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Analysis

Wait and see? Public preferences for the temporal effectiveness of coastal protection

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ABSTRACT

Under uncertainty about the kind, extent, or time frames of coastal threats, efficient protection requires measures that are effective in time and flexible enough to assure protection even if conditions change over time. Existing protection options are unable to offer both attributes simultaneously, creating a trade-off between short-term and long-term effectiveness in protection choice. This paper investigates the role played by differences in the temporal effectiveness of coastal protection measures in the choice of protection modes. Results from a discrete-choice experiment implemented in Papua New Guinea suggest that respondents have a strong preference for long-term over short-term effectiveness; an urgency to protect cannot be identified. Using incentivized preference measures for patience and risk-aversion as well as sociodemographic controls, we account for taste heterogeneity and validate the robustness of our results.

1. Introduction

Coastal protection is a cornerstone in adapting to climate change (IPCC, 2014, 2019). From an engineering point of view, there are two clearly defined approaches: hard and soft (Morris et al., 2018; Temmermann et al., 2013; Menashe, 2001). The term *hard* refers to built structures such as seawalls or groynes. *Soft* coastal protection is ecosystem-based and encompasses so-called working-with-nature strategies designed to enhance natural coastal resilience in a more general sense. These include planting mangroves or coral-reef reforestation.[1] The core features of ecosystem-based protection modes are that they take longer to achieve their full protection potential but are able to adapt to changing site conditions. Hard measures commonly provide immediate protection, but as solid structures they deteriorate over time. For any given coastal hazard, the trade-off between types of protection is then a trade-off between quickly effective protection and the preservation of long-term coastal resilience (Adger et al., 2005; Tessler et al., 2015; Nel et al., 2014; Temmermann et al., 2013; Menashe, 2001). As the climate changes, the prospect of an increase in coastal hazards is certain in general terms, but there is an attendant increase in uncertainty about the kind, extent, and time frame of local hazards (IPCC, 2014, 2019; Cazenave and Llovel, 2010; Han et al., 2010). Under such hazard uncertainty, protection worthy of the name requires measures that are effective in time and flexible enough to ensure protection of the coastline even when conditions change quickly and unexpectedly over time.

As the type of protection used strongly affects the way in which coastal inhabitants can use the coastline, the choice of coastal protection requires knowledge about coastal inhabitants' preferences on this point.[2] Several studies have investigated people's preferences with regard to coastal protection. They show that coastal dwellers both derive utility from an intact coastal ecosystem and also display a preference for effective coastal protection (e.g., Christie, 2009; Imamura et al., 2016; Johnston et al., 2018; Meyerhoff et al., 2021; Remoundou et al., 2015; Saengsupavanich, 2013). There is a lack of knowledge, however, about the social desirability of protection measures under hazard uncertainty, where people need to trade off these two factors and choose between short-term and long-term protection effectiveness.

Abbreviations: DCE, discrete-choice experiment; PNG, Papua New Guinea; WARP, weak axiom of revealed preferences; RUM, random utility maximization; IID, independently and identically distributed; CL, conditional logit; MXL, mixed logit; mWTP, marginal willingness to pay; ASC, alternative specific constant

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[1] See Temmermann et al. (2013) or (Menashe, 2001) for an overview.

[2] See for example (Torabi et al., 2018; Piggott-McKellar et al., 2020; Fazey et al., 2010) for a discussion of the likelihood of maladaptation from the lack of community involvement in coastal protection efforts.

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To our knowledge, this is the first study to examine the role played by differences in the temporal effectiveness of coastal protection measures in the choice of protection modes. More generally, within the large number of studies evaluating public policies, little is known about the role of preferences regarding the time that elapses before a policy becomes effective and its lifespan. We test this relationship empirically in a discrete-choice experiment (DCE) on coastal protection preferences. It builds on a simplistic theoretical framework of intertemporal optimization, where the benefits of protection measures depend on the time one has to wait until protection sets in and on the longevity of the protection measures. In our DCE, we use a generic design. The advantage of such a design is the ordinal comparability of results from different study areas as a way of assessing the external validity of findings. Further, its unlabeled specification enables us to evaluate the preferences not only for the two distinct approaches to protection (hard vs. soft) but also for combined protection solutions. Next, the article is an addition to the growing body of literature combining DCEs with behavioral economic preference data (e.g., Glatt et al., 2019; Non et al., 2019; Reynaud et al., 2018; Fiala and Wende, 2016; Akter, 2020). In particular, we have conducted lab-in-the-field experiments to elicit respondents' patience and risk preferences. These measures are elicited in an incentive-compatible way conducive to closer investigation of preference heterogeneity. This enables us to avoid the endogeneity problems encountered when using stated attitudes as control variables. Finally, the paper adds to the relatively small number of studies focusing on coastal protection in a developing country context (e.g., Brouwer et al., 2008; Reynaud et al., 2018; Barnett, 2001; Akter, 2020; Chang et al., 2012; Saengsupavanich, 2013).[3] We use the example of Bougainville in Papua New Guinea, where (a) people heavily depend on healthy coastal ecosystems for the satisfaction of everyday needs and (b) uncertainty about the kind, extent, or time frame of coastal threats is particularly large as data on coastal hazards is not readily available and scientific expertise is conspicuous by its absence. We provide findings on the protection preferences of these coastal inhabitants.

In line with theory, we find that the long-term effectiveness of protection measures is a highly relevant choice variable. However, a preference for quick protection cannot be identified. We test for the mediating effect of individual-level patience and risk attitudes, finding that risk tolerance (measured in the gain domain) is positively associated with willingness to protect. Patience mediates the role attributed to protection longevity. None of the two controls helps to explain the non-negative value assigned to waiting longer for full protection. In fact, the absence of an urgency to protect is robust to the inclusion of a rigorous set of control variables.

The remainder of the paper is structured as follows: In Section 2 we provide a conceptual framework from which we derive our main hypotheses. Section 3 provides an overview of our study location. Section 4 presents the general survey design, including the choice experiment and the lab-in-the-field experiment. Section 5 describes the econometric models. Section 6 presents the findings of the study. Section 7 discusses the results, and Section 8 concludes.

2. Theoretical background

At its core, the choice between different protection scenarios is an intertemporal optimization problem that can be expressed in a simple discounted expected-utility model. Let us assume that the presence of a hazard is such that in each period n the decision-maker faces the risk of receiving loss x_n with probability μ_n and of being spared the loss with probability $1-\mu_n$.[4] This prospect is re-encountered in each of N periods. If the decision-maker chooses to protect against this hazard, there will be K periods of construction time until protection is achieved. From period K on, the protection measure will reduce potential loss from the hazard, x_n, by $z \in]0, max(x_n)]$. Assuming that measures erode or environmental conditions change over time, protection will fade after M periods. In the following equations, we denote the prospects of a climate change-related hazard accompanied by no protective measures as outcome profile L_1 and the outcome profile involving protection as L_2:

$$
\begin{aligned}
L_1 =& [(-x_1, \mu_1; 0, 1-\mu_1), (-x_2, \mu_2; 0, 1-\mu_2), \dots, (-x_N, \mu_N; 0, 1-\mu_N)] \\
L_2 =& [(-x_1, \mu_1; 0, 1-\mu_1), \dots, (-x_{K+1}+z, \mu_{K+1}; 0, 1-\mu_{K+1}), \dots, \\
& (-x_{K+M+1}, \mu_{K+M+1}; 0, 1-\mu_{K+M*1}), \dots, (-x_N, \mu_N; 0, 1-\mu_N)]
\end{aligned}
$$

Opting for L_2 will induce costs incurred with certainty if L_2 is chosen. The willingness to pay for L_2 depends on the relative attractiveness of L_2 over and against L_1. Assuming an initial wealth level w, a valuation function v, and a discount factor δ, the utilities derived from the two outcome profiles are then given by:

$$
\begin{aligned}
U(L_1) =& \sum_{i=1}^{N} \delta^i v(\mu_i(w-x_i) + (1-\mu_i)w) \\
U(L_2) =& \sum_{i=1}^{K} \delta^i v(\mu_i(w-x_i) + (1-\mu_i)w) + \sum_{i=K+1}^{K+M} \delta^i v(\mu_i(w-x_i+z) + (1-\mu_i)w) \\
& + \sum_{i=K+M+1}^{N} \delta^i v(\mu_i(w-x_i) + (1-\mu_i)w)
\end{aligned}
$$

In our experimental design, we assume protection options that provide full protection once they are established. If the protection measure offers full protection, i.e. $z \geq x_i \forall i \in [K+1, K+M]$, the previous expression boils down to the following.

$$
\begin{aligned}
U(L_2) =& \sum_{i=1}^{K} \delta^i v(\mu_i(w-x_i) + (1-\mu_i)w) + \sum_{i=K+1}^{K+M} \delta^i v(w) \\
& + \sum_{i=K+M+1}^{N} \delta^i v(\mu_i(w-x_i) + (1-\mu_i)w)
\end{aligned}
$$

Consequently, the utility gain from a shift from L_1 to L_2 equals

$$
\begin{aligned}
\Delta =& U(L_2) - U(L_1) \\
=& \sum_{i=K+1}^{K+M} \delta^i [v(w) - v(\mu_i(w-x_i) + (1-\mu_i)w)]
\end{aligned}
$$

Though up to this point this simple framework is agnostic about the specific shape of the value and discounting functions, it enables us to postulate the following baseline hypotheses about protection choice:

- H1 The lower K, (i.e., the time-period until full protection is established), the larger the utility gain Δ, ceteris paribus (for any $0 < \delta < 1$).
- H2 The larger M, (i.e., the duration of protection), the larger the utility gain from protection Δ.
- H3 The utility gain Δ and the impact of changes in M and K on Δ are mediated by an individual's patience level (δ) and risk preferences (the shape of v).

Without any loss of generality, we can add directional precision to the role of patience (δ) in H3. The more impatient a decision-maker is, the closer δ is to zero, which lessens the impact of K and M. Imposing a certain structure on the functional form of the value function (v) enables us also to provide greater precision on the role of risk preferences. For example, assuming that the value function follows the expected utility framework, risk aversion is represented by the concavity of the valuation function. Higher risk-aversion implies that a lower value is assigned to the uncertain outcome $v(\mu_i(w-x_i)+(1-\mu_i)w)$.

[3] For a recent overview of studies conducted in a developed country context, see Meyerhoff et al. (2021).

[4] Note that this framework (as well as the experimental design) focuses on hazards with probabilities that are uncorrelated over time

Consequently, risk-aversion has a positive effect on Δ and amplifies the role of K and M.

Taken together, these derivations show, that regardless of all other features of the protection option (material used, exact height of a sea wall, etc.), duration of protection and the waiting time until protection can be provided are expected to be relevant criteria for protection choices. We test this hypothesis and the relevance of these two criteria for choices of different coastal-protection options.

3. Study location

The study was conducted in Bougainville, Papua New Guinea (PNG) (Fig. 1). This region is particularly well suited to answering the research question for several reasons. First, sea levels in PNG rise twice as fast as the global average (about 7 mm/year since 1993), and the region is repeatedly affected by storm surges (Wadey et al., 2017; Papua New Guinea National Weather Service et al., 2015). Therefore, coastal communities in this region need to make timely decisions on appropriate adaptation measures (United Nations General Assembly, 2008; Climate & Development Knowledge Network, 2014). However, there are hardly any local meteorological forecasts or climate-change projections available creating uncertainty about the kind, extent, or time frame of coastal threats. Accordingly, as we have set out above, accounting for variations in the effectiveness of protection measures over time is of major relevance for coastal protection choices in this region. Second, with a human development index of 0.543 (rank 155 out of 188 countries) (UNDP, United Nations Development Programme, 2019), PNG belongs to the class of low developed countries. It has limited adaptation resources, but many of its communities depend on a healthy coastal ecosystem for the satisfaction of their everyday needs. Third, the sample region in PNG is a matrilineal, mostly Christian society in which the influence of formal institutions is limited by a strong reliance on cultural codes of behavior embedded in the "Wantok System".[5] A strongly bottom-up decision-making structure situates responsibility for coastal protection initiatives (both choice of measures and financing solutions) at the village level. Within villages, choices are made by Big Men, elected Ward Members, or village Chiefs in accordance with opinions voiced at community meetings (Nanau, 2011; De Renzio et al., 2000). This gives much more weight to individual opinions in the decision-making process on coastal protection than is the case in many developed countries.

Due to the small size of (coastal) communities in Bougainville, three nearby coastal villages were included to generate a sufficiently large sample (Fig. 1). All these villages are in close geographic proximity to one another in a region where coastal erosion is visible but not significant, so that (a) public discourse on the topic has not reached an advanced state, and (b) sufficient time remains for the implementation of coastal protection measures.

4. Method

4.1. Discrete-choice experiment

A central element of designing a DCE is deciding on the number and types of alternatives and selecting the attributes and associated levels that describe them. The choice tasks in the present survey gave the individual participants two hypothetical protection alternatives ("Protection 1" and "Protection 2") and the status quo ("No Protection"). We do not make use of labeled alternatives, as the distinction between soft and hard protection structures is unfamiliar to people in the target sample. This also enables us to evaluate the preferences not only for the two different approaches but also for combined protection solutions.

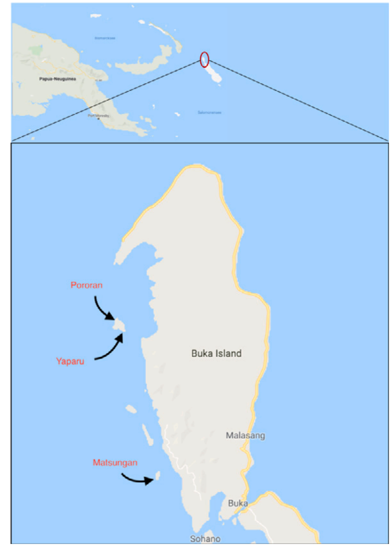

Fig. 1. Geographic location of coastal communities in Bougainville, PNG participating in the survey (Google Maps, 2021).

Coastal engineers use a number of key characteristics to define hard and soft protection measures. First, soft forms of coastal protection are considered to be resilient, meaning that they adapt to changing site conditions and thus display much longer lifetimes. Hard forms of coastal protection deteriorate over time and require costly maintenance to preserve their original protection level or to adjust to new conditions (Morris et al., 2018; Temmermann et al., 2013; Menashe, 2001). Second, soft approaches promote the resilience of the surrounding ecosystem by improving water quality, providing additional habitat space for wildlife and fish stocks, increasing carbon sequestration, etc (Temmermann et al., 2013; Menashe, 2001). Hard approaches have been found to be detrimental to the natural capacity of shorelines to adapt to changing hazard conditions (Temmermann et al., 2013). Third, hard options commonly provide immediate protection, whereas soft alternatives are often ineffective immediately after initiation but become self-perpetuating over time. Accordingly, soft protection measures take longer to achieve their full protection potential (Menashe, 2001). Lastly, while both approaches to coastal protection require in-depth knowledge about the coastal dynamics prevailing at the given site, soft protection approaches allow for community involvement in the construction process and more often make use of materials that are found on-site, such as local plants (Narayan et al., 2016; de Vriend et al., 2015). Hence, in terms of the cost incurred in acquiring materials and obtaining specialized expert advice or laborers, soft protection approaches provide more low-cost adaptation options.

For attribute choice, this characterization was combined with information about protection characteristics relevant for the study populations. The data was collected in June/July 2018, previous to the implementation of the DCE, by way of preliminary household surveys, expert interviews, and focus group discussions.[6] These additional data sources supported the relevance of the features necessary for distinguishing between protection types as described above and involved

[5] https://freedomhouse.org/country/papua-new-guinea/freedom-world/2020, 28.01.2020

[6] This data was collected in other villages of the region to avoid the risk of response bias due to pre-exposure to the survey questions.

Table 1
Attributes and attribute levels.

Attributes	Description	Levels
Time Until Full Protection	The time until full protection is given (construction time), depends on such factors as the necessary work effort or the materials used — plants need to grow and cement needs to dry. Some measures can thus provide full protection after a rather short time while others may need to be fostered for a long period until they serve to protect the coast.	**NA**/1 Year/4 Years
Lifetime	Once full protection is given, protection measures differ in the time it takes before repair or restoration work is required.	**NA**/1 Year/10 Years
Access to Coast	Coastal protection measures vary in the degree to which they limit access to the coast, i.e. the usability of the beach and ocean access. After construction, some only allow for access in some limited zones whereas others still provide full access to the coast.	Limited/**Full**
Changes in Animal and Plant Species	Protection measures can influence the number and diversity of local plants and animals. Protection measures may increase or decrease the amount of species in their proximity.	Increase in Species / **No Change in Species** / Decrease in Species
Weekly Contribution to Community Fund	This is the weekly amount to be paid by a household over a period of 5 years for a particular protection measure.	**K0**/K5/K10/K20/K35

Note: The status-quo levels are shown in bold print.

the addition of an attribute capturing the degree to which the protection measure might restrict coastal access.[7] Further, we tested for the comprehension of relevant terms and identified comprehension ambiguities in connection with the terms "longevity", "resilience", and "environmental externalities". As a result, the characteristics "resilience of the protection measure" and "impacts on the resilience of the ecosystem" were renamed "lifetime of the protection measure" and "changes in animal and plant species". All in all, our DCE encompasses the following five attributes: (1) *Lifetime* of the protection structure, (2) *Time Until Full Protection*, (3) *Changes in Animal and Plant Species*, (4) *Access to Coast*, and (5) Costs.

Pilot surveys were used to determine appropriate attribute levels. To maximize variation[8] and reduce design size,[9] they mostly refer to extremes. Time-related attributes can have either short- or long-term time-horizons.[10] For *Lifetime*, the pilot data suggested that this be represented by 1 year/ 10 years. *Time Until Full Protection* takes on the values 1 year/ 4 years. *Access to Coast* can be either fully available or limited, and *Changes in Animal and Plant Species* can either increase, decrease, or not change at all. Finally, we assessed the validity of different payment vehicles. Contributions to a community fund were found to be the most appropriate choice, and levels are set to K0, K5, K10, K20, and K35 per week.[11] The final choice of attributes and their levels is shown in Table 1. See Fig. A.2 in the Appendix for the example of a choice card.

To lighten the cognitive load for each participant, a fractional orthogonal main-effects design with eight choice cards was generated and divided into two blocks. Accordingly, each participant rated four choice cards. We chose an orthogonal rather than an efficient design due to the novelty of a choice experiment on coastal preferences in this cultural setting, which makes the correct specification of priors for an efficient design challenging. An extrapolation of findings from samples that show different socio-cultural backgrounds did not seem fit to us. On the choice cards, the order in which alternatives were presented was randomized to rule out order effects.

4.2. Lab-in-the-field experiment

In any instance of intertemporal optimization, people with higher discount rates (lower δ in our theoretical framework), i.e., those who are less patient, will attach less importance to outcomes in the more distant future when they make their decisions. Consequently, differences in patience can be expected to affect the assessment (a) of the time one has to wait until protection starts, and (b) of the longevity of the protective measure. In addition, a person's patience level can be assumed to be a likely mediator of general willingness to protect as it may influence the extent to which future threats are recognized (see e.g., Rogers and Prentice-Dunn, 1997; van Valkengoed and Steg, 2019; Bamberg et al., 2017).

[7] For other DCE studies implementing attributes concerning coastal access, see, e.g., Ardeshiri et al. (2019) or Landry et al. (2003).

[8] Maximum information is collected if the Fisher information matrix = $(1/\sigma)X'X$ of the model is maximized. This is achieved by maximizing $X'X$, which requires the diagonal elements to be maximal and the off-diagonal elements to be as close to zero as possible, i.e., if the variance in the levels of an attribute is maximized, and the columns of X are orthogonal. For attributes with presumably linear effects, this means that the most efficient level choice covers the two maximum points on the available scale. Compare Kanninen (2007), Hensher et al. (2015).

[9] It is advisable to maintain attribute balance within a choice experiment. The number of levels per attribute determines the alternatives a respondent needs to be shown for balance to be maintained (lowest common multiple of number of levels per attribute). Accordingly, the lower the number of levels, the lower the amount of choice cards per participant required for balance (cf. Kanninen, 2007; Hensher et al., 2015).

[10] In particular, we elicited acceptable levels for various time-frames. In the DCE, the levels for a short-term time-horizon are set lower than the acceptance cut-off in the pilot data, whereas the levels for the long-term time-horizon are set above this cut-off. Fig. A.1 in the Appendix shows the acceptability of the various levels from the pilot data for *Time Until Full Protection* and *Lifetime*.

[11] The levels of the cost attribute were pre-tested to ensure cost sensitivity. K5 is about USD 1.43 (www.xe.com, last accessed 28.09.2021).

A similarly central role can be attributed to risk preferences (the shape of the value function v in our theoretical framework). Uncertainty about the timing and nature of hazards combined with uncertainty about the effectiveness of protective measures means that choice between options is a choice under uncertainty. It is probable that protection preferences, willingness to wait longer for the effectiveness of protection measures, or the inclination to accept a short lifespan of protective measures will depend on a person's risk preferences.

There are several approaches to measuring patience and risk preferences. The simplest way is to ask respondents to self-assess their level of patience and risk-aversion and to include these mediators in the analysis via interaction terms. However, this approach is problematic for responses that are not directly observable, which is commonly the case for measures of attitudinal or psychological constructs (for a discussion see e.g., Ben-Akiva et al., 2002; Liebe et al., 2018; Ashok et al., 2002). The problem with including self-assessed responses in the DCE analysis lies in their latent structure, i.e., that they are themselves stated evaluations, just as the dependent variable is a stated preference, leading to estimation bias. Given the central role of patience and risk preferences for intertemporal decision-making, we circumvent the endogeneity problem by using revealed preference information for these two mediators obtained in an incentive-compatible lab-in-the field experiment.

For this purpose, we measured patience using decisions respondents made in a two-level price-list task. In this task, they had to make two decisions between receiving a payment of x today or a payment of y in two weeks, with $y > x$. If a respondent took the payment today (in two weeks) in the first task, the payment to come in two weeks was increased (decreased) in the second task. The initial payment offer was K6 today vs. K10 in two weeks.[12] The most patient respondents are expected to wait for the larger amount, while marked impatience would prompt a respondent to choose today in both subsequent cases.

Risk preferences were elicited via an adapted version of the elicitation procedure proposed by Eckel and Grossman (2002), similar to the version implemented by Cardenas and Carpenter (2013). Participants were shown a non-see-through cotton bag in which there were 20 balls. Ten of the balls were blue and ten were yellow. The participant was asked to take a ball from the bag without looking. The color of the ball withdrawn from the bag determined the payoff the participant would receive. Before drawing the ball, however, the participant had to choose the payoff distribution that would be implemented. The offered distribution options were the following five: (10K, 10 K), (7.5 K, 14 K), (5K, 18 K), (2.5 K, 22 K), (0K, 24.5 K). The first number indicates the amount received if the ball turned out to be yellow and the second number the amount received if the ball withdrawn was blue. The larger the variance in the payoff distribution chosen, the less risk-averse the participant is. To ensure sufficient variation in answers from the target sample, the incentivization schemes for preference elicitations were piloted before the survey was conducted.[13]

In our econometric analysis, we scaled the responses for patience and risk preferences to represent standard deviations from mean. See Section 6.2 for further information.

4.3. Implementation of the experiments

The DCE and the lab-in-the-field experiments were implemented in the survey as follows: Every participant was asked a number of introductory questions. They included questions on experiences and expectations with regard to coastal hazards, on how people usually interact with the coast, and on the way in which respondents perceive the current state of the coastal ecosystem.[14] The responses to the latter question provided information on where people located the status-quo level ("no change") of the attribute *Changes in Animal and Plant Species*.

Subsequently, the surveyor introduced the choice setting and explained the choice elicitation along a randomly chosen choice card.[15] To ensure comprehension, this was followed by a short comprehension test.[16] Afterwards, the participants made their choices on the choice cards. To address criticisms of the validity of non-market valuation studies in developing countries (e.g. Whittington, 2002; Bennett and Birol, 2010), we included control questions on choice-experiment performance and an additional choice-consistency check. This check is designed to test the validity of the weak axiom of revealed preferences (WARP). WARP constitutes a basic rationality requirement a person's choices need to fulfill so that they can reasonably be described by means of a utility function (Mas-Colell et al., 1995). As the conceptual basis of choice experiments rests on the optimization of indirect utility functions, a test of WARP serves as a test of the basic consistency in choice assumptions underlying any choice experiment. WARP requires that if x is chosen over y in a situation where the consumption bundles x and y are affordable, then there cannot be another situation in which x and y are affordable and y is chosen over x. We implemented this validity check by confronting a participant with one of the choice cards from the core card-set a second time but with the choice vector across alternatives shifted down by one step. This enables us to analyze the change in choice behavior of a participant across two choice situations in which the same alternatives are presented but the set of affordable alternatives changes. WARP is violated if a participant switches choices between cards in such a way that, on the card with the lower price vector, an alternative is chosen that was already revealed to be affordable on the initial card (with the higher cost vector) but was not selected there.

This part of the survey was followed by a post-experimental questionnaire covering experimental controls, the lab-in-the-field experiment on economic preference parameters, and questions on attitudinal and socioeconomic characteristics.

Data collection took place in September 2019. As shown in Fig. 1, the data was taken from three villages close to one another with 165, 117, and 107 households respectively. All households in each of these villages were invited to have one household member aged 18 or above to take part in the survey. The respondent answered as individuals.[17] Ultimately, 298 people participated (101, 98, and 99 respectively). The experiment was conducted in a paper-and-pen format by local enumerators in secluded spaces set up for the purpose to ensure maximum privacy. The survey material was translated prior to data collection, and enumerators were trained in the conduct of structured interviews so that elicitation modes were neutral and comparable across surveyors.

[12] In the second part, payments were either K6 today vs. K12 in two weeks or K6 today vs. K8 in two weeks.

[13] Both, the risk and the patience tasks are designed such that the underlying preference parameter that can be associated with a particular response increases continuously with the number assigned to the choice variable, to allow for a numeric treatment of the final risk and patience variables.

[14] Respondents were asked to rate the current state of the flora and fauna along the coastline close to their village on a 4-point Lickert scale.

[15] As each participant was assigned to only one of the two blocks of choice cards, the card used for explanations was drawn from the block the participant was not assigned to for actual choice elicitation afterwards.

[16] Participants' comprehension of the choice experiment was assessed in a two-step comprehension test. In particular, respondents had to answer six comprehension questions — one for the comprehension of each attribute. If a question was answered incorrectly, the meaning of the respective attribute was explained to the respondent again, who was then asked to answer this question a second time (first step). If any question was answered incorrectly in the second round, the meaning of the attribute was explained to the respondent again in addition to being told the correct answer (second step).

[17] Upon arrival at the registration desk, respondents indicated which household they belonged to. We used a list of all households provided by the village chief to ensure that no household participated twice.

Table 2
Sample characteristics.

Statistic	N	Mean	St. Dev.	Min	Max
Socio-demographics					
Age	294	38.71	13.69	18.00	87.00
Gender (0 = Male; 1 = Female)	297	0.52	0.50	0	1
Weekly Household Income*	227	50.05	77.37	0.00	600.00
Education (in years completed)	290	8.23	1.95	4.00	12.00
Household Size	279	7.30	3.63	1.00	20.00
Coastal Dependence (0 = Low; 1 = High)	297	0.64	0.17	0.29	0.88
Risk Tolerance	297	0.00	1.00	−0.96	1.57
Patience	295	0.00	1.00	−1.37	1.14
Experience of Coastal Processes (%):					
Coastal Flooding					
Experience	297	0.69	0.46	0	1
Damage	297	0.10	0.30	0	1
Sea Level Rise					
Experience	297	0.84	0.37	0	1
Damage	297	0.23	0.42	0	1
Expectation of Coastal Processes (%):					
Coastal Flooding					
Expectation	295	0.63	0.48	0.00	1.00
Damage	297	0.61	0.49	0	1
Sea Level Rise					
Expectation	296	0.73	0.45	0.00	1.00
Damage	297	0.63	0.48	0	1
Comprehension and Consistency					
Comprehension					
Assessment by Experimenter (1 = Low; 5 = High)	297	4.34	0.84	1	5
Assessment by Participant (1 = Low; 4 = High)	297	3.51	0.67	1	4
Errors in Round1	297	1.48	1.38	0	6
Errors in Round 2	297	0.21	0.59	0	4
WARP consistency	294	0.89	0.31	0.00	1.00

* At time of data collection: K1 = $0.29
** The share of respondents that evaluated the occurrence of an event as “rather likely” or “very likely”.

5. Econometric modeling

The econometric modeling of the choice data is based on well-established random utility maximization (RUM) models (McFadden, 1974). Assuming that the researcher does not possess complete information regarding the preferences of individual n, individual preferences are considered to be the sum of a systematic (V) and a random (ϵ) component:

$$U_{ni} = V_{ni}(x_{ni}, \beta) + \epsilon_{ni} \tag{1}$$

with U_{ni} the true but unobservable utility associated with alternative i out of a set of available alternatives, C, V_{ni} the deterministic part that is a function of the attributes (x_{ni}), and ϵ_{ni} an unknown random part. The vector of coefficients (β) reflects the desirability of the attributes.

Assuming that the error components are distributed independently and identically (IID) following a type-1 extreme value distribution, one gets the conditional logit (CL) model, where the probability of individual n choosing alternative i is:

$$P_{ni} = \frac{\exp(\mu V_{ni})}{\sum_{j\in C} \exp(\mu V_{nj})} \tag{2}$$

The scale parameter μ is commonly normalized to 1. As the CL model assumes same preferences across individuals, we additionally employ a mixed logit (MXL) model. This enables us to account for heterogeneous preferences specified in the random parameters associated with the choice attributes. The adjusted utility function of the MXL model is presented in Eq. (3), where the first part is identical to Eq. (1) but the vector of coefficients β_n is now randomized over the sample population, as shown in Eq. (3). In this study, the distributions of the random parameters related to the choice attributes are all assumed to have a normal distribution.

$$U_{ni} = V_{ni}(x_{ni}, \beta_n) + \epsilon_{ni} \tag{3}$$

Changes in welfare due to a marginal change in a given attribute can be expressed through the marginal willingness to pay ($mWTP$) measure. It is defined as the maximum amount of income an individual is willing to pay in exchange for an improvement in the level of a given attribute. The $mWTP$ is calculated with the coefficient of the attribute of interest and the cost attribute representing the marginal utility of income as follows: $mWTP = -\beta_attribute/\beta_money$.

6. Results

6.1. Descriptives statistics

Table 2 displays descriptive statistics for the sample. The upper part of the table includes socio-demographic information. The sample is balanced in terms of gender, with 52% females and 48% males. The average respondent is 38.7 years old, went to school for 8.23 years, and lives in a household with a weekly income of K50 (USD 14.25). In addition, Table 2 indicates a respondent’s self-assessed degree of coastal dependence. This measure is the weighted and normalized sum of responses to the question of what people use the coast for.[18] Overall, it indicates strong coastal dependence in everyday life. In fact, almost all participants rely on the coast as a source of food.

The next part of Table 2 contains respondents’ experiences and expectations regarding coastal hazards. In the past five years, a large number of participants have experienced erosive coastal processes in the shape of coastal flooding and sea-level rise. More than three-quarters of the participants said they had witnessed sea-level rise in

[18] The highest weights (factor three) are assigned to the answers “food,” “fresh water,” “washing,” “cooking,” “toilet.” The second-highest weight (factor two) is given to “income,” “building materials,” “travel,” and the lowest (factor one) to "leisure”. The sum of a person’s responses is then normalized to the range of 0 to 1. If the participant reports no interaction with the coast, the resulting value is 0.

their region, and roughly two-thirds had encountered coastal flooding. With respect to damages, only a minority of respondents reported that they had suffered any personal or physical damage (e.g., income loss, house damage, loss of assets) from any of these two hazards in the past five years. For the future, the majority of participants, i.e., over 60%, anticipate that coastal flooding will occur (again) and sea-levels will (continue to) rise in the next five years. Nearly all respondents also reckon with personal and /or physical damage from these two potential threats. This suggests that at the time of data collection, the level of actual harm from these two types of events is low, while the felt level of threat from expected damage is high.

The lower part of Table 2 provides information on how difficult it was for respondents to understand the survey, including the choice experiment and the lab-in-the field experiment. Comprehension is measured in several ways. First, respondents were asked to indicate their agreement with the statement "I fully understood the descriptions/attributes". Most of the respondents agreed with this statement. Secondly, experimenters were asked to rate a respondent's level of comprehension. The average score on a scale of 1 (low) to 5 (high) is 4.34. Next, respondents passed the first round of comprehension checks with an average of 1.5 errors out of six questions. This number fell to a mere 0.2 errors in round two. Finally, using our rationality test (explained above), we find that the choices of the vast majority (89%) of respondents are consistent with the weak axiom of revealed preferences (WARP). Overall, these statistics suggest a reasonable understanding of the survey, despite its complexity and educational heterogeneity among the respondents.

6.2. Regression results

The results of the econometric analysis are presented in Table 3.[19] Due to some protest votes and failed comprehension checks, the working sample is slightly smaller than the sampled population.[20] From the conditional logit (CL) model (Model 1) we can infer that all but one attribute influences the choices. Assuming, as the CL model does, that all participants have the same preferences, a longer *Lifetime* of protection measures is highly significant and positive. The time required for a measure to achieve its full protection potential (*Time Until Full Protection*) is also positive and significant. These results are consistent with the overall hypothesis that time-related characteristics of protective measures are important to respondents. Further, the results support the hypothesized valuation of longevity of coastal protection (H2). There is however no indication of longer times until full protection having a negative effect, as hypothesized in H1. Environmental side effects of a measure (*Changes in Animal and Plant Species*)[21] is the most relevant characteristic in terms of coefficient size. The average respondent assigns higher utility to measures with positive impacts on the surrounding environment than to those with negative impacts. The only remaining non-monetary attribute, Access to Coast, is not statistically significant. Even though this attribute was highlighted in the focus group discussions, it does not seem to be of sufficient relevance over and against the other attributes. The cost attribute (*Contribution to Community Fund*) is highly significant and has the expected negative sign.[22] On average, respondents prefer alternatives with lower costs.[23] The alternative specific constant (ASC) separates the protection alternatives from the status quo. The ASC parameter is positive and highly significant, indicating that respondents support community-wide coastal protection over and against no protection, irrespective of the levels of the different choice attributes.[24]

Table 3
Regression results.

	Dependent variable: Choice		
	Model 1	Model 2	Model 3
Parameter Coefficients:			
Time until Full Protection (TFP)	0.046**	0.082*	0.073*
	(0.019)	(0.046)	(0.042)
Lifetime (LT)	0.054***	0.077***	0.081***
	(0.012)	(0.018)	(0.017)
Access to Coast	−0.053	−0.035	−0.066
	(0.080)	(0.171)	(0.157)
Changes in Animal and Plant Species	0.180***	0.271**	0.288***
	(0.056)	(0.110)	(0.100)
Contribution to Community Fund	−0.024***	−0.048***	−0.044***
	(0.006)	(0.015)	(0.012)
ASC (Protection)	3.517***	6.256***	6.708***
	(0.513)	(1.206)	(1.145)
ASC x Risk Tolerance			0.916***
			(0.199)
TFP x Risk Tolerance			−0.028
			(0.040)
LT x Risk Tolerance			−0.002
			(0.010)
ASC x Patience			0.097
			(0.214)
PT x Patience			0.035
			(0.040)
LT x Patience			0.026**
			(0.010)
Standard Deviations of Random Parameters:			
Time until Full Protection		0.271**	0.206
		(0.134)	(0.140)
Lifetime		−0.055	
		(0.040)	
Access to Coast		0.468	
		(0.529)	
Changes in Animal and Plant Species		0.819***	0.736***
		(0.242)	(0.190)
Contribution to Community Fund		0.104***	0.089***
		(0.023)	(0.020)
ASC (Protection)		−3.068***	3.342***
		(0.770)	(0.776)
Cluster Level	Participant	Participant	Participant
Assistant FEs	Yes	Yes	Yes
N	252	252	250
Observations	1,007	1,007	999
Log Likelihood	−818.305	−712.119	−703.732

Note: Fixed effects are included as interaction with the ASC. Standard errors are clustered on participant level. Control variables are normalized to standard deviations from mean.
∗p<0.1; ∗∗p<0.05; ∗∗∗p<0.01.

[19] In order to interpret the magnitude of the regression coefficients as ceteris paribus effects for the average respondent, all control variables were normalized to represent standard deviations from the mean. The estimation was done in R using the mlogit and gmnl package (Croissant et al., 2012; Hlavac, 2014; Sarrias and Daziano, 2017).

[20] Following common procedures in environmental valuation (see e.g. Dziegielewska and Mendelsohn, 2007; García-Llorente et al., 2011; Jorgensen et al., 1999; Meyerhoff and Liebe, 2008), protestors were identified as those respondents who always chose the opt-out and indicated opposition to the topic in a follow-up question. Four participants were classified as protesters and 40 excluded due to poor comprehension (those with errors in the second round of the comprehension test; see footnote 4.3).

[21] This attribute is coded in a [−1, 0, 1]-scheme, as nonlinearity of effects could not be detected.

[22] We also tested models with alternative specifications of the price coefficient that take into account possible nonlinear effects (logarithmic and triangular distribution assumptions). Yet, the results remained robust and model performance did not improve.

[23] Also, we find that high price levels are indeed cutting off choices.

[24] Regarding the choice behavior of the respondents, we find that protection alternatives 1 and 2 were chosen in 93% of all choices, and almost equally within each village and across the whole sample. The status-quo alternative was chosen in 7% of all choices.

The results of the mixed logit (MXL) model (Model 2) show that most of the estimated standard deviations of the random coefficients are significant, implying significant unobserved taste heterogeneity between respondents and justifying the use of the MXL model. Overall, the results are similar to those from the CL model, but the significance levels for two of the attributes are lower. *Time Until Full Protection* is significant only at the 10% level and *Changes in Animal and Plant Species* at the 5% level of statistical significance. Turning to the random effects, significant preference heterogeneity is detected most importantly related to *Changes in Animal and Plant Species*, *Time Until Full Protection* and the price respondents are asked to pay for the measure. The random terms for the ASC are also significant, indicating that preferences among individual respondents vary significantly in terms of support for coastal protection.

To test H3, we estimate extended choice models including risk preferences and patience as possible sources of preference heterogeneity. Given the limited number of participants and the low number of choice cards per person, we include covariates separately in the model. Covariates include interaction terms between (i) *Time Until Full Protection* and risk preferences, (ii) *Time Until Full Protection* and patience, (iii) *Lifetime* and risk preferences, (iv) *Lifetime* and patience, (v) ASC and risk preferences, and (vi) ASC and patience. The results are presented in Table 3 (Model 3). Note that we have limited the number of random parameters to those with significant standard deviations. Further, we have scaled the preference parameters (risk preferences and patience) to represent standard deviations from the mean value.

Although the covariates do not significantly improve model fit, their inclusion seems to capture a significant part of the random parameter for *Time until Full Protection*, and the interaction effects reveal interesting results. The interaction between ASC and risk tolerance is positive and significant, implying that more risk-averse respondents are less likely to indicate a willingness to protect. Further, the interaction between *Lifetime* and patience is positive and significant, indicating that more patient participants show a stronger preference for coastal protection measures with longer lifetimes. None of the other interaction effects are statistically significant. Differences in risk preference show no significant interaction effects with either of the time-related attributes. Also, the interaction between *Time Until Full Protection* and patience is insignificant. With regard to H3, large parts of the hypothesis cannot be supported. Also, even with the inclusion of a large set of covariates, we still fail to detect any urgency to protect, as anticipated under H1.[25]

Finally, in a further attempt to capture unobserved heterogeneity, we specified MXL models with socio-demographic covariates. This includes interactions with (i) respondent's income and the cost attribute, (ii) respondent's gender and *Access to Coast*, (iii) perceived state of the coastal ecosystem and *Changes in Animal and Plant Species*, and (iv) stated responsibility for protection and the ASC. The results are presented in Table A.2 in Appendix. Most importantly, the interaction between the cost attribute and household income shows, as expected in theory, a significant positive effect, indicating that respondents' WTP depends on their ability to pay. Hence, the higher a respondent's household income, the higher on average their WTP. We find no gender effects on the valuation of *Access to Coast* despite the fact that women are responsible, e.g., for fetching salt water for cooking. Fishing, however, is done equally by men and women. Next, respondents that perceive the current state of the coastal ecosystem as dire attach higher importance to positive environmental side effects than those who consider it to be in good condition. Finally, those who see

Table 4
Regression results including attendance weights.

	Dependent variable: Choice	
	Model 2 (unweighted)	Model 2 (weighted)
Parameter Coefficients:		
Time Until Full Protection (TFP)	0.082*	0.003
	(0.046)	(0.074)
Lifetime (LT)	0.077***	0.133***
	(0.018)	(0.027)
Access to Coast (AC)	−0.035	−0.188
	(0.171)	(0.210)
Changes in Animal and Plant Species (EE)	0.271**	0.685***
	(0.110)	(0.162)
Contribution to Community Fund (C)	−0.048***	−0.054***
	(0.015)	(0.014)
ASC (Protection)	6.256***	6.588***
	(1.206)	(1.241)
TFP X TFP Attendance		0.169
		(0.137)
LT X LT Attendance		−0.212***
		(0.053)
AC X AC Attendance		0.456
		(0.383)
EE X EE Attendance		−1.435***
		(0.309)
C X C Attendance		0.037**
		(0.017)
Standard Deviations of Random Parameters:		
Time Until Full Protection	0.271**	0.224*
	(0.134)	(0.135)
Lifetime	−0.055	0.001
	(0.040)	(0.055)
Access to Coast	0.468	0.345
	(0.529)	(0.556)
Changes in Animal and Plant Species	0.819***	0.610***
	(0.242)	(0.194)
Contribution to Community Fund	0.104***	0.091***
	(0.023)	(0.021)
ASC (Protection)	−3.068***	−3.328***
	(0.770)	(0.734)
Cluster Level	Participant	Participant
Assistant FEs	Yes	Yes
N	252	252
Observations	1,007	1,007
Log Likelihood	−712.119	−687.786

Note: Fixed effects are included as interaction with the ASC. Standard errors are clustered on participant level. Weights: "never" = 1, "seldom" = 2/3, "often" = 1/3, "always" = 0. Note: Higher weights denote less attention, such that plain coefficients can be interpreted as coefficients of attentive participants. *p<0.1; **p<0.05; ***p<0.01.

Table 5
Marginal willingness to pay estimates (in Kina/week/household).

	Model 2		Model 3	
	WTP	St. Err.	WTP	St. Err.
Lifetime	1.62***	0.037	1.84***	0.353
Time Until Full Protection	1.73***	0.179	1.65***	0.148
Access to Coast	−0.73**	0.310	−1.50	3.318
Changes in Animal and Plant Species	5.67***	0.541	6.51***	0.527
TFP x Risk Tolerance			−0.63	0.912
LT x Risk Tolerance			−0.05	0.233
TFP x Patience			0.80	0.918
LT x Patience			0.59**	0.273

[25] As a robustness check we assessed correlations with a large set of other control variables, including self-assessed patience and risk preferences, but the results remained unchanged. See Fig. A.3 in the Appendix for correlations of control variables with the individual specific *Time Until Full Protection* coefficient.

the responsibility for coastal protection as lying with leaders rather than local people are significantly less willing to engage in communal protection efforts.

6.3. Attribute non-attendance

The standard deviations of the random parameters in Table 3 show that there are respondents for whom the cost coefficient is positive. Fig. A.4 in the Appendix, which shows the distribution of preference parameters at the individual level based on MXL model 2, confirms this. To investigate this relationship further, we specified latent-class models. The results for an increasing number of classes from one to three classes are shown in Table A.3 in Appendix. For the preferred model with three classes, we find that there is one class of respondents (class 3) for which the cost coefficient is no longer significantly different from zero. Respondents in this group also rarely chose the status quo (cf. extremely large ASC coefficient errors). These results indicate the presence of attribute non-attendance for a subgroup of respondents (class 3; $N = 93$).

Attribute non-attendance can either be a representation of actual preferences, in that respondents actually do not care about a particular attribute, or a sign of a choice heuristic to reduce cognitive complexity, which need not correspond to actual preferences (see e.g. Heidenreich et al., 2018). One-way to cross-check these possibilities, is to use responses from our post-experimental questionnaire. To control for the presence and degree of attribute non-attendance, respondents were asked how often they considered each of the presented attributes in their decision making in the choice experiment. The responses show that the majority of participants indicated either "often" or "always" for the cost attribute (see Fig. A.5 in the Appendix). Barely anyone stated that costs were irrelevant to their decision making. Thus, it can be assumed that the attribute non-attendance in our data reflects cognitive attempts to reduce choice complexity rather than preferences.

In order to test whether the reported strength of attention has an impact on the regression results, we added interaction terms to Model 2 (Table 4). The reported attendance scores were used as parameter weights. The weights range from 0 to 1, with 0 representing full attendance and 1 representing non-attendance. The non-interacted coefficients can thus be interpreted as preference coefficients of fully attentive respondents. The results show that ignoring attribute non-attendance leads to a significant underestimation of the negative influence of costs as well as an underestimation of the role of *Lifetime* and *Changes in Animal and Plant Species*. Furthermore, *Time Until Full Protection* is no longer relevant for the average attentive respondent. Finally, the ordinal interpretation of coefficients is robust to the addition of attendance weights.

6.4. Preferences for coastal protection modes

We use the results of Table 3 to answer the question which protection mode respondents would prefer. In a first step, Table 5 presents the marginal WTP estimates obtained from the MXL models (Model 2 and Model 3). A one-year increase in a measure's lifetime increases the average WTP for protection by K1.62 per week. Equally, a one-year delay in the onset of the protection effect of a measure is worth an additional contribution of K1.73 per week. While the estimated coefficient on *Access to Coast* was insignificant, respondents show a positive significant WTP for coastal access of K0.73 per week.[26] Ensuring positive environmental side effects or preventing negative ones raises the weekly WTP for protection on average by an additional K5.67.

Next, we look at the two modes of coastal protection and calculate the WTP for the implementation of the two approaches ¬- soft vs. hard. Table 6 shows the characterization of the approaches along the attributes of our DCE (columns 2 and 4). The calculation is based on the attribute levels of our DCE (columns 3 and 5) which implies that realistic values, e.g. for the lifetime of soft protection measures, might differ from the values we use for our calculation. However, by doing so, we avoid imposing strong linearity assumptions on the elicited preference parameters for values beyond those used in our design.

Table 6
Mapping of protection type characteristics to quantitative values used in the WTP calculation.

	Soft Protection Measures		Hard Protection Measures	
	Characteristics	Levels	Characteristics	Levels
Lifetime	*Long*	10 Years	*Short*	1 Year
Time Until Full Protection	*Long*	4 Years	*Short*	1 Year
Access to Coast	*Full Access*	1	*Full Access*	1
Changes in Animal and Plant Species	*Increase*	1	*Decrease*	−1

We define soft protection measures as taking a longer time until the full protection potential is reached while hard measures are set up in comparably short time (soft: 4 years, hard: 1 year) and as having longer lifetimes than hard measures before repair or restoration work is necessary (soft: 10 years, hard: 1 year). They also have positive environmental side effects instead of negative ones. *Access to Coast* is kept constant across both protection modes (i.e., at Full Access) as for both modes there are options that allow for full access as well as options that restrict access exist. Using the marginal WTP estimates of Model 2 displayed in Table 5, the average WTP for soft protections defined in this way is K31 higher per week (CI: [28.61, 33.52]) than for hard protections. Given the role of attribute non-attendance in our dataset, these estimates are rather a lower bound of true WTPs. Using the attendance weighted coefficients these estimates become significantly larger (K114, CI: [116.06, 112.84]).

7. Discussion

The results show that respondents prefer protection to no protection, but they do not value earlier onset of protection more than later onset. This is at odds with one of our hypotheses. Along the lines of our theoretical model presented above, there are two potential drivers for this result:

1. The result is driven by (strongly) forward-looking individuals, such that $\delta \leq 1$.
2. The result is driven by the expectation of an intensification of the threat in future periods, either in terms of an intensification of the impact (x_i), or an increase in probability (μ_i), such that protection in the future provides a larger utility gain than earlier protection can offer (with an increase in utility that is sufficiently large to outweigh discounting effects).

The first proposition assumes a significant interaction between the importance of *Time Until Full Protection* and the level of patience. However, this relation cannot be detected by including measures for patience in our empirical analysis. In addition, we are unable to identify any significant interaction between *Time Until Full Protection* and future hazard expectations (compare Table A.2 in the Appendix). In fact, even using the whole set of control variables hardly enables us to identify any mediator of the preference for longer times until full protection. These include controls on cognitive ability, comprehension, and perceived concentration during the elicitation. Hence it also seems unlikely that the estimated coefficient is primarily due to a miscomprehension of the attribute, which supports the robustness of the result.

[26] *Access to Coast* is negatively coded, such that an increase of the variable is referring to a restriction of coastal access.

As a second deviation from the predictions of our theoretical model, we find that more risk-tolerant respondents show a higher willingness to protect than risk-averse ones. This is not the first study to arrive at this conclusion. Fiala and Wende (2016), for example, find that more risk-tolerant individuals are more prone to engage in adaptive behavior in terms of obtaining coastal flooding insurance. The argument proposed by the authors is that insurance investments themselves are seen as gambles, so that risk-averse individuals are less prone to engage in this kind of adaptive behavior. In the context of this study, the protection alternatives are described as community-wide protection projects associated with strategic uncertainty and a change in the status quo. To the extent that uncertainty preferences can be related to an aversion to the strategic uncertainty involved in cooperative situations (e.g., Bohnet and Zeckhauser, 2004; Kocher et al., 2015) or to an aversion to deviations from the status quo (Samuelson and Zeckhauser, 1988), these considerations could provide our findings with intuitive plausibility. Furthermore, we elicit risk preferences in a gain domain by assuming that protection measures provide an improvement to the status quo without protection. However, protection from the impacts of climate change could equally well be seen as an avoidance of losses rather than as a gain. Studies on prospect theory argue for a preference reversal between the gain and the loss domain, so that individuals who are risk-averse in the gain domain become risk-seeking in the loss domain Kahneman and Tversky (1979). This may be an alternative explanation for the results of our study. Indeed, several studies using risk parameters assessed in the loss domain find the expected positive correlation between risk aversion and adaptation motivation (e.g. Petrolia et al., 2013; Glatt et al., 2019). By contrast, several studies measuring risk preferences in the gain domain find a negative relationship between risk aversion and adaptation choice (e.g., Cai and Song, 2017; Reynaud et al., 2018). Thus, in line with prospect theory, the finding from our study in addition to the results from these other papers could be taken to represent support for the proposition that protection decisions are perceived as choices in the loss domain. It should however be noted that the relationship between risk attitudes and adaptation choices could also be bi-directional. Several authors note that the experience of extreme events such as coastal flooding, tsunamis, or violent conflicts lead to an increase in risk tolerance following these events (e.g. Eckel et al., 2009; Page et al., 2014; Voors et al., 2012). This would explain a positive relationship between risk tolerance and the experience of coastal erosion, which has repeatedly been found to increase adaptation motivation. However, scientific consensus on the direction in which preferences shift after a disaster and on the link between experience and adaptive behavior itself has so far been low (e.g. Page et al., 2014; Koerth et al., 2017). Overall, we can thus see this in line with findings from a growing body of literature on the complex relationship between risk attitudes, hazard experience, and protection motivation. Reconciling these existing heterogeneities is however beyond the scope of this study and must be left to future research.

8. Conclusion

Adaptation to climate change is becoming increasingly crucial for coastal areas. This paper analyzes individual preferences for coastal protection focusing on the trade-off between short-term and long-term protection effectiveness. We use data from a DCE that builds on a simplistic theoretical framework of intertemporal optimization where the benefits of protection measures depend on the time it takes for protection to start and the longevity of the measures. The DCE was conducted in Bougainville in Papua New Guinea. In this region, local coastal-hazard projections with adequate certainty levels are unavailable. Accordingly, the choice between protection modes has to be made under hazard uncertainty, i.e. uncertainty about the kind, extent, or time-frame of coastal threats. In the DCE, the trade-off between protection modes is conceptualized in terms of five attributes: *Time Until Full Protection*, *Lifetime*, *Changes in Animal and Plant Species*, *Access to Coast*, and *Contribution to Community Fund*.

Confirming results from previous studies (e.g. Chang et al., 2012; Johnston et al., 2018; Imamura et al., 2016), we find that respondents value both protection effectiveness and environmental conservation. More importantly for the case of hazard uncertainty, however, we find a preference for long-term over short-term effectiveness of coastal protection modes. In fact, our results show a non-negative coefficient for *Time Until Full Protection*. Hence, in the context of our study we cannot identify any urgency to protect, while there is a preference for protection longevity. Lastly, respondents dislike negative environmental side effects of protection measures. The results are robust against corrections for attribute non-attendance and choice inconsistency. In terms of protection modes, the combined results reflect a preference for soft coastal protection measures. The non-negative coefficient for *Time until Full Protection* is robust against the inclusion of a large set of controls. Given that speed of protection is a major advantage of hard protection structures, this finding contributes at least partially to the strong preference for soft protection measures in our data.

We discuss two mechanisms that can be derived from the theoretical model for the lack of urgency to protect: (a) discounting of present utility in favor of future utility gains, and (b) expectations of hazard intensification in the future. Neither of these explanations is supported by an analysis of the interaction between the importance of *Time Until Full Protection* and controls for patience and future expectations. An alternative explanation could be that people have a preference for high-quality protection measures and associate them with longer construction times. Another could be that the level of the threat is simply not yet perceived as high enough to justify an urgency to protect compared to the other attributes. While many participants have experienced erosive coastal processes in the form of flooding and sea-level rise in the past, only a minority reported that they had suffered personal or material damage. This argument would be in line with previous research summarizing reactions to climate change in small island developing states as last-minute coping strategies rather than long-term adaptations (Klöck and Nunn, 2019). Another aspect that might be critical, is how respondents' view the time before full protection. In our model, we assume zero protection being achieved in that time period. However, respondents may assume some partial protection gained during the construction of the protection measure. So, the time before full protection would offer some partial protection. If viewed this way, it implicitly extends the overall life time of the project. As more data is needed to fully identify the mechanism behind this finding, this issue must be left for future research. This might also involve a more complex design than the one used here, testing longer times until full protection.

Another subject for future research is assessing the external validity of our results. While our findings are obtained from a distinct cultural sample, the generic design of the choice experiment provides an opportunity for a direct test of the external validity of our results. Generic designs are less common in the choice-experimental literature as they are said to result in a loss of response accuracy due to a lower level of contextual precision. But assessing external validity by enabling cross-study outcome comparisons is essential for weighing the applicability of benefit transfers and eventually the derivation of robust policy implications (Johnston et al., 2021). This is especially true of areas where cultural differences are relevant determinants of outcomes, as is the case with coastal adaptation (Noll et al., 2020). So far, most of the research on coastal protection preferences has been geared to western samples, whereas a major proportion of regions that will be severely affected by climate change is located in the equatorial zones. Transferring existing findings to these regions requires an understanding of the differences between regions close to the equatorial zone and those further away, as well as the identification of mediating variables (Johnston et al., 2021). A global comparison shows that, on average, people from equatorial zones are less forward-looking and more uncertainty-tolerant than people from countries further away from the equator (Falk et al., 2018). Given the relevance of patience and risk attitudes for protection preferences in our data, differences in these preference parameters may qualify as mediators of protection preferences. The results of our validity check and the overall high comprehension rates in this survey lend support to the feasibility of more generic DCE designs which allow for cross-cultural comparisons of preferences. However, it remains for future research to substantiate this finding.

Overall, the minor importance assigned to short-term effectiveness of protection measures in our study raises the question of whether communities will be able to keep pace with the need for rapid protection expressed by official institutions and climate scientists (IPCC, 2014, 2019; Nurse et al., 2014). Institutionalized efforts could potentially bridge the gap between the urgent science-based necessity to protect and individual inaction. Still, studies repeatedly point to the important role of community involvement in avoiding maladaptation in coastal protection (see e.g., Torabi et al., 2018; Piggott-McKellar et al., 2020). Thus, even when coastal protection is initiated at higher institutional levels, community support should be sought, which is found in our data for measures that provide long-term protection and avoid negative environmental side effects.

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.

Data availability

Data will be made available on request.

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Appendix

See Figs. A.1–A.5 and Tables A.1–A.3

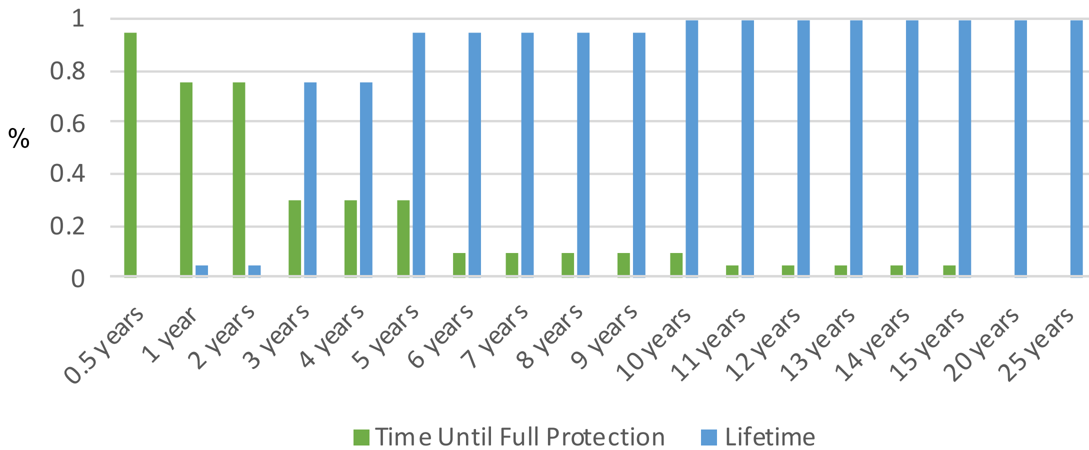

Fig. A.1. Acceptance levels for time-related attributes.

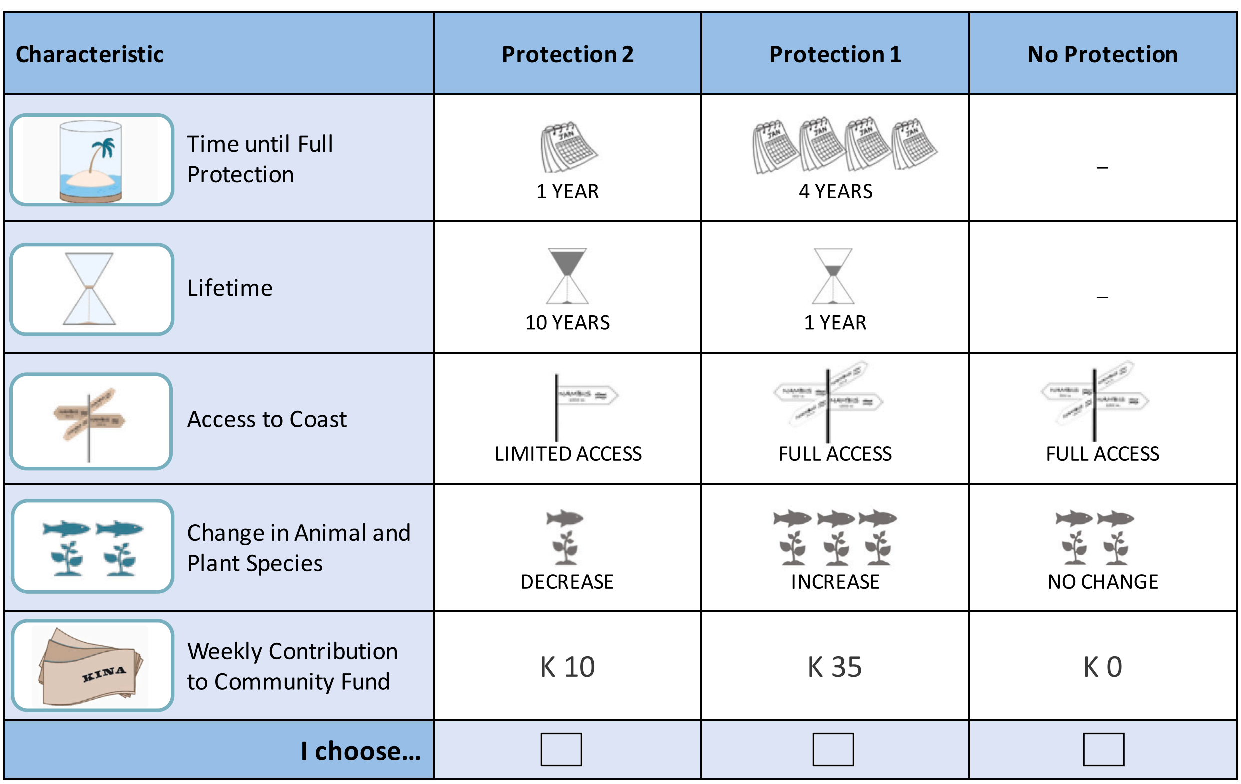

Fig. A.2. Example choice card. Note: Percentage of respondents considering the proposed length of time to be acceptable in terms of *Time Until Full Protection* and *Lifetime*. Results were used to identify the maximum (*Time Until Full Protection*) and minimum (*Lifetime*) values for the attribute levels in the DCE.

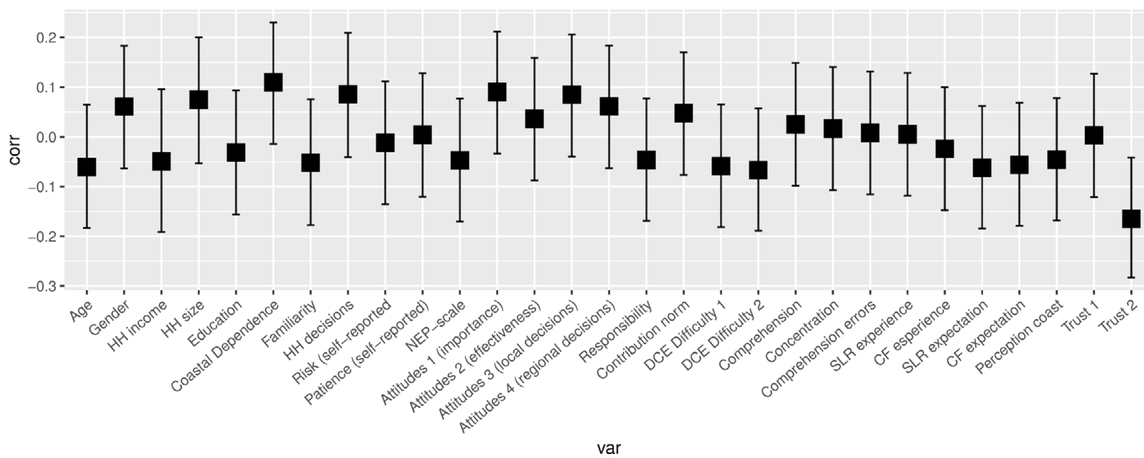

Fig. A.3. Correlations of individual-level *Time Until Full Protection* attribute valuations and control variables. Bars indicate 95%-Confidence Intervals. Note: To test the robustness of the positive Time Until Full Protection coefficient using the full rigor of our dataset, we compute correlations between individual-level coefficient estimates and a large set of control variables. This comprises among other things information on attitudes, trust, expectations, and experience. The individual-level coefficient estimates are obtained from the MXL estimation reported in Table 3 (Model 2). This figure shows the results of this analysis. None of the control variables apart from one are significantly correlated with the coefficient estimates of Time Until Full Protection. The only exception is one of our measures for trust (Trust 2), which shows a significant negative correlation coefficient. In the subsample of respondents with high values in this variable, the average Time until Full Protection coefficient ceases to be positive but becomes indistinguishable from zero (mean=-0.001, p-value=0.98). Overall, the absence of any urgency to protect is remarkably robust.

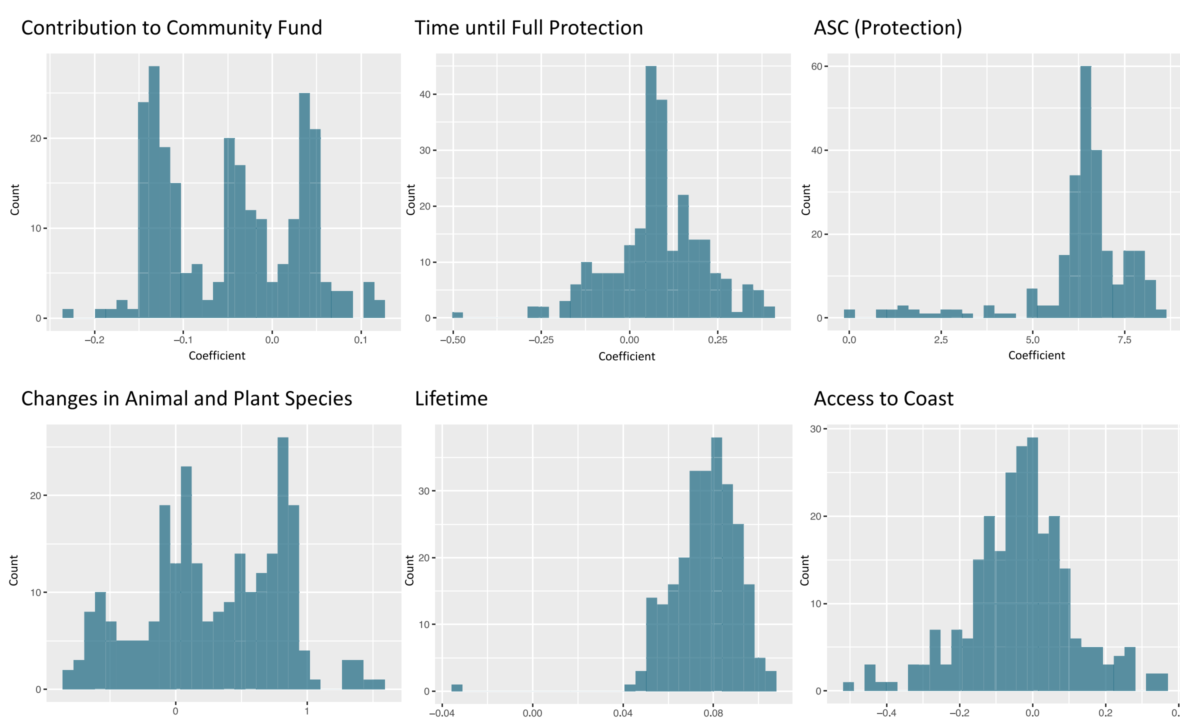

Fig. A.4. Distribution of fitted individual level preference parameters based on mixed logit estimation (Model 2) assuming normal distributions for all attributes.

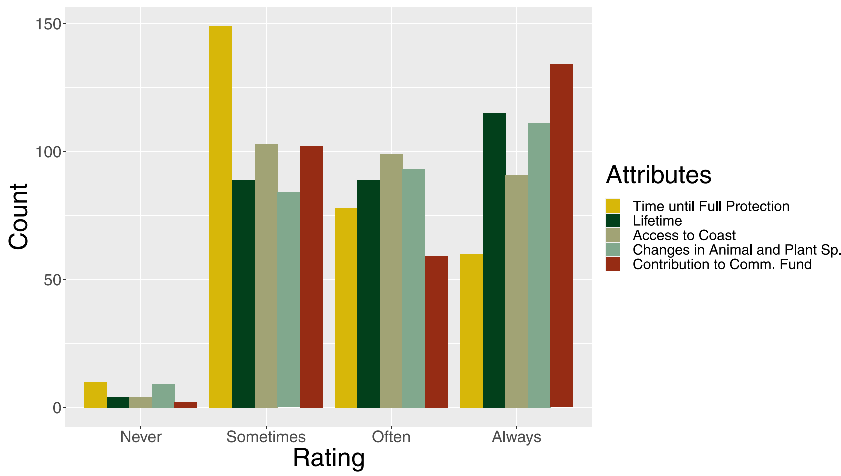

Fig. A.5. Choice relevance of attributes. Note: As part of the post-experimental questionnaire participants were asked "If you think about your choices. To what extent did you take into account each of the individual attributes in your overall decisions?". Answering options were "never", "sometimes", "often", "always". This figure shows the answers to this question for each attribute.

Table A.1
Summary statistics of control variables.

Variable	Description	Min/Max	Mean	Std. Dev.
Age	Age of participant in years.	18/87	38.71	13.69
Gender	Gender of participant, 0=male, 1=female [0,1]	0/1	0.52	0.50
HH income	Self-reported available weekly household budget in Kina.	0/600	50.05	11.37
HH size	Number of household members including the respondent.	1/20	7.30	3.63
Education	Number of years at school.	4/12	8.23	1.95
Coastal dependence	Weighted and normalized sum of responses to the question of what people use the coast for. Highest weights are assigned to the answers "food," "fresh water," "washing," "cooking," "toilet." The second-highest weight is given to "income," "building materials," "travel," and the lowest to "leisure". The sum is normalized. [0,1]	0.29/0.88	0.64	0.17
Familiarity	Number of years the participant has lived in the village where the interview took place.	0.1/86	28.00	16.84
HH decisions	Who usually makes decision regarding money in your household? 1=myself, 0=others [0,1]	0/1	0.68	0.47
Risk (self-reported)	In general, how willing or unwilling are you to take risks? 3=completely willing, 0=completely unwilling, [0,3], compare (Dohmen et al., 2011)	0/3	0.67	1.08
Patience (self-reported)	In comparison to others, are you a person who is generally willing to give up something today in order to benefit from that in the future or are you not willing to do so? 3=completely willing, 0= completely unwilling [0,3], compare (Dohmen et al., 2011)	0/3	2.26	0.87
NEP-scale	Combined measure for environmentalism along the 6-item New Environmental Paradigm scale.	1.33/4	3.19	0.47
Attitude 1 (importance)	Do you agree? Coastal protection is an issue of major importance in our village. [1,4]	1/4	3.93	0.32
Attitude 2 (effectiveness)	Do you agree? Community funds are an effective tool in financing local public projects. [1,4]	1/4	3.85	0.42
Attitude 3 (local decisions)	Do you agree? The opinions of the villagers play a role in the decision-making process in our village. [1,4]	1/4	3.64	0.62
Attitude 4 (regional decisions)	Do you agree? The opinions of the villagers play a role in the decision-making process in Bougainville. [1,4]	1/4	3.40	0.82
Responsibility	Variable indicating where the participant sees the responsibility for coastal protection in the village. 1=people, 2=people and leaders or 3=leaders	1/3	2.68	0.65
Contribution norm	Imagine the people in your village decided to implement a community project financed by a community fund. In such a situation, it would be socially inappropriate for any community member not to contribute to the funding. [1,4]	1/4	3.78	0.50

(*continued on next page*)

Table A.1 (*continued*).

Variable	Description	Min/Max	Mean	Std. Dev.
DCE difficulty 1	Do you agree? I understood the descriptions/attributes completely. [1,4]	1/4	3.51	0.67
DCE difficulty 2	Do you agree? It was easy to decide on each card. [1,4]	1/4	3.40	0.75
Comprehension	Assistant report on comprehension of participant. 5=participant understood perfectly, 1=understood poorly [1,5]	1/5	4.34	0.84
Concentration	Assistant report on concentration of participant. 5=participant was very focused, 1=participant was not focused at all [1,5]	3/5	4.85	0.42
Comprehension errors	Number of mistakes made in first round of comprehension checks. [0,6]	0/6	1.48	1.38
SLR experience	Have you personally observed an increase in sea level? [0,1]	0/1	0.84	0.37
CF experience	Have you ever personally experienced coastal flooding in your life? [0,1]	0/1	0.69	0.46
SLR expectation	Measure of expected event occurrence within the next five years. [1,4]	0/1	0.73	0.45
CF expectation	Measure of expected event occurrence within the next five years. [1,4]	0/1	0.63	0.48
Perception coast	Perception of the current state of the coastal ecosystem measured in terms of agreement with the statement "The vegetation on the coast close to my village is plentiful" and "There are plenty of fish and other animals in the sea on the coast close to my village." 1=fully disagree, 4=fully agree [1,4]	1.5/4	3.22	0.79
Trust 1	How well does the following statement describe you as a person? As long as I am not convinced otherwise, I assume that people have only the best intentions. 1=not at all, 4=perfectly [1,4], compare Dohmen et al. (2011)	1/4	2.63	0.90
Trust 2	Generally speaking, would you say that most people can be trusted or that you cannot be too careful in dealing with people? 0=you cannot be too careful in dealing with people, 1=most people can be trusted[0,1], compare Dohmen et al. (2011)	0/1	0.03	0.16

Table A.2
Regression results of models with socio-demographic variable interactions.

	Dependent variable: Choice			
	Model 1	Model 2	Model 3	Model 4
Parameter Coefficients:				
Time until Full Protection	0.077	0.070*	0.071*	0.068
	(0.048)	(0.043)	(0.042)	(0.042)
Lifetime	0.065***	0.075***	0.076***	0.073***
	(0.018)	(0.016)	(0.015)	(0.016)
Access to Coast	0.062	−0.043	−0.022	−0.030
	(0.177)	(0.163)	(0.155)	(0.154)
Changes in Animal and Plant	0.162	0.273***	0.254***	0.266***
Species (EE)	(0.101)	(0.098)	(0.092)	(0.095)
Contribution to Community	−0.035***	−0.043***	−0.042***	−0.041***
Fund (C)	(0.013)	(0.012)	(0.012)	(0.012)
ASC (Protection)	6.624***	6.365***	6.703***	6.356***
	(1.549)	(1.118)	(1.199)	(1.084)
C x Household Income	0.034***			
	(0.007)			
AC x Gender		−0.125		
		(0.122)		
EE x State of Coast			−0.275***	
			(0.060)	
ASC x Responsibility				−0.279***
				(0.107)
Standard Deviations of Random Parameters:				
Time until Full Protection	0.150	0.227*	0.207	−0.195
	(0.206)	(0.137)	(0.139)	(0.139)
Changes in Animal and Plant	0.685***	0.681***	0.677***	0.649***
Species	(0.214)	(0.186)	(0.178)	(0.182)
Contribution to Community	0.088***	0.107***	0.092***	0.101***
Fund	(0.023)	(0.021)	(0.019)	(0.020)
ASC (Protection)	3.895***	3.399***	3.250***	3.040***
	(1.080)	(0.724)	(0.742)	(0.622)
Cluster Level	Participant	Participant	Participant	Participant
Assistant FEs	Yes	Yes	Yes	Yes

(*continued on next page*)

Table A.2 (*continued*).

	Dependent variable: Choice			
	Model 1	Model 2	Model 3	Model 4
N	186	250	250	250
Observations	743	999	999	999
Log Likelihood	−504.704	−706.172	−699.463	−707.003

Note: Fixed effects are included as interaction with the ASC. Standard errors are clustered on participant level. Control variables are normalized to standard deviations from mean. ∗p<0.1; ∗∗p<0.05; ∗∗∗p<0.01.

Table A.3
Latent class model results.

	Dependent variable: Choice		
	Number of Classes: (1)	(2)	(3)
Class 2		−0.146	−0.231
		(0.105)	(0.209)
Class 3			0.156
			(0.129)
Class 1:			
Time until Full Protection	0.046∗∗	0.102∗∗	0.230∗
	(0.023)	(0.049)	(0.133)
Lifetime	0.054∗∗∗	0.040∗	−0.045
	(0.009)	(0.022)	(0.054)
Access to Coast	−0.053	−0.267	0.144
	(0.096)	(0.213)	(0.422)
Changes in Animal and Plant Species	0.180∗∗∗	−0.159	−0.481∗
	(0.054)	(0.109)	(0.285)
Contribution to Community Fund	−0.024∗∗∗	−0.067∗∗∗	−0.059∗∗
	(0.006)	(0.014)	(0.023)
ASC (Protection)	3.517∗∗∗	3.390∗∗∗	20.404
	(0.529)	(0.822)	(5878.600)
Class 2:			
Time until Full Protection		0.013	0.049
		(0.052)	(0.076)
Lifetime		0.094∗∗∗	0.136∗∗
		(0.024)	(0.059)
Access to Coast		0.218	−0.634
		(0.195)	(0.462)
Changes in Animal and Plant Species		0.588∗∗∗	0.188
		(0.123)	(0.193)
Contribution to Community Fund		0.015	−0.068∗
		(0.013)	(0.035)
ASC (Protection)		2.844∗∗∗	2.661∗∗∗
		(1.069)	(0.758)
Class 3:			
Time until Full Protection			−0.037
			(0.060)
Lifetime			0.112∗∗∗
			(0.029)
Access to Coast			0.280
			(0.250)
Changes in Animal and Plant Species			0.711∗∗∗
			(0.146)
Contribution to Community Fund			0.020
			(0.013)
ASC (Protection)			135.330
			(14720.000)
Assistant FEs	Yes	Yes	Yes
Observations	1,007	1,007	1,007
Log Likelihood	−818.31	−738.59	−695.35
AIC	1654.609	1515.175	1448.703
BIC	NA	1608.555	1591.230

Note: ∗p<0.1; ∗∗p<0.05; ∗∗∗p<0.01.

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