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Research article

Vulnerable entrepreneurs' preferences for climate risk management: A discrete choice experiment with micro-enterprises in the Philippines

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A B S T R A C T

Small enterprises are important contributors to economic development and local employment in low- and middle-income countries. However, they are often highly vulnerable to climate risks and have limited capacity to adapt to them. This study assesses the preferences of micro-enterprises in the Philippines for risk management strategies in response to climate risks and environmental hazards. We conducted a discrete choice experiment with 625 randomly selected entrepreneurs and estimated their preferences for three strategies: improved information sharing and early warning; resilient and protective infrastructure; and climate risk insurance. Using a random parameter logit model, we estimate willingness to pay and compensating variation for all combinations of strategies and enterprise profiles. We find that entrepreneurs consider all strategies highly relevant, with climate risk insurance being the most preferred. Entrepreneurs show a higher willingness to pay for combined strategies, indicating a willingness to allocate at least 7.2% of their net income to an integrated set of climate adaptation strategies. Female entrepreneurs are less willing to pay for any strategy, and rural enterprises are less willing to pay for climate risk insurance. This may be explained by lower financial literacy in both cases. Furthermore, we show that participation in climate risk information events is associated with higher preferences for all strategies. We conclude that small enterprises show a significant but heterogeneous willingness to invest in climate risk management. Raising awareness and providing information about climate risks is likely to increase entrepreneurs' willingness to manage climate risks. Furthermore, expanding the availability of climate risk insurance is crucial to meet the high demand among enterprises. The results of this study can guide policymakers to allocate funds for climate risk management more efficiently and promote needs-based climate adaptation policies to support vulnerable populations.

1. Introduction

Micro-enterprises are important contributors to economic development and local employment in low- and middle-income countries (Gherghina et al., 2020; ILO, 2019; UN-DESA, 2020). However, they are often strongly exposed to extreme climate events due to their geographic location and have limited capacity to adapt to them. They often lack access to relevant options such as early warning systems, resilient and protective infrastructure and financial resources for rebuilding after natural disasters. This presents a challenge to economic development in vulnerable countries. Climate risk management is therefore of high importance for the survival of small enterprises and the long-term prosperity of these countries (Casado-Asensio et al., 2021; Crick et al., 2018; IPCC, 2022; WTO, 2023).

While efforts are being made by national governments and international actors to support vulnerable groups in adapting to climate change, there is still insufficient empirical evidence on the preferences of specific individuals and businesses with respect to climate risk management strategies. However, it is essential to know their preferences in order to address the interests of vulnerable populations and to allocate funds for climate risk management efficiently.

To fill this knowledge gap, the main interest of this paper is to empirically elicit how micro-entrepreneurs value various strategies for managing climate risks and coping with shocks from extreme weather events. We also examine heterogeneity in preferences, recognising that not all entrepreneurs perceive and (aim to) manage climate risks the same way. Finally, because single risk-management strategies are often not sufficient (Asia Pacific Foundation of Canada, 2018; Leppert, 2016;

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Leppert et al., 2021; Meenan et al., 2019), we investigate how entrepreneurs value an integrated set of strategies (i.e., combining risk exposure or impact reduction strategies and risk transfer).

We conduct a lab-in-the-field experiment to elicit vulnerable entrepreneurs' preferences for climate risk management strategies. Micro-enterprises in the Philippines are particularly exposed and prone to extreme weather events, yet they represent a significant part of the Philippine economy and enterprise landscape (Day et al., 2019; Department of Trade and Industry, 2021b). Climate risk management adapted to their needs is important for their survival and for economic prosperity in the Philippines.

We derived strategies that are relevant to increasing entrepreneurs' adaptive capacity from a literature review and in-depth interviews conducted as part of an exploratory qualitative study. Consequently, this paper assesses preferences for (i) improved information sharing and early warning, (ii) resilient and protective infrastructure, and (iii) climate risk insurance.

To uncover enterprise preferences and willingness to pay (WTP) for climate risk management strategies, we implement a discrete choice experiment (DCE). In face-to-face interviews, 625 entrepreneurs were asked to choose between two options to safeguard against climate risks. Each respondent completed six choice cards, resulting in a total of 3750 choice tasks. Each option included up to three non-monetary attributes - early warning systems, resilient and protective infrastructure, and climate risk insurance - and a price attribute.

To analyse the experimental data, we apply a random parameter logit (RPL) model with correlated parameters that accounts for latent and observed heterogeneity. We interpret the results in terms of WTP and calculate compensating variation (CV) for several climate risk management scenarios and enterprise characteristics.

The results show that strategies for managing climate risk are considered highly relevant by people running micro-enterprises in the Philippines. Climate risk insurance is the most preferred strategy among entrepreneurs. Participation in risk information events is significantly related to higher preferences for all presented risk management strategies. Moreover, our results show that entrepreneurs working in firms located in rural areas have significantly lower preferences for climate risk insurance than those working in urban areas. Similarly, female entrepreneurs are, on average, less willing to pay for climate risk management. This may be explained by lower levels of insurance literacy among female entrepreneurs as well as among entrepreneurs operating in rural areas. Our results also show that the potential gains for micro-enterprises from integrating risk transfer strategies and risk exposure or impact reduction strategies are large but highly dependent on firm characteristics. On average, enterprises are willing to pay at least 7.2% of their mean net income for an integrated policy including all three presented risk management strategies compared to the status quo.

With this study, we contribute to the literature examining individual preferences and demand for risk management strategies. While most DCE studies have concentrated on eliciting preferences from households or smallholder farmers, especially in relation to environmental, agricultural, and climate risk management, our study focuses on micro-enterprises.[1] Micro-enterprises are an economically significant group in many low- and middle-income countries, contributing substantially to gross domestic product (GDP) and employment. As important local employers and providers of essential goods and services in their communities, the ability of micro-enterprises to adapt to climate risks directly affects household incomes, access to necessities, and how quickly communities can restore economic and social stability after extreme weather events. However, small enterprises are often located in high-risk areas, have high exposure and have limited adaptive capacity, making them highly vulnerable to extreme weather events such as tropical cyclones (Ballesteros and Domingo, 2015; Casado-Asensio et al., 2021; Department of Trade and Industry, 2021a, 2021b; IPCC, 2022). Despite their crucial role, micro-enterprises have received little attention in the climate change adaptation and stated preference literature (Agrawala et al., 2011; ILO, 2019). By applying a DCE to elicit preferences of micro-entrepreneurs in the Philippines, our study addresses this gap, providing new empirical insights that can inform both policy and future research on climate change adaptation strategies for vulnerable enterprises in the Global South.

Moreover, previous research has often focused on one specific climate risk management instrument, typically climate risk insurance alone.[2] Our study is among the first to examine preferences for a set of climate risk management strategies, which allows to elicit preferences for both single strategies and integrated approaches within a single experiment.[3] This is particularly relevant, as adaptation to climate risks in practice often requires the interplay of multiple instruments rather than reliance on any one strategy (Collier et al., 2009; Leppert et al., 2021).

This study also contributes to the literature on stated preference methods by applying an RPL model with correlated parameters and providing a detailed discussion of the role of the alternative-specific constant (ASC) in preference estimation and compensating variation calculations. Stated preference approaches, including DCEs, have become valuable tools for eliciting individuals' preferences and WTP (Kanninen, 2007; Lancaster, 1966). With our study, we explicitly demonstrate how choice experiments can identify the preferences of small, non-agricultural enterprises in a low- and middle income country context, uncover preference heterogeneity and reveal the underlying factors influencing decision-making. Ultimately, this study supports more informed policymaking for climate risk management in low- and middle-income countries.

2. Study area and sample

Micro-enterprises in the Philippines are important to the country's economic development. They account for more than 90% of all enterprises and more than 30% of all employees in the Philippines (Department of Trade and Industry, 2021b). In 2021, micro-enterprises together with small and medium-sized enterprises contributed 35.7% to the country's total value added (Department of Trade and Industry, 2021a). However, the effects of climate change and environmental hazards pose a threat to their survival. The Philippines is rated among the most affected countries by natural disasters worldwide (Day et al., 2019; Eckstein et al., 2019). Micro-enterprises are strongly affected by extreme weather events (e.g., tropical cyclones) as they are often located in high-risk areas and have low adaptive capacities. Financial losses are often compensated by remittances and loans from relatives or money-lenders. A significant proportion of enterprises affected by climate extremes are no longer able to reopen their businesses, and entrepreneurs often have to take on temporary work instead (Ballesteros and Domingo, 2015; Casado-Asensio et al., 2021).

[1] For examples of DCEs studying farmers' preferences for climate risk management in low- and middle-income countries, see Cranford and Mourato (2014); Houessionon et al. (2017); Khanal et al. (2019); Nthambi et al. (2021); Ortega et al. (2019); Shee et al. (2021); Tadesse et al. (2017). For other DCEs concerning environmental and agricultural risk management among farmers in low- and middle-income countries, see Ali et al. (2021); Čop and Njavro (2022); Ghosh et al. (2021); Kefale et al. (2021); Pham et al. (2022); and Ward and Makhija (2018).

[2] For DCE studies on the demand for flood insurance, see, for example, Brouwer et al. (2014); Botzen and Van den Bergh (2012b); and Shao et al. (2017).

[3] The paper by Crastes et al. (2014) is a notable exception. In their study, the authors examined the preferences of households for different management policies aimed at mitigating the effects of erosive runoff in the European Union (EU).

To identify entrepreneurs' preferences for climate risk management strategies, we conduct a DCE with randomly selected micro-enterprises in five municipalities across four provinces in the Philippines: Las Nieves and Cabadbaran (Agusan Del Norte), Catarman (Northern Samar), Malungon (Sarangani), and Irosin (Sorsogon). The location of the survey areas is shown in Fig. A2 in the Appendix. Within each municipality, various barangays with a sufficient number of enterprises are randomly selected. A barangay, the lowest administrative unit in the Philippines, is similar to a village or town district. Within each selected barangay, enterprises are chosen using *random walk* sampling, where the starting point is the barangay hall, health centre or school. The survey was conducted in English and three regional languages (Bicolano, Cebuano, Waray). A total of 673 individuals were approached by the interviewers for participation in the study, of which 5 (0.74%) declined to take part, and 43 (6.4%) of the interviews were not completed. The reasons for non-completion were diverse, including time constraints, the individual approached was not the owner or a responsible person at the firm, and insufficient information. We did not identify any systematic patterns in non-response. Therefore, it is reasonable to assume that non-response had randomly distributed characteristics. In cases of refusals or incomplete interviews, the interviewer proceeds with the random walk until a total of 125 interviews are completed in each survey area. Finally, 625 interviews were completed between January and February 2020. This is well above our calculated minimum required sample size.[4]

3. Discrete choice experiment

3.1. Motivation

Choice experiments are a valuation method for eliciting individuals' preferences on various attributes and their relative importance in an experiment. The choice experiment dates back to Lancaster's theory of consumer demand, in which the author emphasises that the decision to consume a good or service is determined by the utility obtained by the characteristics (referred to as *attributes*) of this good or service rather than by the good or service itself (Lancaster, 1966). In a choice experiment, the respondents obtain several choice cards with various hypothetical alternatives. A choice experiment consisting of two alternatives is a DCE. On each choice card, the respondents are asked to choose their most preferred alternative. This is assumed to be the option where the sum of the utilities obtained by the combination of attributes is the greatest.

Compared to other stated preference methods, such as those in which respondents have to rank or rate certain characteristics, choice experiments in which respondents have to make compromises between alternatives are more realistic and closer to the actual decisions of individuals. Choice experiments are based on random utility theory, so economic rationality and utility maximisation are assumed (Hanemann, 1984; Mangham et al., 2009). Moreover, it is assumed that the respondents know their preferences and that these are stable and coherent across all choices (Train, 2009). DCEs are comparatively tangible and easy for the respondents, and pose a relatively low cognitive load (Holmes et al., 2017; Johnston et al., 2017; Louviere et al., 2000, 2011; Mangham et al., 2009).

3.2. Development of attributes and levels

To resemble realistic conditions and to ensure the validity of the experiment, we develop attributes and attribute levels following a systematic process. First, we perform a literature review and derive a list of possible important climate risk management strategies for micro-entrepreneurs in the Philippines that aim at managing and reducing the socio-economic impacts of climate risks. Second, we conduct a qualitative study with local authorities, stakeholders and entrepreneurs in the Philippines. During this process, the list of previously developed attributes is progressively narrowed down, as some are considered to be less relevant to the target population. Care was taken to minimise *inter-attribute correlation*, which would lead to an inaccurate estimation of the effects of each attribute on the choice variable (Mangham et al., 2009). Finally, three relevant climate risk management strategies are included in the experiment.

The first strategy *Information* aims to reduce the negative impact of climate hazards through improved risk preparedness. It involves improvements in the generation of locally relevant information and information sharing related to weather, risk, natural hazards, and emergency responses. This includes better information sharing on proactive strategies, such as emergency plans, as well as information on immediate action, such as evacuation. It also includes improved early warning systems for natural hazards. Improving early warning systems and increasing the availability of risk information tailored to local needs is often seen as an important climate risk management strategy because it allows entrepreneurs to take immediate action to mitigate risks, such as securing property, relocating assets, or temporarily halting operations to avoid damage. For example, entrepreneurs can move valuable inventory and equipment to safer locations or higher ground to protect them from flooding or storm damage, secure roofs, or install sandbags to prevent water intrusion. Early warning systems can minimise potential losses and ensure the safety of employees and physical assets. With access to accurate and timely data, entrepreneurs can develop contingency plans to continue operations with minimal disruption during and after climate events. Business owners can adjust inventory levels based on the warning, either by increasing stocks of critical supplies that may be disrupted or reducing perishable goods that may be damaged. If primary supply routes are affected, business owners can establish alternative supply chains. The early warning system in the Philippines is among the most developed in Southeast Asia. However, impact predictions at the local level are still lacking, and further digital innovations could improve entrepreneurs' climate risk management (GSMA, 2022; IPCC, 2012). Although phones as a vehicle to receive an early warning are widespread technologies (Bollettino et al., 2018), communicating risk information and translating it to the community level has proved to be challenging in the past. For example, a misunderstanding at the community level about the term "storm surge" led people not to evacuate immediately or to adopt safety-seeking behaviour, even though the municipality and barangay captains confirmed that they had warned residents about the approaching Typhoon Haiyan. In addition, most municipalities do have contingency plans, but many are outdated or insufficient (Elegado and Borchard, 2014; Yore and Walker, 2021). Likewise, early warnings for the tropical storms Urduja and Vinta in December 2017 were largely ineffective because they were too broad and called for a general forced evacuation in too many provinces, which desensitised people to respond with urgency when needed (Lagmay and Racoma, 2019). A well-developed early warning system would enable entrepreneurs to take actions that preserve their business operations, assets, and overall economic stability, ensuring that businesses can resume operations quickly after the event.

The second strategy *Infrastructure* aims at reducing the exposure to and impacts of natural hazards (e.g., floods, droughts, and tropical storms). The strategy refers to improvements in local climate-resilient and protective infrastructure at the barangay level, primarily through community-based approaches to building climate resilience. Climate-resilient infrastructure involves improvements in green infrastructure such as mangroves and natural water reservoirs and grey infrastructure such as dams and dykes, drainage and irrigation systems, and fortified

[4] The following approach to sample calculation for DCEs developed by R. Johnson and Orme (2003) was used to compute the minimum sample size required: $N = 500*(i/(j*s)$, where N is the required sample size, i the largest product of two attribute levels, j the number of alternatives not including the status quo option, and s the number of choice tasks. According to this, the required sample size for this DCE is 250 to achieve reasonable statistical power.

Table 1
Attributes and levels.

Attribute	Description	Level
Information	This product contains better information on climate change-related risks and hazards. For example, evacuation and emergency plans, daily weather information, and early warning inform you in case of floods, droughts, and typhoons.	yes, no
Infrastructure	This product contains better infrastructure in your barangay. This includes for example better roads, bridges, dams, and drainage.	yes, no
Insurance	This product contains an insurance. In case of impacts from floods, droughts, and typhoons, your enterprise obtains a payment.	yes, no
Price	Total cost for your enterprise per month for the implementation of your chosen option, which can comprise zero, one or multiple products.	50, 100, 150

Note: This table describes the four attributes and their levels used in this choice experiment. The attribute description corresponds to the description on an information sheet given to respondents during the DCE. For the sake of simplicity, the term "product" has been used in the attribute descriptions and choice cards. The status quo (opt-out) alternative is always presented as a separate choice option in the experiment, with none of the climate risk management strategies included and a price of zero.

roads and bridges. These improvements play a crucial role in reducing the impacts of climate risks on enterprises. For example, resilient roads provide uninterrupted transport for employees and goods, evacuation routes and reliable supply chain operations, essential for maintaining customer access and business continuity. In addition, climate-resilient water management systems are essential for maintaining water supply, sanitation and irrigation, critical elements in ensuring operational stability in the face of extreme weather events (Ballesteros and Domingo, 2015; Day et al., 2019). Resilient infrastructure addresses climate risks already at an early stage of the risk management continuum because of its ability to directly prevent or reduce natural hazard damage and losses to enterprises. Furthermore, resilient infrastructure enables immediate action, such as evacuation or emergency responses in the aftermath of a natural disaster.

The third strategy *Insurance* aims at risk mitigation to compensate for losses and damages of hazards (e.g., floods, droughts, and typhoons) through risk finance, applying a risk pooling mechanism. Climate risk insurance aims to transfer the risk and associated losses and costs from an individual to a collective risk pool. An uncertain and undetermined large loss is thereby exchanged for an ex-ante and typically regularly paid, small and certain loss, which is referred to as an *insurance premium*. After an insured event occurs, the insured party should receive timely and reliable financial assistance, and it can thereby increase its financial resilience, stability and credibility. Currently, few micro-enterprises in the Philippines have climate risk insurance or receive adequate other support following a natural disaster. Informal risk sharing among networks of friends, families, or enterprises is common in the Philippines, as it is in many low- and middle-income countries (Fafchamps and Lund, 2003; Pajaron, 2014). In the survey conducted as part of the study at hand, about 58% of all firms reported that they collaborate with other firms in the region to be better protected against climate impacts (Römling and Becker, 2021). However, households and firms are likely to form mutual support arrangements with counterparts who face a similar probability of need, leading to ineffectiveness in cases of common shocks (Will et al., 2023). Climate risk insurance could be an important risk management strategy to financially enable micro-enterprises to restart their business quickly after a natural disaster (Churchill and Matul, 2012; Le Quesne et al., 2017; Supnet et al., 2023), but it is not yet widely adopted in the Philippines (Römling and Becker, 2021).

Lastly, we add a *Price* attribute, indicating the monthly costs of each hypothetical option. We select the price levels based on qualitative research with experts and target groups so that they reflect realistic and affordable values for the micro-enterprises (Abiiro et al., 2014; Osborne et al., 2022).

A brief description of the four attributes and their levels used in this choice experiment is shown in Table 1. This description corresponds to the information given to respondents during the choice experiment. The explanations are quite short in order not to overwhelm the respondents, and simple wording is used since it is assumed that most respondents are unfamiliar with the terminology of the subject. The three non-monetary attributes were broadly defined. This approach provides information on the global preferences of entrepreneurs regarding these strategies.

3.3. Construction of choice cards

In this study, 625 entrepreneurs completed six different choice cards, leading to 3750 choice tasks in total.[5] On each card, respondents are asked to choose their preferred option from two hypothetical options to manage climate risk. An example choice card is depicted in Fig. 1. The options consist of four attributes. Three non-monetary attributes – *Information*, *Infrastructure* and *Insurance* – with two levels describe the three presented strategies for managing climate risk. The ticks (✓) in the columns headed Option A and Option B indicate whether or not a strategy is included in the option. The monetary attribute – *Price* – with three levels (Philippine peso (PHP) 50, PHP 100 and PHP 150) indicates the monthly cost of each option. Respondents were asked to indicate their preferred option at the bottom of the card. A status quo option is included in case the respondent does not prefer any of the proposed strategies to be implemented under the stated costs. Including a status quo option does not give any information on individuals' preferences for the different attributes, but it makes the experiment more realistic and avoids an overestimation of utility parameters (Maxim and Roman, 2019).

3.4. Structure of the questionnaire

The choice experiment was embedded in an overall enterprise survey conducted by the German Institute for Development Evaluation (DEval) as part of an evaluation to analyse Philippine–German development cooperation in the context of managing climate risks (Leppert et al., 2021; Römling and Becker, 2021). The ethical approval for the survey was obtained through the market research agency Kadence International, which also collected the data. Before participating in the survey, each participant was informed about the study and gave their prior consent. Data was collected through face-to-face interviews lasting about one hour each. The interviewers clarified questions and descriptions as needed. First, questions were asked regarding the sociodemographic and socioeconomic characteristics of the respondent or the enterprise. These supporting questions help in analysing the impact of individual and enterprise characteristics on the choices made. Second, the questionnaire contained the choice experiment, introduced by the interviewers. For the choice experiment, interviewers received additional training to ensure that the experiment and the attributes could be accurately explained to the respondents and that questions of the respondents could be correctly answered. Attention was paid to ensure that the wording used by the interviewer resembled real-world conditions as closely as possible to avoid hypothetical bias. The respondents were made aware that they will make decisions in a hypothetical scenario and were explicitly asked by the interviewers to make the decisions as they would in real life (Cummings and Taylor, 1999; Huls

[5] The choice cards are created as follows: First, the 24 possible attribute combinations (2^3*3^1) are divided into four blocks of six rows using a blocking algorithm. Each block is then combined with the other three blocks, with the rows paired randomly. Finally, six different variants exist from which one is randomly assigned to each respondent. The choice cards within each variant appear in a random order to minimise any bias. The experimental design in this study has a D-efficiency of 83% and allows estimation of all main and two-way interaction effects. See Section A.3 for more details on the experimental design.

Product	Option A	Option B
Information		✓
Infrastructure	✓	
Insurance		✓
Price	PHP 50	PHP 100

○ Option A
○ Option B
○ Neither of the two options

Fig. 1. Example choice card
Note: Example of a choice card showing a possible combination of attributes as used for the explanation of the experiment to the respondents.

et al., 2023; Kanninen, 2007). The interviewer provided an information sheet with a description of each attribute in simple, straightforward language, including pictograms for better comprehensibility. To ensure that the respondent clearly understood the choice cards and the attributes, the interviewer showed an example choice card and explained it in detail to the respondent. A diagrammatic illustration of how insurance works was also provided, as it is assumed that respondents' exposure to insurance schemes is limited (see Fig. A1 in the Appendix). The interviewer only proceeded with the first choice card once they were sure that the respondent had a good understanding of the choice experiment. Third, follow-up questions were included to identify so-called *protest responses* and to evaluate how focused the respondents were during the experiment (see Sections 3.5 and 3.6). All study tools were pretested to allow for a refinement of the questions, attributes, choice cards and descriptions.

3.5. Data cleaning

Following the data collection, the sample is reduced to include only respondents who are the main decision-makers in the enterprise. We also exclude firms with more than nine employees or assets exceeding PHP 3 million, as these enterprises are not considered micro-enterprises (Department of Trade and Industry, 2018). In total, six respondents are removed from the sample. Furthermore, protest responses are identified and removed from the sample. Those occur when respondents who reject or disagree with the survey do not respond, make invalid but positive choices or give a zero rating to a good for which they have positive or negative preferences. If protest responses are not identified and excluded from the sample, the results of the study may be misinterpreted (Halstead et al., 1992). In this study, respondents are identified who opted for the status quo alternative two or more times. Such respondents are referred to as serial non-participants (Von Haefen et al., 2005). These respondents receive a follow-up question on their motives for such responses (see Table A1 in the Appendix). Respondents who either indicate that they do not feel a responsibility to pay for climate risk management, assume that the money would be used for other purposes or state that they do not understand the choice experiment are considered protest respondents and excluded from the sample (Crastes et al., 2014). In total, 34 people are considered protest respondents and removed from the survey. Finally, four respondents are excluded due to missing values in survey questions related to socio-demographic or socio-economic variables required for the analysis. At the end of the data cleaning, 581 respondents are left in the final sample.

3.6. Choice consistency

We perform several checks to assess choice consistency. First, the interviewers are asked to rate the degree to which respondents are concentrating during the DCE. Second, we examine whether respondents always choose the same option on all choice cards. Third, we investigate respondents' rationality. In line with economic theory, individual choices should be *monotonic*, i.e., the utility of an individual should decrease as the price increases (Kanninen, 2007). Since no restrictions are posed on the model, for example regarding possible combinations of attribute levels, some choice cards contain *dominated alternatives*, i.e., one alternative is worse than the other in the price attribute but equal in the non-monetary attributes. If a dominated alternative is chosen, the choice may be classified as irrational. Overall, we rate the choices of approximately 85% of all respondents as consistent and rational because they are focused during the choice experiment, do not choose an alternative that is dominated by another alternative and do not always choose the same option on all choice cards.[6]

4. Statistical methodology

4.1. Random parameter logit model

DCEs are based on a utility-maximising framework. It is assumed that each individual chooses the alternative whose attribute combination maximises their utility. The underlying utility of an individual $i \epsilon \{1, \ldots, N\}$ facing alternative $j \in \{1, \ldots, J\}$ on a choice card $t \in \{1, \ldots, T\}$ can be expressed as follows:

$$u_{ijt} = x_{ijt}\beta + \epsilon_{ijt,} \tag{1}$$

[6] The proportion of respondents choosing a dominant alternative is comparable to that found in Soliño et al. (2012). In their experiment on consumer preferences for electricity from forest biomass, the authors conduct detailed tests for stability and choice dominance and show that between 78% and 84% of respondents pass the dominance test, while approximately 35% show unexpected behaviour in any form.

where u_{ijt} is the latent utility. The systematic component is assumed to be a linear function of the observed explanatory variables:

$$x_{ijt}\beta = \beta^{ASC} + \beta^{IN} IN_{ijt} + \beta^{IF} IF_{ijt} + \beta^{IS} IS_{ijt} + \beta^{PR}\, PR_{ijt.} \quad (2)$$

The explanatory variables include the variables information (*IN*), infrastructure (*IF*), insurance (*IS*) with two levels, and price (*PR*) with three levels (see Table 1). Moreover, an alternative specific constant (ASC) is included. This variable captures the effect of all variables not included in the model, but which influence the choice of leaving the current state. It equals 1 if a non-status quo option is chosen, 0 otherwise.[7] It is assumed that the unobserved error term ϵ_{ijt} is independent and identically distributed and follows a standard Gumbel distribution.

The simple multinomial logit (MNL) model described above does not account for individual-specific heterogeneity and assumes that the relative chances of choosing alternative j over alternative k are always the same, independent of the attributes of the other alternatives (*independence of irrelevant alternatives assumption*). To relax these assumptions, we extend the model and allow the parameters to vary randomly over individuals by assuming an a priori parameter distribution. This model, also called the RPL model, accounts for the panel structure of the data and captures everything that is constant across individuals' choices but varies across individuals. In this model, the utility for individual *i* for alternative *j* on choice card *t* is given by:

$$u_{ijt} = x_{ijt}\beta_i + \epsilon_{ijt,} \quad (3)$$

where β_i is an unobserved parameter vector which is assumed to vary across respondents following a multivariate normal distribution (Sarrias and Daziano, 2017).

Allowing both the non-monetary and the monetary parameter to vary randomly across individuals may lead to undefined distributions for the WTP estimates. Therefore, we hold the price coefficient fixed while assuming the other parameters to be normally distributed. To account for heterogeneity in the price coefficient, we follow Crastes et al. (2014) and interact it with observed characteristics. The adjusted price coefficient is given by:

$$\beta^{PR_a} = \beta^{PR} + \beta^{EMP}\overline{EMP} + \beta^{GE}\overline{GE} + \beta^{INV}\,\overline{INV}, \quad (4)$$

where the variables Employees ($\overline{EMP}$), Gender ($\overline{GE}$) and Investment ($\overline{INV}$) are the respective sample averages.

We further allow time-invariant individual characteristics to influence the mean of the non-monetary utility parameters. In particular, we interact the non-monetary parameters with the variables *Information event*, *Urban* and *Impact,* which allows us to study heterogeneity. In addition, we allow for correlation between the random parameters. This enables us to capture scale heterogeneity and avoid imposing a specific and restrictive correlation structure of the random parameters (Mariel et al., 2021a,b; Mariel and Meyerhoff, 2018). The parameter estimates are obtained using maximum likelihood estimation procedures.

4.2. Willingness to pay and compensating variation

The estimated coefficients of the RPL model are marginal utilities and cannot be interpreted in absolute terms. We alter the coefficients to interpret them in terms of WTP. Therefore, WTP is obtained as the negative ratio of the non-monetary attribute coefficient over the adjusted price coefficient from Equation (3):

$$WTP = -\frac{\beta}{\beta_{PR_a}}. \quad (5)$$

Standard errors for the WTP parameters are estimated using the delta method (Holmes et al., 2017).[8]

To measure the effect of a change in one or multiple attributes on respondents' utility based on the random utility framework (Hanemann, 1984), we calculate the *CV* by summing over the relevant WTP estimates:

$$CV = -\frac{V_0 - V_1}{\beta_{PR_a}}, \quad (6)$$

where V_0 is the utility of the current state and V_1 the utility of a change scenario (Crastes et al., 2014). To give an example, the CV for a single management policy consisting of climate risk insurance only is obtained as follows:

$$CV_{IS} = WTP_{ASC} + WTP_{IS} + WTP_{ISxIE}\overline{IE} + WTP_{ISxUR}\overline{UR} + WTP_{ISxIM}\overline{IM}, \quad (7)$$

where the variables Information event ($\overline{\text{IE}}$), Urban ($\overline{\text{UR}}$) and Impact ($\overline{\text{IM}}$) are the respective sample averages.

5. Results and discussion

5.1. Sample characteristics

First, we conduct a descriptive analysis of the sociodemographic and socioeconomic characteristics of the respondents and enterprises (see Table A2 in the Appendix). The age of the respondents in the sample ranges from 18 to 79 years, with an average age of 46 years. More than two-thirds of all respondents in the sample have completed secondary education (71%). Four out of five of the enterprise owners identify themselves as women. This is not surprising because the majority of micro-enterprises operate in wholesale and retail trade, a sector in which female entrepreneurs predominate in the Philippines (Department of Trade and Industry, 2021b; Philippines Statistics Authority, 2020). Moreover, the Philippines has the narrowest gender gap of all Asian countries, and more women than men are in leadership positions (World Economic Forum, 2020). The mean net annual income, calculated as gross income minus all expenses (including labour costs), of a micro-enterprise in a typical year was PHP 82,130 (USD 1619.65, date: 31 December 2019). More than two-thirds of all enterprises are located in rural areas. The number of employees in the enterprises ranges from 1 to 8 ($M = 1.47$, $SD = 0.84$), with most of the enterprises in the sample consisting only of the owner and having no other permanent employees. Most enterprises in our sample operate within the local market. A significant portion of these businesses are sari-sari shops, small, locally owned stores often located within the owner's home, where goods are sold through windows. This is followed by the accommodation and food services sector. These two sectors are also the two leading industries in terms of the number of Micro, Small and Medium-sized Enterprises (MSMEs) in the Philippines in 2022 (Department of Trade and Industry, 2021a). The majority of the enterprises were founded recently, with the median enterprise founded in 2016. This can be explained by a high failure rate and short lifespans of micro-enterprises in the Philippines (Garcia et al., 2019). The majority of the enterprises have made investments in the past 12 months, mostly for business expansion, followed by investments in new technologies or product development. Few enterprises reported

[7] Excluding the ASC from the calculations may result in an overestimation of the results because general preference for change may be absorbed into the attribute estimates. As a result, the non-monetary attribute estimates may become inflated as the model incorrectly attributes the general preference for change to the attributes. Including the ASC separates the unobserved preference for change from attribute-specific effects.

[8] In addition to estimating the random parameter logit model in preference space, we also estimated the model directly in WTP space as a robustness check. In the WTP space specification, WTP estimates are obtained directly as model parameters, rather than being derived as ratios of coefficients. We present these results and discuss their consistency with the main model specification in Section 5.2.4.

investment in climate-resilient infrastructure (6%), although nine out of ten said they had been exposed to at least one shock due to climate risks between 2017 and early 2020, and more than 70% rated its impact on their business as medium or high. Respondents indicated that past extreme weather events have had the greatest impact on markets, followed by the impact on land, housing and buildings. Most respondents did not receive financial compensation for their losses. The few enterprises that received compensation mainly got support from the government, with only a small number receiving payouts from insurance companies. Typhoons and strong winds are the most pressing climate risks faced by enterprises, followed by river or lake flooding and heavy rainfall. More than half of companies reported feeling inadequately prepared for climate risks, with fewer than 5% having climate risk insurance. Notably, around two-thirds of respondents indicated that they had no insurance coverage at all, and nearly half felt they were not well-informed about insurance options. Despite this, enterprises expressed a strong demand for insurance products. Most entrepreneurs stated they would purchase insurance to protect against typhoons and strong winds (98%), river or lake flooding and heavy rains (92%), drought (86%), and heat waves (76%). Of the respondents, 42% stated that their company had participated in at least one climate risk information event, usually conducted by the government. Typically, an event includes a workshop or training, usually lasting a few days, providing information on climate risks and ways to reduce and manage them, including how (index) insurance works.

5.2. Preferences and willingness to pay

5.2.1. Preference estimates

Table 2 shows the RPL estimates (column 1) of our baseline specification. For the RPL estimates, the coefficient of the ASC is positive and significant, thus suggesting that the entrepreneurs are, on average, willing to depart from the status quo to better adapt their enterprises to climate risks. Indeed, only on 4% of all choice cards did a respondent select the status quo option, suggesting a limited status quo *bias,* which would imply aversion to change (Meyerhoff and Liebe, 2009; Samuelson and Zeckhauser, 1988). For the random variables, the estimated means and standard deviations are depicted. The means of the parameter estimates show that the presence of a stated non-monetary attribute significantly increases the probability of selecting an alternative, while a higher price decreases it, with all other attributes constant. The parameter estimates cannot be interpreted directly, but can be compared in magnitude. Entrepreneurs have the highest preference for climate risk insurance, followed by improvements in climate-resilient and protective infrastructure and lastly, by improvements in information sharing related to early warnings. The standard deviations indicate that there is substantial latent heterogeneity in entrepreneurs' preferences since the coefficients *Information.SD, Infrastructure.SD* and *Insurance.SD* are highly significant, supporting the inclusion of random parameters in the model.[9]

When examining heterogeneity in the monetary attribute, it appears that enterprises that have made any investments in the previous 12 months have a higher WTP. This is not surprising, as past investment behaviour is often a good predictor for future investment behaviour (Ajzen, 1991). Moreover, we find that male respondents are, on average, willing to pay more for climate risk management. This result can be partly explained by differences in financial literacy. While more than 60% of all

Table 2
Preference and WTP estimates.

Variable	Preference	WTP
	(1)	(2)
ASC	1.927*** (0.212)	146.260*** (12.866)
Main Effects		
Information	1.156*** (0.244)	87.766*** (19.216)
Infrastructure	1.554*** (0.191)	117.928*** (16.570)
Insurance	3.279*** (0.357)	248.845*** (28.198)
Price	−0.026*** (0.003)	
Latent heterogeneity		
Information.SD	1.144*** (0.280)	
Infrastructure.SD	0.603*** (0.201)	
Insurance.SD	2.160*** (0.396)	
Observed heterogeneity		
Price x Employees	0.001 (0.001)	
Price x Gender	0.005* (0.002)	
Price x Investment	0.012*** (0.002)	
Information x Info. event	0.522** (0.200)	39.631** (15.158)
Information x Urban	0.047 (0.212)	3.533 (16.069)
Information x Impact	0.012 (0.213)	0.932 (16.188)
Infrastructure x Info. event	0.596*** (0.156)	45.199*** (12.044)
Infrastructure x Urban	−0.159 (0.164)	−12.102 (12.461)
Infrastructure x Impact	−0.143 (0.165)	−10.877 (12.563)
Insurance x Info. event	0.577** (0.191)	43.784** (14.473)
Insurance x Urban	0.492* (0.216)	37.350* (16.227)
Insurance x Impact	−0.240 (0.206)	−18.208 (15.725)

Note: Number of observations: 3,486; Number of respondents: 581; AIC: 3722.3; BIC 3863.9, Log-likelihood: -1838.1. The model is estimated with correlated random parameters. The maximum likelihood estimation using the Berndt-Hall-Hall-Hausman (BHHH) optimisation algorithm is based on 1000 pseudo-random draws. Standard errors for the WTP parameters are estimated using the delta method (Hole, 2007). *, ** and *** indicate significance levels of 0.05, 0.01 and 0.001, respectively.

male respondents state they were mostly or completely informed about insurance, less than half of all female respondents agree with this statement.[10] Another factor explaining the heterogeneous preferences between men and women may be differences in the level of trust entrepreneurs have in insurance institutions. For example, Akter et al. (2016) identify differences in institutional trust and financial literacy as the main factors explaining insurance aversion among female farmers in Bangladesh for weather-index insurance. We did not find clear evidence that the number of employees influences entrepreneurs' WTP.

Examining observed heterogeneity in preferences, we find that entrepreneurs who have participated in an information event on climate risks have higher preferences for all proposed climate risk management strategies. This is consistent with other studies showing that communication about climate risks can influence people's risk awareness and adaptation behaviour (Botzen & Van Den Bergh, 2012a; Brouwer and Schaafsma, 2013; Crastes et al., 2014). There is no evidence that respondents' preferences for the given risk management strategies depend on the impacts of past extreme weather events (Abatayo and Lynham, 2020; Shao et al., 2017). This might be explained by the fact that two effects cancel each other out. On the one hand, entrepreneurs who have been severely affected by past weather events might have a higher risk awareness, which could increase their demand for climate risk management. On the other hand, these entrepreneurs might have already taken measures to manage climate risks or to cope with the shocks caused by extreme weather events, e.g., secured access to emergency loans, leading to lower demand for additional strategies. Lastly, we find that respondents living in urban regions have higher preferences for climate risk insurance. This may partly be because entrepreneurs of

[9] The likelihood ratio test is highly significant rejecting the null hypothesis of no random effects ($\chi^2(3) = 121.7$, $p < 0.001$). This confirms that the RPL model with random parameters fits the data significantly better than the basic MNL model. Further, allowing for correlations among the random parameters significantly improves model fit compared to an uncorrelated RPL ($\chi^2(3) = 13.76$, $p < 0.01$), supporting the use of the correlated RPL specification.

[10] A Pearson's chi-squared test run between *Gender* and *Insurance Literacy* was found to be significant $\chi^2(1) = 5.7, p < 0.02$).

enterprises in urban areas indicated being better informed about insurance than entrepreneurs in rural areas.[11]

5.2.2. Willingness to pay

The WTP estimates in column 2 of Table 2 show that entrepreneurs are, on average, willing to pay PHP 146 per month to depart from the status quo of climate risk management. Respondents are willing to pay per month PHP 249 to insure their business against climate risks, PHP 118 to improve and develop local climate-resilient infrastructure and PHP 88 to strengthen early warning systems and to increase the availability of risk information tailored to local needs. The mean WTP values vary greatly and significantly, depending on enterprise characteristics. Entrepreneurs that have participated in a climate risk information event are, on average, willing to pay PHP 40 more for improvements in early warning systems, PHP 45 more for the development of climate-resilient and protective infrastructure and PHP 44 more for climate risk insurance than enterprises that have not participated in such an event. Furthermore, enterprises located in urban areas are, on average, willing to pay PHP 37 more for climate risk insurance than enterprises located in rural areas.

5.2.3. Compensating variation

Table 3 provides CV estimates for various climate risk management scenarios. As discussed in detail in Meyerhoff et al. (2009), the choice of including or excluding the ASC in the model may substantially affect the size and even direction of the estimated coefficients. The ASC reflects unobserved factors that could explain why respondents choose one of the two options for improving disaster risk management. Excluding it from the CV calculations might lead to an underestimation of the results. However, the ASC could also capture *yes-saying* responses. These occur when respondents choose one of the two presented options, regardless of the attribute levels. The inclusion of the ASC in this case would lead to an overestimation of the results. Therefore, we calculate the CV measure twice, once including and once excluding the ASC (Meyerhoff et al., 2009; Morrison et al., 2002).

The mean CV for improvements in early warning systems, the development of climate-resilient and protective infrastructure and climate risk insurance are PHP 106 (252), PHP 126 (272) and PHP 264 (410), respectively, relative to the status quo when excluding (including) the ASC. The results show that entrepreneurs value climate risk insurance about twice as much as the other strategies. The mean CV for a hypothetical strategy including all three presented climate risk management strategies amounts to PHP 496 (642), which corresponds to approximately 7.2% (9.4%) of the mean net income of the enterprises in the sample.[12]

Table 3
Compensating variation for various climate risk management strategies.

	ASC = 0	ASC = 1
Single risk management strategy		
Information	106	252
Infrastructure	126	272
Insurance	264	410
Multiple risk management strategies		
Information and Infrastructure	232	378
Information and Insurance	370	516
Infrastructure and Insurance	390	536
Information, Infrastructure and Insurance	496	642

Note: The monetary values are depicted in PHP per month. The calculations are based on the estimates of the WTP model depicted in column 2 of Table 2. Number of observations: 3,486. Number of respondents: 581.

The results in Table 4 show substantial CV differences depending on enterprise characteristics. The average enterprise located in a rural area that has not been highly impacted by any extreme weather event and participated in a climate risk information event has the largest preferences for the development of climate-resilient and protective infrastructure (PHP 163). In contrast, the benefits of improvements in early warning systems are highest for enterprises located in urban areas that have been highly exposed to at least one extreme weather event and that participated in at least one climate risk information event (PHP 132). Climate risk insurance is most preferred by enterprises in urban areas that have not been highly impacted by any extreme weather event but have participated in at least one climate risk information event (PHP 330). Although preferences for climate risk management strategies vary by enterprise characteristics, climate risk insurance is always the preferred risk management option.

5.2.4. Robustness of the results

The findings of the experiment are robust to variations in model specifications and composition of the final sample. The simple MNL model from Equation (1) and the MNL models accounting for latent heterogeneity are reported in columns 2 and 3 of Table A3. Moreover, we present an RPL model accounting for latent heterogeneity and allowing for correlated random effects (but not observed heterogeneity) in column 4 of Table A3. Lastly, the RPL model, which includes all two-way interaction effects, is reported in column 2 of Table A4. All estimated coefficients remain consistent in magnitude, sign, and significance with those of the baseline model. This reassures us that our key findings are not dependent on the random parameter assumptions.

The baseline model used in this analysis captures everything that is constant across individuals' choices but varies across individuals, thereby accounting for potential differences in interviewer explanations of the experiment and the attributes and levels. This allows us to rule out the possibility that we are measuring heterogeneity in what respondents believed each attribute to be following the interviewer's explanation, rather than heterogeneity in preferences. Moreover, we show that the results do not significantly change by the inclusion of respondents who are found to have given protest responses (column 3 in Table A4). Also, stability and choice dominance are relevant criteria for the internal

Table 4
Compensating variation for various enterprise profiles.

		Rural		Urban	
		Impact = 0	Impact = 1	Impact = 0	Impact = 1
Information	Info. event = 0	88	89	91	92
	Info. event = 1	127	128	131	132
Infrastructure	Info. event = 0	118	107	106	95
	Info. event = 1	163	152	151	140
Insurance	Info. event = 0	249	231	286	268
	Info. event = 1	293	274	330	312

Note: The monetary values are depicted in PHP per month. The calculations are based on the estimates of the WTP model depicted in column 2 of Table 2. Number of observations: 3,486. Number of respondents: 581.

[11] A Pearson's chi-squared test run between *Urban* and *Insurance Literacy* was found to be highly significant ($\chi^2(1) = 16.15, p < 0.001$).

[12] The net income equals the net profit for micro-enterprises and is substantially lower than the gross income. Therefore, the WTP share of net income is higher than it would be if expressed as a proportion of gross income.

validity of choice experiments, as unexpected choices or inconsistencies may distort the estimated preferences (Soliño et al., 2012). Therefore, we conduct a sub-analysis restricting the sample to individuals whose choices are found to be consistent and rational. The results of this analysis confirm the robustness of our baseline model (column 4 in Table A4).

In our baseline specification, we estimate the RPL model in preference space, deriving WTP estimates indirectly. To avoid undefined distributions for the WTP estimates, we fix the price coefficient and interact it with observed characteristics to account for heterogeneity (see Section 4). However, this approach may not fully capture all potential heterogeneity with respect to the monetary attribute (Mariel et al., 2021a,b). To address this, we re-estimate the model in WTP space, directly estimating the WTP for each attribute while allowing for random heterogeneity in the ratio between the non-monetary attribute coefficient and the price coefficient (Mariel et al., 2021a,b; Sarrias and Daziano, 2017). Table A5 in the Appendix presents the main WTP coefficients of our baseline model estimated in preference space (column 1), as well as the WTP estimates for the simple MNL model, which are identical regardless of whether the model is estimated in preference or WTP space (column 2). The WTP estimates from the RPL model with uncorrelated parameters (column 3) and with correlated parameters (column 5), obtained indirectly, hardly deviate from those obtained by estimating the model directly in WTP space (columns 4 and 6). These results confirm the validity of our WTP estimates.

Another point is that using too few draws in maximum likelihood estimation can introduce bias in log-likelihood values, parameter estimates, and the calculation of standard errors (Czajkowski and Budziński, 2019; Mariel et al., 2021a,b). As shown in Table A6, our results remain stable when using 50, 100, 1,000, 2,000, or 5000 pseudo-random or Halton draws. In our baseline specification, we chose 1000 pseudo-random draws, as this ensures robust and reliable estimates while keeping the computational burden manageable.

Lastly, we examine the role of the ASC in our RPL model. As discussed in Section 4.1, the ASC captures unobservable influences beyond present attributes on the likelihood of choosing an alternative over the status quo. Excluding the ASC from our calculations may lead to an overestimation of preference estimates, as the general preference for change may get absorbed into the attribute estimates (Meyerhoff et al., 2009). This effect is evident when estimating our baseline model without the ASC (see column 2 of Table A7 in the Appendix). While the relative magnitude of coefficients remains stable, the non-monetary attribute estimates appear inflated, as the model attributes the general preference for change to the attributes themselves. To further explore heterogeneity in status quo preferences, we allow the ASC to vary randomly across individuals (see column 3 of Table A7). This approach helps us better capture variations in respondents' inherent inclination toward maintaining the status quo. The results of this analysis indicate significant latent heterogeneity in respondents' preferences for the non-status quo option. This suggests that individuals differ systematically in their baseline preferences towards change. When examining the interactions between the ASC and the observed characteristics, we find that entrepreneurs who have experienced at least one climate-related event and those who have participated in climate risk information events exhibit a stronger preference for change compared to the status quo. This suggests that personal exposure to climate risks and increased awareness contribute to a greater willingness to adopt alternative options over maintaining the current situation.

5.3. Limitations and areas for future research

As shown in Section 5.2.4, the results of the DCE are very robust regarding model specifications and sample composition. However, even if the statistical validity is high, there may be small inaccuracies in the WTP estimates. On the one hand, there may be further benefits beyond those of managing climate risks (e.g., more reliable supply chains through infrastructure improvements or a general improvement of information flows). If respondents did not consider the additional benefits in their decision-making during the experiment, this would lead to an underestimation of WTP (Crastes et al., 2014; Westerberg et al., 2010). Moreover, there may be a concern that respondents could strategically underreport their willingness to pay for public goods (*free-rider problem*), or that they are not accustomed to paying directly for public goods, as they perceive these to be services provided by the government. Consequently, we may underestimate their preference for strategies including local public goods, such as infrastructure and information. On the other hand, although we have taken care to avoid hypothetical bias through the use of specific wording, there may be a discrepancy between the decisions made in this non-incentivized experiment and the choices made when entrepreneurs face real-world problems and the consequences of their decisions. This could lead to an overestimation of WTP (Johnston et al., 2017; Kanninen, 2007).

Moreover, using qualitative two-level (yes/no) attributes may not lead to the most statistically efficient design. However, as Johnston et al. (2017) point out, such designs can be practical and appropriate, especially when considering the cognitive load and attention span of respondents. The simplicity of binary attributes reduces respondent fatigue and makes the survey more accessible, potentially improving response quality. Our approach aims to balance statistical efficiency with practical considerations, ensuring that the key effects of interest are estimated reliably.

This study opens several avenues for future research. First, the choice experiment could be expanded to include additional climate risk management strategies. Additional risk transfer measures, such as risk-sharing arrangements or solidarity funds, could be included, as could other community- or firm-level adaptation strategies. This would allow finer distinctions to be made in terms of preferences and WTP and would capture a more comprehensive set of risk management strategies. To ensure the additional strategies are both relevant and feasible, they should be selected based on a thorough literature review and qualitative research, such as expert interviews or focus groups. Furthermore, consideration should be given to the potential cognitive burden placed on respondents.

Second, given that our choice experiment was considered easy to understand and cognitively not too challenging, further variations beyond two-level attributes may be feasible with a similar target group (Johnston et al., 2017). This would provide more detailed insights into how micro-entrepreneurs evaluate variations in strategy intensity, coverage levels, or pricing structures.

Third, the experiment could be replicated in different countries, with different types of enterprises, or as a follow-up study in the Philippines after a certain period. This would enable preferences to be compared across contexts, over time, in relation to firm size or capital stock. These replications would provide a more comprehensive understanding of the factors that determine enterprises' adaptation preferences, such as socio-economic, geographic, or temporal influences.

Finally, the finding that participation in climate risk information events increases preferences for all risk management strategies could be examined through randomised controlled trials. For instance, future studies could randomly assign participants to receive targeted climate risk information and then compare choice outcomes across groups. This would provide more rigorous evidence on the causal role of information in shaping adaptation preferences.

6. Policy implications

The study's findings carry significant policy implications for climate risk management in the Philippines and similar contexts.

First, policymakers should integrate the needs and preferences of MSMEs into climate adaptation plans and policies, and increase public investment to improve climate risk management in the Philippines. Our results show that micro-enterprises are highly exposed to climate extremes and vulnerable to their impacts, with over 70% of surveyed firms experiencing medium or high negative effects from climate-related shocks in recent years. Prior studies have shown that a lack of adequate risk management can force micro-enterprises to close, threatening both livelihoods and the broader economy (Ballesteros and Domingo, 2015; Casado-Asensio et al., 2021). Findings from our DCE reveal that many micro-enterprises recognise these risks and are willing to invest a substantial share of their net income in climate risk management strategies, namely, climate risk insurance, resilient infrastructure, and improved information. These results highlight the urgent need for policymakers to expand and improve climate risk management options for micro-enterprises in the Philippines.

Second, targeted efforts are needed to bridge the gap between the current level of insurance coverage and the strong demand among micro-entrepreneurs. Entrepreneurs in our sample show the strongest preference for climate risk insurance, substantially higher than for resilient infrastructure or improved information. This high preference is likely shaped by previous negative experiences with climate events. Many micro-entrepreneurs reported that strategies to reduce exposure or impact alone were often insufficient to adequately prevent losses and that compensation from other sources, such as government support, was inadequate.

Although climate risk insurance is considered particularly important, only a minority of micro-enterprises in the Philippines are insured. The reasons for this lie on both the supply and demand side of insurance: While enterprises may underestimate future risks as climate change progresses, the feasibility of providing insurance may become increasingly limited (Dougherty et al., 2020). That is because risk increases and negative impacts of climate disasters are often highly correlated, making climate risk insurance a high-risk product. Insurance providers may either choose not to offer an insurance product at all or may not be able to bear the risk alone. Reinsurance or third-party risk finance has to be involved, which in turn increases premium levels or requires external support to bear the risk (Leppert et al., 2021; Mechler et al., 2014; Mechler and Deubelli, 2021). Regulatory constraints, such as insurance taxation, and the costs of obtaining the required client and climatic data further limit the financial viability of climate insurance products. Climate risk insurance is therefore often not available or affordable for individuals, thus explaining the low insurance density (Linnerooth-Bayer and Hochrainer-Stigler, 2015; Surminski and Panda, 2020; Wiedmaier-Pfister, 2022).

To improve access to insurance and provide adequate risk coverage for actors or areas at high risk, third-party risk finance, such as high-risk pools, high-cost pools, or (subsidised) prospective risk adjustment, might be mechanisms for enabling insurers to operate in such markets. They can, if properly designed, increase the economic insurability of those who face high risks, while needs-based premium subsidies can provide coverage for those who have limited ability to pay (Collier et al., 2009; Hill et al., 2014; Leppert, 2012). As direct premium subsidies can provide the wrong economic incentives, such as moral hazard or over-investment in high-risk activities or areas, they need to be used carefully in an indirect and incentive-compatible way to increase coverage and social protection (Becker and Oslislo, 2022; Cummins and Mahul, 2008; Gunnsteinsson, 2020; IPCC, 2022; Linnerooth-Bayer et al., 2009). Index-based insurance may help to overcome adverse selection and moral hazard concerns as well as administrative burdens, and it may support timely payouts.[13]

Based on our findings, policymakers should increase their efforts to bridge the insurance gap in countries that are vulnerable to climate risks. This requires the implementation of innovative instruments to ensure the sustainability and growth of climate risk insurance. These could include promoting index-based insurance, sustaining insurance through reinsurance, providing targeted premium subsidies for vulnerable groups, and expanding access to third-party risk finance mechanisms, such as high-risk or high-cost pools. For the insurance industry, the results of this study signal a strong unmet demand for climate risk insurance among micro-enterprises. Insurance providers could explore developing more accessible, affordable products tailored to small businesses' needs.

Third, policymakers should prioritise integrated climate risk management strategies that combine both instruments to reduce risk exposure or impact and risk transfer instruments. Prior research shows that the interplay of various instruments is important in achieving comprehensive climate risk management (IPCC, 2022; Leppert et al., 2021). This study provides evidence of entrepreneurs' strong preference for integrated policies, including risk exposure or impact reduction and risk-transfer strategies. Our findings indicate that micro-entrepreneurs are, on average, willing to pay at least 7.2% of the mean net income (PHP 625 per month) for an integrated policy including all presented risk management strategies compared to the status quo.[14] Therefore, policymakers should focus on policies including both risk exposure or impact reduction measures and risk transfer instruments, rather than focusing on single measures alone.

Fourth, policymakers should acknowledge that the preferences of micro-entrepreneurs for climate risk management differ. In particular, they should prioritise efforts to strengthen the financial and insurance literacy of entrepreneurs in rural areas and amongfemale entrepreneurs and increase investment in climate risk information campaigns and trust-building measures. Our findings show that enterprises operating in rural areas have considerably lower preferences for climate risk insurance compared to their urban counterparts. Similarly, female entrepreneurs are on average willing to pay less for climate risk management. We find suggestive evidence that lower insurance literacy among female entrepreneurs and entrepreneurs in rural areas explains part of this. Consistent with existing literature, these findings suggest the benefits of strengthening financial and insurance literacy, particularly for female entrepreneurs and those in rural areas, and highlight the importance of information and trust-building measures to enhance institutional credibility (Akter et al., 2016; Carter et al., 2014; Clarke and Grenham, 2013). Moreover, we find that participation in climate risk information events is significantly related to higher preferences for all proposed strategies for managing climate risk. The finding aligns with other studies showing that risk communication by external actors increases preferences for climate risk management strategies (Botzen & Van Den Bergh, 2012a; Brouwer and Schaafsma, 2013; Crastes et al., 2014). These results emphasise the value of targeted financial literacy programs and trust-building initiatives to enhance climate risk management.

[13] In contrast to indemnity-based insurance, in index-based insurance, the payout is not determined by the degree of damage to the insured asset but by a predetermined index of climate risk exposure (proxy or parameter) that should be highly correlated with the insured loss. The most commonly used index is the rainfall level, but temperature and satellite-measured vegetation indices are also used for contract design (Miranda and Farrin, 2012).

[14] While our results indicate substantial stated WTP, actual uptake of climate risk management strategies, such as insurance, may be lower in practice. Real-world adoption could be influenced by factors outside the experiment's scope, including cash flow constraints, limited access to credit, or trust in providers. Although we took care to minimise hypothetical bias by framing scenarios realistically and including a status quo option, non-incentivized stated preference methods can still overstate willingness to pay when choices are not binding. Thus, the reported WTP figures should be interpreted as indicative of potential demand and the relative value micro-entrepreneurs place on different adaptation strategies, rather than as precise forecasts of market behavior (see also Section 5.3).

7. Conclusion

Given the accelerating climate crisis, climate risk management is of utmost importance. At the global level, climate change adaptation actions are expected to increase under international agreements such as the United Nations Framework Convention on Climate Change, global efforts such as the Global Shield by the G7 and V20, and new priorities in development cooperation (Becker and Sieberichs, 2023). To align interventions with recipient interests and needs and to allocate funds efficiently, it is essential to consider vulnerable actors' preferences for dealing with climate risks. However, empirical evidence on the preferences of specific vulnerable groups, such as micro-enterprises in the Philippines, is still insufficient.

In this study, we elicit the preferences of micro-entrepreneurs in the Philippines for relevant climate risk management strategies using a DCE. Our results indicate that micro-enterprises are highly aware of climate risks and are willing to invest a significant share of their net income in risk management. We find the strongest demand for integrated approaches that combine risk exposure or impact reduction measures (better information and infrastructure investments) with risk transfer instruments (climate risk insurance). On average, micro-entrepreneurs are willing to pay at least 7.2% of their net income for comprehensive risk management policies. Out of all single strategies examined, climate risk insurance is the most preferred option among micro-entrepreneurs in the Philippines. Despite this strong stated willingness to pay for insurance, actual uptake remains low, reflecting persistent challenges on both the supply and demand sides.

Moreover, while overall preferences for climate risk management are high, they are markedly heterogeneous across groups. Our results suggest that climate risk information events, as well as targeted financial and insurance literacy initiatives, particularly for female entrepreneurs and enterprises operating in rural areas, may further increase entrepreneurs' preferences and willingness to pay for climate risk management.

With this study, we contribute to the literature on climate risk and environmental management by improving the understanding of vulnerable populations' preferences for climate change adaptation. Conducting a large-scale DCE, we elicit both the latent utilities and the willingness to pay of micro-enterprises for single and integrated climate risk management strategies. These insights are essential for designing needs-based policies and improving access to effective adaptation options, ultimately supporting the climate resilience of vulnerable groups. In addition, we add to the literature on stated preference methods by demonstrating that DCEs are a promising tool for identifying adaptation preferences among micro-entrepreneurs in low- and middle-income countries, with considerable scope for further application in similar contexts.

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CRediT authorship contribution statement

Ann-Kristin Becker: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Gerald Leppert:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Alexandra Köngeter:** Writing – review & editing, Writing – original draft, Resources, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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A Appendix.

A.1 Additional tables

Table A1
Identification of protest responses

	Answer category	Number
A	I am not concerned with climate risks such as floods, droughts and typhoons	14
B	It is not me who has to pay to manage the situation.	18
C	I believe that none of the options will change anything.	20
D	I support the products in general, but my enterprise could not pay for either of the two options.	30
E	I think that the collected money will be used for other purposes.	24
F	I did not understand the cards.	1

Note: This table shows all possible answers to the question of why the respondent chose the status quo option more than once (Answer category) and the frequency with which each of the answer categories was selected (Number). If respondents opted for B, E or F, it was considered an expression of protest behaviour, and they were excluded from the sample. Note that multiple answers were possible. Number of respondents: 58.

Table A2
Descriptive statistics

Variable	Code	Mean	Min	Max	Median	SD
Age	Continuous	46.12	18	79	47	12.03
Gender	1 = man, 0 = woman	0.19	0	1	0	0.4
Education	1 = secondary education or higher, 0 otherwise	0.71	0	1	1	0.45
Urban	1 = urban, 0 = rural	0.27	0	1	0	0.44
Employees	Continuous	1.47	1	8	1	0.84
Foundation	Continuous	2012	1955	2019	2016	9.52
Income[(a)]	Continuous	82.13	0.5	5400	36	257
Investment	1 = any investments in the past 12 months, 0 otherwise	0.88	0	1	1	0.33
Exposure	1 = exposed to any climate risk between 2017 and early 2020, 0 otherwise	0.90	0	1	1	0.3
Impact	1 = exposed to any climate risk with medium or high impact between 2017 and early 2020, 0 otherwise	0.72	0	1	1	0.45
Preparedness	1 = perceives to be not sufficiently prepared for most pressing climate risks, 0 otherwise	0.53	0	1	1	0.5
Information event	1 = participation in any climate risk information event, 0 otherwise	0.42	0	1	0	0.49
Insurance literacy	1 = mostly or completely informed about insurance, 0 otherwise	0.52	0	1	1	0.5

Number of respondents: 581.
[(a)] Annual net income in thousands of PHP is calculated as gross income minus expenses. Number of respondents: 577.

Table A3
Preference estimates with different model specifications

	Baseline	MNL	RPL	RPL Corr.
	(1)	(2)	(3)	(4)
ASC	1.927*** (0.212)	1.441*** (0.137)	1.529*** (0.147)	1.738*** (0.157)
Main Effects				
Information	1.156*** (0.244)	0.763*** (0.073)	0.962*** (0.093)	1.222*** (0.100)
Infrastructure	1.554*** (0.191)	1.028*** (0.063)	1.237*** (0.080)	1.498*** (0.090)
Insurance	3.279*** (0.357)	2.110*** (0.067)	2.758*** (0.134)	2.847*** (0.117)
Price	−0.026*** (0.003)	−0.010*** (0.001)	−0.011*** (0.001)	−0.012*** (0.001)
Latent heterogeneity				
Information.SD	1.144*** (0.280)		0.629*** (0.169)	0.596*** (0.115)
Infrastructure.SD	0.603** (0.201)		0.533*** (0.126)	0.701*** (0.108)
Insurance.SD	2.160*** (0.396)		1.499*** (0.133)	1.479*** (0.134)
Observed heterogeneity				
Price x Employees	0.001 (0.001)			
Price x Gender	0.005* (0.002)			
Price x Investment	0.012*** (0.002)			
Information x Info. event	0.522** (0.200)			
Information x Urban	0.047 (0.212)			
Information x Impact	0.012 (0.213)			
Infrastructure x Info. event	0.596*** (0.156)			
Infrastructure x Urban	−0.159 (0.164)			
Infrastructure x Impact	−0.143 (0.165)			
Insurance x Info. event	0.577** (0.191)			
Insurance x Urban	0.492* (0.216)			
Insurance x Impact	−0.240 (0.206)			
AIC	3722.3	3842.1	3726.4	3651.5
BIC	3863.9	3872.9	3775.7	3719.3
Log-likelihood	−1838.1	−1916	−1855.2	−1814.8
Correlated RP	Yes			Yes

Note: Number of observations: 3,486. Number of respondents: 581. The maximum likelihood estimation using the BHHH optimisation algorithm is based on 1000 pseudo-random draws. *, **, and *** indicate significance levels of 0.05, 0.01, and 0.001, respectively.

Table A4
Preference estimates with different model or sample specifications

Model/Specification	Baseline	Interaction	Protest	Irrational
	(1)	(2)	(3)	(4)
ASC	1.927*** (0.212)	1.708*** (0.334)	1.423*** (0.182)	1.053** (0.400)
Main Effects				
Information	1.156*** (0.244)	1.517** (0.526)	1.322*** (0.243)	2.261*** (0.533)
Infrastructure	1.554*** (0.191)	1.415*** (0.346)	1.739*** (0.190)	2.932*** (0.488)
Insurance	3.279*** (0.357)	3.576*** (0.515)	3.366*** (0.327)	6.247*** (0.996)
Price	−0.026*** (0.003)	−0.022*** (0.004)	−0.029*** (0.002)	−0.044*** (0.005)
Latent heterogeneity				
Information.SD	1.144*** (0.280)	1.410*** (0.304)	1.313*** (0.256)	2.840*** (0.551)
Infrastructure.SD	0.603** (0.201)	0.525* (0.222)	0.623* (0.254)	2.274*** (0.535)
Insurance.SD	2.160*** (0.396)	2.278*** (0.426)	2.020*** (0.362)	3.730*** (0.721)
Observed heterogeneity				
Price x Employees	0.001 (0.001)	0.001 (0.001)	0.003*** (0.001)	0.001 (0.001)
Price x Gender	0.005* (0.002)	0.005* (0.002)	0.002 (0.002)	0.010** (0.004)
Price x Investment	0.012*** (0.002)	0.012*** (0.002)	0.012*** (0.002)	0.018*** (0.004)
Information x Info. event	0.522** (0.200)	0.548* (0.216)	0.431* (0.188)	0.819* (0.381)
Information x Urban	0.047 (0.212)	0.057 (0.227)	−0.096 (0.197)	−0.119 (0.405)
Information x Impact	0.012 (0.213)	0.006 (0.230)	−0.266 (0.212)	0.294 (0.404)
Infrastructure x Info. event	0.596*** (0.156)	0.598*** (0.158)	0.495*** (0.144)	1.117*** (0.314)
Infrastructure x Urban	−0.159 (0.164)	−0.162 (0.167)	−0.208 (0.152)	−0.394 (0.308)
Infrastructure x Impact	−0.143 (0.165)	−0.132 (0.168)	−0.386* (0.160)	−0.080 (0.305)
Insurance x Info. event	0.577** (0.191)	0.591** (0.201)	0.417* (0.174)	1.259** (0.409)
Insurance x Urban	0.492* (0.216)	0.524* (0.229)	0.454* (0.196)	1.491** (0.502)
Insurance x Impact	−0.240 (0.206)	−0.260 (0.216)	−0.487* (0.196)	−0.090 (0.397)
N Observations	3486	3486	3690	2934
N Respondents	581	581	615	489
AIC	3722.3	3721.7	4339.4	2666.4
BIC	3863.9	3900.3	4482.3	2804.
Log-likelihood	−1838.1	−1831.9	−2146.7	−1310.2
Interaction Effects		Yes		

Note: All models are estimated with correlated random parameters. The maximum likelihood estimation using the BHHH optimisation algorithm is based on 1000 pseudo-random draws. *, **, and *** indicate significance levels of 0.05, 0.01, and 0.001, respectively.

Table A5
WTP Estimates of main effects (in preference and WTP space)

Variable	Baseline	MNL	RPL		RPL Corr.	
	(1)	(2)	(3)		(4)	
	Preference	Preference/WTP	Preference	WTP	Preference	WTP
ASC	146.260*** (12.866)	149.376*** (13.571)	134.414*** (11.541)	157.783*** (15.435)	143.286*** (11.135)	151.407*** (12.248)
Main Effects						
Information	87.766*** (19.216)	79.101*** (9.563)	84.591*** (9.991)	87.553*** (8.660)	100.760*** (10.478)	97.527*** (9.788)
Infrastructure	117.928*** (16.570)	106.595*** (10.322)	108.776*** (10.164)	101.281*** (8.764)	123.536*** (10.626)	112.407*** (9.630)
Insurance	248.845*** (28.198)	218.722*** (19.413)	242.521*** (21.520)	214.511*** (18.469)	234.741*** (18.288)	220.372*** (16.981)
AIC	3722.3	3842.1	3726.4	3668	3651.5	3644.7
BIC	3863.9	3872.9	3775.7	3723.4	3719.3	3718.5
Log-likelihood	−1838.1	−1916	−1855.2	−1825	−1814.8	−1810.3
Correlated RP	Yes				Yes	Yes

Note: Number of observations: 3,486. Number of respondents: 581. The maximum likelihood estimation using the BHHH optimisation algorithm is based on 1000 pseudo-random draws. Only the coefficients of the ASC and the main effects are displayed. *, **, and *** indicate significance levels of 0.05, 0.01, and 0.001, respectively.

Table A6
Stability of preference estimates with respect to the number of pseudo-random or Halton draws

Variable	50		100		1000 (Baseline)		2000		5000	
	Random	Halton	Random	Halton	Random	Halton	Random	Halton	Random	Halton
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ASC	1.941***	1.801***	1.932***	1.876***	1.927***	1.935***	1.929***	1.912***	1.932***	1.917***
	(0.208)	(0.183)	(0.209)	(0.200)	(0.212)	(0.211)	(0.215)	(0.210)	(0.215)	(0.211)
Main Effects										
Information	1.237***	1.018***	1.174***	1.071***	1.156***	1.171***	1.161***	1.128***	1.169***	1.140***
	(0.254)	(0.215)	(0.241)	(0.239)	(0.244)	(0.243)	(0.258)	(0.246)	(0.251)	(0.247)
Infrastructure	1.589***	1.442***	1.550***	1.529***	1.554***	1.551***	1.556***	1.549***	1.549***	1.552***
	(0.212)	(0.177)	(0.194)	(0.194)	(0.191)	(0.193)	(0.216)	(0.193)	(0.200)	(0.192)
Insurance	3.416***	2.900***	3.253***	3.263***	3.279***	3.248***	3.300***	3.269***	3.295***	3.316***
	(0.366)	(0.261)	(0.349)	(0.333)	(0.357)	(0.351)	(0.410)	(0.351)	(0.383)	(0.362)
Price	−0.026***	−0.024***	−0.026***	−0.025***	−0.026***	−0.026***	−0.026***	−0.025***	−0.026***	−0.026***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Latent heterogeneity										
Information.SD	1.183***	0.994***	1.119***	1.250***	1.144***	1.143***	1.153***	1.205***	1.135***	1.164***
	(0.279)	(0.233)	(0.285)	(0.263)	(0.280)	(0.274)	(0.308)	(0.279)	(0.293)	(0.282)
Infrastructure. SD	0.716*	0.557**	0.618*	0.599*	0.603**	0.615**	0.609	0.595**	0.577	0.581**
	(0.339)	(0.197)	(0.240)	(0.248)	(0.201)	(0.224)	(0.475)	(0.223)	(0.361)	(0.218)
Insurance.SD	2.303***	1.636***	2.105***	2.125***	2.160***	2.108***	2.185***	2.128***	2.243***	2.212***
	(0.362)	(0.297)	(0.386)	(0.362)	(0.396)	(0.383)	(0.413)	(0.383)	(0.404)	(0.392)
Observed heterogeneity										
Price x Employees	0.001	0.000	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Price x Gender	0.005*	0.005*	0.005*	0.005*	0.005*	0.005*	0.005*	0.005*	0.005*	0.005*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Price x Investment	0.012***	0.011***	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Information x Info. event	0.0527**	0.444	0.504*	0.517*	0.522**	0.515**	0.525**	0.521*	0.520*	0.530**
	(0.201)	(0.176)	(0.197)	(0.202)	(0.200)	(0.199)	(0.203)	(0.202)	(0.203)	(0.202)
Information x Urban	0.041	0.059*	0.049	0.025	0.047	0.048	0.046	0.048	0.041	0.045
	(0.213)	(0.190)	(0.209)	(0.215)	(0.212)	(0.210)	(0.213)	(0.214)	(0.214)	(0.214)
Information x Impact	−0.007	0.019	0.006	0.004	0.012	0.010	0.011	0.015	0.006	0.016
	(0.216)	(0.190)	(0.211)	(0.218)	(0.213)	(0.211)	(0.214)	(0.215)	(0.215)	(0.215)
Infrastructure x Info. event	0.598***	0.539***	0.583***	0.583***	0.596***	0.594***	0.596***	0.593***	0.589***	0.595***
	(0.159)	(0.142)	(0.155)	(0.155)	(0.156)	(0.155)	(0.161)	(0.155)	(0.159)	(0.156)
Infrastructure x Urban	−0.170	−0.149	−0.153	−0.161	−0.159	−0.158	−0.160	−0.155	−0.162	−0.162
	(0.169)	(0.153)	(0.164)	(0.163)	(0.164)	(0.163)	(0.165)	(0.164)	(0.165)	(0.164)
Infrastructure x Impact	−0.151	−0.147	−0.146	−0.174	−0.143	−0.151	−0.145	−0.143	−0.145	−0.145
	(0.169)	(0.153)	(0.164)	(0.165)	(0.165)	(0.164)	(0.165)	(0.165)	(0.165)	(0.165)
Insurance x Info. event	0.580**	0.497**	0.553**	0.538**	0.577**	0.569**	0.578**	0.565**	0.571**	0.577**
	(0.195)	(0.160)	(0.188)	(0.188)	(0.191)	(0.188)	(0.199)	(0.190)	(0.197)	(0.194)
Insurance x Urban	0.487*	0.422*	0.483*	0.493*	0.492*	0.483*	0.496*	0.495*	0.485*	0.499*
	(0.219)	(0.182)	(0.213)	(0.212)	(0.216)	(0.211)	(0.218)	(0.215)	(0.221)	(0.219)
Insurance x Impact	−0.238	−0.231	−0.230	−0.244	−0.240	−0.242	−0.243	−0.244	−0.238	−0.243
	(0.211)	(0.174)	(0.201)	(0.203)	(0.206)	(0.202)	(0.206)	(0.204)	(0.210)	(0.207)
AIC	3723.6	3734.9	3721.9	3734.2	3722.3	3725.0	3722.4	3723.2	3722.8	3723.1
BIC	3865.2	3876.5	3863.5	3875.8	3863.9	3866.6	3864.0	3864.8	3864.4	3864.7
Log-likelihood	−1838.8	−1844.4	−1837.9	−1844.1	−1838.1	−1839.5	−1838.2	−1838.6	−1838.4	−1838.5

Note: Number of observations: 3,486. Number of respondents: 581. All models are estimated with correlated random parameters. The maximum likelihood estimation using the BHHH optimisation algorithm is based on the given number of pseudo-random or Halton draws. *, **, and *** indicate significance levels of 0.05, 0.01, and 0.001, respectively.

Table A7
Preference estimates and the role of the ASC

Variable	Baseline	Without ASC	ASC random
	(1)	(2)	(3)
ASC	1.927*** (0.212)		1.502 (0.849)
Main Effects			
Information	1.156*** (0.244)	1.425*** (0.297)	1.797*** (0.342)
Infrastructure	1.554*** (0.191)	1.806*** (0.214)	2.175*** (0.344)
Insurance	3.279*** (0.357)	4.134*** (0.495)	4.192*** (0.535)
Price	−0.026*** (0.003)	−0.017*** (0.002)	−0.030*** (0.004)
Latent heterogeneity			
Information.SD	1.144*** (0.280)	1.743*** (0.321)	2.928** (0.969)
Infrastructure.SD	0.603** (0.201)	0.798** (0.267)	0.882 (0.457)

(*continued on next page*)

Table A7 (*continued*)

Variable	Baseline	Without ASC	ASC random
	(1)	(2)	(3)
Insurance.SD	2.160*** (0.396)	2.858*** (0.518)	0.903 (0.562)
ASC.SD			2.897*** (0.451)
Observed heterogeneity			
Price x Employees	0.001 (0.001)	0.001 (0.001)	0.000 (0.001)
Price x Gender	0.005* (0.002)	0.004 (0.002)	0.006* (0.003)
Price x Investment	0.012*** (0.002)	0.010*** (0.002)	0.016*** (0.003)
Information x Info. event	0.522** (0.200)	0.502* (0.240)	0.377 (0.231)
Information x Urban	0.047 (0.212)	0.076 (0.251)	−0.009 (0.254)
Information x Impact	0.012 (0.213)	0.039 (0.259)	−0.266 (0.262)
Infrastructure x Info. event	0.596*** (0.156)	0.571*** (0.170)	0.439* (0.192)
Infrastructure x Urban	−0.159 (0.164)	−0.197 (0.180)	−0.281 (0.203)
Infrastructure x Impact	−0.143 (0.165)	−0.146 (0.181)	−0.409 (0.211)
Insurance x Info. event	0.577** (0.191)	0.686** (0.239)	0.416 (0.235)
Insurance x Urban	0.492* (0.216)	0.636* (0.270)	0.455 (0.261)
Insurance x Impact	−0.240 (0.206)	−0.268 (0.256)	−0.503 (0.258)
ASC x Info. event			1.206* (0.554)
ASC x Urban			0.260 (0.438)
ASC x Impact			0.960* (0.441)
AIC	3722.3	3824.9	3693.4
BIC	3863.9	3960.3	3878.1
Log-likelihood	−1838.1	−1890.4	−1816.7

Note: Number of observations: 3,486. Number of respondents: 581. All models are estimated with correlated random parameters. The maximum likelihood estimation using the BHHH optimisation algorithm is based on 1000 pseudo-random draws. *, **, and *** indicate significance levels of 0.05, 0.01, and 0.001, respectively.

A.2 Additional Figures

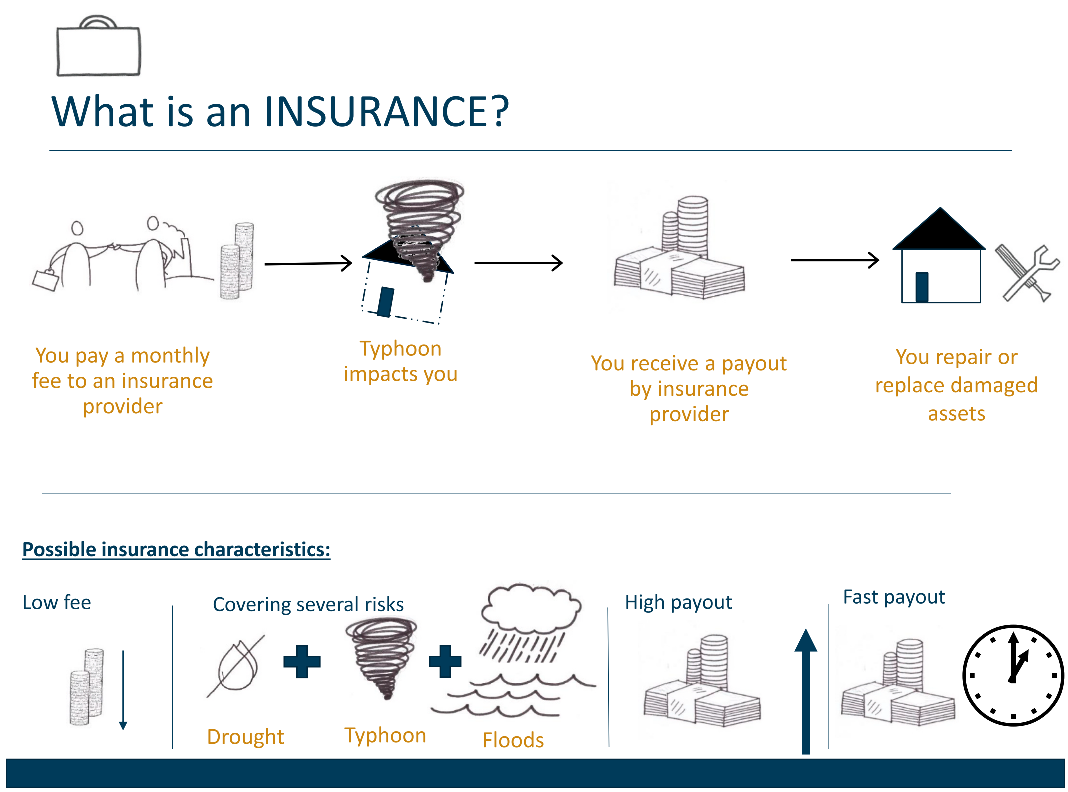

Fig. A1. Illustration: What is insurance?
Note: This figure provides a diagrammatic illustration of how insurance works. It was shown to respondents before the choice experiment to help explain the concept of insurance and ensure understanding of the attribute during the survey.

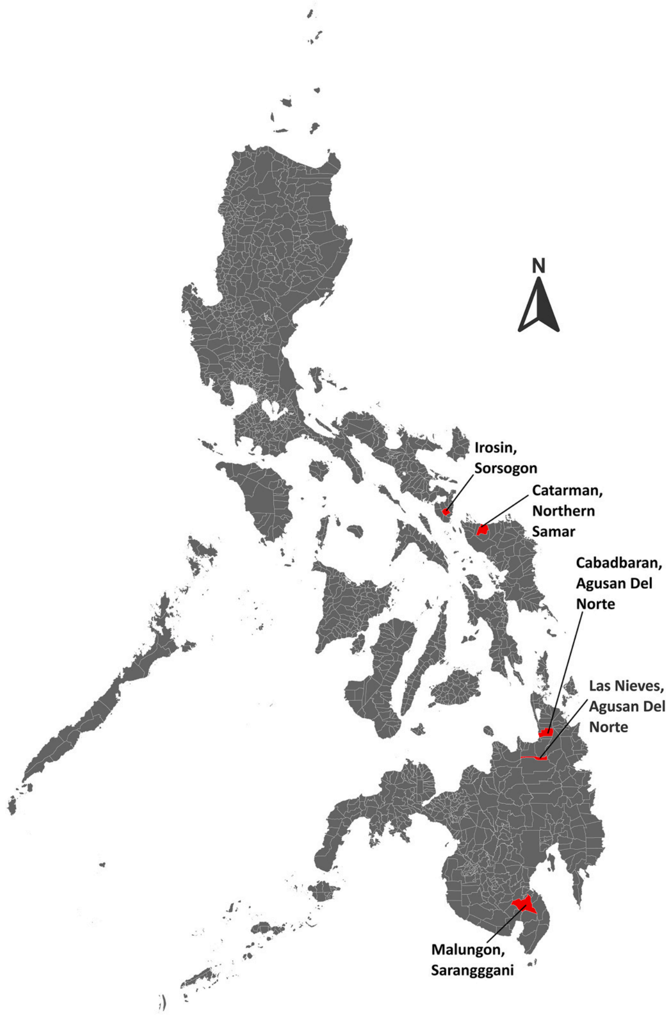

Fig. A2. Map of the survey areas in the Philippines
Note: This figure shows a map of the survey areas in the Philippines. The highlighted areas indicate the municipalities where the sampled micro-enterprises are located.

A.3 Experimental design

In this DCE, each choice card consists of two different hypothetical options for safeguarding against climate risks and a status quo option between which respondents had to choose. The options consist of four attributes with different attribute levels (see Table 1). The choice cards are created using the statistical software R (R Core Team, 2023) and the AlgDesign package (B. Wheeler and Braun, 2019).

A.3.1 Hypothetical attribute combinations

To create hypothetical attribute combinations, the levels of the attributes are first translated into design codes using effect coding. The levels of the non-monetary attributes are coded as 1 if the attribute is included in the alternative, -1 otherwise. The three levels for the price attribute (50, 100 and 150) are coded as -1, 0 and 1. Afterwards, a $2^3 \times 3^1$ full factorial design was generated out of the three two-level and the one three-level attribute. It contains all 24 possible attribute level combinations and allows the estimation of all the main and interaction effects.[15] However, if the full factorial design had been used, each respondent would have received 24 choice cards. This may have resulted in respondents paying less attention to the choice cards and therefore to a lower *response efficiency* (R. F. Johnson et al., 2013). Therefore, the rows from the full factorial design served as a candidate list, which we then divided into a predetermined number of blocks. Thereby, each respondent receives only a subset of all the choice cards.[16] We use a blocking algorithm to create four almost homogeneous blocks. The blocking algorithm selects and replaces elements from the candidate list and iterates until a defined efficiency criterion is maximised (Kanninen, 2007; R. E. Wheeler, 2022).[17] The efficiency criterion used in this work is the

[15] The main effect is the direct independent effect of one attribute on the choice variable. Interaction effects are the effects of varying two or more attribute levels together on the choice variable (Mangham et al., 2009).
[16] It is also possible to use a different design as the candidate list, for example, a fractional factorial design. The fractional factorial design is a subset of the full factorial design and is obtained by algorithmic optimisation techniques. It is often used for large factorial designs as the candidate list (R. E. Wheeler, 2022). In this choice experiment, blocking using the full factorial design as the candidate list proved to be more efficient.
[17] For more details on the blocking algorithm, see Kanninen (2007) and R. E. Wheeler (2022).

D-efficiency criterion, subject to the condition that all two-way interaction effects can be estimated. The D-efficiency criterion is aimed at minimising the overall variance of the parameter estimates for the attributes, which in turn maximises the efficiency of the design. To achieve this, the design matrix is made as orthogonal and balanced as possible.[18] The D-efficiency criterion is a function of the geometric mean of the eigenvalues (Kuhfeld, 2010):

$$D-Efficiency = 100\ det\left(\frac{X_c^T X_c}{N_D}\right)^{\frac{1}{p}}, \tag{8}$$

where X_c is the centred design matrix, which is created by subtracting the within-block means from each value in the block of the (uncentered) design matrix. This cancels out the between-block error components (R. E. Wheeler, 2022). N_D indicates the number of observations in the candidate list (here $N_D = 24$), and p is the number of parameters to be estimated, excluding the intercept (here $p = 10$). The D-efficiency score is normalised and takes values from 0 to 1. In an orthogonal and balanced design, maximal efficiency is achieved (D-efficiency = 100%). The full factorial design is divided into four blocks, with each block containing six elements, which was found to be most efficient considering the response efficiency.[19]

A.3.2 Efficiency of the design

According to the D-efficiency criterion, the design in this study is approximately 83% efficient, indicating that there is only a small efficiency loss. Before the choice experiment was implemented, further design criteria were evaluated. First, the diagonality of the blocking scheme was investigated. Diagonality is a measure of the degree to which a parameter is confounded by other parameters. The design in this study is almost fully diagonal, thus indicating good blocking since all estimable effects are (almost) not confounded.[20] To further assess the success of the blocking scheme, the within-block efficiency can be investigated. It demonstrates the ability of the design to separate the whole and the within-block effects. With a within-block efficiency of 98%, the design is successful in decoupling these effects.

A.3.3 Allocation of attribute combinations into choice sets

After constructing the choice design matrix, the attribute combinations are randomly assigned to choice cards. For this, each block is combined with the other three blocks, with the questions paired randomly (see Table A8). Finally, six different variants exist from which one was randomly assigned to each respondent. The distribution of the variants among the respondents is also depicted. The choice cards within each variant appear in a random order to minimise any bias. Translating back from design codes to the attribute levels, the final choice sets, excluding the opt-out option, are illustrated in Table A9.[21]

Table A8
Blocking scheme

Variant	Combination		Number
1	Block 1	Block 2	101
2	Block 1	Block 3	101
3	Block 1	Block 4	100
4	Block 2	Block 3	93
5	Block 2	Block 4	92
6	Block 3	Block 4	99

Note: This table illustrates the approach to allocating the attribute combinations into choice sets. After data cleaning, the variants are no longer completely evenly distributed among the respondents.

Table A9
Choice sets

Variant	Card	Option A				Option B			
		IN	IF	IS	PR	IN	IF	IS	PR
1	1	no	yes	yes	150	no	no	yes	150
1	2	no	yes	no	50	yes	no	yes	100
1	3	no	no	yes	100	no	no	no	50
1	4	yes	no	yes	50	yes	yes	no	100
1	5	yes	yes	yes	100	no	yes	yes	50
1	6	yes	no	no	150	no	yes	no	150
2	1	no	yes	yes	150	yes	no	no	50
2	2	no	no	yes	100	yes	yes	no	150
2	3	yes	no	no	150	no	yes	yes	100
2	4	yes	no	yes	50	no	no	no	100

(*continued on next page*)

[18] A design is called orthogonal if all level pairs appear equally often and the parameter estimates are uncorrelated. A design is called balanced if each level within each attribute occurs equally often. The same amount of information is obtained on each attribute level, i.e., the variance in the parameter estimates is minimised, which in turn maximises the efficiency of the design (Kuhfeld, 2010).

[19] Several combinations have been tested, and this division was found to be the most efficient.

[20] The diagonality is calculated as follows $(det(M)/\Pi diag(M))^{1/10} = 0.999, where\ M = X_C^T X_c/N_D$.

[21] While effect coding was used to construct the experimental design, all parameter estimates and WTP results in this study are based on the actual price levels (PHP 50, 100, and 150), not the effect-coded values. This ensures that all reported WTP values are directly interpretable in monetary terms.

Table A9 (*continued*)

Variant	Card	Option A				Option B			
		IN	IF	IS	PR	IN	IF	IS	PR
2	5	no	yes	no	50	yes	yes	yes	50
2	6	yes	yes	yes	100	yes	no	yes	150
3	1	no	yes	yes	150	no	no	yes	150
3	2	yes	no	no	150	yes	yes	yes	150
3	3	no	no	yes	100	yes	no	no	100
3	4	yes	yes	yes	100	no	yes	no	100
3	5	no	yes	no	50	no	no	yes	50
3	6	yes	no	yes	50	yes	yes	no	50
4	1	no	yes	no	150	no	yes	yes	100
4	2	no	yes	yes	50	no	no	no	100
4	3	yes	no	yes	100	yes	yes	no	150
4	4	yes	yes	no	100	yes	yes	yes	50
4	5	no	no	yes	150	yes	no	no	50
4	6	no	no	no	50	yes	no	yes	150
5	1	yes	yes	no	100	yes	no	no	100
5	2	no	no	yes	150	no	no	yes	50
5	3	no	no	no	50	yes	yes	yes	150
5	4	yes	no	yes	100	yes	yes	no	50
5	5	no	yes	no	150	no	yes	no	100
5	6	no	yes	yes	50	no	no	no	150
6	1	no	yes	yes	100	no	no	yes	50
6	2	yes	no	yes	150	no	yes	no	100
6	3	yes	yes	no	150	yes	no	no	100
6	4	no	no	no	100	yes	yes	yes	150
6	5	yes	no	no	50	yes	yes	no	50
6	6	yes	yes	yes	50	no	no	no	150

Note: This table depicts the final choice sets. The first column contains the variant index (Variant), and the second column contains the choice card index (Card). The next two columns show the two options (Option A and Option B), with each consisting of the four attributes information (IN), infrastructure (IF), insurance (IS) and price (PR). The attributes take on different values on each choice card. For reasons of clarity, the status quo option is not shown.

Data availability

Data will be made available on request.

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