Unravelling the capacity-action gap in flood risk adaptation

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Abstract. Against the backdrop of increasing climate risks, strengthening the adaptive capacity of citizens is crucial. Yet, the usefulness of the concept of adaptive capacity is currently limited for science and policy, as it is neither clear what exactly constitutes adaptive capacity nor whether capacity translates into adaptation action. Drawing on survey data from 1,571 households in Southern Germany collected in 2022, we use regression analysis to examine the relationship between adaptive capacity indicators and the implementation of pluvial flood risk adaptation measures. Our results confirm a capacity-action gap, as high levels of adaptive capacity do not necessarily translate into household adaptation action. Widely used generic capacity indicators such as income and education are less important for adaptation decisions while specific capacity indicators, such as risk perception, damage experience and motivation, lead to action. We found initial evidence of a nonlinear effect: while a certain stock of financial and human capital is required, additional capital gains do not translate into additional adaptation action. Thus, enhancing the specific capacity of households should be a priority, as generic assets alone will not suffice to cope with climate risk.

1 Introduction

As climate change advances, it becomes increasingly clear that mitigation efforts alone will not suffice and societies have to adapt to more frequent and severe extreme weather conditions. In European welfare states, protection against natural hazards was often provided by structural, mainly government-led interventions in the past. Nowadays, private actors are increasingly being called upon to take action (Mees et al., 2016; Uittenbroek et al., 2019; Doorn et al., 2021), and nudged or even obligated by law to protect themselves and to limit damages. The possession of adaptive capacity is an important precondition for adaptation action (Doorn et al., 2021).

Although the importance of adaptive capacity is widely acknowledged in academic debate, ambiguity exists what exactly constitutes adaptive capacity (Whitney et al., 2017; Siders, 2019). Firstly, the numerous existing definitions in the literature provide little guidance in conceptualising adaptive capacity, as many are very broad and sometimes even contradictory (Siders, 2019, p. 9). Secondly, no standard metrics and methods have evolved so far, leading to a proliferation of different indicators and assessments (Whitney et al., 2017; Siders, 2019). While it is beneficial that researchers have become more open to considering diverse capacities, this vagueness also has brought along limitations. Research is diverse and fragmented, lacking comparative analyses as well as actionable policy guidance (Siders, 2019).

Furthermore, the possession of adaptive capacity is often used as a proxy for adaptation (e.g., Andrijevic et al., 2023) without

critically questioning this assumption. Since more than one decade, the question of whether higher levels of adaptive capacity translate into adoption action is a major concern in adaptation research (Adger and Barnett, 2009, p. 2802; Ara Begum et al., 2022, p. 164). In our opinion, the usefulness of the concept for adaptation research and governance is inherently linked to its

30   ability to infer adaptation behaviour. Therefore, more research on the capacity-action relation is urgently needed.

Case studies are extraordinarily useful research methodologies in this context, as they enable the consideration of the scale- and context-dependent nature of adaptive capacity. Based on the assumption that "adaptations are manifestations of adaptive capacity" (Smit and Wandel, 2006, p. 286), they can provide insights into relevant capacities for different actors and settings, and also help to identify general patterns across diverse contexts.

35   So far, only a handful of studies have empirically examined the relationship between adaptive capacity indicators and adaptation action (Mortreux et al., 2020; Barnes et al., 2020; Green et al., 2021; Bartelet et al., 2023), and, to our knowledge, no study has yet assessed how adaptive capacity translates into adaptation action within a European context. The majority of studies concentrates on assessing the adaptive capacity of households, communities, and companies in coastal areas, thereby considering climate stressors such as sea level rise, degradation of reef ecosystems and associated fisheries and tourism activities

40   (Barnes et al., 2020; Green et al., 2021; Bartelet et al., 2023).

This paper contributes to this under-researched topic by analysing the adaptive capacity and subsequent adaptive behaviour of German households towards urban pluvial flooding. To this end, we draw on data from a household survey to take stock of generic and specific capacities and link them with private flood risk adaptation measures. Our case study area is an affluent and dynamically growing urban-rural region with comparatively high levels of income and wealth in the vicinity of Munich in

45   Southern Germany. The area can serve as a window into a world with increasing heavy precipitation events and pluvial flood risks. The region is already a hotspot for heavy precipitation events (Lengfeld et al., 2021a) and subsequent pluvial flooding due to its geographical location in the foothills of the Alps. Many local authorities currently provide only limited public pluvial flood protection and little information (von Streit et al., 2024), thereby increasingly necessitating households to deal with adaptation privately.

50   After conceptualising adaptation capacity and identifying relevant indicators based on previous literature in Sect. 2, we outline our methodological approach and give more context about the case study region. Our empirical findings are presented and discussed in Sect. 4 and 5. Finally, we summarise the main findings and their implications for research and policy.

2   Conceptualising adaptive capacity

Research on adaptive capacity has grown exponentially in recent years (Siders, 2019), moving from an asset-based under-
55   standing towards a more holistically assessment of adaptive capacity. To describe the evolution of the concept, scholars have identified three research generations (Mortreux and Barnett, 2017; Elrick-Barr et al., 2023). The first generation defines adaptive capacity as a function of access to resources and entitlements, whereby education, health, land ownership, income, material assets, and social capital form the core set of indicators at the household level. This first generation thus concentrates on generic capacities which "[address] deficiencies in basic human development needs" (Eakin et al., 2014, p. 2). Drawing on the sustain-

60 able livelihood framework (Ellis, 2000), this conceptualisation is often employed in the context of resource-dependent societies such as farmers or coastal communities (see, for example, Nelson et al., 2010; Thulstrup, 2015). In the second generation, the research attention expanded to factors which mobilise capacities. Besides generic capacities, studies evaluate threat-specific capacities such as risk awareness, coping capabilities, previous experience and responsibility appraisal (see, for example, Cinner et al., 2018; Barnes et al., 2020; Green et al., 2021). This research body is driven by various theoretical frameworks, e.g. the pro-

65 tection motivation theory (Grothmann and Reusswig, 2006; Oakley et al., 2020), the norm activation model (Schwartz, 1977) and the theory of planned behaviour (Ajzen, 1991), as well as by studies which demonstrated the importance of psycho-social characteristics for adaptation (Grothmann and Patt, 2005; Bamberg et al., 2017; van Valkengoed and Steg, 2019). However, recent publications criticise the isolated view on single actors, thus neglecting the transference and cross-level interactions of adaptive capacities within a system (Vallury et al., 2022; Elrick-Barr et al., 2023). Elrick-Barr et al. (2023) therefore call for a

70 more holistic, third generation of adaptive capacity assessment, which considers the transfer of capacity between individuals, communities and authorities.

Taking stock of the indicators currently used and assessing their relevance across various settings and for different actors is crucial to enhance the practicability of the concept for both research and policy. Previous studies on the capacity-action-relationship also have used a range of different indicator to measure adaptive capacity. One study focuses on the more tra-

75 ditional, capital-based indicators (Mortreux et al., 2020), while the majority follows the broader definition and additionally include second generation, threat-specific capacities (Barnes et al., 2020; Green et al., 2021; Bartelet et al., 2023). The list of potential adaptive capacity indicators has grown long, up to a point where a coherent and comparable assessment is hardly possible. For example, Siders (2019) points out that most studies use a unique set of indicators with little reference to previous work. Overall, she identifies more than 150 determinants in her literature review (Siders, 2019). Yet, research and practice tend

80 to focus on generic capacity (for vulnerability assessments e.g., Cutter et al., 2008; Werg et al., 2013; Eriksen et al., 2020), primarily because these indicators are readily available in official statistics and can be comparable across time and space.

Our understanding and conceptualisation of adaptive capacity are informed by the outlined research, encompassing both generic and specific capacity, while also acknowledging that households' capacities are shaped by social, economic and political processes at the macroscale. Our conceptual understanding of adaptive capacity is best mirrored in the definition provided

85 by Nelson et al. (2007, p. 397), who define adaptive capacity as "preconditions necessary to enable adaptation, including social and physical elements, and the ability to mobilize these elements."

Based on the review of adaptive capacity literature and theoretical frameworks, we identified 18 indicators representing adaptive capacity of households and adapted them for the German pluvial flood context. An overview of the indicators, their operational definitions, and key references is presented in Table 1. To facilitate interpretation, we mapped the indicators into generic and

90 specific capacities. We decided not to consider personal characteristics such as age, migrant background and sex of the primary decision-maker in the household, as they are unalterable and not necessarily representative for the household as a whole.
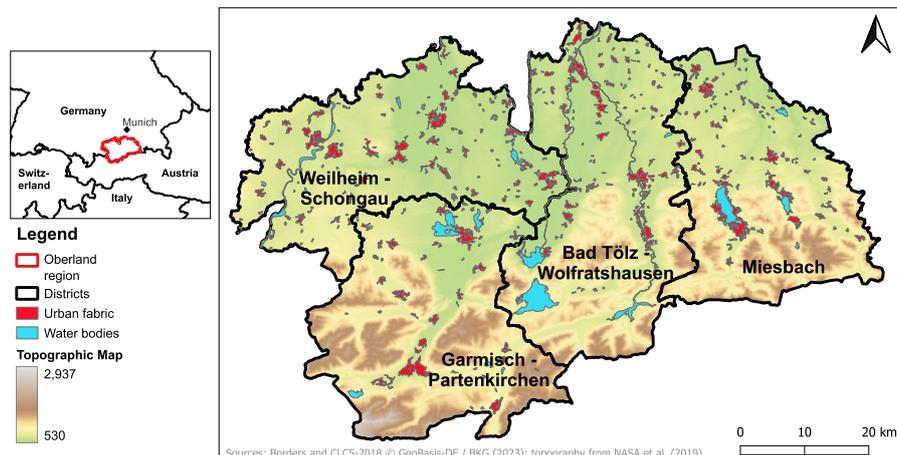
Figure 1. Location and topographic map of the study area

3 Data and methods

3.1 Study area

The Oberland was chosen as case study area because it offers a glimpse into a future world with growing climate risks and urban

95 growth pressure. The region consists of four districts located south of Munich in Upper Bavaria, Southern Germany (Fig. 1). It
is one of the most affluent and dynamically growing regions in Germany with comparatively high levels of income and wealth
(Bundesinstitut für Bau-, Stadt- und Raumforschung, 2021; Heider et al., 2023). The region is typical for prosperous urban-rural
areas in metropolitan regions of western Germany, which benefit significantly from their proximity to the economic centres
and their own dynamic economic structures (Heider et al., 2023, p. 9). However, the dynamic growth also brings challenges.

100 Property prices in the Oberland rank among the highest in Bavaria (Sparkassen Immobilien Vermittlungs-GmbH, 2024), the
real estate market is highly competitive and housing is scarce, the development pressure on land in and around cities is growing.
The Oberland area is already today prone to more intense precipitation, due to its geographical location in the foothills of the
Alps, and has experienced the highest number of heavy precipitation events in Germany (Lengfeld et al., 2021a). Future climate
projections indicate that heavy precipitation will become more frequent (Bednar-Friedl et al., 2022) and changing precipitation

105 patterns reveal that climate change is already advancing in the area (Emeis, 2021).

An analysis of weather prediction data of the region shows that heavy precipitation and resulting pluvial flooding are caused
by different weather patterns. First, a blockage of northerly flows of humid air masses at the northern edge of the Alps can
cause heavy continuous rain for two or three days which then leads to flooding along pre-alpine rivers heading northbound
(Emeis, 2021). This weather situation caused severe flooding in the region e.g. in August 2002, August 2005 and June 2013.

110 Second, deep convection, partly triggered by the mountainous terrain of the Alps, can lead to heavy and often slow-moving
thunderstorms which affect only small areas in the region but cause up to 100 litres of rain per square metre within a few hours
(Emeis, 2021). In June 2016 such events triggered numerous pluvial floods with devastating effects in the region. For example,
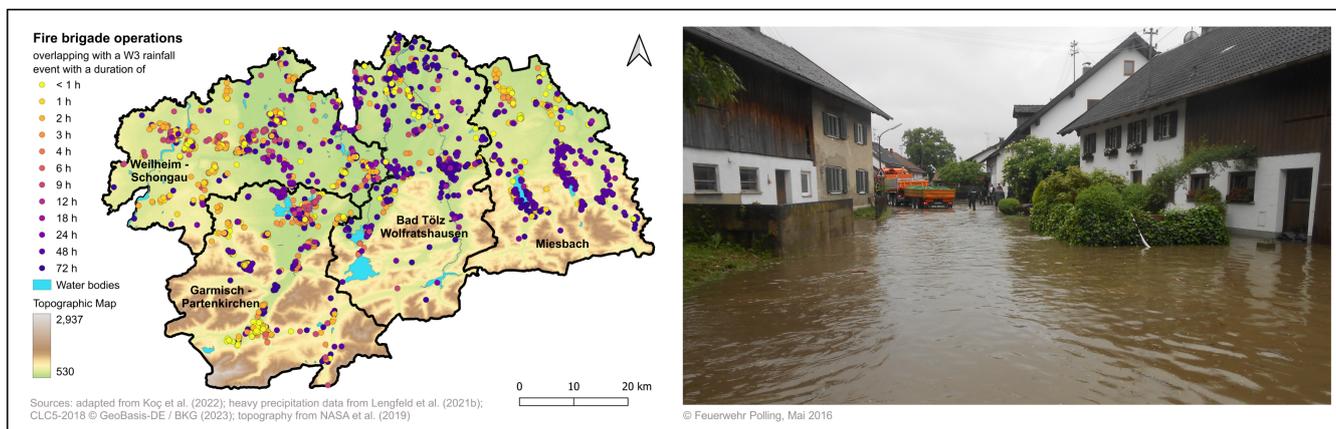
Figure 2. Fire brigade operations in response to heavy precipitation events and pluvial flooding in the Oberland region. The left map displays operations overlapping with heavy rainfall events (DWD warning level 3) from 2011 to 2021, with colours indicating the duration of the rainfall event. The right picture was taken during an operation of the fire brigade in the village of Polling, which was severely affected by pluvial flooding in Mai 2016.

in the small village of Polling (see Fig. 2), building damages amounting to several millions of Euros occurred (Bayerisches Landesamt für Umwelt, 2017). Our analysis of regional fire brigade data revealed that approximately 3,000 operations in the

115   years 2011 to 2021 are attributable to heavy rainfall events (Koç et al., 2022). From the map in Fig. 2, it is apparent that both short and long-lasting precipitation cause fire brigade operations and damages in the region.

3.2   Data

Our study is based on a household survey which was conducted in the Oberland in early 2022. Through a literature review, we identified adaptive capacity indicators (see Sec. 2) and existing questionnaires related to pluvial flooding adaptation (Elmer

120   et al., 2010; Riedl et al., 2016; Kussel and Larysch, 2017; Osberghaus et al., 2020; Dillenardt et al., 2022), which then formed the basis for our questionnaire. This process resulted in a questionnaire with an average length of 36 minutes which covered a broad range of topics such as perceptions about climate change and extreme weather events, risk awareness, pluvial flood damage and event characteristics, private flood risk adaptation measures, housing characteristics, and sociodemographic characteristics (Schubert et al., 2024). We included ten common adaptation options for pluvial flooding, thereby covering a broad

125   range of different actions: low-cost behavioural measures such as information seeking, risk transfer through the purchase of a natural hazard insurance coverage, and more expensive structural measures. For each item, respondents were asked to indicate whether they have implemented it, planned it or neither realised nor planned it. Five cognitive pre-tests were conducted to refine the questions.

A total of 1,865 survey responses were collected, of which 1,571 were included in this analysis. The steps undertaken in the

130   data collection and preparation process are illustrated in Fig. 3. To draw meaningful conclusions about both households affected by heavy precipitation and those not affected, we combined three sampling methods: a random sample, a purposive
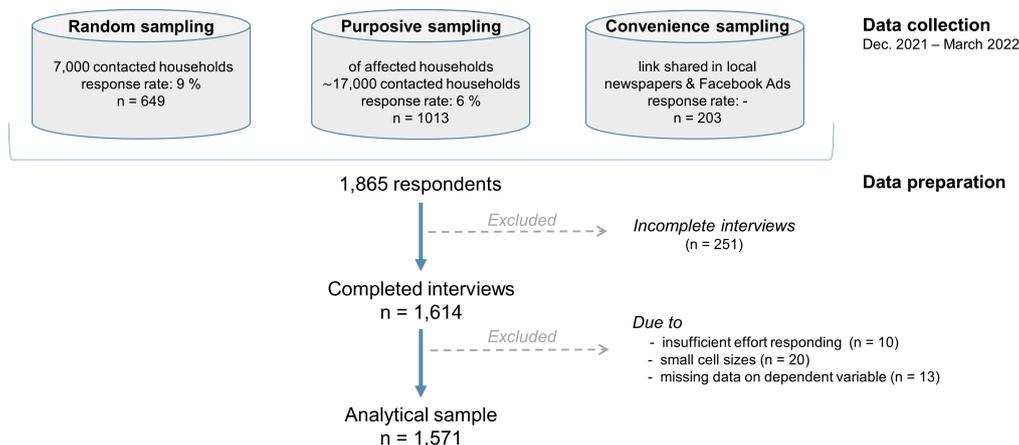
Figure 3. Flowchart of steps undertaken in data collection and preparation

sample of affected households and a convenience sample. We identified addresses and streets affected by pluvial flooding events by collecting data from fire brigades and combining it with radar-based heavy rainfall events (see Fig. 2). To ensure that all participating households were at risk of flooding, two screening questions checked whether the household used rooms in the

135 basement and/or on the ground floor. Within the household, the household member with a leading role in household (financial) decision-making was selected for the interview. The survey used a mixed-mode approach, whereby respondents could choose between a computer-assisted web interview (CAWI) or telephone interview (CATI). To ensure a high data quality, we used standard metrics to detect careless responding, such as the intra-individual response variability (IRV), resampled individual reliability (RIR) and response time (Curran, 2016; Brühlmann et al., 2020; Ward and Meade, 2023).

140 Despite efforts to increase the response rates such as a mixed-mode design, response rates were rather low. A comparison of the survey data with microcensus data for the Oberland region reveals that men, older, highly educated and high-earning respondents are overrepresented while foreign nationals, women, younger, low-educated as well as low-earning citizens are underrepresented (see appendix for details, Table A1). Similar selection biases have been reported in other flood-related studies (Poussin et al., 2015; Spekkers et al., 2017; Dillenardt and Thieken, 2024). This exogenous sample selection can be easily

145 corrected in multivariate models by conditioning on these variables (Wooldridge, 2013, p. 325). However, uni- and bivariate statistics are biased and thus not generalizable.

3.3 Statistical analysis

To examine household adaptation comprehensively, we draw on two dependent variables in our analysis: whether a household adapts (yes or no) and the number of implemented adaptation measures. A binary variable indicates whether a household

150 has implemented at least one adaptation measures (1 yes, and 0 no). While many studies simply focus on such a binary

variable (Barnes et al., 2020; Dillenardt et al., 2022; Bartelet et al., 2023), we assume that adaptation is a continuum and that adaptation cannot be realised by the implementation of a single measure. To this end, we constructed a second discrete variable by summing up the number of implemented measures. The maximum number of implemented measures is ten for property owners, whereas tenants could only implement four non-structural measures. 'Don't know' answers were counted as 0 since –

155 even if they have been implemented – they do not pose a deliberate adaptation action.

Missing data on the independent variables was imputed to increase statistical power and reduce bias in parameter estimates. For the majority of variables, the amount of item nonresponse is rather low, ranging from 0 to 6% (Table 2). Only income – a survey variable which is traditionally prone to higher nonresponse rates (Yan et al., 2010) – is missing for 13.24% of the sample. Assuming that the data is missing at random (MAR), we followed a multiple imputation, then deletion (MID) approach

160 (von Hippel, 2007). Based on von Hippel (2020), the required number of imputations for replicable standard error estimates was determined. Thirty imputed datasets were generated with the mice package (van Buuren and Groothuis-Oudshoorn, 2011). By this means, the sample size increased from 1,020 complete cases to 1,571 households.

We utilise descriptive as well as regression analysis to explore the capacity-action relationship. As a first analytical step, we provide a brief stocktake of private adaptation actions, adaptive capacities, and their relationship in the Oberland using

165 descriptive statistics. Given the exogenous sample selection as well as the interdependence of adaptive capacity indicators (Smit and Wandel, 2006, p. 288), we then turn to multivariate regression analysis. A logistic regression was fitted to the binary adaptation action variable, a Poisson regression for the discrete number of implemented measures. The models were computed for each of the thirty imputed datasets, the resulting parameter estimates were then pooled together into a single set of estimates. As property owners face greater flexibility in their adaptation actions (Laudan et al., 2020; Grothmann and Reusswig, 2006),

170 models were estimated separately for owners and tenants.

For each model, assumptions were checked to ensure the validity and reliability of the results. Predictors are not affected by multicollinearity (variance inflation factor < 2), and the Poisson model is neither overdispersed nor zero-inflated. The violation of the random sampling assumptions is accounted for in two ways. Firstly, we estimate cluster-robust standard errors at the municipal level to account for the fact that respondents from the same municipality might be more similar to each other in terms

175 of adaptive capacity and action. Even though we cannot quantify the cross-scale dynamics with this method, this is an important analytical step to acknowledge the embeddedness of an actor within a system and the alternating influence this has on adaptive capacity and their mobilisation (Elrick-Barr et al., 2023). Secondly, the exogenous sample selection is removed by conditioning on the characteristics which are over- and underrepresented (e.g. age, income, education) (Wooldridge, 2013, p. 325). To fulfil the exogeneity assumption and eliminate spurious correlations, additional variables such as house characteristics and survey

180 mode are controlled for. To address the problem of unobserved heterogeneity in logistic and Poisson models, all effects are presented as average marginal effects (AME) (Mood, 2010; Arel-Bundock et al., Forthcoming).

4 Results

4.1 Adaptive capacity of households in the Bavarian Oberland

While the generic capacities in the sample are above-average high, specific capacities are more varied. Table 2 provides a
detailed overview of the adaptive capacity present in our sample.

Generic capacity indicators such as income, education level and living area are above the German average. More than half
of the respondents have an upper secondary education, the median net household income is between 3500 and 4000 € and
the average living area is roughly 140 m^2. The place attachment in the sample is also quite strong; respondents report an
average duration of residence of 33 years, with the majority expressing intentions to continue residing there for the long
term. Additionally, many respondents possess a high social capital, indicated by a large social network and a high sense of
belonging. In terms of general capacities, there is a slight discrepancy between homeowners and tenants. Owners tend to be
more prosperous, with higher income levels and a larger living area, as well as stronger bonding social capital and attachment
to their residence.

In contrast, specific capacity, such as risk perception, responsibility appraisal and coping capabilities, is less pronounced and
more varied in the sample. The sample is well-informed about climate change as the majority gauges an increase in extreme
weather events in the coming decades as likely. However, the risk perception to suffer from a damage in the next five years
is rather low which indicates that heavy precipitation events are regarded as future problems. Two-thirds of the sample assess
their perceived probability of being flooded in the next five years as not likely at all or rather unlikely. This may also be a result
of the limited experience with heavy precipitation events. So far, 38% have experienced pluvial flooding on their premises,
with 20% suffering financial losses while 18% did not.

Concerning responsibility for flood protection, perceptions of who is responsible for protecting their premises differ. Owners
mostly regard themselves as responsible while the majority of tenants holds the landlord for accountable. However, roughly
one-third of the sample think it is the state's responsibility. Many respondents are willing to implement private measures; only
21% agree that they are not taking private measures as protection is a state task. However, opinions on the effectiveness of
public flood risk management (FRM) provided by the state vary greatly. One half trusts the municipality to effectively protect
them from flooding and agrees that FRM is so good that private measures are not needed, while the other half does not. Tenants
tend to evaluate public FRM slightly better than owners.

Self-efficacy and protection motivation also show a high variability. The answers to these questions are almost uniformly
distributed across the six-point agree-disagree scale. The median and mean for these variables is 3, indicating that roughly half
of the sample feels somewhat incapable of and not engaged in protecting their household from flooding. Other things to worry
about than flooding are reported by 46% of the respondents. Tenants report slightly more competing concerns, less ability to
protect themselves and a lower engagement.

Combinations of pluvial flood adaptation measures by private housholds
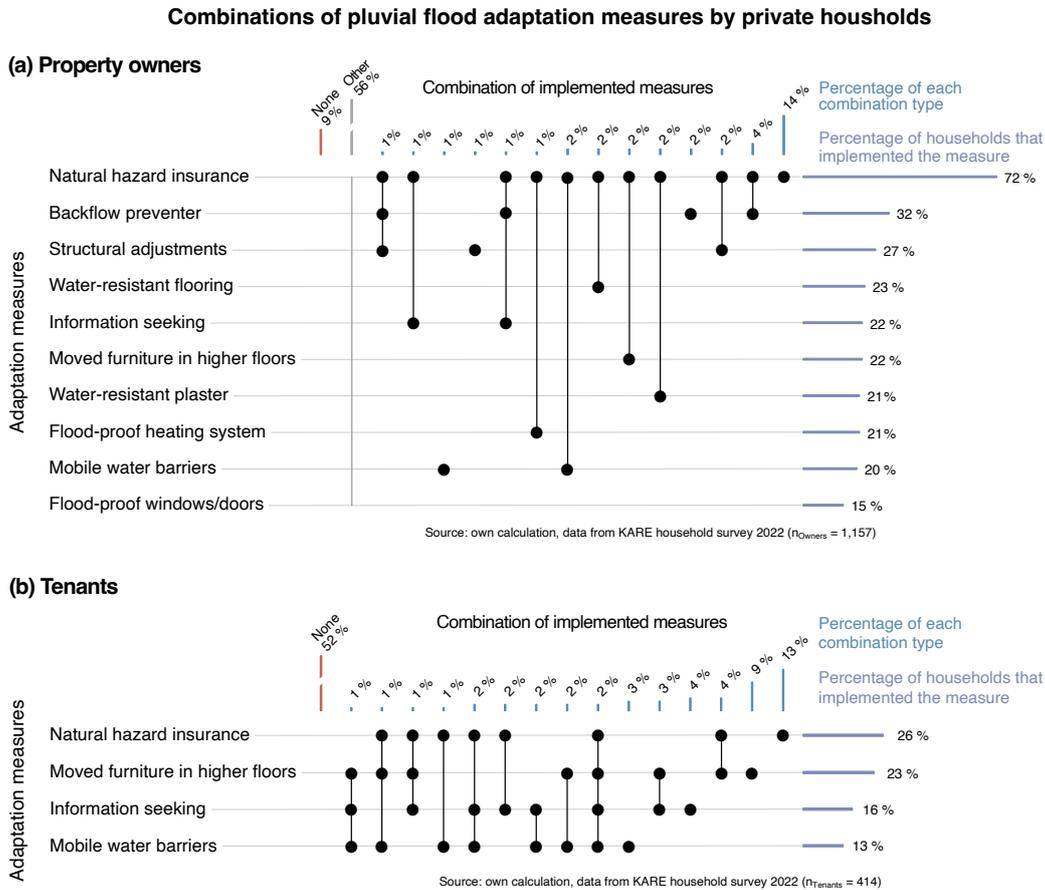
Figure 4. Implemented adaptation measures by a) property owners and b) tenants. Relative frequency for each measure displayed (purple horizontal bars), as well as how often this measure was solely implemented (single dot and blue vertical bars) or in combination with other measures (connected dots and blue vertical bars).

4.2 Adaptation actions of households in the Bavarian Oberland

Given the heterogeneous flood-specific capacity in the sample, the proportion of households that are already adapting is surpris-
215 ingly high. 80% of the respondents indicate that they have implemented at least one adaptation measure (Table 2). However, the
level of involvement differs based on property ownership, with owners demonstrating significantly higher activity compared
to tenants (91% owners vs. 48% tenants, $\chi^2 = 333.09$, p < 0.01). Figure 4 shows an overview of the implemented adaptation
measures by ownership status. The most popular measure for both owners and tenants is to take out natural hazard insurance
coverage for the building and/or contents (72% and 26%, respectively). Regarding structural measures, homeowners most fre-
220 quently reported the installation of a backflow preventer (32%) and structural adjustments to the driveway or garden (27%).
Taking out insurance and installing a backflow preventer also are reported by other studies as common measures (Rözer et al.,

2016; Dillenardt et al., 2022; Wamsler, 2016). High-cost measures, such as a flood-resistant heating system or flood-resistant windows and doors, are less prevalent but still implemented by approximately one in six property owners. Surprisingly, seeking information about flood protection was reported by only a fifth of the sample despite being a little effort and low-cost measure.

225 Similar to Rözer et al. (2016), our results hint that information is more frequently obtained by those households who already experienced a pluvial flooding event.

When examining the number and combination of implemented measures in more detail, it becomes evident that the depth and scope of adaptation efforts is still limited. The distribution of the number of private measures is right-skewed, with the majority of households implementing between zero and three measures. On average, owners implement 2.74 measures (median: 2),

230 whereas tenants undertake 0.78 measures (median: 0). However, some households report high implementation rates; 8.73% of owners indicate the implementation of six or more measures, while 6.52% of tenants report three or four measures.

Examining the combination of implemented measures reveals that a strategic, informed combination of complementary measures rarely takes place at the household level. Figure 4 displays which measures are combined. While taking out natural hazard insurance is the most prominent standalone measure, it is also regularly combined with other adaptive measures. For

235 example, homeowners combine it with structural measures such as the installation of a backflow preventer (4%) or structural adjustments (2%). This result may be partly explained by the fact that a backflow preventer is mandatory for some insurance policies. Moreover, the analysis reveals that structural measures are only on a case-by-case basis combined with each other (e.g. 1% combines insurance, backflow preventer and structural adjustments). For tenants, who have limited options to protect themselves, a common strategy involves adapting the use of flood-prone floors by permanently relocating valuable furniture

240 (9%). This approach is in many cases also combined with other measures, such as obtaining insurance (4%) or seeking information (3%). Seeking information is anyhow rarely pursued as a standalone measure; instead, it is typically undertaken in conjunction with other adaptation actions. Overall, it is noteworthy that the data does not reveal clear sets of measures, which are frequently implemented together. The low and dispersed frequencies suggest that households are not strategically combining complementary adaptation measures but rather decide on a case-by-case basis what to implement.

245 ### 4.3 Exploring the capacity-action relationship

4.3.1 Correlations analysis: Exploring the strength and direction of the association

Adaptive capacity indicators are weakly to moderately related to adaptive behaviour. The correlation heatmap in Fig. 5 illustrates the relationship for the full sample, as well as for the property owners' and tenants' subsamples. Weak to moderate linear associations exist in the full sample, most of them are in the expected directions. Generic capacities are positively correlated

250 with adaptation action and the number of implemented measures; suggesting that as generic capacity increases, adaptation also tends to increase. Property ownership shows the strongest association (r_φ =0.46 for adaptation yes/no, r_{pb} = 0.45 for no. of adaptation measures). Similarly, the specific capacity indicators are weak to moderately correlated with adaptation behaviour. Most indicators are positively associated; however, expectation in authorities, competing concerns and the attitude that public flood protection is sufficient show the expected negative relationship. The strongest associations exist between main respon-
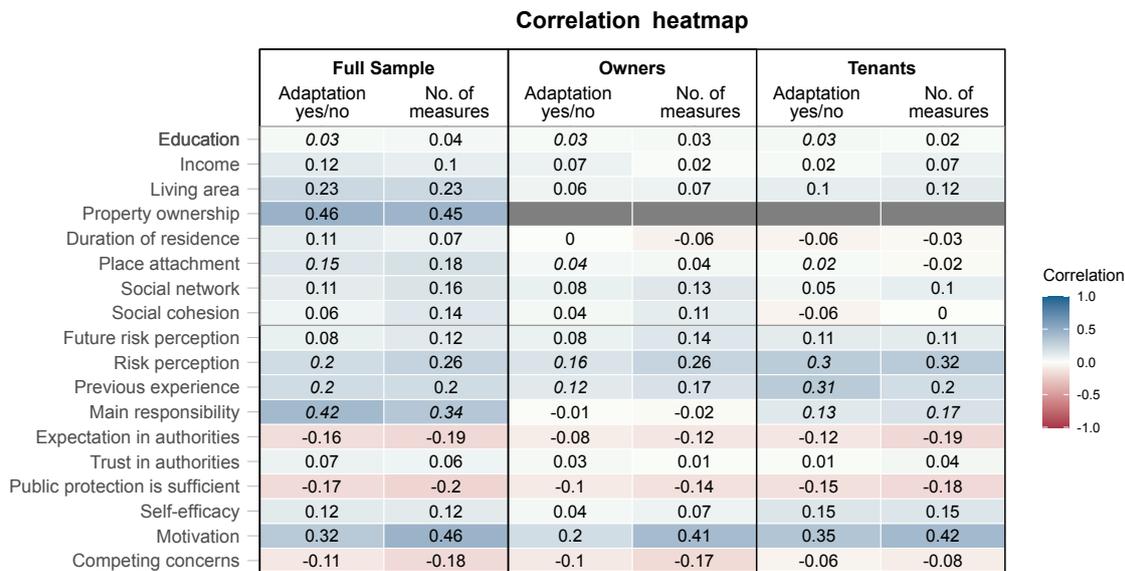
Figure 5. Correlation heatmap showing bivariate associations between adaptive capacity indicators and adaptation action. The appropriate measure of association is determined based on the level of measurement; displayed are Pearson correlation coefficients (r), Spearman rank correlation coefficients (r_s), point-biserial correlation coefficients (r_{pb}), phi coefficients (r_φ) and Cramer's V (φ_C). Colours indicate the strength and direction of the association: Blue indicates a positive relationship, while red indicates a negative relationship; darker colours denote stronger relationships. Cramer's V measures are italicised, as only the strength of association can be quantified (range: 0 to 1).

sibility and adaptation yes/no ($\varphi_C = 0.42$), and motivation to protect the household and number of implemented measures (r = 0.46). Overall, the results vary only slightly between the two dependent variables adaptation yes/no and number of implemented measures.

The analysis shows that bivariate correlations can lead to contradictory and misleading findings regarding the role of adaptive capacity for adaptation. When calculating the correlations for property owners and tenants separately, the positive association of the generic capacity indicators vanishes, leaving only effects which are negligible (all effect sizes < 0.15). The specific capacity associations remain unaltered, except for the main responsibility effect, which weakens in the tenants' subset and disappears in the owners' subset. It appears that the correlation between the generic capacity indicators and adaptation action is spurious. As outlined in Sect. 4.1, property owners tend to have a higher generic capacity and implement more measures than tenants. Therefore, the results for the full model do not represent a "pure" income or living area effect but are confounded by other factors, such as property ownership.

This highlights the importance of contextual factors when exploring the capacity-action relationship. Correlations provide evidence of relationships, however, this does not mean that the adaptive capacity indicators cause the adaptation action. This can only be evaluated with regression models, which control for contextual effects such as property ownership, sociodemographic characteristics (age, gender, migration background) and house characteristics (house type, age of the building).
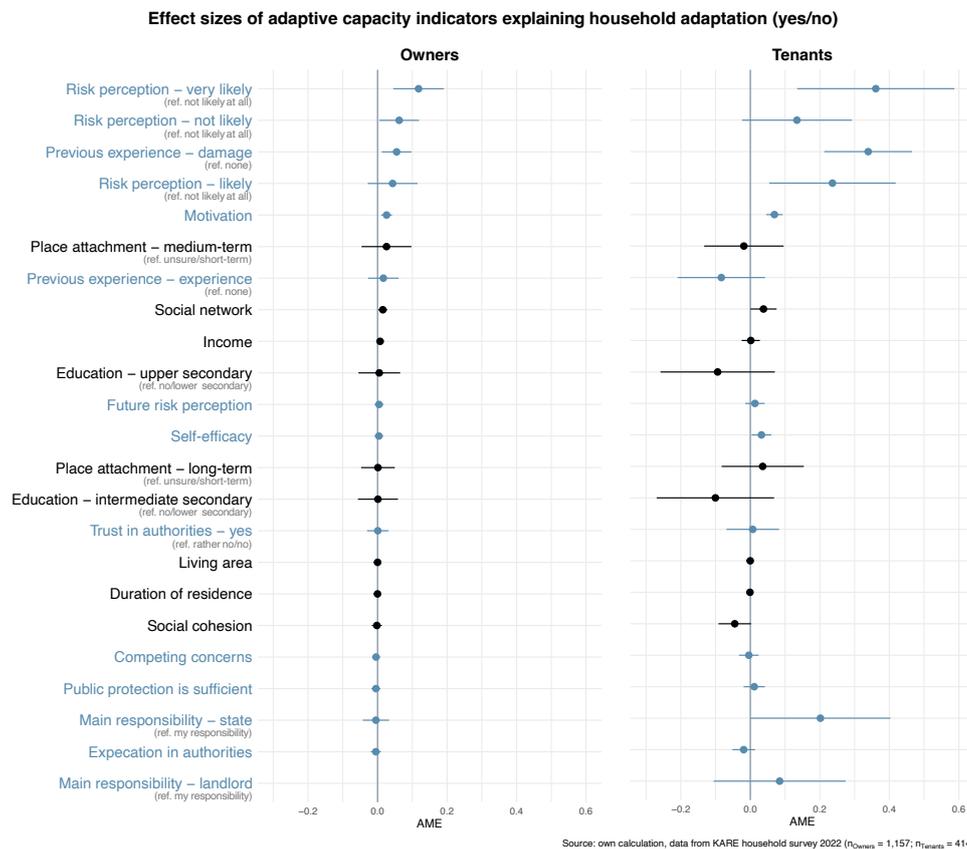
Figure 6. Forest plot summarising the results from the logistic regression explaining household pluvial flood adaptation (yes/no). Average marginal effects (AME) and 95% confidence intervals (CI) are depicted. Effects are sorted by effect size; generic capacity indicators are displayed in black, and specific capacity indicators in blue. The estimated coefficients of categorical predictors are relative to the reference group indicated in brackets. The grey vertical line represents the line of null effect; effects which do not cross this line are statistically significant at $\alpha = 5\%$.

4.3.2 Logistic Regression: Explaining Household Adaptation (yes/no)

The household adaptation decisions of property owners and tenants are mainly driven by specific capacity indicators. Detailed results for the logistic regression explaining whether households implemented at least one adaptation measure (adaptation yes/no) are presented graphically in Fig. 6 and in tabular form in Appendix B1 (Model 1 to 3). Effects with a p-value < 0.05 are considered as statistically significant in the following. In the owner model, only four of the seventeen adaptive capacity indicators have a statistically significant effect on adaptation. It appears that the owners' decision to implement at least one measure is primarily driven by specific capacity, as three of these four significant variables belong to this group. A higher risk perception as well as previous damage experience increase the probability of implementing at least one private flood risk

adaptation measure, ceteris paribus (c.p.). Similarly, the motivation to protect the own premises has a positive effect. Social network is the only generic capacity with a statistically significant effect. Accordingly, a one-unit better evaluation of the social network is associated with a 1.51 percentage points increase in the probability of adapting, c.p. However, this effect size is from a practical perspective rather small.

The results for tenants are similar. Six of the seventeen adaptive capacity indicators are statistically significant, most of which belong to the realm of specific capacity. The confidence intervals are wider compared to the owners' model due to the smaller sample size, and effect sizes are slightly larger. A higher risk perception, damage experience and motivation are again positively and statistically significantly associated with adaptation. Additionally, a higher self-efficacy significantly increases the likelihood of household adaptation for tenants. Holding the state for mainly responsibility for flood protection has a significant effect, likely due to the small size of the reference group. The only significant generic capacities refer to social capital, however, their effects are converse. While a larger social network increases the probability of implementing at least one measure, a stronger social cohesion decreases the adaptation likelihood ($p < 0.1$).

In summary, the logistic regression results underline the importance of specific adaptive capacity in household adaptation decisions. Generic capacity indicators, such as income and education, neither show a statistically nor practically significant effect. However, generic capacity may be more important when it comes to implementing multiple adaptation measures, as this potentially requires more money, time, and knowledge.

4.3.3 Poisson Regression: Explaining the number of implemented measures

The Poisson regression results demonstrate that specific adaptive capacity indicators translate into private flood risk adaptation action, while the role of generic capacity is much less clear. The effects are visualised in Fig. 7 and tabulated in Appendix B1 (Model 4 to 6). Risk perception, damage experience and motivation are important predictors for both property owners and tenants. Furthermore, ownership appraisal indicators substantially influence the number of implemented measures. Social network is the only generic adaptive capacity indicator which significantly positively affects adaptation for owners and tenants.

For property owners, four specific capacity indicators and four generic capacity indicators show a statistically significant effect (p-value < 0.05). Strong effect sizes are again found for a higher risk perception, previous damage experience and motivation. Additionally, a higher perceived probability of extreme weather events in the future (future risk expectation) significantly increases the number of measures. Regarding generic capacity, education has a strong positive effect on the number of implemented measures. Interestingly, the effect size is stronger for the medium-education group (0.54) than for the high-education group (0.36), c.p. Income is significantly negatively associated with the number of implemented measures. A 1000 € income increase is, on average, associated with 0.04 fewer measures, c.p. However, the effect size is quite small, which means that it is practically less relevant. The social capital indicators both positively impact owners' measurement implementation (social network $p < 0.05$, social cohesion $p < 0.1$). Conversely, the duration of residence negatively affects the number of adaptation measures implemented. Besides the statistical significance, the owners' model also contains some variables which might be substantially and socially significant due to comparatively large effect sizes (Bernardi et al., 2017). This mainly refers to the variables capturing responsibility appraisal. Viewing that state as mainly responsible for flood protection as well as high expec-

Figure 7. Forest plot summarising the results from the Poisson regression explaining the number of implemented pluvial flood adaptation measures. Average marginal effects (AME) and 95% confidence intervals (CI) are depicted. Effects are sorted by effect size; generic capacity indicators are displayed in black, and specific capacity indicators in blue. The estimated coefficients of categorical predictors are relative to the reference group indicated in brackets. The grey vertical line represents the line of null effect; effects which do not cross this line are statistically significant at $\alpha = 5\%$.

tations in authorities to provide flood protection decrease the number of implemented measures considerably. Yet, a high trust in the municipal administration to provide effective pluvial flood protection increases the implementation of own measures (p < 0.1).

315   For tenants, only four specific capacity indicators are statistically significant (p < 0.05). Previous damage experience, a high risk perception and motivation have a strong positive influence on measurement implementation. Additionally, responsibility appraisal shapes adaptation decisions of tenants. A high expectation in authorities reduces the number of implemented measures. Due to a small reference group, results for the main responsibility variable cannot be interpreted in the tenants' model. However, the full model (Model 4) in Appendix B1 indicates a strong landlord effect. Respondents who consider their landlord

320   as mainly responsible implement, on average, 0.61 fewer measures than respondents who consider themselves as responsible,

c.p. None of the generic capacity indicators is significant at the 5% level; however, social network is significant with p < 0.1. In contrast to the owners' results, education has a negative and income a positive effect on measurement implementation for tenants. However, the effects are not significant and the confidence interval (CI) for education is rather wide, indicating a greater amount of uncertainty.

325   We estimated additional models to test the robustness of the income effect and found tentative evidence that income groups may differ in their adaptation behaviour. Robustness checks for the income effect were necessary, as household net income was originally collected as binned data, but bin midpoints were used in the models to approximate income (see also Tab. 2, Note). Research has proven that this method works well for mid-income classes (Stauder and Hüning, 2004); however, there are deviations in the tails due to small numbers of observations and broader bins. To compress the range of higher incomes and make

330   the distribution more symmetric, the income variable was log-transformed. Additionally, we account for differences between income groups (low < 1300 € equalised disposable net income, middle between 1300 € and 4000 €, and high > 4000 €). Our results are robust as these adjustments do not alter the findings; the income effect remains non-significant with an effect sizes close to zero (see Appendix B3, Model 1 to 6). Yet, the income group effects signalise that the income effect might vary between different income groups. The effect sizes are insignificant but substantial in the Poisson models. Having an equalised

335   disposable net income below 1300 € is associated with fewer implemented measures compared to the middle-income group (Appendix B3, Model 3 to 6). The rich effect is not consistent across models, but it is negative in the full sample and owners' subsample. Compared with the middle-income group, having an equalised disposable net income is, on average, associated with a decrease of 0.2 implemented measures, c.p. (Appendix B3, Model 4 & 5). These findings indicate that income per se is not a decisive factor in adaptation decisions, but that income groups potentially differ in how they translate their financial

340   assets into adaptation actions.

5   Discussion

5.1   Unravelling the capacity-action gap

The results of our case study provide evidence for a "capacity-action gap" in the German context, as high levels of adaptive capacity do not necessarily translate into household adaptation action. We demonstrate that disaggregating adaptive capac-

345   ity into generic and threat-specific components enhances our understanding of the divergence between adaptive capacity and adaptation action, thereby unravelling the capacity-action gap. In our study context, specific capacity clearly drives adaptation behaviour of households, whereas the role of generic capacity is much less clear. Generic capacity indicators, which are typically highlighted in the scientific literature and policy documents (Andrijevic et al., 2023), are limited in their ability to infer and explain household adaptation. In the following, we illustrate this capacity-action gap and outline the role of generic and

350   specific adaptive capacity indicators in more detail. Additionally, we discuss two possible explanations for the capacity-action gap: the "safe development paradox" (Eakin et al., 2014) and the often implicitly assumed, but potentially misleading 'the more, the better' understanding of adaptive capacity.

Despite a high exposure to heavy precipitation events and above-average generic capacity, our analysis reveals that household

adaptation remains small in scale and unconsolidated. The share of households which already engage in adaptation action is
surprisingly high with 80%; however, property owners are considerably more active than tenants (91% and 48%, respectively).
Yet, the most popular measure is taking out natural hazard insurance, which does not reduce the risk per se but only shifts
financial losses to another party. This finding is in line with other research on pluvial flood risk adaptation in the German con-
text (Rözer et al., 2016; Dillenardt et al., 2022). Additionally, households mostly do not follow a strategic, informed approach
in combining private flood risk measures. On average, Oberland households implement two measures; however, households
are not well-informed about complementary measures and decide on a case-by-case basis. For Europe, the IPPC states that
"although adaptation is happening [. . .], it is not implemented at the scale, depth and speed needed to avoid the risks" (Bednar-
Friedl et al., 2022, p. 1820); this is also true for the Oberland region.

Our analysis shows generic indicators are not the primary drivers for implementing private measures; thus, characterising
households as able to adapt solely based on high levels of generic capacity is misleading. In our models, only two generic indi-
cators substantially affect adaptation decision-making. Owning a property as well as having a larger social network makes flood
risk adaptation more likely; both effects are also well documented in the adaptation literature (for ownership, see Grothmann
and Reusswig 2006, Kuhlicke et al. 2020, Dillenardt et al. 2022; for social network, see, for example, Adger 2003, Pelling and
High 2005, Barnes et al. 2020). The finding that neither wealth nor income are drivers of adaptation action at the household
level is consistent with studies on household flood adaptation in Germany (Grothmann and Reusswig 2006, Dillenardt et al.
2022). Our results also provide some tentative evidence for a nonlinear relationship between generic capacity and adaptation
action. For example, we found that for property owners higher levels of education are associated with more implemented adap-
tation measures. Notably, the positive effect is stronger for the intermediate education group than for the high education group.
A similar, albeit nonsignificant effect was discovered for income groups, where the middle-income group is, on average, more
likely to implement measure than both the low- and high-income group.

By contrast, specific capacity indicators are important predictors of household adaptation and could potentially be an important
leverage point to increase private adaptation efforts. Risk perception, previous damage experience and motivation are important
predictors for both property owners and tenants, as well as for two different adaptation outcomes (adaptation yes/no and num-
ber of implemented measures). The importance of these factors has also been demonstrated in recent meta-analyses (Bamberg
et al., 2017; van Valkengoed and Steg, 2019) and various flood-related studies (e.g. Grothmann and Reusswig, 2006; Bubeck
et al., 2023; Dillenardt and Thieken, 2024). Unlike generic capacity, specific capacity "can potentially be altered within the
short to medium term, and the power to do so lies at least partially with local policy makers and private persons" (Werg et al.,
2013, 1614). Municipalities could therefore play a key role in enhancing the specific capacity and thus private adaptation, as
adaptive capacity at the local level is always shaped by interactions between individual characteristics and the institutional
context (Eakin et al., 2014). This is also supported by our as well as Bamberg et al.'s (2017) finding that trust in public flood
protection promotes adaptation measures at the household level. Yet, empirical research on German municipalities reveals that
they rarely engage with their citizens, for example, to inform them about flood-risk areas or appropriate protective measures
(Wamsler, 2016; Werg et al., 2021; von Streit et al., 2024). At the same time, it is questionable to what extent municipalities
can currently fulfil this task, especially given the limited resources and adaptive capacity many small- and medium-sized mu-

nicipalities possess (Buschmann et al., 2022; Fila et al., 2024). Understanding how adaptive capacity and adaptation action

390 of households and municipalities interact is thus central to enhancing adaptive capacity and promoting adaptation efforts at the local level. More research in this area is needed as adaptive capacity transfers are still scientifically poorly understood (Elrick-Barr et al., 2023).

5.2 Methodological limitations

Despite being consistent with previous findings, our methodological approach is not without limitations. Low response rates are

395 a major concern in survey research and might have also affected our results. Even though a low response rate does not directly imply low validity, it greatly increases the risk of bias due to nonresponse. Our study suffers from nonresponse patterns, which are similar to those reported in other flood-related studies (Poussin et al., 2015; Spekkers et al., 2017; Dillenardt and Thieken, 2024). Due to the rather small sample size, our findings for tenants are characterised by greater uncertainty in the estimates. Our additive, unweighted approach to measuring the number of implemented measures might be disputable, but

400 provides an important first step towards moving beyond the currently dominant dichotomous yes-no-measurement of adaptation (see, for example, Barnes et al., 2020; Dillenardt et al., 2022; Bartelet et al., 2023). Finally, adaptive capacity as well as adaptation actions are not only determined by micro-level variables but also by the institutional context. A more detailed analysis, including macro-level effects, is required but has been hindered due to the unavailability of municipal-level adaptation data.

405 5.3 Explaining the capacity-action gap

The "safe development paradox" proposed by Eakin et al. (2014) aids in determining the transferability of these findings and provides an explanation for the capacity-action gap. Accordingly, a "safe development paradox" occurs in societies with high generic and low specific capacity, where institutional contexts such as public risk management and safety nets decrease incentives for private adaptation (Eakin et al., 2014). Overall, this explanation fits well with our study region with high generic,

410 low specific adaptive capacity and a strong institutional context. Yet, two arguments speak against it. Firstly, our results show that trust in the municipal administration to provide effective flood protection significantly increases private adaptation action. This indicates that public protection does not create a moral hazard but rather motivates households to become active. Secondly, and more importantly, similar findings regarding generic capacity have been reported for both affluent (e.g., Mortreux et al. 2020 for Australian households in the context of wildfire risks) and less affluent contexts (e.g . the meta-analysis of Green et al.

415 2021 on small-scale fishing communities and Mesfin et al. 2020 for a rural Ethiopian region). Nevertheless, we agree with Mesfin et al. (2020, p. 18) that "care must be taken not to underestimate the role of assets as they present the sine qua non of adaptive capacity."

A diminishing marginal utility might offer a second explanation for the missing link between generic capacity and adaptation action. In our models, the middle-education and the middle income groups are most likely to implement multiple measures.

420 Even though not statistically significant, it seems that the high-earning 10% of our respondents might be even less likely to implement private measures than the low-earning 15%. This indicates a nonlinear relationship and challenges the often

inherently assumed 'the more, the better' assumption in the adaptive capacity literature. It is often presumed that as the socio-economic conditions improve, people are less vulnerable and better able to cope with disasters (see, for example, Kuhlicke et al., 2011, p. 809). However, our analysis and existing research (Eriksen et al., 2020) hint that this is not necessarily the case.

Instead of claiming that generic capacity is irrelevant, we suggest that their role in explaining the uptake of adaptation measures is more complicated than previously hypothesised.

The ongoing fixation on material capacity in vulnerability assessments and the assumed linear relationship between material affluence and derived social vulnerability has also been problematized by Eriksen et al. (2020). Generic capacity seems to be a necessary, but not a sufficient condition for adaptation (Eakin et al., 2014, p. 5), which means that affluence alone will not suffice to cope with climate risks.

6 Conclusions

Against the backdrop of increasing climate risks and the debate on a privatisation of risk, strengthening the adaptive capacity of citizens and households is crucial. Yet, the concept's usefulness is currently limited, as it is neither clear what exactly constitutes adaptive capacity nor whether capacity translates into adaptation action. Our case study on pluvial flooding in Germany confirms a gap between adaptive capacity and adaptation behaviour of households. We additionally demonstrate that disaggregating the adaptive capacity into generic and specific components helps unravel the underlying mechanisms of this capacity-action gap. In our study context, adaptation decisions of households are mainly driven by specific capacity. The role of generic capacity is less clear; however, we offer some initial evidence for a nonlinear relationship. The marginal utility of generic capacity such as income and education diminishes, which means that a stock of generic capacity is needed for adaptation but does not yield any benefits after a certain threshold is reached. Strengthening generic capacity is thus more important for underprivileged groups, while increasing specific capacity can benefit all societal groups. To develop a deeper understanding of this nonlinear effects, additional studies should be undertaken.

Taken together, these findings have implications for both the scientific assessment and the practical enhancement of adaptive capacity. Regarding the assessment of household adaptive capacity, a stronger emphasis on specific capacity is urgently needed. The adaptive capacity framework, proposed by Cinner et al. (2018), provides an important step in that direction. Yet, considering specific capacity is often a challenge due to data constraints. For specific capacity to be included in large-scale population surveys, a reduction of indicators is indispensable. More case studies as well as a better integration of meta-analysis on psychosocial factors motivating household adaptive behaviour (Bamberg et al., 2017; van Valkengoed and Steg, 2019) could assist in identifying a set of relevant household adaptive capacity indicators across spatial and cultural contexts. Additionally, greater focus should be placed on enhancing the specific capacity of households, as this can be an effective way to promote household adaptation. Thus, collaborations between households and municipalities in flood risk management, which foster knowledge exchange about risks and establish a clear distribution of responsibilities for adaptation, could be central to promoting adaptation at the local level.

Code and data availability. The data required to reproduce the above findings cannot be shared as the data contains information that could
455 compromise research participant privacy and consent. The data analysis scripts of this article are available as R scripts and interactive
Rmarkdown notebook at https://doi.org/10.17605/osf.io/8fygh.

Appendix A: Comparison of socio-demographic sample characteristics and microcensus data for the Oberland region

Appendix B: Regression tables

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460 - Original Draft, Writing - Review & Editing, Visualization. **Anne von Streit**: Conceptualization, Investigation, Writing - Original Draft,
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Draft, Writing - Review & Editing, Supervision, Funding acquisition. All authors have read and agreed to the published version of the paper.

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Table 1. Conceptualisation of households' adaptive capacity to pluvial flooding

Indicator	Operational definition	Key references
a) Generic adaptive capacity		
Education	Highest level of education completed by the primary decision-maker in the household	Grothmann and Patt, 2005; Mortreux and Barnett, 2017; Whitney et al., 2017; Cinner et al., 2018; Barnes et al., 2020; Mortreux et al., 2020
Financial resources	Approximate net household income	Grothmann and Patt, 2005; Lockwood et al., 2015; Mortreux and Barnett, 2017; Cinner et al., 2018; Mortreux et al., 2020; Green et al., 2021
Wealth	Living area in m^2	Mortreux et al., 2020; Barnes et al., 2020
Property ownership	Ownership of the residential property	Grothmann and Patt, 2005; Mortreux et al., 2020
Duration of residence	Years of residency in the property	Whitney et al., 2017; Cinner et al., 2018; Mortreux et al., 2020
Place attachment	Planned duration of residence in the property	Mortreux and Barnett, 2017; Whitney et al., 2017; Cinner et al., 2018
Social network	Subjective assessment of the number of friends and acquaintances in the area	Whitney et al., 2017; Cinner et al., 2018; Barnes et al., 2020; Mortreux et al., 2020; Green et al., 2021
Social cohesion	Feeling of belonging to the community	Cinner et al., 2018
b) Flood-specific adaptive capacity		
Future risk perception	Subjective likelihood of an increase in extreme weather events at the place of residence in the next decades	Whitney et al., 2017; Barnes et al., 2020
(Flood) Risk perception	Subjective probability of experiencing a financial damage from pluvial flooding on the premises in the next five years	Mortreux and Barnett, 2017; Whitney et al., 2017; Mortreux et al., 2020; Green et al., 2021
Previous (flood) experience	Experience with pluvial flood events on the premises and possibly resulting financial damage	Mortreux and Barnett, 2017; Mortreux et al., 2020; Barnes et al., 2020
Main responsibility	Perception of whether it is the responsibility of oneself, the landlord, or the state to protect the house from damage caused by pluvial flooding	Mortreux and Barnett, 2017; Mortreux et al., 2020
Expectation in authorities	Dismissive attitude towards private measures, as state is seen as responsible for flood protection	Mortreux and Barnett, 2017; Mortreux et al., 2020
Trust in authorities	Trust in municipal administration to provide effective pluvial flood protection	Lockwood et al., 2015; Mortreux and Barnett, 2017; Barnes et al., 2020
Public protection is sufficient	Assessment of whether public flood risk management is sufficiently effective, obviating the need for private measures	Mortreux and Barnett, 2017
Self-efficacy	Perceived ability to protect household from flood damage	Mortreux and Barnett, 2017; Cinner et al., 2018
Motivation	Evaluation of engagement with pluvial flood protection options	Cinner et al., 2018
Competing concerns	Assessment of whether other concerns take precedence over pluvial flooding	Mortreux and Barnett, 2017

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Table 2. Summary Statistics

Variable	Median	Mean	SD	Min	Max	% Missing
Adaptive capacity						
a) Generic capacities						
Education	3 – upper secondary	–	–	1 – no/lower secondary	3 – upper secondary	2.61%
Income	3500 – 4000 €	4209.12 €	2484.91 €	1 – < 1000 €	14 – >9.500 €	13.24%
Living Area	130 m²	140.47 m²	70.32 m²	25 m²	600 m²	3.95%
Property ownership	–	0.74	0.44	0 – no	1 – yes	0%
Duration of residence	31	33.35	20.72	0	93	1.21%
Planned duration of residence	3 – long-term	–	–	1 – unsure/short-term	3 - long-term	0.76%
Large social network	5	4.49	1.41	1 – strongly disagree	6 – strongly agree	1.72%
Sense of belonging	5	4.62	1.33	1 – strongly disagree	6 – strongly agree	2.29%
b) Flooding-specific capacities						
Increase in extreme weather events	5	4.78	1.31	1 – very unlikely	6 – very likely	0.89%
Perceived flood probability	2 – rather unlikely	–	–	1 - not likely at all	4 – very likely	0.19%
Previous flooding experience	1 – no	–	–	1 – none	3 – yes, fin. damage	0%
Main responsibility	2 – landlord	–	–	1 – mine	3 – state	2.80%
Expectation in authorities	2	2.14	1.33	1 – strongly disagree	6 – strongly agree	4.71%
Trust in authorities	–	0.49	0.5	0 – no/rather no	1 – yes/rather yes	2.99%
Public Protection is sufficient	3	3.18	1.51	1 – strongly disagree	6 – strongly agree	2.61%
Self-efficacy	3	3.56	1.73	1 – strongly disagree	6 – strongly agree	3.56%
Motivation	3	3.03	1.66	1 – strongly disagree	6 – strongly agree	1.78%
Competing concerns	3	3.26	1.75	1 – strongly disagree	6 – strongly agree	5.41%
Adaptive behaviour						
Implementation of min. one measure	–	0.8	0.4	0	1	0%
Number of implemented measures	2	2.22	1.93	0	10	0%
N		1,571				

Note: Based on the assumption of equidistance of the response categories, 6-point Likert scales with endpoint labels were treated as quasi-metric in the analyses. To reduce nonresponse, income was measured as binned data in the questionnaire. For the analyses, we decided to approximate it by the bin midpoints. Even when including it as categorical variable, we would still assume that "there is no income effect [...] within the income interval that happens to have been fixed arbitrarily by the survey design, but there can be income effects across income intervals" (Lee and Bhattacharya, 2019). Stauder and Hüning (2004) demonstrated with the German microcensus that especially mid-income classes, which contain the majority of observations, are well represented by the midpoints, and that the approximation is good for bins with small widths. A robust harmonic Pareto midpoint estimator (RPME) (von Hippel et al., 2016) was used to calculate the missing midpoint for the upper bins (single households: bin 14: > 7500 €, multi-person households: bin 11: > 9500 €). We additionally conducted robustness checks to make sure that our results are not driven by this approximation.

Source: own calculations, based on data from the KARE Household survey 2022.

Table A1. Comparison of socio-demographic sample characteristics and microcensus data for the Oberland region

Socio-demographic charateristic	Microcensus 2022	KARE household survey 2022
Age		
25 to 44 year-olds	28.21%	15.11%
45 to 64 years	33.85%	46.90%
over 64 year-olds	26.92%	36.89%
Gender		
male	48.46%	58.71%
female	51.54%	41.29%
Level of Education		
lower secondary	31.28%	11.63%
intermediate secondary	26.67%	29.28%
upper secondary	36.15%	59.08%
Migration		
foreigners[a]	11,43%	1.98%
Net household income of private households		
below 1500 €	16.60%	6.09%
1500 up to 4000 €	55.32%	51.21%
4000 € and above	28.51%	42.70%
N	390.000[b]	1,571

Notes: [a] Data from the 2019 microcensus as the number of foreign nationals is no longer provided at the regional level from 2020 onwards.
[b] We excluded data from respondents younger than 15 from the microcensus calculations as the youngest respondent in our survey was 19 years old.

Source: own calculations, based on data from the KARE household survey 2022, regional data from the 2019 microcensus (Bayerisches Landesamt für Statistik, 2021) and unpublished data from the 2022 microcensus (provided by the Bavarian State Statistical Office based on a data request from the authors).

Table B1. Effects of adaptive capacity indicators on adaptation action (regression results)

	Adaptation (yes/no)			*Number of implemented measures*		
	Logistic regressions			*Poisson regressions*		
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
	Full sample	Owners	Tenants	Full sample	Owners	Tenants
	AME	AME	AME	AME	AME	AME
	(SE)	(SE)	(SE)	(SE)	(SE)	(SE)
Generic capacity						
Education *(ref. no/lower secondary)*						
intermediate secondary	-0.0234	0.0010	-0.1004	0.3863***	0.5399***	-0.1293
	(0.0287)	(0.0294)	(0.0861)	(0.1292)	(0.1702)	(0.1782)
upper secondary	-0.0172	0.0049	-0.0940	0.2646**	0.3601**	-0.1026
	(0.0303)	(0.0306)	(0.0839)	(0.1168)	(0.1495)	(0.1643)
Income (in 1000 €)	0.0055	0.0073	0.0014	-0.0305*	-0.0425**	0.0345
	(0.0053)	(0.0055)	(0.0134)	(0.0163)	(0.0209)	(0.0232)
Living area	0.0001	0.0001	-0.0002	0.0005	0.0005	-0.0001
	(0.0002)	(0.0002)	(0.0008)	(0.0005)	(0.0006)	(0.0010)
Property ownership *(ref. tenant)*						
owner	0.2417***			1.4551***		
	(0.0461)			(0.1320)		
Duration of residence	-0.0002	-0.0001	-0.0009	-0.0058***	-0.0075***	0.0000
	(0.0006)	(0.0006)	(0.0012)	(0.0022)	(0.0028)	(0.0023)
Planned duration of residence *(ref. unsure/short-term)*						
medium-term	0.0056	0.0257	-0.0185	0.1780	0.3083	0.0530
	(0.0262)	(0.0366)	(0.0583)	(0.1641)	(0.2310)	(0.1022)
long-term	0.0110	0.0011	0.0356	0.0392	0.0752	0.1209
	(0.0263)	(0.0247)	(0.0603)	(0.1326)	(0.1703)	(0.1262)
Social network	0.0196**	0.0151**	0.0379**	0.1007**	0.1106**	0.0703*
	(0.0080)	(0.0066)	(0.0192)	(0.0437)	(0.0541)	(0.0392)
Social cohesion	-0.0144*	-0.0021	-0.0446*	0.0479	0.0854*	-0.0622
	(0.0082)	(0.0074)	(0.0239)	(0.0362)	(0.0483)	(0.0405)
Specific capacity						
Future risk perception	0.0059	0.0042	0.0133	0.0793***	0.1032***	0.0030
	(0.0065)	(0.0064)	(0.0142)	(0.0293)	(0.0383)	(0.0344)
Risk perception *(ref. not likely at all)*						
rather unlikely	0.0886***	0.0622**	0.1341*	0.5763***	0.6534***	0.3315**
	(0.0314)	(0.0292)	(0.0805)	(0.1125)	(0.1424)	(0.1405)
rather likely	0.1055**	0.0433	0.2363**	0.6105***	0.6492***	0.4358***
	(0.0428)	(0.0365)	(0.0928)	(0.1306)	(0.1584)	(0.1576)
very likely	0.1735***	0.1180***	0.3610***	0.7027***	0.8122***	0.4269**
	(0.0433)	(0.0372)	(0.1154)	(0.1551)	(0.1924)	(0.1740)

Table B2 (continued). Effects of adaptive capacity indicators on adaptation action (regression results)

	Adaptation (yes/no)			*Number of implemented measures*		
	Logistic regressions			*Poisson regressions*		
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
	Full sample	Owners	Tenants	Full sample	Owners	Tenants
	AME (SE)	AME (SE)	AME (SE)	AME (SE)	AME (SE)	AME (SE)
Previous experience *(ref. no)*						
damage	0.1152*** (0.0231)	0.0549** (0.0218)	0.3391*** (0.0644)	0.5137*** (0.1054)	0.5221*** (0.1351)	0.7121*** (0.2022)
experience	-0.0092 (0.0266)	0.0166 (0.0224)	-0.0834 (0.0642)	0.0866 (0.1015)	0.1024 (0.1422)	0.0736 (0.1218)
Main responsibility *(ref. my responsibility)*						
landlord	-0.0415 (0.0417)		0.0844 (0.0969)	-0.6126*** (0.1947)		-0.1171 (0.2434)
state	0.0062 (0.0236)	-0.0048 (0.0193)	0.2016** (0.1027)	-0.1229 (0.0867)	-0.1614 (0.1055)	0.1130 (0.2551)
Expectation in authorities	-0.0102 (0.0073)	-0.0050 (0.0075)	-0.0191 (0.0166)	-0.0810** (0.0369)	-0.0721 (0.0470)	-0.0785** (0.0375)
Trust in authorities *(ref. rather no/no)*						
rather yes/yes	0.0014 (0.0139)	0.0007 (0.0157)	0.0070 (0.0386)	0.1301* (0.0744)	0.1817* (0.0989)	0.0135 (0.1061)
Public protection is sufficient	-0.0018 (0.0064)	-0.0047 (0.0067)	0.0114 (0.0156)	-0.0126 (0.0256)	-0.0146 (0.0323)	0.0106 (0.0323)
Self-efficacy	0.0110** (0.0053)	0.0038 (0.0062)	0.0321** (0.0144)	0.0236 (0.0254)	0.0123 (0.0364)	0.0389 (0.0305)
Motivation	0.0378*** (0.0066)	0.0260*** (0.0079)	0.0694*** (0.0121)	0.2960*** (0.0296)	0.3451*** (0.0394)	0.1510*** (0.0232)
Competing concerns	-0.0040 (0.0059)	-0.0044 (0.0058)	-0.0042 (0.0144)	-0.0292 (0.0263)	-0.0454 (0.0334)	-0.0280 (0.0284)
Household characteristics						
Gender of the primary decision maker *(ref. male)*						
female	0.0035 (0.0205)	0.0152 (0.0205)	-0.0213 (0.0464)	-0.1173 (0.0850)	-0.1406 (0.1109)	-0.0380 (0.0922)
Age of the primary decision maker	0.0001 (0.0008)	0.0010 (0.0007)	-0.0019 (0.0016)	0.0005 (0.0033)	0.0003 (0.0043)	-0.0034 (0.0031)

Table B2 (continued). Effects of adaptive capacity indicators on adaptation action (regression results)

	Adaptation (yes/no)			*Number of implemented measures*		
	Logistic regressions			*Poisson regressions*		
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
	Full sample	Owners	Tenants	Full sample	Owners	Tenants
	AME	AME	AME	AME	AME	AME
	(SE)	(SE)	(SE)	(SE)	(SE)	(SE)
Migrant background of the primary decision maker *(ref. no)*						
migrant background	0.0316	0.0348	0.0342	0.4242	0.7144	-0.1489
	(0.0521)	(0.0578)	(0.1249)	(0.3058)	(0.4747)	(0.1622)
Household size	0.0051	0.0082	-0.0021	0.0432	0.0464	-0.0213
	(0.0089)	(0.0098)	(0.0227)	(0.0379)	(0.0512)	(0.0395)
House characteristics						
Housing type *(ref. single family home)*						
duplexe/terraced house	-0.0217	-0.0187	-0.0107	-0.2273***	-0.3139***	0.1248
	(0.0225)	(0.0199)	(0.0875)	(0.0821)	(0.1020)	(0.1232)
apartment building	-0.0391	-0.0212	-0.0847	-0.0923	-0.1026	0.0426
	(0.0240)	(0.0207)	(0.0799)	(0.0998)	(0.1334)	(0.1056)
Year of construction	0.0001	-0.0002	0.0009	-0.0034***	-0.0049***	0.0006
	(0.0003)	(0.0003)	(0.0007)	(0.0011)	(0.0015)	(0.0014)
Survey design						
Mode *(ref. CAWI)*						
CATI	0.0471**	0.0362*	0.0910	0.3703***	0.4490***	0.2576
	(0.0197)	(0.0190)	(0.0616)	(0.1033)	(0.1324)	(0.1604)
unsure	-0.0350	0.0021	-0.1229**	0.0420	0.1280	-0.1303
	(0.0343)	(0.0372)	(0.0575)	(0.1480)	(0.1722)	(0.1096)
N	1,571	1,157	414	1,571	1,157	414
Nagelkerke-R^2	0.4166	0.1664	0.3427	0.5198	0.2836	0.3313
BIC	1,358.97	850.94	649.35	5,448.09	4,508.57	1,057.31

Notes: Entries are pooled AME from a binary logistic regression (Model 1-3) and a poisson regression (Model 4-6) with cluster-robust standard errors at the household level. Multiple imputation with a Markov chain Monte Carlo (MCMC) algorithm was performed to account for missingness in the predictors (m = 30). The impact of missing data on parameter estimations in a particular model of interest was captured with the fraction of information missing due to nonresponse (FMI) and the proportion of the variation attributable to the missing data (λ) (van Buuren, 2018, p. 46). The severity of the missing data problem in our regression models can be classified as moderate to moderately large (FMI = 0.23 for income (Model 2) and FMI = 0.23 for year of house construction (Model 3 & 6), FMI $\leq$ 0.2 for all remaining coefficients). However, the presented results are not highly dependent on the handling of missing data ($\lambda \leq 0.23$ for all coefficients).

Statistical significance level: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Source: own calculation, based on data from the KARE household survey 2022.

Table B3. Effects of adaptive capacity indicators on adaptation action (regression results for detailed income analysis)

	Adaptation (yes/no) Logistic regressions			Number of implemented measures Poisson regressions		
	Model 1 Full sample AME (SE)	**Model 2** Owners AME (SE)	**Model 3** Tenants AME (SE)	**Model 4** Full sample AME (SE)	**Model 5** Owners AME (SE)	**Model 6** Tenants AME (SE)
Generic capacity						
Education *(ref. no/lower secondary)*						
intermediate secondary	-0.0230 (0.0287)	-0.0017 (0.0295)	-0.0919 (0.0874)	0.3916*** (0.1289)	0.5488*** (0.1704)	-0.1163 (0.1818)
upper secondary	-0.0167 (0.0308)	0.0030 (0.0308)	-0.0898 (0.0839)	0.2788** (0.1191)	0.3821** (0.1518)	-0.0848 (0.1638)
Income (in log €)	-0.0056 (0.0313)	0.0112 (0.0310)	-0.0536 (0.0752)	-0.0991 (0.1297)	-0.1505 (0.1684)	0.0067 (0.1436)
Income group *(ref. middle)*						
low	-0.0405 (0.0412)	-0.0214 (0.0460)	-0.0772 (0.0710)	-0.0884 (0.1725)	-0.0724 (0.2286)	-0.1583 (0.1490)
rich	0.0248 (0.0359)	0.0183 (0.0370)	0.0678 (0.0905)	-0.2045 (0.1464)	-0.2337 (0.1944)	0.0789 (0.2205)
Living area	0.0001 (0.0002)	0.0001 (0.0002)	-0.0002 (0.0008)	0.0005 (0.0005)	0.0005 (0.0007)	0.0000 (0.0009)
Property ownership *(ref. tenant)*						
owner	0.2434*** (0.0466)			1.4550*** (0.1324)		
Duration of residence	-0.0002 (0.0006)	-0.0001 (0.0006)	-0.0009 (0.0013)	-0.0059*** (0.0022)	-0.0076*** (0.0028)	-0.0004 (0.0024)
Planned duration of residence *(ref. unsure/short-term)*						
medium-term	0.0053 (0.0260)	0.0277 (0.0370)	-0.0172 (0.0585)	0.1708 (0.1645)	0.2981 (0.2317)	0.0480 (0.0983)
long-term	0.0103 (0.0264)	0.0009 (0.0246)	0.0372 (0.0601)	0.0413 (0.1340)	0.0762 (0.1716)	0.1217 (0.1259)
Social network	0.0191** (0.0079)	0.0153** (0.0066)	0.0361* (0.0186)	0.1031** (0.0446)	0.1152** (0.0553)	0.0648* (0.0392)
Social cohesion	-0.0145* (0.0081)	-0.0026 (0.0075)	-0.0446* (0.0235)	0.0467 (0.0362)	0.0832* (0.0480)	-0.0545 (0.0401)
Specific capacity						
Future risk perception	0.0057 (0.0065)	0.0042 (0.0064)	0.0123 (0.0146)	0.0791*** (0.0290)	0.1027*** (0.0381)	0.0047 (0.0349)

Table B3 (continued). Effects of adaptive capacity indicators on adaptation action (regression results for detailed income analysis)

	Adaptation (yes/no)			Number of implemented measures		
	Logistic regressions			Poisson regressions		
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
	Full sample	Owners	Tenants	Full sample	Owners	Tenants
	AME	AME	AME	AME	AME	AME
	(SE)	(SE)	(SE)	(SE)	(SE)	(SE)
Risk perception *(ref. not likely at all)*						
rather unlikely	0.0874***	0.0604**	0.1339*	0.5840***	0.6614***	0.3330**
	(0.0314)	(0.0288)	(0.0789)	(0.1124)	(0.1423)	(0.1388)
rather likely	0.1042**	0.0405	0.2351**	0.6160***	0.6558***	0.4499***
	(0.0428)	(0.0363)	(0.0941)	(0.1305)	(0.1582)	(0.1608)
very likely	0.1709***	0.1149***	0.3563***	0.6982***	0.8061***	0.4293**
	(0.0431)	(0.0379)	(0.1159)	(0.1566)	(0.1940)	(0.1739)
Previous experience *(ref. no)*						
damage	0.1161***	0.0557**	0.3459***	0.5234***	0.5308***	0.7270***
	(0.0230)	(0.0221)	(0.0632)	(0.1058)	(0.1355)	(0.1940)
experience	-0.0085	0.0154	-0.0745	0.0863	0.1012	0.0861
	(0.0267)	(0.0225)	(0.0649)	(0.1023)	(0.1430)	(0.1229)
Main responsibility *(ref. my responsibility)*						
landlord	-0.0407		0.0893	-0.6172***		-0.0959
	(0.0411)		(0.0990)	(0.1957)		(0.2426)
state	0.0056	-0.0054	0.2046*	-0.1376	-0.1777*	0.1361
	(0.0231)	(0.0190)	(0.1048)	(0.0862)	(0.1055)	(0.2569)
Expectation in authorities	-0.0097	-0.0044	-0.0187	-0.0810**	-0.0722	-0.0792**
	(0.0072)	(0.0074)	(0.0168)	(0.0363)	(0.0466)	(0.0375)
Trust in authorities *(ref. rather no/no)*						
rather yes/yes	0.0027	0.0016	0.0109	0.1295*	0.1801*	0.0162
	(0.0139)	(0.0158)	(0.0389)	(0.0741)	(0.0984)	(0.1056)
Public protection is sufficient	-0.0021	-0.0049	0.0112	-0.0154	-0.0182	0.0084
	(0.0065)	(0.0068)	(0.0160)	(0.0256)	(0.0321)	(0.0322)
Self-efficacy	0.0112**	0.0040	0.0325**	0.0217	0.0096	0.0393
	(0.0053)	(0.0063)	(0.0141)	(0.0255)	(0.0364)	(0.0295)
Motivation	0.0379***	0.0266***	0.0675***	0.2945***	0.3430***	0.1483***
	(0.0067)	(0.0080)	(0.0124)	(0.0299)	(0.0398)	(0.0236)
Competing concerns	-0.0035	-0.0038	-0.0035	-0.0280	-0.0457	-0.0217
	(0.0060)	(0.0060)	(0.0144)	(0.0268)	(0.0339)	(0.0293)

Table B3 (continued). Effects of adaptive capacity indicators on adaptation action (regression results for detailed income analysis)

	Adaptation (yes/no)			Number of implemented measures		
	Logistic regressions			Poisson regressions		
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
	Full sample	Owners	Tenants	Full sample	Owners	Tenants
	AME	AME	AME	AME	AME	AME
	(SE)	(SE)	(SE)	(SE)	(SE)	(SE)
Household characteristics						
Gender of the primary decision maker *(ref. male)*						
female	0.0033	0.0153	-0.0220	-0.1193	-0.1452	-0.0457
	(0.0209)	(0.0207)	(0.0468)	(0.0842)	(0.1100)	(0.0904)
Age of the primary decision maker	0.0001	0.0010	-0.0017	0.0008	0.0005	-0.0031
	(0.0008)	(0.0007)	(0.0016)	(0.0032)	(0.0043)	(0.0030)
Migrant background of the primary decision maker *(ref. no)*						
migrant background	0.0361	0.0367	0.0403	0.4190	0.7031	-0.1160
	(0.0513)	(0.0553)	(0.1250)	(0.3032)	(0.4718)	(0.1756)
Household size	0.0124	0.0123	0.0155	0.0381	0.0386	0.0074
	(0.0117)	(0.0133)	(0.0249)	(0.0478)	(0.0658)	(0.0468)
House characteristics						
Housing type *(ref. single family home)*						
duplexe/terraced house	-0.0236	-0.0196	-0.0108	-0.2251***	-0.3110***	0.1356
	(0.0230)	(0.0206)	(0.0893)	(0.0820)	(0.1022)	(0.1188)
apartment building	-0.0385	-0.0206	-0.0849	-0.0880	-0.1000	0.0511
	(0.0237)	(0.0205)	(0.0805)	(0.0991)	(0.1322)	(0.1025)
Year of construction	0.0001	-0.0003	0.0009	-0.0035***	-0.0051***	0.0006
	(0.0003)	(0.0003)	(0.0008)	(0.0011)	(0.0015)	(0.0015)
Survey design						
Mode *(ref. CAWI)*						
CATI	0.0474**	0.0365*	0.0919	0.3671***	0.4447***	0.2705
	(0.0197)	(0.0192)	(0.0619)	(0.1036)	(0.1337)	(0.1694)
unsure	-0.0314	0.0049	-0.1148**	0.0389	0.1198	-0.1078
	(0.0339)	(0.0365)	(0.0584)	(0.1483)	(0.1731)	(0.1216)
N	1,571	1,157	414	1,571	1,157	414
Nagelkerke-R^2	0.4194	0.1687	0.3449	0.5213	0.2866	0.3301
BIC	1369.91	863.71	660.5	5458.05	4517.92	1070.01

Notes: Entries are pooled AME from a binary logistic regression (Model 1-3) and a poisson regression (Model 4-6) with cluster-robust standard errors at the household level. Multiple imputation with a Markov chain Monte Carlo (MCMC) algorithm was performed to account for missingness in the predictors (m = 30). The impact of missing data on parameter estimations in a particular model of interest was captured with the fraction of information missing due to nonresponse (FMI) and the proportion of the variation attributable to the missing data (λ) (van Buuren, 2018, p. 46). The severity of the missing data problem in our regression models can be classified as moderate to moderately large (FMI = 0.23 for income (Model 2) and FMI = 0.23 for year of house construction (Model 3 & 6), FMI $\leq$ 0.2 for all remaining coefficients). However, the presented results are not highly dependent on the handling of missing data ($\lambda \leq 0.23$ for all coefficients).

Statistical significance level: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Source: own calculation, based on data from the KARE household survey 2022.