explain. In this section we work through four candidate channels – changes in product knowledge and beliefs, changes in agent effort and sales behavior, changes in trust in agents, and heterogeneity in baseline knowledge – and show that the first three are insufficient on their own. The evidence points instead to a specific interaction: tailored advice makes salient to consumers that insurance is not universally beneficial and reduces their trust in agents, but this skepticism only translates into changed behavior when agents are no longer financially rewarded for counteracting it. We close the section by disentangling the role of the video framework from the individualized recommendation itself, which helps pin down where in the advice delivery process the behavioral effect originates.

7.1 Knowledge and beliefs about the insurance

Tailored advice could improve decision-making by increasing product understanding, beliefs about the product, or altering its perceived value. To assess this channel, we measure IBLI knowledge using ten questions on product attributes and payout scenarios, elicit subjective beliefs about drought risk, index triggering, and basis risk, and measure respondents perceived value of IBLI.

We find no evidence that either tailored advice or consumer-welfare incentives for agents improved product knowledge or overall perceived value. The treatment arm that generates welfare

gains, Advice+Welfare, does not significantly affect performance on any knowledge question (Appendix Table B3; Appendix Table B4).[8] Similarly, subjective beliefs about drought likelihood, index triggering, or livestock survival remain largely unchanged (Appendix Table B5).

The only detectable belief effect is a small increase in perceived upside basis risk among households receiving tailored advice (Appendix Table B5 column (5)). Increased overall basis risk, both positive and negative deviations of the index from actual losses, has been shown to adversely affect demand for IBLI (Jensen, Mude, and Barrett, 2018). An induced increased in subjective expectations of positive basis risk should, if anything, induce more purchase of IBLI, not less. So this does not seem a likely mechanism behind the effects we observe.

7.2 Agent effort, compensation and propensity to push IBLI

An alternative explanation is that consumer-welfare incentives for agents reduced insurance sales by inducing agents to reduce effort in the Advice+Welfare arm. We measure effort using administrative data on commissions and agent-consumer interactions based on the raffle tickets collected.

Neither tailored advice nor consumer-welfare incentives for agents affect the overall number of raffle tickets collected from potential consumers or the share of potential consumers per community from which they collected them (Appendix Table B6, columns (1)-(2)). While consumer-welfare incentives for agents increase the share of households generating an incentive payment (Appendix Table B6, columns (3)), that mechanically reflects agent rewards for adherence to non-purchase advice. Overall incentives earnings remain unchanged (Appendix Table B6, columns (4)). These results suggest that reduced take-up under Advice+Welfare does not stem from diminished agent effort.

We next examine whether agents exhibit a baseline predisposition to promote IBLI and whether information and incentives modify that tendency. In a lab-in-the-field experiment conducted in all 240 villages,[9] agents made purchase decisions on behalf of a randomly selected potential consumer

[8] Pastoralists in the Advice+Sales arm did show significant decreases in correct answers to two of the ten questions, regarding the index used for payments and the third payout scenario (Appendix Table B4).

[9] The lab-in-the-field experiments were conducted during the Midline 1, Midline 2, and Endline surveys, during the visit to each village. Agents were told, prior to the experiment, that they would make choices to purchase insurance or not purchase insurance against risks that would be realized in the experiment, on behalf of one of the 10 respondents in each community. They were informed that a random draw would first determine the specific decision that would be selected for payment, than another set of random draws would realize the experimental risk for that decision, determining the earnings for the respondent, and that another random draw would select one of the 10 respondents to receive the earnings. They were also informed that if the specific decision that was randomly drawn for payment was a decision with sales or consumer-welfare incentives, that they would be the beneficiaries of the incentives, and would receive those as payment. The remaining parts of the experimental protocol are provided in Appendix.

from that village under varying information and incentive conditions. The results are presented in Appendix Table B8.

In the baseline scenario, the randomly selected potential consumer received no tailored advice, did not state any preference to purchase or not purchase the insurance, and there was no incentive for the agent. Despite this lack of incentive, 98 percent of agents purchased on behalf of the consumer.

Even when the agent was informed that the potential consumer preferred not to buy the insurance or that tailored advice recommended against purchase, 90-92 percent of agents still purchased on the consumers' behalf. Consumer-welfare incentives for agents reduced the likelihood of purchasing on the consumer's behalf by approximately 6 percentage points, while sales incentives increased it by 3 percentage points. These shifts are statistically significant but small relative to the high baseline propensity to promote insurance. The experimental evidence reveals a strong status quo bias among agents toward selling IBLI, only partially attenuated by consumer-welfare incentives for agents. This is consistent with the field evidence that consumer-welfare incentive alignment reduces over-purchase but does not induce substantial increases in welfare-enhancing demand.

7.3 Trust in insurance agents

The provision of tailored advice introduces a second source of information about the product and its value to consumers that may conflict with the information consumers receive from the first source: the agent. We therefore examine whether advice affects trust in agents. We construct a standardized trust index based on survey responses regarding whether agents act in the household's best interest, whether the agents' advice is important to the respondent, and whether agents can be trusted to handle premiums and payouts. Receiving tailored advice significantly reduces trust in agents by approximately 0.05–0.06 standard deviations, regardless of the incentive scheme (Appendix Table 7). This decline is concentrated in trust related to the content and credibility of advice, rather than in trust related to the handling of premiums and payouts. Importantly, trust declines under both Advice+Sales and Advice+Welfare. Thus, reduced trust alone cannot explain why behavioral and welfare effects arise only when incentives are aligned with consumer welfare. Instead, tailored advice appears to induce greater skepticism toward agents, but only when incentives are aligned does this skepticism translate into welfare-improving reductions in over-purchase.

Table 7: Trust in insurance agents

	Composite trust scale	Scale for advice-related trust	Scale for money-related trust	Agents advise in my best interests	Agents' advice is important	Agents deliver premium to insurer	I will receive entitled payment	Trust the information from agent (=1)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Advice+Sales vs. Control	-0.058**	-0.082***	-0.025	-0.080***	-0.077***	-0.031	-0.016	-0.017*
	(0.0218)	(0.00281)	(0.277)	(0.00338)	(0.00464)	(0.181)	(0.470)	(0.0782)
	[0.0570]	[0.0150]	[0.359]	[0.0180]	[0.0240]	[0.279]	[0.545]	[0.140]
Advice+Welfare vs. Control	-0.047*	-0.051*	-0.035	-0.057**	-0.040	-0.036	-0.032	-0.021**
	(0.0536)	(0.0532)	(0.121)	(0.0293)	(0.130)	(0.113)	(0.168)	(0.0335)
	[0.0930]	[0.0900]	[0.191]	[0.0600]	[0.203]	[0.183]	[0.270]	[0.0810]
Advice+Sales vs. Advice+Welfare	0.011	0.031	-0.011	0.023	0.037	-0.005	-0.015	-0.004
	(0.616)	(0.174)	(0.595)	(0.313)	(0.106)	(0.800)	(0.445)	(0.677)
	[0.930]	[0.922]	[0.454]	[0.949]	[0.861]	[0.773]	[0.290]	[0.698]
Model	OLS	OLS	OLS	OLS	OLS	OLS	OLS	Logit
N	6686	6686	6686	6686	6686	6686	6686	4789
Control Mean	-2.46e-09	4.41e-09	-1.25e-09	1.04e-08	5.47e-10	4.17e-09	7.00e-09	0.897

All columns present (average) marginal effects from OLS or Logit regressions, p-values calculated with standard errors clustered at the village level (in parentheses), and randomization inference p-value [in bracket]. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include kebele $\times$ round fixed effects. All outcome variables measured on a scale of 0 to 10, where 10 indicates the strongest trust in agent. Outcome variable of column (1) is the composite trust scale – the average score of the four following variables. Responses are scored on a scale from 0 to 10, with a higher score indicating greater trust. To facilitate interpretation, we standardize the composite trust scale by subtracting the control group mean and dividing by its standard deviation, since Likert-type responses do not have inherent cardinal meaning. Outcome variable of column (2) is to what extent pastoralists agree that the sales agents advise in their best interest. Outcome of column (3) is to what extent pastoralists agree that the sales agents' financial advice is important for them. Outcome of column (4) is to what extent the pastoralist think that the agent will deliver the paid premium to the insurer. Outcome of column (4) is to what extent the pastoralist think that they will receive the insurance payout if it occurs. All columns use 4,270 observations (2,416 x 2 rounds) - 562 (control households randomized to additional treatment at endline). We use two rounds – midline 2 and endline for this analyses, as these outcomes were measured between the video treatment and the advice in midline 1.

7.4 Heterogeneity by baseline insurance knowledge

To further clarify the mechanism, we examine heterogeneity by baseline IBLI knowledge, measured prior to treatment. Among households with below-median baseline knowledge, tailored advice significantly reduces insurance take-up (Appendix Table B9). While this happens for both the group that is advised to purchase (Appendix Table B10, column (3)) as well as the group that is advised not to purchase (column (4)), under both incentive schemes, the resulting welfare gains are concentrated in Advice+Welfare villages, where reduced over-purchase translates into higher expected consumer surplus (Appendix Table B11, column (3)). In contrast, high-knowledge households increase purchase, adhere less to advise not to purchase, and experience a 9 percent reduction in consumer welfare (Appendix Tables B9–B11), although all these results are marginally insignificant. These patterns suggest that the intervention primarily protects less-informed households from welfare-reducing purchases when agent face consumer-welfare incentives. More knowledgeable households appear less susceptible to sales pressure and less affected by the intervention.

7.5 Is it the advice itself or the thought process?

Finally, we disentangle two components of the tailored advice intervention: (i) the video explaining the welfare framework and (ii) the individualized recommendation itself. In a supplementary experiment in the final survey round, households in control villages, where agents receive standard revenue-based sales incentives, were randomized at the individual level to receive either the video only, individualized advice only, or no intervention. We find suggestive evidence that the tailored advice itself, rather than the video, drives the behavioural and welfare effects. Receiving tailored advice only, significantly reduces the difference between the actual and advised number of animals to insure in the Advice Only group (Table B13), generating significantly higher ECS (Appendix Table B15). Neither advice alone nor the video alone impact IBLI knowledge (Appendix Table B16), while both reduce respondents' belief that insurance agents' advice is important (Appendix Table B17). This pattern is consistent with objective, third-party recommendations altering purchase decisions, while general decision frameworks alone do not.

7.6 Synthesis

The evidence points to the following account. Tailored advice shifts consumer beliefs about the value of agent guidance, reducing trust in agents regardless of the incentive environment. Under standard sales incentives, agents retain strong financial motivation to promote insurance and exercise sufficient persuasive influence to prevent this skepticism from affecting purchase decisions. Under welfare-aligned incentives, agents have less reason to counteract non-purchase decisions, and the consumer skepticism induced by advice is no longer neutralized. The result is a reduction in welfare-harming over-purchase, concentrated among low-knowledge consumers who are most susceptible to agent influence. The intervention does not, however, address the problem of under-purchase – which reflects a different failure, one that neither personalized information nor incentive realignment resolves, and which we leave as an open challenge for future work.

8 Conclusions

This paper documents a striking asymmetry. A combination of personalized, model-based financial advice and welfare-aligned agent incentives successfully reduces welfare-harming insurance purchases – curbing the overselling that harms the minority of consumers for whom purchase reduces expected welfare. Yet neither intervention, alone or in combination, induces welfare-enhancing purchases among the large majority of households who stand to benefit from insurance but opt not

to buy. This asymmetry is not a failure of implementation or statistical power. It is a substantive finding that reveals the distinct nature of the two market failures at work in this setting, and that points toward different policy responses for each.

The null effect of advice alone is not surprising once the institutional environment is taken seriously. Agents have both the financial incentive and, as our lab-in-the-field experiment reveals, a strong baseline propensity to promote insurance regardless of whether purchase serves the consumer's interest. Advice that conflicts with agent incentives is effectively neutralized by continued sales pressure. Welfare-aligned incentives break this dynamic – not by changing what agents know or how hard they work, but by removing their financial motivation to counteract the skepticism that advice induces in consumers. The two interventions are complements: advice shifts consumer priors, and incentive alignment ensures agents do not undo that shift.

The asymmetry in these results is the paper's most important finding. Over-purchase and under-purchase are not the same problem. The former is driven by misaligned intermediary incentives that distort the agent-consumer interaction at the point of sale, and can be partially corrected by realigning those incentives. The latter appears to reflect something else entirely – liquidity constraints, distrust of formal financial institutions, basis risk concerns, or behavioral inertia – and is unresponsive to both personalized information and incentive realignment. Treating these as a single demand problem, or assuming that fixing intermediary incentives will also solve the take-up problem, would be a mistake. They require fundamentally different policy instruments.

Our findings have direct implications for the design and regulation of financial advice systems. As digital financial services expand across low- and middle-income countries, the instinct of regulators and programme designers has often been to improve consumer information – through disclosure mandates, simplified product terms, or personalized data-driven recommendations. Our results suggest this instinct is insufficient when advice flows through incentive-distorted intermediaries. Realizing the welfare potential of personalized financial advice requires complementary reforms to the incentive structures governing financial intermediation. But even well-designed advice systems with properly aligned intermediary incentives will not solve persistent non-take-up among households who stand to gain. Understanding why so many households fail to purchase products that would benefit them in expectation – and what it would take to close that gap – remains one of the central open questions in the economics of financial inclusion. This paper helps to sharpen that question by showing what the answer is not: it is not primarily a problem of biased intermediaries or poor information delivery.

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Appendix A Calculation of Expected Consumer Surplus

We calculate the expected consumer surplus of a pastoral household assuming that individuals behave consistently with expected utility theory framework. Our starting point is the set up from Clarke (2016b). A pastoral household with livestock herd value H bears the risk of livestock loss L, with probability p. The household makes a decision on whether or not to purchase insurance. The amount of insurance premium is denoted as R. When the index is triggered with probability q, the consumer will receive payout I. The household also faces a basis risk with probability r, which reflects a joint probability that the index is not triggered but a herd loss occurs.

Without insurance, a herder faces two states of the world – no herd loss, or herd loss. But when they purchase insurance, there are four states of the world for the pastoralist:

- s_1: (No herd loss, Index not triggered),
- s_2: (No herd loss, Index triggered),
- s_3: (Herd loss, Index not triggered),
- s_4: (Herd loss, Index triggered)

In each state, we assume that the consumers have a CRRA utility function:

$$u(X) = \begin{cases} \frac{x_{iazkt}^{1-\theta}}{1-\theta} & \theta \neq 1 \\ ln(x_{iazkt}) & \theta = 1 \end{cases} \tag{4}$$

where x_{iazkt} is the outcome in each state, for household i with livestock species a in village z in kebele k in round t, and θ is the relative risk aversion parameter of individual j in household i, who is responsible for herd management.

The consumer maximizes the expected utility from the decision given by:

$$EU = pr(s_1) \cdot u_{s_1} + pr(s_2) \cdot u_{s_2} + pr(s_3) \cdot u_{s_3} + pr(s_4) \cdot u_{s_4} \tag{5}$$

To calculate the expected utility, we need payoffs and probabilities for each state. Table A1 presents the payoffs in each state, with (Panel B) or without insurance (Panel A), while Panel C presents the probabilities for each state.

Then, using these probabilities and payoffs for each state, we calculate the expected utility and certainty equivalent of each decision: buy or not to buy insurance.

Table A1: Payoffs and probabilities for each state without insurance

Panel A: Payoffs without insurance

	Index not triggered	Index triggered
No herd loss	H	H
Herd loss	$H-L$	$W-L$

Panel B: Payoffs with insurance

	Index not triggered	Index triggered
No herd loss	$H-R$	$H-R+I$
Herd loss	$H-L-R$	$W-L-Y+I$

Panel C: Probabilities for each state

	Index not triggered	Index triggered	
No herd loss	$1-q-r$	$q+r-p$	$1-p$
Herd loss	r	$p-r$	p
	$1-q$	q	

Notes: H denotes total livestock value, L value of lost animal, R the amount of insurance premium paid, and I indemnity payout, p subjective expectation of livestock survival, q subjective expectation of IBLI index trigger, r joint probability that the index is not triggered but a loss occurs.

For purchasing insurance:

- $EU_{buy} = (1-q-r)\cdot u(H-R) + r\cdot u(H-L-R) + (q+r-p)\cdot(H-R+I) + (p-r)\cdot u(H-L-R+I)$
- $CE_{buy} = (EU_{buy} - \theta EU_{buy})^{\frac{1}{1-\theta}}$

For not purchasing insurance:

- $EU_{nobuy} = (1-q-r)\cdot u(H) + r\cdot u(H-L) + (q+r-p)\cdot(H) + (p-r)\cdot u(H-L)$
- $CE_{nobuy} = (EU_{nobuy} - \theta EU_{nobuy})^{\frac{1}{1-\theta}}$

The expected consumer surplus (ECS) of insuring different number of animals is then quantified by subtracting the certainty equivalent of not purchasing any insurance policies from the certainty equivalent of insuring animals:

- $ECS_{buy} = CE_{buy} - CE_{nobuy}$

Appendix A.1 Tailored advice

To generate the advice in real-time, we computed ECS of the clients before the survey visits. The parameters for ECS calculation includes relative risk aversion parameter (θ from Equation 4), herders' beliefs about the probability that the index will trigger (q from Table A1), about livestock loss (p from Table A1) in the next herding season(s), and about the basis risk (r from Table A1. We elicit risk preference parameter θ via risky lottery choice exercises at baseline, and use the estimated risk preferences as our priors and use it throughout all survey rounds. We have two versions of p – probabilities of livestock loss in the upcoming season and the subsequent season.To allow real-time provision of the advice, we restricted choices of probabilities: we choose to use values of p and q which range from 5 percent to 95 percent at 10 percentage point interval. Since there are three probabilities that takes 10 potential values, we have 1000 combinations of these probabilities for the ECS calculation.

For each combination of the parameters, we compute ECS for insuring a range of number of animals from zero to a species-specific maximum based on the previous round of data collected.[10] The number of animals insured that produces the highest positive ECS is chosen for the advice.

[10]For camels, we set the maximum as 3, for cattle 5, for goats 8, and for sheep 5, which are based on median number of animals for each animal species from the the data collected.

When the optimal number of insured animal is strictly greater than zero, then we advise the herder to insure that species. When the selected number equals to zero, then the advice is not to insure that species. However, when the difference in CE is not substantial between buying and not buying insurance, then we reported that the advice is inconclusive. We then convert the advised number of animals to insure to the share of animals to insure.

During the survey, p and q are collected by asking the following questions:

> for p: "How many of your N [animal species] do you think will still be alive by the end of [the next herding season]?"
>
> for q: "How likely do you think it is, from 0-10% being least likely and 91-100% being most likely, that IBLI payments will be made in your IBLI index unit during [the next herding season]?"

We use the estimate of the basis risk from Jensen, Barrett, and Mude (2017), 0.3, combined with p and q to determine r.

We match the survey responses with the computed ECS-maximizing share of animals to offer the tailored advice in real-time.

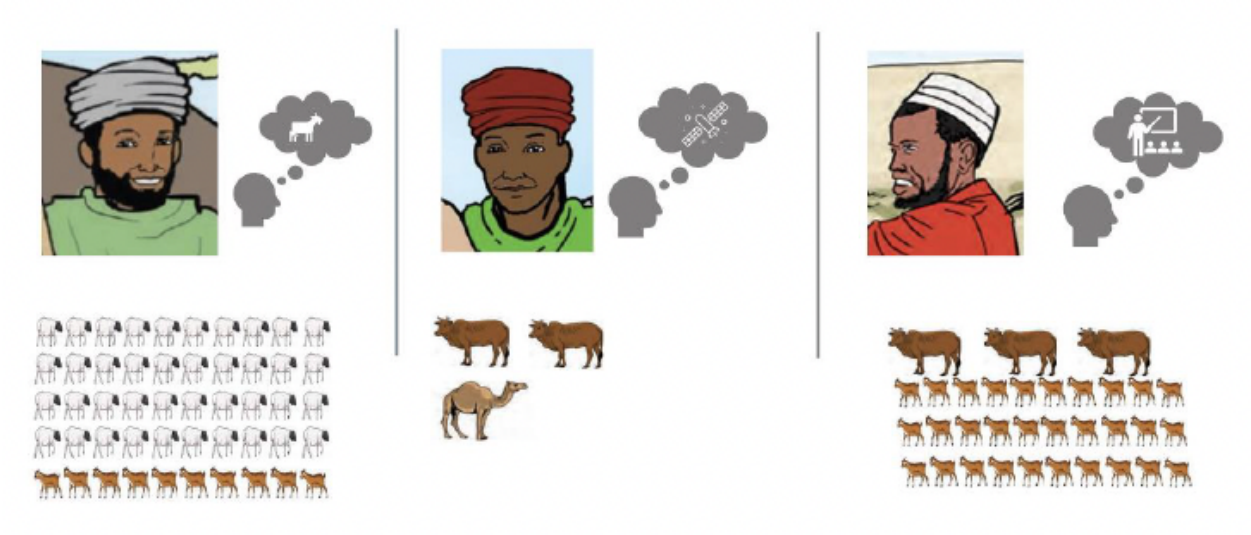
Since herders make insurance purchase decision for each of four animal species, camels, cattle, goats, and sheep, the ECS (and the tailored advice) is calculated for each animal species, resulting in four distinct advice if the herder has all four animal types.

Appendix A.2 Consumer welfare

We compute the consumer welfare using the same structure. For the consumer welfare, we use actual herd size as an input. Secondly, the consumer welfare from the product is defined by the difference of the certainty equivalent from herder's decision and the certainty equivalent from the maximum ECS generating insurance purchase decision.

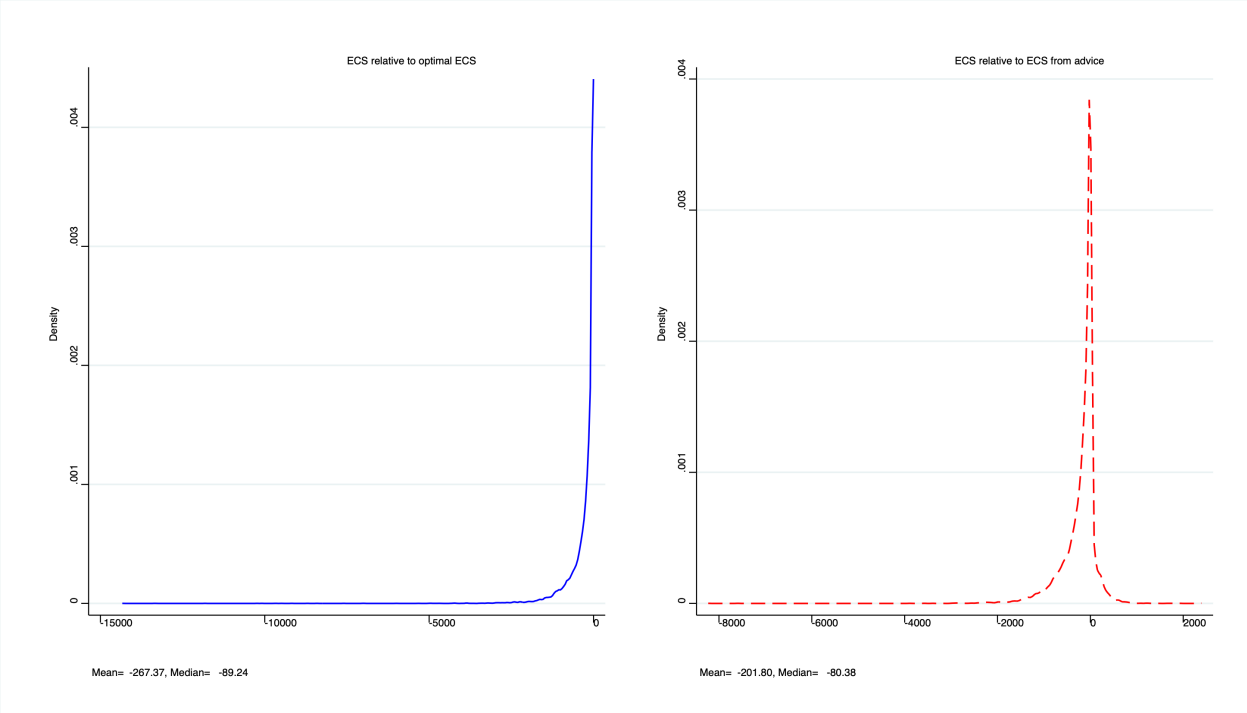
Appendix B Additional Figures and Tables

Figure B1: Example video screen



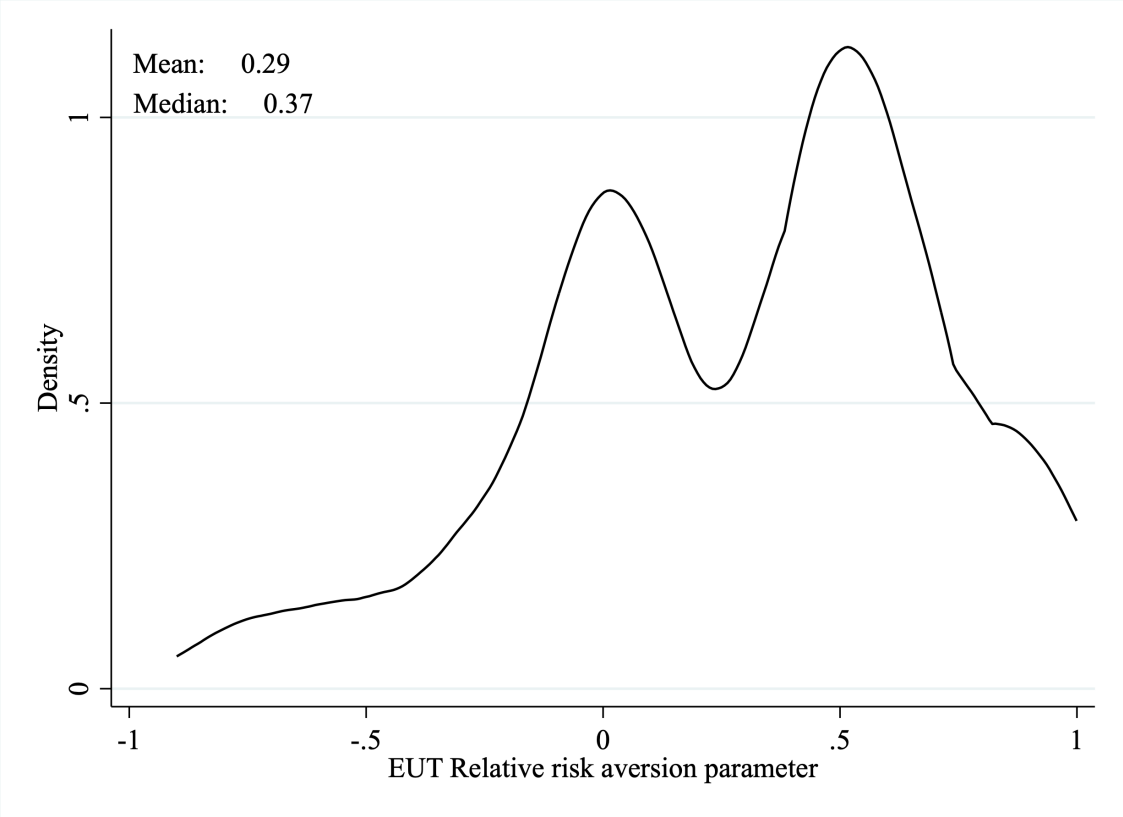
Notes:

Figure B2: Distribution of Expected consumer surplus



Notes: This figure presents distributions of the two measures of consumer welfare: i) Expected consumer surplus relative to the optimal ECS, and ii) ECS relative to the ECS from advice.

Figure B3: Distribution of Relative Risk Aversion Parameter



Notes: The figure plots distribution of the EUT risk aversion parameter at baseline. Vertical axis indicates the density while horizontal axis indicates the risk averstion parameter value.

Table B1: Tailored Advice

	Advice to Purchase	Advised Number of Animals
	(1)	(2)
Advice+Sales vs. Control	-0.004	-0.017
	(0.620)	(0.939)
	[0.715]	[0.948]
Advice+Welfare vs. Control	-0.008	-0.018
	(0.351)	(0.939)
	[0.484]	[0.956]
Advice+Sales vs. Advice+Welfare	-0.004	-0.001
	(0.648)	(0.996)
	[0.514]	[0.997]
Model	Logit	OLS
N	17064	15325
Control Mean	0.825	6.221

All columns present coefficient estimates, p-values calculated with standard errors clustered at the village level (in parentheses), and randomization inference p-value [in bracket]. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include kebele $\times$ fixed effects.

Column (1) presents the difference in probability of receiving an advice to purchase insurance across the treatment arms. The variable equals to one if the pastoralist received the advice to purchase insurance. Columns (2) depicts the differences in the number of animals to insure across the treatment arms.

Table B2: Advised vs. Actual Insurance Decisions of Control Group

	Advice received		Total
	Purchase	Do not purchase	
	(1)	(2)	
Actual: Purchased	0.122	0.094	0.082
Actual: Did not purchase	0.878	0.906	0.918
Total	0.852	0.148	

Table B3: Understanding and Perceived Value of Insurance

	IBLI knowledge score (0-10)	Everyone should buy IBLI if affordable (=1)
	(1)	(2)
Advice+Sales vs. Control	-0.081	-0.005
	(0.287)	(0.683)
	[0.358]	[0.718]
Advice+Welfare vs. Control	-0.009	0.005
	(0.904)	(0.677)
	[0.914]	[0.702]
Advice+Sales vs. Advice+Welfare	0.072	0.011
	(0.286)	(0.328)
	[0.548]	[0.400]
Model	OLS	Logit
N	4270	4270
Control Mean	4.210	0.766

All columns present coefficient estimates, p-values calculated with standard errors clustered at the village level (in parentheses), and randomization inference p-value [in bracket]. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include kebele $\times$ fixed effects.

Column (1) presents the difference in probability of receiving an advice to purchase insurance across the treatment arms. The variable equals to one if the pastoralist received the advice to purchase insurance. Columns (2) depicts the differences in the number of animals to insure across the treatment arms.

The number of observations for all columns is 4,270, calculated as (2,416 x 2 rounds) - 562 (control households randomized to additional treatment at endline).

Table B4: Understanding of Insurance: All Questions Separated

	Premium payment frequency (=1)	Refund premium in case there is no drought	Format of receiving payment	IBLI covered risks	Payout-triggering measure-ments	Index upon which com-pensation is made	Payout delivering orgniza-tions	Payout scenario 1	Payout scenario 2	Payout scenario 3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Advice+Sales vs. Control	0.019	-0.015	0.006	-0.010	-0.002	-0.033**	0.009	-0.010	-0.015	-0.029**
	(0.112)	(0.350)	(0.637)	(0.482)	(0.902)	(0.0248)	(0.520)	(0.432)	(0.266)	(0.0325)
	[0.168]	[0.418]	[0.675]	[0.527]	[0.920]	[0.0670]	[0.575]	[0.514]	[0.361]	[0.0710]
Advice+Welfare vs. Control	0.014	-0.021	0.014	0.007	0.007	-0.021	0.018	-0.000	-0.014	-0.012
	(0.257)	(0.185)	(0.264)	(0.626)	(0.593)	(0.149)	(0.204)	(0.991)	(0.296)	(0.417)
	[0.335]	[0.264]	[0.359]	[0.710]	[0.649]	[0.231]	[0.318]	[0.989]	[0.375]	[0.504]
Advice+Sales vs. Advice+Welfare	-0.005	-0.006	0.008	0.017	0.009	0.012	0.009	0.010	0.001	0.018
	(0.625)	(0.671)	(0.405)	(0.148)	(0.454)	(0.374)	(0.438)	(0.391)	(0.950)	(0.161)
	[0.781]	[0.537]	[0.297]	[0.414]	[0.425]	[0.820]	[0.326]	[0.509]	[0.946]	[0.686]
Model	Logit	Logit	Logit	Logit	Logit	Logit	Logit	Logit	Logit	Logit
N	4270	4270	4270	4270	4270	4270	4270	4270	4270	4270
Control Mean	0.272	0.573	0.841	0.692	0.614	0.527	0.662	0.650	0.703	0.564

All columns present coefficient estimates, *p*-values calculated with standard errors clustered at the village level (in parentheses), and randomization inference *p*-value [in bracket]. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include kebele $\times$ fixed effects.

All outcome variables equals 1 if the answers to the following questions were correct. Questions for each outcome variables are as follows. Column 1: How often does an IBLI client have to pay a premium in order to remain insured?; Column 2: If you did not receive indemnity payout (compensation) from the livestock insurance, would you expect to receive your premium back?; Column 3: When you receive an indemnity payment (compensation) in what form do you expect to receive it in?; Column 4: Which of the following risks related to livestock does IBLI cover?; Column 5: Based on your understanding of the livestock insurance, what measurements trigger an insurance payout?; Column 6: Based on your understanding of IBLI, what does the index upon which compensation is made, represent?; Column 7: What institution will provide you payout in the upcoming season if there is a payout? Column 8: The forage in his region was normal in 2021 but Boru lost 8 cattle due to disease outbreak. Will he receive indemnity payout?; Column 9: The forage in his area was very bad, indicated by a black reading of IBLI index. But all of Diba's cattle survived. Will he receive indemnity payout?; Column 10: The forage in his region was normal in 2021 but he lost 3 cattle. Will he receive indemnity payout?

The number of observations for all columns is 4,270, calculated as (2,416 x 2 rounds) - 562 (control households randomized to additional treatment at endline).

Table B5: Subjective Expectations about Product Performance

	Index triggered	Severe Drought	Severe drought but index not triggered	No severe drought but index triggered	Index triggered but no animal die	Index not triggered but animals die	Index triggered payments arrive too late
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Advice+Sales vs. Control	-0.017	-0.028	0.048	-0.011	0.136*	0.051	0.040
	(0.837)	(0.677)	(0.515)	(0.888)	(0.0614)	(0.420)	(0.584)
	[0.858]	[0.734]	[0.552]	[0.911]	[0.106]	[0.436]	[0.641]
Advice+Welfare vs. Control	-0.103	-0.046	0.038	-0.085	0.157**	0.006	-0.038
	(0.184)	(0.501)	(0.607)	(0.226)	(0.0333)	(0.932)	(0.589)
	[0.253]	[0.615]	[0.634]	[0.285]	[0.0810]	[0.943]	[0.605]
Advice+Sales vs. Advice+Welfare	-0.086	-0.017	-0.010	-0.074	0.021	-0.045	-0.077
	(0.168)	(0.780)	(0.876)	(0.188)	(0.692)	(0.433)	(0.164)
	[0.194]	[0.688]	[0.862]	[0.207]	[0.741]	[0.556]	[0.371]
N	4270	4270	4270	4270	4270	4270	4270
Control Mean	5.082	6.969	6.045	4.075	4.271	6.042	5.902

All columns present coefficient estimates, p-values calculated with standard errors clustered at the village level (in parentheses), and randomization inference p-value [in bracket]. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include kebele $\times$ fixed effects.

Column (1) presents the difference in probability of receiving an advice to purchase insurance across the treatment arms. The variable equals to one if the pastoralist received the advice to purchase insurance. Columns (2) depicts the differences in the number of animals to insure across the treatment arms.

The number of observations for all columns is 4,270, calculated as (2,416 x 2 rounds) - 562 (control households randomized to additional treatment at endline).

Table B6: Insurance Agents' Effort

	Raffle			Incentives	
	Raffle ticket was collected in a village (=1)		Share of herders an agent collected raffle tickets from	Share of herders an agent earned incentive on	Sales agent incentives (ETB)
	(1)	(2)	(3)	(4)	(5)
Advice+Sales vs. Control	0.118	0.008	-0.071	-1.026	18.420
	(0.462)	(0.547)	(0.948)	(0.566)	(0.291)
	[0.787]	[0.787]	[0.944]	[0.506]	[0.307]
Advice+Welfare vs. Control	-0.127	-0.008	0.072	3.642*	28.957
	(0.409)	(0.505)	(0.946)	(0.0944)	(0.104)
	[0.728]	[0.728]	[0.948]	[0.122]	[0.127]
Advice+Sales vs. Advice+Welfare	-0.246	-0.017	0.142	4.668**	10.537
	(0.103)	(0.204)	(0.886)	(0.0260)	(0.549)
	[0.358]	[0.358]	[0.794]	[0.0570]	[0.305]
Model	Logit	OLS	OLS	OLS	OLS
N	720	720	720	720	720
Control Mean	0.537	0.537	42.47	20.26	117.5

All columns present coefficient estimates, p-values calculated with standard errors clustered at the village level (in parentheses), and randomization inference p-value [in bracket]. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include kebele $\times$ round fixed effects.

Column (1) presents an indicator equals one if an agent collected at least one raffle ticket from a village. Column (2) displays the share of herders an agent collected raffle tickets from. Column (3) presents the outcome variable, which equals one if an agent earned incentive in a village. Column (4) displays the proportion of pastoralists whose insurance purchase decision resulted in agents' incentives. Column (5) shows the total amount of incentives earned by agents during the sales season.

The number of observations for all columns are 720 – calculated by 240 villages $\times$ 3 rounds.

Table B7: Frequency of Agent Decision to Buy IBLI for Herder

Incentive Structure	Herder Decision	Tailored Advice	Midline 1	Midline 2	Endline	All Periods
No Incentive	No Decision	No Tailored Advice	0.970	0.963	0.996	0.976
No Incentive	Herder chooses to buy	No Tailored Advice	0.978	0.988	0.992	0.985
No Incentive	Herder chose to not buy	No Tailored Advice	0.892	0.913	0.824	0.877
No Incentive	No Decision	Tailored advice to not buy	0.922	0.934	0.890	0.915
No Incentive	No Decision	Tailored Advice to buy	0.989	0.992	0.996	0.992
No Incentive	Herder chooses to buy	Tailored advice to not buy	0.944	0.955	0.943	0.947
No Incentive	Herder chose to not buy	Tailored Advice to buy	0.825	0.847	0.788	0.820
Sales Incentive	No Decision	No Tailored Advice	0.978	0.988	0.988	0.984
Sales Incentive	Herder chooses to buy	No Tailored Advice	0.978	0.983	1.000	0.987
Sales Incentive	Herder chose to not buy	No Tailored Advice	0.951	0.950	0.914	0.939
Sales Incentive	No Decision	Tailored advice to not buy	0.951	0.955	0.914	0.940
Sales Incentive	Herder chooses to buy	Tailored advice to not buy	0.948	0.917	0.963	0.943
Sales Incentive	Herder chose to not buy	Tailored advice to not buy	0.907	0.884	0.861	0.885
Welfare Incentive	No Decision	Tailored advice to not buy	0.896	0.773	0.873	0.849
Welfare Incentive	Herder chooses to buy	Tailored advice to not buy	0.862	0.690	0.661	0.742
Welfare Incentive	Herder chose to not buy	Tailored advice to not buy	0.858	0.805	0.812	0.826

Table B8: Average Marginal Effects of Information or Incentives on Agent IBLI Purchase Decisions

	(1)	(2)	(3)
Herder chose to buy=1	-0.00793	-0.00792	-0.00812
	(0.01)	(0.01)	(0.01)
Herder chose not to buy=1	-0.0744***	-0.0744***	-0.0751***
	(0.01)	(0.01)	(0.01)
Tailored advice to buy=1	0.00922	0.00919	0.00980
	(0.01)	(0.01)	(0.01)
Tailored advice not to buy=1	-0.0628***	-0.0627***	-0.0625***
	(0.01)	(0.01)	(0.01)
Sales incentive=1	0.0292***	0.0292***	0.0298***
	(0.01)	(0.01)	(0.01)
Welfare incentive=1	-0.0592***	-0.0589***	-0.0585***
	(0.01)	(0.01)	(0.01)
Observations	12079	12079	12079
Omitted category average	98.0	98.0	98.0
VIP Fixed effects		✓	✓
Time Fixed effects			✓

We estimate the probit regression probit$(Recommend_purchase)_{ai} = \beta_0 + \beta_i D_i + \delta_{ij}(D_i \cdot D_j) + \gamma_a X_a + \ + \varepsilon_{ai}$ where agent a makes a binary purchase (=1) or no purchase (=0) decision for the herder given a vector D_i of indicator variables that represents each of the experimentally varied incentives (sales or consumer welfare, with neither as the omitted baseline category) and information conditions no herder choice, the herder wants to buy or not buy, (or neither as baseline), there is no tailored advice or the tailored advice is to purchase or not purchase and the ECS model recommends purchase or no purchase (or no recommendation as baseline). X_a is a vector of agent characteristics, and ε_{ai} is the error term. Standard errors in parentheses. * denotes significance at 0.10; ** at 0.05; and *** at 0.01.

Table B9: Heterogeneous effects by knowledge on IBLI purchase

	IBLI Purchase		Number of animals insured	Number of animals insured (Purchase=1)
	(1)	(2)	(3)	(4)
Advice+Sales	-0.024**	-0.011**	-0.032	0.105
	(0.0315)	(0.0396)	(0.195)	(0.623)
	[0.0950]	[0.0820]	[0.248]	[0.666]
Advice+Welfare	-0.029***	-0.013**	-0.042	0.272
	(0.00663)	(0.0119)	(0.128)	(0.378)
	[0.0270]	[0.0250]	[0.201]	[0.568]
Advice+Sales × High IBLI knowledge	0.050**	0.025**	0.070	-0.355
	(0.0144)	(0.0172)	(0.261)	(0.373)
	[0.0190]	[0.0190]	[0.347]	[0.454]
Advice+Welfare × High IBLI knowledge	0.026	0.011	0.075	0.162
	(0.229)	(0.321)	(0.249)	(0.714)
	[0.323]	[0.411]	[0.370]	[0.756]
	Logit	OLS	OLS	OLS
Coefficient: Advice+Sales + Advice+Sales × High knowledge	0.025	0.014	0.037	-0.25
p-value: Advice+Sales + Advice+Sales × High knowledge	0.12	0.11	0.53	0.50
Coefficient: Advice+Welfare + Advice+Welfare × High knowledge	-0.0038	-0.0021	0.033	0.43
p-value: Advice+Welfare + Advice+Welfare × High knowledge	0.83	0.82	0.58	0.23
N	26744	26744	26744	1909
Control Mean	0.0818	0.0818	0.312	3.812

We estimate the following OLS equation $y_{(a)izkt} = \alpha_0 + \alpha_1 \cdot T1_{zk} + \alpha_2 \cdot T2_{zk} + \alpha_3 \cdot \text{High Knowledge}_{izk} + \alpha_4 \cdot T1_{zk} \times \text{High Knowledge}_{izk}$
$+ \alpha_5 T2_{zk} \times \text{High Knowledge}_{izk} + \delta_{kt} + \varepsilon_{(a)izkt}$ where High Knowledge$_{izkt}$ equals 1 if a herder i in village z of kebele k has an IBLI knowledge score was higher than the baseline median value. All other variables are defined as per equation (2). Coefficients α_4 and α_5 denote the differential effect of tailored advice combined with sales incentives, and tailored advice with consumer welfare incentives for agents incentives, respectively, for herders with above-average comprehension of the IBLI product. All columns present coefficient estimates, *p*-values calculated with standard errors clustered at the village level (in parentheses), and randomization inference *p*-value [in bracket]. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include kebele × fixed effects. All outcome variables are standardized using the mean and the standard deviation of the control group for each round. Outcome variable of column (1) is the composite trust scale – the average score of the four following variables. Outcome variable of column (2) is to what extent pastoralists agree that the sales agents advise in their best interest. Outcome of column (3) is to what extent pastoralists agree that the sales agents' financial advice is important for them. Outcome of column (4) is to what extent the pastoralist think that the agent will deliver the paid premium to the insurer. Outcome of column (4) is to what extent the pastoralist think that they will receive the insurance payout if it occurs.The number of observations for all columns is 4,270, calculated as (2,416 x 2 rounds) - 562 (control households randomized to additional treatment at endline).

Table B10: Heterogeneous effects by knowledge on adherence to the advice

	Any advice		Advised to purchase		Advised not to purchase	
	Adhere to Advice=1	|Purchase - Advice|	Adhere to Advice=1	|Purchase - Advice|	Adhere to Advice=1	|Purchase - Advice|
	(1)	(2)	(3)	(4)	(5)	(6)
Advice+Sales	-0.016	-0.239	-0.037**	-0.239	0.064*	-0.039
	(0.106)	(0.340)	(0.0236)	(0.415)	(0.0507)	(0.491)
	[0.199]	[0.385]	[0.0820]	[0.463]	[0.107]	[0.550]
Advice+Welfare	0.009	-0.101	-0.027*	0.082	0.094***	-0.068
	(0.379)	(0.691)	(0.0871)	(0.786)	(0.00225)	(0.132)
	[0.459]	[0.712]	[0.171]	[0.809]	[0.0210]	[0.106]
Advice+Sales × High IBLI knowledge	0.030	0.778	0.063*	0.878	-0.111**	0.166
	(0.194)	(0.157)	(0.0542)	(0.173)	(0.0245)	(0.111)
	[0.203]	[0.135]	[0.0850]	[0.155]	[0.0430]	[0.111]
Advice+Welfare × High IBLI knowledge	-0.026	0.219	0.016	-0.109	-0.089	0.062
	(0.256)	(0.621)	(0.637)	(0.829)	(0.116)	(0.594)
	[0.303]	[0.622]	[0.739]	[0.810]	[0.241]	[0.624]
Model	Logit	OLS	Logit	OLS	Logit	OLS
Coefficient: Advice+Sales + Advice+Sales × High knowledge	0.014	0.54	0.026	0.64	-0.047	0.13
p-value: Advice+Sales + Advice+Sales × High knowledge	0.47	0.24	0.35	0.24	0.16	0.13
Coefficient: Advice+Welfare + Advice+Welfare × High knowledge	-0.017	0.12	-0.011	-0.027	0.0054	-0.0057
p-value: Advice+Welfare + Advice+Welfare × High knowledge	0.36	0.75	0.71	0.95	0.90	0.96
N	17064	17064	14123	14123	2914	2914
Control Mean	0.263	5.307	0.125	6.391	0.915	0.209

We estimate the following OLS equation $y_{(a)izkt} = \alpha_0 + \alpha_1 \cdot T1_{zk} + \alpha_2 \cdot T2_{zk} + \alpha_3 \cdot \text{High Knowledge}_{izk} + \alpha_4 \cdot T1_{zk} \times \text{High Knowledge}_{izk} + \alpha_5 T2_{zk} \times \text{High Knowledge}_{izk} + \delta_{kt} + \varepsilon_{(a)izkt}$ where High Knowledge$_{izkt}$ equals 1 if a herder i in village z of kebele k has an IBLI knowledge score was higher than the baseline median value. All other variables are defined as per equation (2). Coefficients α_4 and α_5 denote the differential effect of tailored advice combined with sales incentives, and tailored advice with consumer welfare incentives for agents incentives, respectively, for herders with above-average comprehension of the IBLI product. All columns present coefficient estimates, *p*-values calculated with standard errors clustered at the village level (in parentheses), and randomization inference *p*-value [in bracket]. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include kebele × fixed effects. The number of observations in Columns (1) and (2) is 17,064, which is the number of herders received any tailored advice across midline 1, 2 and endline. The number of observations in Columns (3) and (4) is 14,539, which is the number of herders who received advice to buy insurance across midline 1, 2 and endline. The number of observations in Columns (5) and (6) is 2,499, which is the number of herders who received advice not to buy insurance across midline 1, 2 and endline (2,525) after dropping 26 singleton observations.

Table B11: Heterogeneous effects by knowledge on consumer welfare gains relative to maximum ECS

	Any Advice	Advice: Purchase insurance	Advice: Do not purchase insurance
	(1)	(2)	(3)
Advice+Sales	15.084	15.132	2.300
	(0.134)	(0.189)	(0.679)
	[0.169]	[0.231]	[0.739]
Advice+Welfare	15.825	9.291	10.374***
	(0.129)	(0.450)	(0.00788)
	[0.216]	[0.537]	[0.0340]
Advice+Sales × High IBLI knowledge	-35.746*	-41.248*	-9.766
	(0.0919)	(0.0862)	(0.432)
	[0.0870]	[0.0960]	[0.477]
Advice+Welfare × High IBLI knowledge	-6.467	1.080	-5.993
	(0.763)	(0.965)	(0.342)
	[0.769]	[0.969]	[0.377]
Coefficient: Advice+Sales + Advice+Sales × High knowledge	-20.7	-26.1	-7.47
p-value: Advice+Sales + Advice+Sales × High knowledge	0.21	0.17	0.39
Coefficient: Advice+Welfare + Advice+Welfare × High knowledge	9.36	10.4	4.38
p-value: Advice+Welfare + Advice+Welfare × High knowledge	0.57	0.59	0.46
N	16947	13726	2878
Control Mean	-233.5	-284.5	-20.72

We estimate the following OLS equation $y_{(a)izkt} = \alpha_0 + \alpha_1 \cdot T1_{zk} + \alpha_2 \cdot T2_{zk} + \alpha_3 \cdot \text{High Knowledge}_{izk} + \alpha_4 \cdot T1_{zk} \times \text{High Knowledge}_{izk}$
$+ \alpha_5 T2_{zk} \times \text{High Knowledge}_{izk} + \delta_{kt} + \varepsilon_{(a)izkt}$ where High Knowledge$_{izkt}$ equals 1 if a herder i in village z of kebele k has an IBLI knowledge score was higher than the baseline median value. All other variables are defined as per equation (2). Coefficients α_4 and α_5 denote the differential effect of tailored advice combined with sales incentives, and tailored advice with consumer welfare incentives for agents incentives, respectively, for herders with above-average comprehension of the IBLI product. All columns present coefficient estimates, p-values calculated with standard errors clustered at the village level (in parentheses), and randomization inference p-value [in bracket]. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include kebele × fixed effects. Column (1) uses the full sample of household × animal species which ECS can be generated. Column (2) and (3) uses the sample who received advice to insure animal and advice not to insure animal, repectively.The number of observations in Columns (1) is 16,630, which is the number of herders that maximum ECS was calculated across midline 1, 2 and endline. The number of observations in Columns (2) is 14,153, which is the number of herders who received advice to buy insurance across midline 1, 2 and endline. The number of observations in Columns (3) is 2,470, which is the number of herders who received advice not to buy insurance across midline 1, 2 and endline (2,525) after dropping 55 singleton observations.

Table B12: IBLI purchase, within-control randomization

	IBLI purchase=1	N of animals insured	N of animals insured (Purchase=1)
	(1)	(2)	(3)
Video only vs. Control	-0.008	-0.001	0.744
	(0.301)	(0.978)	(0.271)
Advice only vs. Control	-0.012	-0.040	0.303
	(0.125)	(0.205)	(0.451)
Video only vs. Advice only	-0.005	-0.039	-0.442
	(0.518)	(0.241)	(0.419)
N	3220	3220	160
Control Mean	0.0576	0.152	2.643

All columns present coefficient estimates, p-values calculated with standard errors clustered at the household level (in parentheses), and randomization inference p-value [in bracket].
* denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include village fixed effects.

Table B13: Adherence to advice, within-control randomization

	Any advice		Advised to purchase		Advised not to purchase	
	Adhere to advice=1	|Purchase - Advice|	Adhere to advice=1	|Purchase - Advice|	Adhere to advice=1	|Purchase - Advice|
	(1)	(2)	(3)	(4)	(5)	(6)
Video only vs. Control	0.006	-0.214	-0.008	-0.214	0.120*	-0.224
	(0.798)	(0.442)	(0.508)	(0.445)	(0.0841)	(0.104)
Advice only vs. Control	0.038	-0.642**	-0.015	-0.501*	0.072	-0.170
	(0.172)	(0.0197)	(0.268)	(0.0869)	(0.245)	(0.322)
Video only vs. Advice only	0.032	-0.428*	-0.007	-0.286	-0.047	0.054
	(0.203)	(0.0784)	(0.538)	(0.269)	(0.280)	(0.646)
N	1881	1881	1658	1658	208	208
Control Mean	0.158	4.047	0.0785	4.451	0.889	0.333

All columns present coefficient estimates, p-values calculated with standard errors clustered at the household level (in parentheses), and randomization inference p-value [in bracket].
* denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include village fixed effects.

Table B14: ECS, within-control randomization

	Any Advice	Advice: Purchase insurance	Advice: Do not purchase insurance
	(1)	(2)	(3)
Video only vs. Control	-2.216	-0.680	-20.506
	(0.950)	(0.985)	(0.241)
Advice only vs. Control	69.591**	59.478	-0.672
	(0.0427)	(0.111)	(0.964)
Video only vs. Advice only	71.806**	60.159*	19.834
	(0.0181)	(0.0641)	(0.231)
N	1862	1642	204
Control Mean	-407.9	-459.4	-23.58

All columns present coefficient estimates, p-values calculated with standard errors clustered at the household level (in parentheses), and randomization inference p-value [in bracket].
* denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include village fixed effects.

Table B15: ECS relative to ECS from advice, within-control randomization

	Any Advice	Advice: Purchase insurance	Advice: Do not purchase insurance
	(1)	(2)	(3)
Video only vs. Control	14.757	12.463	4.869
	(0.541)	(0.616)	(0.262)
Advice only vs. Control	50.165**	33.699	13.742**
	(0.0457)	(0.205)	(0.0295)
Video only vs. Advice only	35.408	21.236	8.873*
	(0.135)	(0.396)	(0.0549)
N	1862	1642	204
Control Mean	-324.1	-367.3	-2.171

All columns present coefficient estimates, p-values calculated with standard errors clustered at the household level (in parentheses), and randomization inference p-value [in bracket].
* denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include village fixed effects.

Table B16: IBLI knowledge, within-control randomization

	IBLI knowledge score (0-10)	Everyone should buy IBLI if affordable (=1)
	(1)	(2)
Video only vs. Control	-0.067	0.030
	(0.749)	(0.456)
Advice only vs. Control	0.255	-0.021
	(0.231)	(0.629)
Video only vs. Advice only	0.322	-0.050
	(0.120)	(0.209)
N	805	805
Control Mean	6.229	0.684

All columns present coefficient estimates, p-values calculated with standard errors clustered at the household level (in parentheses), and randomization inference p-value [in bracket].
* denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include village fixed effects.

Table B17: Trust in agents, within-control randomization

	Composite trust scale	Scale for advice-related trust	Scale for money-related trust	Agents advise in my best interests	Agents' advice is important	Agents deliver premium to insurer	I will receive entitled payment	Trust the information from agent (=1)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Video only vs. Control	-0.128	-0.154*	-0.080	-0.117	-0.176**	-0.112	-0.042	0.019
	(0.122)	(0.0616)	(0.334)	(0.150)	(0.0365)	(0.179)	(0.610)	(0.274)
Advice only vs. Control	-0.118	-0.152*	-0.063	-0.113	-0.175**	-0.107	-0.015	0.008
	(0.187)	(0.0912)	(0.463)	(0.209)	(0.0498)	(0.219)	(0.862)	(0.653)
Video only vs. Advice only	0.010	0.003	0.016	0.004	0.001	0.004	0.027	-0.011
	(0.903)	(0.976)	(0.842)	(0.960)	(0.995)	(0.958)	(0.737)	(0.498)
N	805	805	805	805	805	805	805	805
Control Mean	-7.09e-11	6.01e-09	1.99e-09	-4.17e-09	-6.13e-10	2.51e-09	-6.87e-09	0.947

All columns present coefficient estimates, p-values calculated with standard errors clustered at the household level (in parentheses), and randomization inference p-value [in bracket].
* denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include village fixed effects.

Appendix C Instructions

Appendix C.1 Atemporal Risk Preferences - English and Oromia

Risky choices

Filannoo rakkoo qabduu

[TITTLE 5 SECONDS]
[BLACK SCREEN]

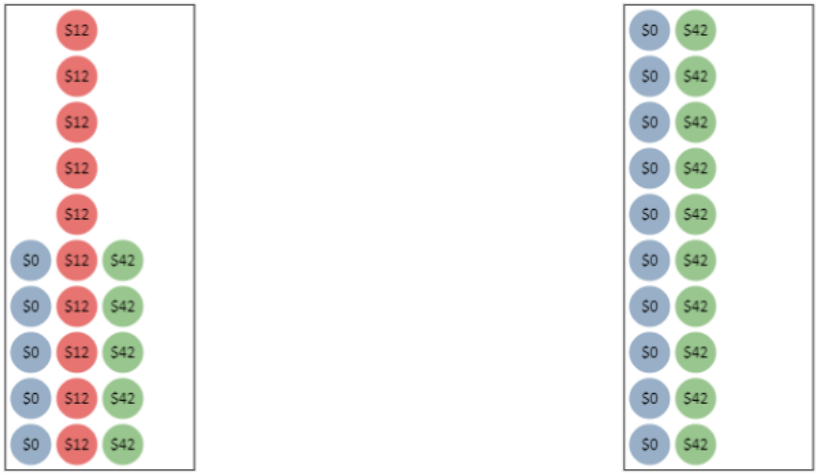
This is a task where you will choose between two options, called LEFT and RIGHT, that are presented to you on the computer screen. You will make 30 decisions in total in this task by selecting the LEFT or RIGHT option in each decision. On many screens both the LEFT and RIGHT option will each present one large bag that each contains 20 colored balls which represent a monetary amount and chances of earning the monetary amount. Once you decide which bag you prefer on each screen, either the LEFT option or RIGHT option, you will select it by clicking on your preferred bag. At the end of the task, one of the screens will be chosen at random, and this screen will be used to pay you. To determine how much you will be paid we will put the exact number of colored balls in the bag in your chosen option, the LEFT or RIGHT option, in a real bag in front of you. You will then pull a ball from this bag. The color of the ball you pull will determine the monetary amount in ETB that you earn in this task. It is therefore important that you think carefully about which option you prefer on each screen that is presented to you, the LEFT one or the RIGHT one, as it may be the one determining your earnings in this task.

Hujii tana kheessatti wa lama kheessaa filatta, tunilleen BITAA fi MIRGA; fuula koompuutaraa irratti sii dhiyaatu. Walumaa galatti murtee tamuu kheessatti BITAA yokan MIRGA jechuun filannoo 30 tolchita. Fuula hedduu gubbaatti filannoo lamaanuu, BITAA fi MIRGA, borsaa guddaa tokko kha kuwaasii/imbiiraa bifa qabdu 20, ta haga beessee himtutti dhiyaata, carraa haga beessee waliin. Eegii fuula khamuu irraa borsaa filattu murteessiteen filannoo BITAA yokaan MIRGAA, borsaa feete tuquun filatta. Gara miishoo hujii tanaatti, fuulii tokko akkuma carraa filama, fuula khana laalanii waan sii baasan sii baasan. Haga waan sii baasanii beekuuf, iluma tantee duratti haga kuwaasii/imbiiraa bifa qabdu borsuma atin filatte, kha BITAA yokaan kha MIRGAA, keessa kheenna. Achiin duuba, atin kuwaasii/imbiiraa khana borsaa khana kheessaa harkiftee baafta. Biftii kuwaasii/imbiiraa atin harkiftee baaftuu haga waan sii baasanii murteessiti. Tanaaf, filannoo fuula cufaa gubbaatti sii dhiyaattu kheessaa filachuuf akka dansaa itti herreguu malte, ta gama BITAA yokaan ta MIRGAA, hujii tana kheessatti waan sii baasan murteessuu waan dandeettuuf.

[PAUSE FOR 10 SECONDS]
[SCREEN]

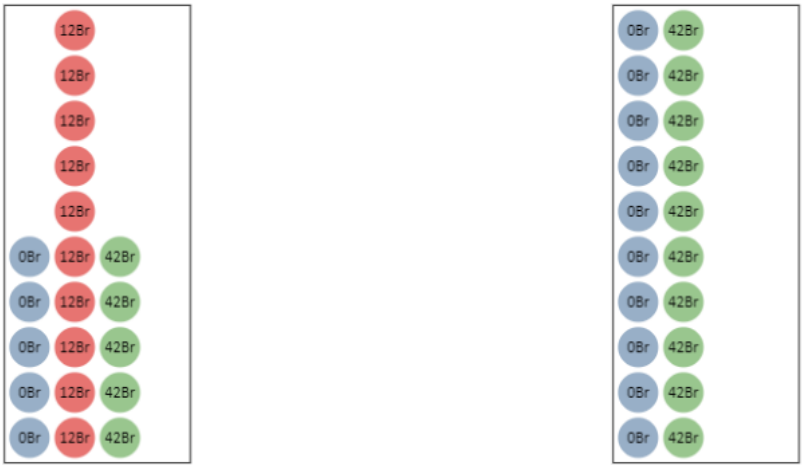
Here is an example of what the screen may look like.

Round 2 of 2



Submit

Filannoo 2 2 kessaa



Ergi

In this example, both the LEFT and the RIGHT option contain bags with a total of 20 balls.

Tunin fakkeenna fuulii akkanaan mullachuu dandaha.

Fakkeenna kana kheessatti, filannoon lachuu, kha BITAA fi MIRGAA'lleen kuwaasii/imbiiraa 20 of kheessaa qaba.

[CALL OUT LEFT OPTION]

The LEFT bag pays 0 Br with a chance of 5 out of 20, since there are 5 blue balls. It also pays 12 Br with a chance of 10 out of 20, since there are 10 red balls. And finally, it pays 42 Br with a chance of 5 out of 20, since there are 5 green balls. In this screen, if you selected the LEFT bag, and this screen was selected for payment at the end, and then you pulled out a red ball you would earn 12 Br. On the other hand, if you pulled out a green ball you would earn 42 Br. However, notice that there are 10 red balls in the bag, but only 5 green balls, so the chance of getting a red ball is 2 times the chance of getting a green ball.

Borsaan BITAA 0 baasa, carraa 20 keessaa 5 qabaatullee, sababa kuwaasii/imbiiraan buleen 5 jiruuf, ammallee birrii 12 baasa, carraa 20 keessaa 10 qabaachuun, sababa kuwaasii/imbiiraa diimtuun 10 jirtuuf. Miishoo gubbaatti, birrii 42 baasa, carraa 20 keessaa 5iin, sababa kuwaasii/imbiiraan dotii 5 waan jirtuuf. Fuula khana kheessatti, yo borsaa BITAA filatte, miishoo gubbaatti fuulii kuni waan sii baasaniif filatame, kuwaasii/imbiiraa diimtuu waan baafteef birrii 12 argatta. Gama dhibiin, yo kuwaasii/imbiiraa dotii harkiftee baafte, birrii 42 argatta. Kha taatuu ammo, wannii atin hubachuu malte, kuwaasii/imbiiraan diimaan 10, dotiin ammo 5; tanaaf, carraan kuwaasii/imbiiraa diimaa harka 2n kha kuwaasii/imbiiraa dotii caala.

[CALL OUT RIGHT OPTION]

Now look at the RIGHT bag in the example. Again, there are 20 balls in total. This bag pays 0 Br with a chance of 10 out of 20, since there are 10 blue balls. It also pays Br 42 with a chance of 10 out of 20, since there are 10 green balls. So if you choose this RIGHT bag, and this screen was selected for payment at the end, and you pulled out a green ball, you would earn 42 Br. On the other hand, if you pulled out a blue ball you would earn 0 Br. There are 10 green balls and 10 blue balls in this bag, so the chance of pulling a green ball is the same as the chance of pulling the blue ball.

Each of the LEFT or RIGHT options will be shown on a separate screen on the computer, and 30 such screens will be presented to you, so you are asked to make a choice 30 times. On each screen, you should indicate which option you prefer by clicking on the LEFT or RIGHT option. Once you have made your choice on the screen you can click the button saying "Submit" to move on to the next screen. If you would like to change your choice, you can do so on any screen, but it must be done before clicking "Submit."

Amma ammo, fakkeenna khana kheessatti borsaa MIRGAA laali. Khunilleen kuwaasii/imbiiraa 20 qaba. Borsaan kuni birrii 0 baasa, carraa 20 kheessaa 10niin, sababa kuwaasii/imbiiraa bulee 10 qabuuf. Tana malee, birrii 42 baasa, carraa 20 kheessaa 10niin, waan kuwaasii/imbiiraa dotii 10 qabuuf. Tanaaf, yo borsaa MIRGAA kana filatte, miishoo gubbaatti fuulii khunin wa sii baasuuf filatame, kuwaasii/imbiiraa dotii birrii 42 argatta. Gama dhibiin, yo ammo kuwaasii/imbiiraa bulee baafte, birrii tokkollee hin argattu. Kuwaasii/imbiiraan buleefi dotiilleen 10, 10 waan taateef carraan warra lamaan baasuu walqixa jechuu.

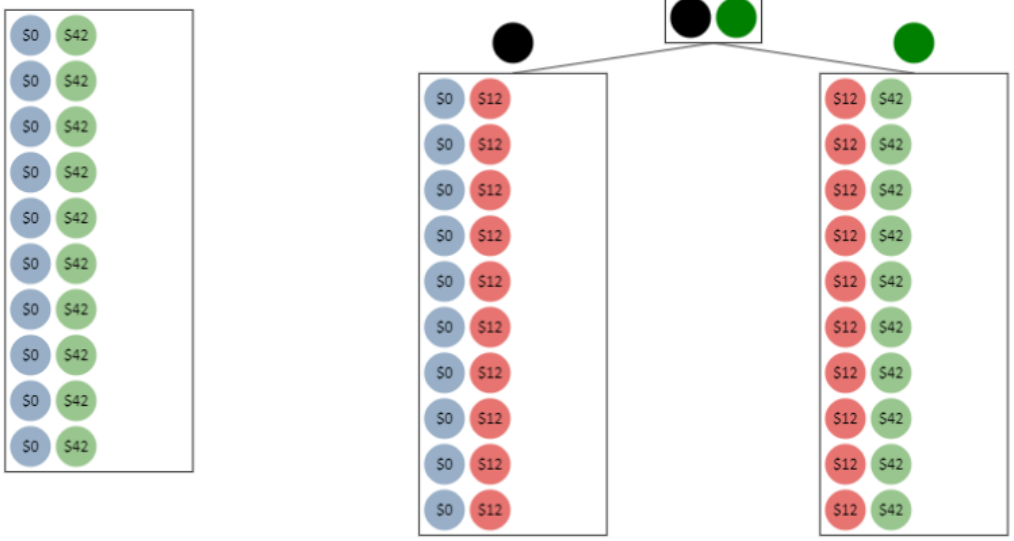
Filannoon BITAA fi MIRGAA khophaa khophaa fuula koompuutaraa gubbaatti mullatti, fuula akkanaa 30tti sii dhiyaata; tanaaf, mara 30 akka atin filannoo tolchitu si gaafatan. Fuula khamuu irratti filannoo tantee, BITAA yokaan MIRGAA tuquun garsiifta. Eegii filatteen duubatti, fulaa "Ergi" jettu tuquun gara fuula itti aanuutti dabri. Yo filannoo tantee jijjiiruu feete immoo, fuula khamuu irratti jijjiiruu in-dandeetta atoo fulaa "Ergi"jettu hin tuqiniin duratti.

[PAUSE FOR 10 SECONDS]
[SCREEN]

You could also get a decision screen where the LEFT option represents one large bag with 20 balls, just like the example above, but the RIGHT option consists of two large bags. In a RIGHT option like this, a prior small bag, with colored balls in two colors, determines which of the two large bags below it will be used for payment. Here is an example of this type of decision screen.

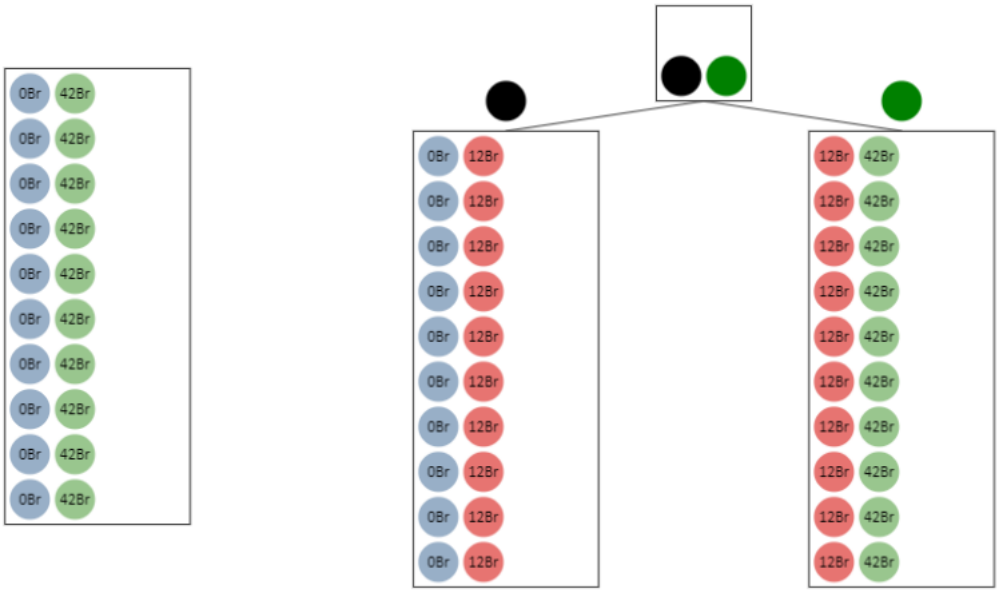
Akkuma fakkeennaa gubbaa, filannoo BITAA'lleef fuula wa murteessu birsaa guddaa tokko kheessaa kha kuwaasii/imbiiraa 20 qabutti jira; garuu, filannoon MIRGAA borsaa gugurdaa lama qaba. Filannoo MIRGAA akkanaa kheessatti, borsaan diqqaan gararroo kuwaasii bifa lama of keessaa qabu kunin borsaa gugurdaa lamaa gar-jaloo keessaa khami akka kaffaltii murteessu garsiisa. Fakkeennii fuula gosa khanaalleen kana fakkaata.

Round 1 of 2



Submit

Filannoo 1 2 kessaa



Ergi

[CALL OUT LEFT OPTION]

The LEFT option on this screen contains one large bag as before. There are 20 balls in total and this bag pays 0 Br with a chance of 10 out of 20, since there are 10 blue balls. It also pays 42 Br with a chance of 10 out of 20, since there are 10 green balls. So if you choose this LEFT option, and this screen was selected for payment at the end, and then you pulled out a green ball from this bag, you would earn 42 Br. On the other hand, if you pulled out a blue ball you would earn 0 Br.

Filannoo tana keessatti borsaan BITAA, akkuma kha duraa borsaa guddaa tokko qaba. Borsaan kuni walumattuu kuwaasii/imbiiraa 20 of-keessaa qaba, birrii 0 baasa, carraa 20 keessaa 10 qaba, waan kuwaasii/imbiiraa bulee 10 qabuuf. Tana malee, birrii 42 baasa, carraa 20 keessaa 10 qaba, waan kuwaasii/imbiiraa dotii 10 qabuuf. Tanaaf, yo filannoon tee ta BITAA tana taate, fuulii kuni miishoo gubbaatti waan sii baasaniif filatame, kuwaasii/imbiiraa dotii borsaa kana kheessaa harkiftee baaftee, birrii 42 argatta. Gama dhibiin yo kuwaasii/imbiiraa bulee harkiftee baafte, birrii 0 argatta.

[CALL OUT RIGHT OPTION]

The RIGHT option on this screen is different than the other options. It first contains a small bag on top, with two large bags below. The small bag contains 2 balls in total, 1 black ball and 1 green ball. The colored ball that is pulled from the small bag will determine which of the two large bags will be selected for you. For instance, if this screen is chosen at the end of this task to determine your earnings, and you selected the RIGHT option on the screen, you would first draw a ball from the small bag. The color of the ball that you pull from the small bag will determine which large bag below it you get to play out.

Filannoo MIRGAA ta fuula khana gubbaa jirtuufi filannoon dhibiin gargarii gortii. Jalqaba kuwaasii/imbiiraa didiqqaa lama borsaa diqqaa gararroo qabdi; gar-jaloo ammo, borsaa gugurdaa lamattti jira. Borsaan diqqaan gararroo, kuwaasii/imbiiraa lama, gurraattii 1 fi haddhoo 2, of-keessaa qaba. Kuwaasiin/imbiiraan bifa qabdu tunin, kha atin borsaa diqqaa khana kheessaa harkiftee baaftu, borsaa gugurdaa lamaan gar-jaloo kheessaa kami akka sii filan murteessiti. Fakkeennaa, miishoo hujii tanaatti, yo fuulii kunin waan sii baasaniif filatame, yo atilleen filannoo MIRGAA filatte, jalqaba borsaa diqqayyaa gararroo sun kheessaa kuwaasii/imbiiraa baafta. Biftii kuwaasii/imbiiraa atin baaftuu borsaa gar-jaloo lamaan kheessaa borsaa kamin akka hujii tana aansitu murteessa.

[CALL OUT RIGHT OPTION – BLACK BALL]

So, if you pull the black ball from the small bag on top, the large bag below will then contain 10 blue balls with value 0 Br and 10 red balls with value 12 Br. In this case the chance of drawing the blue ball and earning 0 Br is 10 out of 20, and the chance of drawing the red ball and earning 12 Br is also 10 out of 20.

Tanaaf, yoo kuwaasii/imbiiraa gurraacha borsaa diqqaa gararroo kana keessaa baafte, borsaan guddaan gar-jaloo, kha kuwaasii/imbiiraa bulee 10 qabu, gatii birrii 0 fi kuwaasii/imbiiraa diimaa 10

gatii birrii 12 qaba. Armatti carraan kuwaasii/imbiiraa bulee baasuufi birrii 0 argachuu 20 keessaa 10 yoo tahu, carraan kuwaasii/imbiiraa diimtuu baasuufi birrii 12 argachuulleen akkasuma 20 keessaa 10.

[CALL OUT RIGHT OPTION – GREEN BALL]

If instead you pull the green ball from the small bag on top, the large bag below will then contain 10 red balls with value 12 Br and 10 green balls with value 42 Br. In this case the chance of drawing the red ball and earning 12 Br is 10 out of 20, and the chance of drawing the green ball and earning 42 Br is also 10 out of 20. You can see that the color of the ball pulled from the small bag on top determines which large bag under it is then used. In turn, this large bag will determine your final earnings.

Yo ammo, borsaa diqqayyaa gararroo keessaa kuwaasii/imbiiraa dotii baafte, borsaan gar-jaloo kha kuwaasii/imbiiraa diimaa 10 fi birrii 12 waliin, fi kuwaasii/imbiiraa dotii 10 birrii 42 waliin qabuuti. Armatti, carraan kuwaasii/imbiiraa diimaa baasuufi birrii 12 argachuu 20 keessaa 10; fi carraan kuwaasii/imbiiraa dotii baasuufi birrii 42 argachuulleen akkasuma 20 keessaa 10. Bifa kuwaasii/imbiiraa borsaa diqqayyaa gararroo keessaa baafte laaltee borsaa gugurdaa gar-jaloo lamaan keessaa borsaa khamitti akka dabartu hubatta. Borsaan guddaan khunilleen akkanaan waan miishoo gubbaatti atin argattu murteessa.

[PAUSE FOR 10 SECONDS]
[BLACK SCREEN]

After you have worked through all 30 screens and selected the LEFT or RIGHT option you prefer, you and the enumerator will then determine your payment for this task. You will first determine which screen out of the 30 screens will be used for payment. This will be done by you rolling two 10-sided dice until a number between 1 and 30 comes up to determine which screen will be played out. The decision screen selected will then be called back on the computer and we will see what LEFT or RIGHT option you had chosen.

If the option you selected included a small bag at the top, the enumerator will first prepare that smaller bag for you by putting the same number of colored balls in a bag in front of you as shown on the screen. You will then reach in the bag and pull one ball from the small bag. The color of that ball determines which large bag will be used to determine your earnings. The enumerator will then prepare the large bag by putting the same number of colored balls in a bag in front of you as shown on the screen. You will then be asked to reach in and pull one ball from this large bag to determine your final earning for this task. Since **each** of the 30 screens **might** be selected to determine your earnings, you should think very carefully about each pair of bags you choose between.

Eegii hujii tana keessatti fuula 30, filannoo feedhii teetiin, BITAA yokaan MIRGAA tolchiteen duuba, namii qorqortii hujii tanaatiif deemu waan sii baasan murteessa. Qara sitti fuula 30n kheessaa

fuula kaffaltiif in-taha jettu murteessa. Tana ammo, saddeeqa lama ta gama-10 qabdu gara gaggalchuun lakkoobsa 1 fi 30 jidduu dhufee fuula itti kheeyyataniin murteessanitti. Fuulii murteef filatame deebiyee akkasiin filannoo tee ta BITAA yokaan MIRGAA atin filatte taani argina.

Yo filannoon tantee borsaa diqqayyaa gararroo qabaate, namii qorqortii hujii tanaatiif deemu borsaa diqqayyaa khana qopheessetti akkuma fakkeenna fuula kana gubbaatti agarsiisan kana kuwaasii/imbiiraa bifa qabdu ta lakkoobsaan walqixxee atoo atin agartuu kheessa kaawa. Achiin, atin borsaa diqqayyaa kana kheessaa kuwaasii/imbiiraa tokko baafta. Biftii kuwaasii/imbiiraa atin baaftuu borsaa gugurdaa lamaan kheessaa kamitti akka taakkitu fi waan sii baasanillee murteessiti. Namii qorqortii hujii tanaatiif deemu borsaa guddaa qopheessee, akkuma fuula kana irraa mullatu kanatti, kuwaasii/imbiiraa lakkoobsaan walqixxee atoo atin agartuu kheessa khaawa. Borsaa kana kheessaa kuwaasii/imbiiraa tokko akka atin harkiftee baaftu si gaafachuun miishoo hujii tanaaf waan sii baasan murteessa. Fuula tokko tokkoon 30 filaman waan sii baasan murteessuu waan dandahaniif akka dansaa itti herreddee borsaa xindii khana lamaan jidduu filachuu malte.

[PAUSE FOR 10 SECONDS]
[BLACK SCREEN]
[SCREEN WITH THE BULLET ITEMS BELOW]

Therefore, your earnings for this task are determined by four things:

- Which screen out of the 30 screens is selected by the number you roll with the two 10-sided dice.
- By the choice you made to select the LEFT or the RIGHT option, on that particular screen.
- By the color of the ball that you pull from the large bag for the option you selected for this particular screen.
- If your choice was for an option with a small bag at the top, both the color of the ball you pull from the small bag, and the color of the ball you subsequently pull from the selected large bag below it, determine your earnings.

Tanaaf, wannii afur waan atin argattu murteessiti:

- Fuula 30'n kheessaa fuula lakkoobsa saddeeqaa gama-10 qabuu atin gara gaggalchiituun dhufuun filama.
- Filannoo tee ta BITAA yokaan ta MIRGAA atin tolchituun, fuula murtaawaa gubbaatti.
- Bifa kuwaasii/imbiiraa atin borsaa guddaa kheessaa baaftuun.
- Yo filannoon tee filannoo borsaa diqqaa gararroo qabdu taate, biftii kuwaasii/imbiiraa atin borsaa gararroo diqqaa kana kheessaa baaftuufi borsaa guddaa gar-jaloo kheessaa walitti aansitee baaftuu haga waan sii baasanii murteessiti.

Which option of the LEFT or RIGHT option you prefer to choose on each screen is a matter of personal taste. The people next to you may be presented with different options, and may have different preferences, so their responses should not matter to you. Please work silently and make your choices by thinking carefully about the LEFT and RIGHT option on each screen.

Payment for this task is in cash and is in addition to the show-up fee that you receive just for being here.

Fuula khamuu gubbaatti filannoo BITAA yokaan MIRGAA jettee filachuun fedhii tanteeti. Namii dhawaattuu te tataawu filannoo dhibii dhiyeessuu dandahan. Tunin si cinquu hin qabdu. Tanaaf, fuula khamuu gubbaatti filannoo tolchitu akkuma dansaa ta BITAA fi MIRGAA'llee itti herregii calleessaan filadhi.

Hujii tanaaf beessee kaasha sii kaffalla. Ammallee beessee wayii waan atin nu waliin miila dhaabatteefillee wa sii baamna.

Appendix D Supplementary Appendix: Robustness Check

This document contains the Supplementary Appendix for the paper.

Appendix D.1 Adding Control Variables

Table D1.1: IBLI Purchase, Control Variables Added

	IBLI purchase=1	N of animals insured	N of animals insured |Purchase=1
	(1)	(2)	(3)
Advice+Sales vs. Control	-0.004	-0.012	-0.013
	(0.316)	(0.628)	(0.951)
	[0.511]	[0.696]	[0.993]
Advice+Welfare vs. Control	-0.011**	-0.023	0.314
	(0.0143)	(0.372)	(0.215)
	[0.0700]	[0.548]	[0.316]
Advice+Sales vs. Advice+Welfare	-0.006*	-0.011	0.327
	(0.0556)	(0.591)	(0.156)
	[0.0700]	[0.593]	[0.173]
N	26680	26680	1909
Control Mean	0.0818	0.312	3.812

All columns present coefficient estimates, p-values calculated with standard errors clustered at the village level (in parentheses), $and randomization inference p\text{-}value[in bracket]$. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include kebele $\times$ round fixed effects, and the following variables as control: respondent's age at baseline, gender, marital status, household size, literacy, years of education, baseline herd size, livestock expenditure, agricultural activity, prior engagement with IBLI. Column (1) presents the impact on the insurance take-up at the extensive margin, denoted as 1 if a pastoralist purchased insurance in each sales season, and 0 otherwise. Columns (2) and (3) depict the impact at the intensive margin of insurance take-up. The intensive margin refers to the number of animals insured in each sales season. In Column (2) the number of insured animals is recorded, with the count treated as 0 if a pastoralist did not purchase insurance. Column (3) presents the number of animals insured, conditional on a pastoralist purchasing insurance. The number of observations in Columns (1) and (2) is 26,744, calculated as (2,416 x 4 animal species x 3 rounds) - 562 (control households randomized to additional treatment at endline). In Column (3) the number of insured animals, conditional on purchasing insurance, is estimated with 1,909 households, since 1,915 households purchased insurance, and 6 singleton observations were dropped to avoid biases in the standard error.

Table D1.2: Adherence to the Advice, Control Variables Added

	Any advice		Advised to purchase		Advised not to purchase	
	Adhere to advice=1	|Purchase - Advice|	Adhere to advice=1	|Purchase - Advice|	Adhere to advice=1	|Purchase - Advice|
	(1)	(2)	(3)	(4)	(5)	(6)
Advice+Sales vs. Control	-0.006	0.019	-0.008	0.044	0.006	0.010
	(0.421)	(0.921)	(0.246)	(0.845)	(0.526)	(0.824)
	[0.552]	[0.972]	[0.347]	[0.955]	[0.562]	[0.842]
Advice+Welfare vs. Control	0.000	0.014	-0.011	0.102	0.022**	-0.060
	(0.972)	(0.947)	(0.115)	(0.677)	(0.0189)	(0.185)
	[0.910]	[0.870]	[0.225]	[0.878]	[0.0610]	[0.394]
Advice+Sales vs. Advice+Welfare	0.007	-0.005	-0.003	0.057	0.016*	-0.070*
	(0.334)	(0.976)	(0.584)	(0.778)	(0.0639)	(0.0670)
	[0.455]	[0.787]	[0.559]	[0.862]	[0.0570]	[0.238]
N	17058	17058	14117	14117	2914	2914
Control Mean	0.263	5.307	0.125	6.391	0.915	0.209

All columns present coefficient estimates, p-values calculated with standard errors clustered at the village level (in parentheses), $and randomization inference p\text{-}value[in bracket]$. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include kebele $\times$ round fixed effects, and the following variables as control: respondent's age at baseline, gender, marital status, household size, literacy, years of education, baseline herd size, livestock expenditure, agricultural activity, prior engagement with IBLI. Columns (1) and (2) compare the adherence to advice across treatment arms, irrespective of whether the advice pertains to purchasing insurance or refraining from it. Column (1) represents adherence to the advice, while Column (2) indicates the absolute difference in the number of insured animals. Columns (3) and (4) display estimates for advice recommending the purchase of insurance, while Columns (5) and (6) show estimates for advice advising against purchasing insurance. The number of observations in Columns (1) and (2) is 17,064, which is the number of herders received any tailored advice across midline 1, 2 and endline. The number of observations in Columns (3) and (4) is 14,539, which is the number of herders who received advice to buy insurance across midline 1, 2 and endline. The number of observations in Columns (5) and (6) is 2,499, which is the number of herders who received advice not to buy insurance across midline 1, 2 and endline (2,525) after dropping 26 singleton observations.

Table D1.3: Expected Consumer Surplus Relative to Maximum Expected Consumer Surplus, Control Variables Added

	Any Advice	Advice: Purchase insurance	Advice: Do not purchase insurance
	(1)	(2)	(3)
Advice+Sales vs. Control	-1.946	-4.100	-3.441
	(0.831)	(0.702)	(0.433)
	[0.995]	[0.896]	[0.526]
Advice+Welfare vs. Control	11.284	7.467	9.722**
	(0.212)	(0.478)	(0.0199)
	[0.252]	[0.479]	[0.0810]
Advice+Sales vs. Advice+Welfare	13.230	11.567	13.163***
	(0.126)	(0.240)	(0.00439)
	[0.168]	[0.264]	[0.0690]
N	16624	13720	2878
Control Mean	-243.1	-291.5	-21.22

All columns present coefficient estimates, p-values calculated with standard errors clustered at the village level (in parentheses), $and randomization inference p\text{-}value[in bracket]$. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include kebele $\times$ round fixed effects, and the following variables as control: respondent's age at baseline, gender, marital status, household size, literacy, years of education, baseline herd size, livestock expenditure, agricultural activity, prior engagement with IBLI. Columns (1) and (2) compare the adherence to advice across treatment arms, irrespective of whether the advice pertains to purchasing insurance or refraining from it. Column (1) uses the full sample of household $\times$ animal species which ECS can be generated. Column (2) and (3) uses the sample who received advice to insure animal and advice not to insure animal, respectively. Column (1) uses 16,630 observations, the number of herders for whom maximum ECS was calculated across midline 1, 2 and endline. Column (2) uses 14,153 observations, the number of herders who received advice to buy insurance across midline 1, 2 and endline. Column (3) uses 2,470 observations, the number of herders who received advice not to buy insurance across midline 1, 2 and endline (2,525) after dropping 55 singleton observations.

Appendix D.2 Adding Kebele Fixed Effects Only

Table D2.1: IBLI Purchase, Kebele Fixed Effects Only

	IBLI purchase=1	N of animals insured	N of animals insured |Purchase=1
	(1)	(2)	(3)
Advice+Sales vs. Control	-0.010**	-0.050*	-0.105
	(0.0266)	(0.0613)	(0.630)
Advice+Welfare vs. Control	-0.017***	-0.060**	0.247
	(0.000226)	(0.0221)	(0.339)
Advice+Sales vs. Advice+Welfare	-0.006*	-0.009	0.351
	(0.0668)	(0.657)	(0.144)
N	26744	26744	1915
Control Mean	0.0818	0.312	3.812

All columns present coefficient estimates, p-values calculated with standard errors clustered at the village level (in parentheses), $and randomization inference p\text{-}value[inbracket]$. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include kebele fixed effects. Column (1) presents the impact on the insurance take-up at the extensive margin, denoted as 1 if a pastoralist purchased insurance in each sales season, and 0 otherwise. Columns (2) and (3) depict the impact at the intensive margin of insurance take-up. The intensive margin refers to the number of animals insured in each sales season. In Column (2) the number of insured animals is recorded, with the count treated as 0 if a pastoralist did not purchase insurance. Column (3) presents the number of animals insured, conditional on a pastoralist purchasing insurance. The number of observations in Columns (1) and (2) is 26,744, calculated as (2,416 x 4 animal species x 3 rounds) - 562 (control households randomized to additional treatment at endline). In Column (3) the number of insured animals, conditional on purchasing insurance, is estimated with 1,909 households, since 1,915 households purchased insurance, and 6 singleton observations were dropped to avoid biases in the standard error.

Table D2.2: Adherence to the Advice, Kebele Fixed Effects Only

	Any advice		Advised to purchase		Advised not to purchase	
	Adhere to advice=1	|Purchase - Advice|	Adhere to advice=1	|Purchase - Advice|	Adhere to advice=1	|Purchase - Advice|
	(1)	(2)	(3)	(4)	(5)	(6)
Advice+Sales vs. Control	-0.024***	-0.355*	-0.022***	-0.471*	0.010	0.011
	(0.00660)	(0.0857)	(0.00298)	(0.0548)	(0.249)	(0.797)
Advice+Welfare vs. Control	-0.019**	-0.364*	-0.023***	-0.441*	0.025***	-0.070*
	(0.0285)	(0.0828)	(0.00139)	(0.0700)	(0.00237)	(0.0864)
Advice+Sales vs. Advice+Welfare	0.005	-0.009	-0.001	0.030	0.016*	-0.081**
	(0.492)	(0.959)	(0.846)	(0.890)	(0.0528)	(0.0490)
N	17064	17064	14123	14123	2941	2941
Control Mean	0.263	5.307	0.125	6.391	0.915	0.209

All columns present coefficient estimates, p-values calculated with standard errors clustered at the village level (in parentheses), $and randomization inference p\text{-}value[inbracket]$. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include kebele fixed effects. Columns (1) and (2) compare the adherence to advice across treatment arms, irrespective of whether the advice pertains to purchasing insurance or refraining from it. Column (1) represents adherence to the advice, while Column (2) indicates the absolute difference in the number of insured animals. Columns (3) and (4) display estimates for advice recommending the purchase of insurance, while Columns (5) and (6) show estimates for advice advising against purchasing insurance. The number of observations in Columns (1) and (2) is 17,064, which is the number of herders received any tailored advice across midline 1, 2 and endline. The number of observations in Columns (3) and (4) is 14,539, which is the number of herders who received advice to buy insurance across midline 1, 2 and endline. The number of observations in Columns (5) and (6) is 2,499, which is the number of herders who received advice not to buy insurance across midline 1, 2 and endline (2,525) after dropping 26 singleton observations.

Table D2.3: Expected Consumer Surplus Relative to Maximum Expected Consumer Surplus, Kebele Fixed Effects Only

	Any Advice	Advice: Purchase insurance	Advice: Do not purchase insurance
	(1)	(2)	(3)
Advice+Sales vs. Control	-46.349***	-50.915***	-1.645
	(0.00000482)	(0.00000778)	(0.717)
Advice+Welfare vs. Control	-33.305***	-38.142***	9.645**
	(0.000945)	(0.000761)	(0.0165)
Advice+Sales vs. Advice+Welfare	13.045	12.773	11.289***
	(0.152)	(0.218)	(0.00950)
N	16630	13726	2904
Control Mean	-243.1	-291.5	-21.22

All columns present coefficient estimates, p-values calculated with standard errors clustered at the village level (in parentheses), $and randomization inference p\text{-}value[in bracket]$. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include kebele fixed effects. Columns (1) and (2) compare the adherence to advice across treatment arms, irrespective of whether the advice pertains to purchasing insurance or refraining from it. Column (1) uses the full sample of household $\times$ animal species which ECS can be generated. Column (2) and (3) uses the sample who received advice to insure animal and advice not to insure animal, respectively. Column (1) uses 16,630 observations, the number of herders for whom maximum ECS was calculated across midline 1, 2 and endline. Column (2) uses 14,153 observations, the number of herders who received advice to buy insurance across midline 1, 2 and endline. Column (3) uses 2,470 observations, the number of herders who received advice not to buy insurance across midline 1, 2 and endline (2,525) after dropping 55 singleton observations.

Appendix D.3 Adding Kebele and Survey Round Fixed Effects Separately

Table D3.1: IBLI Purchase, Kebele and Survey Round Fixed Effects

	IBLI purchase=1	N of animals insured	N of animals insured |Purchase=1
	(1)	(2)	(3)
Advice+Sales vs. Control	-0.003	-0.012	-0.030
	(0.449)	(0.639)	(0.884)
Advice+Welfare vs. Control	-0.010**	-0.022	0.356
	(0.0344)	(0.423)	(0.154)
Advice+Sales vs. Advice+Welfare	-0.006*	-0.009	0.386
	(0.0668)	(0.657)	(0.104)
N	26744	26744	1915
Control Mean	0.0818	0.312	3.812

All columns present coefficient estimates, p-values calculated with standard errors clustered at the village level (in parentheses), $and randomization inference p\text{-}value[in bracket]$. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include kebele and survey round fixed effects. Column (1) presents the impact on the insurance take-up at the extensive margin, denoted as 1 if a pastoralist purchased insurance in each sales season, and 0 otherwise. Columns (2) and (3) depict the impact at the intensive margin of insurance take-up. The intensive margin refers to the number of animals insured in each sales season. In Column (2) the number of insured animals is recorded, with the count treated as 0 if a pastoralist did not purchase insurance. Column (3) presents the number of animals insured, conditional on a pastoralist purchasing insurance. The number of observations in Columns (1) and (2) is 26,744, calculated as (2,416 x 4 animal species x 3 rounds) - 562 (control households randomized to additional treatment at endline). In Column (3) the number of insured animals, conditional on purchasing insurance, is estimated with 1,909 households, since 1,915 households purchased insurance, and 6 singleton observations were dropped to avoid biases in the standard error.

Table D3.2: Adherence to the Advice, Kebele and Survey Round Fixed Effects

	Any advice		Advised to purchase		Advised not to purchase	
	Adhere to advice=1	|Purchase - Advice|	Adhere to advice=1	|Purchase - Advice|	Adhere to advice=1	|Purchase - Advice|
	(1)	(2)	(3)	(4)	(5)	(6)
Advice+Sales vs. Control	-0.005	-0.027	-0.011	-0.008	0.009	0.015
	(0.582)	(0.899)	(0.147)	(0.976)	(0.288)	(0.744)
Advice+Welfare vs. Control	0.000	-0.036	-0.011	0.009	0.027***	-0.073*
	(0.970)	(0.868)	(0.117)	(0.972)	(0.00141)	(0.0763)
Advice+Sales vs. Advice+Welfare	0.005	-0.009	-0.001	0.016	0.018**	-0.087**
	(0.465)	(0.961)	(0.872)	(0.940)	(0.0285)	(0.0362)
N	17064	17064	14123	14123	2941	2941
Control Mean	0.263	5.307	0.125	6.391	0.915	0.209

All columns present coefficient estimates, p-values calculated with standard errors clustered at the village level (in parentheses), $and randomization inference p\text{-}value[inbracket]$. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include kebele and survey round fixed effects. Columns (1) and (2) compare the adherence to advice across treatment arms, irrespective of whether the advice pertains to purchasing insurance or refraining from it. Column (1) represents adherence to the advice, while Column (2) indicates the absolute difference in the number of insured animals. Columns (3) and (4) display estimates for advice recommending the purchase of insurance, while Columns (5) and (6) show estimates for advice advising against purchasing insurance. The number of observations in Columns (1) and (2) is 17,064, which is the number of herders received any tailored advice across midline 1, 2 and endline. The number of observations in Columns (3) and (4) is 14,539, which is the number of herders who received advice to buy insurance across midline 1, 2 and endline. The number of observations in Columns (5) and (6) is 2,499, which is the number of herders who received advice not to buy insurance across midline 1, 2 and endline (2,525) after dropping 26 singleton observations.

Table D3.3: Expected Consumer Surplus Relative to Maximum Expected Consumer Surplus, Kebele and Survey Round Fixed Effects

	Any Advice	Advice: Purchase insurance	Advice: Do not purchase insurance
	(1)	(2)	(3)
Advice+Sales vs. Control	-0.155	-1.258	-2.462
	(0.987)	(0.910)	(0.587)
Advice+Welfare vs. Control	13.279	9.090	8.486**
	(0.186)	(0.425)	(0.0387)
Advice+Sales vs. Advice+Welfare	13.434	10.348	10.948**
	(0.134)	(0.310)	(0.0119)
N	16630	13726	2904
Control Mean	-243.1	-291.5	-21.22

All columns present coefficient estimates, p-values calculated with standard errors clustered at the village level (in parentheses), $and randomization inference p\text{-}value[inbracket]$. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include kebele and survey round fixed effects. Columns (1) and (2) compare the adherence to advice across treatment arms, irrespective of whether the advice pertains to purchasing insurance or refraining from it. Column (1) uses the full sample of household $\times$ animal species which ECS can be generated. Column (2) and (3) uses the sample who received advice to insure animal and advice not to insure animal, respectively. Column (1) uses 16,630 observations, the number of herders for whom maximum ECS was calculated across midline 1, 2 and endline. Column (2) uses 14,153 observations, the number of herders who received advice to buy insurance across midline 1, 2 and endline. Column (3) uses 2,470 observations, the number of herders who received advice not to buy insurance across midline 1, 2 and endline (2,525) after dropping 55 singleton observations.

Appendix D.4 Household Level Analysis

Table D4.1: IBLI Purchase, measured at HH level

	IBLI purchase=1	TLU insured	TLU insured | Purchase=1
	(1)	(2)	(3)
Advice+Sales vs. Control	-0.013	0.014	0.030
	(0.254)	(0.824)	(0.891)
	[0.353]	[0.866]	[0.919]
Advice+Welfare vs. Control	-0.019*	-0.062	-0.187
	(0.0734)	(0.290)	(0.391)
	[0.126]	[0.336]	[0.521]
Advice+Sales vs. Advice+Welfare	-0.007	-0.076	-0.217
	(0.445)	(0.137)	(0.393)
	[0.304]	[0.239]	[0.281]
N	6686	6686	1295
Control Mean	0.219	0.610	2.792

All columns present coefficient estimates, p-values calculated with standard errors clustered at the village level (in parentheses), and randomization inference p-value [in bracket]. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include kebele $\times$ fixed effects. Column (1) presents the impact on the insurance take-up at the extensive margin, denoted as one if a pastoralist purchased insurance in each sales season, and zero otherwise. Columns (2) and (3) depict the impact at the intensive margin of insurance take-up. The intensive margin refers to the number of animals insured in each sales season. In Column (2), the number of insured animals is recorded, with the count treated as zero if a pastoralist did not purchase insurance. Column (3) presents the number of animals insured, conditional on a pastoralist purchasing insurance.

Table D4.2: Adherence to the advice, measured at HH level

	Any advice		Advised to purchase		Advised not to purchase	
	Adhere to advice=1	|Purchase - Advice|	Adhere to advice=1	|Purchase - Advice|	Adhere to advice=1	|Purchase - Advice|
	(1)	(2)	(3)	(4)	(5)	(6)
Advice+Sales vs. Control	-0.015	0.925	-0.011	0.985	-0.011	0.002
	(0.353)	(0.202)	(0.502)	(0.183)	(0.835)	(0.767)
Advice+Welfare vs. Control	0.001	0.206	-0.007	0.286	-0.014	-0.009
	(0.929)	(0.723)	(0.658)	(0.633)	(0.848)	(0.267)
Advice+Sales vs. Advice+Welfare	0.017	-0.719	0.004	-0.699	-0.003	-0.011
	(0.304)	(0.223)	(0.809)	(0.249)	(0.948)	(0.186)
N	2367	765	2317	733	68	2407
Control Mean	0.313	4.747	0.287	4.716	0.853	0.0159

All columns present coefficient estimates, *p*-values calculated with standard errors clustered at the village level (in parentheses), and randomization inference *p*-value [in bracket]. Columns (1) and (2) compare the adherence to advice across treatment arms, irrespective of whether the advice pertains to purchasing insurance or refraining from it. Column (1) represents adherence to the advice, while Column (2) indicates the absolute difference in the number of insured animals. Columns (3) and (4) display estimates for advice recommending the purchase of insurance, while Columns (5) and (6) show estimates for advice advising against purchasing insurance. The number of observations in Columns (1) and (2) is 17,064, which is the number of herders received any tailored advice across midline 1, 2 and endline. The number of observations in Columns (3) and (4) is 14,539, which is the number of herders who received advice to buy insurance across midline 1, 2 and endline. The number of observations in Columns (5) and (6) is 2,499, which is the number of herders who received advice not to buy insurance across midline 1, 2 and endline (2,525) after dropping 26 singleton observations. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include kebele fixed effects.

Table D4.3: Expected Consumer Surplus Relative to Maximum Expected Consumer Surplus, measured at HH level

	Any Advice	Advice: Purchase insurance	Advice: Do not purchase insurance
	(1)	(2)	(3)
Advice+Sales vs. Control	-25.299	-24.103	-1.197
	(0.312)	(0.332)	(0.557)
	[0.400]	[0.414]	[0.671]
Advice+Welfare vs. Control	-5.533	-8.426	2.893
	(0.828)	(0.740)	(0.125)
	[0.868]	[0.801]	[0.161]
Advice+Sales vs. Advice+Welfare	19.766	15.676	4.090**
	(0.434)	(0.534)	(0.0312)
	[0.533]	[0.572]	[0.134]
N	6686	6686	6686
Control Mean	-587.7	-578.5	-9.175

All columns present coefficient estimates, p-values calculated with standard errors clustered at the village level (in parentheses), and randomization inference p-value [in bracket]. Columns (1) and (2) compare the adherence to advice across treatment arms, irrespective of whether the advice pertains to purchasing insurance or refraining from it. Column (1) uses the full sample of household $\times$ animal species which ECS can be generated. Column (2) and (3) uses the sample who received advice to insure animal and advice not to insure animal, respectively. All columns (1)-(3) use 6,686 observations, the number of households for whom maximum ECS was calculated across midline 1, 2 and endline.

Appendix D.5 Multi-way Clustering at the Village and Survey Round levels

Table D5.1: IBLI Purchase, Multi-way Clustering

	IBLI Purchase		Number of animals insured	Number of animals insured |Purchase
	(1)	(2)	(3)	(4)
Advice+Sales vs. Control	-0.007	-0.003	-0.012	0.002
	(0.348)	(0.323)	(0.539)	(0.989)
Advice+Welfare vs. Control	-0.021**	-0.010***	-0.022	0.354
	(0.0411)	(0.00880)	(0.251)	(0.285)
Advice+Sales vs. Advice+Welfare	-0.015**	-0.006***	-0.009	0.352
	(0.0283)	(0.00529)	(0.690)	(0.231)
Model	Logit	OLS	OLS	OLS
N	11944	26744	26744	1909
Control Mean	0.0818	0.0818	0.312	3.812

All columns present coefficient estimates, *p*-values calculated with standard errors clustered at the village and survey round level (in parentheses), and randomization inference *p*-value [in bracket]. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include kebele $\times$ round fixed effects. Column (1) presents the impact on the insurance take-up at the extensive margin, denoted as 1 if a pastoralist purchased insurance in each sales season, and 0 otherwise. Columns (2) and (3) depict the impact at the intensive margin of insurance take-up. The intensive margin refers to the number of animals insured in each sales season. In Column (2) the number of insured animals is recorded, with the count treated as 0 if a pastoralist did not purchase insurance. Column (3) presents the number of animals insured, conditional on a pastoralist purchasing insurance. The number of observations in Columns (1) and (2) is 26,744, calculated as (2,416 x 4 animal species x 3 rounds) - 562 (control households randomized to additional treatment at endline). In Column (3) the number of insured animals, conditional on purchasing insurance, is estimated with 1,909 households, since 1,915 households purchased insurance, and 6 singleton observations were dropped to avoid biases in the standard error.

Table D5.2: Adherence to the Advice, Multi-way Clustering

	Any Advice		Advised to purchase		Advised not to purchase	
	Adhere to Advice	|Purchase - Advice|	Adhere to Advice	|Purchase - Advice|	Adhere to Advice	|Purchase - Advice|
	(1)	(2)	(3)	(4)	(5)	(6)
Advice+Sales vs. Control	-0.007	-0.009	-0.016	0.018	0.017**	0.011
	(0.402)	(0.968)	(0.153)	(0.950)	(0.0315)	(0.510)
Advice+Welfare vs. Control	0.001	-0.043	-0.022	0.043	0.058***	-0.048*
	(0.888)	(0.888)	(0.109)	(0.915)	(1.09e-09)	(0.0921)
Advice+Sales vs. Advice+Welfare	0.008	-0.035	-0.007	0.025	0.041***	-0.059**
	(0.345)	(0.826)	(0.464)	(0.900)	(0.0000482)	(0.0428)
Model	Logit	OLS	Logit	OLS	Logit	OLS
N	15731	17064	6418	14123	1105	2914
Control Mean	0.263	5.307	0.125	6.391	0.915	0.209

All columns present coefficient estimates, p-values calculated with standard errors clustered at the village and survey round level (in parentheses), $and randomization inference p\text{-}value[in bracket]$. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include kebele $\times$ round fixed effects. Columns (1) and (2) compare the adherence to advice across treatment arms, irrespective of whether the advice pertains to purchasing insurance or refraining from it. Column (1) represents adherence to the advice, while Column (2) indicates the absolute difference in the number of insured animals. Columns (3) and (4) display estimates for advice recommending the purchase of insurance, while Columns (5) and (6) show estimates for advice advising against purchasing insurance. The number of observations in Columns (1) and (2) is 17,064, which is the number of herders received any tailored advice across midline 1, 2 and endline. The number of observations in Columns (3) and (4) is 14,539, which is the number of herders who received advice to buy insurance across midline 1, 2 and endline. The number of observations in Columns (5) and (6) is 2,499, which is the number of herders who received advice not to buy insurance across midline 1, 2 and endline (2,525) after dropping 26 singleton observations.

Table D5.3: Expected Consumer Surplus Relative to Maximum Expected Consumer Surplus, Multi-way Clustering

	Any Advice	Advice: Purchase insurance	Advice: Do not purchase insurance
	(1)	(2)	(3)
Advice+Sales vs. Control	0.082	-1.527	-3.689**
	(0.995)	(0.929)	(0.0146)
Advice+Welfare vs. Control	13.511**	10.165	8.564***
	(0.0331)	(0.105)	(1.33e-15)
Advice+Sales vs. Advice+Welfare	13.429	11.692	12.253***
	(0.333)	(0.428)	(4.79e-08)
N	16630	13726	2878
Control Mean	-243.1	-291.5	-21.22

All columns present coefficient estimates, p-values calculated with standard errors clustered at the village and survey round level (in parentheses), *and randomization inference p-value* [*in bracket*]. * denotes significance at 0.10; ** at 0.05; and *** at 0.01. All columns include kebele $\times$ round fixed effects. Columns (1) and (2) compare the adherence to advice across treatment arms, irrespective of whether the advice pertains to purchasing insurance or refraining from it. Column (1) uses the full sample of household $\times$ animal species which ECS can be generated. Column (2) and (3) uses the sample who received advice to insure animal and advice not to insure animal, respectively. Column (1) uses 16,630 observations, the number of herders for whom maximum ECS was calculated across midline 1, 2 and endline. Column (2) uses 14,153 observations, the number of herders who received advice to buy insurance across midline 1, 2 and endline. Column (3) uses 2,470 observations, the number of herders who received advice not to buy insurance across midline 1, 2 and endline (2,525) after dropping 55 singleton observations.

Appendix D.6 Wild-cluster Bootstrap

Appendix D.7 Consumer Welfare: Winsorizing ECS

Table D7.1: Expected Consumer Surplus Relative to Maximum Expected Consumer Surplus, Winsorized

	Any Advice				Advice: Purchase insurance				Advice: Do not purchase insurance			
	No winsor	1%	5%	10%	No winsor	1%	5%	10%	No winsor	1%	5%	10%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Advice+Sales vs. Control	0.625	4.544	5.665	5.679	-1.378	3.488	5.094	5.274	-1.665	-0.175	-0.252	-0.552
	(0.945)	(0.559)	(0.377)	(0.305)	(0.895)	(0.696)	(0.484)	(0.399)	(0.645)	(0.955)	(0.906)	(0.746)
Advice+Welfare vs. Control	14.598	14.032*	11.875*	10.636*	10.387	10.192	8.486	7.568	6.565*	6.191**	3.749*	2.497
	(0.108)	(0.0780)	(0.0709)	(0.0596)	(0.324)	(0.266)	(0.258)	(0.239)	(0.0611)	(0.0484)	(0.0802)	(0.143)
Advice+Sales vs. Advice+Welfare	13.973	9.489	6.209	4.957	11.765	6.704	3.392	2.294	8.230**	6.365*	4.001*	3.049*
	(0.113)	(0.192)	(0.291)	(0.319)	(0.239)	(0.415)	(0.604)	(0.677)	(0.0488)	(0.0531)	(0.0533)	(0.0766)
N	16947	16947	16947	16947	14135	14135	14135	14135	2470	2470	2470	2470
Control Mean	-239.1	-233.5	-217.4	-200.5	-283.8	-277.0	-258.1	-238.2	-14.44	-14.32	-12.04	-10.36

All columns present coefficient estimates, *p*-values calculated with standard errors clustered at the village level (in parentheses), and randomization inference *p*-value [in bracket]. Columns (1) and (2) compare the adherence to advice across treatment arms, irrespective of whether the advice pertains to purchasing insurance or refraining from it. Column (1) uses the full sample of household $\times$ animal species which ECS can be generated. Column (2) and (3) uses the sample who received advice to insure animal and advice not to insure animal, respectively. Column (1) uses 16,630 observations, the number of herders for whom maximum ECS was calculated across midline 1, 2 and endline. Column (2) uses 14,153 observations, the number of herders who received advice to buy insurance across midline 1, 2 and endline. Column (3) uses 2,470 observations, the number of herders who received advice not to buy insurance across midline 1, 2 and endline (2,525) after dropping 55 singleton observations.

Appendix D.8 Consumer Welfare: Using the Mean Risk Aversion Parameter for All Respondents

Table D8.1: Expected Consumer Surplus Relative to Maximum Expected Consumer Surplus, Using the Mean Risk Aversion Parameter

	Any Advice	Advice: Purchase insurance	Advice: Do not purchase insurance
	(1)	(2)	(3)
Advice+Sales vs. Control	2.960	1.266	-0.115
	(0.832)	(0.937)	(0.995)
Advice+Welfare vs. Control	23.600	21.967	6.203
	(0.116)	(0.186)	(0.772)
Advice+Sales vs. Advice+Welfare	20.640	20.701	6.318
	(0.158)	(0.197)	(0.706)
N	16632	13728	2878
Control Mean	-404.6	-472.2	-94.25

All columns present coefficient estimates, p-values calculated with standard errors clustered at the village level (in parentheses), and randomization inference p-value [in bracket]. Columns (1) and (2) compare the adherence to advice across treatment arms, irrespective of whether the advice pertains to purchasing insurance or refraining from it. Column (1) uses the full sample of household $\times$ animal species which ECS can be generated. Column (2) and (3) uses the sample who received advice to insure animal and advice not to insure animal, respectively. Column (1) uses 16,630 observations, the number of herders for whom maximum ECS was calculated across midline 1, 2 and endline. Column (2) uses 14,153 observations, the number of herders who received advice to buy insurance across midline 1, 2 and endline. Column (3) uses 2,470 observations, the number of herders who received advice not to buy insurance across midline 1, 2 and endline (2,525) after dropping 55 singleton observations.