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ARTICLE

Residents' Preferences for Rural Housing Disaster Insurance Attributes in Central and Western Tibet

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Abstract
Understanding the heterogeneous preferences of individuals for disaster insurance attributes is critical for product improvement and policy design. In an era of global environmental change, the Qinghai-Tibet Plateau is a hotspot of natural hazards. Improving the capability of rural housing disaster insurance to foster local residents' disaster resilience is of great significance but remains under addressed. We used a discrete choice experiment approach to provide the first estimates of rural residents' preferences for rural housing disaster insurance attributes in central and western Tibet. We estimated residents' preferences and willingness-to-pay for the sum insured, subsidy rate, insured object, and perils covered. The potential impacts of increasing the sum insured, expanding the insured object, and lowering subsidy rates were evaluated. Our results suggest that residents prefer products with a high sum insured, high subsidy rate, and a complete list of insured objects. Residents who have experienced specific hazards tend to prefer the corresponding perils covered. Females and residents who have a closer social network are more likely to purchase insurance. Product improvement and policy simulation results suggest that, while lowering the subsidy rate, increasing the sum insured and expanding the insured object could promote participation and improve residents' welfare. Our results could improve the understanding of the preferences of households in remote regions and support policy implementations.

Keywords Discrete choice experiment · Preference for insurance attributes · Qinghai-Tibet Plateau · Rural housing disaster insurance · Willingness-to-pay

1 Introduction

The Qinghai-Tibet Plateau (QTP) has experienced the world's fastest uplift and is the highest elevated region in the world; the area is also known as the "third pole of the Earth" (Yao et al. 2012) and the "Asian water tower" (Immerzeel et al. 2010). It experiences active tectonic activity, huge altitude differences, complex terrain, and a diverse climate. The QTP and its surrounding mountainous areas are highly prone to earthquakes, geological hazards, flash floods, and cryosphere hazards (Luo et al. 2019; Tian et al. 2020; Zou et al. 2020). In spite of its environmental harshness and remoteness, more than 13 million people reside on the QTP. Rural residents are highly exposed and vulnerable to multiple hazards. Disasters have claimed people's lives and damaged physical assets and production capacity, causing serious threats to the sustainability of rural livelihoods (Feng et al. 2021; Ye et al. 2022).

The Chinese central and provincial governments have made significant efforts to reduce and transfer the disaster

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risks borne by rural residents in the QTP. A variety of natural hazard-related disaster insurance products has been developed to help local rural residents transfer natural hazard-related disaster risks and avoid the chronic negative impacts of poverty traps (Wang et al. 2012). Among the measures promoted is a rural housing insurance program that has provided coverage against damage to domestic structures caused by earthquakes, geological and meteorological hazards, floods, and other perils with a government subsidy of 96% and a premium rate of 1%. The sum insured is divided into three levels, the highest being RMB 14,000 yuan.

Although the rural housing insurance system in Tibet has developed over the years, it has three disadvantages. First, the sum insured is far below the replacement cost of rural houses. Second, the insurance only protects the primary house structure, but not the indoor property or farm machinery. Third, the subsidy level is so high (up to 96%) that rural residents show poor understanding of the insurance policy, and simultaneously, the subsidy places a heavy burden on local governments. Consequently, local governments wish to strengthen insurance protection by increasing the sum insured and expanding the insured object while lowering the subsidy rate to reduce people's reliance on the government. Rural residents would favor increasing the sum insured and expanding the insurance object. However, lowering the subsidy rate could substantially lower their participation probability (Ye et al. 2017). This research addresses how product improvement and policy instruments could influence potential policyholders' welfare and participation probability.

There is a need to understand local rural residents' preferences for the proposed insurance attributes as well as the socioeconomic and demographic drivers of particular preference features to answer those questions. Recently, discrete choice experiments have been widely applied to measure respondents' preferences by assessing marginal willingness-to-pay (WTP) for insurance attributes (Brouwer et al. 2014; Wang et al. 2020; Ghosh et al. 2021). More studies focused on crop and livestock insurance, while less attention has been paid to rural housing insurance. Insurance premiums, the sum insured, and the insurance provider were the most frequently included insurance attributes.

Earlier results generally suggested that respondents preferred insurance with a low premium, a high sum insured, and the central government as provider (Brouwer and Akter 2010). Additionally, researchers always use interaction terms between insurance attributes and corresponding socioeconomic characteristics to understand the socioeconomic and demographic drivers of preferences. For instance, Darlington and Yiannakoulias (2022) found that Canadians' demand for flood insurance depended on dwelling value, and respondents with high dwelling value tended to prefer high coverage. Botzen and van den Bergh (2012) focused on the interaction between insurance coverage and flood risk (that is, distance to the main river), and insurance policy premium and policyholders' income. The results obtained from the interaction of these variables indicated that respondents with high flood risk preferred higher insurance coverage and respondents with high income were less sensitive to premium cost. On the other hand, researchers also use the interaction terms between alternative specific constant (ASC) and basic socioeconomic characteristics or risk perception to explore what would affect individuals' preferences for an insurance purchase. Reynaud et al. (2018) and Brouwer and Akter (2010) found that respondents who had experienced flood or were exposed to high flood risk preferred purchasing insurance, and males with a university degree more often than not also preferred insurance protection (Botzen and van den Bergh 2012).

This study investigated residents' preferences and WTPs for rural housing disaster insurance in central and western Tibet, China, using a discrete choice experiment (DCE) approach, which targeted evaluation of the comprehensive impact of product and policy improvement. The project addressed the following research questions: (1) What product attributes are of most interest to local residents?; (2) How do insurance purchase decisions and marginal WTP for attributes differ by the sociodemographic features and disaster experiences of respondents?; and (3) What is the potential impact of increasing the sum insured, expanding the insured object, and lowering the subsidy rate in terms of residents' participation probability and policyholders' welfare?

To the best of our knowledge, this study is the first to analyze residents' preferences for rural housing disaster insurance in the QTP. Other studies in this region have mostly focused on livestock insurance (Liu et al. 2021), or explored the preferences of residents in low-altitude areas with relatively high living standards and higher education levels. We examined not only rural residents' preferences for specified insurance attributes, such as insured object, but also the heterogeneous preferences for these attributes driven by individuals' characteristics. Our results could enrich the understanding of preferences regarding natural hazard-related disaster insurance product attributes, particularly with evidence from rural residents in a remote region, thereby enabling the provision of policy recommendations for these and other local areas.

2 Methodology

This section outlines the methodology employed in the study, including the design of the DCE, field survey and data collection, the model specifications to estimate preferences, subpopulation WTP, and the simulation impact on welfare change and participation probability.

Table 1 Attributes and levels in the discrete choice experiment in the Qinghai-Tibet Plateau

Attribute	Level
Insured object	House structure; House structure and indoor property; House structure and farm machinery; All the above
Sum insured (1000 yuan/household)	14; 30; 50; 80
Perils covered	Earthquakes; Geological hazards; Meteorological hazards; Floods
Premium rate (%)	0.5; 1.0; 2.0; 2.5
Subsidized rate (%)	40; 60; 80; 96

Underline indicates the status quo.

2.1 Choice Experiment Design

As a stated preference method, the DCE, based on random utility theory (McFadden 1973), has been widely applied to analyzing consumers' preferences for the attributes of goods. In the present study, a DCE was applied to understand preferences for potential insurance product attributes. The experiment was designed by following the mainstreaming approach advocated by Hanley et al. (1998). The design involved three stages: the design of an attribute-level table, the creation of hypothetical products, and the assembling of choice sets (Ye et al. 2017). The design of the attribute-level table involved a focus group interview, conducted in summer 2020, which involved rural respondents and insurance agents in Lahsa and Shigatze in Tibet. The potential needs involved in revising the present rural house insurance product and the corresponding premium subsidy policy were summarized to highlight the key attributes and levels that should be prioritized in the DCE.

Five attributes were considered in the experiment: insured object, sum insured, perils covered, government subsidy provided, and effective premium paid by policyholders. Table 1 shows the detailed attribute-level design:

(1) Insured object. In addition to the house structure covered in the present rural housing insurance, indoor property and farm machinery were added to the list to ensure the completeness of insurance protection;
(2) Sum insured. The sum insured in current rural housing insurance in Tibet is RMB 14,000 yuan, which would hardly provide sufficient funds should major damage occur. Our experiment increased the sum insured. Therefore three possible levels were considered according to the sum insured by commercial insurance products proposed by the local insurance company;
(3) Perils covered. The present insurance product provides a multi-peril scheme. To understand residents' preferences over different perils, four major hazard types were listed as perils covered—earthquakes, geological hazards, meteorological hazards, and floods;
(4) Premium rate. Tibet's pilot rural housing insurance policy uses a flat premium rate of 1%, which ignores the vast regional difference in disaster loss risks. Three different premium rates were derived from insurance companies' books: 0.5%, 2%, and 2.5%. The thinking behind setting different levels for the premium rate is to allow a wider range of alternatives to obtain reliable results (Liesivaara and Myyrä 2014);
(5) Premium subsidy rate. Tibet's government-provided premium subsidy rate has been high for a long time (96%). This imposes a heavy burden on local governments. We set three lower levels by considering three scenarios: (a) An 80% subsidy rate would be suggested if the county government withdrew its subsidy; (b) A 40% subsidy rate would be effective if both provincial and county governments withdrew their subsidies; and (c) A subsidy rate between the two cases (60%).

Product ID	A	B	N
Insured object	House structure and farm machinery	House structure, indoor property and farm machinery	
Sum insured	14,000 yuan	50,000 yuan	
Perils covered	Meteorological hazards	Earthquakes	I would not buy any insurance
Subsidy rate	96%	96%	
Premium paid by yourself	5.6 yuan	20 yuan	
Please check one only			

Fig. 1 A sample choice set presented to respondents in the discrete choice experiment survey in the Qinghai-Tibet Plateau

The experiment adopted a five-attribute and four-level structure for each design, which would yield $4^5 = 1024$ hypothetical products if a full factorial design were used. Instead, an orthogonal design was developed to focus on the main effects of each attribute, with a final set of 16 choice sets selected by using help from *R* (the *support.CEs* package) employed by Aizaki (2012) with a good D-efficiency of 100%. The 16 choice sets were divided into eight blocks,

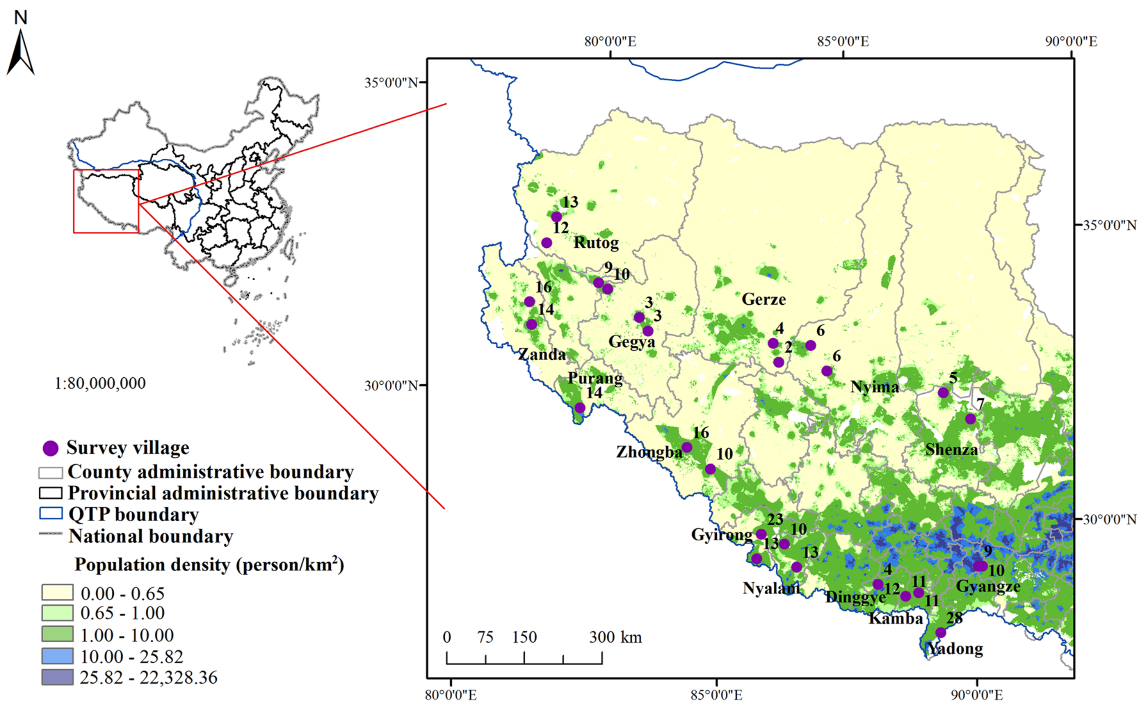

Fig. 2 The study area and the location of the survey sites in the Qinghai-Tibet Plateau (QTP). The numbers on the map indicate the number of questionnaires finished in each survey location.

each with two choice sets. During the experiment, a respondent was randomly allocated two out of the eight blocks. Then, the respondent was asked to indicate the alternative they preferred in each choice set. Each choice set comprised two alternatives and an opt-out option, as Fig. 1 shows.

2.2 Field Survey and Data Collection

Data were collected from a questionnaire survey conducted by the research group in 14 counties of Shigatse, Ngari, and Naqu Prefectures in July 2021 (Fig. 2). Shigatse, Ngari, and Naqu Prefectures are typical hazard-prone zones in the QTP. More than 1.4 million people resided in the three prefectures in 2020, accounting for just over 39% of the total population of Tibet. Local residents are highly exposed and vulnerable to multiple hazards. A glacial lake outburst flood and mudslides in Naqu prefecture in 2013 caused severe damage to infrastructure, such as houses, bridges, and roads, and direct economic losses of USD 40.5 million.[1] The 2015 Nepal earthquake caused damages in 14 counties of Shigatse and Ngari in which 2511 houses collapsed and 24,797 houses were damaged to varying degrees. To transfer property risk caused by natural hazards and disasters, a rural housing disaster insurance program has been implemented in Tibet for years. The total written premium of the three prefectures accounted for 53.64% of the total for Tibet in 2020.

Due to the vast area and sparsely distributed population in rural Tibet, we used a stratified sampling approach. First, we selected the counties with higher population density in rural areas (1.00–10.00 person/km^2) in each prefecture-level city. The grid-cell population density data are from WorldPop[2] at a spatial resolution of 1 km. Seven counties from Shigatse, four from Ngari, and three from Naqu were selected. Then, 1 to 3 villages were randomly drawn from each county. Finally, around 20 respondents in each county were invited to complete the questionnaires. This sampling approach is inferior to the random sampling approach, but it guaranteed the implementation of the entire process without a significant sacrifice in sample representativeness. During the survey, local residents were preparing for the Shoton Festival, making it difficult to invite more respondents to complete questionnaires. The entire process resulted in a valid sample of 291 respondents.

The central part of the survey was the choice experiment. In the experiment under a hypothetical environment, the respondents might show excessive preferences, which forms the "hypothetical bias" (Murphy et al. 2005). So the chief coordinator, Tao Ye, introduced the survey and emphasized its practical significance in potential policy revision:

[1] CNY 1 yuan = USD 0.15 (20 May 2022).

[2] https://hub.worldpop.org/geodata/listing?id=77.

Table 2 Descriptive statistics of the respondent sample for the Qinghai-Tibet Plateau survey

Independent variable	Description	Mean	SD	Minimum	Maximum
Age	Continuous (years)	43.04	13.05	17	80
Gender	Dummy (1 if male, and 0 otherwise)	0.59	0.49	0	1
Education years	Continuous	5.21	4.81	0	16
Household size	Continuous	4.88	1.87	1	11
Annual net income	Continuous (10,000 yuan)	3.30	3.75	0.1	35
Famach	Dummy (1 if having farm machinery, and 0 otherwise)	0.49	0.70	0	1
Warning information	Dummy (1 if received warning information, and 0 otherwise)	0.82	0.39	0	1
The number of neighbors	Continuous	11.06	5.65	2	18
Exp_earthquke	Dummy (1 if experienced earthquakes, and 0 otherwise)	0.50	0.50	0	1
Exp_geological	Dummy (1 if experienced geological disasters, and 0 otherwise)	0.06	0.24	0	1
Exp_meteorological	Dummy (1 if experienced meteorological disasters, and 0 otherwise)	0.30	0.46	0	1
Exp_flood	Dummy (1 if experienced floods, and 0 otherwise)	0.15	0.36	0	1
Housing value	Continuous (10,000 yuan)	27.05	18.34	4.46	114.62

Ye stressed that answers would provide very important information for the government of Tibet and for insurance companies concerning related insurance products in the future, and might directly affect respondent's own interests. Participants were urged to check one option according to their personal preference. Then the village cadres translated for the respondents. After the emphasis, respondents would consider their own actual needs and give accurate willingness-to-pay. This is one of the approaches to solve hypothetical bias, which is called "cheap talk" (Ladenburg et al. 2011, p. 26; Carson et al. 2014). Then, the trained investigators conducted one-on-one interviews and invited the respondents to pick their favorite choice with the help of interpreters. Due to language differences and the complexity of the questionnaire, each questionnaire generally took 40–60 min to complete.

Additional information was also collected following the DCE, including household socioeconomic and demographic characteristics and past disaster experience. The socioeconomic and demographic characteristics included age, gender, years of education, household size, annual net income, whether the household had farm machinery, whether the family received early warning information, the number of neighbors that can be contacted in an emergency, and the building costs of the house. Respondents' experiences of the four major hazard types, including the time, disaster type, degree of damage to house, and economic loss, were also recorded.

Table 2 summarizes the descriptive statistics of the survey. The average age of the respondents was 43, and nearly 60% were male, with an average household size of greater than four. Most respondents had received less than six years of education. The average annual household net income was RMB 33,000 yuan, with a standard deviation of RMB 37,500 yuan, suggesting a large income disparity. Of the respondents, 49% had farm machinery. About 82% of the respondents could receive early warning information, and the average number of neighbors who can be contacted in an emergency was 11. Because many houses in this region were built by the government, the respondents could not tell the exact construction costs. Housing values were estimated by the local housing area as were the average house construction costs (yuan/m^2). There are no official figures for the cost of house construction in Tibet. Therefore, we used the house construction costs of Aba Tibetan and Qiang Autonomous Prefecture in Sichuan Province.[3] Where disaster experience is concerned, most respondents had experienced earthquakes, followed by meteorological disasters, floods, and rare geological disasters.

2.3 Model Specifications

The empirical analyses used conditional and random parameter logit models to estimate the marginal effect of each product attribute-level on respondents' decision.

2.3.1 Basic Model

The estimation of preferences from the DCE results was based on the Lancaster utility theory that consumers consider the objective attributes of goods rather than the goods themselves when choosing a bundle of goods (Lancaster 1966; McFadden 1973; Ghosh et al. 2021). The utility function consists of two segments: observable and unobservable utility.

$$U_{ncj} = V_{ncj} + \varepsilon_{ncj} \tag{1}$$

[3] http://www.scnj.gov.cn/public/6598191/12944961.html.

$$V_{ncj} = \sum_{k=1}^{K} X_{ncjk}\beta_{nk} \tag{2}$$

U_{ncj} is the utility when an individual n chooses alternative j among all J presented alternatives in a choice set c. V_{ncj} is the observable utility, consisting of a vector of attributes for the jth alternative and a vector of preference coefficients β. ε_{ncj} is a residual component of utility that is independently and identically distributed across individuals and alternatives.

Here, the conditional logit (CL) model and random parameter logit (RPL) model were used to estimate the preference parameters (McFadden and Train 2000; Ye et al. 2017; Wang et al. 2020). Following Train (2009), the probability of decision maker n choosing c in a given choice set j can be expressed as the logit probability of utility of choice c over the sum of the utilities of all possible choices.

$$P_{ncj} = \frac{\exp\left(V_{ncj}\right)}{\sum_{j=1}^{J}\exp\left(V_{ncj}\right)}, \quad j = 1, 2, \ldots J \tag{3}$$

The CL model is an easier model to estimate but suffers from the problem of independence from irrelevant alternatives and the incapability of identifying individual heterogeneity preferences (Train 1998). The RPL model is highly flexible, complementing the CL model, and capable of approximating any random utility model (McFadden and Train 2000):

$$P(\theta) = \int \prod \frac{\exp\left(V_{ncj}\right)}{\sum_{j=1}^{J}\exp\left(V_{ncj}\right)} f(\beta|\theta)\mathrm{d}\beta \tag{4}$$

Compared with the CL model, preference coefficients β are assumed to be random variables that can vary across individuals following the probability density function of $f(\beta|\theta)$ with the parameter θ, and any distribution may be used for any parameter. The most common distribution is the normal distribution, but the lognormal distribution is recommended for coefficients known to have the same sign over individuals in practice, such as price and cost (Hensher and Greene 2003; Train and Weeks 2005).

In our estimation, coefficients of the insurance attributes were assumed to vary across individuals, and Table 3 lists the distributional forms. Most coefficients were assumed to follow the normal distribution, thereby guaranteeing convergence with the limited sample size (Greene et al. 2006). The exception was premium cost, whose coefficient was assumed to follow lognormal distribution and was forced to be strictly negative. In general, a high premium always lowers consumers' demand. Therefore premiums have a negative effect on utility (Yi et al. 2020). We multiplied premium by "− 1" to ensure that the coefficient of the opposite of premium would be strictly positive.

Additionally, we used the interaction terms between the opt-out choice and the characteristics of individuals to understand the socioeconomic and demographic drivers of insurance purchase decisions. We proposed four hypotheses to test whether the corresponding socioeconomic characteristics would impact the preferences for insurance attributes. All coefficients of interaction terms were assumed to be nonrandom.

Classical economic theory about insurance demand assumes that an accounting of assets at risk may influence insurance purchase decisions (Smith 1986). Respondents with higher housing value may prefer a higher sum insured, since increasing the sum insured is an investment into protecting that asset (Darlington and Yiannakoulias 2022). This is also the same for the insured object, that is, respondents with farm machinery preferred to purchase insurance that was designed to protect this asset. Based on these considerations, research hypotheses 1 and 2 propose:

H1 Respondents with higher housing value preferred a higher sum insured. This hypothesis was tested by introducing the interaction term of *Sum insured* × *Housing value*.

H2 Respondents who had farm machinery preferred Object_HF as the insured object. This hypothesis was tested by introducing the interaction term of *Object_HF* × *Famach*.

In empirical studies, income is used to reflect the capability of risk management (Chantarat et al. 2017; Fonta et al. 2018). Respondents with higher income have a stronger sense of risk management; as a result, they are more willing to buy insurance to protect their property, then they are less sensitive to premium cost. Government subsidies can reduce the effective premium that farmers actually need to pay, which is called the income effect of premium subsidy (Yi et al. 2020). So, respondents who have higher income may be less sensitive to subsidy amount. Based on these hypotheses, research hypothesis 3 was proposed:

H3 Respondents with higher net income would be less sensitive to premium and subsidy rates. This hypothesis was tested by introducing the interaction terms of *Premium* × *Income* and *Subsidy rate* × *Income*.

Earlier empirical evidence suggests that disaster experience is a significant factor in influencing respondents' risk perceptions and hazard mitigation behaviors, and risk management measures are easier to implement in areas where a hazard has occurred (Yang et al. 2020). Past disaster experiences can leave a lasting and deep impression on respondents; they could have a higher perception of risk, and thus

Table 3 Variable specifications in the random parameter logit (RPL) model

Attribute	Specifications
Premium	Continuous; multiplied by − 1; lognormal
Subsidy rate	Continuous; normal
Sum insured	Continuous; normal
Insured object	Dummy; House structure (baseline, did not enter the model) House structure and indoor property **(Object_HI)**; Normal House structure and farm machinery **(Object_HF)**; Normal All the above **(Object_HIF)**; Normal
Perils covered	Dummy; Floods (baseline, did not enter the model) Earthquakes; normal Geological hazards; normal Meteorological hazards; normal
Opt-out	Dummy (1 if chose the opt-out choice, 0 otherwise); Normal
Interaction terms	
Opt-out × Age	Continuous; non-random
Opt-out × Gender	Dummy; non-random
Opt-out × Education years	Continuous; non-random
Opt-out × Household size	Continuous; non-random
Opt-out × Warning information	Dummy; non-random
Opt-out × The number of neighbors	Continuous; non-random
Sum insured × Housing value	Continuous; non-random
Premium × Income	Continuous; non-random
Subsidy rate × Income	Continuous; non-random
Object_HF × Famach	Dummy; non-random
Earthquakes × Exp_earthquake	Dummy; non-random
Geological hazards × Exp_geological	Dummy; non-random
Meteorological hazards × Exp_meteorological	Dummy; non-random

Terms in bold are the names of dummy variables

tend to prefer insurance that covered the corresponding perils. Based on these observations, research hypothesis 4 was proposed:

H4 Respondents who had experienced a specific type of hazard tended to prefer the insurance that covered the corresponding peril. This hypothesis was tested by introducing the interaction term of hazard types in attributes and corresponding hazard experience, that is, *Geological hazards* × *Exp_geological*.

2.3.2 Estimation of Subpopulation Willingness-to-Pay

The estimated coefficients of the conditional logit model allow straightforward calculation of WTPs for individual attribute levels by $\beta(attribute)/\beta(price)$ (Wang et al. 2020), which means that the population shares an identical test. The estimation of subpopulation WTP aims at differentiating the heterogeneity of respondents' tests over different attributes. It is the WTP of a group of individuals who made the same choice in the same choice sets (Campbell 2007). The estimation enables the identification of common-choice-specific parameters based on the chosen alternative and the derivation of more behaviorally accurate distributions of WTPs and associated mean and standard deviation indicators of WTPs (Hensher and Greene 2003). Following Greene et al. (2005) and Train (2009), we used a Bayesian updating approach to estimate individual-specific WTPs. The individual-level parameter $\hat{\beta}_n$ can be estimated as follows:

$$\hat{\beta}_n = \sum_{d=1}^{D} w^d \beta^d \text{, where the weights } w^d = \frac{\Pr\left(x_{nj} \middle| x_{nJ}, \beta^d\right)}{\sum_{d=1}^{D} \Pr\left(x_{nj} \middle| x_{nJ}, \beta^d\right)} \tag{5}$$

$$\Pr\left(x_{nj} \middle| x_{nJ}, \beta^d\right) = \prod_{c=1}^{C} L_{nc}\left(x_{nc} \middle| \beta^d\right) \tag{6}$$

The estimation was conducted with a pseudo-random number simulation. D indexes the simulation times (that is, 500 Halton draws), w^d is the weighting function for Bayesian updating of individual n, that is, the ratio of logit probability of the alternative chosen to all logit probabilities for each choice set faced by the individual. β is drawn from the population probability distribution $f(\beta|\theta)$. Then, the marginal WTP for each attribute can be simulated:

$$E\left[\mathrm{WTP}_n\right] = \sum_{s=1}^{S} w\left(\hat{\beta}_{ns}\right) \frac{\hat{\beta}_{ns}(attribute)}{\hat{\beta}_{ns}(price)} \tag{7}$$

where S indexes another 500 Halton draws, $w\left(\hat{\beta}_{ns}\right)$ is the weighting function calculated by the individual-level parameters above. $\hat{\beta}_{ns}(atttribute)$ and $\hat{\beta}_{ns}(price)$ are drawn from Eq. 6. Then, the individual-level WTPs of the 291 respondents for each attribute can be calculated by Eq. 7.

The DCE assumes that individuals have continuous preferences in the decision-making process, meaning that they consider all the available information when making decisions (Hess and Hensher 2010). This may not always be the case in practice, and some respondents might only consider a subset of attributes, ignoring others, a feature known as ANA or attribute non-attendance (Gonçalves et al. 2020). Following Hess and Hensher (2010) and Ghosh et al. (2021), we calculated the probability of attribute non-attendance to take the salience of different attributes into account when evaluating choice sets. We established a noise-to-signal ratio of the standard deviation of the subpopulation WTP to the absolute value of the WTP for each individual and for each attribute. Respondents are deemed to have ignored the insurance attribute if the ratio > 2.

$$R = \frac{SD\left(\mathrm{WTP}_{attribute}\right)}{\left|\mathrm{WTP}_{n,attribute}\right|} \tag{8}$$

2.3.3 Welfare Changes and Participation Probabilities Under Simulation

The simulation was conducted to evaluate the comprehensive impact of increasing the sum insured, expanding the insured object, and lowering the subsidy rate on rural residents' participation probability and participants' welfare. We specified the perils covered as earthquakes and the premium rate as 1% to simplify the simulations. Then we created insurance products following the combinations of sum insured (RMB 14,000, 30,000, 50,000, and 80,000 yuan), subsidy rate (40%, 60%, 80%, and 96%), and two types of insured object ("House structure only" and "House structure, indoor property, and farm machinery"). We also considered the possibility of completely withdrawing premium subsidy by the government (*Subsidy rate* = 0).

We assumed that the market offered only one type of rural housing disaster insurance product in our simulation, facing respondents with two alternatives in a choice set: purchase or not. We focused on welfare changes and participation probabilities in response to the three changed attributes. Welfare change that results from insurance products change can be estimated with the compensation variation (CV) approach (Hanemann 1984). The individuals' welfare change and insurance participation probability can be derived with the following simulation (Train 2009):

$$E[\mathrm{CV}_n] = \sum_{s=1}^{S} w\left(\hat{\beta}_{ns}\right) \frac{\ln \sum_k^K \exp_{\text{after}}\left(V_{nk}, s\right) - \ln \sum_k^K \exp_{\text{before}}\left(V_{nk}, s\right)}{\hat{\beta}_{ns}(price)} \tag{9}$$

$$E\left[\mathrm{Pr}_n\right] = \sum_{s=1}^{S} w\left(\hat{\beta}_{ns}\right) \frac{\sum_k^K \exp_{buy}(V_{nk}, s)}{1 + \sum_k^K \exp_{buy}(V_{nk}, s)} \tag{10}$$

3 Empirical Results

This section presents the results based on models defined in Sect. 2, including the estimated coefficients of the CL model and RPL model, subpopulation willingness-to-pay, and the results of product improvement and policy impact simulation.

3.1 Preference Estimates

The CL model and RPL model were estimated by NLOGIT 6.[4] Three model results are presented in Table 4. The CL model with interaction terms is presented in column #2. The RPL model with interaction terms is presented in columns #3 (mean estimates of coefficients) and #4 (standard deviation estimates of coefficients), respectively.

For the RPL model, the McFadden Pseudo R^2 was 0.3069, indicating a fairly good model fit. Overall, the mean estimate of attributes had the same sign as the CL model. It should be noted that the coefficient of − *premium* was assumed to follow a lognormal distribution, the mean estimate of premium should be $-\exp(\beta + \sigma^2/2)$, and β, σ were parameters estimated in the model. So, the mean estimate of premium was − 0.0013, while in the CL model it was − 0.0003, indicating that premium had a negative impact on local residents' utility. The significantly negative mean estimate of the opt-out choice indicated that the absence of rural housing disaster insurance meant a loss in rural residents' utility. In other words, they were more likely to purchase it than not. Its significant standard variation estimates also suggested that the preferences were heterogeneous among individuals. The coefficients of sum insured and subsidy rate suggested that respondents in our sample preferred higher sum insured and subsidy levels, although this preference was statistically insignificant. For insured object, local residents preferred to

[4] https://www.limdep.com/features/whatsnew_nlogit.php.

Table 4 Estimation of the conditional logit (CL) models and the random parameter logit (RPL) model

Variable	CL model	RPL model	
		Mean estimates	SD estimates
Opt-out	−1.3039 (1.2254)	−7.1368* (3.6421)	6.7167** (3.0380)
Opt-out × age	0.0116 (0.0148)		
Opt-out × gender	1.1022*** (0.3851)		
Opt-out × education level	0.0560 (0.1703)		
Opt-out × household size	−0.0171 (0.0896)		
Opt-out × warning information	0.1807 (0.4689)		
Opt-out × the number of neighbors	−0.1013*** (0.0316)		
Sum insured	0.0709 (0.0454)	0.1039 (0.1258)	0.0743 (0.5313)
Subsidy rate	0.0081 (0.0057)	0.0133 (0.0173)	0.0047 (0.0617)
Insured object: Object_HI	0.1837 (0.1800)	0.5045 (0.5076)	1.6280 (1.7648)
Insured object: Object_HF	−0.0498 (0.2413)	−0.0280 (0.6015)	1.1379 (2.3442)
Insured object: Object_HIF	0.7223*** (0.2191)	1.9244** (0.8982)	0.8215 (2.5824)
Perils covered: earthquakes	0.0051 (0.2331)	0.0102 (0.5630)	2.1736 (1.3561)
Perils covered: geological hazards	−0.2487 (0.2201)	−0.7632 (0.6542)	2.5729** (1.2490)
Perils covered: meteorological hazards	0.6131*** (0.2160)	1.3983* (0.8181)	2.8047* (1.6520)
−Premium	0.0003 (0.0008)	−7.0329 (5.1787)	0.6406 (8.5047)
Sum insured × housing value	−0.0009 (0.0011)	0.0008 (0.0030)	
Subsidy rate × income	−0.0011** (0.0005)	−0.0032 (0.0023)	
Premium × income	0.2941×10^{-4} (0.7515×10^{-4})	0.5570×10^{-4} (0.0002)	
Object_HF × Famach	0.1505 (0.2003)	0.3997 (0.4718)	
Earthquakes × Exp_earthquake	1.1206*** (0.2566)	2.4019** (1.1447)	
Geological hazards × Exp_geological	1.4226** (0.5580)	3.4642* (2.1015)	
Meteorological hazards × Exp_ meteorological	0.2050 (0.2766)	0.6132 (0.7795)	
Log likelihood	−470.1620	−443.1499	
McFadden Pseudo R^2		0.3069	
Number of Halton draws		1000	

The estimates obtained by the RPL model were associated with the logarithm of the coefficient of premium. Standard errors are shown in parentheses

*Significant at the 10% level

**Significant at the 5% level

***Significant at the 1% level

Table 5 The Random Parameter Logit (RPL) model estimates of subpopulation willingness-to-pay for attributes

Attribute	Mean	SD	25th	Median	75th
Sum insured	97.27	10.35	89.35	98.33	102.68
Subsidy rate	12.39	0.52	12.06	12.39	12.67
Insured Object: Object_HI	466.02	554.61	121.24	479.76	909.00
Insured Object: Object_HF	−4.25	285.26	−156.93	−27.60	56.11
Insured Object: Object_HIF	1741.69	216.30	1616.51	1780.01	1837.17
Perils covered: Earthquakes	158.24	1161.42	−626.61	277.82	1118.94
Perils covered: Geological hazards	−780.34	996.40	−1245.97	−720.01	−655.85
Perils covered: Meteorological hazards	1496.38	1506.02	455.27	1753.81	2692.33

include indoor property, but not necessarily farm machinery. Adding indoor property and farm machinery to the object yielded a significantly positive impact on residents' WTP. Where perils covered were concerned, meteorological hazards was preferred to floods (the baseline group). Meantime, the standard variation estimates of geological hazards and meteorological hazards were both significant, indicating strongly heterogeneous preferences.

In the RPL model with interaction terms, *Earthquakes* × *Exp_earthquake* and *Geological hazards* × *Exp_geological* were all significant. The coefficients of *Sum insured* × *Housing value* and *Object_HF* × *Famach* were positive but not significant, and so, the null hypotheses of H1 and H2 were not rejected by the empirical evidences. The coefficient of interaction term, *Subsidy rate* × *Income*, was significant in the CL model but insignificant in the RPL model. The insignificantly positive effect of *Premium* × *Income* meant that the null hypothesis of H3 was not rejected. Most notably, the null hypothesis of H4 was rejected by the significant positive effects of *Earthquakes* × *Exp_earthquake* and *Geological hazards* × *Exp_geological*, showing that residents who had experienced such hazards tended to prefer the insurance that covered the corresponding perils (earthquakes or geological hazards).

In the CL model, we added the interaction terms between the opt-out choice and basic socioeconomic characteristics to understand the heterogeneous source of respondents' preferences for insurance purchase. The interaction between the opt-out choice and gender was significant, which suggested that females preferred more insurance than did males. Also the interaction term between the opt-out choice and the number of neighbors who can be contacted in an emergency was significant, which meant that residents who have a closer social network would be more likely to purchase insurance. Our results also showed that the older residents were, the less likely they were to buy insurance. Residents who were well educated and could receive warning information preferred no insurance, while residents with large household size preferred purchasing insurance.

3.2 Subpopulation Willingness-to-Pay

We used the Bayesian updating approach to estimate respondents' individual-level WTPs based on the results simulated from the RPL model (Table 5). The mean estimates of the sum insured suggested that every RMB 10,000 yuan increase in the sum insured would increase WTP by 97.27 yuan, equivalent to a premium rate of 0.97%; the standard deviation was 10.35 yuan. For subsidy rate, the results showed that every 1% increase in subsidy rate would increase WTP by 12.39 yuan; the standard deviation was 0.52 yuan. The insured object and perils covered were dummy variables, so the WTPs in Table 5 suggested the difference compared with the corresponding baseline group. The WTP of house structure and indoor property was 466.02 yuan higher than the WTP of house structure (baseline), but the WTP of house structure and farm machinery was 4.25 yuan lower than the WTP of house structure (baseline). The WTP for house structure, indoor property, and farm machinery was higher than for the other three groups. For perils covered, changing the perils from floods to earthquakes and meteorological hazards increased local residents' WTP by mean estimates of 158.24 yuan and 1,496.38 yuan respectively. Changing the perils from floods to geological hazards decreased WTP by a mean estimate of 780.34 yuan.

We calculated the mean marginal WTPs for each attribute in different counties in our survey area. The WTPs for specific hazard perils show significant differences among counties (Fig. 3). Respondents in Yadong, Nyalam, Purang, and Kamba Counties (Fig. 2) showed relatively higher WTP for earthquakes compared with Gegya and Rutog, consistent with their past disaster experience and the ground motion parameter zoning map of China (GB18306-2015).[5] Yadong, Nyalam, Purang, and Kamba suffered enormous losses from earthquakes in recent years, especially the 2015 Nepal earthquake. Therefore residents' demands for earthquake prevention and relief were great. The WTP for geological hazards was the lowest among the four hazard types, echoing the lack of experience of local residents. In the survey, respondents

[5] https://www.gb18306.net/.

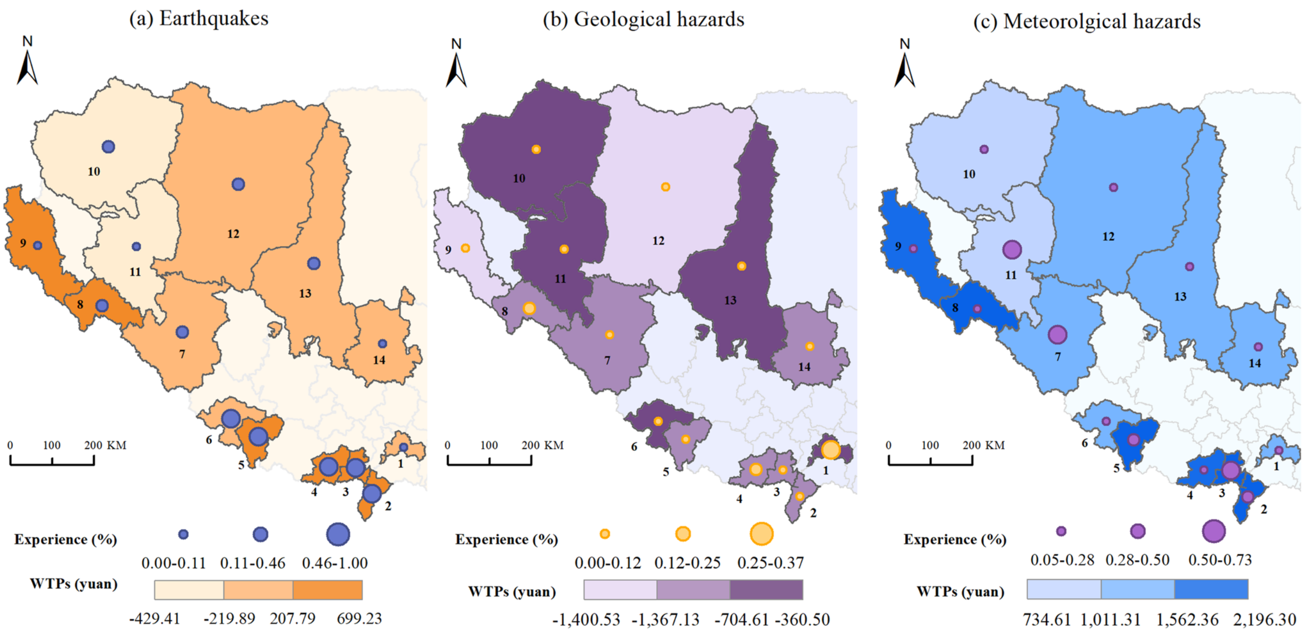

Fig. 3 Respondents' disaster experience and mean marginal willingness-to-pay (WTP) for different hazard perils across counties. *Note* Experience is the ratio of respondents who had experienced corresponding hazards in each county. County names are 1: Gyangze; 2: Yadong; 3: Kamba; 4: Dinggye; 5: Nyalam; 6: Gyirong; 7: Zhongba; 8: Purang; 9: Zanda; 10: Rutog; 11: Gegya; 12: Gerze; 13: Nyima; and 14: Shenza.

reported that they had rarely experienced any landslides, debris flows, or other geological hazards in our survey areas. In addition, several village settlements close to geological hazard sites were abandoned, and villagers were resettled in a nearby safer area. Roadway signage indicating hidden risks of geological disasters and the installation of property protection projects could indicate that residents' property has been adequately protected in our survey area. The spatial pattern of WTP for meteorological hazards seemed weakly consistent with disaster experience compared to the other two hazards, which was probably related to the high frequency of floods and other meteorological disasters.

Table 6 reports the proportion of respondents in the sample who, based on our simulation, were deemed not to have considered the insurance attributes (see Eq. 8). The results showed that local residents were more sensitive to the sum insured and the subsidy rate, which are more related to the premium. Other insurance attributes had a higher likelihood of non-attendance (ANA). For the insured object, 32% of the respondents were not attending to Object_HI and 48% of the respondents were not attending to Object_HF when responding to the choice scenarios, while none of the respondents ignored Object_HIF. The results showed that residents could easily distinguish between protecting their house structure only and including indoor property and farm machinery. The relatively high proportion of perils covered showed that local residents were deemed to have ignored these attributes.

Table 6 Non-attendance to insurance attributes

Attribute	Proportion not attending to attribute
Sum insured	0
Subsidy rate	0
Insured Object: Object_HI	0.32
Insured Object: Object_HF	0.48
Insured Object: Object_HIF	0
Perils covered: Earthquakes	0.33
Perils covered: Geological hazards	0.10
Perils covered: Meteorological hazards	0.23

3.3 Product Improvement and Policy Impact Simulation

Figure 4 reports the simulation results, from which the individual and comprehensive impact of increasing the sum insured, expanding the insured object, and lowering the subsidy rate can be obtained. Increasing the sum insured would increase respondents' welfare (positive CV) and participation probability when the premium subsidy rate and insured object were constant. Our simulation results show that if we increased the sum insured from RMB 14,000 to 30,000 yuan while keeping the subsidy rate at 40–96%, the participation probability would show a negligible increase.

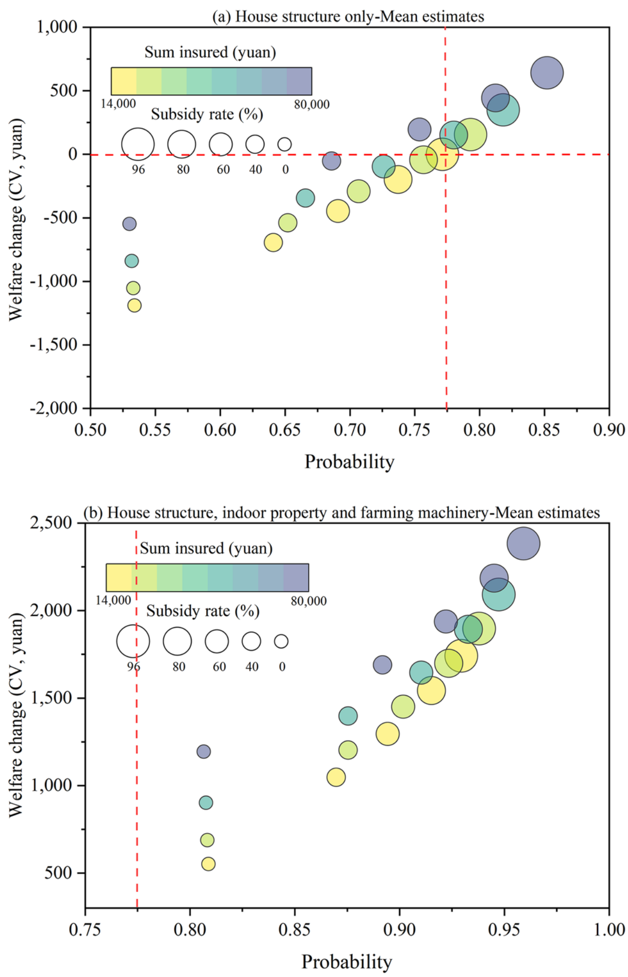

Fig. 4 Simulated participation probability and welfare change measured with CV calculated based on perils covered setting as earthquakes, and premium as 1%. *Note* The red dotted line represents the welfare change (CV = 0) and participation rate (77%) under sum insured (RMB 14,000 yuan) and premium subsidy rate (96%).

However, if the sum insured increased to 80,000 yuan, the increase in participation probability would be greater. Nevertheless, the participation probability would change little with increases in the sum insured when the subsidy was completely withdrawn.

Lowering the subsidy rate would decrease participants' welfare (negative CV) and participation probability simultaneously when other conditions hold constant. At the baseline sum insured level (RMB 14,000 yuan) and insured object (house structure only), the CV would be −198.21 yuan. The participation probability would decrease by 3.42% if the subsidy rate dropped from 96 to 80%. Most notably, if the government withdrew the subsidy rate completely, the participation probability would decrease to 53.39%, indicating that only slightly more than half of rural residents would continue to purchase insurance products.

Expansion of the insured object would increase participation probability substantially when the sum insured and the subsidy rate remained unchanged. For example, if the subsidy rate was kept at 80%, changing the insured object from house structure alone to house structure, indoor property, and farm machinery, this would bring a 17.80% increase in probability when the sum insured was RMB 14,000 yuan. When we retained house structure, indoor property, and farm machinery as the insured object, the participation probability increased measurably when increasing the sum insured, even if the subsidy rate decreased from 96 to 40%. Therefore, the strong preferences for a complete list of insured objects can mostly offset the disutility arising from a lower subsidy rate.

4 Discussion

Our study showed that the sum insured and the subsidy rate had positive impacts on local residents' demands, and the results of ANA also showed that residents were rather sensitive to these two attributes, which is consistent with general results (Wang et al. 2020; Ghosh et al. 2021). Moreover, compared with insurance only covering the house structure, residents would be more likely to purchase blanket insurance that also covered indoor property and farm machinery. According to the *Tibet Statistical Yearbook 2021* (Tibet Autonomous Region Provincial Bureau of Statistics 2021), the number of color TV sets owned per 100 of rural households at year-end had increased from 73.45 in 2010 to 113.27 in 2020; the total power consumption of agricultural machinery increased from 4.12 million kW in 2010 to 13.69 million kW in 2020. The risks to property are increasing with expansion in the types and value of residents' property, and the present policy-based insurance in Tibet cannot meet the increasing demand for property risk protection.

Our study also suggested that local residents showed strong heterogeneous preferences for perils covered, and the WTP for corresponding peril protection was related to residents' disaster experience, especially of earthquakes and geological hazards. This finding is similar to the findings of Wang et al. (2012), Tian and Yao (2015), namely, past disaster experience has a positive effect on demand. We also found that some residents could hardly distinguish the differences among the four hazards in the survey, which suggests that their knowledge about disaster was insufficient.

Our study indicated that local residents showed strong individual preferences for different attributes and insurance purchases, and that these heterogeneous preferences were driven by specific socioeconomic and demographic features. We found that residents with higher net income were less sensitive to subsidy, a feature consistent with earlier findings (Ye et al. 2017; Liu et al. 2021), suggesting that residents with high income have a strong sense of risk management, and the government subsidy shows an income effect rather than an incentive effect in our study area. Unfortunately, our estimates did not provide significant evidence that residents with higher housing value preferred a higher sum insured, or that residents who had farm machinery preferred including farm machinery in the insured object, nor that residents with higher net income were less sensitive to premium cost. Darlington and Yiannakoulias (2022) presented contrasting evidence that respondents with high dwelling value tended to prefer a higher sum insured in Canada. Our results did not provide strong evidence for that behavior, probably due to the unfamiliarity of our local residents with actual housing values. We used estimated reconstruction costs in the model, which could have introduced uncertainty into our results. Ye et al. (2017) found that farmers with higher net income were less sensitive to premium cost in Hunan Province, China. In our study area, the long-term heavy subsidy fostered ambiguous perceptions of the nominal insurance premium in local residents. In addition, our results also suggested that females preferred insurance more than males, which is related to their degree of risk aversion, as females are generally more risk averse than males (Ye and Wang 2013). We also found that residents who could contact more neighbors in an emergency would be more likely to purchase insurance. To some extent, a closer social network can effectively promote the diffusion of insurance knowledge (Cai et al. 2015), and residents would adjust their decision-making behaviors through learning and imitating others' behaviors (Takahashi et al. 2020).

There are several limitations in this study. First, the sample size is relatively small due to the linguistic difficulty of survey implementation. Second, since there is no financial consequence of choices made in the experiment, the results of DCEs are subject to potential hypothetical bias, which would lead to higher WTP estimates, in spite of our effort to use cheap talk to mitigate this problem.

5 Conclusion

This study employed the DCE with a sample of rural residents in central and western Tibet and directly estimated residents' WTPs for rural housing disaster insurance product attributes. We found that residents showed positive preferences for the sum insured, the subsidy rate, and the completeness of the insured object. They showed negative preferences for premium costs, and the preferences for perils covered were strongly heterogeneous among the population. These preferences were driven mainly by socioeconomic and demographic features, and past disaster experience. The results of this study have three implications:

(1) Promoting rural housing disaster insurance by increasing the sum insured and expanding the insured object, effectively improving the ability to guarantee property security in remote areas. Our simulation results suggested that if we changed the insured object from only house structure to house structure, indoor property, and farm machinery (that is, a complete list of insured objects), and increased the sum insured, the participation probability and welfare would increase significantly. With the further improvement of residents' living standards, existing rural housing insurance cannot meet residents' demands for higher insurance protection capacity, and should adapt to the new needs of local residents for property security under the new situation;

(2) Lowering government premium subsidies is feasible with product improvement, while withdrawing completely is not a feasible option in the short term in central and western Tibet. Our policy simulation results indicated that if the government were to withdraw the subsidy completely, the participation probability would decrease sharply. When the insured object was expanded, although the participation probability showed a tiny increase compared to the baseline, it was unsuccessful in improving participation (far below 100%). To strike a balance between financial burden on the government and the development of insurance, the government could lower subsidy levels judiciously but completely withdrawing them is not feasible; and

(3) Strengthening an improved rural housing insurance pilot in disaster-prone areas and raising residents' awareness of frequent natural hazards and disasters through education are conducive to the promotion of insurance uptake. Our results showed that the respondents' past disaster experience had a positive impact on WTPs. Residents in typical disaster-prone areas were more willing to purchase insurance, and, as a result an upgraded pilot program would be more likely to succeed in those areas. It is also important to intensify publicity and education about natural hazard-related disaster risks, since some residents showed a poor understanding of natural hazard-related disasters in our study.

Although crop insurance and livestock insurance have been well studied, rural housing disaster insurance, which is also an important part of rural safety-nets to protect farmers' property, needs further investigation. This can be advanced by incorporating new comparative evidence from more regions, especially in remote and less developed areas. Among the population in those areas, the influence of social networks could be strong on insurance purchase, and rural residents hardly ever make decisions in isolation. Future studies should be shifted from an individual risk decision-making framework to a collective risk decision-making framework. Moreover, recent studies generally use one-year data to analyze rural residents' preferences for insurance, which could introduce uncertainty into estimates. Long-term dynamic data in future studies would help improve the understanding of rural residents' demand characteristics for insurance.

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