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Adapting to Climate Change: Threat Experience, Cognition and Protection Motivation^{*}

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Abstract

Climatic changes largely unfold by means of two types of events: extreme events and gradual long-term changes. This paper highlights how the difference in occurrence probability and (marginal) impact between the two event types leads to structural differences in cognitive processing of event experiences. Building upon insights on imperfect memory and optimization behaviour under (inter-temporal) uncertainty, I theoretically argue how differences are likely to occur at the level of event awareness, expectation formation and adaptation motivation. This postulation is empirically corroborated using data on the willingness to protect against coastal hazards from a sample population that is simultaneously exposed to sea level rise and coastal flooding. For both event types, event awareness is found to be heterogeneous across individuals with comparable actual experience levels. These variations in awareness are able to explain variations in expectations and protection motivation, however, only in the case of sea level rise. Instead, in case of coastal flooding, protection motivation is found to be sensitive to variations in expectations which are decoupled from heterogeneities in event awareness. These findings outline two structurally different cognitive routes underlying protection motivation. They indicates that the effectiveness of policy approaches to overcome climate change adaptation thresholds is likely to depend on the particulars of the threat type and calls for more nuanced future research.

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1 Motivation

While climate change related threats are projected to intensify (IPCC, 2014), the dimension of social and economic damages they cause strongly depends on the way people react to these hazards.¹ So far, adaptational reactions are often found to be suboptimal.² This creates a need to understand barriers to adaptation to reduce expected losses. Yet, up until now, the relation between hazard experience and adaptation motivation remains largely unclear.^{3,4} One likely reason for heterogeneity in adaptation outcomes can be the sensitivity of the cognitive process that underlies adaptation motivation. This process can be structurally divided into the following three steps: (1) the processing of information about some event gained either through descriptions or personal experience, (2) the formation of future expectations based on this information, and (3) the translation of these future prospects into behavioral intent.^{5,6} Each of these steps is providing ample opportunities for decision heuristics and cognitive biases to create variation in adaptational outcomes. Given that the degree to which certain biases are activated depends on specific situational cues or on individual level characteristics, these variations are likely structural variations between groups of people or situations.

In order to investigate this claim, I study the response to variations in two specific situational cues: impact and occurrence probability of hazards. Whereas high impact events are likely to be more memorable and influential in expectation formation due to the strong emotional response they trigger,⁷ even traceable low impact events are at risk to remain undetected as long as changes are sufficiently small.⁸ Further, how people react to future expectations of an event is subject to a mental weighting procedure dependent on the events impact and likelihood profile.⁹ Consequently, two hazard types that differ in terms of impact and likelihood are likely to induce non-homogeneous adaptational reponses by stimulating

¹Aerts et al. (2018); Nicholls and Cazenave (2010); Desmet et al. (2021); Heutel et al. (2020); Butler and Huybers (2013); Hinkel et al. (2014)

²e.g. Burke and Emerick (2016); Gallagher (2014); Wachinger et al. (2013); Meyer (2012)

 $^{^{3}}$ In an attempt to identify relevant barriers to optimal adaptation, a long strand of literature investigates the relation of hazardous event experience and individual level adaptation motivation. This literature reports a large variation in correlation coefficients between experiences and adaptation motivation, lacking consensus already with regard to the overall sign of the relation (van Valkengoed and Steg, 2019; Koerth et al., 2017; Bubeck et al., 2012; Bamberg et al., 2017).

⁴Several studies investigated the influence the kind of adaptation has on adaptation motivation, in particular comparing self-protection i.e. reducing the loss probability with self-insurance i.e. reducing the size of losses (Di Mauro and Maffioletti, 1996; Ozdemir, 2017; Shogren, 1990). Since these do not provide evidence for robust differences between modes, it is not differentiated between studies on the basis of adaptation mode at this point.

⁵If the perceived ability to show a behavioural response with sufficient success probability is low, people might also divert to a cognitive instead of behavioral coping strategy such as denying the existence of the threat. (Babcicky and Seebauer, 2019; Grothmann and Reusswig, 2006; Mulilis and Duval, 1997; Lindell and Perry, 2012)

⁶Imagine for example the apparent threat of a fist soaring towards your face. At first your brain receives the information of this fist coming closer and closer. In the next step this will trigger the expectation that if nothing changes this fist will touch your face soon and induce a considerable level of pain. Lastly, your brain will weigh behavioural response options to avert this threat and, in this scenario, likely produce an imperative to duck down. Even though all of this happens in a split second, it is a palpable example of the three steps in the process that triggers protection motivation.

⁷Slovic et al. (2004); Loewenstein et al. (2001)

⁸Simons et al. (2000)

 $^{^9 \}mathrm{Bordalo}$ et al. (2012); Bushong et al. (2021); Koszegi and Szeidl (2013)

different results throughout the underlying cognitive process. Variations are likely at the stage of event awareness, in how future expectations are constructed and in the translation of expectations into behavioural intent.

The sensitivity of adaptational reactions to these two specific situational cues gains empirical relevance especially in the field of climate change economics, as it translates into structural differences in the adaptational response to the two main types of events by which climate change unravels - extreme events and long-term gradual changes. These event types markedly differ along the lines of occurrence probability and impact. Extreme events, such as coastal flooding, heat waves, heavy rainfall or droughts, show a generally low occurrence probability and infer large damages once they occur. Opposed to that, long-term gradual changes are marked by a high occurrence probability (up to certainty), yet low marginal impacts. This class of events encompasses hazards such as desertification, loss of biodiversity, gradual temperature increase or sea level rise, which are in spite of their marginal daily impact projected to cause massive damages in the longterm.¹⁰

Using insights from studies on imperfect recall and belief formation as well as optimization under uncertainty, this study offers a theoretical argument for heterogeneities in the cognitive processing of events that differ in terms of impact an occurrence probability. The theoretic predictions are empirically investigated in a systematic comparison of the cognitive response to the exposure to extreme events and gradual long-term changes using field experimental data from a sample that is simultaneously exposed to both types of hazards. In particular, I collected data from coastal inhabitants from a small island region in Papua New Guinea, who face the threat of, both, coastal flooding and sea level rise. The data set contains survey data on personal experiences and expectations with regard to both hazard types, as well as choice experimental data on the willingness to protect against coastal threats, which allows to infer deviations in the motivational response to hazard exposure between event types. A common issue with the use of survey data on event experience is that any answer will be the outcome of the cognitive process described above. This process might lead people to exaggerate or devalue any experience memory, such that answers do not need to align with actual "objective" event experiences.¹² One way to disentangle variation in actual event experience between respondents from variation in event recall (also referred to as event awareness or reported event experience in this paper), would be to compare reported experiences to actual event records. As sufficiently detailed official event data is not available for the study region, this paper establishes another way to single out the underlying cognitive process. Making use of geographically narrow sampling, subgroups with a joint objective experience background (i.e. objective experience groups, OEGs) can be characterized along observables. This step minimizes the variation in actual event experience within OEGs and allows to relate remaining within OEG heterogeneity in the collected measures back to variations in cognitive processing.

¹⁰Rising sea levels are estimated to cause losses of up to 4.5% of real global GDP under intermediate projection scenarios, necessitating the displacement of roughly 1.5% of the global population by the year 2200 (Desmet et al., 2021). Equally, increasing average temperatures are estimated to lead to an undiscounted global annual damage of \$63 billion - \$128 billion¹¹ in the agricultural sector alone (Iizumi et al., 2020) and an increase in elderly mortality of 2.5% based on US sample estimates (Heutel et al., 2020). Beyond that, the progress of these gradual changes increases extreme event likelihoods.

 $^{^{12}}$ compare e.g. Guiteras et al. (2015)

The experimental design allows to make a multitude of empirical contributions. First of all, the comparison of the threat of coastal flooding and sea level rise allows to analyze differences in hazard type with regard to occurrence probability and impact while keeping contextual components such as the source of the threat as well as the domain of affected environmental and personal assets constant.¹³ Furthermore, making use of analysis results on OEG level from a geographically proximate sample allows to investigate cognitive process variations with survey data from the field. Hence, this design circumvents the pitfalls of the recreation of the two threat structures in the laboratory.¹⁴ Lastly, the sample chosen for this study allows to investigate difference in reactions to the two event types ex-ante to any adaptational efforts, such that any confounding influences of previous/ existing adaptation on threat perceptions and adaptation motivation can be ruled out.

The results show heterogeneity in event experience reporting within OEGs for both types of events. This heterogeneity is driven by different individual level characteristics, in line with the proposition that different cognitive biases are activated for each event type. In case of sea level rise, the found differences in experience reporting translate into variation in expectations and can be found to significantly impact protection motivation. For coastal flooding, heterogeneities in experience reporting cannot be found to affect flooding expectations nor explain variation in protection motivation. Instead, protection motivation is significantly correlated with coastal flooding expectations. As these are insensitive to differences in event awareness, protection motivation is decoupled from variations in cognitive processing of event experiences in case of coastal flooding in this dataset. Overall, this dataset shows differences in the cognitive processes translating event experience into adaptation motivation between extreme events and gradual changes at all three steps, namely: the variables that influence event awareness, the degree to which event awareness drives expectation formation, and the determinants of behavioral intent.

Overall, this paper offers two essential conceptional contributions to the literature. Up to this point, there is no existing consensus, neither in field nor lab experimental investigations,¹⁵

¹³In order to plausibly infer that any difference in outcomes can be traced back to the difference in event type by means of differences in event probability and impact, it is necessary to ensure as little deviations of the two compared events along other dimensions. For example, Goeschl et al. (mimeo) provide evidence that people are sensitive to the source of a risk that they face. In detail, participants in their lab experiments react different to risk that is caused by humans than risk that is caused by non-human factors as nature or pure chance. Next, Löckenhoff et al. (2019) find differences in event perception for events of different domains. Domain in this case refers to the kind of assets at stake or the kind of efforts that have to be taken to avoid a threat, for example work effort or cash payments. People will respond differently if their family picture books are at stake than if there is a threat to loose a collection of garden tools, for example. Going back to the study of Browne et al. (2015) comparing bicycle theft to coastal flooding, none of the previously presented dimensions are kept constant, such that it is difficult to argue where differences in outcome originate from.

¹⁴Most notably this concerns the credible reconstruction of catastrophic losses in the lab in case of the low probability event as well as reconstructing a long-term gradual event that causes minimal consequences per period yet can still culminate into catastrophic losses, eventually and is thus conceivable as a threat.

¹⁵Several laboratory studies investigates adaptation choices varying the occurrence probability of hazards while keeping the size of expected losses constant (e.g. Laury et al., 2009; Di Mauro and Maffioletti, 1996; Shafran, 2011; Ganderton et al., 2000). Consequently, the reaction to low probability-high impact hazards is compared to the reaction to high probability – low impact hazards.¹⁶ Even though the laboratory setting allows a high degree of experimental control, results are largely heterogeneous across studies.¹⁷ The same conclusion can be drawn across studies using field data. Browne et al. (2015) conducted a within subject comparison of insurance take up against flooding and bicycle theft, finding that people were significantly more

on the impact of a simultaneous decrease in impact and increase in occurrence probability on protection choice. This study is the first to introduce a conceptional basis that allows to acknowledge the complexity of the cognitive process behind adaptation behaviour and, thus, is able to place explanatory power on the determination of cognitive sources of outcome heterogeneity. Further, a large majority of the literature on climate change adaptation focuses on reactions to extreme event experiences. This paper shows that this focus likely prohibits insights on adaptation reactions to the large and in the context of climate change highly relevant class of gradual long-term changes. The results presented in this paper strongly question the transferability of results on adaptation motivational processes from research based on extreme event data to the class of long-term gradual changes. In addition, the findings of this paper outline different policy needs for adaptation enforcement against long-term gradual changes than against extreme events. The correction of event (mis-)perceptions is likely to stimulate adaptation motivation only for certain types of hazards.

The paper is structured as follows: In section 2, the argumentative basis is provided that justifies the assumption of difference in the motivation process from extreme event and gradual change exposure and provides hypotheses to guide the analysis. In section 3, I provide details on the experimental design and measurement and section 4 follows up with the results of the investigation. Finally, section 5 discusses the findings and section 6 concludes.

2 Theoretical Background

This section outlines likely sources of heterogeneity in the cognitive response between the two event types following the described three step procedure: event perception, expectation formation and the translation of future prospects into behavioural intent.

2.1 Event Perception, Recall and Expectation Formation

Personal (past) experiences are used as a key information source for people's mental representations of the world. They inform the process of generating beliefs about the current state of the world and expectations about the future (D'acunto et al., 2021; Loewenstein et al., 2003; Lucas, 1973, 1975; Fuster et al., 2010). This is reflected in theoretic accounts on drivers of adaptation motivation in which experiences are repeatedly ascribed the role of an information source on the likelihood of occurrence and severity of likely damages (Rogers and Prentice-Dunn, 1997; Lindell and Perry, 2012; Grothmann and Reusswig, 2006).

Yet, other than assumed under the rational expectations hypothesis, people are repeatedly found to not make optimal use of all available information. In fact, recall of personal experiences and previously gained information is often imperfect. On one hand, recall is largely

likely to insure against the high probability-low impact hazard of bicycle theft. Closer to the concept of long-term gradual changes, Koubi et al. (2016) study the role of slow-onset and sudden-onset environmental hazards for migration choice. The authors compare experience descriptions of migrants and non-migrants from regions that are affected by either form of hazard and report a negative correlation between slow-onset event experience and the probability to migrate while the correlation between sudden-onset events and the probability to migrate is positive. In a meta-analytical investigation of the difference in impact of slow- and rapid-onset environmental changes on international migration, Hoffmann et al. (2020) find both estimates to be positive.

partial and, on the other hand, the determination of which event/ information is recalled is context and individual specific. For example, evidence on memory being associative implies that contextual cues enhance the recall probability of events encountered in contexts similar to the current one (Bordalo et al., 2020; Enke et al., 2020; Mullainathan, 2002; Gilboa and Schmeidler, 1995). The personal degree of selective attention, in addition, influences which facets of the current context are attended to (Schwartzstein, 2014; DellaVigna, 2009; Kahneman, 1973) and the personal state at the time the initial event took place can influence the way in which the event is memorized (Haggag et al., 2019). Personal and situational characteristics, thus, influence the ease of recall of an event. Accordingly, even if people have the same actual experiences, recall is likely to be heterogeneous.¹⁸

Let the difference between extreme events and long-term gradual changes be given along the dimensions of impact and probability with expected losses being the same for both event types.¹⁹ Imposing rational expectation formation along factual experience accounts, there is no reason to expect any differences in expected beliefs between these two event types. However, allowing the ease of recall to be mediated by cognitive heuristics that respond to attributes of the situation, causes the ease of recall of instances of either event type to be structurally different. Two heuristics of this kind are the following:

1. Recall is found to be mediated by the degree of emotional reaction an event triggers (Slovic et al., 2004; Slovic and Peters, 2006; Loewenstein et al., 2001). This is, events with impact levels high enough to induce an affective reaction are more easily remembered as well as more effective in triggering activism.²⁰ In line with this, this phenomenon is often referred to as "affect heuristic". Given that extreme events strike strongly once they occur while the impact of long-term gradual changes is for a long time hardly palpable, the affective sensitivity of people induces heterogeneity in the ease of recall between instances of the two event types. Furthermore, this affect heuristic will generate heterogeneities in recall of one and the same event between people to the degree to which the affective sensitivity is heterogeneously distributed between people. This way, this heuristic is likely to generate an upwards bias in extreme event recall and intensify heterogeneity in extreme event recall, but is unlikely to affect recall of long-term gradual changes (Weber, 2006). Further, given that event recall informs the generation of future expectations, these differences in recall generated by the affect heuristic might lead to similar structural variations in the formation of future expectations.

2. A memory can only be created if the event is recognized. In the research of Simons et al. (2000) on "change blindness", people are found unable to acknowledge incremental changes, if they are only sufficiently small. Depending on the speed of gradual events, i.e., the size of marginal changes, they might be completely unacknowledged for a long time. This cognitive tendency has gained comparably little attention within the economic profession, yet, is par-

¹⁸For findings in line with this in the realm of flooding experiences see for example Guiteras et al. (2015).

¹⁹The argument is abstracting from the accumulating losses under long-term gradual changes and from the potential interrelation between the two event types. Extreme events are consequently classified as low probability - high impact events and long-term gradual changes as high probability - low impact events. Even though it is a simplification, it is a valid representation for the initial periods under any long-term gradual change, while the exact length of applicability of this simplification depends on the speed of the change process. Given the largely separate treatment of impact and occurrence probability related biases, however the argument contains informative value even beyond this classification.

²⁰This point of sufficiency might well be heterogeneous between Individuals.

ticularly noteworthy for the study of low impact events. It implies that events are recalled at all only if they show a visible impact above some minimal threshold level. Accordingly, change blindness induces a mental underrepresentation of instances of low impact up to the point that expectations about future changes might be fully independent from developments of this threat in the past or present. This cognitive bias is highly unlikely to be of relevance for high impact events such as extreme events but is likely to influence expectation formation for long-term gradual changes.

These derivations outline the argumentative ground for the postulation that the cognitive process translating experience of extreme events and gradual long-term changes into future expectations is likely to be structurally different. Given that the argumentative framework from this section, the following hypotheses can be raised:

H1: Event recall is heterogeneous between individuals with the same experiences for both event types.

H2: Recall is structurally different between event types, in particular:

H2.1: Susceptibility to the affect heuristic biases recall of extreme events upwards, yet does not impact recall of longterm gradual changes.

H2.1: Susceptibility to change blindness biases recall of longterm gradual changes downwards, yet does not impact recall of extreme events.

H3: Differences in experience recall translate into variation in expectations.

2.2 Behavioural Intent

A second factor for dissimilarities in adaptation reaction between event types is the likely non-homogeneity in the reaction to the expectation profiles of high probability-low impact and low probability-high impact events. There are two reasons for this postulation. First of all, people tend to construct *non-linear* mental representation of probabilities. Prospect theory (Kahneman and Tversky, 1979) and studies on cognitive uncertainty (Enke and Graeber, 2020) trace systematic biases in mental probability representations towards 50-50 prospects. People tend to overestimate the occurrence likelihood of low probability events but underestimate the occurrence likelihood of high probability events. Consequently, this cognitive process would induce an overestimation of expected losses of extreme events along side an underestimation of expected losses of long-term gradual changes.

Secondly, people engage in non-linear outcome weighting. In particular, theories of focusing argue that the most salient outcomes gain disproportionate weight in their mental representation (Bordalo et al., 2012; Bushong et al., 2021; Koszegi and Szeidl, 2013). In a choice situation between a safe outcome option and a lottery, people will, consequently, show risk seeking behaviour (i.e. be more likely choose the lottery) if most attention is placed on positive outcome states of the lottery. If negative outcome states are most attended to, a decision maker will show risk aversion by more likely choosing the safe option. Theories differ on the part of which aspect of the choice context determines what outcomes gain most attention. Bordalo et al. (2012, 2013) argue that the outcome that differs the most from the average value in a choice set is most salient. Koszegi and Szeidl (2013) and Bushong et al. (2021) suggest that most weight is given to those outcomes which present the largest variation across choice options leading to a so called "concentration bias" in which dispersed outcomes gain less attention than those concentrated in time. Up to this point, empirical evidence lends support to the second proposition (Dertwinkel-Kalt et al., 2019; Bushong et al., 2021). Translating this over to the choice between protection or no protection vis a vis any of the two kinds of hazard. A susceptibility to a concentration bias would lead to a strong focus on the large potential one time gain that protection against extreme events would offer. Less focus will be attracted by the small per period gains dispersed over time from protection against long-term gradual changes. If protection costs are the same in both cases, a protective response is more likely stimulated by the expectation profile of extreme events. In sum, both of these aspects provide ground for the following hypothesis:

H4: Expectations of extreme events leave a stronger mental impression and are, thus, more likely to trigger a behavioural response than the expectation of long-term gradual changes.

In addition, there might be differences in the role of related individual level preference parameters between the two types of events. Adaptation choices are an inter-temporal optimization problem over risky prospects, such that they involve at least two levels of uncertainty: one regarding the probability of experiencing losses at all and one regarding the timing of expected losses. The role of expectations for the generation of an intention to adapt is consequently likely to be mediated by a person's patience and risk preference. Under the expected utility approach, the shape of the utility function over outcome states defines a person's risk attitudes. Risk aversion is associated with a concave utility function over all outcomes. Assuming equality in expected losses, differences in risk attitudes should have a stronger influence on the reaction to the prospects of low probability-high impact risk structures than to high probability-low impact risks.²¹ The theory on loss aversion assumes that people are more sensitive to losses than to gains evaluated against some given reference point and a diminishing sensitivity to outcome size also for losses (Kahneman and Tversky, 1979; Koszegi and Rabin, 2006, 2007, 2009). This renders a representative agent to be risk seeking in the loss domain and, again, for risk preferences to mediate the attitudes especially towards low probability - high impact event expectations.

The inter-temporal dimension of uncertainty can be incorporated in the theory of focusing in that standard models of inter-temporal discounting might be considered as a case of time-dependent focusing. More recent realizations are weighted more than realizations to come in the more distant future, with present biased behaviour to be found if a person places a disproportionately stronger focus on today than on any future date (O'Donoghue and Rabin, 1999; Dertwinkel-Kalt et al., 2019). The predictions that can be made for the difference in adaptation motivation for either threat type based on inter-temporal focusing remain ambiguous, however. On one hand, it could be the case that a strong present bias omits protection motivation in any case, as future prospects are gaining no to minimal weight in the present-day decision making. On the other hand, it could be the case that when a DM places an enhanced focus on a single day i.e., today, a high perceived threat from extreme

 $^{^{21}{\}rm Given}$ a concave utility function the marginal effect of variations in risk aversion is increasing in the size of the stakes.

events induces an instantaneous willingness to protect, given the uncertainty about the timing of the next event occurrence. Delaying protections to some future date involves the risk of suffering severe damages before protections are established. Contrary to that, delaying protection efforts against only slowly and gradually intensifying events grants the benefit of pushing protection costs into the future at the cost of only a marginal increase in personal damage likelihood.

While these considerations outline the potentially different role of individual level patience and risk preferences for the translation of expectations into behavioural intent between event types, they do not offer a clear directional prediction. For this reason these theoretic thoughts shall be raised as a basis for more exploratory investigations of the role of these preference parameters in the following.

3 Experimental Design

The sample used to empirically investigate the validity of these claims are coastal inhabitants from northern Bougainville, Papua New Guinea. Papua New Guinea is a developing country with a strong rule of customs and norms based on the traditional wantok system instead of formal institutions (Nanau, 2011; De Renzio, 2000).^{22,23} Accordingly, most problems (including coastal protection) are solved in a bottom-up process with the communities themselves as primal actors. This renders individual protection motivation an important factor for regional climate change adaptation in the study region.

On top of that, the region of Papua New Guinea is facing the threat of coastal flooding as well as high rates of sea level rise. In the period of 1980 - 2010 tropical cyclones crossed the region up to three times per year and while the National Weather Service forecasts a decrease in cyclone likelihood in the future their intensity is anticipated to increase (Papua New Guinea National Weather Service et al., 2015). In addition, sea levels rise with 7-10 mm/year at more than twice the global average speed (Papua New Guinea National Weather Service et al., 2015; Albert et al., 2016). Accordingly, coastal inhabitants from Bougainville are simultaneously exposed to gradual long-term changes along the coastline as well as to the hazard of extreme flooding events. These hazards differ in terms of their occurrence probability and impact level, but are both threatening by means of coastal erosion and saltwater intrusion. Given this congruency in the threat domain, a multitude of event characteristics are kept constant between the two hazards. This is, the source of risk, the domain of affected goods and the set of potential remedies are largely the same, minimizing the range of alternative characteristic differences between event types that might drive outcome variation.^{24,25}

 $^{^{22}}$ The UNDP assigns a human development index in 2019 of 0.555 (rank 155 out of 189 countries (UNDP, 2020).

²³https://freedomhouse.org/country/papua-new-guinea/freedom-world/2020, 08.01.2021

²⁴The degree to which adaptation options are available and perceived as feasible is heterogeneous between people and event types. It can be influenced by factors such as kind of affected goods, available materials, income, physical abilities or educational attainment of the respondent. This creates a pathway for differences in adaptational responses to two different event profiles to be driven by differences in the set of feasible strategies rather than by differences in impact and probability of the hazard.

 $^{^{25}}$ see for example Diekert et al. (2021) or Löckenhoff et al. (2019) for evidence on the outcome relevance of

The communities of Bougainville are composed out of a multitude of small (secluded) villages and show a large range of subcultures and languages. Given the small size of villages, three villages had to be included in the study to insure sufficient sample size. These villages are drawn from the same geopolitical subregion in the north west of Bougainville in order to provide as much homogeneity in cultural variables as well as in threat dynamics as possible within the sample (compare figure 1).



Figure 1: Coastal communities included in the sample

3.1 Event Perception

To map heterogeneity in event awareness, i.e., how people recall events, every participant answered the following questions on personal event experiences for both hazard types:

- Q1: Have you personally experienced sea level rise/ coastal flooding?
- Q2: How much of a rise in sea level did you experience in the past five years?/ How many coastal flooding events did you experience in the past five years?
- Q3: Did the rise in sea level/ coastal flooding cause any personal or physical damages to your household in the past five years?

While the first and the third question were answered in yes/no fashion, the second question had to be answered in a binary format for sea level rise (*mild increase, severe increase*) and by means of a discrete number in case of coastal flooding. For all three questions, heterogeneity in answers between subjects can be driven by two processes: 1) differences in actual event experience, or 2) differences in cognitive processing of the same event. Given that the goal is to investigate the latter, the variation in cognitive processing is isolated in a two-step

these factors.

process. First of all, the geographically narrow sampling reduces the exogenous variation in actual event experiences by design. The proximity of villages and their small sizes rule out large heterogeneities in experiences. If sea levels rise at the coast close to a village or a village is struck by coastal flooding this renders either all villagers exposed to this hazard or none. This leaves likely variation in actual experiences to occur, if present, between villages (Q1, Q2, Q3), age groups (Q1) or distance to coast if damages are considered (Q3). Thus, in a second step, objective experience groups (OEGs) are constructed based on these variables for each question. These are subsets of the sample that can be credibly assumed to have the same level of actual experiences. The answers to the experience questions are then transformed to be given in terms of standard deviations from OEG mean, such that any remaining within OEG heterogeneity in experience reporting can be expected to be driven by variations in cognitive processing of the same events.

3.2 Threat perception

Future hazard expectations are collected to serve as a measure for experienced risk also referred to as threat perception or threat awareness in this paper. These terms are used interchangeably. In line with other studies, risk perception is defined as the composite measure of the likelihood that one will experience an event and the likelihood that one will be affected by this event for example by suffering personal damages (compare e.g. Bubeck et al., 2012; Grothmann and Reusswig, 2006, and references therein). Accordingly, the survey included five year expectations of respondents about event occurrence and damages, that had to be answered on a four-point lickert scale from *very unlikely* to *very likely* for both event types:

- Q1: How likely or unlikely do you think it is that sea levels will (continue) to rise/ coastal flooding will occur in the next 5 years in your area?
- Q2: How likely or unlikely do you think is it that sea level rise/ coastal flooding causes personal or physical damage to your household in the next 5 years?

The final measure for threat perception is given by the product of the answers to each of these two questions, i.e. likelihood of occurrence times likelihood of personally being affected.

3.3 Adaptation Motivation

The measure for adaptation motivation is collected through a discrete choice experiment (DCE) on the willingness to contribute to a community fund for the construction of coastal protections along the coast close to the village. Every person saw four choice cards. On each card the participant was asked to choose between two unlabeled protection alternatives ("Protection 1", "Protection 2") and the status quo ("No Protection"). The alternatives were described in terms of the time it takes until the protection is fully provided, the length of time that the measure could be expected to provide full protection without need of restoration, the environmental side effects, the degree to which it would block access to the coast, and the costs in terms of weekly contributions to a community fund. An example choice card as well as an overview over all attributes and their levels can be found in the Appendix (Section A.1). Each of these attributes and its respective levels was selected based on previous focus group discussions, expert interviews and a preliminary household survey. For more details on

the design of the choice experiment as well as the particulars of its implementation see Adloff and Rehdanz (2020).

Analytically it is assumed that individual *i* chooses the alternative $a \in a_1, ..., a_N$ that offers the largest utility gain on a card, i.e. chooses a_1 iff

(1)
$$U_i(a_1) \ge U_i(a_n) \ \forall \ a_n \ne a_1$$

If the utility is separable into an observable (V_{ia}) and an unobservable part (ϵ_{ia}) , i.e. $U_{ia} = V_{ia} + \epsilon_{ia}$, the choice probability of a person *i* choosing alternative a_1 becomes

(2)
$$Prob_i(a_1) = Prob(\epsilon_{ia_1} - \epsilon_{ia_n} > V_{ia_n} - V_{ia_1}) \ \forall \ a_n \neq a_1$$

Assuming the unobservable part of utility to follow a generalized extreme value distribution, the estimation results of a maximum likelihood estimation allow the choice probability of protection over the status quo to be calculated as:

(3)
$$Prob(a_{Protection}) = \frac{exp(U_{Protection})}{exp(U_{Protection}) + exp(U_{Status Quo})}$$

The use of a hypothetical stated preference measures offers a key benefit for this study as it allows to collect attitudes ex-ante to any protection implementation. Protections established in the past are likely to reduce stated protection motivation as well as stated risk perceptions, which is a common confounder in studies based on (past) revealed protection efforts. This concern is further attempted to reduce, by including villages in the sample, in which signs of coastal erosion were visible, yet mostly no coastal protection implemented at the stage of data collection.

3.4 Socioeconomic Controls

To investigate structural differences in the cognitive process between event types and test the validity of potential narratives, a variety of socioeconomic control variables is collected.

As measure for affect, I use individual level uncertainty preferences. As far as I am aware of, there is no distinct measure for emotional sensitivity. However, according to the literature on "risk as a feeling" (e.g. Slovic et al., 2004; Slovic and Peters, 2006; Loewenstein et al., 2001), a link between uncertainty attitudes and affective reactions to losses can be drawn. Respondents that show more uncertainty aversion in the experimental elicitations anticipate a stronger reaction to negative outcome states or a lower utility gain from positive outcome states than more uncertainty tolerant respondents, i.e. they show a stronger negative affect anticipation (Kermer et al., 2006). This renders uncertainty aversion measures to comprise a self-reported measure of affect. H2.1 will be tested making use of this relation. An affect heuristic should induce a positive relation between uncertainty aversion and coastal flooding experience reporting. Given the state of sea level rise driven erosion in the participating villages this relation is unlikely to be found for sea level rise experience reporting.

In addition to the relation between uncertainty aversion and experience recall via the affect

heuristic, there might also be a counteracting effect driven by cognitive coping mechanisms.²⁶ While the affect heuristic outlines a positive relation between uncertainty aversion and event recall, the cognitive coping mechanism offers that high levels of uncertainty aversion might actually lead to a reduction in recall and expectations, if behavioural adaptation options appear unavailable. The design of this study attempts to minimize concerns for low or varying levels of coping appraisal in two ways. First of all, by using a sample case in which both types of events are coastal threats, which both require coastal protection measures as a response. If a person feels incapable of engaging in coastal protections, this will affect the perceived coping ability for both event types equally, rendering it a level effect. Secondly, this is addressed by making use of the choice experiment. A DCE elicits answers to a given closed set of adaptation options, i.e. it offers potential protection options, which works against a potentially perceived unavailability of options. On top of that, it allows to look at the willingness to protect which precedes the question whether a person will actually show an adaptive response or not, and, thus, potentially also the cognitive step of evaluating ones personal qualification to actually implement a chosen protection. Consequently, the counteracting relation between uncertainty preferences and event recall should be minimal and would, in any case, if present, work against the raised hypothesis.

Uncertainty attitudes, in addition to patience, are likely mediators in the investigation of the relation between future expectations and the willingness to contribute to coastal protection, capturing the duality in uncertainty involved in the translation of expectations into behavioural intent. Measures for both, patience and uncertainty preferences are assessed in incentive compatible lab in the field experiments. There are two ways to conceptualize climate change related uncertainty, either as risk (precise statistical probabilities) or as ambiguity (imprecise time-variant likelihood description) (Millner et al., 2013; Eismont and Welsch, 1996). Given the discussion on the validity of either of the two conceptualizations, a measurement for both conceptual representations is collected. Risk tolerance is measured through the decision made in an adapted version of the risk elicitation task of Eckel and Grossman (2002): Respondents were presented a non-see-through bag containing 10 blue (B) balls and 10 yellow (Y) balls. In a first step respondents were asked to choose a payout scheme and subsequently draw a ball from the bag. The payout calculation followed the color of the ball drawn in combination with the payout scheme chosen. Possible schemes from least to most risky were (Y: 10K / B: 10K), (Y: 7.5K / B: 14K), (Y: 5K / B: 18K), (Y: 2.5K / B: 22K), (Y: 0K / B: 24.5K). The risk tolerance measure is a binary variable, that is one when the scheme chosen is among the third, fourth or fifth, and zero otherwise. Ambiguity tolerance is measured via an adaptation of the risk elicitation task. Participants again had to draw a ball from a bag with 20 balls. Yet, this time the payout scheme across events was fixed, and participants could instead choose between two probability distributions: a) 50/50 and b) unknown probabilities for both events i.e., ?/?. In other words, they could choose to draw from a bag containing ten balls of each color or from a bag with twenty balls with an unknown color distribution,

²⁶A large body of literature argues, that adaptation behavior is found only if a decision makers perceived ability to adapt, i.e., to avert the threat, is high enough to keep up with the perceived threat. If the belief in the personal ability to adapt is below the level of threat experienced, people are described to divert to a cognitive instead of behavioral coping strategy such as denying the existence of the threat (Babcicky and Seebauer, 2019; Grothmann and Reusswig, 2006; Mullils and Duval, 1997; Lindell and Perry, 2012). Vis a vis a certain expectation profile, those more uncertainty averse would consequently be more likely to revert to cognitive coping strategies which might involve a devaluation of memories.

while the payout was Y: 0K / B: 10K in both cases. Patience is measured as the decisions people made in a two-level price-list task in which people had to choose between receiving some amount of money now or a larger amount in two weeks in two stages. In the second stage the amount to be received in two weeks was increased or lowered with regard to the one offered in stage one depending on the choice of the participant in stage one.

On top of that, a set of sociodemographic variables was collected. These include a measure on gender, education, income, occupation, age, place of birth, religion, cultural tribe, for how long the respondent has been living in the respective village and a variable for the degree of coastal dependence. This last measure is derived as a weighted average of answers to a question inquiring what the respondent commonly uses the coast for. Possible answers were *source* of food (fish, shells, seaweed, etc), source of income (getting fish, shells, sea cucumber etc. for selling), leisure activities (relax, picnic, play, etc.), getting freshwater, travel/ transport, washing, else, I don't spend time at the coast (multiple answers were possible). The weighting was done according to the degree of necessity of each interaction with the coast for daily life. Consequently, this measure serves as proxy for the intensity of the interaction of respondents with the coast. This is not only likely to mediate the degree to which a person suffers damages from coastal hazards but also provides a proxy for the length of the time interval with which a person acquires updates on the current state of the coast. As shorter updating intervals imply smaller marginal changes in coastal appearance between two updating instances, the degree of coastal dependence serves as control for change blindness susceptibility.

Given these variables the theoretical hypotheses can be translated into specific empirical predictions:

EP1: There is heterogeneity in experience reports within OEGs with regard to both event types.

EP2: The set of socio-demographic factors that mediate experience heterogeneity is structurally different between event types. In particular, ...

EP2.1: uncertainty-aversion is positively correlated with coastal flooding recall. Sea level rise recall is not affected by differences in uncertainty-aversion.

EP2.2: coastal dependence negatively influences sea level rise awareness but does not affect coastal flooding event reporting.

EP3: Differences in within OEG experience reports translate into heterogeneities in expectations.

EP4: Coastal flooding threat awareness (i.e., expectations) has a larger (positive) impact on the willingness to protect measured in the DCE, than threat awareness of sea level rise.

3.5 Elicitation

Data collection took place in August and September 2019. In each village all households were invited to take part in the survey. The interviews were done in a paper and pen format by local assistants in the local language (Tok Pisin) in small, secluded spaces at a central place of the village. Assistants were extensively trained beforehand to ensure professional conduct and homogeneity in elicitation styles. Interviews took approximately 40 minutes. Each participant received 5K for participation and the payout of one randomly chosen decision made in course of the preference elicitations. The average total payout was 14.42K.

4 Results

The sample is evenly distributed across villages: From the 298 people that eventually participated, 101 are from the first, 98 form the second and 99 from the third village. Table 1 provides an overview over the sample characteristics. Participants are aged between 18 and 87 years, with an average of 39 years. Every participant completed at least four years of school, with an average of 8.23 years, providing an in comparison to PNG average values high level of literacy.²⁷ Roughly half of the respondents are not originally from the village of the interview. Still, the average length of residence in the respective village is 28 years and the percentage of respondents that live in the village for more than five years at the time of the interview is 89 percent. The following analyses control for this fact, wherever possible. The average degree of coastal dependence is 0.64 on a scale from zero to one, with a majority in the sample depending on coastal access for the acquisition of food and income. Next, Table 1 shows the average scores of the two uncertainty measures and patience, which provide that the chosen incentivation formats do not seem to evoke strong ceiling effects in any direction. Lastly, the respondent's comprehension of the survey including the DCE and the preference elicitation games was evaluated by the interviewers on a scale from one to five. The average comprehension level is 4.34 and correlates strongly with answers to self-evaluative comprehension questions of respondents. As every participant answered event related questions for both event types, i.e., sea level rise and coastal flooding, there are no compositional differences that could interfere with found differences in answers between event types.

4.1 Event Recall and Expectation Formation

69 percent of respondents reported to having personally experienced coastal flooding in the past. Of these, roughly two thirds did not report any flooding event within the past five years. 10 percent of the sample answered that they suffered damages from coastal flooding at least once. Sea level rise experiences are reported by 84 percent of the sample. One third of those aware of sea level rise classify the increase as *severe*. Lastly, 23 percent of respondent state to have suffered damages due to sea level rise up to this point.

Due to variance limitations of Q2 (amount/severity experienced) and Q3 (damage experienced), the core analysis is conducted along the first of the three experience questions, i.e. whether a person ever experienced sea level rise (slr) or coastal flooding (cf). Figure 2 shows the average answer to the question (as is, i.e. unscaled). As the question was posed in a yes/ no fashion, a deviation from zero or one shows heterogeneity in event perception. 84 percent of people answered that they did experience sea level rise along the coast close to their village and 16 percent said that they did not (sd = 0.3687). Further, 69 percent

²⁷PNG average: 4.5 (2011) according to most recent official information from the National Statistics Office PNG statistics available at: https://www.nso.gov.pg/statistics/education/, 19.01.2020

	Mean	St.Dev.	Min	Max
Age	38.71	13.69	18	87
Gender ($0 = \text{Male}; 1 = \text{Female}$)	0.52	0.50	0	1
Education (in years of schooling)	8.23	1.95	4	12
Monthly Household Income in \mathbf{K}^*	200.20	309.50	0	2400
Moved to Village	0.56	0.50	0	1
Moved to Village in last 5 years	0.11	0.32	0	1
Years of Residence in Village	28.05	16.78	0.08	86
Coastal Dependence $(0 = \text{Low}; 1 = \text{High})$	0.64	0.17	0.29	0.88
Risk Tolerance	1.19	1.04	0	4
Ambiguity Tolerance	0.297	0.46	0	1
Patience (0-impatience)	2.42	0.94	0.38	3.67
Comprehension $(1 = \text{Low}; 5 = \text{High})$	4.34	0.84	1	5

* At time of data collection: $K1 = \bigcirc 0.26$

Table 1: Sample Characteristics

of respondents answered that they witnessed coastal flooding and 31 percent said that they did not experience any coastal flooding event personally (sd = 0.4646). This heterogeneity in event reporting for both event types in the unscaled experience measure cannot be explained by between village variation, but shows a mildly significant relation to age. Figure 3 displays the average experiences reported for each of the OEGs. It is verified, that age bins are set such that scaling successfully eliminates all age effects. Furthermore, no significant relation can be found between within-OEG reporting heterogeneity and whether a person grew up in the village where he/she was interviewed or moved there at some point in life (compare Table 6 in the Appendix). The average stated experience level within OEGs varies between 0.50 and 0.81 for coastal flooding, and between 0.67 and 0.95 for sea level rise with an average standard deviation of answers within-OEGs of 0.4618 (cf) / 0.3755 (slr). In line with Hypothesis H1/EP1, removing plausible channels of actual differences in event experience, thus, does not eliminate the heterogeneity in experience statements, placing relevance on the differences in cognitive processing between individuals with similar experiences.

Tables 2 and 3 report the regression results of uncertainty tolerance and coastal dependence on the dependent variable event reporting scaled on OEG group mean for each event type (cf = coastal flooding, slr = sea level rise).²⁸ Standard errors are bootstrapped clustered on OEG group level and the robustness against the inclusion of other sociodemographic variables is tested. They show, first, that more uncertainty averse individuals are more likely to report coastal flooding experiences. For variation in sea level rise reporting, uncertainty

²⁸In a pearson correlation analysis of the relevance of a variety of control variables uncertainty aversion, coastal dependence and gender were, in fact, the only variables showing significant correlations (compare Table 6 in the Appendix). Gender was of relevance for sea level rise reporting heterogeneity and is correlated with coastal dependence, given that a variety of daily coastal interactions such as cooking or washing clothes falls into the set of chores most commonly executed by women in Bougainville. Controlling for gender and coastal dependence simultaneously, the relevance of gender vanishes.

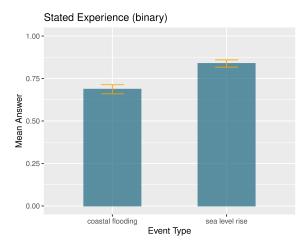


Figure 2: Average answer to the Question "Have you personally experienced coastal flooding/ sea level rise?".

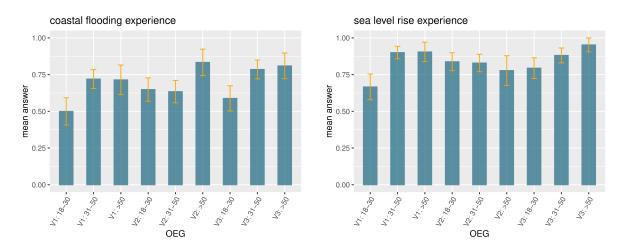


Figure 3: Average answer to the Question "Have you ever personally experienced coastal flooding/ sea level rise?" along OEGs.

aversion does not come through as an explanatory variable. Second, people reporting to interact more frequently with the coast are less likely to report to be aware of rising sea levels, but do not differ in their coastal flooding reporting behavior. This is in line with the hypothesized structural difference between reporting heterogeneities (H2/EP2). The found relation between uncertainty tolerance and experience reporting is also in agreement with the propositions of an affect heuristic (H2.1/EP2.1). To the degree to which cognitive coping strategies are not contained by the design, the results represent a lower bound of any actual effect strength, given that cognitive coping creates a negative relation between uncertainty aversion and recall. Additionally, the negative relation between coastal dependence and sea level rise reporting is in line with the predictions from change blindness (H2.2/EP2.2). People that are interacting with the coast on a more regular basis are less likely to recognize marginal long-term changes in sea level. The measure for uncertainty tolerance used for these regressions is the one for risk tolerance. All results are robust to the use of ambiguity tol-

	CF (2) -0.244***	SLR (3) -0.063	SLR (4) -0.078
()			
0.265^{***}	-0.244***	-0.063	-0.078
(0.088)	(0.092)	(0.093)	(0.127)
No Yes	Yes Yes	No Yes	Yes Yes
296 0.021	216 0.041	296 -0.003	$216 \\ 0.005 \\ 1.170$
	No Yes 296	No Yes Yes Yes 296 216 0.021 0.041	No Yes No Yes Yes Yes 296 216 296 0.021 0.041 -0.003

erance instead, as an alternative measure for uncertainty tolerance (compare Table 7 in the Appendix)).

 $Note: \ ^{\rm p}<0.1; \ ^{\rm **p}<0.05; \ ^{\rm ***p}<0.01;$ Sociode
omgr. Controls: Age, Gender, Education, HH Income, Moved to Village; Clustered SEs: bootstrapped clustered std errors on OEG level

Table 2:	Role of	Uncertainty	Tolerance
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	Dependent variable: Experience Statements				
	CF	CF	SLR	SLR	
coastal dependence	$0.445 \\ (0.408)$	$0.364 \\ (0.490)$	-1.018^{***} (0.274)	-0.869^{***} (0.243)	
Sociodemogr. Controls	No	Yes	No	Yes	
Clustered SEs	Yes	Yes	Yes	Yes	
Observations	297	216	297	216	
Adjusted \mathbb{R}^2	0.003	0.021	0.028	0.006	
F Statistic	1.797	1.914^{*}	9.603***	1.239	

 $Note: \ ^*p{<}0.1; \ ^{**}p{<}0.05; \ ^{***}p{<}0.01;$ Sociode
omgr. Controls: Age, Gender, Education, HH Income, Moved to Village; Clustered SEs: bootstrapped clustered std errors on OEG level

Table 3: Role of Coastal Interaction

In the next step expectations are investigated. Overall, 63 percent of respondents consider it at least rather likely that coastal flooding will occur in their region within the next five years and 61 percent consider personal damages from these events as at least rather likely within this time frame. On top of that, 73 percent of respondents expect sea levels to (continue to) rise within the next five years, with 64 percent of the sample expecting to suffer damages from it. Average threat awareness is 8.6 (cf) and 9.2 (slr) on a scale of 1 to $16.^{29}$

To investigate the relation between imperfect memory and expectation formation, Figure 4 shows the interaction between differences in event reporting and threat expectations. In particular, the graphs display the expectation means for low (below OEG average) and high (above OEG average) experience reporters. The left hand graph presents the results for coastal flooding and the right hand graph those for sea level rise. Differences in coastal flooding experience reporting do not impact the level of expected coastal flooding. Yet, differences in sea level rise experience reporting significantly influence the degree of perceived threat, in terms of expectations. Respondents that are classified as high sea level rise reporters assign a higher likelihood to future (continuing) sea level rise. Tables 9 and 10 in the Appendix show the robustness of these results to the inclusion of controls and cluster-robust standard errors. These results imply partial agreement of the data with H3/EP3. While it is supported for the case of sea level rise, this is not the case for coastal flooding.

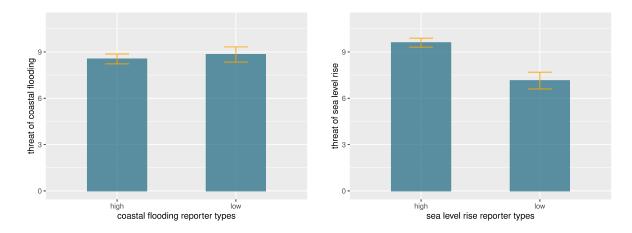


Figure 4: Average threat awareness in terms of future expectations for coastal flooding (left) and sea level rise (right) by experience reporter types.

4.2 Adaptation Motivation

The impact of event awareness and future expectations on willingness to protect measured in the choice experiment is analyzed by multinomial logit estimation of the underlying random utility model in R using the MLogit package (Croissant et al., 2012; Hlavac, 2014). Table 4 shows the average marginal effects of threat experience reporting and expectations for each event type on the choice probability of a coastal protection option over the status quo. The respective control variable is inserted into the conditional logit model as an interaction with

 $^{^{29}\}mathrm{Answers}$ on the likelihood of event occurrence and on the likelihood of being affected are coded on a scale of 1-4.

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(0.0069) - None None Yes Yes	-0.0014	0.001	0.0303^{***}		0.0310^{***}	0.0313^{***}
None None Yes	(0.0069)	(0.0103)	(0.0070)	I	(0.0072)	(0.0094)
Yes Yes	None	UA, CD	None	None	None	UA, CD
μ μ	Yes	${ m Yes}$	\mathbf{Yes}	\mathbf{Yes}	Yes	\mathbf{Yes}
Cluster Level Participant Participant	nt Participant	$\operatorname{Participant}$	Participant	Participant	$\operatorname{Participant}$	Participant
Observations 1,007 1,003 Log Likelihood -816.279 -793.984	1,003 1 -792.550	1,003-769.563	1,007-799.924	1,003-790.778	1,003-777.049	1,003-757.873
Note: * $p<0.1$; ** $p<0.05$; *** $p<0.01$; UA - uncertainty aversion (risk), CD- coastal dependence	$(0.01; UA - uncert_s)$	ainty aversion (risk), CD- coas	stal dependence	٥	

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the attributes of the choice experiment. Significant effects are found for coastal flooding expectations while the level of coastal flooding experience reporting does not seem to be influencing the willingness to protect of respondents. Further, in the case of sea level rise the relation is switched. Whereas sea level rise experience reporting has a significant positive impact on willingness to protect, the perceived threat in terms of future expectations of sea level rise shows no influence. The findings are robust to the inclusion of controls mediating experience reporting, i.e. uncertainty aversion and coastal dependence. Table 4 uses again risk tolerance as measure for uncertainty aversion. The results are robust also to the alternative specification using ambiguity tolerance (compare Table 11 in the Appendix). These results are in line with the hypothesis, that future hazard expectations do not play the same role in the adaptation motivation process of long-term gradual changes and extreme events and also follow the proposition that extreme event expectations are more effective in stimulating an intention to protect (H4/EP4). In fact, the role of expectations fully vanishes for sea level rise.

To investigate the role of expectations in more detail, Table 5 reports the interaction effects of expectations and the two controls uncertainty preference and patience on adaptation motivation for each event type.³⁰ Model 1 focuses on the role of inter-temporal focusing in adaptation choice by interacting future expectations with patience. It shows that the degree to which expectations influence adaptation motivation is for both event types significantly mediated by the degree to which respondents take future prospects into account. Whereas the anticipation of future sea level rise is not influencing adaptation choices for the average respondent, it still becomes a relevant mediator for forward looking individuals. Additionally, for both event types an increase in threat awareness, i.e., expectations has negative impacts on the adaptation motivation for individuals with below average patience levels. Hence, procrastination seems to be of relevance in both cases and does not seem to explain the difference in the relevance of expectations for the average respondent's protection motivation between events. Models 2a and 2b interact future expectations with each one of the two measures for uncertainty tolerance - risk and ambiguity tolerance. Significant interaction effects can be found for risk tolerance and coastal flooding expectations, however this effect is not robust to the use of ambiguity aversion as measure for uncertainty preferences. For sea level rise, in none of the two models an interaction effect between uncertainty tolerance and the degree to which expectations influence protection motivation can be identified. The degree to which future hazard anticipations trigger protection motivation, thus, seems to be mainly mediated by inter-temporal focusing for both event types in this data set.

5 Discussion

Bringing together these individual results, two quite different routes of adaptation motivation formation between extreme events and gradual long-term changes can be traced. First of all, in the case of sea level rise, differences in event experience reporting can be seen, which do not only impact expectations in that non-reporters have markedly lower expectations of future sea level rise and ensuing damages than reporters do. Also, they are found to be a significant explanatory variable for the willingness to engage in coastal protection. Alternative infor-

³⁰Note: This results table follows the common ways of interpretation, i.e., reporting results from running one regression per model involving all three controls stated on the left.

	CF	SLR			
Model 1: Procrastin	ation				
expectations	0.0141^{*}	-0.0013			
	(0.0082)	(0.0073)			
patience	0.0310^{***}	0.0314^{***}			
	(0.0080)	(0.0080)			
expectations x patience	0.0248^{***}	0.0187^{**}			
	(0.0081)	(0.0080)			
Model 2a: Uncertainty Aversion					
expectations	0.0200**	0.0028			
-	(0.0086)	(0.0078)			
ambiguity tolerance	0.0110	0.0101			
	(0.0076)	(0.0071)			
expectations x amb. t.	0.0043	-0.0028			
	(0.0081)	(0.0077)			
Model 2b: Uncertair	nty Aversion	L			
expectations	0.0202**	0.0007			
-	(0.0088)	(0.0079)			
risk tolerance	0.0150	0.0113			
	(0.0079)	(0.0072)			
expectations x risk t.	0.0176^{**}	-0.0092			
	(0.0078)	(0.0079)			

Table 5: The Role of procrastination and uncertainty tolerance (std. dev. in brackets)

mation sources for the expectation formation process seem to offset the effect of experience reporting differences on adaptation motivation such that the variation in expectations is no longer able to explain variation in the willingness to protect. For coastal flooding, too, heterogeneities in event reporting can be detected. However, these are neither significantly related to variations in future expectations nor to willingness to protect. Nonetheless, coastal flooding expectations can be found to be a significant explanatory variable for the willingness to protect. This lends importance to other sources of heterogeneity in expectation formation in the case of coastal flooding. Such other sources might be descriptive information on the threat structure provided by official sources such as governmental education programs, schools, the media, or personal social networks (e.g. Ngo et al., 2020; Kasperson et al., 1988, and citations therein). Learning about a threat from description of the underling hazard structure is found to trigger differential cognitive results than learning about it from experience, such that it is not uncommon to differentiate between these two paths of learning (e.g. Hertwig and Erev, 2009; Simonsohn et al., 2008; Barron and Erev, 2003). Additionally, social networks are influential for risk perceptions as they serve on one hand as an informal insurance mending risk perceptions (e.g. Babcicky and Seebauer, 2017). On the other, they become effective mediators of beliefs via the social norms they postulate on opinions and behaviour (Seebauer and Babcicky, 2020; Bollinger et al., 2020; Mccright and Dunlap, 2011).

Taken together, the results of this study show a traceable difference between event types

in the role that learning from experiences plays for the formation of an adaptation motivation. While it is of marginal relevance in the process stimulated by extreme events, it is a key element in the process stimulated from exposure to long-term gradual changes. One intuitive explanation for this differential role of learning from experience especially for expectation formation might be attributed to the difference in occurrence probabilities of the event types. For a low probability event, the information one gains from the absence of any experience about whether the threat is present or not, is by definition low. Not encountering signals from a low probability event could equally well mean that one was lucky in the past years. Opposed to that, it is highly unlikely that a high probability threat is present if no signs of it can be seen over a longer stretch of time. Consequently, it is plausible that not being aware of sea level rise in the past leads to a lower sense of sea level rise threat and not being aware of coastal flooding in the past years is not convincingly diminishing the sense of threat.

6 Conclusion

This paper presents a theoretic argument as well as experimental evidence for the difference in cognitive processes following the experience of extreme events and long-term gradual changes. Due to their differences in occurrence probability and (marginal) impact, the two event types are likely to trigger different cognitive biases that influence event recall and the threat perception in terms of future expectations. As primal examples the role of the affect heuristic and change blindness are outlined. The different future prospects given by each event type, furthermore, are likely to trigger differential behavioural responses according to various theories of decision making under uncertainty. These theoretical predictions are empirically investigated in a data set on protection motivation from coastal inhabitants in Papua New Guinea, who are simultaneously exposed to the hazard of coastal flooding and sea level rise. The results outline two structurally different cognitive routes underlying protection motivation. While event recall is heterogeneous with regard to both event types, these heterogeneities are correlated with different individual level variables. Variation in coastal flooding recall can be explained by variation in uncertainty tolerance, sea level rise perception, however, varies with the respondent's degree of coastal dependence. The directions of these correlations are in line with predictions from the affect heuristic and change blindness. Further, the role that heterogeneities in event awareness play in expectation formation and protection motivation differ. Future expectations are essential for coastal flooding protection motivation, but are not sensitive to variations in event awareness. With regard to sea level rise respondent's protection motivation is affected by the degree to which participants are aware of sea level rise, yet, not to threat perception in terms of expectations.

Even though the results on perceptional heterogeneities can be interpreted to be in line with the affect heuristic and the theory on change blindness, it is outside the scope of this study to offer causal evidence on the role of these heuristics. For example, several studies report findings on a relation from the affective reaction experienced in negative outcome states on uncertainty attitudes (Eckel et al., 2009; Page et al., 2014; Said et al., 2015). In the presented dataset event experience itself as well as the level of background risk is a level effect by design, which should not confound the presented results. Yet, the degree to which people show affective reactions to the event is heterogeneous and it cannot be ruled out that the results might rather read that those showing more affective reactions to an event are those who better recall the event and simultaneously had an increase in risk tolerance after the experience. To investigate causality in this realm will be an essential task for future research. Furthermore, this paper does not claim to provide an exhaustive list of relevant heuristics, but rather attempts to open up the exploration of any cognitive determinants of the heterogeneity in adaptational responses to threat experiences. As another likely driver of heterogeneities in adaptational reactions one could, for example, think of the recency bias (Tversky and Kahneman, 1973, 1974). It holds that a higher occurrence probability of an event translates into an increase in the ease of recall of this event type. The higher the occurrence probability of an event across a fixed period of time, the lower is the expected time between the last event occurrence and any point in time, as it is in expectation experienced more often. In the field of adaptation motivation, for example Meyer (2012) and Gallagher (2014) present evidence of people's adaptation motivation being influenced most by recently experienced events and to be reverting back to initial levels as the time distance to the event increases. Being exposed to the constantly present threat of long-term changes could be expected to ease recall of the threat presence and induce a stronger influence on expectation formation and adaptational responses. In the dataset used for this study, heterogeneity in the timing of threat experiences is reduced to a level effect such that it cannot be exploited. Hence, an empirical test of the potential relevance of the recency bias remains a potential avenue for future research. This further extents to any investigation of the role of variations in actual threat experience on the process of event processing and expectation formation.

Overall, this paper contributes to the field of climate change adaptation motivation (van Valkengoed and Steg, 2019; Koerth et al., 2017; Bamberg et al., 2017) highlighting the relevance of opening up the cognitive black box underlying the formation of adaptation motivation in order to rationalize the existing heterogeneity in findings. Furthermore, it highlights the relevance of careful examination of relevant threat types and their characteristics. Doing so, this paper adds to the literature comparing adaptational reactions to high probability-low impact events and low probability-high impact events (Shafran, 2011; Laury et al., 2009; Shogren, 1990) by providing a systematic field experimental comparison of the reaction to hazards of the two types. On top of that, this study contributes to the literature on learning from experience versus learning from description (Hertwig and Erev, 2009; Simonsohn et al., 2008; Barron and Erev, 2003). While Hertwig et al. (2004) highlight the cognitive limitations in producing rational inferences from experiences of low probability events, this study shows the relevance of experience mis-perception also for large probability events if only the (marginal) impact is sufficiently low. In this case, change blindness can lead to a minimal number of event related experience memories, causing similar concerns of small sample biases in inferences as Hertwig et al. (2004) propose for small probability events. Furthermore, in line with Weber (2006) the results in this study highlight the importance of awareness of long-term gradual change impacts for adaptation motivation.

Lastly, this paper provides evidence that the type of barriers to optimal protection one faces likely depend on the kind of hazard encountered. This has important implications on the effectiveness of policy instruments to stimulate adaptation motivation. Whereas ensuring event awareness takes on a promising role in the stimulation of adaptation to long-term gradual changes, optimal protection levels against extreme events seem rather dependent on the stimulation of a balanced sense of threat and coping appraisal that can be achieved through information provision via news or social media or the strengthening of social networks. This latter approach is likely to be effective for long-term gradual changes only once accumulated impacts become large.

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A Appendix

A.1 Choice Experiment Details

Example Choice Card						
Characteristic	Protection 2	Protection 1	No Protection			
Time until Full Protection	1 YEAR	4 YEARS	-			
Life time	10 YEARS	1 YEAR	-			
Access to Coast	LIMITED ACCESS	FULL ACCESS	FULL ACCESS			
Change in Animal and Plant Species	DECREASE	INCREASE	NO CHANGE			
Weekly Contribution to Community Fund	К 10	К 35	К 0			
I choose						

Example Choice Card

Attributes	Description	Levels
Time Until Full Pro- tection	The time until full protection is provided, i.e the construction time, depends e.g. on the necessary work effort or the materials used - plants need to grow and cement needs to dry. Some measures thus can provide full protec- tion already after a rather short time while others might need to be fostered for a long period until they serve to protect the coast.	NA / 1 Year / 4 Years
Lifetime	Protection measures differ in the time until repair or restoration work is required, once full protection is granted.	NA / 1 Year / 10 Years
Access to Coast	Coastal protection measures vary in the de- gree to which they limit access to the coast, i.e. the usability of the beach and ocean ac- cess. After construction, some only allow for access in some limited zones and others still provide full access to the coast.	Limited / Full
Changes in Animal and Plant Species	Protection measures can influence the amount and diversity of local plants and animals. Protection measures might increase the amount of species in its proximity or decrease the amount of species in its 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 your household over a period of 5 years for a par- ticular protection measure.	K0 / 5K / 10K / 20K / 35K

A.2 Rep	orting I	Heterogeneity:	Pearson	Correlation	Coefficients
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	Coastal F	looding	Sea Leve	l Rise
	coeff	р	coeff	р
risk tolerance	0.0318	0.5851	0.0779	0.1806
ambiguity tolerance	-0.1556^{***}	0.0073	-0.0212	0.7165
patience	0.0447	0.4441	-0.0792	0.1747
coastal dependence	0.0778	0.1811	-0.1776^{***}	0.0021
gender	-0.0061	0.9170	-0.1722^{***}	0.0029
age	0.0612	0.2955	0.0363	0.5350
educ. $(grades)$	-0.0967	0.1003	-0.0065	0.9121
moved to village	-0.0392	0.5094	0.0483	0.4163

Table 6: Pearson correlation coefficients for correlation between control variables and the experience deviation from OEG-level means.

	Depende	Dependent variable: Experience Statements				
	CF	CF	SLR	SLR		
	(1)	(2)	(3)	(4)		
uncertainty tolerance	-0.332^{**} (0.133)	-0.350^{*} (0.179)	-0.046 (0.097)	$0.132 \\ (0.142)$		
Sociodemogr. Controls Clustered SEs	No Yes	Yes Yes	No Yes	Yes Yes		
Observations Adjusted R ²	$296 \\ 0.021$	$\begin{array}{c} 216 \\ 0.041 \end{array}$	296 -0.003	$\begin{array}{c} 216 \\ 0.005 \end{array}$		
F Statistic	7.293^{***}	2.530^{**}	0.132	1.170		

A.3 Alternative uncertainty tolerance specification of Table 2

 $Note: \ ^*p{<}0.1; \ ^{**}p{<}0.05; \ ^{***}p{<}0.01;$ Sociode
omgr. Controls: Age, Gender, Education, HH Income, Moved to Village; Clustered SEs: bootstrapped clustered std errors on OEG level

Table 7: Role of Uncertainty Tolerance (alternative specification using ambiguity)

A.4 Expectations Heterogeneity

	Coastal Flo	oding Expectations	Sea Level R	ise Expectations
	coeff	р	coeff	р
risk tolerance	0.0775	0.2706	0.0760	0.2813
ambiguity tolerance	0.0322	0.6478	0.0433	0.5399
patience	0.1251^{*}	0.0784	0.0502	0.4821
trust	0.1632^{**}	0.0200	0.0831	0.2396
coastal dependence	-0.2083***	0.0028	-0.2227^{***}	0.0014
gender	-0.4049^{***}	0.0000	-0.4094^{***}	0.0000
age	0.0592	0.4037	0.0410	0.5645
educ. (grades)	0.0796	0.2662	0.0968	0.1770
moved to village	0.1169	0.1063	-0.0232	0.7500
household income	0.2818^{***}	0.0003	0.2271^{***}	0.0042

A.4.1 Pearson Correlation Coefficients for Experience Report = 1

Table 8: Pearson correlation coefficients between control variables and 5 year threat expectations for respondents with event recall = 1.

A.4.2 Experience Reporting

		Depende	nt variable:	
	Coasta	al Flooding	g Threat Aw	vareness
	(1)	(2)	(3)	(4)
Experience Reporting (CF)	-0.234 (0.262)	-0.230 (0.289)		
Experience Reporting (SLR)	`` ,	`` ,	0.995^{***} (0.106)	$\begin{array}{c} 0.706^{***} \\ (0.139) \end{array}$
Sociodemogr. Controls	No	Yes	No	Yes
Clustered SEs	Yes	Yes	Yes	Yes
Observations	295	282	295	282
\mathbb{R}^2	0.002	0.136	0.046	0.156
Adjusted \mathbb{R}^2	-0.001	0.117	0.043	0.138

Table 9: Coastal Flooding Threat Awareness

Note: p<0.1; p<0.05; p<0.01; Sociodeomgr. Controls: Uncertainty Aversion (amb, risk), Coastal Dependence, Gender, Moved to Village; Clustered SEs: bootstrapped clustered std errors on OEG level

	Dependent variable:			
	Sea l	Level Rise	Threat Awa	reness
	(1)	(2)	(3)	(4)
Experience Reporting (CF)	-0.247 (0.204)	-0.268 (0.212)		
Experience Reporting (SLR)		× ,	0.786^{***} (0.126)	$\begin{array}{c} 0.551^{***} \\ (0.129) \end{array}$
Sociodemogr. Controls	No	Yes	No	Yes
Clustered SEs	Yes	Yes	Yes	Yes
Observations	296	283	296	283
\mathbb{R}^2	0.003	0.170	0.029	0.181
Adjusted \mathbb{R}^2	-0.001	0.152	0.026	0.163

Note: p<0.1; p<0.05; p<0.01; Sociodeomgr. Controls: Uncertainty Aversion (amb, risk), Coastal Dependence, Gender, Moved to Village; Clustered SEs: bootstrapped clustered std errors on OEG level

A.5 Alternative uncertainty tolerance specification of Table 4

			Depen	Dependent variable: Willingness to Protect	Willingness to .	Protect		
		C	CF			SI	SLR	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
expectations	I	0.0184^{**} (0.0086)	0.0184^{**} (0.0087)	0.0191^{*} (0.0102)	I	0.002 (0.0077)	-0.0018 (0.0078)	-0.0014 (0.0101)
experiences	-0.0030 (0.0069)		-0.0014 (0.0069)	(0.0104)	0.0303^{***} (0.0070)		(0.0072)	(0.0093)
Controls Assistant FEs Cluster Level	None Yes Participant	None Yes Participant	None Yes Participant	UA, CD Yes Participant	None Yes Participant	None Yes Participant	None Yes Participant	UA, CD Yes Participant
Observations Log Likelihood	1,007-816.279	1,003-793.984	1,003-792.550	999 -766.260	1,007-799.924	1,003 -790.778	1,003 -777.049	999 -755.008
Note:	*p<0.1; **p<	*p<0.1; **p<0.05; ***p<0.01; UA - uncertainty aversion (ambiguity), CD- coastal dependence	11; UA - uncert	ainty aversion	(ambiguity), C	D- coastal depε	ndence	
Table 11: WTP Antecedent: Average marginal effects of experience reporting and future threat expectation variations on willingness	Antecedent: A	verage margina	ul effects of exp	erience reportin	ng and future t	hreat expectati	on variations o	n willingness

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Table 11: W	to protect