

Anchoring Effect and Fusion Mechanism in Farmers' Insurance Decision-Making Based on Behavioral Experiments

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ABSTRACT Current research on farmers' insurance decision-making lacks rigorous behavioral experiments capable of revealing the micro-level psychological pathway through which long-term subsidy policies induce anchoring effects and hinder insurance conversion. This paper adopts a hybrid contextualized randomized controlled trial to study anchoring effects and intervention mechanisms in farmers' insurance decisions. Real field decision-making elements are embedded into a controlled laboratory environment to construct a contextualized task with high ecological validity. Initial premium anchors and multidimensional intervention strategies are randomly manipulated as experimental stimuli, enabling precise measurement of anchoring strength and behavioral correction effects. The results show that long-term subsidies, as a price anchor, produce an 18.2 yuan/mu group bias in farmers' willingness to pay. Under a low-anchor background, a combined intervention integrating loss-frame information and a default insurance structure increases the insurance conversion rate to 84.2%, while the matching rate of insurance adequacy reaches 0.92. This study provides micro-causal evidence for irrational bias in farmers' insurance decisions and supports low-cost, high-precision behavioral intervention policy design.

INDEX TERMS behavioral experiment, farmers insurance, anchoring effect, insurance decision-making, nudging mechanism

I. INTRODUCTION

IN addition to being a tool for coping with their losses due to natural disasters, farmers' insurance has historically been a stabilizer for farmers' income. An increase in the availability of agricultural insurance has occurred largely as a result of continuous increases in the amount of fiscal subsidies provided by governments in recent years. However, the growth rate of participation has gradually entered a plateau period, the situation in which a high level of subsidy dependence is experienced by farmers, while participation remains low is now a core issue facing many farmers' insurance programs and indicates that the exclusive use of economic incentives to create an ideal policy framework for agricultural insurance is encountering bottlenecks [1-2]. To resolve this dilemma, it is essential to examine farmers' decision-making processes through the lens of behavioral science to determine the psychological mechanisms that deter them from participating in agricultural insurance and develop appropriate behavioral interventions to improve the overall effectiveness of agricultural risk management through improved policy implementation and better quality of risk management.

Existing research faces three specific difficulties in explaining and resolving this dilemma. First, it lacks causal

identification of the micro-psychological pathways through which policy variables (such as long-term subsidies) affect decision-making. Traditional research, mostly based on macro data or questionnaires, has confirmed the positive correlation between subsidies and participation rates, but has failed to isolate and quantify how subsidies, as a "price anchor," distort farmers' independent judgment of the intrinsic value of insurance. This distortion is the psychological root cause of "subsidy dependence" [3-4]. Second, there is insufficient diagnosis of key obstacles in the transformation from "insurance intention" to "insurance behavior." Although some studies have pointed out the importance of factors such as perceived risk and trust, cross-sectional data makes it difficult to capture the specific obstacles faced by decision-makers in key stages such as dynamically assessing information and completing payment confirmation, resulting in an unclear internal mechanism for the transformation from insurance intention to actual insurance behavior [5-6]. Third, there is a lack of targeted behavioral intervention programs and insufficient localization adaptability [7-8]. Existing policy discussions mostly focus on macro-institutional optimization, while "nudge" intervention research based on behavioral science is mostly derived from Western contexts. The assumptions about the decision-making context in rural

China are not similar to the assumptions made by surrounding social networks, the accompanying trust structures and how risk is communicated in other parts of the world. This leads to uncertainty about how effective direct application can be.

To resolve the uncertainties regarding the influence of psychological factors on decision making, a variety of data collection methodologies have been used. Some researchers have used structural equation modelling or mediation analysis, attempting to demonstrate the mediating influence of psychological constructs (e.g., perceived utility and ease of use). However, these methodologies are reliant on self-report measures from participants, making the control of method variance challenging, and researchers cannot manipulate independent variables, such as initial anchor information, to infer causation across a population [9-10]. While the collected data based on fieldwork case studies contain rich contextual information, their internal validity relates to how researchers select a representative sample [11-12]. In recent years, economic research incorporating laboratory experiments has isolated the single anchoring effect by controlling the environment. These experiments ensure internal validity, but their highly abstract task settings strip away the social context and emotional elements of real-world decision-making, resulting in insufficient external ecological validity of the findings and an inability to directly guide policy design for complex rural societies [13-14]. Therefore, current research lacks a research method that can maintain the rigor of causal inference while fully incorporating real-world decision-making contexts, thereby systematically revealing the specific psychological pathways of the anchoring effect caused by long-term subsidies and testing the effectiveness of localized support programs. To address the core issue of accurately identifying the psychological pathways of the anchoring effect induced by subsidies and verifying effective facilitation mechanisms within a controlled ecological validity context, this paper designs and implements a hybrid contextualized randomized controlled trial (HCRCT). The core steps of this method are: first, based on field research, key contextual elements of rural insurance decision-making in China are extracted and structurally embedded into a standard experimental framework to construct a contextualized decision-making task; second, participants are randomly assigned to different experimental groups, and initial premium information anchors and different types of facilitation interventions are manipulated respectively; finally, by collecting continuous behavioral data from participants in the simulated insurance task and combining this with a post-experiment questionnaire, the strength of the anchoring effect and the net impact of facilitation measures on behavioral transformation are quantitatively analyzed. The study integrates experimental control and contextualized embedding in their novel methodological framework, using micro-label data with both internal and ecological validity to create an understanding of farmers' decision making. They also have the potential to develop useful intervention

tools and empirical data for more accurately defining future policy innovation and changing how people think about and develop policy Innovation - shifting from "supply-side subsidy" to "demand-side behavioral design".

II. HYBRID CONTEXTUALIZED RANDOMIZED CONTROLLED EXPERIMENTAL DESIGN FOR ANCHORING EFFECT AND NUDGING MECHANISM

A. OVERALL FRAMEWORK AND THEORETICAL LOGIC

Through a structured process of behavioral experimentation, the anchoring effect (a supply side source of risk) and the fusing mechanism (an economic decision making aid) that affect farmers' insurance selection are identified and quantified accurately under controlled conditions. The methodology follows a clear progression of context construction, stimulus manipulation, observation of resultant behavior, and drawing of conclusions about causes, as illustrated in Figure 1.

A full overview of the steps taken from abstraction to empirical testing and back to empirical tests can be seen in Figure 1. The first step uses field data to determine key contextual variables and encode them into a series of experimental modules. These modules allow for the construction of an experimental decision-making environment with high ecological validity. The second step utilizes rigorously controlled experimental conditions by randomizing and grouping each experimental group's independent variable. Randomization and grouping are both essential for achieving internal validity within the context of making future causal inferences based on the collected data. In the third step, the multi-dimensional behavioral and psychological data of each experimental participant are collected via a procedural interface. By collecting these data simultaneously, a micro-foundation is created for analyzing them. Lastly, the final stage processes the collected data with an econometric model, allowing for the quantification of the various effects, the testing of the observed heterogeneity of the effects, and generating the empirical evidence needed for the theoretical verification of the study's hypotheses and the theoretical modeling of any policies that are tested within the context of the experimental design. The process combines the internal validity and external validity of the research methodology, creating a fully rounded process.

B. OPERATIONALIZATION OF CORE CONCEPTS

To ensure the observability and measurability of the research, it is necessary to transform core concepts at the theoretical level into operational variables in the experiment. The "anchoring effect" is operationalized as a systematic bias of initial information on subsequent judgments, achieved by manipulating the initial premium reference value. Its strength is measured by the difference in median willingness to pay, i.e., the anchoring bias value ΔWTP [15-16]. It is defined as follows:

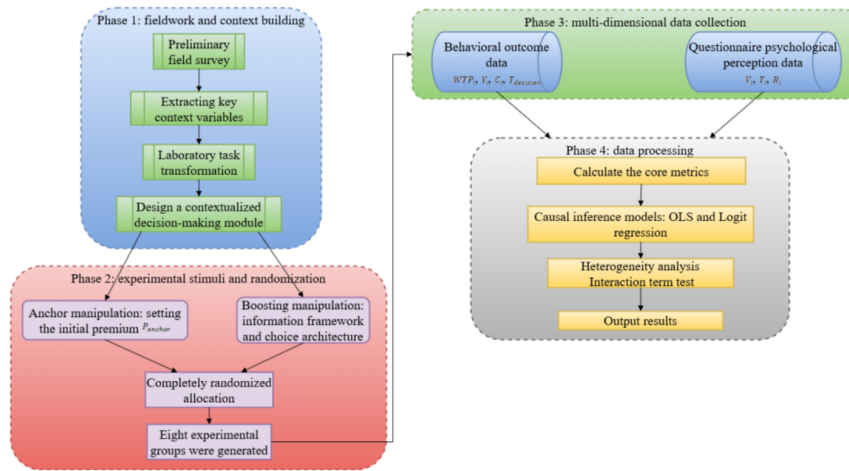


FIGURE 1. Overall framework of the hybrid contextualized randomized controlled behavioral experiment

$$\Delta WTP = \text{Median}(WTP_{\text{high}}) - \text{Median}(WTP_{\text{low}}) \quad (1)$$

In Formula 1, WTP_{high} and WTP_{low} represent the individual's willingness to pay induced under high and low anchoring scenarios, respectively. The statistical significance of ΔWTP is direct evidence of the anchoring effect.

The “boosting mechanism” is operationalized as a non-mandatory, minor modification of the decision-making information framework and choice framework based on behavioral science principles. Specifically, the information framework switches between “gain” and “loss” frameworks; the choice framework sets “default enrollment” and “active selection” options. Effectiveness is assessed through the behavioral conversion rate ϕ :

$$\phi = \frac{N_{\text{actual}}}{N_{\text{willing}}} \quad (2)$$

N_{actual} is the number of participants who completed the insurance purchase, and N_{willing} is the number of participants who express a positive willingness to pay in the early stages. Furthermore, decision rationality is quantified by the coverage adequacy matching rate γ , which is the ratio of the individual's chosen coverage amount to the recommended coverage amount. The recommended value is objectively determined by multiplying the virtual farm's total planted area (A_i) by the regional average target output value per mu, providing a non-arbitrary benchmark for optimal risk protection. The closer the value is to 1, the more the decision is detached from bias and tends towards rationality.

C. CONTEXTUALIZED DECISION-MAKING TASK DESIGN

This study constructs a highly ecologically valid experimental environment through a “contextualized decision-making task” to connect laboratory control with field reality. The task design originates from three key field elements extracted during the pre-survey: local social networks, historical risk and policy memory, and trust transfer based on

familiar social networks. These elements are structured, encoded, and integrated into a simulated agricultural insurance purchase process.

The core of the task is a multi-stage dynamic simulation. Participants first obtain initial parameters for their virtual farm, such as the planted area A_i and the basic risk level R_i^b . Subsequently, the system presents three types of contextualized information modules: first, social reference information, explicitly displaying “the current insurance participation rate of farmers in this village is S_{village} ”; second, a historical information panel, displaying the disaster loss rate sequence $L_{t-3}, L_{t-2}, L_{t-1}$ and the corresponding policy subsidy ratio sequence $Sub_{t-3}, Sub_{t-2}, Sub_{t-1}$ for the past three years in chart form; third, trust cues, manipulating the source of trust by indicating that the insurance recommendation comes from “the village insurance coordinator” or “the town agricultural station”. Finally, participants evaluate and select insurance products. Product attributes such as coverage and deductibles are standardized, but price information is embedded with different initial anchor values P_{anchor} based on the experimental group. The visual presentation and order of all information are standardized to ensure consistency across all factors except for the manipulated variables. In designing the study, the researchers are attempting to provide a realistic basis for participants' observed anchoring and boosting effects through the activation of cognitive and socio-psychological processes they can normally use when making these types of decisions in the real world.

D. EXPERIMENTAL FACTORS, GROUPS, AND VARIABLE MANIPULATION

The experiment is conducted using a three-factor between-subjects design where each participant has been assigned randomly to one of the three versions of the experiment. The experiment includes three additional independent variables that are systematically manipulated across each participant group: the anchor; the information frame; and the choice framework. The anchor is stimulated through a reference value for each premium P_{anchor} set according to both the

benchmark premium P_{base} and by using a manipulation coefficient k , which is calculated as follows:

$$P_{\text{anchor}} = k \times P_{\text{base}} \quad (3)$$

For Formula 3, the k value is set to 1.5 for the high-anchored group (simulating the high out-of-pocket cost under a no-subsidy scenario) and 0.5 for the low-anchored group (simulating the low out-of-pocket cost resulting from high subsidies). This is done to create a significant psychological difference between the resulting reference prices. P_{base} is derived based on the virtual farm parameter and calculated using standard rates. The insurance product's description information frame is manipulated using semantic transformation achieved. The "benefit frame" emphasizes the certain protection and financial stability available by indoctrinating an insurance product; the "loss frame" emphasizes the potential crop loss and associated income risk when not buying insurance. The information content, word count, and reading difficulty are all held constant, but the frame is altered. The method for manipulating the selection frame utilized in the final stage of decision interface, the default enrollment frame, is set to "agree with insurance" and requires an active click to cancel insurance. The active selection frame requires an explicit action to agree to insurance ("agree to insurance") or cancel insurance ("cancel"). All manipulations are randomly assigned through the experimental procedure, and the presentation is standardized.

E. EXPERIMENTAL PROCEDURE AND DATA COLLECTION

The experiment is conducted on a centrally controlled computer terminal, following a standardized single-session procedure. Participants first read the informed consent form and complete a basic information questionnaire, collecting individual characteristic control variables X_i (age, education level, planting history, risk experience, etc.). They then enter the main module of the contextualized decision-making task. The system records two key behavioral sequences: first, after presenting the anchor information P_{anchor} , a modified Becker-DeGroot-Marschak (BDM) mechanism is used to elicit the participant's maximum willingness to pay for the insurance product WTP_i [17-18]; second, after completing all information presentation and facilitator interventions, the participant's final insurance choice $Y_i \in \{0, 1\}$ and selected coverage amount C_i are recorded. During the decision-making process, the program background records the participant's dwell time T_{decision} on the key decision page with millisecond precision. After the main task is completed, participants immediately complete a short post-experiment questionnaire to measure their perceived value V_i , trust level T_i , and rating of the authenticity of the experimental situation R_i . All behavioral data, WTP_i , Y_i , C_i , and T_{decision} , and questionnaire data, V_i , T_i , and R_i , are automatically collected through the experimental platform

and associated with the participant IDs to form a structured dataset for subsequent analysis.

F. DATA ANALYSIS STRATEGY

Data analysis aims to identify the causal effects of core variables and test theoretical hypotheses. For continuous outcome variables, the Ordinary Least Squares (OLS) regression model is used to estimate the average treatment effect (ATE) [19-20]. The baseline regression model is set as follows:

$$Y_i = \alpha + \beta_1 \text{Anchor}_i + \beta_2 \text{Frame}_i + \beta_3 \text{Architecture}_i + \theta X_i + \epsilon_i \quad (4)$$

Anchor_i , Frame_i , and Architecture_i are dummy variables representing experimental groups; X_i is the control variable vector, including age, education, and planting experience. In the final estimation, these variables were treated as fixed effects; specifically, planting experience and education were found to be significant moderators ($p < 0.05$), while age was controlled to account for life-cycle decision biases; ϵ_i is the random error term. The coefficient β_1 is the estimator of the anchoring effect ΔWTP , and its statistical significance is tested by the standard error.

For binary outcome variables such as the final insurance decision Y_i , the Logit model is used to estimate the treatment effect [21-22]. The model is set as follows:

$$\Pr(Y_i = 1) = \Lambda(\alpha + \beta_1 \text{Anchor}_i + \beta_2 \text{Frame}_i + \beta_3 \text{Architecture}_i + \theta X_i) \quad (5)$$

$\Lambda(\cdot)$ is the logistic function, responsible for converting linear predictions into probabilities [23-24]. Marginal effects are calculated at the mean of each independent variable to be interpreted as changes in probability.

Analysis of behavioral conversion rate ϕ is achieved by comparing the conversion rates of each experimental group within the intention-to-treat framework, and the significance of differences between groups is tested using the chi-square test [25-26]. Heterogeneity analysis is achieved by introducing an interaction term between the treatment variable and the characteristic variable into the baseline model to examine differences in treatment effects among subgroups. All analyses consider potential clustered sampling designs and used robust standard errors.

III. SPECIFIC EXPERIMENTAL DESIGN

A. SUBJECT SAMPLING AND SAMPLE CHARACTERISTICS

To ensure the representativeness of the experimental sample and the external validity of the research conclusions, this study uses a multi-stage stratified random sampling method to select experimental subjects [27-28]. Sampling is first conducted according to the division of major grain-producing areas, economic crop areas, and agro-pastoral

transition zones, randomly selecting three prefecture-level cities as primary sampling units within the target major agricultural province. Subsequently, within each prefecture-level city, two townships are selected using a probability sampling method proportional to the size of the rural population and the per capita arable land area. Finally, in each sample township, two villages are randomly selected from the list of all administrative villages, and approximately 25 eligible households (whose main source of income is agriculture and whose head of household is the primary decision-maker) are selected from the household register of each sample village using a systematic sampling method. Ultimately, 300 households from 12 administrative villages participate in this experiment. The distribution of the basic socioeconomic characteristics and production risk characteristics of the sample is shown in Table 1.

Table 1 shows that the sample exhibits good diversity and representativeness across key dimensions. The average age of household heads aligns with the aging trend of the agricultural workforce, and the high proportion of agricultural income indicates that the sample represents typical agriculture-dependent households. The average number of insurance policies taken over the past three years is greater than two, suggesting that the sample generally has some insurance experience, while the proportion with claims experience is close to 40%, providing necessary variation for studying the impact of risk memory on decision-making. Furthermore, the large standard deviation of planting scale indicates significant heterogeneity within the sample, providing a basis for subsequent analysis of group differences in treatment effects.

B. EXPERIMENTAL FACTORS AND GROUP DESIGN

The current research uses a three-factor design that separates and tests all main effects and interactions for each of the three core independent variables (anchor point, information frame, and choice framework). The anchor point factor consists of a high/low split; the information frame factor is a gain/loss frame split; the choice framework factor is a split of default participation and active selection participation. All three factors are fully crossed with each other to create a total of eight experimental treatment conditions. The experiment employs complete randomization. After completing the basic information questionnaire, each participant is uniquely assigned to one of the eight experimental groups using a random number generation algorithm. This ensures homogeneity among the groups in terms of expected outcomes, and any differences between groups can be attributed to experimental manipulation. The specific treatment conditions and sample size allocation for each group are shown in Table 2.

Table 2 presents the complete design matrix of this experiment. From the sample size distribution, the sample sizes of each experimental group are between 37 and 38, achieving a good balance and contributing to the accuracy and power of statistical tests. This design allows researchers

to purely estimate the main effect of the anchor by comparing high and low anchor groups, while controlling for information framing and choice architecture. This design allows for the estimation of the main effects of information framing and choice architecture separately by systematically comparing data from different experimental groups, and for testing second- or third-order interactions, such as analyzing whether there is a synergistic boosting effect between the “loss framing” and “default participation” architectures. This complete factorial design provides a rigorous data structure foundation for in-depth analysis of the psychological mechanisms of decision bias and the effectiveness of combined intervention strategies.

IV. RESULTS

A. EXISTENCE TEST OF ANCHORING EFFECT

To empirically test the systematic distorting effect of long-term subsidies as an external anchor on farmers' willingness to pay, this study compares the decision responses of participants under two initial premium anchor scenarios: high and low. By performing a standardized insurance product valuation task on two randomly assigned groups of samples, data on their maximum willingness to pay is collected. Descriptive statistics and parametric tests are used to analyze the differences between the groups, thereby verifying the existence and strength of the anchoring effect. The analysis results are shown in Figure 2.

Figure 2(a) shows that the median payment willingness in the low anchor group is 59.5 yuan/mu, significantly higher than the 41.3 yuan/mu in the high anchor group, with an inter-group difference ΔWTP of 18.2 yuan/mu ($p < 0.001$). This difference stems from the differentiated value reference system shaped by the initial anchor information: the high anchor directly raises farmers' perceived benchmark for insurance costs, thus inhibiting their willingness to pay; the low anchor lowers the perceived cost threshold, releasing a higher willingness to pay. In terms of distribution, the 75th percentile of the low anchor group data reaches 69 yuan/mu, with some farmers' estimates higher than the median; the 25th percentile of the high anchor group data is 31.4 yuan/mu, indicating that the anchor has a downward compressive effect on the valuation range. Kernel density curves of Figure 2(b) further reveal that the modes of the two distributions are concentrated around 41.2 yuan/mu and 61.9 yuan/mu, respectively, showing a clear separation interval. The experimental results confirm that external anchoring information can systematically interfere with farmers' independent value judgments of insurance products, forming a significant anchoring effect.

B. IMPACT OF NUDGING MECHANISMS ON BEHAVIORAL TRANSFORMATION

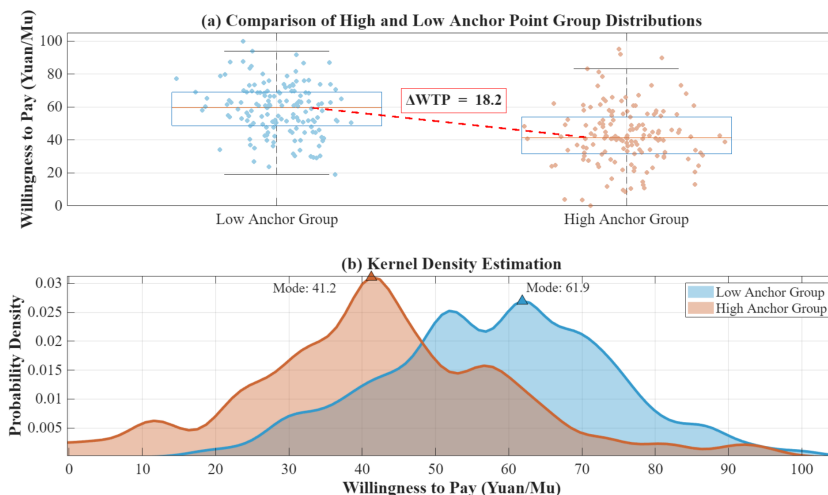
After establishing the anchoring effect, this study investigates which type of behavioral nudges help farmers transition from wanting to buy insurance to actually purchasing insurance through systematic controlled manipulation of

TABLE 1. Distribution of basic characteristics of the experimental sample (N=300)

Feature variables	Proportion/mean	Standard deviation / percentage
Average age of household head	52.3 years old	10.2
Gender of the head of household (male percentage)	86.0%	–
Proportion of high school graduates and above	24.5%	–
Average number of agricultural laborers per household	2.4	0.8
Average planting area	35.6 mu	28.7
Average proportion of agricultural income to total income	68.5%	21.3
Average number of insurance policies over the past three years	2.1 times	1.5
The percentage of people with insurance claims experience	38.7%	–

TABLE 2. Experimental factor design and group sample size allocation

Group number	Anchor point horizontal	Information framework	Choose architecture	Sample size (N)
1	High subsidy anchor	Loss framework	Default insurance coverage	38
2	High subsidy anchor	Loss framework	Active choice	37
3	High subsidy anchor	Benefits framework	Default insurance coverage	38
4	High subsidy anchor	Benefits framework	Active choice	37
5	Low subsidy anchor	Loss framework	Default insurance coverage	38
6	Low subsidy anchor	Loss framework	Active choice	37
7	Low subsidy anchor	Benefits framework	Default insurance coverage	38
8	Low subsidy anchor	Benefits framework	Active choice	37

**FIGURE 2.** Comparison of payment willingness distribution among anchored groups: (a) Comparison of payment willingness distribution between high and low anchor groups; (b) Kernel density estimation

the information and choice framing dimensions. There are eight total groups created by varying the anchoring level (groups 1-4 representing high anchoring points, groups 5-8 representing low anchoring points). This experiment seeks to determine the best combination of interventions that can effectively close the “willingness-behavior” gap; the analysis results are presented in Figure 3.

The horizontal axis of Figure 3 lists the eight experimental combinations of anchors, information frames, and choice frameworks for this study. The vertical axis is the behavioral conversion rate ϕ . Findings indicate that participants in the experiment receiving the “loss frame” in combination with the “default option” produce the highest conversion rates. Specifically, under a background of low anchor points, the conversion rate of lost frame/default option combinations is 84.2 percent, which is much higher than the 48.6 percent of “benefit frames/active choice” for the same background.

The difference between these two combinations is likely due to the fact that by highlighting the risks associated with uninsured losses, the “loss frame” triggers greater levels of risk aversion among farmers. At the same time, by removing some of the cognitive and operational costs that can be incurred in applying this choice on another topic, these two strategies are related and combine to eliminate decision-making inertia and procrastination. On the other hand, the “benefit frame” emphasizes insured benefits has a relatively weak incentive for more complex decisions pertaining to risk. The “active choice” framework requires explicit affirmation and implicitly creates barriers to decision-making. Overall, the results of these experiments support that employing a “nudge strategy” based on loss aversion and choice framework design is a viable strategy for directing farmers’ conversion of their decision-making behaviors regarding the use of insurance.

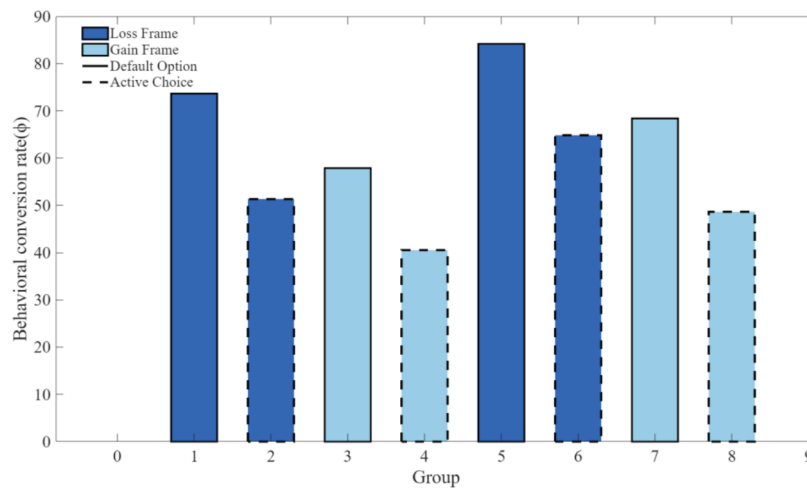


FIGURE 3. Impact of nudging strategies on behavioral conversion rates under different experimental condition combinations

C. IMPACT OF NUDGING INTERVENTIONS ON DECISION QUALITY

While advancing the understanding of how different nudging mechanisms influence farmer decision making by analyzing how these mechanisms affect the conversion rates, this study also evaluates the impact of various types of interventions on the quality of farmer insurance purchase decision making. This evaluation aims to determine if, when using nudging techniques to facilitate an increase in the likelihood of purchasing insurance, the resulting rationality of farmer choice for levels of coverage are appropriate relative to their actual risk exposures, as opposed to simply inducing irrational or inadequate coverage without any discrimination as to what is appropriate coverage level. By calculating and comparing the coverage adequacy matching rate γ of participants in each experimental group, the impact of information frames and choice structures on the rationality of decision-making is assessed. Four groups (A, B, C, and D) are included, corresponding to different combinations of information frames and choice structures. The analysis results are shown in Figure 4.

Figure 4(a) shows the horizontal axis representing the four core boosting conditions combination, and the vertical axis representing the coverage adequacy matching rate γ . Figure 4(b) shows the same horizontal axis as Figure 4(a), and the vertical axis representing the proportion of farmers in different matching intervals. Data shows that the intervention using the “loss framework” and “default coverage” combination achieves a mean matching rate γ of 0.92, with 71% of farmers’ decisions falling within the rational range. In contrast, the mean γ of the “benefit framework” and “active selection” combination is only 0.76, with an under-coverage rate as high as 40%. The difference in outcomes is due to the manner in which the “loss framework” encourages prudent coverage assessments of farmers by emphasizing the risk impacts on them. The use of a default option, consistent with a reasonably calculated amount of coverage, creates a decision-standard for farmers who do not pos-

sess insurance-related professional knowledge and makes finding a suitable insurance provider easier. Combined with the “loss framework”, the default coverage approach helps reduce the impact of information complexity and cognitive limitations on farming decisions by reducing bias. The profit framework’s lack of equal emphasis on risk warning for farmers and “active selection” as the basis for choice increases the risk associated with the resultant uncertainty and potential for mistakes in the decision-making process. Experiments have shown that the nudge strategy combining loss framework and default options not only can increase coverage levels for farmers, but also enhance the quality of rational decision-making.

D. HETEROGENEITY TREATMENT EFFECT

Based on confirming the effectiveness of the nudge mechanism on the overall sample, this study further explores the heterogeneity of its effects among different groups of farmers with different characteristics. The aim is to identify how key farmer characteristics (historical risk experience and scale of operation) moderate the impact of the nudge strategy on behavioral transformation and decision quality, thereby testing the universality of the intervention and the necessity of precise implementation. By constructing an econometric model including interaction terms, the conditional average treatment effect of the core nudge strategy on the two subgroups is estimated, and the analysis results are shown in Figure 5.

The horizontal axis of Figure 5(a) represents the marginal effect change (percentage points) on behavioral conversion rate, and the horizontal axis of Figure 5(b) represents the coefficient change on decision quality. The vertical axis lists the estimated effects of the four treatments grouped by farmer characteristics. Data shows that the loss framing information improves the behavioral conversion rate of farmers with risk experience by 22.5 percentage points, significantly higher than the 8.3 percentage points for farmers without such experience. This difference stems from

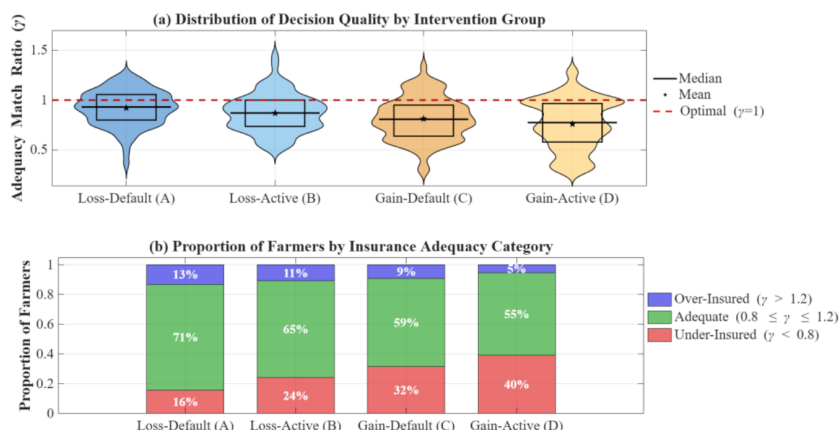


FIGURE 4. Comparison of coverage adequacy matching rates under different boosting interventions: (a) Distribution of decision quality by intervention group; (b) Proportion of farmers by insurance adequacy

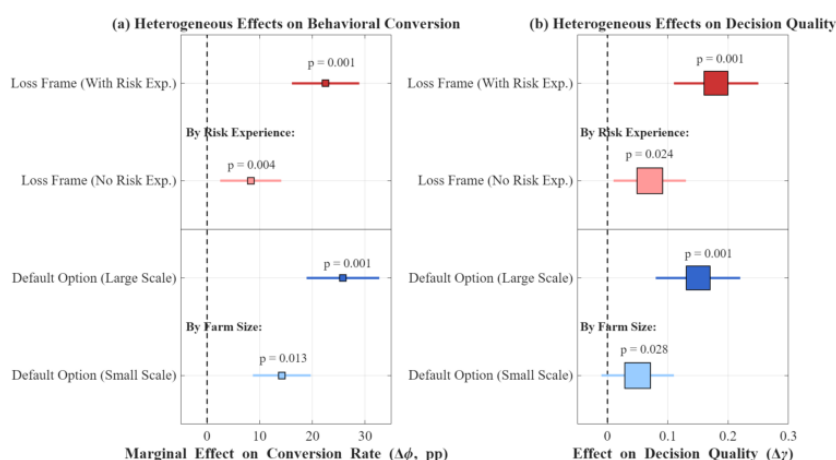


FIGURE 5. Group heterogeneity analysis of the effects of fueling strategies: (a) Heterogeneous impact on behavioral conversion; (b) Heterogeneous impact on decision quality

the fact that risk experience strengthens farmers' perception and memory association of risk signals in the loss framing, making the evoking and persuasive effects of this information framing more powerful. The default insurance framework improves the behavioral conversion rate of large-scale farmers by 25.8 percentage points, higher than the 14.2 percentage points for small-scale farmers. This is because large-scale farmers face higher complexity in their insurance decisions, and the default option, by providing a pre-set reasonable choice, more effectively reduces their cognitive load and executive resistance in the decision-making process. Regarding decision-making quality, the loss framework improves the matching rate for farmers with risk experience by 0.18, more than twice that of farmers without such experience (0.07). This is because risk experience provides farmers with a more accurate basis for risk assessment, and the loss framework encourages them to use this experience more prudently in matching decisions. Default insurance only significantly improves decision-making quality for large-scale farmers (0.15), while having no significant effect on small-scale farmers (0.05). This is because preset default

values may be more suitable for standardized risk calculation models in large-scale production. The study confirms that the effectiveness of boosting interventions exhibits significant group heterogeneity, and precise intervention design needs to fully consider farmers' past experiences and production characteristics.

V. DISCUSSION

A. THEORETICAL IMPLICATIONS

The findings from this research show a strong confirmation of long term subsidy payments for agricultural insurances being an external anchor impacting farmers' willingness to pay, thereby adding empirical evidence to the anchoring effect theory based on policy intervention. Furthermore, this study shows that using two methods of boosting the farmer's adoption of agricultural insurance, by "framing the losses" and using the "default option", allows those farmers to bridge the gap between their "willingness to pay" and "behavior towards buying", thus highlighting the importance of decision-making frameworks and information frameworks in both behavioral transformation. The mixed randomized

controlled trial method used in this study, combined with the actual situation of agricultural insurance, is an effective approach for causal inference in a real-world environment.

B. POLICY IMPLICATIONS

Policy creators must consider the potential effect of high subsidy levels creating psychological dependence and value perception bias. To this end, measures should be put into place to incorporate an anchoring methodology into subsidy policies. In practice, low-cost boosting tools such as “loss framing” promotions and frameworks for “default participation” can likely produce optimal rates of increase in participation and improve the rationality of decision-making. However, the implementation of ‘default enrollment’ must be navigated carefully within legal and ethical boundaries; policymakers should ensure that such choice architectures do not violate the principle of ‘informed consent’ and remain transparent to prevent exploitative practices in agricultural insurance contracts. In addition, interventions based on a farmer’s risk experience and operational scale should be developed to enhance the precision of subsidy policy implementation.

C. LIMITATIONS AND FUTURE PROSPECTS

Simulated decision-making is expressed in an experimental context through contextualization, but this study’s findings should not be interpreted to mean that boosting can lead to more favorable decisions in actual conditions beyond this research environment. Research is needed to evaluate the impact of boosting over the longer term, and this study is conducted in one agricultural region. Therefore, verifying whether the results can be applied across regions requires conducting additional studies. This study also evaluates short-term behavior. The way participants behave over longer periods (behavioral dynamics) and how they learn from those behaviors (learning effects) are other areas for future research. Additional opportunities for research in this area may include developing personalized and adaptable boosting systems that utilize digital technology.

VI. CONCLUSION

Through a randomized controlled trial design using a mixed-methods approach, this research investigates (through controlled experiments) how risk memories and social networks of farmers are embedded in the local environment, how to use them as anchors for decision making, and what effect to have on farmers’ insurance purchase decisions. The experiment demonstrates that long-term subsidies, acting as a price anchor, cause a 18.2 yuan/mu between-group bias in farmers’ willingness to pay. Under a low anchoring context, the boosting strategy integrating loss framing information and default insurance structure can increase the insurance conversion rate to 84.2% and achieve a superior level of 0.92 for the decision rationality index (coverage adequacy matching rate γ). Through a heterogeneity analysis, it can be found that these boosting effects are significantly higher for

both experienced and scale-oriented farmers. The benefit of this approach is that it gives a practical way to identify the micro-causal connections that influence how farmers make their decisions in real-world situations. This can provide a potential new pathway for overcoming the policy barriers related to “subsidy dependence” and low levels of participation in agricultural insurance by enabling a transition from providing broad, macro-level subsidies to providing more targeted, contextually-based, and differentiated “nudge-in” interventions based on an understanding of farmers’ behavioral responses. This creates a strong foundation to help improve the effectiveness of agricultural risk governance policies.

AUTHOR CONTRIBUTIONS

Conceptualization – Han Zhou and Huimin Guo; methodology – Han Zhou and Huimin Guo; investigation – Han Zhou and Huimin Guo; writing-original draft preparation – Han Zhou and Huimin Guo. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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