

Essays on the Behavioural Adaptation to Environmental Change

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List of Abbreviations

PNG	Papua New Guinea
DCE	Discrete Choice Experiment
WARP	Weak Axiom of Revealed Preferences
RUM	Random Utility Model
IID	Independently and Identically Distributed
CL	Conditional Logit
MXL	Mixed Logit
ASC	Alternative Specific Constant
WTP	Willingness to Pay
SLR	Sea Level Rise
CF	Coastal Flooding
OEG	Objective Experience Group
AME	Average Marginal Effect
IOS	Inclusion of Other in Self
DG	Dictator Game

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Introduction

Environmental economics strives to understand and solve market failures at the interdependencies between society and the natural environment. Especially in times of environmental crisis knowledge about this interrelation becomes indispensable. An essential determinant of this relationship is human behaviour. In fact, human behaviour is as much at the source of most environmental issues of our time as it is the central force for overcoming them. This renders a sound understanding of human behaviour a valuable ingredient to the study of environmental economics.

Initially, the economic science utilized a highly stylized, simplistic representation of human behaviour as that of a rational *homo oeconomicus*. By now, the field of behavioural economics has led to a deeper understanding of human behaviour. For example, we know that people often have a present bias (Frederick et al., 2002; O'Donoghue and Rabin, 1999), are sensitive to reference points (Koszegi and Rabin, 2006), show loss aversion (Tversky and Kahneman, 1991), care for others (Fehr and Schmidt, 2006) or have inaccurate mental probability representations (Kahneman and Tversky, 1979). Behavioural economic research has produced an enormous body of evidence that underlines one main insight: an individual's behaviour diverts strongly from that of a *homo oeconomicus*. Mullainathan and Thaler (2000) group these behavioural deviations into three domains: bounded rationality (cognitive mis-perceptions and inference errors), bounded willpower (self-control problems) and bounded self-interest (other-regarding preferences). Many of these deviations from the rational type are central to the field of environmental economics.

First, many environmental goods and services are commons, where there are rivalries in use, yet it is difficult to exclude others from using them. This threatens their continued existence as a single user benefits from the use of the commons, yet the costs of her actions are passed on to all users. At the same time, many solutions to environmental issues involve the establishment of public goods, which are costly to provide, yet, finally available not only to those who invested in their establishment but essentially everyone in a community. This means, that while an individual bears all the costs of his or her contribution to a public good, the benefits are shared among all. Solving these dilemma situations requires inter- and intragenerational cooperation among all participants, i.e. sacrificing personal self-interest for the long-term benefit of the group. Consequently, environmental economics benefits from insights into the limits of self-interest and suggested policy tools that spur cooperation (Ostrom, 1990, 2000; Jacquet et al., 2013;

Fehr and Gächter, 2000; Gächter et al., 2017; Shogren et al., 2021; Botelho et al., 2015). For example, differences in the level of intrinsic cooperation between people can be observed. While some can be classified as pure altruists, i.e. people who cooperate out of intrinsic motivation irrespective of what others do, others are conditional cooperators who rely on enforcements from their social environment. The number of conditional cooperators is in general found to be non-negligible in size, i.e. up to 50% of a group of people (Fischbacher et al., 2001). In behavioural economics, a suite of social contextual forces have been identified that effectively induce cooperation, such as communication (Balliet, 2010), punishment (Fehr and Gächter, 2000; Sefton et al., 2007), reputation concerns (Bursztyn and Jensen, 2017) and social norms (Gächter et al., 2017; Nyborg et al., 2016; Bicchieri, 2006).

Second, human nature interactions induce consequences that are lagged in time. For example, the IPCC provides that the climatic consequences of present-day behaviour will take approximately 20 years to realize (IPCC, 2021). Given this delay in consequences, inter-temporal discounting will lead to a reduced representation of an action's delayed impact. This might be a reduced representation of the costs of one's actions vis-a-vis a full representation of the benefits or, analogously, a reduced weighting of the future benefits of an action vis-a-vis the full weighting of the costs. Findings on bounded self-control provide evidence that this tendency is enhanced by a cognitive overweighting of the presence ("present bias") which people tend to have (Frederick et al., 2002; O'Donoghue and Rabin, 1999). In the end, actions that induce immediate benefits and only delayed costs are pursued much more than optimally (e.g. air travel, non-organic purchasing choices) and actions that require effort now but only provide benefits in the future are pursued less than optimally (e.g. mitigation, adaptation). Behavioural economic findings on bounded self-control and present bias can help uncover drivers of unsustainable behaviour and are key to correct for this sub-optimality. For example, one essential application is the calculation of the cost of carbon which crucially depends on the assumed underlying social discount rate (Drupp et al., 2018; Harrison et al., 2002).

Third, many ecological consequences of human behaviour are uncertain, i.e. assigned some probability of occurrence (unequal to one) introducing probability distributions into the optimization problem. Research on bounded rationality contributes strongly to a better understanding of people's behaviour in light of uncertainty. It, for example, produces evidence of several regularities in how people's cognitive representation of probability distributions deviate from the true distribution (Bordalo et al., 2012; Kahneman and Tversky, 1979; Enke and Graeber, 2019). Also, people have general attitudes towards risk (Rabin, 2000). This leads some people to be sub-optimally wary of any uncertainty and others to be overly responsive to it. In addition, these attitudes are not the same for the domain of losses and the domain of gains (Tversky and Kahneman, 1991). These findings on bounded rationality essentially help advance

the understanding of barriers to sustainable human-nature interactions as much as to optimal adaptation to environmental changes (Alló and Loureiro, 2014; Schill et al., 2016). Furthermore insights from behavioural economics allow us to understand the degree of uncertainty present within social interactions, independent of the ecological system component. As soon as people cannot be assumed to maximize payoff following full rationality and self-interest, uncertainty arises with regard to the likely behaviour of interaction partners in any situation (Gächter, 2004).

The relevance of behavioural economic insights for the field of environmental economics spurs more and more research on the interrelation between behavioural and environmental economics.¹ This thesis adds to this line of research in three chapters. In the following, I briefly summarize each chapter and how it is placed in the presented framework of behavioural environmental economics.

Chapter 1: "Wait and See? Public preferences for the temporal effectiveness of coastal protection". The first chapter presents joint work with Katrin Rehdanz (Kiel University) and highlights the role of bounded willpower and uncertainty attitudes as barriers and mediators of preferences for adaptation to environmental change. It studies people's preferences for coastal protection along choice experimental data from coastal communities in Papua New Guinea (PNG). The focus of the study is on timing of protection, asking how people trade off the rapid onset of protection with longevity of protection. This trade-off is central to the choices between hard and soft coastal protection measures, especially in regions with hazard uncertainty, such as the coasts of Bougainville, PNG.² In a stylized model of rational utility maximization, both, longevity of protection and rapid onset of protection should be desirable attributes.

The results of the study present evidence for the desirability of protection longevity, yet lack any sign of protection urgency, in spite of the fact that there is a high willingness to protect, in general. This is especially surprising given that PNG was termed one of the hot-spot regions of climate change and sea levels at its coasts are rising at a rate more than twice the global average (Papua New Guinea National Weather Service et al., 2015). To investigate mechanisms behind this finding, this study draws on control variables from the behavioural economics toolbox. In particular, we elicited simple measures of risk attitudes and patience in lab-in-the-field experiments. Common narratives from the domain of behavioural economics for this finding could be high degrees of risk tolerance or strong rates of future discounting. We find no evidence in support of either of these narratives. Rather, the lack of urgency to protect is surprisingly robust to

¹Compare e.g. Kesternich et al. (2017); Croson and Treich (2014); Velez and Moros (2021)

²Soft protections: working with nature-based solutions for protection such as beach nourishment, mangrove planting or coral reef reforestation; hard protections: implementation of solid protection structures such as sea walls, dikes or groynes. Hazard uncertainty: Uncertainty about the kind, extent or timing of hazards that is prevalent especially in regions with lack of fine-grained climate data.

the inclusion of a long list of controls, and we find a positive association between risk tolerance and willingness to protect. Both of these findings are discussed in light of the existing literature. While the first result potentially calls for more elaborate measures of time preferences that allow to distinguish e.g., between present bias and discounting, the second result is in line with a list of other studies in the field of climate change adaptation and hints at a complex relation between uncertainty attitudes and protection motivation.

Chapter 2: "Adapting to climate change: the role of event type for protection motivation". The second chapter presents work on cognitive barriers to adaptation from a behavioural economics perspective. In particular, it examines how sensitive the cognitive process underlying the motivation to protect is to differences in the type of hazard a person faces. Types of hazards are distinguished on the basis of differences in probability of occurrence and magnitude of impact. These two characteristics are especially relevant in the field of climate change-related hazards, which can be divided into the two broad categories of extreme events (low occurrence probability, high impact) and long-term gradual changes (high occurrence probability and low (marginal) impact). To open up the cognitive black box of adaptation, the cognitive process is divided into three main steps: i) awareness of change, ii) formation of expectations that classify a change as a threat and iii) behavioural intentions stimulated by the corresponding future expectations. The chapter lays out how along these three steps cognitive biases can interfere with the process, and how the type of biases triggered depends on the type of hazard. These theoretical postulations are empirically tested with data from coastal communities in PNG, who are simultaneously exposed to the long-term gradual rise of sea levels as well as the extreme event of coastal flooding.

The chapter shows that differences in occurrence probability and impact levels of hazards induce significant variations in cognitive responses at all three steps of the process. Specifically, the role of change awareness is central for adaptation against long-term gradual changes, but largely irrelevant for the extreme event case. The awareness of long-term gradual changes is, however, distorted in ways that be explained by change blindness. In contrast, adaptation to extreme events is primarily driven by the level of future expectations, and, while change awareness is distorted by the affect heuristic, this heterogeneity in change awareness does not affect expectation levels. These differences in the cognitive response depending on the hazard type show the role of bounded rationality for the study of adaptation responses in all its rigor. Crucially, the results, first, cast doubt on the transferability of scientific findings for one type of hazards onto another and, second, highlight the need for different policy tools in order to promote adaptation against to either of the two hazard types.

Chapter 3: "Social Image, Social Norms and Social Networks". The third chapter presents work done in collaboration with Andreas Pondorfer (TU Munich) and focuses on the role of social context for decision making. In this chapter we ask how social image effects to social context. Social image effects play a central role in environmental economics through their motivational influence on conditional cooperators (Sexton and Sexton, 2014; Friedrichsen and Engelmann, 2018; Nguyen-Van et al., 2021; Filiz-Ozbay and Ozbay, 2014). In this chapter it is asked how social image effects interact with two contextual variables. One of them are social norms. Social norms gain equally much interest in environmental economics due to their central role as an informal institution guiding behaviour in social dilemma situations (Nyborg et al., 2016; Le Coent et al., 2021; Alló and Loureiro, 2014; Allcott, 2011; Cialdini and Jacobson, 2021). The other contextual factor is interpersonal relationships, which have also been found to interact with pro-environmental behaviours (Henry and Vollan, 2014; Welsch and Kühling, 2009; Nguyen-Van et al., 2021; Bissing-Olson et al., 2016). The hypotheses derived and analyzed in this study postulate tight interrelations between these three aspects of a person's social environment in decision-making. In particular, it is hypothesized that norms serve as reference points for image effects, and also that the relationship to the observer of an action is just as important for image effects as involvement of the observer into specific network structures. These hypotheses are tested using lab-in-the-field experimental data from village communities in PNG (coastal as well as non-coastal). Participants had to decide how much of a given amount of money they wanted to share with an unknown other and how much to keep for themselves. This decision had to be made once in private and once in the presence of a fellow villager. The social norms for how to behave in this situation are measured using state of the art tools from behavioural economics, i.e. incentivized measures of second order normative beliefs. To account for personal relations, we used detailed social network data as well as a subjective evaluation of personal distance between subject and observer.

Using this data, the study finds that image effects are norm enforcing, meaning that norms qualify as focal points for image effects. However, this effect is strongly heterogeneous with regard to the personal relation between subject and observer, and the network position of the observer. Specifically, the closer the subject feels to the observer the lower the norm-enforcing effect of the observer. Similarly, a lower norm-enforcing power is found for observers with whom the subject commonly cooperates. This role of social distance between subject and observer on norm enforcement is significantly mediated by the observer's position in the conversation network and fully gone for observers that are highly central in these networks. These findings have important implications for environmental economics. For example, they suggest that norm nudges might be even more effective when combined with image concerns. Furthermore, they offer guidance on the effectiveness and direction of effects from reputational interventions. They can be assumed to be most useful in domains in

which a behavioural norm exists and are likely to be effective in promoting sustainable behaviour only if the norm prescribes sustainable actions. If the norm supports alternative behaviours, an intensification of image concerns could actually be counter-productive. Finally, our results show that only distant observers exert a norm enforcing power. Thus, within the family or close circle of friends these effects are unlikely to be observed. This implies that addressing norms for behaviours that are visible to the broader public is potentially more effective than addressing norms for behaviours that are only observable for close others.

In sum, the chapters of this thesis contribute in two ways. First, they contribute to the research frontier in behavioural environmental economics in all three dimensions of behavioural deviations from rationality mentioned above. Chapter 1 highlights the role of bounded willpower and uncertainty attitudes for adaptation choices. Chapter 2 shows the importance of accounting for bounded rationality in understanding adaptation barriers. The final chapter presents the complexity that arises from the many dimensions of bounded self-interest and our embeddedness in social contexts. Second, each of the chapters, also presents a distinct level at which insights from behavioural economics are conducive to environmental economic research. While in the first chapter behavioural economic controls are added to an otherwise purely environmental economic research question and methodology, the second chapter follows an environmental research question through a behavioural economic lens. The third chapter can be attributed to the domain of fundamental behavioural economic research. Yet, it advances a topic that is of central concern for the stimulation of sustainable behaviours and much discussed in environmental economics. Beyond that, taking together the results of all three chapters, they conjointly display the insights that can be gained from understanding human adaptation to environmental changes not as a result from rational but behavioural optimization.

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Chapter 1

Wait and See? Public Preferences for the Temporal Effectiveness of Coastal Protection

Susann Adloff, Katrin Rehdanz

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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.

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Chapter 2

Adapting to Climate Change: The Role of Event Type for Protection Motivation

Susann Adloff

Abstract:

Climate change largely unfolds by two types of events - extreme events and gradual long-term changes - which differ markedly in occurrence probability and (marginal) impact. This paper shows evidence that these differences in characteristics induce two structurally different cognitive routes underlying people's protection motivation. Using field data on the willingness to protect against coastal hazards in a sample simultaneously exposed to sea level rise and coastal flooding, variation in cognitive processing of events is identified at the level of event awareness, expectation formation and adaptation motivation. In particular, for both event types, I find imperfect memory of event experience. This heterogeneity can be rationalized with an inability to acknowledge incremental changes for sea level rise and emotionally distorted memories for coastal flooding experiences. For sea level rise, this heterogeneity in event awareness influences future hazard expectations as well as overall protection motivation. For coastal flooding, future expectations and protection motivation are independent of variations in event awareness. Yet, they significantly correlate with one another. The results strongly question the transferability of results found for one event type onto another. In addition, the data suggests that policy interventions to stimulate protection motivation require to be fitted to the specific hazard type.

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2.1 Motivation

The extent of social and economic damages that climate change related threats will cause strongly depends on the way people react to these hazards (e.g. Aerts et al., 2018; Desmet et al., 2021; Heutel et al., 2020). These adaptational reactions are often found to be suboptimal (e.g. Burke and Emerick, 2016; Gallagher, 2014; Wachinger et al., 2013; Meyer, 2012). For this reason, attempts to reduce expected costs crucially necessitate a sound understanding of the barriers to adaptation. A long strand of literature regarding drivers of adaptation motivation leaves the relation between hazard experience and adaptation motivation largely unclear. Instead, it reports a large variation in correlation coefficients between experiences and adaptation motivation and lacks consensus even about the overall sign of the relation (van Valkengoed and Steg, 2019; Koerth et al., 2017; Bubeck et al., 2012; Bamberg et al., 2017).¹

A question that arises is how general cognitive processes that generate adaptation motivation might help explain the heterogeneity in adaptation outcomes. Existing modeling approaches from psychology and social science reflect the complexity of this process, which creates ample opportunities for decision heuristics and cognitive biases to cause variation in outcomes (e.g. Rogers and Prentice-Dunn, 1997; Lindell and Perry, 2012; Grothmann and Reusswig, 2006; Ajzen, 1985; Moser and Ekstrom, 2010; Moser et al., 2022). The degree to which certain biases are activated commonly depends on specific situational cues or on individual level characteristics. Thus, variations in adaptational outcomes might not be random but could reasonably be assumed to be structural variation between particular groups of people or situations.

This paper studies this question by looking at two likely candidates of such situational cues: the impact and occurrence probability of a hazard. Especially in the field of climate change economics, differences in these two specific situational cues gain empirical relevance. This is because they allow to distinguish between the two main types of events by which climate change unravels - extreme events and long-term gradual changes. 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.²

¹Several studies investigated the influence the type 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.

²Rising 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

Theoretically, the cognitive process underlying protection motivation can be subdivided into three essential steps: (1) the processing of information about some event gained either through description or personal experience, (2) the formation of future expectations based on this information, and (3) the translation of these future prospects into behavioral intent. High impact events commonly trigger strong emotional responses that increase memorability and their influence on expectation formation (Slovic et al., 2004; Loewenstein et al., 2001). This is not the case for low impact events. Opposed to that, even traceable low impact events are at risk to remain undetected as long as changes are sufficiently small (Simons et al., 2000), which is unlikely for high impact events. Next, it is easier to judge the presence of a hazard, and accordingly set expectations on the basis of experiences, when a hazard belongs to the class of high probability events. Lastly, how people react to future expectations of an event is subject to a mental weighting procedure dependent on the event's impact and likelihood profile (Bordalo et al., 2012; Bushong et al., 2021; Koszegi and Szeidl, 2013). Consequently, two hazard types that differ in terms of impact and occurrence probability are likely to induce non-homogeneous adaptational responses by stimulating different results throughout the underlying cognitive process.

This claim is empirically investigated in a systematic comparison of the cognitive response of people to the exposure to extreme events and gradual long-term changes. This is done using field experimental data from coastal inhabitants of a small island region in Papua New Guinea. This sample provides a unique setting, in which villagers simultaneously face the long-term gradual change of sea level rise and the extreme event hazard of coastal flooding. As both are coastal hazards, they share many attributes but strongly differ in impact and likelihood. In addition, the low presences of formal institutions renders villagers directly responsible for protection at their shoreline. 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. This allows to trace differences between event types at each of the three steps of the cognitive response to hazard exposure. To circumvent issues arising from the use of survey data on event experiences (compare e.g. Guiteras et al., 2015), I focus on variation in experience reporting only within subgroups with a joint "objective" experience background (i.e. objective experience groups, OEGs). Due to a geographically narrow sampling procedure, these can be defined along readily available observables. This step renders variation in actual experiences to be captured by between OEG differences and allows to relate remaining within OEG heterogeneity in the collected measures back to variations in cognitive processing.

year 2200 (Desmet et al., 2021). Equally, increasing average temperatures are estimated to lead to an undiscounted global annual damage of \$63 billion - \$128 billion³ 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.

Using this setup, I find 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 role of event awareness for expectation formation, and the determinants of behavioral intent. In particular, there is heterogeneity in experience reporting within OEGs for both types of events. In line with the proposition that different cognitive biases are activated for each event type, this heterogeneity is driven by different individual level characteristics. In case of sea level rise, the differences found in experience reporting translate into variation in expectations and can be found to significantly impact protection motivation. For coastal flooding, protection motivation is sensitive to variations in expectation, but not in event awareness. As these future expectations are insensitive to differences in event awareness, protection motivation is, thus, decoupled from variations in cognitive processing of event experiences in the case of coastal flooding.

On an empirical level, the contribution of the study is twofold. 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.⁴ Second, making use of analysis results on the OEG level from a geographically proximate sample allows us to investigate cognitive process variations with survey data from the field. Hence, this design circumvents the pitfalls of the replication of the two threat structures in the laboratory.⁵

In addition, this paper offers three essential conceptional contributions to the literature. Up to this point, there is no existing consensus, neither in field nor lab experimental investigations,⁶ on the impact of a simultaneous decrease in impact and increase in

⁴In 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 minimal or no difference of the two compared events along other dimensions. For example, Diekert et al. (2021) provide evidence that people are sensitive to the source of a risk that they face. In detail, participants in their lab experiments react differently to risk that is caused by humans than risk that is caused by non-human factors such 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 lose 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.

⁵Most notably, this concerns the credible reconstruction of catastrophic losses in the lab in the 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.

⁶Several laboratory studies investigate 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.⁷ Even though the laboratory setting allows a high degree of experimental control, results are largely heterogeneous across studies. Shafran

occurrence probability on protection choice. This study introduces a simple conceptual basis that allows us 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. Lastly, the findings of this paper outline different policy needs for adaptation enforcement against long-term gradual changes than against extreme events. For sea level rise, the correction of event (mis-)perceptions appears as the most promising way to stimulate adaptation motivation. Instead, for coastal flooding, interventions should rather be designed to target expectation levels.

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 concludes.

2.2 Theoretical Background

Cutting across disciplines, several conceptualizations of the cognitive process underlying adaptation motivation can be found (e.g. Rogers, 1975; Grothmann and Reusswig, 2006; Lindell and Perry, 1992; Ajzen, 1985). While these offer much rigor in the identification of subcomponents, this paper abstracts from much of this complexity and instead proposes a conceptualization that largely focuses on common elements across approaches. In particular, this paper uses a representation of the cognitive process underlying protection motivation that highlights three steps: (i) Experiences: A change

(2011) reports decision makers (DMs) to protect more against high probability-low impact threats. In line with this, Ganderton et al. (2000) find DMs to increase insurance purchase in reaction to increases in probability but to be largely unresponsive to variations in impact. Yet, for example, Laury et al. (2009); Loubergé and François Outreville (2001) or Bajtelsmit et al. (2015) present evidence for a stronger preference to insure against low probability-high impact losses than against high probability-low impact risks. 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 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.

in the environment needs to be recognized. This recognition might be stimulated by personally experiencing an event and/or equally well by receiving information about a change taking place.⁸ (ii) Expectations: This change awareness will need to trigger the future expectation that this change can lead to personally relevant harm if nothing is done to avert it, such that this event is evaluated as a hazard. (iii) Behavioural intent: Lastly, these future expectations need to induce a motivation to take precautions to reduce the threat. In a simplified way, this can be illustrated by 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.

The separation between hazard acknowledgment and behavioral intent included in this three step procedure can be found in many other conceptualizations, such as the Protection Motivation Theory (Rogers, 1975, 1983; Rogers and Prentice-Dunn, 1997), the Theory of Planned Behaviour (Ajzen, 1985), the theory of protective action decision making (Lindell and Perry, 1992, 2003, 2012) or the process model of private proactive adaptation to climate change (Grothmann and Reusswig, 2006). Beyond that, however, the representation used here abstracts from complexity most importantly regarding the translation of future expectations into behavioural intent, and intent into action. For example, other models single out the evaluation of a persons adaptation options and ability, which is subsumed by the function translating expectations into behavioural intent in the representation used here. Equally, if the perceived ability to show a behavioural response with sufficient success probability is low, people might divert to a cognitive instead of a behavioral coping strategy such as denying the existence of the threat (Babicky and Seebauer, 2019; Grothmann and Reusswig, 2006; Mulilis and Duval, 1997; Lindell and Perry, 2012). The representation used in this paper can thus be seen as a stylized simplistic cognitive model of protection motivation, to which more rigor can be easily added. This simplistic representation, however, is sufficient to point out likely sources of heterogeneity in the cognitive response to extreme events and long-term gradual changes.

⁸A lot of information on the underlying threat structure can be gained from second hand information, such as media, school, neighbors. This information is provided as a description of the threat. While the mode of learning about an event - through experience or through description - matters, in that it triggers differential cognitive results (e.g. Hertwig and Erev, 2009; Simonsohn et al., 2008; Barron and Erev, 2003), it is not differentiated between the two modes in the three step procedure. Information acquisition is considered to be included in the set of experiences.

2.2.1 Experiences: Event awareness

Personal 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 theoretical accounts of 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). This renders the step of change awareness an essential necessity for adaptation motivation, yet, people are repeatedly found to not make optimal use of all available information. In fact, people are largely unable to process all information around them. Consequently, also recall of personal experiences and previously gained information, as their lasting mental imprint, is often imperfect. On one hand, attention and recall are largely partial and, on the other hand, the determination of which event/information is attended to and recalled is context and individual specific. For example, the personal degree of selective attention influences which facets of the current context are attended to (Schwartzstein, 2014; DellaVigna, 2009; Kahneman, 1973). In addition, 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), 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 recognition and ease of recall of an event. Accordingly, even if people experience the same situation, the perception of this situation and its recall is likely heterogeneous.⁹ Given this argument, in the following it will be differentiated between objective experiences describing the actual situation a person lived through, and experience reporting, recall or awareness which refer to the subjective mental representation of the situation of the individual person. This heterogeneity in event awareness can be expected irrespective of the kinds of biases at work and, thus, is expected to arise for any event type.

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

The type of event gains relevance at the point of the drivers of this heterogeneity. Allowing event awareness and ease of recall of an event to be mediated by cognitive heuristics that respond to attributes of the situation, the ease of recall of instances of either event type is highly likely to be structurally different. This postulation is based on the following two considerations. First of all, people are found to be unable to acknowledge incremental changes if they are only sufficiently small (Simons et al., 2000).

⁹For findings in line with this in the realm of flooding experiences see for example Guiteras et al. (2015).

This implies, that 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, termed "Change Blindness", has gained comparably little attention within the economic profession, yet, is particularly noteworthy for the study of low impact events. At the same time, it is unlikely to interfere with high impact event awareness. Secondly, the likelihood of event recall is found to be influenced by the degree of emotional reaction an event triggers (Slovic et al., 2004; Slovic and Peters, 2006; Loewenstein et al., 2001). Thus, events with impact levels high enough to induce an affective reaction are more easily remembered as well as more effective in triggering activism.¹⁰ 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, this heuristic likely affects extreme event recall, but is unlikely to affect recall of long-term gradual changes (Weber, 2006). 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. In this way, it is likely to introduce an upwards bias as well as increase heterogeneity in extreme event recall.

This argumentation provides the following hypotheses regarding the differences in event processing between extreme events and long-term gradual changes:

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

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

H2.2: Susceptibility to the affect heuristic biases recall of extreme events upwards, yet does not impact recall of longterm gradual changes.

2.2.2 Expectations: Threat perception

Whether some change in ones environment will be classified as a threat depends on the expectations about its consequences that this change triggers. Different cognitive responses between the two hazard types can also be expected at the level of expectation formation. First of all, expectation formation is strongly influenced by experience recall biases. The human brain builds future expectations, at least partially, from personal experiences (Mullainathan, 2002). The greater the ease of retrieving a memory of an event the higher its occurrence likelihood is evaluated (Tversky and Kahneman, 1973). The easier it is to remember accounts of a certain characteristic related to an event, the more probable it is considered to be a common characteristic of this event type (Kahneman and Tversky, 1972). For this reason, it can be expected that

¹⁰This point of sufficiency might well be heterogeneous between individuals.

differences in event perception generated by change blindness or the affect heuristic translate over to expectation formation. This means that similar structural variations can be expected for future expectations as for event recall. Secondly, the difference in occurrence probabilities between the two hazard types induces a strong difference in the informational content of personal hazard experiences. For a low probability hazard, the information one gains from the absence of any personal 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. Hence, not experiencing a sign of a high probability event is strong evidence for its absence. This offers, that, for the class of long-term gradual changes, event experiences are informative for expectation formation, but less so in the case of extreme event type hazards.

Taken together, this raises the hypothesis that variations in event awareness translate over to the process of expectation formation in the case of the high probability event class of long-term gradual changes. For low probability but high impact hazards, such as extreme events, the two points outlined describe counteracting forces instead. Even though this renders the analysis of the relation between experiences and expectations to be of a more exploratory nature for extreme events, the following hypothesis shall be used for the analysis.

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

2.2.3 Behavioural intent

Lastly, dissimilarities in adaptation reaction between event types can also be expected due to 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 alongside 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 person 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., 2022; 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 between event types in the role that individual preferences play for adaptation motivation. 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.¹¹ 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.

¹¹Given a concave utility function, the marginal effect of variation in risk aversion increases with the size of the stakes.

The inter-temporal dimension of uncertainty can be incorporated into the theory of focusing in the sense 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., 2022). 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 person places an enhanced focus on a single day i.e., today, a high perceived threat from extreme 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 theoretical considerations are examined as a basis for exploratory investigations into the role of these preference parameters.

2.3 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 and Kavanamur, 1999; De Renzio, 2000).^{12,13} 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.

In addition, 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

¹²The UNDP assigns a human development index in 2019 of 0.555 (rank 155 out of 189 countries (Programme), 2020).

¹³<https://freedomhouse.org/country/papua-new-guinea/freedom-world/2020>, 08.01.2021

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. That 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.^{14 15}

The communities of Bougainville are composed 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 a 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 2.1).

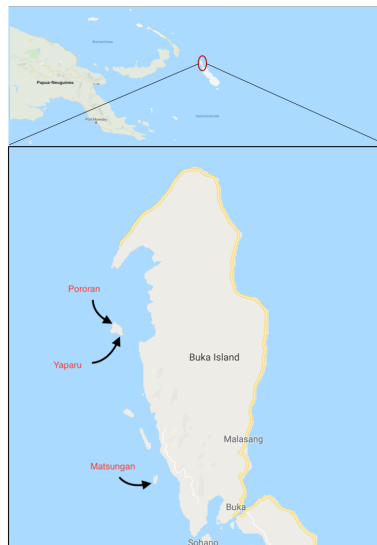


Figure 2.1: Coastal communities included in the sample

¹⁴The 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.

¹⁵see for example Diekert et al. (2021) or Löckenhoff et al. (2019) for evidence on the outcome relevance of these factors.

2.3.1 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 have you experienced in the past five years? / How many coastal flooding events did you experience in the past five years?
- Q3: Has the rise in sea level/ coastal flooding caused 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 the case of coastal flooding. Q2 and Q3 were only asked if Q1 was answered with "yes". 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 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 (relevant for 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.

2.3.2 Threat perception

To capture threat perception, future hazard expectations are collected. In line with other studies, threat 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 will cause personal or physical damage to your household in the next 5 years?

Answers to these questions are numerically coded¹⁶ and the final measure for threat perception is constructed as the product of the answers to each of these two questions, i.e. the likelihood of occurrence multiplied by the likelihood of personally being affected.¹⁷

2.3.3 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 (Figure B.1 and Table B.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 (2023).

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

$$U_i(a_1) \geq U_i(a_n) \quad \forall a_n \neq a_1 \quad (2.1)$$

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

$$Prob_i(a_1) = Prob(\epsilon_{ia_1} - \epsilon_{ia_n} > V_{ia_n} - V_{ia_1}) \quad \forall a_n \neq a_1 \quad (2.2)$$

¹⁶1 - "very unlikely", 2 - "rather unlikely", 3 - "rather likely", 4 - "very likely"

¹⁷A person who considers it very unlikely that a hazard will strike and that there will be any personal or physical damage has a threat level of 1 (1x1), while a person who considers it very likely that sea levels will rise and but rather unlikely that this will cause damages within the next 5 years will be assigned a threat level of 8 (4x2).

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:

$$Prob(a_{Protection}) = \frac{\exp(U_{Protection})}{\exp(U_{Protection}) + \exp(U_{Status Quo})} \quad (2.3)$$

The use of a hypothetical stated preference measure 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. Next to measuring willingness to protect to circumvent this critique, the sample includes villages, in which signs of coastal erosion were visible, yet mostly no coastal protection implemented at the stage of data collection.

2.3.4 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 elicitation 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. H2.2 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.

Measures for uncertainty preferences are collected in an incentive compatible lab-in-the-field experiment. As 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) - both dimensions are assessed. 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 used in the analysis 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 (Y: 0K / B: 10K), and participants could instead choose which bag to draw from. One bag contained ten balls of each color; the other bag contained twenty balls with an unknown color distribution. Patience is measured as per the decisions people made in a two-level stair-case task. In detail, participants had to choose, first, between receiving 6K right on the day of the interview or a larger amount two weeks after the interview. This was done in two stages. In the first stage, the offered later payment was 10K. If the immediate (later) payment was chosen in the first stage the later amount offered in the second stage increased to 12K (decreased to 8K). The choice patterns in this task allow to differentiate between four patience types (now / now, now / later, later / now, later / later) which provide the patience measure used in the analysis.

Additionally, I use a measure on coastal dependence as a proxy for susceptibility to change blindness. The degree of coastal dependence is derived as a weighted average of answers to a question inquiring what the respondent commonly uses the coast for.¹⁸ The weighting was done according to the degree to which each of these usages is a necessity 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 this empirical set up, the theoretical hypotheses can be translated into specific empirical predictions, which are displayed in Table 3.1.

2.3.5 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 carried out in a paper and pen format by local assistants in the local language (Tok Pisin) in small, secluded

¹⁸Possible 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).

	Theoretical	Empirical
H1	Event recall is heterogeneous between individuals with the same experiences for both event types.	There is heterogeneity in experience reports within OEGs with regard to both event types.
H2.1	Susceptibility to change blindness biases recall of longterm gradual changes downwards, yet does not impact recall of extreme events.	Coastal dependence negatively influences sea level rise awareness, but does not affect coastal flooding event reporting.
H2.2	Susceptibility to the affect heuristic biases recall of extreme events upwards, yet does not impact recall of long term gradual changes.	Uncertainty-aversion is positively correlated with coastal flooding recall. Sea level rise recall is not affected by differences in uncertainty-aversion.
H3	Differences in experience recall translate into variation in expectations.	Differences in within OEG experience reports translate into heterogeneities in expectations.
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.	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.

Table 2.1: Hypotheses

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.

2.4 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 2.2 provides an overview of 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.¹⁹ 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. Additionally, Table

¹⁹PNG 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

2.2 shows the average scores of the two uncertainty measures and patience, which provide that the chosen incentivisation 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 differences found in answers between event types.

2.4.1 Event recall

69 percent of respondents reported 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 using the first of the three experience questions, i.e. whether a person ever experienced sea level rise (slr) or coastal flooding (cf). As the question was posed in a yes/ no fashion, a deviation from zero or one shows heterogeneity in event perception. Thus, given a mean of 0.84 for sea level rise reporting (sd = 0.3687) and 0.69 for coastal flooding reporting (sd = 0.4646), heterogeneity can be identified for both event types.

Accounting for potential between village and age group differences, Figure 2.2 displays the average experiences reported for each of the OEGs. It is verified that age bins are set such that scaling on OEG means successfully eliminates all age effects.²⁰ 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 B.2 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*, 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.

²⁰Specifically, it is ensured that there is no significant correlation between age and event reporting within age bins.

	N	Mean	St.Dev.	Min	Max
Sociodemographics:					
Age	294	38.71	13.69	18	87
Gender (1 - female)	297	0.52	0.50	0	1
Education (in years of schooling)	290	8.23	1.95	4	12
Monthly Household Income in K ^a	227	200.20	309.50	0	2400
Moved to Village ^b	285	0.56	0.50	0	1
Moved to Village in last 5 years ^b	285	0.11	0.32	0	1
Years of Residence in Village	285	28.05	16.78	0.08	86
Coastal Dependence (0 = low; 1 = high)	297	0.64	0.17	0.29	0.88
Comprehension (1 = low; 5 = high)	297	4.34	0.84	1	5
Experience of Coastal Processes (%):					
<u>Coastal Flooding</u>					
Experience	297	0.69	0.46	0	1
Damage	297	0.10	0.30	0	1
<u>Sea Level Rise</u>					
Experience	297	0.84	0.37	0	1
Damage	297	0.23	0.42	0	1
Expectation of Coastal Processes (%):^c					
<u>Coastal Flooding</u>					
Expectation	295	0.63	0.48	0.00	1.00
Damage	297	0.61	0.49	0	1
<u>Sea Level Rise</u>					
Expectation	296	0.73	0.45	0.00	1.00
Damage	297	0.63	0.48	0	1
Preference Measures:					
Risk Tolerance (0 = low; 4 = high)	297	1.19	1.04	0	4
Ambiguity Tolerance (0 = low; 1 = high)	296	0.297	0.46	0	1
Patience (0 = low; 4 = high)	295	2.42	0.94	0.38	3.67

^a At time of data collection: K1 = 0.26 Euro; ^b Dummy variable that is 1 if respondent moved to the village at some point in life and 0 if the respondent was born in the village. ^c The share of respondents that evaluated the occurrence of an event with “rather likely” or “very likely”.

Table 2.2: Sample Characteristics

Tables 2.3 and 2.4 report the regression results of uncertainty tolerance and coastal dependence on event reporting scaled on the OEG group mean for each event type (cf = coastal flooding, slr = sea level rise). Standard errors are bootstrapped clustered on OEG group level and the robustness against the inclusion of other sociodemographic variables is tested (columns 2 and 4).²¹ The measure for uncertainty tolerance used for these regressions is risk tolerance. All results are robust to the use of ambiguity tolerance instead, as an alternative measure for uncertainty tolerance (compare Table

²¹For a version of the tables displaying control coefficients see Tables B.3 and B.4 in the Appendix.

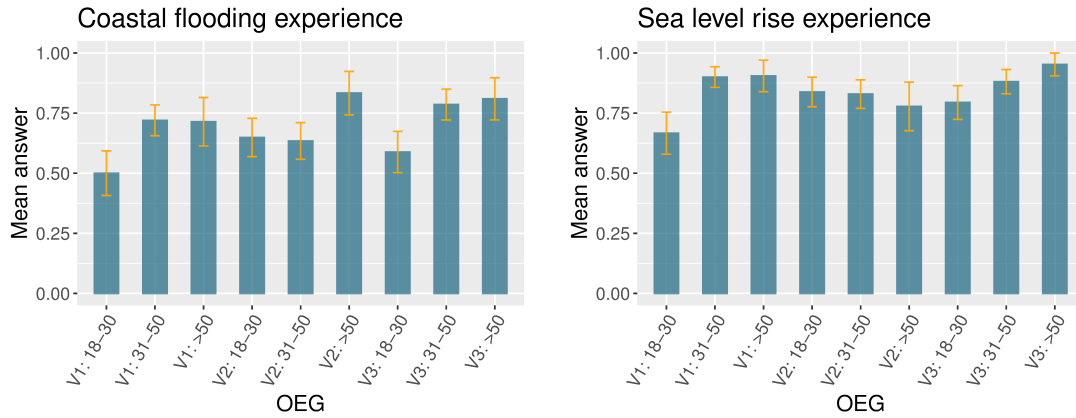


Figure 2.2: Average answer to the Question "Have you ever personally experienced coastal flooding/ sea level rise?" along OEGs.

B.5 in the Appendix). Overall, they provide support for the hypothesis that there are structural differences in the drivers of distortions in experience awareness (*H2*). In particular, columns 1 and 2 in Table 2.3 show that more uncertainty averse individuals are more likely to report coastal flooding experiences. For variation in sea level rise reporting, uncertainty aversion does not come through as an explanatory variable (compare columns 3 and 4 Table 2.3). Next, Table 2.4 shows that people reporting to interact more frequently with the coast are less likely to be aware of rising sea levels (compare columns 3 and 4), but do not differ in their coastal flooding reporting behavior (compare columns 1 and 2). The relation found between uncertainty tolerance and experience reporting is in line with the propositions of an affect heuristic (*H2.2*). To the degree to which cognitive coping strategies are not contained by the design, the results represent a lower bound of the actual effect strength, given that cognitive coping creates a negative relation between uncertainty aversion and recall.²² Additionally, the negative relation between coastal dependence and sea level rise reporting is in line with

²²If 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 (Babicky and Seebauer, 2019; Grothmann and Reusswig, 2006; Mulilis 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 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. 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. Furthermore, it allows to look at the willingness to protect, which precedes the question of whether a person will actually show an adaptive response or not, and, thus, potentially also the cognitive step of evaluating one's personal qualification to actually implement a chosen protection. Consequently, the counteracting relation between uncertainty preferences and event recall should be minimal and would, if present, work against the raised hypothesis.

the predictions from change blindness (H2.1). People who interact with the coast on a more regular basis are less likely to recognize marginal long-term changes in sea level.

<i>Dependent variable: Experience Statements</i>				
	CF		SLR	
	(1)	(2)	(3)	(4)
Uncertainty tolerance	−0.241** (0.107)	−0.244*** (0.093)	−0.066 (0.129)	−0.078 (0.129)
Sociodemogr. Controls	No	Yes	No	Yes
Clustered SEs	Yes	Yes	Yes	Yes
Observations	216	216	216	216
R ²	0.014	0.059	0.001	0.031

Note: *p<0.1; **p<0.05; ***p<0.01; Sociodemogr. Controls: Age, Gender, Education, HH Income, Moved to Village; Clustered SEs: bootstrapped clustered std errors on OEG level

Table 2.3: Role of Uncertainty Tolerance

<i>Dependent variable: Experience Statements</i>				
	CF		SLR	
	(1)	(2)	(3)	(4)
Coastal dependence	0.482 (0.504)	0.364 (0.490)	−0.791*** (0.250)	−0.869*** (0.244)
Sociodemogr. Controls	No	Yes	No	Yes
Clustered SEs	Yes	Yes	Yes	Yes
Observations	216	216	216	216
R ²	0.007	0.044	0.021	0.029

Note: *p<0.1; **p<0.05; ***p<0.01; Sociodemogr. Controls: Age, Education, HH Income, Moved to Village; Clustered SEs: bootstrapped clustered std errors on OEG level

Table 2.4: Role of Coastal Interaction

2.4.2 Expectations

In the next step, the perceived level of threat measured through expectations is 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. Additionally, 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. Combined, the average threat perception is 8.6 (cf) and 9.2 (slr) on a scale of 1 to 16.²³

Figure 2.3 shows the interaction between differences in event reporting and threat perception. In particular, the graphs display the future hazard 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. No difference in average threat perception can be traced between low and high coastal flooding reporters. Yet, differences in sea level rise reporting significantly influence the degree of perceived threat from sea level rise. Respondents that are classified as high sea level rise reporters assign a significantly higher likelihood to future (continuing) sea level rise or damages from sea level rise. Tables B.6 and B.7 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*. While it is supported for the case of sea level rise, this is not the case for coastal flooding. Rather, the results are in line with the second argument provided in section 2.2. Even if the affect heuristic leads to an exaggeration of experience recall, experiences are less informative for expectation formation, such that this bias does not translate over to the level of expectations.

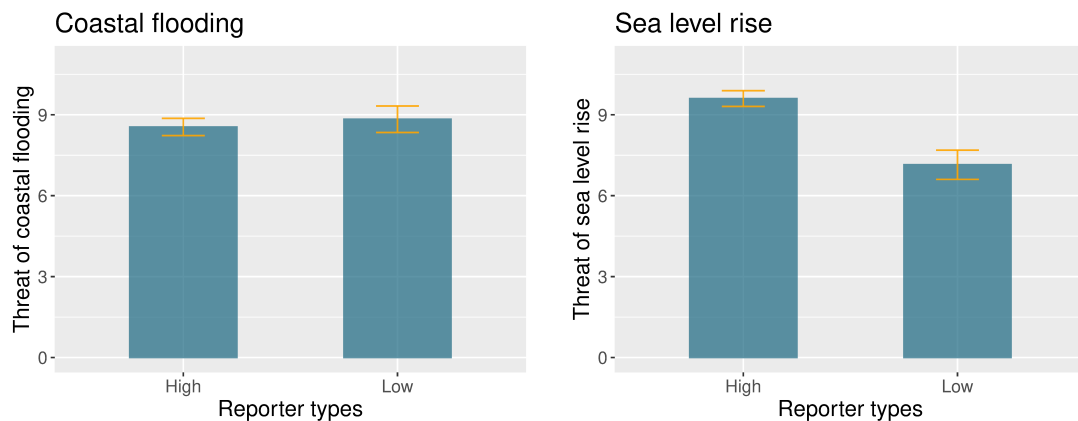


Figure 2.3: Average threat perception in terms of future expectations for coastal flooding (left) and sea level rise (right) by experience reporter types.

2.4.3 Adaptation motivation

The impact of event awareness and future expectations on willingness to protect measured in the choice experiment is analyzed by conditional logit estimation of the underlying random utility model in R using the MLogit package (Croissant et al., 2012;

²³Answers on the likelihood of event occurrence and on the likelihood of being affected are coded on a scale of 1-4.

Hlavac, 2014). Table 2.5 shows the average marginal effects of experience reporting and expectations for each event type on the choice probability of coastal protection over the status quo. The respective control variable is inserted into the conditional logit model as an interaction with 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 influence the willingness to protect. Furthermore, in the case of sea level rise, the relation is switched. Whereas variations in sea level rise awareness have 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.²⁴ Table 2.5 uses risk tolerance as a measure for uncertainty preferences. The results are robust also to the alternative specification using ambiguity tolerance (compare Table B.9 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*). In fact, the role of expectations fully vanishes for sea level rise.

²⁴The focuses is set on these two variables as these are one significantly correlating with experience reporting and could be assumed to play a role also for adaptation motivation, potentially inducing an omitted variable bias. A table that also shows coefficients for those controls is provided in the Appendix (Table B.8).

<i>Dependent variable: Willingness to protect</i>								
	CF				SLR			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Expectations	-	0.0248*** (0.009)	0.0247*** (0.0091)	0.0242** (0.0108)	-	0.007 (0.0079)	0.0022 (0.0079)	0.0011 (0.01)
Experiences	-0.0013 (0.007)	- -	0.0001 (0.007)	0.0022 (0.0104)	0.0367*** (0.0081)	- -	0.036*** (0.0081)	0.0349*** (0.01)
Controls	None	None	None	UA, CD	None	None	None	UA, CD
Assistant FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster Level	Participant	Participant	Participant	Participant	Participant	Participant	Participant	Participant
Observations	1,003	1,003	1,003	1,003	1,003	1,003	1,003	1,003
Log Likelihood	-814.633	-793.984	-792.550	-769.563	-797.392	-790.778	-777.049	-757.873
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01; UA - uncertainty aversion (risk), CD- coastal dependence								

Table 2.5: WTP Antecedent: Average marginal effects of experience reporting and future threat expectation variations on willingness to protect.

As speculated in section 2.2, the role of expectations for protection motivation in the domain of long-term gradual changes might be suppressed by procrastination in the sense of high future discounting, such that they are of relevance only for very patient individuals. This is tested in a separate set of regressions, the average marginal effects of which are presented in columns 1 and 2 of Table 2.6. It reports the interaction effects of expectations and patience on the willingness to protect for both event types. The coefficients show that the degree to which sea level rise expectations influence adaptation motivation is, indeed, significantly affected 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 nonetheless shows itself to be a relevant mediator for forward looking individuals. Other than speculated in 2.2, however, this is the same for coastal flooding. In addition, in case of coastal flooding, expectations remain significant also for participants with average patience levels. Further, for both event types, an increase in expectation of future threat has negative impacts on the adaptation motivation for individuals with below average patience levels. Hence, procrastination might be of relevance in both cases. In general, the patience variable does not seem to explain the difference in the relevance of expectations for the average respondent's protection motivation between events.

Lastly, Table 2.6, further, shows the average marginal effects from models in which future expectations are interacted with risk (columns 3 and 4) and ambiguity tolerance (columns 5 and 6). 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 a measure for uncertainty preferences. For sea level rise, neither of the two models show a significant interaction effect between uncertainty tolerance and expectations. 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.

2.5 Discussion and Conclusion

This paper proposed that there are systematic differences in how people react to hazards that differ in their impact level and occurrence probability. Using a simplistic three step representation of the cognitive process underlying protection motivation, it is shown that from a theoretical perspective systematic deviation can be expected to occur at the level of event awareness, future expectations and behavioural intent. This is empirically validated along survey data from coastal inhabitants in Papua New Guinea, who are simultaneously exposed to the long term-gradual change of sea level rise as well as the extreme event hazard of coastal flooding. Summing across results, three distinct insights can be identified. First, the fact that event recall is heterogeneous within OEGs shows that there is variation in the level of change awareness. This is the case for both

<i>Dependent variable: Willingness to protect</i>						
	CF	SLR	CF	SLR	CF	SLR
Expectations	0.0141* (0.0082)	-0.0013 (0.0073)	0.0200** (0.0086)	0.0028 (0.0078)	0.0202** (0.0088)	0.0007 (0.0079)
Patience (P)	0.0310*** (0.0080)	0.0314*** (0.0080)				
Risk tolerance (RT)			0.0150 (0.0079)	0.0113 (0.0072)		
Ambiguity tolerance (AT)					0.0110 (0.0076)	0.0101 (0.0071)
Expectations x P	0.0248*** (0.0081)	0.0187** (0.0080)				
Expectations x RT			0.0176** (0.0078)	-0.0092 (0.0079)		
Expectations x AT					0.0043 (0.0081)	-0.0028 (0.0077)
Assistant FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SEs	No	No	No	No	No	No
Observations	995	995	1,003	1,003	999	999
Log Likelihood	-773.445	-773.764	-787.893	-786.983	-784.432	-782.308

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; depicted are average marginal effects (AMES) and according standard errors in brackets, all variables are scaled to represent standard deviations from mean, AMEs are derived from estimation of the MNL model in which individual level variables (and their interactions) are included as interactions with the attributes.

Table 2.6: The Role of procrastination and uncertainty tolerance (std. dev. in brackets)

event types. However, the long-term gradual change of sea level rise seems to trigger a different perceptual bias than the extreme event hazard of coastal flooding. This can be derived from the fact that different individual level characteristics drive this heterogeneity in event recall. Second, there is a strong difference between the two event types in the role that this distortion in change awareness has on expectations and protection motivation. For sea level rise, distortions in event awareness directly translate over to heterogeneity in expectations and also protection motivation. Those who are not aware of sea level rise at their coastline have significantly lower expectations of future sea level rise and a significantly lower willingness to protect. For coastal flooding, distortions in event awareness neither affect expectation levels nor willingness to protect. Biased experience recall, consequently, is unlikely to induce sub-optimality in adaptation behaviour in the domain of extreme events. Third, differences between event types can be seen in the role of future hazard expectations for protection motivation. While extreme event expectations are significantly affecting willingness to protect, there is no effect on willingness to protect from variations in sea level rise expectations.

There are several potential rationalizations for these results. Most importantly, at the level of event awareness, the correlation patterns between uncertainty tolerance

and experience reporting are in line with the hypotheses derived based on the affect heuristic (Slovic et al., 2004; Slovic and Peters, 2006). Similarly, the relation between coastal dependence and experience reporting is in line with hypotheses derived on the basis of change blindness (Simons et al., 2000). The difference in the relation between experience awareness and expectation formation between the two event types is in line with the postulation that instances of high probability events are more informative about the presence and future experience likelihood of a hazard than instances of low probability events. Lastly, the differential role of event awareness and future expectations for protection motivation can be rationalized on the grounds of inter-temporal focusing. What is surprising is that there is no significant correlation between future sea level rise expectations and the willingness to protect, even when not controlling for experience reporting, in spite of their strong relation. One potential explanation for this could be the role of alternative information sources regarding the threat for the expectation formation process, which potentially offset the effect of experience reporting differences on adaptation motivation. As provided earlier, there are two routes of how information can be obtained about a hazard. One is through experiences and the other through descriptive second hand information. Examples for this would 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 the description of the underlying hazard structure is found to trigger differential cognitive results than found from 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. Babcock and Seebauer, 2017) and on the other they become effective mediators of beliefs via the information on social norms they spread (Seebauer and Babcock, 2020; Bollinger et al., 2020; McCright and Dunlap, 2011).

Beyond this, this paper provides a starting point for future research in a several directions. One avenue would be the explicit test of the validity of the proposed drivers of the results in this paper. For example, even though the results on perceptual 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. Other studies report findings on a relation between the affective reaction experienced in negative outcome states and 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. Next, 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. Lastly, this paper does not shed light on the role of variation in actual event experience but only on differences in processing of the same event experience. Investigating the role of variation in actual event experiences certainly opens the doorway to a even longer list of biases that can be investigated. For example, the recency bias (Tversky and Kahneman, 1973, 1974) 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.

Irrespective of these limitations, the results of this paper show two generally different cognitive routes underlying protection motivation. This finding has three essential implications. First, it provides important evidence that the type of barriers to optimal protection likely depend on the kind of hazard encountered. This has direct implications on the effectiveness of policy instruments to stimulate adaptation motivation. Whereas correcting biases in event awareness will be able to stimulate adaptation to long-term gradual changes, protection from extreme events will be much more sensitive to an increase in the level of perceived threat as given by future expectations. This latter approach is likely to be effective for long-term gradual changes only once accumulated impacts become large, such that they fall out of the class of high probability - low impact events. Second, this finding strongly questions the transferability of findings on hazard protection against one event type to the domain of protection against other event types. This crucially calls for extending research to cover various hazard types instead of narrowing down on one. Third, it shows that opening up the cognitive black box offers great potential to put structure on the identified heterogeneity in adaptational responses to hazard exposure. In the data, variations in processing are found at all three of the processing steps which are investigated in this paper. However, neither in the list of biases discussed, nor the characteristics inspected, nor in the depth of conceptualization of the underlying cognitive process, does this paper claim to be exhaustive. This outlines the many potentially fruitful ways in which the approach taken in this study can be extended upon in order to improve our understanding of people's adaptation reactions.

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Appendix

Figure B.1: 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	K 10	K 35	K 0
I choose...	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Table B.1: Description of attributes used in the choice experiment (?)

Attributes	Description	Levels
Time Until Full Protection	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 already provide full protection 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 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 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 particular protection measure.	K0 / 5K / 10K / 20K / 35K

Table B.2: Pearson correlation coefficients for correlation between control variables and the experience deviation from OEG-level means.

	Coastal Flooding		Sea Level Rise	
	coeff	p	coeff	p
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 B.3: Role of Coastal Dependence (including sociodemographic control coefficients)

<i>Dependent variable: Experience Statements</i>				
	CF		SLR	
	(1)	(2)	(3)	(4)
Coastal dependence	0.482 (0.503)	0.364 (0.503)	−0.791*** (0.246)	−0.869*** (0.239)
Age		0.002 (0.004)		−0.001 (0.005)
Education		−0.032 (0.044)		−0.018 (0.071)
Income		−0.002* (0.001)		−0.001 (0.001)
Moved to village		−0.197** (0.100)		0.048 (0.110)
Constant	−0.310 (0.293)	0.127 (0.492)	0.519*** (0.133)	0.771 (0.769)
Clustered SEs	Yes	Yes	Yes	Yes
Observations	216	216	216	216
R ²	0.007	0.044	0.021	0.029

Note: *p<0.1; **p<0.05; ***p<0.01; Clustered SEs: bootstrapped clustered std errors on OEG level

Table B.4: Role of Uncertainty Tolerance (including sociodemographic control coefficients)

<i>Dependent variable: Experience Statements</i>				
	CF	CF	SLR	SLR
	(1)	(2)	(3)	(4)
Uncertainty tolerance	-0.241** (0.109)	-0.244*** (0.092)	-0.066 (0.130)	-0.078 (0.134)
Gender		0.143 (0.148)		-0.312** (0.130)
Age		0.002 (0.003)		-0.002 (0.005)
Education		-0.027 (0.046)		-0.018 (0.069)
Income		-0.002* (0.001)		-0.001 (0.001)
Moved to village		-0.209* (0.108)		0.079 (0.117)
Constant	0.101 (0.067)	0.376 (0.375)	0.066 (0.082)	0.476 (0.650)
Clustered SEs	Yes	Yes	Yes	Yes
Observations	216	216	216	216
R ²	0.014	0.059	0.001	0.031

Note: *p<0.1; **p<0.05; ***p<0.01; Clustered SEs: bootstrapped clustered std errors on OEG level

Table B.5: Role of Uncertainty Tolerance (alternative specification using ambiguity)

<i>Dependent variable: Experience Statements</i>				
	CF	CF	SLR	SLR
	(1)	(2)	(3)	(4)
Uncertainty tolerance	-0.302*	-0.350**	0.107	0.132
	(0.168)	(0.173)	(0.133)	(0.145)
Gender		0.164		-0.316**
		(0.154)		(0.132)
Age		0.005		-0.003
		(0.004)		(0.005)
Education		-0.025		-0.022
		(0.040)		(0.066)
Income		-0.002*		-0.001
		(0.001)		(0.001)
Moved to village		-0.218**		0.080
		(0.088)		(0.118)
Constant	0.066	0.212	0.006	0.457
	(0.041)	(0.344)	(0.055)	(0.655)
Clustered SEs	Yes	Yes	Yes	Yes
Observations	216	216	216	216
R ²	0.018	0.068	0.002	0.032

Note: *p<0.1; **p<0.05; ***p<0.01; Clustered SEs: bootstrapped clustered std errors on OEG level

Table B.6: Relation between coastal flooding and sea level rise experience reporting and coastal flooding threat perception.

<i>Dependent variable:</i>				
	Coastal Flooding Threat Perception			
	(1)	(2)	(3)	(4)
Experience Reporting (CF)	-0.234 (0.262)	-0.230 (0.289)		
Experience Reporting (SLR)			0.995*** (0.106)	0.706*** (0.139)
Sociodemogr. Controls	No	Yes	No	Yes
Clustered SEs	Yes	Yes	Yes	Yes
Observations	295	282	295	282
R ²	0.002	0.136	0.046	0.156
Adjusted R ²	-0.001	0.117	0.043	0.138

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

Table B.7: Relation between coastal flooding and sea level rise experience reporting and sea level rise threat perception.

<i>Dependent variable:</i>				
	Sea Level Rise Threat Perception			
	(1)	(2)	(3)	(4)
Experience Reporting (CF)	-0.247 (0.204)	-0.268 (0.212)		
Experience Reporting (SLR)			0.786*** (0.126)	0.551*** (0.129)
Sociodemogr. Controls	No	Yes	No	Yes
Clustered SEs	Yes	Yes	Yes	Yes
Observations	296	283	296	283
R ²	0.003	0.170	0.029	0.181
Adjusted R ²	-0.001	0.152	0.026	0.163

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

Table B.8: WTP Antecedent: Average marginal effects of experience reporting and future threat expectation variations on willingness to protect.

<i>Dependent variable: Willingness to Protect</i>		
	CF	SLR
Expectations	0.0242** (0.0108)	0.0011 (0.01)
Experiences	0.0022 (0.0104)	0.0349*** (0.01)
Uncertainty Tolerance	0.0103 (0.0111)	0.0116 (0.011)
Coastal Dependence	-0.1588* (0.0937)	-0.1557* (0.0881)
Assistant FEs	Yes	Yes
Cluster Level	Participant	Participant
Observations	1,003	1,003
Log Likelihood	-769.563	-757.873

Note: *p<0.1; **p<0.05; ***p<0.01; UA - uncertainty aversion (risk), CD- coastal dependence

Table B.9: WTP Antecedent: Average marginal effects of experience reporting and future threat expectation variations on willingness to protect.

<i>Dependent variable: Willingness to protect</i>									
	CF				SLR				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
Expectations	-	0.024*** (0.009)	0.0241*** (0.009)	0.0237** (0.0105)	-	0.0086 (0.0079)	0.0035 (0.008)	0.0014 (0.01)	
Experiences	0.001 (0.0071)	-	0.0023 (0.0071)	0.0066 (0.0105)	0.0361*** (0.008)	-	0.0354*** (0.0081)	0.0332*** (0.0099)	
Uncertainty Tolerance				0.0158 (0.0109)				0.0117 (0.0108)	
Coastal Dependence				-0.1806* (0.0967)				-0.1724* (0.0904)	
Assistant FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster Level	Participant	Participant	Participant	Participant	Participant	Participant	Participant	Participant	Participant
Observations	999	999	999	999	999	999	999	999	999
Log Likelihood	-811.739	-791.004	-789.667	-766.260	-794.537	-787.135	-773.635	-755.008	

Note: *p<0.1; **p<0.05; ***p<0.01; UA - uncertainty aversion (ambiguity), CD- coastal dependence

Chapter 3

Social Image, Social Norms and Social Networks

Susann Adloff, Andreas Pondorfer

Abstract:

This paper studies the dependence of social image effects on two essential components of social context: social norms and social network relations. Comparing behaviour in a dictator game played in private and in front of an observer, we find that people's behaviour converges towards the experimentally measured social norm. This effect is strongly heterogeneous with regard to the relation between subject and observer. The larger the perceived social distance to the observer the stronger is the norm enforcing effect of being watched on the subject. No social image effect can be detected if subject and observer are close. Similarly, convergence to the norm in public is lower if subject and observer share a link in cooperation networks. In addition, the relation between social distance and observer effect is strongly mediated by an observer's centrality in conversation networks and strongest for observers with low centrality. As social norms are endogenous within groups, the finding that norms serve as reference points for social image effects provides a structural foundation for the heterogeneity of social image effects. Further, in a world where one is often surrounded by close others, our results challenge the external validity of the size of social image effects identified in anonymous observer treatments in the lab. Lastly, hypotheses derived from the literature on cooperation enforcement cannot be validated in this paper, instead it seems that they are overshadowed by the strong impact of social distance and observer centrality on conformity.

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3.1 Introduction

Human behaviour is strongly influenced by the social environment. We, as individuals, are embedded in social networks and consciously as well as subconsciously learn from and adapt to the behaviour of others (Dimant, 2019; Isler and Gächter, 2022; Kosse et al., 2020). We care about how others perceive us and conform to spectator expectations (Bursztyn and Jensen, 2017). We compare ourselves to others, compete with peers, and follow herd behaviour (Sacerdote, 2011; Bramoullé et al., 2020; Falk and Ichino, 2006; Cornelissen et al., 2017). Even in the absence of others, we follow internalized codes of conduct of peer groups (Krupka and Weber, 2013; Bicchieri, 2006). These findings are based on the results of a growing number of studies in three largely secluded strands of literature that focus on the influence of social environment on individual behaviour, i.e. studies on social image concerns, the influence of social norms, and the role of connectedness within social networks. This paper adds to the literature, by explicitly studying interrelations between these three components of our social environment. In particular, we study the dependence of social image effects on the social context provided by social norms and interpersonal relations.

We derive theoretical interrelations between social image, social norms, and social networks. These are, first, that social norms qualify as reference points for image effects and that image effects are an essential norm enforcement tool. Consequently, it can be expected that social image concerns motivate norm conformity. Second, social image concerns are only relevant when behaviour is observed. We argue that the social relationship between decision maker and observer influences the decision maker's degree of norm conformity. These dynamics are strongly influenced by the social relationships of subject and observer as preferences for norm conformity are likely heterogeneous across observers: People care most about sustaining a favorable social image in the eyes of close observers (e.g. Bohnet and Frey, 1999), such that observers whom subjects consider to be close can be expected to have stronger norm enforcing power (Akerlof and Kranton, 2000; Bicchieri, 2006). In addition, the literature on cooperation enforcement implies that signaling cooperativeness through norm following can be expected to be most useful towards those whom one commonly cooperates with (e.g. Henrich, 2016). Hence, an observer who has direct cooperative relations with the decision maker or an observer who can easily spread information to other people with whom the decision maker regularly cooperates with, can be expected to be more effective in triggering norm conformity of the decision maker, than observers who are irrelevant to the decision maker's cooperative relations.

We test these theoretical predictions using data collected in a lab in the field experiment conducted in small villages in Papua New Guinea. Papua New Guinea offers ideal conditions for the study at hand. Due to the weak rule of centralized institutions and the still largely traditional way of living, social norms are the primary regulating

force in social life. Additionally, Papua New Guinea is one of the last places on earth with locally cohesive communities, allowing us to collect detailed social network data. Participants played the Dictator Game (DG), i.e. they are endowed with money and could decide how much of it to share with an unknown other person.¹ To introduce social image effects, the dictator game was played once in private and once under the eyes of an observer, in randomized order. The social norm in the DG is measured through incentive compatible second-order normative beliefs, i.e. what one believes others believe is the normatively appropriate thing to do.^{2,3} Social relationships are captured, in this paper, in two dimensions: (i) perceived social distance (i.e. contact quality) measured using the inclusion of other in self (IOS) scale (Gächter et al., 2015), and (ii) social interaction patterns (i.e. contact quantity) measured through social network data. Overall, six network dimensions are captured, of which three map communicative relationships (conversation, advice, gossiping) and three cooperative relationships (food sharing, labor assistance, support in hardship). This data provides information on whether subject and observer share direct ties in cooperative networks and on the observer's position in communication networks. To ensure variation in the social relationship between observer and participant, we randomly assigned observers from different centrality percentiles of the villages' union network.⁴

Previous studies present evidence on interactions between, at most, two of the three components considered in this paper: social image, social norms, and social networks. First, the relevance of social image concerns for social norm conformity repeatedly finds voice in theoretical works (Ali and Bénabou, 2020; Bicchieri, 2006, 2017), is often implicitly assumed and utilized as a treatment manipulation (Bursztyn and Yang, 2022; Dear et al., 2019), and empirically tested (Andreoni and Douglas Bernheim, 2009; Rege and Telle, 2004; Gächter and Fehr, 1999). Second, there is evidence that observer characteristics such as social distance to the decision maker or the observer's network centrality matter for image effects (Breza and Chandrasekhar, 2019; Bohnet and Frey, 1999; Gächter and Fehr, 1999). Third, previous studies highlight the role of observer characteristics on social norm conformity. These studies describe, for example, that the identity of the observer affects the kind of norms that are relevant in a setting (Bicchieri, 2006, 2017; Krupka et al., 2022). Also, it is postulated that social distance between

¹For studies on the role of varying the social distance between subject and recipient, see Hoffman et al. (1996); Bohnet and Frey (1999).

²An alternative technique proposed by Krupka and Weber (2013) is not feasible in our field context, though we adopt their more detailed rating technique.

³Occasionally dictator games are said to be ill-fit as a playing field to study social norms as they are omitting any true interpersonal interactions and chance moves by being composed of only one decision of a single person. This argument however loses its validity once we include social context. The role of social norms might be reduced in the private setting yet should be fully fleshed in the public condition as the observer is a fellow villager who the subject will interact with/ encounter repeatedly in the future such that the field setting offers the called for consequentiality for future interactions that might be found in the response of a second mover in other game contexts.

⁴The union network is a network aggregating all elicited individual network layers. The centrality measure used is page rank centrality

decision maker and observer prevents social norms from being activated and that a shared group identity is necessary for a preference for norm following (e.g. Bohnet and Frey, 1999; Gächter and Fehr, 1999). This paper adds to this body of work by extending the analysis to simultaneously studying interrelations between all three of the components - social image, social norms, and social relationships. This is achieved by proposing a novel empirical set-up that advances on many features disregarded in previous work. First, we acknowledge the endogeneity of social norms and empirically elicit the location of normative beliefs using an incentivized norm measure. This approach strongly deviates from previous studies in which social norms are often not elicited but assumed to coincide with meta morals such as pro-sociality or fairness. Thus, this paper can be considered a first explicit test of the causal impact of social image concerns on norm conformity. Second, our set-up allows to disentangle the effect of social distance on image effects from the effects of social distance on pro-sociality. This is achieved by not varying the social distance between subject and recipient but between the subject and the observer. Third, we add depth to the analysis of social interaction patterns in this context by employing detailed social network data and deriving novel hypotheses on heterogeneous effects of different types of social networks (cooperation vs. communication). Three other studies also investigate how observability, social norm adherence, and social connectedness interact (Dimant, 2019; Bicchieri et al., 2022; Gächter et al., 2017). These studies are complimentary to our research. In particular, there are two sources of peer effects: (i) watching the behaviour of others and (2) being watched by others. The above-mentioned papers focus on the first of the two sources of peer effects, i.e. the role of watching others. This way, they provide insights on the role of network characteristics on norm uptake and erosion. Our paper, however, adds insights on the second source, illustrating the role of network characteristics for norm enforcement through being watched.

Overall, our results show that social norms serve as reference points for social image effects. The amount of money shared in the DG moves towards the social norm under observation. Furthermore, we also show that the perceived social distance between observer and subject matters. We find that distant observers are strongly norm enforcing. Close observers induce basically no change in behaviour. In addition, we find evidence of differential roles of cooperation and communication networks on observer effects. In the cooperation network, the relationship between observer and subject matters, whereas the observer's position within the network is not relevant. Direct links in the cooperation network reduce the observer effect on norm conformity. In the communication network, the effects are reversed. We identify no effect from direct links between subject and observer, but recognize a significant role of the observer's centrality in the communication network. While the overall pattern of the network findings is as expected (direct links matter only in the cooperation network, observer centrality matters only in the communication network), the effect signs are in stark contrast to the

hypotheses derived from the literature on cooperation enforcement. Instead, the effects are in line with the main finding of this paper that the strongest norm enforcing power is identified for distant observers.

These results are of relevance for the field of social image as well as for the fields of social norms, social networks, and peer effects. Most importantly, this paper provides a causal identification of drivers of heterogeneity in image effects, i.e. dependence on the underlying norm and sensitivity to the identity of the observer. In addition, this study provides causal evidence on the effectiveness of an often presupposed norm enforcement mechanism. Lastly, it offers a series of surprising results on the role of personal relationships on norm enforcement, which call for more research on the external validity of lab findings on social image effects employing anonymous observer treatments.

In the following we derive our theoretical hypotheses in section 2 and provide an explanation of the empirical procedure in section 3. Section 4 shows descriptive statistics on the social context of our sample before the results are presented in section 5. Finally, section 6 discusses findings and concludes.

3.2 Theoretical Background

From a theoretical perspective, there are tight interrelations between the workings of social image effects, social norms, and social connectedness. First, people care about what others think about them. For this reason, people tend to show social image effects, i.e. different behaviour in public than in private (Bursztyn and Jensen, 2017). Generally, it is assumed that people aim at being seen as a *good* person in the sense that they seek public approval of their behaviour. However, there is also evidence of non-conformism, where people seem to strive towards opposing what is generally considered as good behaviour (Bursztyn et al., 2019). This implies that, on one hand, it is common knowledge that people dance around some reference point of "good social image", by conforming or opposing it. On the other hand, it is largely unclear what determines this reference point. We propose that social norms provide a very likely candidate for such a reference point. Social norms (synonymously used: norms) can be defined as rules or standards that express what kind of behavior is considered as "appropriate", "proper" or "correct" in a specific reference community, i.e. they specify what one *ought* to do. This definition is common in the social sciences; similar definitions are, for instance, given by Cialdini et al. (1990), Elster (1989), Granovetter (2017), Henrich (2016), Krupka and Weber (2013), and Sunstein (1996).⁵ Wanting to leave a good impression on others i.e. creating a good social image can be synonymously

⁵Other authors have proposed more elaborate definitions such as Bicchieri (2006). Note, however, that the normative quality of the rules is the key element of Bicchieri's definition as well. Also note that, in the terminology of Cialdini et al. (1990, 1991), the above definition corresponds to *injunctive* rather than *descriptive* norms.

translated into behaving in ways others approve of, i.e. following the social norm.⁶ Consequently, we argue that social norms are likely reference points for image effects.

Secondly, looking at the relation between image and norms from the perspective of the norms literature, image effects serve as an essential norm enforcement tool. A social norm is a convergence in second-order beliefs about good and appropriate behaviour. Yet, while the existence of convergent second-order beliefs is a precondition, it is not sufficient to ensure social norm following within a community. Norm following needs to be enforced within a community by establishing a preference for conformity in a sufficiently large part of the community. A preference for conformity is often argued to stem from two sources: a. fear of punishment, or b. future benefits from signaling norm conformity (indirect reciprocity) (e.g. Nowak and Sigmund, 1998; Bowles and Gintis, 2004; Fehr et al., 2002; Henrich et al., 2010). Both of these sources are able to trigger norm conformity only if behaviours are observable. Hence, visibility of behaviour and a concern for what others think about ones behaviour, i.e. social image concerns are indispensable for norm enforcement. These two arguments both lead to our first hypothesis:

[H1] Social image effects increase social norm conformity.

Furthermore, preferences for norm conformity are strongly influenced by the personal relations between subject and observer. Relating back to the two sources regarding a preference for norm conformity, the signaling value of an action as well as the capacity to enact punishment are likely to be heterogeneous across observers. It is the core feature of identity economics that people gain direct value from identifying with certain groups and distancing themselves from other groups (Akerlof and Kranton, 2000). A common strategy to do this is by behaving in line with common behaviours of a group one likes to be associated with or equivalently behaving in ways that oppose the common behaviours of a group one likes to distance oneself from. Depending on the group membership of an observer, a person thus might want to conform to expectations to signal like-mindedness or oppose observer expectations to distance herself from the observer (Schneeberger and Krupka, 2022). Assuming that people self-select into relationships with people they like to associate with, it can be hypothesized that the social distance between subject and observer mediates the degree to which the observer is norm enforcing, in particular:

[H2] The larger the social distance between subject and observer, the lower the norm enforcement from observation.

In addition, signaling cooperativeness through norm following is most useful towards those who one commonly cooperates with. Akin to the literature on the evolution of cooperation and societal fitness, norm following contains an instrumental value as

⁶This does not have to be the only motive people follow when showing image effects.

a tool to represent one's cooperativeness by following rules of the community. This signal of cooperativeness is essential to stir direct and/or indirect reciprocity of other members in the community (Nowak and Sigmund, 1998; Panchanathan and Boyd, 2004; Nowak, 2006; Henrich and Henrich, 2007; Nowak and Sigmund, 2005). Following this argument, the value of being seen as a cooperator by another person can be assumed to be heterogeneous depending on the relation one entertains with the recipient of the signal. The signaling value is likely high with regard to others on whom one relies for help or support in everyday life and low for those with whom one barely interacts. Furthermore, depending on his or her power to influence the cooperative relations of a person, observers have differing degrees of power to punish a person in case of norm violations. Punishment power is, firstly, high for those with whom a person has cooperative relations, such that future cooperation with the observing person might be in danger from norm violation. Secondly, it can be assumed to be high for any observer who has a strong influence on others with whom the observed person has cooperative relations (Wu et al., 2016). If a subject does not care about the observer him- or herself and the observer cannot influence what others, whom the subject cares about, think or do, then there will barely be any consequences from the observer witnessing norm violations. Consequently, the observer's cooperative relations to the subject as well as the observer's position in any communication related network can be expected to mediate an observer's norm enforcement ability. This offers two more hypotheses on the role of specific social network characteristics of the observer:

[H3] Norm enforcement is positively related to the degree to which subject and observer entertain cooperative interactions.

[H4] Norm enforcement is positively related to the degree to which the observer can pass on information about the subjects' behaviour to others.

3.3 Experimental Design

The data was collected in villages on the island of Bougainville in Papua New Guinea (PNG) (compare Figure 3.1). PNG has been called an "ideal environment for the study of social norms" (Bernhard et al., 2006, , p. 218) due to (i) its diversity of local customs and social norms, (ii) the importance of group identity, and (ii) the absence of centralized institutions, meaning that social life is regulated mostly by informal rules such as social norms (Bernhard et al., 2006). Finally, Papua New Guinea is one of the remaining few places on earth where high quality social network data can be collected because the social community of individuals' is largely confined to the village they inhabit.

Participants played the dictator game. The dictator game (DG) is one of the most simplistic games in the experimentalists toolbox such that the DG strongly reduces cognitive demand on the participants part and limits the space of counteracting forces



Figure 3.1: Map of the sampling region, Bougainville, Papua New Guinea.

that might correlate with the study's treatment effects. In detail, every participant obtained 10 Kina⁷ and was asked to split this money between him- or herself and an anonymous other person.⁸ After the "dictator" made this choice the game ended.

To introduce image effects, we placed a within-subject manipulation of image concerns. Every subject played the dictator game twice - once in a private, and once in a public condition. Whereas the choice was made following a double blind procedure in the private condition, an observer watched the subject's decision in the public condition.⁹ The observer was a randomly assigned other villager who was instructed to watch but not communicate with the participant. The order of the public and the private choice was randomized. At the time of their first decision, subjects did not know which other decisions they would have to make afterwards. Consequently, the first decision can be used for a between-subject analysis. The subjects received instructions that they need to make several decisions, of which one is chosen for payment.¹⁰

To identify social norms in the DG, we collected an incentivized measure of second-order normative beliefs – a core element of social norms (Bicchieri, 2006, 2017; Bicchieri and Xiao, 2009) strongly related to the Krupka and Weber (2013) measure of norms. In particular, after participants made their decision in the DG, they were asked to guess how other inhabitants of their village perceive the moral appropriateness of giving 0 Kina, 5 Kina and 10 Kina to the other person in the dictator game on a 4-point scale of appropriateness ("very inappropriate", "rather inappropriate", "rather appropriate",

⁷This was equivalent to roughly \$2.50 at the time of data collection.

⁸It was varied whether the person was "identified" as someone from the village of the participant or from another village. As this does not have any effects on our results, we do not further discriminate along this fact.

⁹The interview took place in tents that served as experimental booths. After explaining the game to the participant the interviewer left the tent in both conditions. The participants had to make their choice by placing the respective money share into an envelope labeled "my money" ("money bilong me") and an envelop labeled "money for the other person" ("money bilong narapela man o meri"). Both envelops were then placed into a sealed box. After the participants had made their choice, they rang a bell which informed the interviewer that he may return. Even while outside, the interviewer remained close to the experiment tent to verify that subject and observer did not talk to each other.

¹⁰The recipient of the amount shared in the private and the public condition is not the same but differs. This is known by the survey participants. We hope that this is more intuitive for subjects and renders it less suspicious that the observers is present only during one decision.

"very appropriate"). Beforehand, we asked other villagers who did not participate in the experiment to directly rate the appropriateness of giving 0 Kina, 5 Kina or 10 Kina to the other person in the DG on the same scale. Their responses were used to incentivize the second-order normative belief elicitation with 1 Kina per correct guess. As a robustness check, we also collected second-order normative beliefs from subjects that did not play the game before norm elicitation ($N = 45$).

The relationship between subject and observer was measured in two distinct domains. First, we elicited perceived social distance by means of the inclusion of other in self (IOS) scale (Aron et al., 1992; Gächter et al., 2015). This scale maps the degree to which a person identifies with another person. It is measured by presenting subjects with 7 images of two entities that gradually move from being fully separated (1) to fully overlapping (7). After the dictator games, and consequently after learning who the observer is, subjects were asked which of these images best reflects their relationship with the observer.

Second, we traced relationships through detailed social network data for our sample (Grimalda et al., 2022). Social networks were mapped ex-ante to the experiment in each of the participating villages by first taking pictures of the villagers. Then, every villager was shown the pictures of the other villagers and asked to answer relational questions by marking the pictures of the respective people. Overall we mapped six distinct network dimensions - 3 cooperation related networks (i. food sharing: "With whom did you share your food in the past week?" ii. gardening: "With whom did you do garden work together in the past month?" iii. trust: "Whom do you ask if you need someone to take care of something important to you?") and 3 communication related networks (iv. advice: "Whom do you turn to for advice?" v. conversation: "Whom did you talk to in the past week?" vi. gossip: "Suppose you see someone misbehaving, whom would you go talk to about it?"). During the experiments subjects were randomly assigned an observer from a pre-selected pool of observers. This pool of observers was for each village chosen such that it systematically varied the social centrality of the observers. In particular, observers were chosen by randomly drawing from each decile of the page rank centrality distribution in the union network aggregating all 6 network layers (see below for an explanation of page rank centrality). Using a fixed pool of observers per village allowed us to identify observer effects at the subject level and simultaneously account for unobservable subject fixed effects. As, both, observer and subject can be located within each of the networks, we gain a profound understanding of recent interaction patterns (direct and indirect via common network contacts) between subject and observer.

Given our hypotheses we focus on two aspects of network patterns: the observer-subject relation and the observer's position. In terms of the observer-subject relation, we are interested in whether a subject and the observer have a direct link in a certain

network. For this reason, we use the adjacency measure. Adjacency is a binary variable which is one whenever subject and observer have a direct link in the network, i.e. either the observer was nominated by the subject, or the other way around, or both, and zero otherwise. The observer's position in a network is measured through page rank centrality. Page rank centrality is among the most commonly used centrality measures. Centrality, in general, captures the degree of influence a person has on others in a network. Page rank centrality measures the number of links a person has with others in the network and also accounts for how many links those others have to yet other network participants, and so forth. The advantage of page rank centrality compared to eigenvector or degree centrality is that it takes into consideration the link direction and (if available) link weights. These properties make page rank centrality a rigorous measure of a network participant's ability to reach or influence other network participants (Bloch et al., 2021; Banerjee et al., 2013, 2019). For the analysis, we constructed one aggregate network for cooperation links (joining the food sharing, gardening and trust networks) and one for conversational links (joining the communication, advice and gossip network).

Using the IOS and social network data allows capturing two essential dimensions of any relationship: interaction quantity and quality. A subjective measure of social distance has likely plenty determining factors and, hence, may arguably be a crude measure for social relations. However, compared to network measures the depth of the IOS measure becomes an important advantage, since it also contains information on contact quality or history, capturing for example (dis-)similarities in individual level characteristics, shared experiences or differences in attitudes and convictions. Thus, the IOS scale represents a valuable measure that goes beyond what is retrievable from interaction patterns measured by social network data. The network patterns instead provide interaction snapshots that allow to differentiate between different interaction domains, which is a level of detail not achievable with the IOS.

Table 3.1 shows how our theoretical hypotheses are tested given this experimental design.

3.3.1 Implementation

The data collection took place in summer 2018 in 7 villages on the island of Bougainville in Papua New Guinea. Every village was visited for several days, during which village inhabitants first participated in the network survey and then in the experimental sessions. Overall, we selected small villages such that a complete network mapping was feasible. The average number of inhabitants above the age of 18 was 131 across all villages and never exceeded 215. In each village, 100 villagers were randomly chosen and invited to participate in the experimental sessions. The eligibility criteria for participation in the experimental sessions were a minimal age of 18 years and

	theoretical	empirical
H1	Social image effects increase social norm conformity.	The amount sent converges towards the social norm in the public treatment compared to the private treatment. The social norm is given by a convergence of second-order normative beliefs about the most appropriate behaviour in the dictator game.
H2	The larger the social distance between subject and observer the lower the norm enforcement from observation.	This observer effect increases in the degree of social identification between subject and observer measured by the IOS scale rating of the subject.
H3	Norm enforcement is positively related to the degree to which subject and observer entertain cooperative interactions.	The observer effect is larger for those observers who have direct relational ties with the subject in cooperation networks. Relational ties between subject and observer in conversation networks do not influence the observer effect.
H4	Norm enforcement is positively related to the degree to which the observer can pass on information about the subjects' behaviour to others.	The observer effect is larger for those observers who have a central position in conversation networks. Observer centrality in cooperation networks does not influence the observer effect.

Table 3.1: Hypotheses

prior participation in the network survey. Observers were determined based on the network centrality prior to the draw of participants. The economic game interviews were undertaken by local enumerators in small tents set up for the purpose of the survey in local language, Tok Pisin, in a paper and pen approach. To maximize privacy and reduce contagion, it was ensured at all times that no other villager was in the vicinity of the tents. Overall, one interview in the experimental session included the dictator game in private and public, the norm elicitation as well as a post-experimental questionnaire and lasted roughly 45 minutes.

3.4 Descriptives

In total, 477 people participated in the experiment. Table 3.2 shows the sample composition with regard to socio-demographics, social norm perception and social network position for the full sample (column 1), the subset of participants who first encountered the private condition (column 2), the subset of participants who first encountered the public treatment (column 3) and the observers (column 4). The full sample is well-balanced in terms of gender. The average participant is 36 years. Observers are slightly older with an average age of 45 years. Given the history of violent conflict on Bougainville the socio demographics also include war involvement. This variable is a proxy for the exposure to violence during the civil war. Given the fact that

violence exposure can significantly affect peoples' social demeanors (e.g. Voors et al., 2012; Bauer et al., 2016) it is used as a control variable throughout the analyses.

	Full Sample	S1 - Private	S2 - Public	Observer
Gender (1=male)	0.47 (0.50)	0.51 (0.50)	0.43 (0.50)	0.63 (0.49)
Age	35.48 (14.50)	36.53 (14.82)	34.40 (14.12)	44.60 (14.71)
Understanding (1 = low, 5 = high)	3.94 (1.12)	4.01 (1.11)	3.88 (1.14)	4.31 (1.15)
War Involvement (0 = low, 1 = high)	0.41 (0.28)	0.39 (0.28)	0.43 (0.29)	0.47 (0.31)
Norm Perception:				
Min. contribution in line with norm	4.66 (2.55)	4.69 (2.33)	4.64 (2.76)	5.32 (2.18)
Max. contribution in line with norm	6.22 (2.69)	6.25 (2.57)	6.18 (2.81)	6.11 (2.61)
Network Position:^a				
Centrality (WPR ^b)	0.01 (0.005)	0.01 (0.01)	0.01 (0.005)	0.02 (0.01)
Indegree ^c	35.42 (16.82)	36.71 (17.40)	34.11 (16.14)	61.65 (32.85)
Outdegree ^c	37.00 (25.44)	35.87 (24.98)	38.16 (25.90)	35.61 (27.15)
N	477	240	237	63

Standard deviations in brackets. ^a The network used is the weighted union network. ^b WPR - weighted page rank; ^c In-/Outdegree measures the number of in-/outgoing links of a person, e.g., A person who nominates two others and was nominated by 5 others for a network question has an outdegree of 2 and an indegree of 5 in this network.

Table 3.2: Sample characteristics for the full sample (column 1), the subsample that started with the private treatment ("S1 - Private", column 2), the subsample that started with the public treatment ("S2- Public", column 3) and the group of observers (column 4)

3.4.1 Social norm

The basis for our study is the existence of a social norm in the dictator game. Figure 3.2 shows the distribution of second-order normative beliefs about the appropriateness of the three sharing options 0 Kina, 5 Kina and 10 Kina. The left panel displays the responses of the full sample whereas the right shows the responses of those participants in the robustness check sample who did the norm elicitation without prior game engagement.

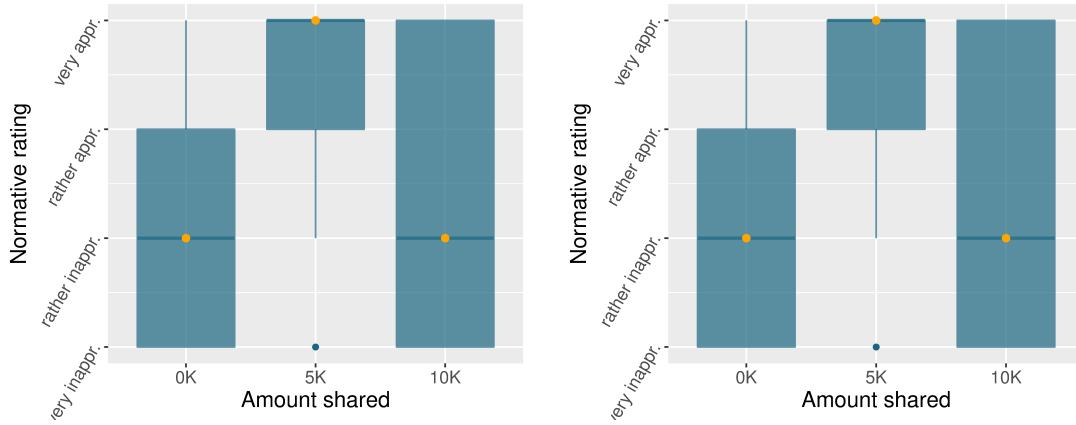


Figure 3.2: Boxplots of norm perception in terms of second-order beliefs about appropriateness of giving 0K/5K/10K. Left: Full Sample; Right: Additional "clean" sample (n=45) that only participated in the norm elicitation but not in the DG.

Second-order normative beliefs converge on the evaluation of giving 5 Kina as being very appropriate as well as on giving 0 Kina as being inappropriate. There is normative heterogeneity surrounding the action of giving 10 Kina to the recipient. This can be seen in the left panel but becomes even more clear cut in the right panel with those responses which are non-congested by previous game play, i.e. the clean sample.¹¹ Intuitively, while giving more can be considered generous in WEIRD societies,¹² it is traditionally considered a misdemeanor in societies with strong rules of reciprocity as it implies indebting the recipient (Ensminger and Henrich, 2014).

Making use of additional control variables surrounding the norm perception, we find that 47% of participants state that they are fully certain about their answers in the norm elicitation, and 64% also believe that the observer norm perception is in line with their answers, i.e. their community norm perception. Furthermore, a majority of participants believes that others in the village behave according to the norm.¹³

¹¹Comparing those two images, the second-order belief elicitation after game play is distorted in the expected direction, which is, we find a more positive display of the selfish choice if people played the game before the norm elicitation.

¹²WEIRD stands for western, educated, industrialized, rich and democratic.

¹³For the relevance of empirical beliefs, e.g. what people think what others do, for norm following see for example Bursztyn and Yang (2022); Bicchieri (2017, 2006); Bursztyn et al. (2020)

In terms of behaviour, we find a non-negligible degree of norm internalization. Figure 3.3 shows the distribution of the amount given in private (both for those who started with the public ["public first"] and those who started with the private treatment ["private first"]). It displays a strong peak at the most selfish option of giving 0 Kina and an equivalent peak at the normatively prescribed choice of giving 5 Kina to the receiver.

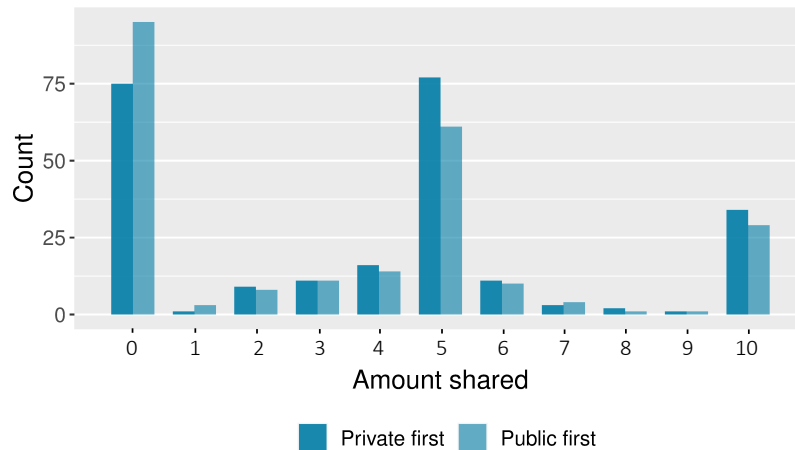


Figure 3.3: Distribution of the amount sent in the private condition, differentiated by the treatment order - either **private first** and public second or **public first** and private second.

3.4.2 Networks and observer characteristics

Figure 3.4 and Table 3.3 provide descriptives on the social connectedness in our sample. In particular, Figure 3.4 shows the distribution of social distances between subject and observers in terms of IOS scale ratings. Most participants classify their relation to the observer as close, with a median IOS scale rating of 6 out of 7.

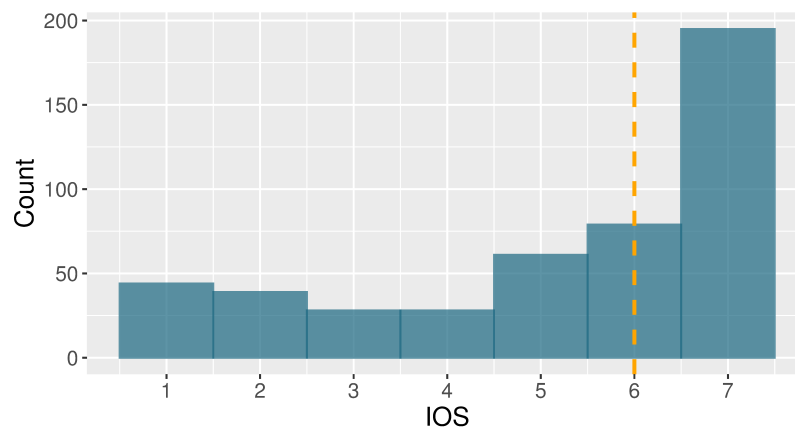


Figure 3.4: Distribution of IOS scale ratings. 1 = no overlap at all (maximal distance), 7 = full overlap (maximal proximity). The orange line marks the median answer.

Table 3.3 provides an overview of the average network composition across villages for our aggregate communication network (column 1) and the aggregate cooperation network (column 2). The average amount of nodes (i.e. people covered in the network) is 131 in both network types (as all networks are measured for the same people, i.e. all villagers). We find slightly more links (edges) between villagers in the communication network than in the cooperation network. This is not surprising, given that communicative links are more easily established than cooperative relationships. Accordingly, the average number of nominations (indegree) is higher in the communication network, and it also shows a higher variation between network participants than can be found for cooperative relationships. Reciprocity describes the likelihood that person A nominates person B, if B nominated A in a network. The reciprocity values for the two networks show that there also seems to be slightly more ambiguity in the degree to which both interaction partners agree on the interaction pattern in the communication network than in the cooperation network. Lastly, the diameter shows the maximum length of the shortest paths between any two network participants, which on average is slightly lower in the communication network (4.43) than in the cooperation network (5.14).

	Communication	Cooperation
Nodes	131	131
Edges	3474.43	3155.14
Indegree	25.30	23.11
Density	0.20	0.19
Reciprocity	0.30	0.37
Diameter	4.43	5.14

Table 3.3: Descriptive network characteristics for the aggregate communication and cooperation network. Nodes - number of network participants, Edges - overall number of links between nodes, Indegree - average number of links towards a node, Density - network tightness (total number of actual links divided by number of potential links), Reciprocity - likelihood of a reverse link for every link in the network, Diameter - maximum length of shortest network path.

Finally, Table 3.4 shows descriptive statistics of the observers' centrality and relational variables in the two network types. Observers were chosen from different centrality deciles of the page rank centrality distribution in the weighted union network of the respective village. The more fine-grained objective of this paper is however, to study variations in observer characteristics in the cooperation and communication networks. To ensure that manipulations in the page rank centrality of observers in a village's weighted union network did induce variation in observer characteristics in the cooperation and communication network of the same village, we calculated simple regression coefficients with the page rank centrality in the union network (column 3). The coefficients are significant for all characteristics except for adjacency in the cooperation network. Nevertheless, we find considerable degrees of variation in this

observer characteristic, even though this variation does not appear to be induced by the treatment manipulation.

Statistic	Mean	Min/Max	β
<i>- Communication -</i>			
Position: page rank centrality	0.022 (0.017)	0.001/0.070	0.5682*** (0.0190)
Relation: adjacency	0.516 (0.504)	0/1	0.0071*** (0.0023)
<i>- Cooperation -</i>			
Position: page rank centrality	0.012 (0.007)	0.002/0.032	0.9509*** (0.1463)
Relation: adjacency	0.290 (0.458)	0/1	0.0027 (0.0027)

Table 3.4: Observer network characteristics

3.5 Results

The dependent variable for our analyses is the observer effect on the deviation from the norm. This is given by the difference in the absolute deviation of the amount shared from the norm in public and private.¹⁴ The community norm is set to 5 Kina in accordance with the results shown in the previous section. The distribution of the dependent variable can be seen in figure 3.5 panel a). Table 3.5 shows the results for the first two hypotheses.¹⁵ Columns 1-3 are based on the data from those subjects who encountered the private treatment first and the public treatment second. This is considered the cleanest specification, as it rules out potential priming effects on the norm from exposure to the public treatment before playing the private condition. Column 4 provides a test of this intuition by including the full sample and controlling for possible order effects.

The constant in column 1 shows that the average observer effect is not significantly distinguishable from zero without controlling for the subject observer relation. This means that on average there is no change in the degree of norm following due to observation. However, looking at the individual level behaviour, Figure 3.5 suggests that this result is driven by individual heterogeneity in behaviour. Specifically, panel

¹⁴In detail, the dependent variable is calculated as $|x_{pub} - x_{norm}| - |x_{priv} - x_{norm}|$, with x_{pub}/x_{priv} - amount shared in public/private and x_{norm} - amount in line with community norm, i.e., 5. We look at absolute deviation as the norm lies in the center of the choice space which gives room to overshooting in both directions.

¹⁵Compare Table C.2 in the Appendix for the long version including control coefficients.

<i>Dependent variable: Δ in abs. deviation from norm</i>				
	(1)	(2)	(3)	(4)
Constant	-0.599 (0.606)	-1.758*** (0.596)	-2.020** (0.915)	-2.322*** (0.737)
IOS		0.203*** (0.072)	0.216*** (0.076)	0.253*** (0.073)
Public first				1.194** (0.500)
IOS x Public first				-0.335*** (0.089)
Sample	S1-Private	S1-Private	S1-Private	Full
Individ. Controls	No	No	Yes	Yes
Assistant FEs	Yes	Yes	Yes	Yes
Day FEs	Yes	Yes	Yes	Yes
Village FEs	Yes	Yes	Yes	Yes
Clustering	Obs.	Obs.	Obs.	Obs.
Observations	195	193	191	363
R ²	0.094	0.133	0.145	0.094

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 3.5: Community norm convergence and psychological social distance: This table displays the effectiveness of the observer treatment for community norm conformity as well as the effect of the social distance between observer and subject. The measure used as social distance proxy is the indication made by the respondent on the inclusion of other in self scale. Individual level controls are age, gender, understanding, war involvement and community role (i.e. leader or not).

(a) of Figure 3.5 shows that a significant share of respondents show no observer effect, while roughly 20% of the sample show positive and another 20% negative observer effects. Further, panels (b)-(d) of Figure 3.5 show that positive (negative) observer effects can be attributed to below (above) norm sharing in private. Those who give less than the norm in private increase their contributions on average in the public condition (panel (b)), and those who give more than the norm prescribes in private reduce their contribution on average under observation (panel (d)). Those who behave in line with the norm in private do not significantly change their average behaviour in public (panel (c)).¹⁶ The fact that on average there is no change in absolute deviation from the norm, thus, indicates that people seem to overshoot the norm (in both directions). This could be rationalized with moral cleansing and is in line with the fact that giving in private is significantly correlated with giving in public (compare Table C.3 in the Appendix). Thus, we do not find support for H1 when averaging across the whole sample. However,

¹⁶For a test of significance see table C.1 in the appendix.

disaggregating results to the individual level reveals that behavioural responses are heterogeneous and depend on the direction of the deviation from the social norm.¹⁷

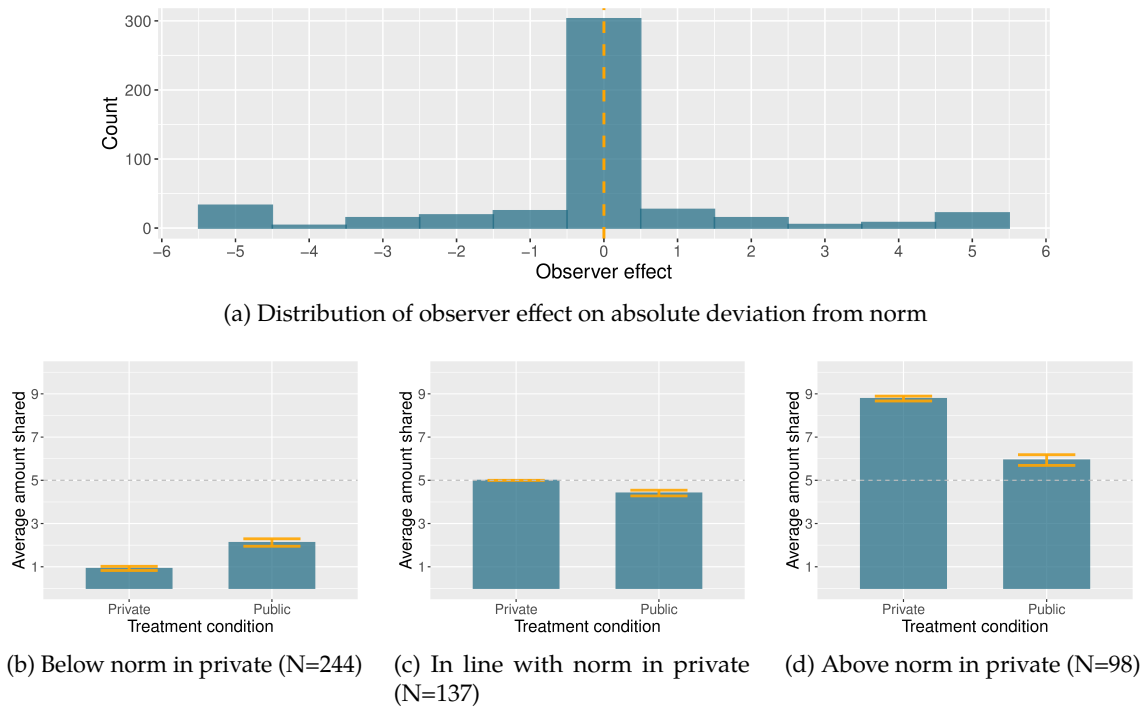


Figure 3.5: Image effect patterns. Top: Individual level image effect distribution (absolute deviation from the norm in public - absolute deviation from the norm in private). Bottom: giving in private and public for those giving below (b)/in line with (c)/above the norm in private (d).

The average treatment effect becomes significant in table 3.5 columns 2 and 3 where we account for heterogeneity in the subject-observer relation through controlling for perceived social distance. Specifically, we find a strong negative treatment effect which is counterbalanced by a positive effect of social distance between subject and observer. That is, subjects who perceive the observer as socially distant -represented by lower values on the IOS scale- converge more towards the community norm in public compared to subjects who perceive the observer as socially close. This result is robust against individual level controls (compare column 3). As hypothesized in H2, perceived social distance to the observer is an important determinant that influences norm conformity. However, contrary to our expectation, the effect of social distance is positive rather than negative. People are more concerned about their social image when facing a socially more distant observer. Figure 3.6 shows the projected effect for each level of the IOS scale based on model (2). An observer who is socially close will trigger less of a convergence. In fact, significant convergence is only found for an IOS rating

¹⁷This is an anomaly of a setting in which the normative focal point lies in the center of the distribution instead of being at one of the extreme points. If the latter would be the case observing overshooting would be impossible by design.

of 1 - 4. Given that the degree of norm internalization is high and a large percentage of observer subject relations are ranked at the top of the IOS scale (6 or 7), this might explain the insignificance of the average observer effect when not controlling for social distance.

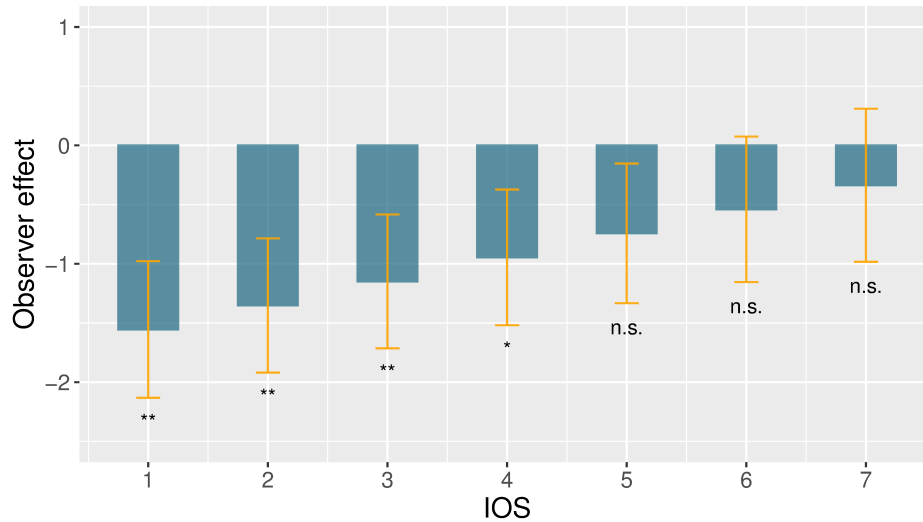


Figure 3.6: Observer effect by subject observer relation as evaluated by the subject on the ios scale. (1 - completely different, 7 - one entity)

Table 3.5 column 4 repeats the same analysis for the full sample, i.e. including observations of subjects playing the public condition first (public first = 1). The results show significant order effects not only in the differences between norm conformity in public and private, but also in the role played by the observer subject relation. In particular, the direction of effects shows that the observer effect is smaller for those who played in the public condition first compared to those subjects who played in the private condition first, and the observer subject relation is close to zero. These results are in line with a potential priming on the norm and social image concerns during the public treatment which influences the choice in the private treatment, such that differences in game play become small.

In the next step, we include the network data into the analysis to investigate how direct links between subject and observer as well as observer centrality affect the convergence to the norm in the dictator game. Table 3.6 shows the results on the role of subject observer adjacency, i.e. whether subject and observer have a direct link in a network.¹⁸ As hypothesized in H3, we find strong support for the fact that a direct link in the cooperation network significantly influences the observer effect, whereas this is not the case for the communication network. This finding is robust to the inclusion of IOS. However, the sign of the coefficient is contrary to our prediction. We expected a stronger pull towards the norm from observers with whom subjects have a cooperative

¹⁸Compare Table C.4 in the Appendix for the long version including control coefficients.

link, yet we find a weaker pull for this group of observers. This parallels the trend we found for IOS - a closer social relation leads to a reduction in the observer effect.¹⁹ The average observer effect and the IOS coefficient are robust to the addition of network adjacency variables.

<i>Dependent variable: Δ in abs. deviation from norm</i>				
	Communication		Cooperation	
	(1)	(2)	(3)	(4)
Constant	-0.676 (1.067)	-1.984** (0.924)	-0.854 (1.118)	-2.032** (0.931)
Observer relation (netw.)	0.319 (0.201)	0.231 (0.205)	0.684** (0.275)	0.563** (0.283)
IOS		0.210*** (0.077)		0.192** (0.078)
Sample	S1-Private	S1-Private	S1-Private	S1-Private
Individ. Controls	Yes	Yes	Yes	Yes
Assistant FEs	Yes	Yes	Yes	Yes
Day FEs	Yes	Yes	Yes	Yes
Village FEs	Yes	Yes	Yes	Yes
Clustering	Obs.	Obs.	Obs.	Obs.
Observations	192	190	192	190
R ²	0.108	0.149	0.129	0.163

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 3.6: Role of the subject observer relation in terms of network interactions on the observer effect in norm conformity. The network relation is measured by adjacency (whether subject and observer have a direct link in the network or not). Columns 1-3 report results for communication network adjacency. Columns 4-6 report results for cooperation network adjacency. Individual level controls are age, gender, understanding, war involvement and community role (i.e. leader or not).

Testing for H4, Table 3.7 shows the impact of the observer's network position in the communication (columns 1-3) and cooperation network (columns 4-6) on the norm enforcing power of observation.²⁰ We find no direct support for an effect of observer centrality on the convergence towards the norm in the dictator game in both the cooperation and the communication network (see Table 3.7 model (1) and (4)). This finding is robust when controlling for IOS (model (2) and (5)). However, allowing for an interaction between observer centrality and IOS reveals that observer centrality significantly affects the convergence to the norm in the communication network, but not in the cooperation network. While the pattern regarding the type of network in which centrality matters fits H4, the effect sign is, again, contrary to the hypothesized

¹⁹In fact, regressing IOS rating on cooperation network adjacency, it can be seen that a direct link in the cooperation network can be significantly associated with a higher IOS ranking ($\beta = 0.66$, $p=0.0289$).

²⁰Compare Table C.4 in the Appendix for the long version including control coefficients.

impact. Instead of a stronger role of more central observers, we find that observer centrality offsets the norm conforming impact of observation for the larger part of the IOS scale. This is illustrated in Figure 3.7, which shows the predicted observer effect based on the interacted model results for central (blue line) and non-central observers (red line) in the communication network (left panel) and the cooperation network (right panel). As illustrated in the left panel, observer centrality has the largest effect in the communication network when social distance is low. If the subject feels close to the observer, the mediating role of observer centrality becomes smaller. In addition, other than for low IOS values, an observer who is close to the subject ($\text{IOS} > 5$) and has high communication network centrality induces mildly more norm conformity than a less central one. The right panel of Figure 3.7 also shows a decreasing trend in the observer effect from an increase in observer centrality, which is, however, not statistically significant and there is also no interaction with perceived social distance.

<i>Dependent variable: Δ in abs. deviation from norm</i>						
	Communication			Cooperation		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-0.645 (1.076)	-2.008** (0.949)	-2.885*** (1.004)	-0.868 (1.061)	-2.219** (0.971)	-2.573** (1.218)
Observer centrality	4.242 (8.048)	3.616 (8.378)	31.345** (15.212)	35.838 (25.233)	33.781 (25.053)	56.201 (50.256)
IOS		0.216*** (0.076)	0.341*** (0.114)		0.214*** (0.077)	0.264* (0.152)
Observer centrality x IOS			-5.510* (2.982)			-4.303 (9.722)
Sample	S1-Private	S1-Private	S1-Private	S1-Private	S1-Private	S1-Private
Individ. Controls	Yes	Yes	Yes	Yes	Yes	Yes
Assistant FEs	Yes	Yes	Yes	Yes	Yes	Yes
Day FEs	Yes	Yes	Yes	Yes	Yes	Yes
Village FEs	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Obs.	Obs.	Obs.	Obs.	Obs.	Obs.
Observations	192	190	190	192	190	190
R ²	0.103	0.146	0.157	0.109	0.152	0.153

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 3.7: Role of the observer's network centrality on the observer effect in norm conformity. Centrality in the network is measured by page rank centrality. Columns 1-3 report results for communication network centrality. Columns 4-6 report results for cooperation network centrality. Individual level controls are age, gender, understanding, war involvement and community role (i.e. leader or not).

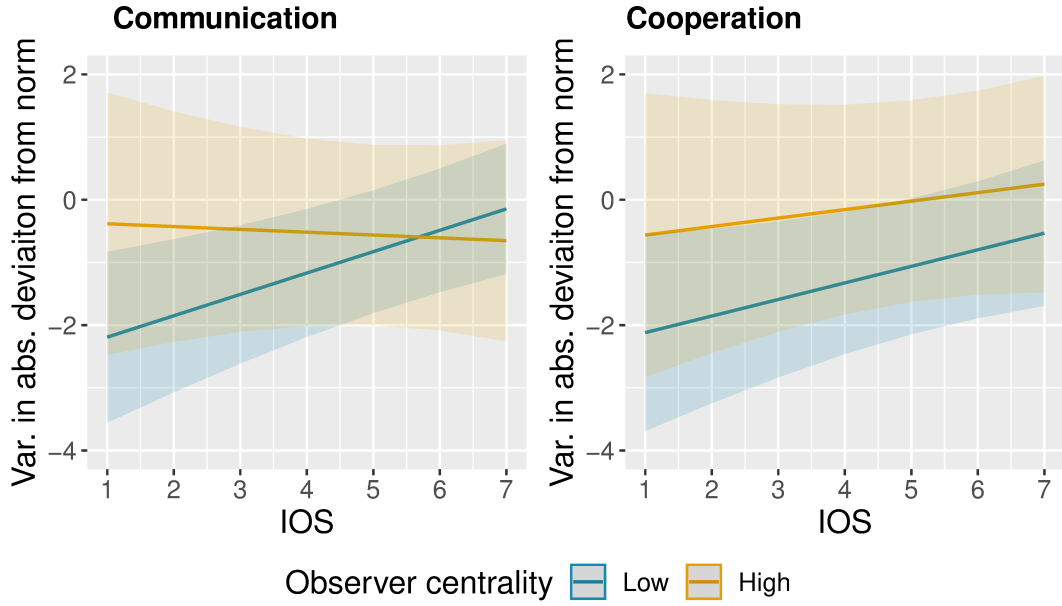


Figure 3.7: Predicted effect of an observer's network centrality on the observer effect in norm conformity. Centrality is measured through page rank centrality. Left: Conversation network centrality, Right: Cooperation network centrality. Based on Table 3.7 column 3/6.

3.6 Discussion and Conclusion

This paper presents novel evidence on the social context dependence of social image concerns. In particular, we outline strong interactions between social image, social norms, and perceived and actual social connectedness. Our theoretical predictions were tested in a lab in the field experiment in Papua New Guinea by means of a dictator game. Image concerns are introduced through an observer treatment. The observer is a fellow villager and identifiable to the participant. The social norm is measured through an incentivized elicitation of second-order normative beliefs. Interpersonal relations are tracked through the inclusion of other in self (IOS) scale and detailed social network data collected in each of the villages ex-ante to the experiment. Summing up our results, we find support for the hypothesis that social image effects increase norm conformity, which is, however, strongly heterogeneous. One significant source of this heterogeneity is the shape of the observer-subject relation. Not accounting for observer characteristics, we do not find an observer effect on the average degree of norm conformity in dictator game play. Controlling for social distance between subject and observer, however, reveals an average observer effect of an increase in norm conformity of roughly 20%. This average effect is strongly mediated by the social distance between subject and observer. In fact, for close observers it fully vanishes. Moreover, the pull towards the norm is significantly reduced if respondents usually cooperate with the observer i.e. share a direct link in the cooperation network. Further, a significant mediating role

can be identified for the observer's position in the communication network that is at the basis of information flow in villages. The strong offsetting impact of perceived social distance on the observer effect cannot be found for observer's who are central in communication networks.

These results should be interpreted in light of the fact that we find a strong degree of norm internalization and tight social networks in all of the communities studied, with barely any true outsiders and high average IOS ratings. This limits the ability to investigate the whole gradient of social distance and implies that our results might represent a lower bound of the heterogeneity that can be expected from a larger gradient. Alternatively, a u-shape in the relation is possible and could realign findings of previous studies that vary social distance at the high ends of the scale, i.e. comparing fully anonymity and shallow knowledge of the other (e.g. Gächter and Fehr, 1999; Bohnet and Frey, 1999; Gächter et al., 2017; Bicchieri et al., 2022). Additionally, in order to limit the cognitive demand on side of the participants, our norm measure covers only the three focal points within the choice space. This introduces room for measurement error. For example, we are not able to rule out that the norm is not actually at 4 instead of 5. Lastly, we only use binary interaction variables (Do you interact? Yes/No), which limits the extend to which we can explore the role of interaction patterns on norm enforcement more deeply.

Nonetheless, these results are surprising in two ways. First, we derived from the literature under H1 that observers whom the subject feels closest to are the most powerful in enforcing norm conformity. Yet, we find that it is observers to whom the subject feels most distant to that trigger the strongest pull towards the norm in our sample. This result raises the question of which the relevant reference group in fact is towards whom one wants to signal norm conformity (Bicchieri, 2006, 2017) or in the eyes of which one wants to preserve a *good* social image (Bénabou and Tirole, 2006). One narrative to rationalize our finding, might be the signaling value of the subject's behavior towards the observer. It can be plausibly assumed that people interact regularly with others whom they feel close to. Consequently, one instance of observance might contain low informational value for an observer who is already familiar with the subject's character. Behaving in a certain way once will not receive much weight in shaping the impression the observer has of the subject. Instead, it might even seem peculiar in the eyes of the observer if the subject would diverge from her usual type in this one instance. For a distant observer, however, who does not have much or even any previous information about the subject's typical behavior, this one observation is likely relevant for shaping the impression the observer gains about the subject. This argument might also extend to the fact, that other than hypothesized, the strongest norm convergence is found for the least central observer, assuming that those central in communication networks hold on average more information on any other network participant than those in the periphery.

An alternative narrative for the role of social distance and community norm following is provided in a psychology paper by Ledgerwood and Callahan (2012). In this paper, the authors manipulate psychological distance between an experiment participant and the choice task and find, similarly to our finding, that more psychological distance leads to more community norm following. In their paper, the manipulation was not with regard to relational distance between people but targeted at the psychological distance to other components of the task.²¹ The authors relate their finding to the differences in how situations are evaluated across variations in psychological distance. If the distance is large, one shifts to a more abstract mindset in evaluating the situation, while low psychological distance triggers a more contextual evaluation of the situation. Translating this explanation approach to our findings, it provides an alternative narrative for our findings. The normative standard we used as the reference point for behaviour is the community norm. While a person has less information about a distant observer and, thus, shifts into a more abstract mode of evaluating the situation and its norms of behavior, close observers are known and might, thus, trigger a more nuanced context-related evaluation of the situation and its ensuing norms of conduct. That is, while subjects might converge towards the community norm for an observer they do not know very well, they might conform to the personal normative beliefs of the observer for an observer they know very well. Whereas an investigation of the validity of this narrative is beyond the scope of this paper, it strongly lends relevance to more research into the role of normative heterogeneity at the individual level (Bašić and Verrina, 2021).

Second, we derived from existing theories on cooperation enforcement that the observers' position can be expected to matter for norm enforcement only in the communication network, while being of no relevance in the cooperation network. In addition, the direct relation between subject and observer can be expected to matter in the cooperation network, but not in the communication network. These patterns can be validated in the presented data. Yet, the direction of effects is contrary to the derived hypotheses, in both cases. It is those observers that are not directly linked to subjects in the cooperation network and those less central in the communication network who show the strongest norm enforcing impact. These results are at odds with the results of Wu et al. (2016) or Breza and Chandrasekhar (2019) who study the role of an observer's ability to spread news on image effects. Without controlling for social distance, these authors find evidence in line with our hypothesis H4. Our findings, consequently, raise the question of how social distance between subject and observer influences the content and weight of signals that are sent to the observer and, thus, how social distance interferes with much discussed theories on cooperation enforcement strategies.

²¹The dimensions manipulated were the distance to the consequences of the choice and the level of abstraction to increase overall distance to the task and the hypothesized mechanism directly.

Overall, this study adds to the literature on social image effects by providing an explicit empirical test of the role of social norms for image effects. While previous research provided evidence that observability increases pro-social behavior (Lacetera and Macis, 2010; Ariely et al., 2009; Bolton et al., 2021; Filiz-Ozbay and Ozbay, 2014), we show in a cultural context in which giving more does not coincide with the normative optimum that observability increases norm conformity. This finding implies that norms serve as reference points for image effects. Hence, our results offer a potential micro-foundation for the direction of image effects that can be expected in different situations. In general, norms are often local (Buggle and Durante, 2021; Gelfand et al., 2017; Buggle, 2020; Alesina et al., 2013; Jackson et al., 2020). They are enforced by a reference group and different groups uphold different norms. Thus, a person's beliefs about what the appropriate behaviour in a given situation is and what the expectations of a spectator in this situation are likely, vary with the group the person belongs to, the group the spectator belongs to or the particulars of the situation. This reference group dependence of norms was theoretically reasoned, for example, by Bicchieri (2006) and Bicchieri (2017), and most recently empirically corroborated by Krupka et al. (2022). Furthermore, our results allow implications for the expected size of image effects. The larger the social distance between the observer and a person, the stronger the image effect that can be expected. Normative heterogeneity or heterogeneity in the social relations between observers and subjects might serve as an explanation for the heterogeneity in image effects (Bursztyn and Jensen, 2017). Understanding drivers of heterogeneity in image effects is essential. For example, in studies on image effects the observer is commonly kept anonymous in that she remains unknown to the experiment participant whose behaviour is under inspection. Our findings imply that results from these studies deliver potential upper bounds for image effects that can be expected in daily life in which people are often surrounded by people they are close to.

Next, this study also adds to the literature on peer effects. Several recent studies that similarly investigate the interrelation between peers around us and norm following (e.g. Bicchieri et al., 2022; Gächter et al., 2017; Isler and Gächter, 2022) study the role of observing peers on personal behaviour and norm following. This allows to answer questions on behavioural spill over effects, norm formation and erosion. We add to this by studying the other side of the interaction with peers, i.e. focusing on the role of being observed by others, which allows understanding mechanisms of norm enforcement of existing norms. Most notably, Bicchieri et al. (2022) find that social proximity plays a significant role for norm uptake, as people in their experiments do not adopt norm conforming behaviours from distant peers but only from socially close ones. Norm violations are adopted independent of social distance such that there is a tendency towards norm erosion from observing the behaviour of distant peers. Our results show that it is likely those distant peers who are able to enforce norm following if they are

the ones in the role of observer and the one being observed is the person him-or herself. This will influence the likelihood for a distant observer to witness norm violations.

Lastly, this paper also adds to literature on the influence of network connectedness on behaviour. First, it outlines how the interaction between networks, norms and social image concerns theoretically gives importance to different types of social networks, as it implies different roles for cooperation networks and information flow networks. Second, the paper contributes by empirically investigating the often hypothesized but rarely studied relation between social norms and social networks (Coleman, 1988, 1990; Granovetter, 2017; Jackson et al., 2017). While, for example, Jackson et al. (2017) also raise the hypotheses that greater ease in information spreading and close social relations are related to more norm enforcement and Breza and Chandrasekhar (2019) validate that an observer's network centrality can increase social image effects, we, in fact, find the opposite correlation.

From a policy perspective, this finding implies that real world image effects might be significantly smaller than those that are identified in a large part of the literature. This is due to the fact that most studies on image effects use anonymous observer treatments, which circumvent social proximity between observer and subject. As the image effects we find are largest for distant observers, the question is raised of how well these lab results are transferable to real life contexts in which people surround themselves with those they are close to.

In sum, our results offer causal evidence on the impact of social context on social image effects. Hence, together with other recent studies such as Bicchieri et al. (2022); Bolton et al. (2021); Nieper et al. (2022); Bursztyn and Yang (2022); Dimant (2019), they underline the importance of the social context for understanding behavior in general and social image effects as well as social norm enforcement in particular.

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Appendix

Table C.1: Observer effect on absolute amount shared

	<i>Dependent variable:</i>	
	Amount sent	
	(1)	(2)
Public	-0.404 (0.323)	-0.597 (0.380)
$I(x_{private} < \text{norm})$		-3.711*** (0.377)
$I(x_{private} > \text{norm})$		3.869*** (0.434)
Public $\times I(x_{private} < \text{norm})$		1.609*** (0.513)
Public $\times I(x_{private} > \text{norm})$		-2.070*** (0.599)
Baseline	4.145*** (0.253)	4.915*** (0.290)
Sample	S1-Private	S1-Private
Ind. Controls	Yes	Yes
FEs	Yes	Yes
Clustering	No	No
N / Observations	193/386	193/386
R ²	0.134	0.588

Note: *p<0.1; **p<0.05; ***p<0.01. FEs account for day, assistant and village level effects.

Ind. controls account for age, gender, understanding and war involvement. Baseline effects provide the average *Constant* coefficient across all possible FE default combinations.

Table C.2: Community norm convergence and psychological social distance (long version, including control coefficients)

<i>Dependent variable: Δ in abs. deviation from norm</i>				
	(1)	(2)	(3)	(4)
Constant	-0.599 (0.606)	-1.758*** (0.596)	-2.020** (0.915)	-2.322*** (0.737)
IOS		0.203*** (0.072)	0.216*** (0.076)	0.253*** (0.073)
Public first				1.194** (0.500)
IOS x Public first				-0.335*** (0.089)
Age			0.011 (0.009)	0.008 (0.007)
Male			-0.046 (0.351)	0.006 (0.295)
Understanding			-0.028 (0.175)	0.105 (0.113)
Community leader			0.154 (0.673)	-0.452 (0.429)
War Involvement			-0.207 (0.408)	-0.377 (0.313)
Sample	S1-Private	S1-Private	S1-Private	Full
Assistant FEs	Yes	Yes	Yes	Yes
Day FEs	Yes	Yes	Yes	Yes
Village FEs	Yes	Yes	Yes	Yes
Clustering	Obs.	Obs.	Obs.	Obs.
Observations	195	193	191	363
R ²	0.094	0.133	0.145	0.094

Note:

*p<0.1; **p<0.05; ***p<0.01

Table C.3: Overshooting as overcompensation.

<i>Dependent variable: dev. from comm. norm in public</i>		
	(1)	(2)
dev. comm. norm in private	−0.219*** (0.075)	−0.214*** (0.081)
Individ. Controls	<i>No</i>	<i>Yes</i>
Order FE	<i>Yes</i>	<i>Yes</i>
FEs	<i>Yes</i>	<i>Yes</i>
Clustering	<i>Obs.</i>	<i>Obs.</i>
Observations	157	153
R ²	0.218	0.239

Note:

*p<0.1; **p<0.05; ***p<0.01

Table C.4: Role of the subject observer relation in terms of network interactions (long version, including control coefficients)

<i>Dependent variable: Δ in abs. deviation from norm</i>				
	Communication		Cooperation	
	(1)	(2)	(3)	(4)
Constant	−0.676 (1.067)	−1.984** (0.924)	−0.854 (1.118)	−2.032** (0.931)
Observer relation (netw.)	0.319 (0.201)	0.231 (0.205)	0.684** (0.275)	0.563** (0.283)
IOS		0.210*** (0.077)		0.192** (0.078)
Age	0.011 (0.009)	0.010 (0.010)	0.013 (0.009)	0.011 (0.010)
Male	−0.141 (0.367)	−0.036 (0.346)	−0.200 (0.379)	−0.093 (0.358)
Understanding	−0.092 (0.180)	−0.053 (0.175)	−0.065 (0.173)	−0.036 (0.169)
Community leader	0.006 (0.698)	0.129 (0.679)	−0.020 (0.715)	0.091 (0.701)
War involvement	−0.108 (0.401)	−0.207 (0.410)	−0.136 (0.438)	−0.216 (0.438)
Sample	S1-Private	S1-Private	S1-Private	S1-Private
Assistant FEs	Yes	Yes	Yes	Yes
Day FEs	Yes	Yes	Yes	Yes
Village FEs	Yes	Yes	Yes	Yes
Clustering	Obs.	Obs.	Obs.	Obs.
Observations	192	190	192	190
R ²	0.108	0.149	0.129	0.163

Note:

*p<0.1; **p<0.05; ***p<0.01

Table C.4: Role of the observer's network centrality (long version, including control coefficients)

<i>Dependent variable: Δ in abs. deviation from norm</i>						
	Communication			Cooperation		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-0.645 (1.076)	-2.008** (0.949)	-2.885*** (1.004)	-0.868 (1.061)	-2.219** (0.971)	-2.573** (1.218)
Observer centrality	4.242 (8.048)	3.616 (8.378)	31.345** (15.212)	35.838 (25.233)	33.781 (25.053)	56.201 (50.256)
IOS		0.216*** (0.076)	0.341*** (0.114)		0.214*** (0.077)	0.264* (0.152)
IOS x Observer centrality			-5.510* (2.982)			-4.303 (9.722)
Age	0.013 (0.009)	0.011 (0.009)	0.012 (0.009)	0.014 (0.009)	0.012 (0.009)	0.012 (0.009)
Male	-0.156 (0.373)	-0.045 (0.350)	-0.043 (0.347)	-0.194 (0.375)	-0.083 (0.350)	-0.088 (0.353)
Understanding	-0.077 (0.183)	-0.039 (0.177)	0.012 (0.178)	-0.075 (0.179)	-0.037 (0.175)	-0.020 (0.188)
Community leader	0.003 (0.715)	0.127 (0.694)	0.203 (0.684)	0.022 (0.685)	0.142 (0.667)	0.150 (0.665)
War involvement	-0.090 (0.405)	-0.198 (0.420)	-0.197 (0.416)	-0.102 (0.397)	-0.209 (0.410)	-0.181 (0.419)
Sample	S1-Private	S1-Private	S1-Private	S1-Private	S1-Private	S1-Private
Assistant FEs	Yes	Yes	Yes	Yes	Yes	Yes
Day FEs	Yes	Yes	Yes	Yes	Yes	Yes
Village FEs	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Obs.	Obs.	Obs.	Obs.	Obs.	Obs.
Observations	192	190	190	192	190	190
R ²	0.103	0.146	0.157	0.109	0.152	0.153

Note:

*p<0.1; **p<0.05; ***p<0.01

Appendix

Erklärung zum selbständigen Verfassen der Arbeit:

Ich erkläre hiermit, dass ich meine Doktorarbeit „Essays on the Behavioural Adaptation to Environmental Changes“ selbstständig und ohne fremde Hilfe angefertigt habe und dass ich als Koautor maßgeblich zu den weiteren Fachartikeln beigetragen habe. Alle von anderen Autoren wörtlich übernommenen Stellen, wie auch die sich an die Gedanken anderer Autoren eng anlehnenden Ausführungen der aufgeführten Beiträge wurden besonders gekennzeichnet und die Quellen nach den mir angegebenen Richtlinien zitiert.

Datum, Unterschrift

Beitragserklärung für

„Wait and See? Public preferences for the temporal effectiveness of coastal protection“

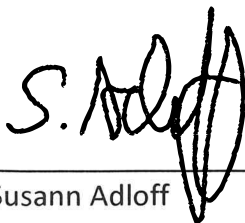
Arbeitspakete Susann Adloff

- Entwicklung der Forschungsfrage
- Studien - Design
- Datenerhebung
- Datenauswertung
- Schreiben des Papers

Arbeitspakete Katrin Rehdanz

- Entwicklung der Forschungsfrage
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- Schreiben des Papers

Alle beteiligten Autorinnen bestätigen die Einhaltung der DFG-Richtlinien zur Sicherung guter wissenschaftlicher Praxis bei der Ausführung der einzelnen Arbeitspakete.



Susann Adloff



Katrin Rehdanz

Beitragserklärung für
„Social Image, Social Norms and Social Networks“

Alle unten genannten Autoren haben einen signifikanten Beitrag zu dem Papier geleistet. Sie waren insbesondere wie folgt beteiligt:

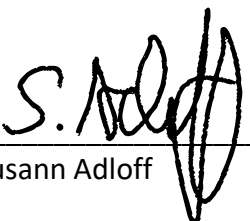
Arbeitspakete Susann Adloff

- Entwicklung der Forschungsfrage
- Studiendesign
- Datenerhebung, -aufbereitung
- Datenauswertung
- Schreiben des Papiers

Arbeitspakete Andreas Pondorfer

- Studiendesign
- Datenerhebung

Alle Autoren bestätigen zudem die Einhaltung der DFG-Richtlinien zur Sicherung guter wissenschaftlicher Praxis bei der Ausführung der einzelnen Arbeitspakete.



Susann Adloff



Andreas Pondorfer