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Using Panel Data to Understand the Dynamics of Human Behavior in Response to Flooding

Philip Bubeck,* Lisa Berghäuser, Paul Hudson, and Annegret H. Thieken

ABSTRACT: Insights into the dynamics of human behavior in response to flooding are urgently needed for the development of effective integrated flood risk management strategies, and for integrating human behavior in flood risk modeling. However, our understanding of the dynamics of risk perceptions, attitudes, individual recovery processes, as well as adaptive (i.e., risk reducing) intention and behavior are currently limited because of the predominant use of cross-sectional surveys in the flood risk domain. Here, we present the results from one of the first panel surveys in the flood risk domain covering a relatively long period of time (i.e., four years after a damaging event), three survey waves, and a wide range of topics relevant to the role of citizens in integrated flood risk management. The panel data, consisting of 227 individuals affected by the 2013 flood in Germany, were analyzed using repeated-measures ANOVA and latent class growth analysis (LCGA) to utilize the unique temporal dimension of the data set. Results show that attitudes, such as the respondents' perceived responsibility within flood risk management, remain fairly stable over time. Changes are observed partly for risk perceptions and mainly for individual recovery and intentions to undertake risk-reducing measures. LCGA reveal heterogeneous recovery and adaptation trajectories that need to be taken into account in policies supporting individual recovery and stimulating societal preparedness. More panel studies in the flood risk domain are needed to gain better insights into the dynamics of individual recovery, risk-reducing behavior, and associated risk and protective factors.

KEY WORDS: Adaptation behavior; floods; individual recovery; LCGA; panel data

1. INTRODUCTION

Against the background of severe flood events, continuously high accumulative flood losses, and the projected increase in flood risks, as well as uncertainties due to global warming (Alfieri et al., 2017; Hirabayashi et al., 2013; Jongman et al., 2014), many countries have replaced traditional flood protection strategies with integrated flood risk management concepts (Bubeck et al., 2017; de Moel, van Alphen, & Aerts, 2009; Thieken et al., 2016a). The latter acknowledge that comprehensive protection against flooding cannot be guaranteed and therefore adopt complementary measures such as building codes, land-use planning, and risk communication to reduce flood impacts in case flood defenses fail (Kreibich, Bubeck, Vliet, & de Moel, 2015). Accordingly, citizens have increasingly become an integral part of integrated flood risk management strategies and are, for instance, expected to contribute to risk reduction by implementing adaptation (i.e., damage-reducing) measures at the building level (Bubeck et al., 2017). Previous events demonstrated that households can substantially contribute to reducing flood losses (Bubeck, Botzen, Kreibich, &

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Aerts, 2012; Hudson, Botzen, Kreibich, Bubeck, & Aerts, 2014; Kreibich et al., 2017; Kreibich, Thieken, Petrow, Müller, & Merz, 2005). At the same time, it has been repeatedly observed that people living in flood-prone areas do not adequately prepare themselves (Bamberg, Masson, Brewitt, & Nemetschek, 2017; Kunreuther, 1996; Weyrich et al., 2020).

Following from the shift to integrated risk management concepts, there has been a quickly growing body of literature examining the role of citizens in contemporary flood risk management through the use of surveys. Important topics addressed in surveys among citizens include flood risk perceptions (Botzen, Aerts, & Van Den Bergh, 2009; Ludy & Kondolf, 2012; Siegrist & Gutscher, 2006), attitudes toward risk management, as well as trust in different stakeholders to manage flood risk (Bubeck et al., 2012; Grothmann & Reusswig, 2006; Terpstra & Gutteling, 2008), and factors that motivate residents to undertake damage-reducing measures (Babcicky & Seebauer, 2019; Bubeck, Botzen, Kreibich, & Aerts, 2013; Grothmann & Reusswig, 2006; Koerth, Vafeidis, Hinkel, & Sterr, 2013), as well as individual recovery following a flood event (Bubeck & Thieken, 2018; Hudson, Pham, & Bubeck, 2019; Lamond, Joseph, & Proverbs, 2015; Zhong et al., 2018).

While these studies address very different aspects of the role of citizens in integrated flood risk management, the vast majority of them have a methodological commonality in that they are based on a cross-sectional survey design. Their cross-sectional nature means that the data collected are taken at only one point in time and thus provide a snapshot of citizens' risk perceptions, attitudes, and behavior. In their review of studies on flood risk perceptions and communications, Kellens, Terpstra, and De Maeyer (2013), for instance, point out that only two of the 57 studies assessed used an experimental design, and none were longitudinal. In addition, the review of Bubeck, Botzen, and Aerts (2012) on the factors influencing damage-reducing behavior lists only cross-sectional studies. The review of Zhong et al. (2018) on the long-term physical and psychological health impacts of floods also reveals the predominant focus on cross-sectional survey designs. The recent systematic literature review conducted by Hudson, Thieken, and Bubeck (2019) confirms that only few panel (or longitudinal) studies, following specific individuals over time, are available in the flood risk domain, as compared to other fields of study. Although cross-sectional studies can provide important insights for risk management, it is not reasonable to assume that perceptions and behavior are indeed constant over time (Bubeck & Botzen, 2013; Hudson et al., 2019; Siegrist, 2013; Weinstein, 1989). As a result, cross-sectional studies may even produce paradoxical results, for instance, by neglecting feedback from previous behavior (Bubeck et al., 2012; Siegrist, 2013; Weinstein, Rothman, & Nicolich, 1998).

Longitudinal studies instead, allow for the direct identification and explanation of changes, and therefore enable a better understanding of causality. They can reveal patterns (trajectories) that cannot be detected in cross-sectional studies by monitoring changes over time as they occur. This is an improvement on detecting these relationships via attempts at reconstructing temporal patterns from static snapshot data points from cross-sectional data sources. The use of cross-sectional data sets in this way can introduce measurement errors via temporal feedback loops masking the true relationships (Bubeck et al., 2012; Siegrist, 2013; Weinstein et al., 1998). Likely reasons for the lack of panel studies in the flood risk domain, such as the rare and unpredictable occurrence of flood events (at least in industrialized countries), and the small initial sample population compared with generalized data sets, are discussed in Hudson et al. (2019).

The few existing panel studies in the flood risk domain surveyed respondents mostly only twice and over relatively short time periods of one to two years (see Hudson et al., 2019, for an overview). A small number of panel studies exists that examined the long-term health impacts of flooding (Norris, Baker, Murphy, & Kaniasty, 2005; Norris, Murphy, Baker, & Perilla, 2004; Waite et al., 2017). Given the overall lack of panel studies, our understanding of the dynamics of human perceptions and behavior in response to flooding are currently limited. The following two research topics illustrate how panel studies can add to the existing cross-sectional literature and can advance risk management capacities.

First, the current cross-sectional literature indicates that flood events can have severe and long-lasting negative psychological impact on affected citizens (Bubeck & Thieken, 2018; Thieken et al., 2016b; Zhong et al., 2018). The literature on human response to potentially traumatic life events such as military deployment, divorce, or the loss of a beloved one suggests heterogeneous trajectories of recovery (Bonanno, 2004; Galatzer-Levy, Huang, & Bonanno, 2018). This means that only some individuals exposed to a potentially traumatic event such as a

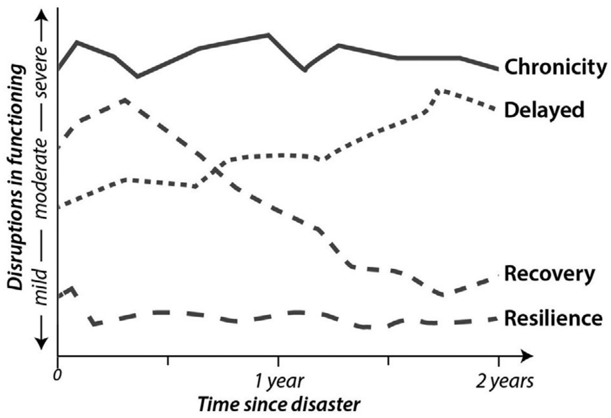

Fig 1. Prototypical response of individuals to a potentially traumatic event.
Source: Bonanno (2004, p. 21). Copyright 2004 by the American Psychological Association. Adapted with permission.

severe flood will face psychological distress in the aftermath of an event, depending on unique characteristics, referred to as risk (e.g., a lack of social support) and protective factors (e.g., high income). The review and statistical analysis of 54 panel studies of Galatzer-Levy et al. (2018) identified four prototypical trajectories of human response following potential trauma, which are schematically depicted in Fig. 1. The four most common response trajectories identified across various potentially traumatic events are referred to as "resilience," "recovery," "delayed onset," and "'chronic." Resilience refers to respondents who were only mildly affected by the event across all time steps. Recovery refers to respondents who suffered a moderate to severe impact from the event but show continuous improvements in their recovery status in the aftermath. The chronic group refers to individuals who were severely affected by the event and show no real recovery over time. Finally, delayed onset refers to respondents who were affected mildly at first but show continuous worsening in their recovery status over time (Fig. 1).

While these patterns have been consistently identified across a wide range of potentially traumatic events (Galatzer-Levy et al., 2018), insights into the response and recovery of individuals to floods is largely lacking. The review of Galatzer-Levy et al. (2018) shows that only seven studies addressed or included natural hazards. Of these seven studies, the majority-examined responses to Hurricane Katrina that hit the United States in 2005 (e.g., Self-Brown, Lai, Thompson, McGill, & Kelley, 2013). Due to the lack of panel studies in the flood risk domain, insights into heterogeneous response trajectories following a severe flood event, as well as risk and protective factors, are largely lacking.

Second, previous cross-sectional research suggests that direct flood experience is an important driver of risk-reducing behavior (Bubeck et al., 2012; Grothmann & Reusswig, 2006; van Valkengoed & Steg, 2019; Weinstein, 1989). However, the fact that many people affected by flooding do not adequately prepare themselves for flooding, while others undertake multiple risk-reducing measures immediately after the event (Bubeck et al., 2012; Kienzler, Pech, Kreibich, Muller, & Thieken, 2015), may indicate that heterogeneous trajectories also exist in terms of adaptation behavior, as found in relation to mental coping (Galatzer-Levy et al., 2018). This is further supported by Weyrich et al. (2020), who found that different groups of flood-prone residents in northern Italy are motivated by different factors to undertake risk-reducing behavior and should therefore not be considered as a "homogeneous community" (Weyrich et al., 2020, p. 296). Still, insights into the dynamics and timing of adaptive behavior following a flood, and potentially heterogeneous adaptation trajectories, as well as risk and protective factors, are largely unknown due to missing panel studies. In addition, many cross-sectional studies elicit intentions to adopt adaptation measures in the future instead of actual behavior to avoid methodological problems from possible feedback associated with cross-sectional survey designs (Bubeck et al., 2012; van Valkengoed & Steg, 2019; Weinstein et al., 1998). To date, it remains largely unclear, though, to what extent stated intentions to undertake adaptation measures translate into actual risk-reducing behavior. For integrated flood risk management, however, the actual employment of risk-reducing measures is of key interest and importance.

Insights into heterogeneous trajectories of recovery as well as adaptive behavior and the associated risk and protective factors derived from panel studies are urgently needed to move from identification to prediction of groups at risk of psychological distress and lack of preparedness. These insights would enhance risk management capacities by enabling the development of tailored (i.e., group specific) policies supporting recovery and stimulating preparedness. An understanding of the dynamics would also allow taking suitable timing into account, for instance, for best exploiting the "window of opportunity" that is assumed to open in the aftermath of a flood to enhance societal preparedness (Kreibich et al., 2011).

Furthermore, empirical insights on adaptive behavior from panel studies would allow us to take changes in vulnerability in flood risk assessments into account (Aerts et al., 2018; Haer, Botzen, & Aerts, 2019). Currently, vulnerability is usually held constant in flood risk modeling, likely resulting in inaccurate flood risk projections (Haer et al., 2019), because it has been shown that especially changes in vulnerability significantly alter overall flood losses over time (Kreibich et al., 2017).

Accordingly, several scholars have pleaded for the implementation of panel studies in the natural hazards and flood risk domain in recent years (Bubeck et al., 2012; Kuhlicke et al., 2020; Osberghaus, 2017; Siegrist, 2013; Zhong et al., 2018). We address this important shortcoming of the current literature by providing empirical insights into the dynamics of risk perceptions, attitudes, individual recovery, and risk-reducing intentions and behavior over time using panel data. A core research objective is to understand whether we can identify heteorogenous trajectories of individual recovery and adaptation behavior within our sample of flood-affected residents. The panel data set employed consists of three consecutive surveys with computer-aided telephone interviews (CATI) that were implemented among 227 flood-affected individuals in Germany over a period of almost four years after a damaging flood event took place. To the best of our knowledge, this is the first panel study (following specific individuals over time) focused specially on flooding that provides insights into the dynamics of a wide range of topics, heteorogenous response trajectories, a longer duration (i.e., four years), and over three time steps.

2. CASE STUDY, SAMPLE CHARACTERISTICS, AND METHODS

2.1. The Flood Event of 2013

Here, we use a panel data set that was collected in Germany after a severe riverine flood event hit central Europe in May/June 2013. The flooding occurred due to high rainfall in May that had left the soil saturated and with little to no ability to store the additional intense rainfall that occurred between May 31 and June 4 (Merz et al., 2014). In Germany, for most rivers, high water levels were observed, many record setting values among them. The eastern and southern regions of Germany were particularly affected. Of the 16 German federal states, eight declared a state of emergency (Thieken et al., 2016b).

Uhlemann, Thieken, and Merz (2010) introduced a severity index to quantify the severity of trans-basin large-scale floods in hydrological terms. Using this scale identifies the 2013 flood as the most severe flood in Germany for, at least, the past 60 years (Merz et al., 2014). Its diverse impacts range from financial losses, traffic and business interruptions and damage to structures and infrastructure, to physical and mental health issues, and environmental problems (Thieken et al., 2016b). A total monetary damage of 6 to 8 billion euros is reported by Thieken et al. (2016b). Detailed evaluations of the flood event and its impacts can be found in Merz et al. (2014) and Thieken et al. (2016a).

2.2. The Panel Data Set

To generate a panel data set, streets affected by the flood event of May/June 2013 in Germany were compiled, landline numbers were researched, and respondents were called. Only respondents who reported damage to the building structure or household contents were included in the survey. Each of the respondents included was surveyed three times, i.e., 9, 18, and 45 months after the flood event, using CATI. At the end of each of the three survey waves, respondents were asked if they were willing to participate in a follow-up survey. At the beginning of survey waves two and three, it was requested that the interview takes place with the initial respondent again. However, if the initial respondent was not available, also other members of the household were allowed to answer, but were not included in the panel data set used for this article. This is because their inclusion would no longer allow us to follow specific individuals over time. To identify respondents who answered all three survey waves, the age and gender of the respondents were compared across the three time steps. Respondents who did not display plausible consistency in this regard were not included in the panel data set. As a result, a total of 227 respondents constituted the final panel data set.

A potential problem associated with panel surveys is attrition bias (Cheng & Trivedi, 2015), which relates to respondents dropping out of the panel nonrandomly. This could result in findings that reflect underlying changes in the sample composition rather than those related to temporal changes. Hudson et al. (2019) showed that there is overall little concern regarding attrition bias for the panel data used in this article. They examined a set of important variables such as origin (i.e., federal state), gender, knowledge of flood risk, flood damage, and inundation-depth qualitatively and quantitatively through a regression analysis in relation to the probability of a respondent completing the survey or progressing to the next survey wave. It was found that the majority of variables did not relate to attrition other than older respondents and those who suffered high flood damage, who were slightly more likely to remain in the survey, *ceteris paribus*.

The CATIs were based on standardized questionnaires. The questionnaire of the first survey wave focused on the flood damage and event characteristics experienced by the respondents, while the second and third waves mainly addressed the recovery process and intangible flood impacts over the longer term. In order to gain insights into the dynamics of human behavior in response to flooding, several variables eliciting perceptions, attitudes, individual recovery as well as adaptive intentions and behavior were included in all three survey waves. The questions were derived from the literature, represent key elements of the risk management cycle, and, as such, have been tested and applied extensively in previous surveys examining the role of citizens in integrated flood risk management (Bubeck et al., 2013; Kienzler et al., 2015; Kreibich et al., 2005, 2011; Thieken, Kreibich, Muller, & Merz, 2007; Thieken, Müller, Kreibich, & Merz, 2005).

The majority of the respondents lived in the two federal states Saxony-Anhalt (41%) and Saxony (27%) who were affected most severely by the flood event of 2013 (DKKV, 2015), followed by Bavaria (16%) and Thuringia (10%). The rest of the respondents came from Baden-Württemberg, Brandenburg, Lower-Saxony, and Schleswig-Holstein. The majority of the respondents are property owners and the average age at survey wave one was 62 years. The relatively high average age of the sample compared to the average age of the German population (44.3 years as of 2016) can be explained because children were excluded from the survey and because only households with landlines were sampled. The sample is biased toward women (65%), but appears to be representative in terms of income (Bubeck & Thieken, 2018).

2.3. Methods

Three different types of analyses were carried out to gain insights into the dynamics of human behavior in response to flooding. First, we conducted repeated-measures ANOVA (analysis of variance) to gain an overall overview of changes in risk perceptions, attitudes, individual recovery, and intentions to undertake adaptation measures (Section 2.3.1). A definition of the examined variables is provided in the supplementary files (Table AI). Differences in the number of observations included in the statistical analyses are due to missing answers.

A potential shortcoming of ANOVA is the underlying assumption that the respondents of a given sample show homogenous developments (i.e., response trajectories) over time. In cases where theory or empirical evidence suggests otherwise, using a single averaged response trajectory will not capture important individual differences within the sample and could lead to misleading conclusions (Andruff, Carraro, Thompson, Gaudreau, & Louvet, 2009). Therefore, second, based on the results of the repeated-measures ANOVA and guided by prior empirical findings (Galatzer-Levy et al., 2018; Weyrich et al., 2020), latent class growth analyses (LCGA) were carried out for assessing heterogeneous trajectories of recovery (Section 2.3.2) and adaptation behavior (Section 2.3.3).

Third, descriptive statistics were applied to evaluate the implementation of specific risk-reducing measures over time and to examine to what extent stated intentions to undertake a damage-reducing measure translate into actual behavior (Section 2.3.3).

2.3.1. *Overall Assessment of Changes in Risk Perceptions, Attitudes, Individual Recovery, and Intentions to Undertake Adaptation Measures*

To evaluate within-participant variance in risk perceptions, attitudes and behavior across different time steps, we applied repeated-measures ANOVA. Repeated-measures ANOVA is used because the same respondents participated in all three waves of the panel survey. It can thus be assumed that the scores taken in each time step are likely to be related because they come from the same respondents, thus violating the assumption of independent ANOVA. The results from Friedman's ANOVA, which is the nonparametric equivalent, are provided in the supplementary information (Table AII). Since repeated-measures ANOVA yielded similar results in terms of statistical significant variables, it is reported here due to more intuitive interpretations of the results.

For each variable, a separate repeated-measures ANOVA was carried out. To account for potential problems associated with sphericity, the Mauchly's Test was applied for each variable. The Mauchly's Test tests the hypothesis that the variances of the differences between time steps are equal. A violation of the sphericity assumption would result in an inaccurate *F*-test. For those variables, for which the assumption of sphericity was violated, as indicated by a significant Mauchly's Test, Greenhouse–Geisser corrected significance values of the *F*-test are reported.

For those variables where the repeated-measures ANOVA yielded a significant *F*-test, effect sizes are reported in the text. Instead of reporting effect sizes across the three conditions, we report effect sizes (Cohen's *d*) for focused contrasts between two time steps of the survey. This provides more meaningful insights into whether changes in risk perceptions, attitudes, and behavior occurred rather in the immediate aftermath of the flood, or in a longer time span. In line with Cohen (1988), Cohen's *d* values of $d = 0.2$ are considered a small effect size, $d = 0.5$ a medium effect size, and from $d = 0.8$ a large effect size.

2.3.2. Analysis of Individual Recovery Following the Flood Event

Since the literature suggests heterogeneous trajectories for recovery, in which both the strength and the direction of change may vary within the sample, we apply LCGA to examine whether we find the prototypical response trajectories schematically shown in Fig. 1 also in relation to experiencing a flood. LCGA was mainly developed and extended by Nagin and colleagues and is specifically designed and used to analyze longitudinal data (Galatzer-Levy et al., 2018; Jones & Nagin, 2013; Jones, Nagin, & Roeder, 2001; Nagin, 1999). It is a group-based modeling strategy, which is based on the assumption that the overall sample is composed of a mixture of distinct subgroups of individuals that exhibit a similar pattern of change (i.e., response trajectories) over time (Andruff et al., 2009; Jones & Nagin, 2007; Nagin & Odgers, 2010). Finite mixtures of suitable probability distributions are used for identifying representative clusters of individual trajectories within the population as well as the characteristics that distinguish individuals within a cluster from others (Jones & Nagin, 2013). The heterogeneity in response trajectories within the sample is summarized by a finite set of unique polynomial functions, each representing a distinct subgroup (Andruff et al., 2009), such as "resilience" or "delayed onset" (Galatzer-Levy et al., 2018). For each distinct trajectory, the individuals within that trajectory group are represented by the same polynomial function (i.e., the same slope and intercept). While the slope and intercept are fixed to equality, there remains a degree of freedom in determining the shape of the particular function, being linear, quadratic (requiring at least three measurement points), or cubic (requiring at least four measurement points). A detailed documentation of the modeling approach is provided in Andruff et al. (2009); Jones and Nagin (2007), (2013); Nagin (1999); and Nagin and Odgers (2010).

To identify distinct trajectories within our sample, unconditional LCGA models (i.e., models without any risk or protective factors) were analyzed using the Stata extension Traj (Jones & Nagin, 2013) in a Stata/SE15 environment.[1] The optimal number of trajectories was identified in an iterative process on the basis of model fit indices, interpretability, and theory (Galatzer-Levy et al., 2018; Nagin & Odgers, 2010; Self-Brown et al., 2013). Based on theory (Galatzer-Levy et al., 2018; see Fig. 1), censored-normal models with one to four trajectories assuming group-specific standard errors were run and compared against each other. For each of the four models, quadratic functions were run first. If the quadratic shape of the functions proved to be insignificant, a linear trend was chosen (Andruff et al., 2009). Following this procedure, we first tested a model, which summarizes the data in a single trajectory. Afterward, the number of trajectories used for summarizing the data was increased stepwise, and the more complex models (i.e., models with one additional trajectory) were compared against simpler models (i.e., models with fewer trajectories). Models with a lower sample size adjusted Bayesian information criterion (BIC) were preferred over others, using the guidelines of Jones et al. (2001) for interpreting the estimate of the log Bayes factor defined as:

$$2\log_e(B_{10}) \approx 2(\Delta BIC),$$

where ΔBIC is the sample size adjusted BIC of the more complex model less the sample size adjusted BIC of the null (simpler) model. According to Jones et al. (2001), a log Bayes factor of 2 to 6 is considered positive, of 6 to 10 strong, and a log Bayes factor > 10 is considered as very strong evidence in favor for the more complex model.

[1]The Stata code Traj can be downloaded from https://www.andrew.cmu.edu/user/bjones/ under a 3-Clause BSD license; © Carnegie Mellon University.

Moreover, to examine the suitability of the identified response trajectories, average posterior probabilities across each identified group (trajectory) were examined. Posterior probabilities estimate the probability that each respondent, with his/her specific change in recovery over time, belongs to the identified finite response trajectories. For calculating the average posterior probabilities, maximum-probability assignment was applied (Andruff et al., 2009). Following Nagin and Odgers (2010), it was checked whether average posterior probabilities of group membership exceeded a minimum threshold of 0.7, which indicates that the derived trajectories cluster respondents with similar patterns of change and discriminate between respondents with different patterns of change (Andruff et al., 2009).

The thus identified best-fitting model was then used to run a conditional LCGA model (i.e., a model including risk and protective factors) to examine which risk or protective factors influence group membership. Due to the relatively small sample size, only a selected number of variables were included in the conditional model. Variables included in the conditional model were preselected from the literature and comprise key variables representing different categories of factors that influence individual recovery in the study area (Bubeck & Thieken, 2018).

2.3.3. Analysis of Changes in Risk-Reducing Intentions and Behavior

To understand the dynamics in risk-reducing behavior, interviewees were asked in each survey wave, whether they had employed 16 specific adaptation measures before the flood event, employed them since the last survey, intend to employ them in the next six months, or do not intend to employ the respective measure at all. As it was previously found that the employment of precautionary measures varies depending on the necessary financial investments associated with their implementation (Rözer et al., 2016), we grouped the 16 measures into three types of cost categories to examine potential differences among types of measures: measures that need low-cost (six measures), medium-cost (six measures) and high-cost (four measures) monetary effort to employ (see Table AI for variable definitions and details on the grouping). To evaluate the dynamics in adaptive intention and behavior, we first applied descriptive statistics.

To explore whether we can identify distinct subgroups within our sample, LCGA was applied to adaptation behavior, too. For the LCGA, we calculated an adaptation index for each respondent and the four different time steps, namely: before the 2013 flood event (as stated in the first survey) and for the three survey waves reflecting the state of adaptation at the time of the survey. To construct the index, the amount of implemented measures was counted for each respondent and for each time step. For the index, we focused on measures that effectively reduce damage in case of flooding only, and, therefore, excluded the six low-cost measures that are mainly informatory measures (see Table AI). Accordingly, each respondent could achieve a minimum value of zero and a maximum value of 10. If a measure was implemented once, it was counted also in the indices of the subsequent time steps, thus assuming that the measure was maintained over time.

For conducting the LCGA, the same procedure in terms of model selection was followed as described in Section 2.3.2 with regard to individual recovery. The only difference was that the best-fitting model was selected on the basis of model fit parameters, only, due to lack of guiding theories on heterogeneous adaptation trajectories from the existing literature. The LCGA on adaptation behavior can thus be considered as an explorative research approach and offers an indication of potential heterogeneous trajectories upon which a guiding theory could be developed if replicated also by other studies (Nagin & Odgers, 2010).

3. RESULTS

3.1. Changes in Risk Perceptions, Individual Recovery, and Adaptive Intentions and Behavior

When examining overall changes in risk perceptions, attitudes, individual recovery, and intentions to undertake measures, the results of the repeated-measures ANOVA show that a considerable number of variables remained largely constant over time (Table I).

In terms of risk perceptions, only the perceived probability changed significantly over the three survey waves. The follow-up pairwise comparisons showed that perceived probability decreased between waves 2 and 3 ($d = -0.38$), representing a small to medium effect size (Cohen, 1988). No significant change was observed for the perceived consequences.

Table I. Results of Repeated-Measures ANOVA

Variable (Number of Valid Cases)	First Wave Mean (*SD*)	Second Wave Mean (*SD*)	Third Wave Mean (*SD*)	*F*-test
Risk perceptions				
Perceived probability (205)	4.48 (1.614)	4.59 (1.488)	3.98 (1.722)	$F(2, 408) = 12.943, p < 0.0001$
Perceived consequences (177)	4.15 (1.944)	4.31 (1.751)	3.98 (1.796)	$F(2, 352) = 1.785, p = 0.169$
Attitudes				
Helplessness (210)	3.98 (1.736)	3.92 (1.721)	3.76 (1.781)	$F(2, 418) = 1.063, p = 0.346$
Avoidance (215)	5.29 (1.304)	5.05 (1.451)	5.05 (1.467)	$F(2, 428) = 2.775, p = 0.063$
Response efficacy (206)	2.69 (1.913)	2.54 (1.484)	2.83 (1.726)	$F(2, 410) = 2.077, p = 0.127$
Response cost (179)	2.93 (1.705)	3.19 (1.539)	3.24 (1,650)	$F(1.928, 343.22) = 2.102$, p = 0.126[a]
Responsibility (193)	3.19 (1.682)	3.16 (1.588)	3.22 (1.583)	$F(2, 384) = 0.082, p = 0.921$
Trust in federal government (197)	3.35 (1.486)	3.48 (1.202)	3.58 (1.187)	$F(1.931, 378.44) = 2.335, p = 0.100$[a]
Trust in insurance (all) (183)	4.05 (1.564)	3.93 (1.496)	3.75 (1.614)	$F(2, 364) = 3.576, p = 0.029$
Trust in insurance (insured) (115)	4.48 (1.372)	4.18 (1.525)	4.05 (1.605)	$F(2, 228) = 5.504, p < 0.005$
Individual Recovery				
Self-reported flood burden (199)	3.79 (1.765)	3.40 (1.711)	3.19 (1.778)	$F(2, 396) = 11.04, p < 0.0001$
Intention to undertake adaptation measures				
Stated motivation (188)	5.61 (1.016)	5.43 (1.034)	5.14 (1.261)	$F(2, 374) = 9.603, p < 0.0001$
Intended measures index (118)	1.09 (1.462)	1.54 (2.637)	0.58 (1.179)	$F(1.55, 181.98) = 7.293\ p < 0.001$[a]

[a]Mauchly's test indicated that the assumption of sphericity had been violated. Therefore, Greenhouse–Geisser corrected tests are reported.

The majority of the examined attitudes remained stable over the three survey waves, as indicated by an insignificant *F*-test. No significant changes over time were found for feelings of helplessness, avoidance, perceived response efficacy and response cost of risk-reducing measures, perceived responsibilities in flood risk management, and trust in the federal government. A significant change was observed for trust in insurance, both for the sample as a whole and for those respondents that held a flood insurance policy at the time the flood occurred in 2013. For the sample as a whole, effect sizes of pairwise comparisons were negligible and well below $d = -0.2$. The trust in insurance of those respondents that held a flood insurance policy before the flood event of 2013 decreased between waves 1 and 2 ($d = -0.2$), indicating a weak effect.

According to the increasingly influential concept of resilience (Weichselgartner & Kelman, 2015), a speedy recovery after a flood event occurred is a key aspect in integrated flood risk management (Thieken, Mariani, Longfield, & Vanneuville, 2014). The variable we used to capture recovery from flood impacts indicates significant changes over time. People's self-reported recovery status, indicated by the variable "Self-reported flood burden" improved over time. Pairwise comparisons show that self-reported recovery improved between waves 1 and 2 ($d = -0.23$), indicating a weak effect.

In terms of intention to implement risk-reducing measures, we found that both variables measuring intentions to undertake adaptation measures decreased significantly over the three time steps (see Table I). Focused pairwise comparisons show that the stated motivation of respondents to reduce flood damage decreased between waves 2 and 3 ($d = -0.25$) (see Table AI for the wording of that item). For the intended measures index, which counts how many of the 16 specific adaptation measures (see Table AI) a respondent intends to undertake in the upcoming six months, we first observed a small increase between waves 1 and 2 ($d = 0.21$) and a medium decrease in intentions between waves 2 and 3 ($d = -0.47$). In this context, it should be noted that intentions could decrease because people implemented risk-reducing measures in the meantime (Bubeck & Botzen, 2013).

Overall, results from the repeated-measures ANOVA and the *post hoc* comparisons show that especially attitudes remain rather constant over time. Significant changes over time were mainly observed for individual recovery and intentions to implement adaptation measures. Accordingly, individual recovery and intentions to undertake adaptive measures are analyzed in-depth in Sections 3.2 and 3.3.

3.2. Individual Response Trajectories (Recovery) Over Time

Guided by empirical evidence (Galatzer-Levy et al., 2018) (see Fig. 1), we tested models with one to four response trajectories using LGCA. The

Table II. Fit Indices and Trajectory Assignment Accuracy for the Four Tested Unconditional Latent Class Growth Analysis Models

# of Trajectories	Sample Size Adjusted BIC	Null Model	$2\log_e$ (B_{10})	Av. Post. Probabilities	Smallest Group (%)
1 Group	−1,228.09			1	100
2 Groups	−1,195.36	1	65.46	0.88–0.95	24
3 Groups	−1,154.74	2	81.24	0.86–0.94	30
4 Groups	−1,158.72	3	−7.96	0.77–0.91	4

Table III. Parameter Estimates for the Best-Fitting Three-Trajectory Model

		Intercept		Linear Term		Quadratic Term	
Class	% of Sample	Estimate	SE	Estimate	SE	Estimate	SE
Resilient	29.9	1.375*	0.760	−0.065**	0.027	n.a.	n.a.
Slight Recovery	29.8	3.466****	0.174	−0.013**	0.006	n.a.	n.a.
Chronic	40.3	8.503****	1.129	−0.266***	0.103	0.004**	0.002

*$p < 0.1$;
**$p < 0.05$;
***$p < 0.01$;
****$p < 0.001$.

results of the fit indices and the accuracy of these unconditional models are reported in Table II. A three-group trajectory model yielded the best results based on sample size adjusted BIC. The log Bayes factors provide strong evidence for the model with three response trajectories as compared to a model with one, two, or four trajectories.

The parameter estimates of the best-fitting model are provided in Table III. The three trajectories of the best-fitting model are depicted in Fig. 2. In the best-fitting model, 30% of the respondent can be grouped as "resilient," 40% as "chronic," and 30% follow a response trajectory we defined as "slight recovery." The resilient group represents individuals who reported to be only mildly impacted by the flood at wave 1 and showed subsequent improvement; the slight recovery group represents individuals who were moderately affected at wave 1 and showed a slight (but statistically significant) recovery process afterward, moving them from above the middle score to below the middle score of the item's scale. However, overall recovery of that group is less pronounced than it would be expected according to the schematic representation of the prototypical response trajectories depicted in Fig. 1. Finally, the chronic group represents individuals who reported to be strongly impacted by the flood over all three time steps and that showed no continuous recovery. The chronic group is characterized by a relative wide 95% confidence interval but is still distinguished from the other groups. Average posterior probabilities of the three groups are all higher than 0.86, which further indicates that the three trajectories group flood-affected individuals with similar patterns of change, and discriminate between individuals with dissimilar patterns of change (Andruff et al., 2009). Trajectories of the resilience and recovery follow a linear trend while trajectory three (chronic) follows a quadratic trend.

Finally, the best-fitting three-group unconditional model was used to run an additional conditional model by adding potential risk and protective factors such as event characteristics, socioeconomic, and psychological factors (see Table IV). The conditional model thus provides insights into the characteristics that may influence group membership. We use the resilient group as a baseline, and, as such, significant parameter estimates indicate a higher (or lower) probability of belonging to the recovery and chronic group, respectively, as compared to the resilient group. Due to limitations in sample size (see Section 4.4), the risk and protective factors included in the conditional model, namely, gender, flow velocity, and mental preoccupation, were preselected from a cross-sectional analysis on individual flood recovery in the study area (Bubeck & Thieken, 2018). In addition, income as a standard socioeconomic parameter was included.

The conditional model shows that gender (being a woman) appears to have a marginally significant predictive effect ($p = 0.059$) on group membership for the recovery group but not for the chronic group

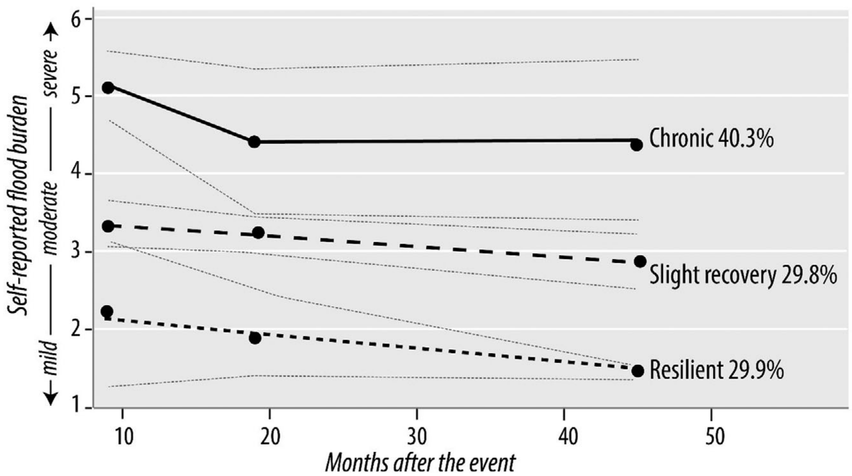

Fig 2. Group trajectories of the best-fitting three trajectory model of resilience, slight recovery, and chronic with 95% confidence intervals.

Table IV. Predictive Effects of Risk and Protective Factors for Group Membership (Best-Fitting Three Trajectory Group Conditional Model) with Resilience as Baseline Group

	Recovery		Chronic	
Risk/Protective Factor	Estimates	SE	Estimates	SE
Constant	−5.295	5.173	−0.810	6.606
Gender	1.848*	0.976	1.930	1.230
Flow velocity	0.536	0.377	0.985*	0.503
Mental preoccupation	1.939***	0.500	2.998***	0.608
Income	−0.215	0.322	−0.937**	0.436

*$p < 0.1$;
**$p < 0.05$;
***$p < 0.0001$.

(when compared to the resilient group). The flood impact parameter flow velocity, which captures self-reported observations of flow velocity at the building, appears to have no predictive effect for belonging to the recovery group but for the chronic group. Respondents who observed high flow velocities at their building level are more likely to be grouped chronic. Mental preoccupation, which captures how often respondents still think about the flood event at wave 3 is the most significant predictor and has a significant effect for both the recovery and the chronic group. The effect sizes of mental preoccupation point in the expected direction and are considerably stronger for the chronic group as compared to the recovery group. People who think back to the event frequently are more likely to be grouped chronic. Income appears to be a protective factor: respondents with higher incomes are less likely to be grouped chronic (as compared to the resilient group).

3.3. Risk-Reducing Behavior and Intentions Over Time

3.3.1. Implementation of Specific Risk-Reducing Measures Over Time

The implementation of 16 different precautionary measures over time is depicted in Fig. 3. We found that the highest share of all 16 measures was implemented before the June 2013 flood and between survey waves 1 and 2. In relation to that, relatively few measures were employed between the flood event and survey wave 1 and between survey waves 2 and 3. For example, 44% of the interviewed residents already used flood-prone floors in an adjusted way (medium-cost measure) before the flood event. A total of 13% employed this measure in the nine months after the flood event (before wave 1), while 30% employed this measure between survey waves 1 and 2, and 13% between survey waves 2 and 3. Across all measures, 52% were employed before the flood, 14% in the nine months after the flood, 25% between waves 1 and 2, and 9% between survey waves 2 and 3.

We found that low-cost and medium-cost measures are the most commonly employed measure categories in comparison to high-cost measures (see Fig. 3). The amount of people seeking information on protection and flood hazards, or avoided environmental damage (all low-cost measures) were the highest in comparison to the other measures. Followed by that, using flood-adapted floors, installing pumps (medium-cost measures), using flood-adapted interiors (high-cost measure), and preparing for a flood event (low-cost measure) were among the second mostly employed measures. In contrast to that,

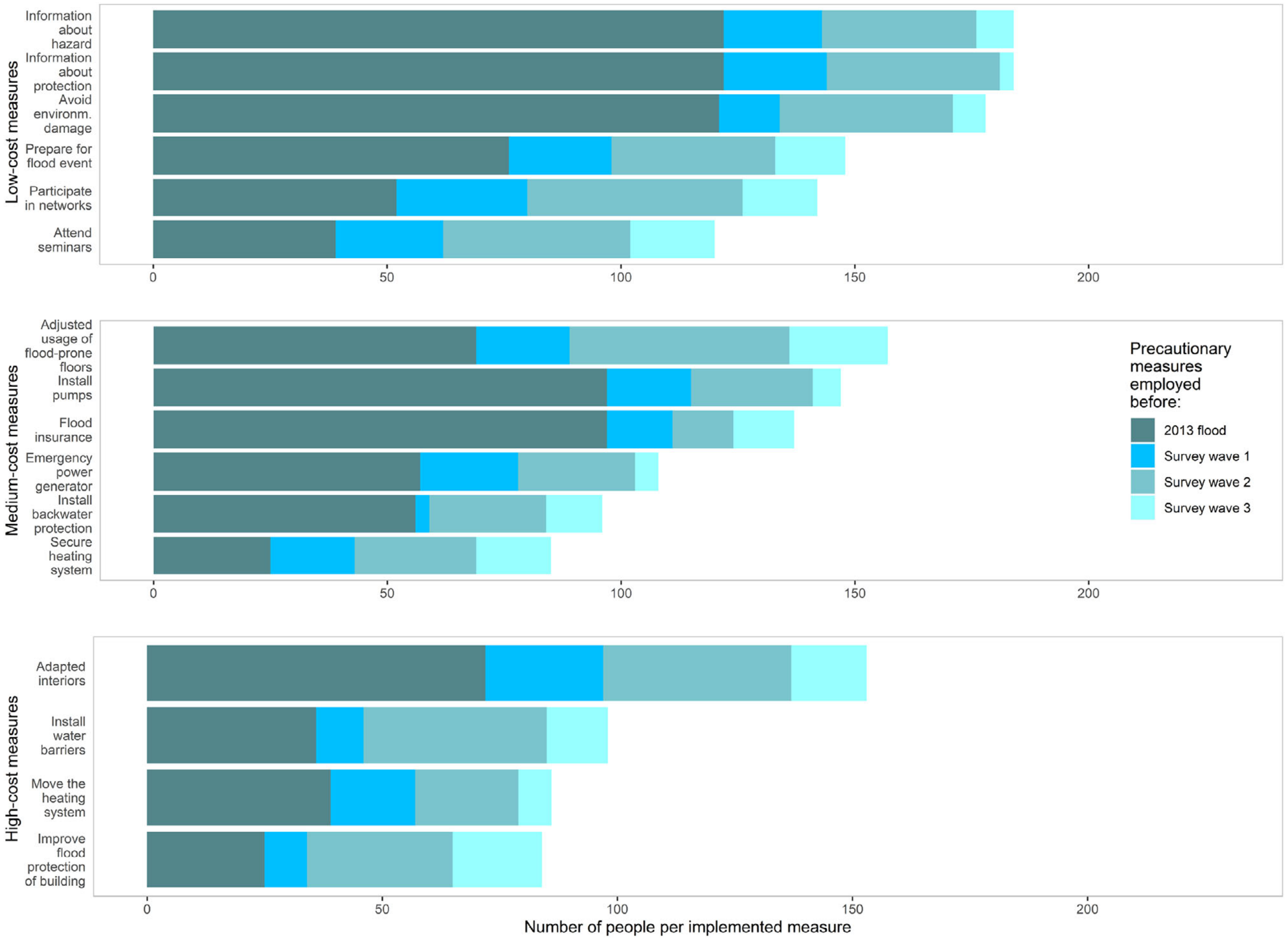

Fig 3. Temporal development of the employment of precautionary measures by their cost category: the stacked bars represent the number of people that reported whether they had employed a measure before the flood event 2013, before the survey wave 1 (i.e., up to nine months after the flood event), before survey wave 2 (i.e., up to 18 months after the flood event), or before survey wave 3 (i.e., up to 45 months after the flood event).

using a flood-adapted heating system (medium-cost measure), installing water barriers, moving the heating system to higher floors and improving flood protection of a building (high-cost measures) were among the least employed measures (see Fig. 3). After all three survey waves, low-cost measures were employed with an average of 70% among all survey participants, medium-cost measures with 54%, and high-cost measures with 46%.

3.3.2. *Intentions to Implement Adaptation Measures and Actual Behavior*

The relation between stated intentions to implement a precautionary measure in wave 1 and the share of actual implementation afterward (waves 2 and 3) is provided in Fig. 4. The absolute number of people that reported a motivation to implement a measure in the first survey wave (shown in green bars in Fig. 4) and the reported actual employment in survey wave 2 or 3 ranged between 4 (e.g., attend seminars) and 20 people (e.g., purchase an emergency power generator). Here, the striking low numbers of the green bars in the low-cost category show that although Fig. 3 revealed that low-cost measures are—in absolute terms—the most commonly implemented measure category, surprisingly few people stated an intention to implement this type of measures in the first survey wave after the 2013 flood (see Fig. 4). The bars in blue show the implementation ratio that was reported in survey wave 2 or 3. The share of employment after a stated intention as well as the timing of employment varied between the precautionary measures and between the cost categories. We found that

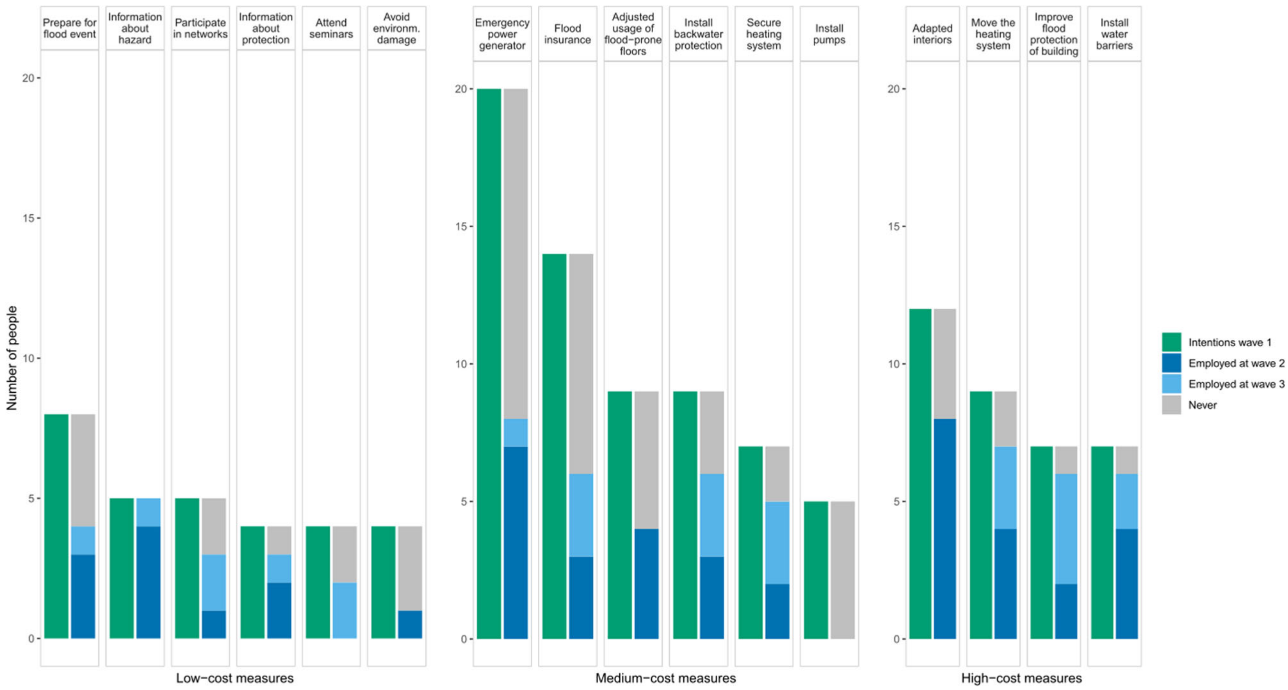

Fig 4. Implementation ratios of each precautionary measure, sorted by its cost category. The green bars represent the number of people that reported an intention to implement a measure in survey wave 1, the second stacked bar shows the number of reported implementations in survey wave 2 (dark blue), in survey wave 3 (bright blue) or no implementation (gray).

the high-cost measure category showed the highest implementation ratio: on average 79% of the people who expressed an intention to implement a high-cost measure had also employed the measure after wave 3. The high-cost measures are followed by the low-cost measures with an implementation ratio of 60%. With 44%, the medium-cost measures have the least implementation ratio.

3.3.3. *Heterogeneous Adaptation Trajectories*

In terms of the LCGA for adaptation behavior, we explored models with one to five adaptation trajectories on the basis of model fit indices. The results of the fit indices and the accuracy of these unconditional models (i.e., without risk and protective factors) are reported in Table V. A model with five trajectories could not be statistically derived. For adaptation behavior, a four-trajectory model yielded the best results based on the sample size adjusted BIC. The log Bayes factors provide strong evidence for the model with four adaptation trajectories, as compared to previous models with less groups. The parameter estimates of the best-fitting model are provided in Table VI.

The predicted values of the trajectories of the best-fitting model are plotted in Fig. 5. In this model, a group referred to as "low" (21% of the

Table V. Fit Indices and Trajectory Assignment Accuracy for the Four Tested Unconditional Latent Class Growth Analysis Models

# of Trajectories	Sample Size Adjusted BIC	Null Model	$2\log_e (B_{10})$	Av.Post. Probabilities	Smallest Group (%)
1 Group	−2,110.58			1	100
2 Groups	−1,948.66	1	323.84	0.94–0.96	44
3 Groups	−1,886.58	2	124.16	0.90–0.96	32
4 Groups	−1,834.19	3	104.78	0.93–0.96	12

Table VI. Parameter Estimates for the Best-Fitting Four-Trajectory Model for Adaptation Behavior

		Intercept		Linear term		Quadratic term	
Class	% of Sample	Estimate	SE	Estimate	SE	Estimate	SE
Group 1	21.2	0.152	0.440	0.052**	0.008	n.a.	n.a.
Group 2	44.4	2.055**	0.191	0.177**	0.022	−0.002**	0.000
Group 3	22.1	5.488**	0.202	0.123**	0.020	−0.002**	0.000
Group 4	12.3	4.189**	0.681	−0.130	0.187	0.031*	0.010

*$p < 0.01$;
**$p < 0.001$.

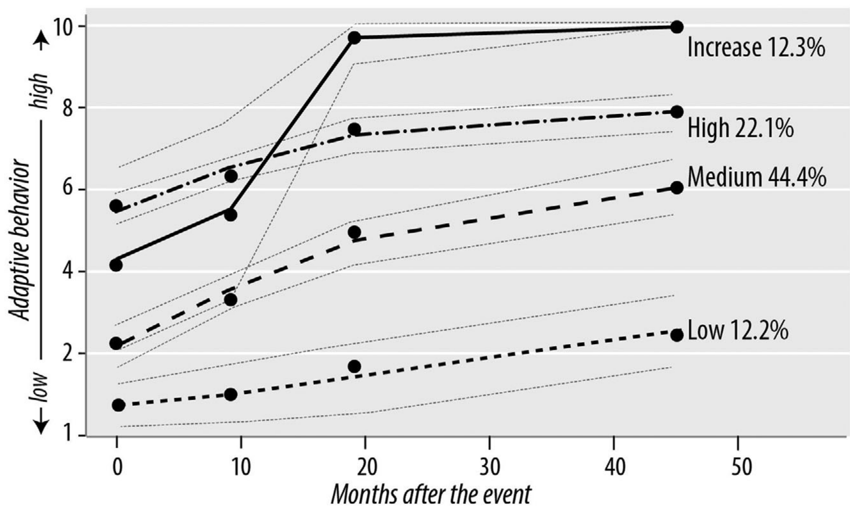

Fig 5. Group trajectories of the best-fitting four-trajectory model explaining adaptation trajectories with 95% confidence intervals.

respondents) shows a very low level of adaptation behavior across all four time steps. Group "medium," which is the largest group comprising 44% of the respondents shows a slightly higher but still low starting point and a slightly stronger increase in implemented measures over time. Group "high," which reflects 22% of the respondents, shows a medium to high level of preparedness already before the flood event of 2013 (i.e., at month 0 in Fig. 5) and further increase in measures over time. Group "increase" (12.3% of the respondents) shows a low to medium level of implemented measures before the flood of 2013 and the strongest increase in measures of all groups over time, particularly between waves 1 and 2. While group "increase" starts from a lower level than group "high," it reaches the highest level of implemented measures over time. Group "increase" is characterized by a much wider 95% confidence interval than the other three groups in the beginning of the trajectory (shown in dotted gray line in Fig. 5). Therefore, it is difficult to separate group "increase" from group "medium" and group "high" until the second survey wave. Still, average posterior probabilities of the four groups are all higher than 0.90, which indicates that the four trajectories group individuals with similar patterns of adaptation behavior, and discriminate between individuals with dissimilar patterns of change over all survey waves.

In line with the analysis on trajectories of individual recovery, the best-fitting four-group unconditional model was finally used to run a conditional model by adding potential risk and protective factors (see Table VII), using the group "low" as a baseline. Accordingly, significant parameter estimates indicate a higher or lower probability of belonging to one of the other groups (i.e., "medium," "high," and "increase"), respectively. As discussed previously in Section 3.2., this analysis is constrained by limitation in terms of sample size (see also Section 4.4.). Compared with the conditional model predicting individual recovery (Table IV), restrictions in sample size are more pronounced for this model given the larger number of groups. Therefore, only two

Table VII. Predictive Effects of Risk and Protective Factors for Group Membership (Best-Fitting Four-Trajectory Group Conditional Model) with "Low" as Baseline Group ($n = 192$)

	Medium		High		Increase	
Risk/Protective Factor	Estimate	SE	Estimate	SE	Estimate	SE
Constant	0.078	0.550	−0.860	0.653	−0.450	0.688
Flood experience	−0.031	0.091	0.206**	0.091	−0.019	0.119
Perceived self-efficacy	0.075	0.111	0.027	0.125	−0.105	0.144

**$p < 0.05$.

variables were added to the model that have been found to be linked to adaptive behavior in the cross-sectional literature (Bubeck et al., 2013; van Valkengoed & Steg, 2019), namely, flood experience and self-efficacy (i.e., the perceived ability to actually implement a risk-reducing measure). Results show that respondents who had experienced flood events also before the event in 2013 are more likely to belong to the group 'High'. Both variables had no other significant effect on group membership.

4. DISCUSSION

This article aimed for improving our understanding of the dynamics of risk perceptions, attitudes, individual recovery, and risk-reducing intentions and actual behavior of individuals affected by flooding. In doing so, a key research objective was to understand whether we can identify representative trajectories of individual recovery and adaptation behavior within our sample of flood-affected residents. Such insights are needed to improve integrated flood risk management strategies, for instance, by developing tailored, group-specific policies to support recovery, and enhance societal preparedness.

4.1. Overall Changes in Risk Perceptions, Attitudes, Individual Recovery, and Risk-Reducing Intentions and Behavior

The strongest overall changes over time were observed for perceived probabilities, individual recovery, and intentions to implement adaptation measures, which also play a key role for the development of sound flood risk management strategies (Bubeck & Thieken, 2018; Bubeck et al., 2012; Grothmann & Reusswig, 2006; Thieken et al., 2014).

It has been argued that both risk perceptions and intentions to undertake adaptation measures and consequently risk-reducing behavior decrease in the aftermath of a flood event, if no subsequent flood events occur (Viglione et al., 2014), for instance due to the presence of levees and a false sense of safety (Di Baldassarre et al., 2018), or simply availability heuristics in which the perceived importance of the event decreases over time (Tversky & Kahneman, 1973). This assumption and its effect on flood risk developments over time were also incorporated in flood risk modeling and referred to as "memory loss rate" (Di Baldassarre et al., 2015). However, empirical evidence showing fading risk perceptions, adaptation intentions, and behavior over time was largely lacking and only indicated by cross-sectional studies (Bubeck et al., 2012). Based on the analysis of panel data, our results partly confirm the above assumptions. We find that the perceived probability, but not the perceived consequences, and intentions to engage in risk-reducing behavior decreased over time. Effect sizes range from weak to medium. The pairwise comparisons indicate that the perceived probability stays rather constant in the aftermath of the event (i.e., up to the second survey wave after 18 months) and only then decreases with time as suggested in the literature. A similar result is found for intentions to implement adaptation measures, which also remained rather constant or even increased in the immediate aftermath of the flood event and only then decreased. These findings are in line with a recent cohort study that found decreasing risk awareness and preparedness among flood-affected residents in Italy (Mondino et al., 2020).

Furthermore, we found that attitudes of flood-prone residents toward responsibilities and trust in organizations and the government remained fairly stable over time. For many of these variables, such as the perceived efficacy and costs of risk-reducing measures, the results of repeated measures ANOVA remained insignificant (Table I). For those variables for which a significant F-test was reported, such as trust in insurance, focused comparisons between two survey waves revealed weak and negligible effect sizes. The fact that attitudes remain rather stable was also found in other risk contexts. Siegrist and Visschers (2013), for instance, found, that acceptance of nuclear power in Switzerland only changed moderately over time, despite the fact that the nuclear accident in Fukushima occurred in between the survey waves. In addition, perceived risk and benefit of biotechnology were found to be moderately stable (Connor & Siegrist, 2016). This stability in attitudes and partly risk perceptions may pose a challenge for the envisaged shift to integrated risk management strategies, which explicitly aims for increasing risk awareness and changing perceptions regarding responsibilities to contribute to damage reduction (Thieken et al., 2016a).

4.2. Individual Trajectories of Recovery Over Time

In terms of recovery processes, our results confirmed that heterogeneous recovery trajectories exist also in our sample of flood-affected residents. The three trajectories identified in the best-fitting model, which are "resilient," "slight recovery," and "chronic," are well in line with the theory on prototypical trajectories of individuals in response to potentially traumatic events (Galatzer-Levy et al., 2018). The group "slight recovery" showed a weaker overall recovery than it was to be expected from the prototypical response trajectories schematically depicted in Fig. 1. That we only identified a "slight recovery" could be linked to the fact that we implemented the first survey wave only nine months after the event and thus might have "missed" part of the initial recovery process in the immediate aftermath. The only group out of the four prototypical trajectories reported by Galatzer-Levy et al. (2018) that is not represented in the best-fitting model is "delayed onset." This is in line with the literature on other potentially traumatic events, which identified this trajectory as the least common (Galatzer-Levy et al., 2018). The response trajectory "delayed onset" becomes apparent, though, in the four-trajectory model, even though the group following this trajectory is very small, being only 4.1% of the sample (see Fig. A1).

The fact that about 40% of the respondents were grouped "chronic" according to self-reported recovery (indicated by the variable self-reported flood burden) indicates that severe flood events have long-lasting effects on those affected, which is in line with previous findings that show that mental health impacts of floods can be long-lasting, i.e., for several years (Hudson et al., 2019; Thieken et al., 2016b; Zhong et al., 2018). This occurs despite the fact that physical damage to household contents and building structures were replaced and compensated relatively quickly after that flood event (Bubeck & Thieken, 2018). On the basis of the results of the conditional model, especially respondents that experienced high flow velocities and thus a dangerous situation in the vicinity of their house and those with a higher degree of mental preoccupation are more likely to report a lower recovery status.

4.3. Risk-Reducing Behavior Over Time

In terms of risk-reducing behavior, we find that relatively few measures are implemented in the immediate aftermath of the flood (i.e., up to nine months), when people are still busy with repairing buildings and replacing contents (Bubeck & Thieken, 2018). The majority of the measures were implemented before the flood event in 2013 or between survey waves 1 and 2. This indicates that cross-sectional surveys, which are implemented too soon after the flood event, will likely miss a substantial part of risk-reducing behavior. The somewhat delayed implementation of adaptive measures also suggests that risk management efforts aiming to stimulate adaptive behavior are likely most effective after flood-affected individuals had some time to repair and replace damaged assets. At the same time, this finding might also indicate that repair works are currently hardly combined with implementing adaptation measures, which would constitute a missed opportunity to enhance societal preparedness.

The fact that many measures were already implemented before the flood event of 2013 can be explained by the fact that the sampled regions were affected by flooding before. Several regions were affected both by the 2002 and the 2013 event (DKKV, 2015) as well as some smaller floods in 1999, 2005, 2006, 2010, and 2011 (Kienzler et al., 2015). A considerable increase in private precaution after the 2002 event was also reported by other studies (Kienzler et al., 2015; Kreibich et al., 2005, 2011). This is further confirmed by the fact that respondents who had observed flood events before 2013 were grouped "high" in the LCGA on adaptation behavior.

Previous research suggested that the implementation rate of precautionary measures is related to the costs of implementation. Rözer et al. (2016) identified low-cost and medium-cost precautionary measures as the most commonly employed precautionary measures in the case of pluvial floods and highlighted the measures getting information about flood protection and flood hazard (low cost) and purchasing flood insurances (medium cost). Our results are in accordance with Rözer et al. (2016) as we also find that low- and medium-cost measures are implemented most frequently.

Contrary to the already implemented measures, we find that intentions to implement additional low-cost measures are relatively low. This can be likely explained by the fact that the sampled areas had been affected by severe flooding before. It is thus reasonable to assume that many individuals are informed about the hazard situation and had already implemented these types of measures, as also indicated by the high total number of already implemented low-cost measures that includes search for information.

While according to our results, the low-cost measures are the—overall—most commonly implemented precautionary measures (Fig. 3), the actual implementation after a stated intent in wave 1 (i.e., implementation ratio) of precautionary measures was found to be highest for high-cost measures (Fig. 4). This could reflect that high-cost measures need substantially more planning and investment and, thus, stated intentions to implement such measures may be more reliable than stated intentions to adopt low-cost measures. These findings further support the results from the LCGA that different groups of risk-reducing behavior exist. One type of behavior would be driven by a full commitment for precautionary behavior, where people plan and adapt according to their intentions. Another type of behavior could be characterized by less binding intentions that do not (or only partly) translate into actual risk-reducing behavior.

While there is an extensive literature that indicates heterogeneous trajectories of recovery following potential trauma, no insights were previously available if such heterogeneous trajectories also exist for flood adaptation behavior. In our explorative LCGA on adaptation behavior, we identify four representative trajectories of adaptation behavior. However, likely due to restrictions in sample size, we could not derive characteristics (i.e., risk and protective factors) other than flood experience profiling these groups.

4.4. Limitations

As mentioned in the introduction, generating a panel data set in the flood risk domain is challenging. Here, we managed to collect a panel sample of 227 flood-affected individuals over almost four years. This rather small sample size required us to keep the conditional (i.e., models including risk and protective factors) models simple and to stick to a small number of preselected factors derived from the literature (Bubeck & Thieken, 2018; Bubeck et al., 2012, 2013; van Valkengoed & Steg, 2019). Thus, the results from the conditional model should be interpreted with care. Future works into risk and protective factors are needed.

Another limitation relates to the fact that we sampled in areas that were at least partly also affected by a severe flood event before the flood in 2013, namely, in 2002. Thus, we can expect flood-driven dynamics of human behavior also before we implemented the first survey. This is shown by the fact that many measures were already implemented before the flood event of 2013 and the positive influence of flood experience on being grouped "high." It can be expected that this already had an influence on the intentions reported in our panel as we found low intentions for implementing additional low-cost measures. It may also be the case that mental preoccupation is not only influenced by the 2013 event but also by the 2002 event, as research showed that individuals can be mentally preoccupied by a flood event even after 10 years (Thieken et al., 2016b).

In addition, the overall focus on flood-affected individuals does not provide an indication of how other individuals in the area might have also responded to a near miss situation. Hudson, Botzen, Poussin, and Aerts (2019) find that even a near miss situation produces a negative impact on well-being, which could also alter an individual's decision process in the wake of a flood. The focus on flood-affected households equally provides no indication of how individuals without prior flood experience prepare for potential flooding, and if risk and protective factors are similar.

5. CONCLUSION

Residents of flood-prone areas are expected to play an increasingly important role in integrated flood risk management concepts. Consequently, there has been a growing interest in their risk perceptions, attitudes toward flood risk management, individual recovery and risk-reducing intentions and behavior. However, due to the predominant focus on cross-sectional survey designs in the flood risk domain, there is little understanding about the dynamics of these aspects. Accordingly, there has been a call for the implementation of panel studies in the flood risk domain. Here, we presented results from a unique panel data set in the flood risk domain covering a relatively long period of time (i.e., almost four years after the damaging event), three survey waves and a wide range of topics relevant for the role of citizens in integrated flood risk management.

We find that both attitudes of flood-prone residents toward responsibilities and trust in insurance and the government remained fairly stable over time. The strongest changes over time were observed for perceived probabilities, individual recovery, and risk-reducing intentions and behavior, which play a key role for the development of sound flood risk management strategies.

Even though our data indicate a recovery process for many respondents, we also find that a substantial part of the respondents is chronically affected by the event. This finding indicates that more long-term psychological assistance to flood-affected citizens is needed for creating more flood-resilient societies. Based on our results, especially households that experienced a dangerous situation in the direct vicinity of their house and those with a high degree of mental preoccupation are in need for support. In this context, the particular impacts of repeated flooding on recovery trajectories should be investigated, which would require, however, very long and larger panel studies.

Furthermore, our results indicate that different types of risk-reducing behavior may exist. These would need different handling in risk communication and integrated management and we suggest further research here to clarify how these groups are characterized, identified, and best addressed in communication strategies. Future works need to investigate whether similar trajectories of adaptation behavior are replicated in other studies, across a range of geographical and cultural contexts, to establish whether the trajectories represent meaningful strata (Nagin & Odgers, 2010).

A shortcoming of current flood risk modeling is that vulnerability is usually held constant, likely resulting in inaccurate flood risk projections (Haer, Botzen, de Moel, & Aerts, 2017). The heterogeneous response trajectories identified in this article could be used in future flood risk modeling studies to better reflect changes in recovery and adaptation behavior over time. Since climate change leads to increasing risk also in areas previously not at risk of flooding, further insights also for such respondents would be of interest, both in terms of recovery and adaptive behavior. Also, future works could be improved by more frequent survey waves to generate more data points to detect more variability.

Concerning the survey designs employed in research, our results indicate a differentiated message. On the one hand, our findings demonstrate that panel data are urgently needed to capture the dynamics of heterogeneous recovery trajectory, intentions to adapt and risk-reducing behavior. The heterogeneous recovery trajectories identified in this article cannot be captured by cross-sectional surveys but are needed to inform recovery policies. Panel studies are also needed to examine to what extent stated intentions translate into actual behavior. However, panel studies come at a substantially higher cost, both in terms of effort and money, compared with cross-sectional studies. These extra efforts are a challenge in a research environment, where funding is often project-bound and provided for relative short time periods. On the other hand, regarding attitudes toward responsibilities in flood risk management, trust in the government, and insurance involved in risk management remained fairly stable over time. Here, cross-sectional studies, which come at substantially lower costs and efforts, may be sufficient. However, given the very low numbers of panel studies, future studies need to still corroborate these findings.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Table AI: Variable description and coding.
Table AII: Results of the Friedman's ANOVA on central tendencies (ranks) in risk perceptions, attitudes, protection motivation and behavior as well as recovery over three survey waves.
Figure A1: Group trajectories of the four trajectory model reported in Table 2.