

# The day after the disaster: Risk-taking following large- and small-scale disasters in a microworld

Garston Liang\*   Tim Rakow†   Eldad Yechiam‡   Ben R. Newell§

## Abstract

Using data from seven microworld experiments (N = 841), we investigated how participants reacted to simulated disasters with different risk profiles in a microworld. Our central focus was to investigate how the scale of a disaster affected the choices and response times of these reactions. We find that one-off large-scale disasters prompted stronger reactions to move away from the affected region than recurrent small-scale adverse events, despite the overall risk of a disaster remaining constant across both types of events. A subset of participants are persistent risk-takers who repeatedly put themselves in harm's way, despite having all the experience and information required to avoid a disaster. Furthermore, while near-misses prompted a small degree of precautionary movement to reduce one's subsequent risk exposure, directly experiencing the costs of the disaster substantially increased the desire to move away from the affected region. Together, the results point to ways in which laboratory risk-taking tasks can be used to inform the kinds of communication and interventions that seek to mitigate people's exposure to risk.

Keywords: disaster reaction, risky choice, sequential choice analysis

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\*Corresponding author. School of Psychology, The University of New South Wales, Sydney, Kensington, NSW, Australia 2052. Email: [garston.liang@gmail.com](mailto:garston.liang@gmail.com). <https://orcid.org/0000-0002-9230-7258>.

†Institute of Psychiatry, Psychology and Neuroscience, Kings College London. Email: [tim.rakow@kcl.ac.uk](mailto:tim.rakow@kcl.ac.uk). <https://orcid.org/0000-0002-7127-8793>.

‡Faculty of Industrial Engineering and Management, Technion-Israel Institute of Technology. Email: [yeldad@tx.technion.ac.il](mailto:yeldad@tx.technion.ac.il). <https://orcid.org/0000-0003-0389-2131>.

§University of New South Wales, Sydney. [ben.newell@unsw.edu.au](mailto:ben.newell@unsw.edu.au). <https://orcid.org/0000-0003-1898-205X>.

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All authors contributed to conceptualisation and design of the experiments. GL & TR collected the data. GL ran the analyses and wrote the paper. BN, TR, EY provided critical revisions and suggestions throughout the project.

All data and analysis scripts are available at <https://osf.io/FVK4S/>.

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# 1 Introduction

When disaster strikes, the question that friends and family often ask is ‘what did you do next’? Disasters bring on dramatic upheavals to daily life and making sense of their causes guides one’s future actions (Erev, Plonsky & Roth, 2020). A large body of research on risk perception suggests that disasters with the potential for widespread catastrophe have a powerful hold over people’s thinking even when their chance of occurrence is very low (Slovic, Fischhoff & Lichtenstein, 1980; Slovic, 1987). For example, airline accidents overwhelmingly command attention despite their low rates of occurrence whereas less punctuated but persistent risks, such as driving accidents, tend to be relatively underappreciated. The influence of such large-scale calamities can also lead individuals to take on small-scale risks and inadvertently put themselves in harm’s way. Indeed, in the year following the September 11 terrorist attacks, the switch from air travel to road transport led to substantially more fatalities due to highway collisions than had those travelers flown to their destination (Gigerenzer, 2006). Therefore, understanding how people react to calamity is important for how broader society designs risk management, communication, and regulation strategies.

In this paper, we investigate people’s behavioural reactions to different types of simulated disasters in a microworld (see Figure 1; and Liang, Newell, Rakow & Yechiam, 2019; Newell, Rakow, Yechiam & Sambur, 2016). The disasters were tailored into two distinct risk profiles: a *concentrated-rare* profile with large-scale though infrequent disasters, and a *scattered-common* profile with smaller-scale adverse events that occur often. We contrast these two risk profiles across seven existing datasets ( $N = 841$ ) with over a thousand simulated disaster events to examine three main questions: 1. Do scattered-common disasters prompt different reactions to concentrated-rare disasters? 2. What does experience with multiple disasters indicate about one’s tolerance for risk? 3. How does one’s reaction to experiencing a disaster compare to merely escaping with a near-miss? By focussing on people’s choices immediately following a disaster, we seek to understand better what people do when disaster strikes.

## 1.1 Scattered-common versus concentrated-rare disasters

People’s perceptions of risk are entwined with the hazard’s potential for catastrophe (Lichtenstein, Slovic, Fischhoff, Layman & Combs, 1978; Sjöberg, 2000; Slovic, 1987). In the public consciousness, natural and man-made disasters are judged against the possibility of catastrophe, even if that possibility is remote in the eyes of experts. Fears of shark attacks at beaches and vaccine side-effects dramatically shape people’s behaviour despite the actual risk of harm being relatively low (Midway, Wagner & Burgess, 2019; Syan et al., 2021). This divergence might arise because even a small possibility is enough to evoke vivid imagery of, and feelings associated with, catastrophe (Loewenstein, Weber, Hsee & Welch, 2001; Rakow, Heard & Newell, 2015). Collectively, this research suggests that risk

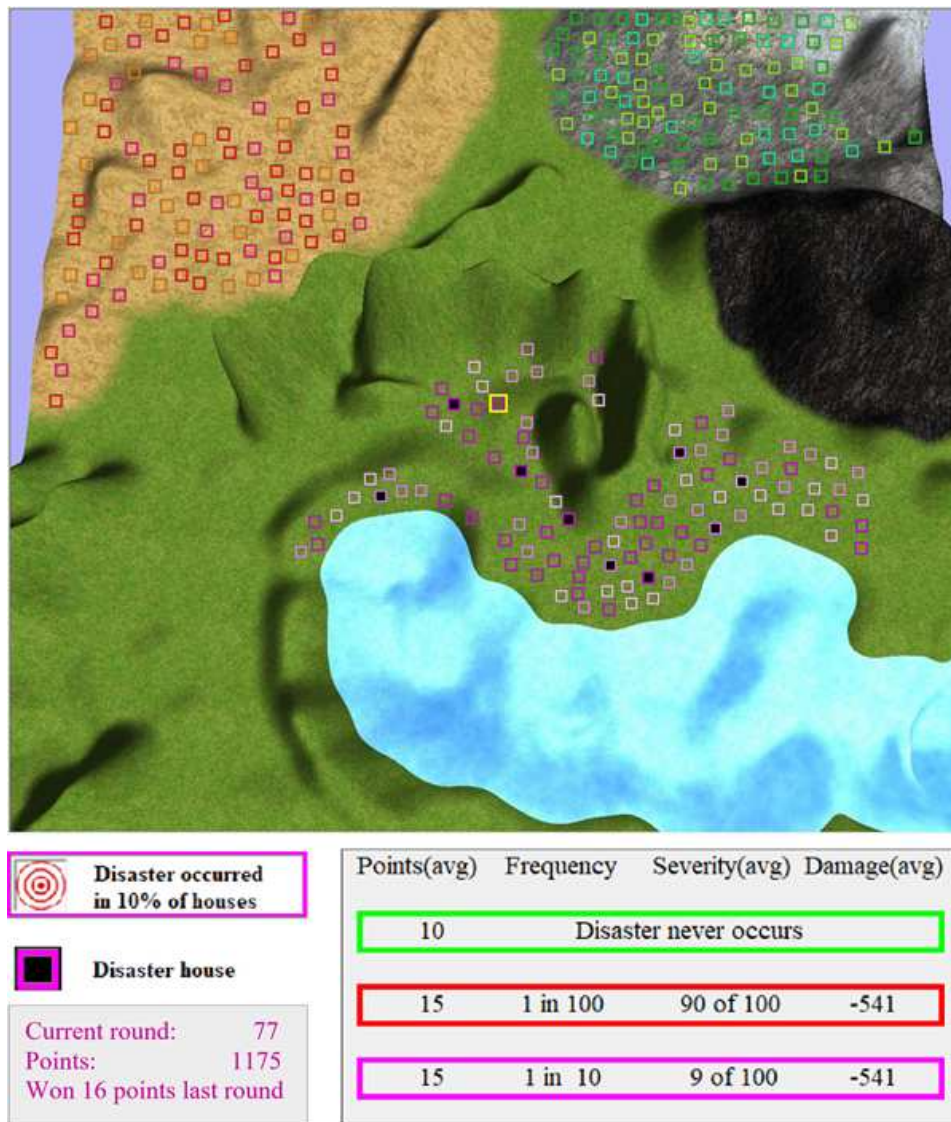


FIGURE 1: A modified screenshot of the microworld’s geographical map, feedback panels, and description panel of disaster risks. On each trial, participants selected a house (yellow outline in centre purple village) and received feedback as to their payoff, and whether a disaster occurred (lower left boxes). The filled-in black squares on the map indicate houses that were affected by a disaster on the previous round (e.g., 10/100 purple village houses, corresponding to the purple bordered feedback box). Descriptions of the disaster risk (bottom right panel) were presented throughout the experiment. Points refer to the payoff in a non-disaster trial; frequency refers to how often disasters occur, severity (scale) refers to the number of houses affected by a disaster, and damage refers to points deducted by a disaster. Concentrated-rare village is red (1/100 frequency & 90/100 houses affected), Scattered-common village is purple (1/10 frequency & 9/100 houses affected), and Safe village is green. Experiment length was 400 rounds of choices. Modifications to screenshot for visual clarity, unmodified version shown in Figure A1 of Appendix.

perception is based upon more than just the probability of the consequences affecting any individual.

The scale of any hazard also plays an important role in risk perception (Slovic, 1987). One-off events that rarely occur but have the potential to affect a large number of people tend to weigh substantially on people's thinking about disasters (Slovic et al., 1984). Known as *dread risks*, Slovic et al. found that respondents rated large-scale but rare events, such as nuclear power incidents and industrial chemical accidents, as the most dangerous to society. In contrast, hazards that affected only a small number of people in any one adverse event, such as the side-effects of medication, were of less concern. This divergence in risk perception suggests that different behavioural reactions may emerge for small- and large-scale disasters.

However, the design of traditional risk experiments presents a barrier to experimental investigations into disaster scale. This limitation emerges from the fact that conventional repeated-choice experiments, such as decisions from experience tasks (Barron & Erev, 2003), offer the decision maker a choice between a small number of options (most commonly, only two) where the consequences of that decision can only affect the individual decision maker. Therefore, the experience-based tradition does not accommodate rare events that may affect more than one agent. (For a review of risky decision making for others agents in the context of one-shot description-based tasks see Polman & Wu, 2020.) To address this constraint, our microworld incorporates a novel spatial dimension that expands the number of potential choices that share an overarching risk profile (i.e., houses grouped into villages). This spatial dimension provides a visual means of depicting the scale of a disaster and allows the decision maker to consider the effects of scale across multiple options. Disaster scale is symbolised by the number of locations (i.e., houses in a village) that experience adverse outcomes. This representation of disasters affecting multiple houses extends the risk of negative events beyond the single house that the decision maker selected. Therefore, a principal advancement of our microworld design is that it allows us to directly test the impact of disaster scale while retaining the fundamental choice between risk and safety.

In the microworld, two disaster scales were instantiated in separate risky villages. One village was exposed to *concentrated-rare disasters*, akin to the rare but devastating dread risks, whereas the other village was exposed to smaller-scale but more frequent *scattered-common disasters*. By examining people's choices following each type of disaster, our data provides a behavioural extension to the risk perception research investigating disaster scale. This extension permits us to address our first question: *Do scattered-common disasters prompt different reactions to concentrated-rare disasters?*

## 1.2 Experience with disasters and risk-taking

Using data from tens of thousands of microworld decisions, we aimed to understand how experience of disasters shapes how one reacts. Will experiencing disasters lead one to

mitigate future risks by moving to safer areas or will individuals become hardened by its impact and remain in harm's way? Critical to this dynamic is what individuals learn about the risks after each disaster event and how this information is communicated. Experience-based studies of risky choice, where risk information is learnt through iterative rounds of choice and feedback about the outcomes, have shown that people do not learn to avoid environments with rare losses (Barron & Erev, 2003; Rakow & Newell, 2010; Wulff, Mergenthaler-Canseco & Hertwig, 2018; Yechiam, Barron & Erev, 2005). Rather, repeated choice and feedback leads individuals towards *underweighting* rare events as though they are less likely to occur than their true probability (Camilleri & Newell, 2011). Such an experience-based account suggests that individuals are likely to favour re-exposure to risk in the long run.

Against this backdrop, a number of studies have introduced descriptions into experience-based tasks, analogous to adding warning signs where risks are explicitly enumerated (e.g., medication side effect labels; Barron, Leider & Stack, 2008; Rakow & Miler, 2009; Weiss-Cohen, Konstantinidis, & Harvey, 2018; 2021). Although some of these studies have found a mitigating effect of descriptions on risk taking (e.g., Barron et al., 2008), others report an accentuation of underweighting when descriptive summaries are presented (e.g., Yechiam, Rakow & Newell, 2015). In our experiments, we hold the presentation format of information constant – all participants receive full descriptive information and gain trial-by-trial experience (see lower right panel of Figure 1) – and focus on the immediate impact of each disaster (i.e., where do people move to on the very next trial). Because our study participants expose themselves to known risks over many rounds of choices, the microworld permits examining the question: *What does experience with multiple disasters indicate about one's tolerance for risk?*

### 1.3 Disasters and near-misses in the microworld.

One does not have to be directly affected by a disaster to feel its force. Googling the 'luckiest person in the world' is as likely to return stories of people *narrowly escaping* catastrophe as those winning lotteries. For lotteries, near-miss events feel tantalisingly close and have been found to increase the gambler's desire to play again (Clark, Lawrence, Astley-Jones & Gray, 2009). Compared to the agony of a near-win, might a close brush with danger be a valuable opportunity to reconsider one's exposure to catastrophe?

In the microworld, disaster-struck homes were visually depicted by blackened squares (see Figure 1). A near-miss meant that individuals could see that neighbouring houses within the village were affected while their chosen house remained unscathed. It is this novel design feature of our microworld that allowed exploration of our third question: *How does one's reaction to experiencing a disaster compare to escaping with a near-miss?*

A crucial question is how experiencing a disaster affects subsequent decisions about risk exposure – and whether this differs between direct experience (i.e., *your* house is damaged) or vicarious experience (i.e., *your* house is unscathed, but it was a near miss).

Past research has suggested that vicarious experience of negative rare events in the form of forgone payoffs carries a similar weight to direct experience in a simple binary choice task (Grosskopf et al., 2006; Yechiam & Busemeyer, 2006). However, this work focused on overall choice preferences for risk and did not examine the specific reactions in the trials following negative events. The current research extends these findings into a more elaborate decision environment involving multiple options to specifically examine the immediate reactions to experienced or near-miss disasters.

## 2 Methods

### 2.1 Participants

We aggregated data across seven existing datasets consisting of 841 undergraduate participants ( $M_{age} = 19.85$ , 67% identified as female) who experienced a total of 1611 rare disaster events. These data were collected at UNSW, Sydney, Australia and the University of Essex, Colchester, UK, and we obtained informed consent from all participants. In exchange for participation, course credit or a flat-rate payment was awarded alongside a monetary bonus proportional to the final point tally (approximately ~\$2.50 USD).

### 2.2 Existing datasets

Disaster events were extracted from seven previous experiments examining risky choices in the same simulated microworld. All previous experiments were designed with two types of disaster profiles. For the *concentrated-rare disaster* profile (analogous to dread risks) disasters rarely struck the village but affected many houses when they did so. Conversely, for the *scattered-common disasters* profile, disasters occurred more frequently but were smaller in scale (i.e., affecting fewer houses). Importantly, the risk exposure for an individual house exposed to either disaster profile was equivalent.

We chose to aggregate data from seven different datasets (see Table 1) because examining disaster reactions within each experiment presented a fundamental challenge; rare disasters, by definition, occurred infrequently. This sparsity of rare events did not permit direct investigation at the experiment level. However, by collating disaster events across multiple datasets with the same disaster profiles, we were able to analyse a sufficiently large sample of rare events and examine people's reactions to simulated adversity.<sup>1</sup> We describe the manipulations of the previous datasets in full in the Appendix. For clarity, Table 1 refers to manipulations of previous experiments and highlights the number of disaster-datapoints

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<sup>1</sup>Datasets are published in two previous papers separate to the current line of investigation. Datasets 1 & 2 were published in Newell, Rakow, Yechiam & Sambur (2016) investigating the effect of forgone feedback on risky choices. Datasets 3 to 7 published in Liang, Rakow, Yechiam & Newell (2019) were attempts to replicate and extend the previous findings to a loss framing and a disaster information history. We present further details about each dataset in the Appendix.

that each experiment contributes. In the main, these datasets were originally generated to investigate the effects of foregone feedback in the microworld on risky choice. Foregone feedback refers to participant knowledge of disasters that affected *other houses* beyond their chosen house, which means participants could learn about the outcomes for houses they did not select. *Local-village feedback* informed participants of disaster damage that affected houses in the selected village whereas *all-village feedback* provided information about disasters that struck any village.<sup>2</sup> Participants in both feedback conditions could encounter a *near-miss* where they learn about disasters that struck their neighbours in the same village, while only the *all-village* feedback condition could encounter a *far-miss* where they witnessed disasters strike the non-selected village. In our third question, we analyse how near-miss and far-miss events impact people’s reactions to disasters. These feedback effects were the main focus of datasets 1, 2 and 7. Dataset 3 and 4 included an additional manipulation of disaster history that examined whether visually highlighting houses that were damaged from previous disasters affected people’s overall preference for risky village choices. In a separate vein, the loss framing experiments in dataset 5 and 6 contrasted risk-taking behaviour when the points for a non-disaster trial were framed as a deduction of rent rather than accrual of reward. As noted above, the specific impact of these additional manipulations on behaviour is not our focus here but we do discuss these results briefly in the Appendix.

TABLE 1: Summary of previous datasets with relevant notes on previous experiments in the Appendix. Column titles C.rare refers to concentrated-rare disasters. S.common refers to scattered-common disasters. Note that some participants did not experience any disasters while others experienced multiple. The distribution of experienced disasters is presented in *Figure A2* of the Appendix.

Dataset	Primary manipulation	$N$ participants exp. disaster	$N$ disasters C. rare	$N$ disasters S. common
1	Feedback – local vs. all villages	43/60	40	52
2	Feedback – local vs. all villages	46/60	65	52
3	Feedback + disaster history	96/120	123	113
4	Feedback + disaster history	91/120	107	104
5	Feedback + loss framing	88/100	110	128
6	Feedback + loss framing	114/139	154	131
7	Feedback registered replication	203/242	221	222
		681/841	828/1611	783/1611

<sup>2</sup>For transparency, we present our analyses by feedback in the Appendix and note that they do not compromise our conclusions in the main text.

## 2.3 Design

The microworld was presented as a top-down view of three villages where houses within a village shared a common exposure to disasters. The scale, frequency, and damage of a disaster were displayed in an information panel throughout the experiment (bottom right panel of Figure 1 and shown below in Table 2). The scale of a disaster – labelled *severity* in the experiment – determined the number of damaged houses per disaster strike, shown visually on the map as filled-in black boxes. The *frequency* indicated how often disasters occurred in each village, and the *damage* designated the number of in-game points lost due to a disaster striking the chosen house. On non-disaster rounds, the participant accrued a small number of points.

TABLE 2: Descriptions of risk information in microworld experiments and the proportion of choices for each village as a function of the environment. Column titles C.rare refers to concentrated-rare disasters. S.common refers to scattered-common disasters.

	Moderate environment			Severe environment		
	Safe	C. Rare	S. Common	Safe	C. Rare	S. Common
Frequency	0	0.01	0.10	0	0.01	0.10
Severity (avg)	N/A	0.90	0.09	N/A	0.90	0.09
<b>Damage (avg)</b>	N/A	-541	-541	N/A	-819	-819
Risk of disaster	0	0.009	0.009	0	0.009	0.009
<b>EV</b>	<b>+10</b>	<b>+9.996</b>	<b>+9.996</b>	<b>+10</b>	<b>+7.494</b>	<b>+7.494</b>
Proportion of choices	0.41	0.30	0.29	0.52	0.23	0.25

**Note.** Points refer to the payoff in a non-disaster trial; frequency refers to how often disasters occur, severity (scale) refers to the number of houses affected by a disaster, and damage refers to points deducted by a disaster. Boldface font for damage highlights that across the environments, the damage of the disaster increased and subsequently reduced the EV of the risky villages by 25%. Safe village profile remains the same in both environments. Avg refers to the fact the values presented in the table are mean values whereas in the task, uniform variability  $[-3, +3]$  was added to each value.

The three villages comprised of a *safe* village, which was disaster-free but awarded only a modest number of points, and two risky villages that were exposed to disasters. In the *concentrated-rare* village, disasters were infrequent though the impacts were widespread, affecting nearly all the houses within the village. Specifically, a concentrated-rare disaster occurred 1/100 rounds and 90% of houses were affected (red village in Figure 1). By comparison, disasters in the *scattered-common* village occurred more frequently though the damage was contained to a small fraction of the houses. On average, a scattered-common disaster occurred 1/10 rounds with 9% of houses affected (purple village in Figure 1). The



disaster damage was identical for both risky villages and resulted in the loss of a substantial number of in-game points.

Notably, the risk of a disaster striking any individual house was the same for both risky villages (disaster affecting 90% houses & occurring 1/100 rounds = disaster affecting 9% houses & occurring 10/100 rounds). This also means both risky villages had equivalent *expected value* (EV) as they also awarded the same number of points per non-disaster round. Therefore, despite the trade-off in disaster scale and frequency between the risky villages, participants faced identical risks of a disaster in either village.

The experiment was also split into two EV environments. Half of the participants' choices were conducted in the 'moderate' environment where the EV of the safe village was identical to the risky villages (see Table 2). The other half of the experiment was conducted in the 'severe' environment where the EV of the two risky villages was reduced by 25%. This reduction in EV was implemented by increasing the damage (points penalty) of the disasters affecting both villages.<sup>3</sup> Normatively, the *safe* village was the EV-maximising choice in the severe environment whereas in the moderate environment, the choice of any village is mathematically identical in long-run EV. Across both environments, however, we preserved the equivalence in EV for both the risky villages so as to examine how the profile of the risks affected the reactions to each type of disaster. The colour and position of the safe/risky villages were randomised for each participant and participants inputted their choice of house with a mouse-click.

## 2.4 Procedure

Participants were introduced to the microworld features (e.g., villages, houses, etc.) and instructed that their task was to accumulate game points by choosing a house on each round from which they would accrue (or possibly lose) points. The initial instructions defined the frequency, scale, disaster damage, and points for each village and provided in-text explanations of these properties. These properties were displayed as a table throughout the task and reminder definitions appeared whenever participants hovered their cursor over the table.

On each round, the chosen house was highlighted in a yellow box on the map. Feedback following each choice updated the participant's point total and stated the amount awarded/lost in the current round (bottom-left panel, Figure 1). If a disaster occurred, the microworld display was updated to show which houses were damaged. For participants with all-villages feedback, the disaster feedback covered all the villages whereas the local-village feedback was only privy to disasters in the chosen village. Participants who wished to move house on a subsequent round were first shown a small moving cost calculated according

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<sup>3</sup>In 5/7 datasets, the moderate environment preceded the severe environment and vice-versa for the remaining two. We did not find any evidence that this ordering affected the reaction to disasters and include further details in the Appendix.

to distance from the current house before committing to their choice.<sup>4</sup> Once participants confirmed their move to the highlighted prospective house, the moving cost was subtracted from the point total and, if a disaster did not occur, points for the new house were added.

Participants made 400 choices in total that were split into the ‘moderate’ and ‘severe’ environments. After 200 choices in one environment, an on-screen prompt signalled the environment change and stated that the damage of the disasters had changed. The ‘damage’ information in the risk distribution table was then updated and participants completed the final 200 rounds of choices under the new environment.

## 2.5 Variables

The main dependent variable in our analyses was move rate. Move rate refers to the proportion of individuals who moved houses on a given trial. The aforementioned house-moving cost implies a strict preference for the new location as choosing it also included a small deduction of points. Moves could be *within* the same village (i.e., moving to another house within the safe village), or *between* villages (i.e., moving from the concentrated-rare village to the safe village). To capture this difference, our analysis also displays the destination of these moves. One benefit of analysing destination is that it can also be used to index risk preference. For example, movement to a risky village following a disaster implies an appetite for risk even in the face of experienced catastrophe. In addition, we examined response time defined as the time from the start of a round to when participants confirmed their chosen house (i.e., second click on the chosen house).

## 3 Results

Our primary research question examines whether experiencing a *concentrated-rare* disaster prompted different reactions to *scattered-common* disasters. We initially focus the analyses on the *first* experienced disaster for each participant. This was to ensure a degree of parity in task experience because some participants only experienced one disaster while others experienced multiple.<sup>5</sup> Our second research question is directed towards understanding multiple disaster experiences and the specific reactions to each. The third research question takes an overview of all experienced disasters and compares them against near-misses. It is also worth noting that it was possible to complete the experiment without experiencing a disaster at all, for instance, by repeatedly choosing the safe option or simply by being lucky.

### 3.1 Reactions to scattered-common versus concentrated-rare disasters

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<sup>4</sup>Move cost was always smaller than the maximum payoff in a single choice i.e., lower than 15 points for a non-disaster round in the risky village. See Appendix for exact calculation based on distance.

<sup>5</sup>Distribution of number of experienced disasters is shown in Figure A2 of the Appendix.

We first describe the different behavioural reactions of individuals who had just experienced a disaster. These individuals suffered a substantial loss of in-game points and then faced the choice of where to live in the next round. This first analysis looks at whether disasters of different scales prompted different propensities to move between the villages.

Figure 2 is a flow diagram over the disaster reaction sequence. The main objective of the figure is to identify where a disaster occurred and to where a participant moved on the subsequent trials. Each bar represents a trial in the trial sequence, the height of which shows the collective choices made across all participants. The coloured segments within each bar represent the village chosen on that trial.

The ribbons between the bars track participants' movements. Following a coloured ribbon allows one to trace a move from the origin to the destination on the next vertical bar. By focussing on the ribbons, move rate can be decomposed into the movement destination. By focussing on the height of a coloured bar relative to the height of the entire bar combined, the proportion of choices for a given village can be determined.

Following the movement ribbons, we can now identify two types of moves; a between-village move, and a within-village move. Recall that the microworld was composed of two risky villages (*concentrated-rare* & *scattered-common* villages) and a safe disaster-free village. In Figure 2, a between-village move is shown by the darker ribbons that criss-cross to a different coloured bar. For example, a between-village move from the *scattered-common* village to the *safe* village is shown by a green ribbon originating in the purple segment of the first vertical bar and ending in the green segment of the next vertical bar.

A within-village move involves moving to another house within the same village and is shown by the darker ribbons that *horizontally* connect same-colour bars. Darker ribbons indicate an individual who chose a different house within the same village (same colour bars for both origin and destination). The remaining lighter shaded ribbons represent individuals who did not move and persisted with their original choice. Considered together, the village colours and house shading capture the people's reactions to the first experienced disaster.

From Figure 2, one immediate observation is that most of the reaction is contained in the trial following the disaster (i.e., the ribbon between first two bars). In this immediate reaction, 474/681 participants – a move rate of 0.70 – moved houses after experiencing a disaster (darker ribbons vs. lighter ribbons between first two bars). Descriptively, between-village moves were more common compared to within-village moves (289 between-village vs. 185 within-village). Because choice patterns in the second and third trials following a disaster exhibit dramatically less movement ( $t_{2\text{move rate}} = 0.25$ ,  $t_{3\text{move rate}} = 0.20$ ) we focus our destination analyses on the immediate reaction (i.e., trial  $t + 1$ ).

The type of disaster affected the destinations of people's movement. Focussing on the *scattered-common* village (purple bar at trial 0), disasters prompted relatively little between-village movement. The majority of these disaster-struck participants chose to remain in the *scattered-common* village ( $199/277 = 72\%$  stayed), either in the same house (lighter purple shaded horizontal ribbon 37%) or moving to a different house in the same village

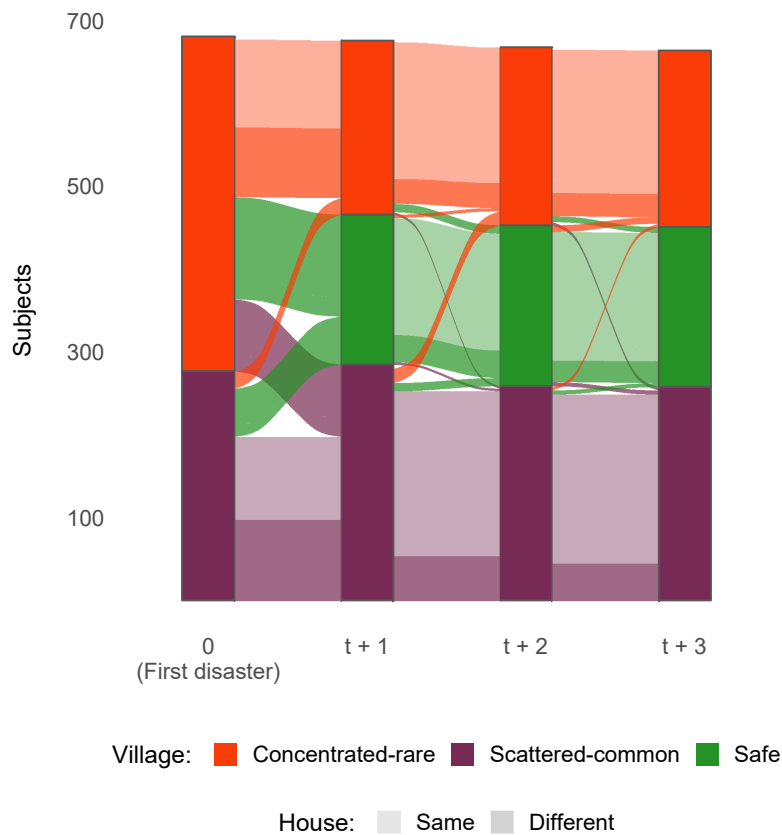


FIGURE 2: Destination of movement over the reaction sequence following the *first experienced* disaster. Trial sequence plotted on x-axis. Y-axis indicates number of participants. Bar colour denotes the chosen village. Strip colour between the bars link the origin to the destination. Darker shading indicates movement (i.e., chose to move to a different house). Lighter shading indicates no movement from current house. Darker shading within the same colour indicates a within-village movement (i.e., move to a different house within the same village). Darker shading to a different colour (i.e., criss-crossing ribbons) indicates a between-village move. For example, a green ribbon originating from a purple bar and terminating in a green segment indicates a move between villages from the *scattered-common* to the *safe* village. Note, the slight attrition in the height of the bars results from removing a small number of individuals who experienced another disaster in those subsequent trials.

(darker purple shaded horizontal ribbon = 35%). Only a small proportion of individuals made a between-village move to the safer village (green ribbon originating in the purple bar = 21%) and even fewer moved to the concentrated-rare village (orange ribbon originating from purple bar = 7%). Intriguingly, the majority of participants exhibited a tolerance for risk, by remaining in a risky village, despite having only just experienced the impact of the disaster.

Following a disaster in the *concentrated-rare* village, shown by the red segments, most participants moved away from the affected region ( $211/404 = 52\%$  left village). This majority comprised of individuals that moved to safety (green ribbon originating from orange bar and terminating in green section of the second vertical bar = 31%) alongside those that moved to the *scattered-common* village (purple ribbon originating in the orange

bar = 21%). Comparing the two types of disasters, concentrated-rare disasters prompted more individuals to abandon their village compared to scattered-common disasters (72% vs. 52% leaving;  $\chi^2(1) = 37.99, p < .001$ ).

### 3.2 Deciding whether to leave

To further understand the process of deciding whether to remain in or leave the disaster-struck village, we examined response times in the immediate reaction trial. We hypothesized that reaction times may differ according to the type of disaster, given that more people stayed in the *scattered-common* village while most left the *concentrated-rare* village. We first separated individuals who left their village from those who stayed in their village. Difference scores were calculated by subtracting response time in the following trial from that on the disaster trial. Therefore, positive difference scores after a disaster indicate an increase in response time, implying a longer period of deliberation. Note that difference scores rather than raw response times were calculated to control for participant-level variation in response times. To aid with interpretation, descriptive statistics are shown in Table 3.

TABLE 3: Statistics for reaction time increases in the trial following A. the first disaster, and B. non-event moves from Figure 3. Units = seconds. Differences scores calculated from the individual participant reaction times for the trial before a disaster/non-event compared to the trial afterwards.

		A. First disaster move			B. Non-event moves	
		<i>n (sub.)</i>	Mean	Median	Mean	Median
Concentrated-rare	Leave	211	11.20	8.9	5.85	3.5
	Stay	193	9.93	7.8	2.11	0.6
Scattered-common	Leave	78	10.50	8.1	5.58	3.3
	Stay	199	5.99	5.1	1.71	1.0

Across both risky villages, response times (RT) increased in the reaction trial compared to the disaster trial, shown by positive difference values in Figure 3. Concurrent with the risk tolerance described above, individuals made the decision to stay in the *scattered-common* village faster than those that decided to leave (mean RT, 5.99 vs. 10.50 seconds; 95% CI [1.81, 6.60],  $t(119.96) = 3.48, p < .001, d = 0.54$ ). The choice to stay in the village was also faster for the *scattered-common* village compared to *concentrated-rare* village (mean RT, 5.99 seconds vs. 9.93; 95% CI [1.91, 5.96],  $t(326.72) = 3.82, p < .001, d = 0.50$ ). Relatively longer response times for the concentrated rare village suggest that larger scale disasters caused additional deliberation, likely because the risk exposure to the disasters was so immediately apparent.

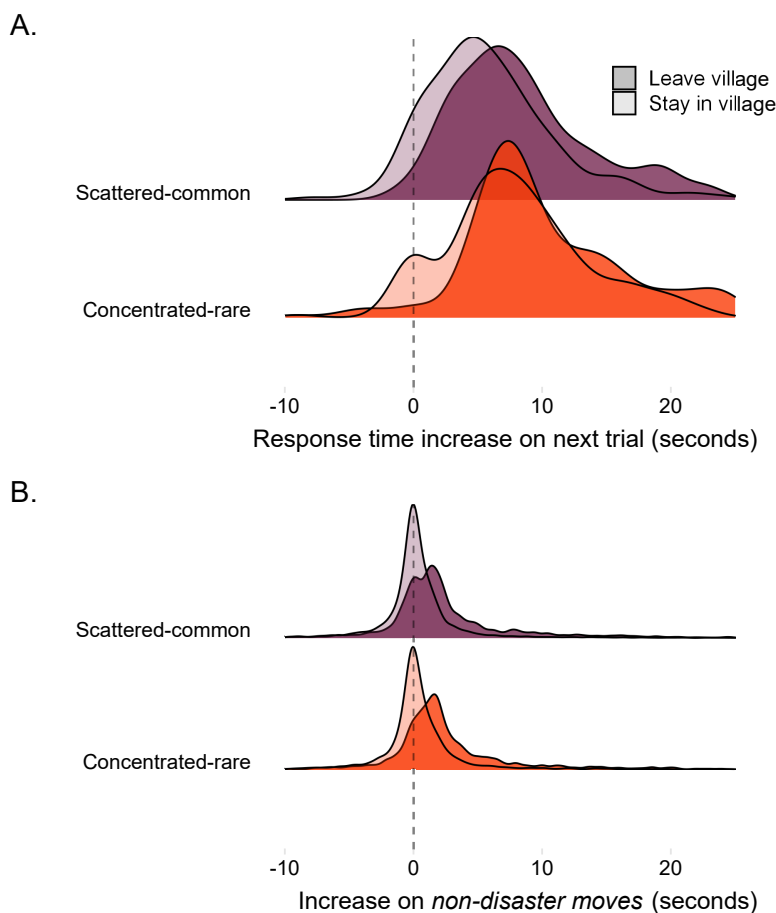


FIGURE 3: Density plots of reaction time differences after the *first experienced* disaster in panel A and after non-disaster events in Panel B. Type of disaster is separated by colour. The subsequent choice to move within the village or leave the village is shown by different shading. Reaction time difference units in seconds on the x-axis. Differences are calculated at the participant-level by subtracting reaction times on the subsequent trial from the disaster trial. Intercept line shows 0 difference indicating the reaction trial response time was identical to the previous, non-disaster, trial.

To understand better the extent of this deliberation, we analysed trials when the same participants moved and a disaster *did not* occur. The data for non-disaster event moves are shown in the lower panel B of Figure 3 with accompanying statistics in Table 3. We analysed the mean response time differences using a 2 x 2 ANOVA with disaster village (concentrated-rare, scattered common) and movement reaction (leave, stay) as factors. When disasters did not occur, there is little separating the two risky villages in movement response time differences (main effect of village,  $F(1, 1725) = 0.54, p = 0.46$ ) and no evidence of an interaction ( $F(1, 1725) = 0.01, p = 0.91$ ). Indeed, leaving the village led to larger increases in response time compared to staying in either village (main effect of movement,  $F(1, 1725) = 49.12, p < 0.001, \eta^2 = 0.003$ ), at least in part due to the additional movements of the mouse cursor to select another village on the map. However, compared to when a disaster

occurs, shown in the upper panel of Figure 3, it is clear that experiencing disasters extends the amount of time people need to make a movement decision. Partially speaking to this point is the fact that disaster-struck individuals who stay in the *concentrated-rare* village exhibited similar reaction time to village leavers (9.93 vs. 11.20 seconds; 95% CI [-0.86, 3.35],  $t(354.82) = 1.16$ ,  $p = 0.25$ ,  $d = 0.10$ ).

An interesting question raised by these analyses is whether an individual's reaction was shaped by a predisposing factor, such as risk preference, that guided their previous village choices. We acknowledge that such causal inferences cannot be made definitively given our focus on the disaster reaction, though we made preliminary in-roads by examining risk-taking behaviour before the disaster. We calculated the proportion of village choices before the first disaster, as an index of prior village preference, that matched the individual's reaction choice. A proportion close to 1 indicates an individual strongly preferred one village whereas a proportion close to 0 suggests the chosen village in the disaster reaction was rarely chosen before the disaster. We found that for both types of disasters, the proportion of matched choices were evenly distributed between 0 and 1 which indicates that most individuals varied their village choices before the first disaster (median concentrated-rare participant = 0.51, scattered-common participant = 0.55; see Figure A7 in Appendix for full distribution of matched proportions). Therefore, despite the explicit descriptions of the risks, most participants chose to explore the microworld across different villages before they were struck by a disaster. However, this shared tendency to explore *before* the disaster then predictably diverged into distinct movement patterns according to the scale of the disaster.

### 3.3 Experience with multiple disasters.

In our second question, we seek to understand the reactions of people who accrued disaster experience. Specifically, we examined participants that were affected by multiple disasters over the course of the experiment. Building from our analysis of the *first* disaster reaction in Question 1, we now ask whether and how participants' responses change as they encounter subsequent disasters. We selected participants who experienced at least three disasters ( $N = 261$ ). The column pairs across Figure 4 track the reactions to each consecutive disaster in the subsequent choice.

As a broad observation, there is a remarkable consistency across the disasters. For most individuals, the immediate response following each experienced disaster was to move houses. The colour proportions of the bars show that the destinations of participants' movement also remained similar across disasters. For example, the relative proportion of participants who moved to the Safer village is similar across successive experienced disasters (green segment of 't+1' bar; first reaction = 18%, second reaction = 18%, last reaction = 21%). Similarly, moving from the *concentrated-rare* to the *scattered-common* villages (purple ribbon originating from orange bar) is consistently more common than moving in the other direction (orange ribbon originating from purple bars). This consistency suggests

that, at least in the aggregate, people who experienced multiple disasters tended to react in similar manners across disaster instances.<sup>6</sup>

However, the data also highlights a cautionary warning, that reactionary moves to the *safe* village were only temporary. By the fact that they were struck again, these participants must have eventually returned to the disaster-exposed villages. In other words, the momentary desire for safety after a disaster subsequently yielded to a habitual tolerance for risk.

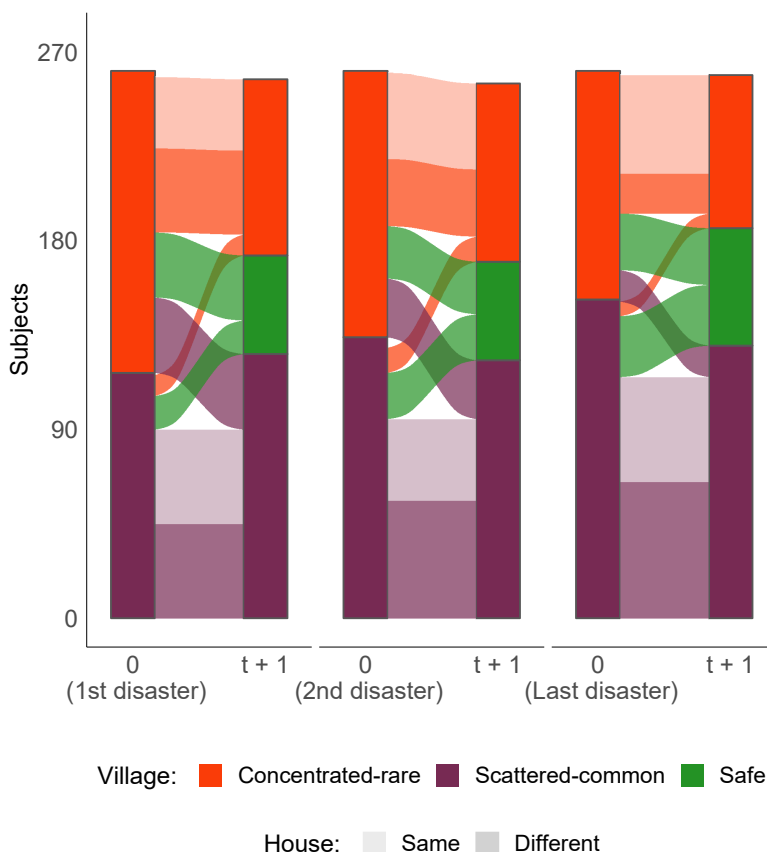


FIGURE 4: Destination of movement for the immediate trial following three disasters. Column pairs show data for the *first*, *second* and *last* disaster when a participant experienced at least three disasters over the experiment. Y-axis indicates the number of participants. Bar colour denotes the chosen village. Strip colour between the bars link the origin to the destination. Darker shading indicates movement (i.e., chose to move to a different house). Lighter shading indicates no movement from current house. Darker shading within the same colour indicates a within-village movement (i.e., move to a different house within the same village). Darker shading to a different colour (i.e., criss-crossing ribbons) indicates a between-village move. For example, a green strip originating from the purple bar indicates a between-village move from the scattered-common to the safer village.

<sup>6</sup>One plausible explanation for this consistency is that those who have experienced repeated disasters were ‘risk-takers’ who had exposed themselves to risk more often than others. To examine this possibility, we regressed the average risky choice proportions as a function of the number of experienced disasters (see Figure A2 of the Appendix). On average, participants with more extensive disaster experience made riskier choices over the experiment ( $r = 0.52$ ,  $t(839) = 17.87$ ,  $p < 0.001$ ).



### 3.4 Near-misses & experienced disasters

To address our third question, we first identified trials in which participants either experienced a disaster or escaped with a near-miss. We then selected a sequence of trials based on the three subsequent trials and the preceding trial. For each of the five choices in this sequence we examined average move rates with the aim of determining how preceding movement behaviour may differ from the disaster reaction. We acknowledge that the analysis of proportions for discrete choices can be problematic (Jaeger, 2008) and primarily rely on the statistical analysis to illustrate the broad patterns in the data.

Figure 5 displays move rates for experienced disasters and near misses as separate lines for types of disaster. The sequence of trials is shown along the x-axis with the disaster occurring on trial 0. Specifically, we calculated the move rates for each individual prior to and following each disaster event and plotted the changes at the aggregate-level in Figure 5. To gauge the immediate impact of the disaster, we calculated a difference score at the individual-level for move rates on the disaster trial compared to the immediate trial afterwards (i.e., move rate difference  $t_0$  vs.  $t_1$ ). This move rate difference score was then analysed using a 3 x 2 ANOVA with disaster event type (experienced disaster, near-miss, far-miss) and disaster village (concentrated-rare, scattered-common) as between-participants factors, and participant as a random-factor. The analyses revealed significant main effects of disaster event ( $F(2, 2180) = 337.80, p < 0.001, \eta^2 = 0.24$ ), and disaster village ( $F(1, 2180) = 7.44, p < 0.001, \eta^2 = 0.003$ ), but without evidence of an interaction ( $F(2, 2180) = 1.06, p < 0.35$ ). To unpack these results, we examined the specific disaster events for each village in greater detail.

Both experiencing and witnessing a disaster prompted reactionary movement. However, the reaction was stronger for those who experience the effects as compared to those who vicariously witnessed its effects (experienced disaster in red vs. near-miss in yellow lines, *concentrated-rare*  $M_{\text{difference}} = 0.53$  vs. 0.14; *scattered-common*  $M_{\text{difference}} = 0.45$  vs. 0.08,  $F(1, 1618) = 155.94, p < 0.001, \eta^2 = 0.09$ ). Concurrent with our central investigation into disaster scale, we found individuals were more likely to move following *concentrated-rare* disasters than *scattered-common* disasters ( $F(1, 1618) = 5.67, p < 0.001, \eta^2 = 0.003$ ).

Near-misses also prompted a degree of precautionary movement (shown in yellow lines). When a near-miss struck neighbouring houses but not one's own, we found a small but non-negligible reaction in both villages ( $M_{\text{difference}}$  versus 0; *concentrated-rare*  $M_{\text{difference}} = 0.14$ , 95% CI [0.26, 0.03],  $t(64) = 2.423, p_{\text{Bonf}} = 0.036, d = 0.30$ ; *scattered-common*  $M_{\text{difference}} = 0.08$ , 95% CI [0.10, 0.06],  $t(630) = 7.97, p_{\text{Bonf}} < 0.001, d = 0.32$ ). Notably, most near-miss events (91%) occurred in the *scattered-common* village, by nature of the disaster frequency in that village. Despite the fact only a small proportion of the houses were affected, this slight but non-trivial increase in move rate implies caution in some participants' reactions. Put simply, learning that one has escaped a nearby disaster unharmed was sufficient to prompt a change in behaviour.

Importantly, disasters that are further afield do not appear to prompt the same precaution

(green line, concentrated-rare  $M_{\text{difference}} = -0.01$ , scattered-common  $M_{\text{difference}} = -0.04$ ). The design of the All-villages feedback condition meant participants were privy not only to near-miss events, but also far-miss events when a disaster struck another village but not their chosen one. This unique feature allowed us to determine that individuals do not exhibit a change in their move rates to far-miss disasters (concentrated-rare vs.  $M_{\text{difference}} = 0$ ,  $[-0.01, 0.03]$ ,  $t(366) = 1.23$ ,  $p = 0.22$ ; scattered-common vs.  $M_{\text{difference}} = 0$ ,  $[-0.01, 0.08]$ ,  $t(196) = 1.75$ ,  $p = 0.08$ ). In other words, we can distinguish the effects of a near-miss from any disaster event that occurs in the microworld based on the proximity of the danger. The surprise that comes from witnessing any disaster is insufficient to prompt precautionary movement. Rather, it was only when the danger was close by or after it just struck that individuals reconsidered their risk exposure.<sup>7</sup>

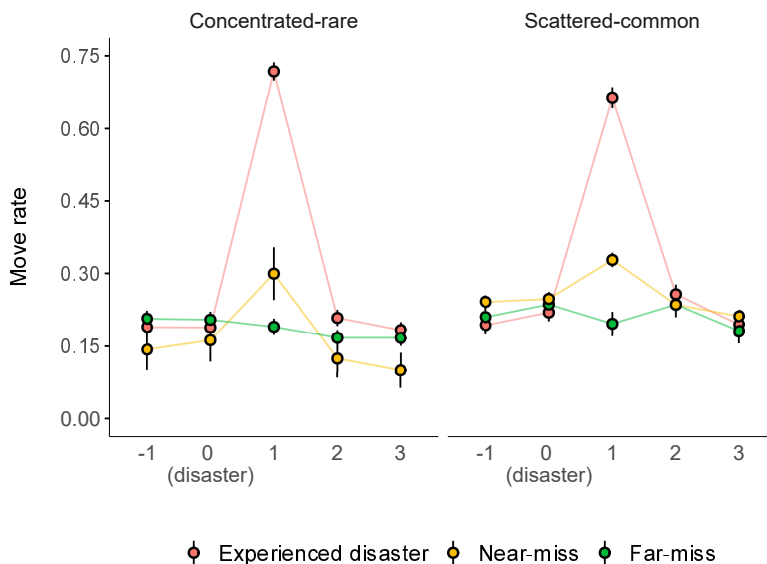


FIGURE 5: Average move rates shown as a function of trial sequence (x-axis) and disaster profile across panels. Error bars show standard error of the mean. Different disaster events are shown in separately coloured lines. *Experienced disasters* where the participant’s chosen house is hit are shown in the red line, *near-misses* where neighbouring houses are hit but the chosen house is unscathed shown in the yellow line, and *far-misses* where disasters strike another village, but the chosen village is unscathed shown in the green line.

## 4 Discussion

Our studies explored how participants reacted to simulated disasters. The principal feature of our microworld was that it allowed us to characterise the scale of disasters and examine how that impacted people’s subsequent choices. This design feature enabled us to experimentally

<sup>7</sup>Note that near misses occurred in both feedback conditions and, due to the similarity in their patterns, have been aggregated in Figure 5. However, for transparency, we present plots separating near-misses for each feedback condition in Figure A6 of the Appendix.

clarify a key factor in risk perception (dread risks) that has been suggested by a large body of research on self-reported risk judgements (Slovic et al., 1984). A detailed examination of responses to different types of disaster events identified distinct patterns of reactions, that allow us to answer our three research questions.

#### **4.1 Scattered-Common vs. Concentrated-Rare Disasters:**

A key advantage of our microworld is that we were able to tailor the risk profiles of each location to ensure the objective risk to any individual house was equivalent in each village. This aspect of our design allowed us to see that while most individuals moved away from the *concentrated-rare* village after being struck, most individuals remained within the *scattered-common* village, content to run the gauntlet again. Thus, comparatively frequent disasters that were limited in scale seemed to lead individuals to accept a cumulatively larger degree of risk than rare events with widespread impact. Analyses of reaction times lent weight to this conclusion showing that participants took longer to decide what to do next following a disaster in the *concentrated-rare* village than in the *scattered-common* village.

#### **4.2 Exposure to multiple disasters:**

About a third of our participants experienced 3 or more disasters (31%). These risk-tolerant individuals persisted in their pattern of movement behaviours across subsequent disasters, and if they did seek safety immediately following a disaster, they soon returned to ‘old habits’ of living in risk-prone locations (Figure 4). Thus, these individuals appeared to persist in *underweighting* the impact of rare events despite – or perhaps because of – the provision of detailed descriptions of risks alongside their trial-by-trial experience (Yechiam, Rakow & Newell, 2015). Indeed, one possibility is that the descriptions may have reassured individuals that disasters were quite rare, and thereby encouraged returning to the affected region sooner than had descriptions been absent<sup>8</sup>.

#### **4.3 Experienced Disasters vs. Near Misses:**

Being hit by a disaster was more likely to prompt reactionary movement compared to when the experience was only vicarious. Such was the case in both villages where the increase in movement after an experienced disaster was at least three times higher compared to following a near-miss. These results suggest that while a near-miss can lead to necessary evasive action, the more visceral impact of a substantial loss is what drives people to get out of harm’s way. Along a similar vein, a recent Dutch study used virtual reality to simulate the experience of a flood which encouraged decision makers to increase their flood insurance spending in subsequent simulations (Mol, Botzen & Blasch, 2022).

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<sup>8</sup>We thank an anonymous reviewer for suggesting this intriguing possibility.

One explanation of our findings is that the surprise of a rare disaster was sufficient to trigger a re-evaluation of choices (Nevo & Erev, 2012). In other words, the surprise of any disaster occurring in the microworld may have triggered a reaction. However, our analysis of far-misses, where a disaster struck but not in one's chosen village, shows that participants were unfazed by the distant occurrence of rare events. Rather than surprise alone, it was the accompanying risk of the disaster's consequences that tested the nerves of our participants.

A natural caveat to these observations and conclusions is that within the confines of the microworld task, participants might hold very different beliefs about the causes of disasters and may be testing idiosyncratic hypotheses about (illusory) sequences. For example, those who move permanently away from a risky area following an experienced (or even a near-miss) disaster, exhibit behaviour akin to the hot stove phenomenon (Denrell & March, 2001) whereby 'burning one's hand' leads one never to return to the same location – consistent with belief in a constant level of unacceptable risk. Alternatively, those whose flight from the disaster zone is temporary are perhaps gaining some utility from attempting to guess when the next disaster will strike or are pursuing other illusory patterns in the sequences of events which may reflect belief in a fluctuating probability of disaster (e.g., Plonsky, Teodorescu & Erev, 2015; Szollosi et al., 2019). Capitalising on these fluctuations resembles a form of gambling within the microworld where movement only occurs to avoid being 'caught out' by the disaster. Recent work suggests that this behaviour is better discouraged by the occurrence of more frequent but less damaging punishments, and so individuals that habitually selected the concentrated-rare village, where 'punishments' were rarer, may have been more prone to anticipatory reactions to illusory patterns (Teodorescu, Plonsky, Ayal & Barkan, 2021).

Arguably all laboratory risk-taking tasks are participant to such vagaries of interpretation (Szollosi & Newell, 2020). Our geographic frame, however, might guide the kinds of beliefs people generate about the task by layering concrete visual features onto abstract sets of payoff distributions. Features like recently damaged houses, geographically separating the villages, and knowledge of other disasters make the idea of risk concrete and accessible. People's hypotheses about the task are anchored by these environmental details that, while requiring some initial orienting, help direct attention towards avoiding the disasters.

An interesting direction for further work with this task would be to vary the causal explanations for the disasters, perhaps in ways that change the statistical structure of the task. For example, introducing sequential dependencies for disaster probabilities would mirror the way in which real-world earthquakes and aftershocks can increase in likelihood following an initial disaster (Öncel & Alptekin, 1999). Causal explanations would provide a foundation upon which features like disaster scale, duration, and impact could be understood beyond the rigid numerical descriptions of risks. Such explanations might also be informative as to what reactions and mitigation strategies may be more useful for different types of hazards. For example, unlike the random distribution of damaged houses in our experiment, the physical constraints of real-world events (e.g., rural regions prone to bushfire; mountain

regions prone to mudslides; river courses prone to flooding) mean neighbours are likely to share similar risk profiles. Promisingly, this means any regularity of small-scale disasters is directly informative for neighbouring individuals which may help to rally a community response. However, policy makers may also be conscious that an extensive history of disaster exposure may encourage a culture of risk tolerance, regardless of how explicit the warnings of the risks may be (Palm, 1981; Nakayachi, 2014; Oki & Nakayachi, 2012).

## 5 Conclusions

It is common to distinguish between high-risk and low-risk events, and this distinction is reflected in the policies and procedures for the management, regulation, and communication of risk. However, our data highlight that people's reactions to adverse events go beyond objective distinctions between low- and high-risk and vary according to the *profile* of the risks they face. This point is implied by research on the psychometrics of risk perception (Slovic, 1987; Slovic, Fischhoff, & Lichtenstein, 1986, 2000). This body of research finds that, in comparison to other potential hazards, people perceive those hazards which have catastrophic and widespread potential to be riskier overall, and in greater need of regulation and management. Lay people also judge that accidents involving these hazards should be acted upon as warnings. However, it is not straightforward to identify whether these perceptions and prescriptions are at odds with the true state of the world, because quantifying risk is a tricky business for complex hazards such as mass transportation or chemical production.

Therefore, it is notable that in our carefully controlled experiments, we see markedly different reactions in environments where disasters are large-scale but rare as compared to environments in which disasters are more common but of more limited scope. That people react differently even though their overall risk exposure is the same in both environments could have important implications for risk communication and interventions that seek to mitigate people's exposure to risk. To ensure their effectiveness, such communications and interventions will likely need to be tailored to take account of how people's natural reactions to adverse events vary according to the frequency and scope of those events.

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## Appendix

### Unmodified participant display

Figure A1 shows a screenshot of the participant's display during the geographical risk task. The map is flanked on the right by three distinct information panels. The top panel displays the description of the risks in each village. The green text middle panel displays the feedback and point total summaries that is updated on each round. The lower green box displays the disaster summary of the affected houses in that round.

### Existing datasets

Disaster events were collated from seven existing datasets using the microworld task (see Table 1). The procedure for all datasets were identical to that outlined in the main manuscript. Participants were presented with instructions that their task was to accrue as many points as possible and that disasters could occur in the two risky villages. The *concentrated-rare* and *scattered-common disaster* villages were identical across the seven datasets with only minor changes according to the manipulations described below.

### Procedure

Participants made 400 rounds of choices where an un-sigaled change to the damage of the disasters occurred midway through the experiment. This divided the experiment into a *moderate* and *severe* environment. In the moderate environment, the expected value of all three villages (concentrated-rare, scattered-common, & safe village) were equivalent. In the severe environment the expected value of the disaster villages was 25% lower than the safe village as described in the main manuscript. In Dataset 1, 3, 4, 6, & 7, the first half



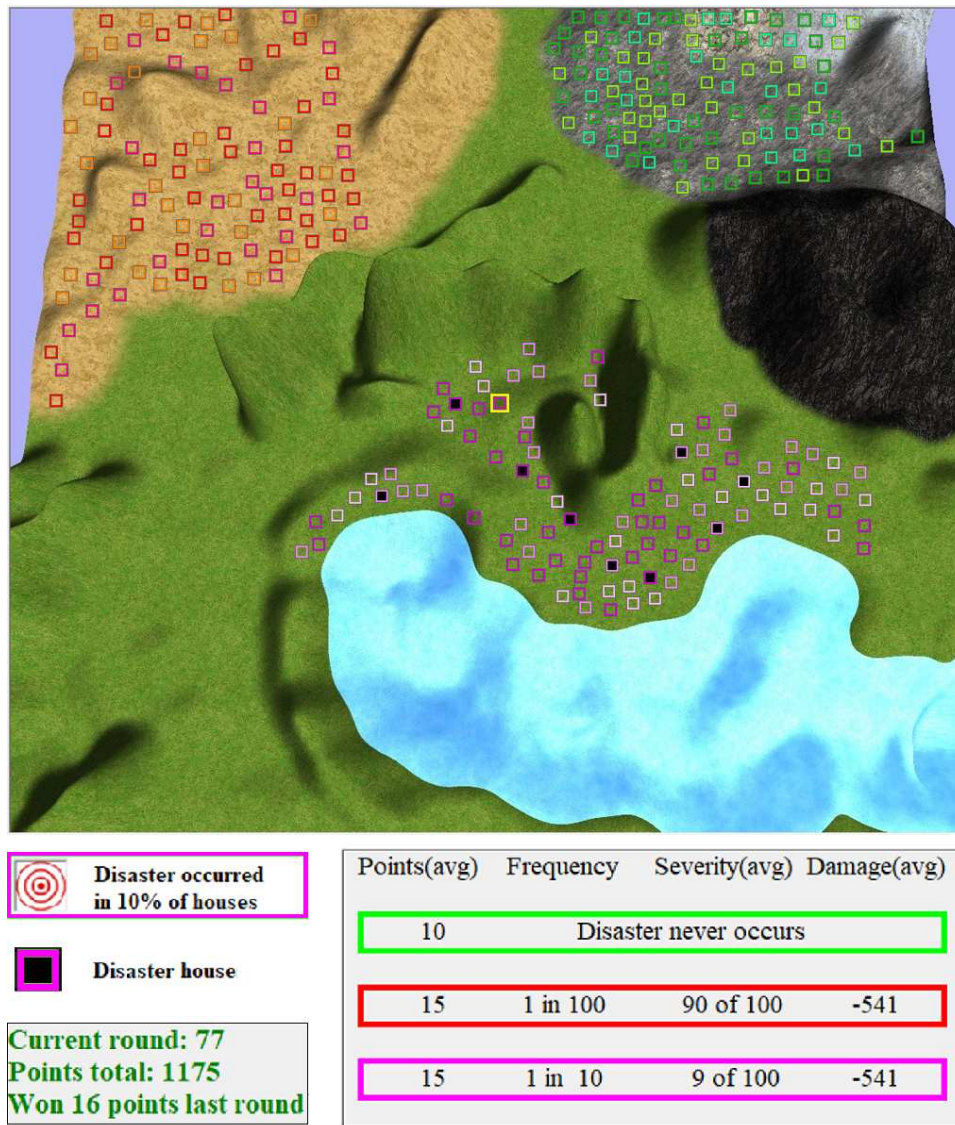


Figure A1. An unmodified screenshot of the microworld’s geographical map, feedback panels, and description panel of disaster risks. The filled-in black squares on the map indicate houses that were affected by a disaster on the previous round (e.g., 10 /100 purple village houses, corresponding to the lower-right, purple, feedback box). Experiment length was 400 trials per participant. Concentrated-rare village is red (1/100 frequency & 90/100 houses affected), scattered-common village is purple (1/10 frequency & 9/100 houses affected), and safe village is green.

of the experiment was in the moderate environment while the second half was in the severe environment. In Dataset 2, the severe environment preceded the moderate and in Dataset 5, the order was randomized. All participants were incentivized on their point totals at the end of the task that was converted at a rate of 1,100 points to \$1.00AUD ( $M = \$3.30$ ). Compared to the specific focus in the main manuscript on immediate reactions to a disaster, the analyses of previous datasets focused on the aggregate-level proportion of risky choices.

*Table A1.* Details of experiments with sample sizes and the total number of experienced disasters in the experiment. For further details and data, Experiments 1 & 2 are published in Newell et al., (2016), Experiments 3 to 6 in the supplementary materials and Experiment 7 is the main text of Liang et al., (2019).

Experiment	Manipulation notes	<i>N</i> participants exp. disaster	<i>N</i> disasters C. rare	<i>N</i> disaster S. common	Total <i>N</i> disasters
1	Disaster feedback – local vs. all villages	43/60	40	52	92
2	Disaster feedback – local vs. all villages	46/60	65	52	117
3	Feedback + disaster history on map	96/120	123	113	236
4	Feedback + Disaster history on map	91/120	107	104	211
5	Feedback + losses framing	88/100	110	128	338
6	Feedback + losses framing	114/139	154	131	285
7	Feedback registered replication	203/242	221	222	443
		681/841	828	783	1611

## Design & Results

Originally, these experiments investigated the role of foregone feedback on risky choice where feedback provided additional information about disasters in non-selected villages (i.e., the forgone options). Although not the focus here, these feedback-centric analyses were the core components of two separate publications. Datasets 1 and 2 were originally published in Newell, Rakow, Yechiam, & Sambur (2016) that reported a counter-intuitive effect of increased risk-taking following more comprehensive forgone feedback. The primary manipulation was forgone feedback that covered disasters across all three villages (all-villages condition) as compared to only the chosen village (local-villages condition). A third experience-only condition only received information about disasters affecting their own house. The main finding was that greater amounts of disaster information (i.e., all-villages feedback) led to increased risk-taking, in the aggregate, compared to disaster information for only the chosen local village. Subsequent experiments sought to replicate and extend the feedback effect into related disaster information manipulations.

The second publication, Liang, Rakow, Yechiam, & Newell (2019), was a registered replication report of the original feedback effect (Dataset 7) in which the Supplementary materials contained results of four unpublished follow-up experiments (Dataset 3 to 6). Datasets 3 and 4 explored the impact of *disaster history*, where houses damaged by a disaster were marked by a red-colored fill for 50 rounds on the map. The prediction was that historical information would reduce the overall proportion of risky choices, although the results did not show evidence of any impact of history. These datasets also preserved the original feedback conditions and compared local-village feedback against all-villages

feedback.

Datasets 5 & 6 explored manipulations involving a *loss framing*, where participants were endowed with a starting total of 10,000 points from which ‘rent’ was deducted on each non-disaster round. The risky villages deducted less rent on a round-by-round basis but were accompanied by the risk of a large loss due to the disasters. Conversely, the safe village deducted more points per round but did not experience disasters. In Experiment 5, we observed an effect of framing where losses increased the proportion of risky choices. However, we did not observe any effect of framing in Experiment 6.

Lastly, dataset 7 was a registered replication of the original conditions from Experiment 1 & 2 in Newell, et al., (2016). We increased the sample size to  $N = 242$  and compared two original feedback conditions, local-village feedback and all-villages feedback. The results failed to show the predicted increase in risky choice proportions associated with all-villages feedback.

## Moving cost

On any trial, participants could choose to move houses within their own village, or to another village. The cost of moving was set by the following equation:

$$\text{Cost} = 1 + .03\sqrt{\text{Euclidean distance}} + C_i$$

$C_i$  is a constant added to a between village move. The maximum possible move cost is 8.9 points which is a move from the southeastern-most house to the northwestern-most house in another village. The lowest move cost (i.e., to the house next door, within the same village) is 1.7 points. This moving cost calculation is the same as in Newell et al. (2016) and Liang et al. (2019).

## Risky choice proportions

In the main text for Question 2, we raised the possibility that those who experienced multiple disasters were ‘risk-takers’ who had exposed themselves to risk more often than others. To examine this possibility, we regressed the average risky choice proportion of each participant as a function of the number of experienced disasters across the experiment (see Figure A2). On average, participants with more extensive disaster experience made riskier choices over the experiment ( $r = 0.52$ ,  $t(839) = 17.87$ ,  $p < 0.001$ ). This analysis suggests chance, or simply being unlucky, is a poor explanation for why some participants were struck by more disasters. Instead, the individuals with multiple disaster experience were habitual risk-takers who chose to re-expose themselves to danger.

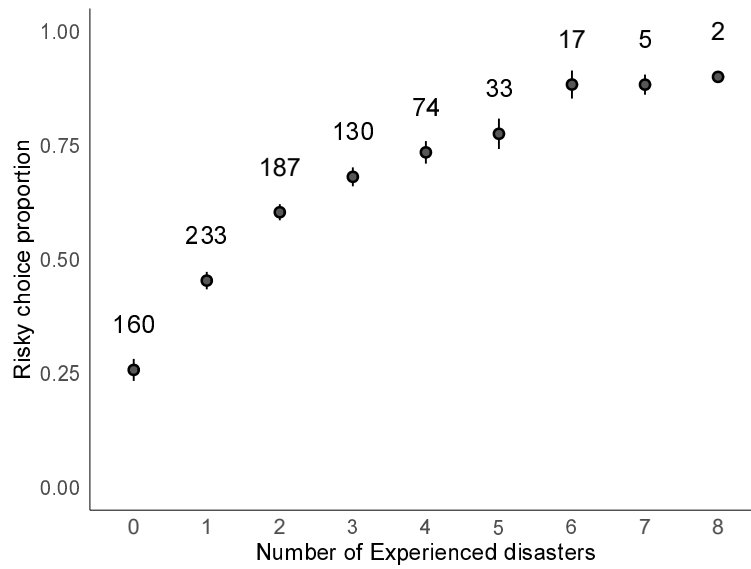


Figure A2. Risky choice proportions as a function of the number of experienced disasters with points representing means and lines as standard errors. Numbers above points represents the number of participants in each bin.

**Analyses separated by feedback condition.**

**Question 1: Scattered-common versus concentrated-rare disasters.**

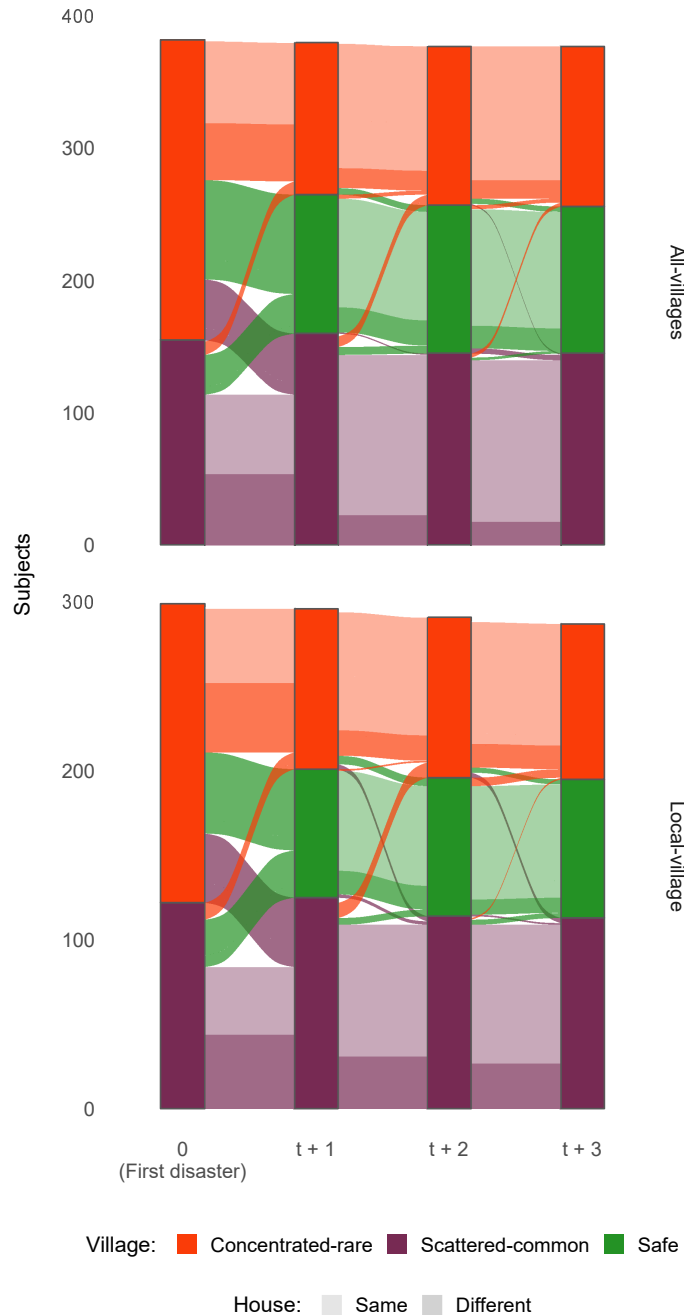


Figure A3. Destination of movement over the reaction sequence following the *first experienced* disaster, separated by feedback condition. Trial sequence plotted on x-axis. Y-axis (i.e., height of the bar) indicates number of participants. Bar colour denotes the chosen village. Strip colour between the bars link the origin to the destination. Darker shading indicates movement (i.e., chose to move to a different house). Lighter shading indicates no movement from current house. Darker shading within the same colour indicates a within-village movement (i.e., move to a different house within the same village). Darker shading to a different colour (i.e., criss-crossing ribbons) indicates a between-village move.

**Reaction time analyses**

*Table A2.* Descriptive statistics for the All-villages feedback condition. Reaction time increases in the trial following A. the first disaster, and B. non-event moves from Figure 3. Units = seconds. Differences scores calculated from the individual participant reaction times for the trial before a disaster/non-event compared to the trial afterwards.

		<b>A. First disaster move</b>		<b>B. Non-event moves</b>		
		<i>n (sub.)</i>	Mean	Median	Mean	Median
Concentrated-rare	Leave	121	10.60	8.42	6.31	3.66
	Stay	106	9.17	7.76	1.33	0.64
Scattered-common	Leave	40	11.40	6.52	5.57	3.2
	Stay	115	6.30	4.83	1.93	1.14

*Table A3.* Descriptive statistics for local-village feedback condition. Reaction time increases in the trial following A. the first disaster, and B. non-event moves from Figure 3. Units = seconds. Differences scores calculated from the individual participant reaction times for the trial before a disaster/non-event compared to the trial afterwards.

		<b>A. First disaster move</b>		<b>B. Non-event moves</b>		
		<i>n (sub.)</i>	Mean	Median	Mean	Median
Concentrated-rare	Leave	90	11.90	10.70	5.28	3.19
	Stay	87	10.80	8.02	2.97	0.59
Scattered-common	Leave	38	8.90	8.27	5.59	3.33
	Stay	84	5.57	5.61	1.57	0.8

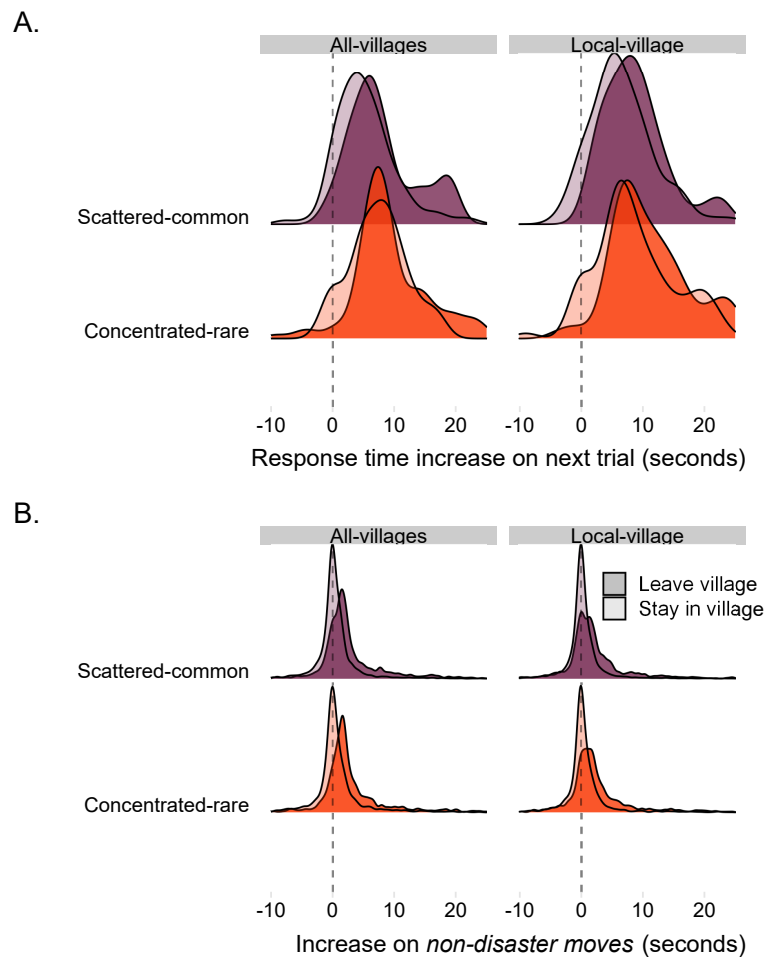


Figure A4. Density plots of reaction time differences after the *first experienced* disaster in panel A and after non-disaster events in Panel B. Type of disaster is separated by colour. The subsequent choice to move within the village or leave the village is shown by different shading. Reaction time difference units in seconds on the x-axis. Differences are calculated at the participant-level by subtracting reaction times on the subsequent trial from the disaster trial. Intercept line shows 0 difference indicating the reaction trial response time was identical to the previous, non-disaster, trial.

**Question 2: Experience with multiple disasters and risk-taking**

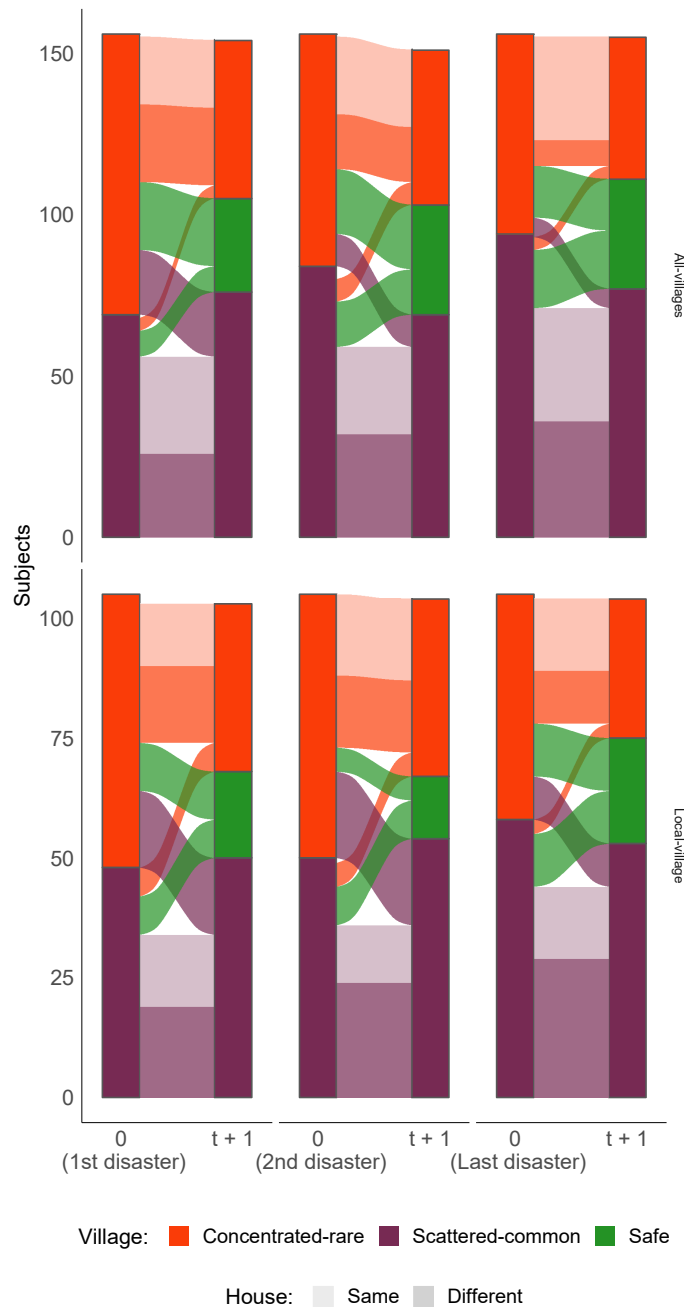


Figure A5. Destination of movement for the immediate trial following three disasters. Column pairs show data for the *first*, *second* and *last* disaster when a participant experienced at least three disasters over the experiment. Trial sequence plotted on x-axis. Y-axis (i.e., height of the bar) indicates number of participants. Bar colour denotes the chosen village. Strip colour between the bars link the origin to the destination. Darker shading indicates movement (i.e., chose to move to a different house). Lighter shading indicates no movement from current house. Darker shading within the same colour indicates a within-village movement (i.e., move to a different house within the same village). Darker shading to a different colour (i.e., criss-crossing ribbons) indicates a between-village move. For example, a green ribbon originating from a blue bar and ending in a green segment indicates a between-village move from the Intermittent to the Safer village.



**Question 3: Near-misses, far-misses and experienced disasters**

The figure below is the companion plot that separates the move rate data for near-miss disasters in Figure 5 of the manuscript by the feedback factor. One consistency that emerges is that near-misses in both the *all-villages* and *local-village* condition reliably show a reliable immediate reaction in the trial following the disaster.

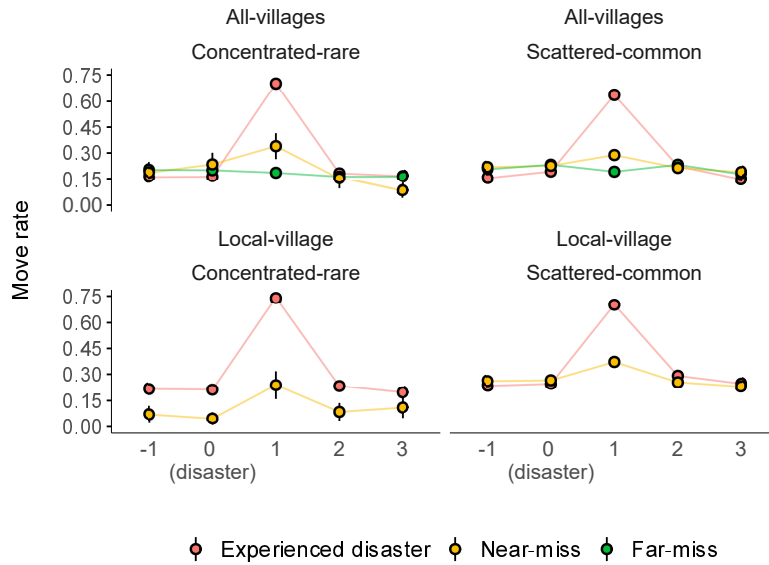
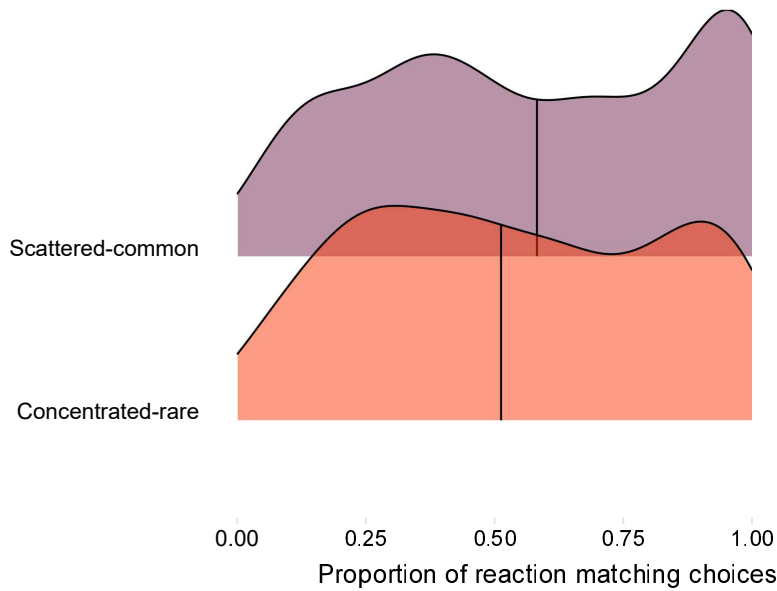


Figure A6. Average move rates shown as a function of trial sequence (x-axis) and disaster profile and feedback across panels. Error bars show standard error of the mean. Different disaster events are shown in separately coloured lines. *Experienced disasters* where the participant's chosen house is hit are shown in the red line, *near-misses* where neighbouring houses are hit but the chosen house is unscathed shown in the yellow line, and *far-misses* where disasters strike another village, but the chosen village is unscathed shown in the green line. Note the absence of the far-miss data in the local-village condition where it could not occur.

### Proportion of reaction matching choices



*Figure A7.* Density plot of the proportion of village choices for individual participants prior to the *first disaster* that matched the choice of village in the disaster reaction. Median participant proportion shown in solid black line where values approaching 1 represent a reaction choice that is consistent with the participant’s village preference *before* the first disaster whereas values approaching 0 indicate a reaction choice that was rarely chosen before the first disaster. Conceptually, these proportions map onto all previous trials before ‘0 disaster trial’ in Figure 2 of the manuscript.