// NO.22-055 | 11/2022

DISCUSSION PAPER

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The Intention-Behavior Gap in Climate Change Adaptation

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Abstract

Most empirical studies on private climate change adaptation rely on self-reported intentions which often fail to translate into real actions. Consequently, this strand of literature can only insufficiently account for the intention behavior gap (IBG) in climate change adaptation, which complicates the deduction of policy recommendations for stimulating adaptation behavior. Using a large unique longitudinal survey data set from Germany covering more than 5,000 households, our study offers extensive insights into the IBG in climate change adaptation by analyzing intentions and actual implementations of both flood-proofing and heat stress reduction measures. Our results do not only reveal a substantial IBG for most stated intentions but also show that intentions can rarely serve as good predictors for realized actions. At the same time, the IBG itself can hardly be explained by observable household data characteristics which in turn again makes it difficult to reveal information on realized actions out of stated intentions only. However, we also find that drivers of adaptation intentions are often reasonable proxies for assessing the drivers of behavior. This implies that similar explanatory variables affect both intentions and implementations, but they provide only limited insights on the actual levels of implemented intentions. In line with regret theory, the IBG in our data can be partly explained by anticipated regret caused by a feeling of having invested in vain in cases where adaptation measures are installed but extreme weather events do not occur for the time being.

JEL-Codes

Q54, D91

Keywords

Intention-behavior gap, Adaptation, Climate Change, Flooding, Heat

Funding source

This research was funded by the Federal Ministry of Education and Research, Germany, FKZ 01LA1823B, “Evaluating Germany’s Climate Mitigation and Adaptation Practice.”

Acknowledgements

We are grateful for the insightful and constructive comments offered by Philip Bubeck, Paul Hudson, and Brayton Noll. We would like to thank Ekaterina Iurkova for providing excellent research assistance. Any remaining errors are our own.

Introduction

An expanding field of research is focusing on how individuals take action to limit private impacts of natural disasters and climate change (van Valkengoed and Steg 2019). Understanding the underlying decision processes with respect to private adaptation measures provide important insights why some individuals prepare well for natural disaster and climate risks, while many others do not engage in adaptive behaviors (Meyer and Kunreuther 2017). Such insights may be used for improving policies that help individuals in better preparing for natural disasters and climate change, for instance through communication strategies, behavioral nudges, or financial incentives from insurances (Kousky et al. 2018; Mol et al. 2020; Robinson et al. 2021). Examples of these measures that individuals can undertake are making buildings more resistant to damage from extreme weather, such as flood-proofing properties (e.g., Beasley and Dundas 2021), or limiting health consequences during heat waves by cooling homes.[1] As an illustration, Kreibich et al. (2015) review various flood damage mitigation measures, which can limit damage to individual properties up to 50% or more in case a flood happens. Proactive disaster risk management strategies are becoming increasing important since worldwide natural disaster losses have been rising during the last decades (Botzen et al. 2019a; Davlasheridze et al. 2017). The recent IPCC (2021) report presents evidence indicating that this trend is likely to accelerate in the future, due to an increasing frequency and severity of various extreme weather events as a result of climate change.

A branch of this literature on disaster preparedness and climate adaptation has examined how the actual implementation of adaptation measures relates with explanatory variables that are grounded in decision theories from psychology (e.g. Protection Motivation Theory and Theory of Planned Behavior) or behavioral economics (e.g. Subjective Expected Utility Theory and Prospect Theory) (van Valkengoed and Steg 2019; Koerth et al. 2019). The data of undertaken adaptation measures and explanatory variables used in these studies are commonly collected with cross-sectional household surveys. However, this results in the well-known problem that the influence of important theoretical drivers of adaptation decisions, such as risk perceptions, cannot be well identified in case these explanatory variables change after the measure is in place (Bubeck et al. 2012). For instance, high risk perceptions may trigger the implementation of adaptation measures, but after the measures are taken risk perceptions may decline. Hence, surveys that estimate relationships between implemented adaptation and risk perception may find weak or even negative relationships (Bubeck et al. 2012).

Several solutions have been applied to address this issue. Instead of variables of the perceived likelihood and severity of disaster losses, risk perceptions may be proxied with a geographical indicator of the local risk[2], for which a stable positive relationship can be expected with the implementation of adaptation measures elicited with a cross-sectional survey (Botzen et al. 2019b). However, a disadvantage of this approach is that geographical indicators of a risk may be imprecise, and only partially explain perceptions of natural disaster and climate risks (e.g. Lechowska 2018). Another solution is to use economic experiments that aim to establish causal relationships with investments in adaptation measures, although challenges exist with framing and incentivizing these experiments in a high loss context (Robinson and Botzen 2019a). Using panel data surveys that allow examining how developments in implemented adaptation measures over time are influenced by theoretically informed drivers of these decision are an effective way to overcome the aforementioned identification issue in cross-sectional surveys (Osberghaus 2017). However, few researchers have the resources for monitoring households with such survey approaches that require repeated surveys of large samples over long time periods, which are combined with monetary incentives to ensure high response rates and limit attrition bias (Hudson et al. 2019).

[1] Heatwaves and extreme temperatures pose a relevant natural hazard in Germany, as shown by a comprehensive study on hospital admissions and mortality by Karlsson and Ziebarth (2018).
[2] An example of such an indicator is a variable that indicates whether or not a respondent lives in a high risk flood zone to explain implemented flood adaptation measures.

A more easily applied and widespread solution that many studies have adopted is to elicit intentions to implement specific adaptation measures in surveys as a proxy, and examine which theoretical constructs drive these intentions (e.g. Botzen et al. 2012; Maidl and Buchecker 2015; Murtagh et al. 2019; Noll et al. forthcoming; Richert et al. 2017). Focusing on intentions instead of implementations circumvents the problem of feedback effects, as there should be no effect of intentions on risk perceptions. Hence, this should allow for causally testing theories of decision making under risk, such as the influence of risk perceptions on adaptation behavior, as long as these intentions closely relate to adaptation actions (Bubeck and Botzen 2013).

For understanding the reliability of elicited levels of intentions to take climate change adaptation measures, it would be important to assess whether these intentions lead to action: i.e. actual implementation of these measures. However, few studies examined this issue. An exception is Bubeck et al. (2020) who showed with panel data of flood-proofing measures in 227 German households that 79% who intended to take high-costs measures also did so in practice, while this proportion is 60% for low-cost measures and 44% for medium-cost measures, resulting in a substantial intention-behavior gap (IBG). Their hypothesis for explaining the highest implementation rate (i.e., the lowest IBG) for high-cost measures is that these require substantially more planning and investment resulting in more reliable stated intentions to take those measures (Bubeck et al., 2020). These estimates might however rather provide a lower-bound estimate of the magnitude of the IBG as the survey only includes households that reported damages to their buildings from a recent flood event, and thus a population with a higher urgency to implement measures compared with the general population.[3]

Using a large unique longitudinal survey data set from Germany covering more than 5,000 households, our study offers extensive insights into the adaptation IBG by analyzing intentions and actual implementation of both flood-proofing and heat stress reduction measures. We have four main research results that contribute to the literature.

As a first step, building up on the results provided by Bubeck et al. (2020), we assess and quantify the size of the IBG but for a large set of specific private adaptation measures and for a larger set of households. We are particularly interested in the question to what extent the IBG varies in the cost (i.e. financial cost, time) e.g. for planning and implementation of a respective adaptation measure. In this context, we also test whether intentions contribute to the relative goodness of fit of models on adaptation action. Given a large (small) IBG, a model including intentions as an explanatory variable should be similar to (preferred over) a corresponding model without intentions in the set of explaining variables. As a first important finding we observe a sizeable IBG in a wide range of different adaptation measures. This casts first doubts on the general reliability of survey studies that use stated intentions as a proxy for implemented actions.

As the second research question, we assess whether intentions and realized action can be described by similar explanatory variables. If the estimated coefficients in a model of intentions serving as the dependent variable are similar in terms of sign, size and statistical significance to the coefficients explaining realized actions, we can have (at least to a certain degree) some confidence that empirical evidence resulting from a regression analysis on intentions is also insightful for realized actions. Our results suggest that a broad set of explanatory variables are indeed significant predictors of both intentions and actions. This finding means that an analysis of drivers of intentions to adapt may give useful insights for factors that lead to the implementation of adaptation measures, although the absolute levels of adaptation intentions and actions are likely to differ due to the IBG. However, there are nuanced differences between these drivers, e.g. in the effects of flood experience. In contrast to the previous literature, which so far lacks a joint and detailed analysis of both intentions and realized actions, we find

[3] As we will show in our study, the IBG in the context of flood adaptation tends to be lower for flood-affected households. Given this finding, we interpret the IBG reported by Bubeck et al. (2020), which is only based on information from flood-affected respondents, as a lower-bound estimate.

that flood experience turns out to be more predictive for actual implementations than for stated intentions.

In a third step, we analyze whether the IBG itself may be explained by similar factors as intentions and realized actions, hence whether we can identify observable household characteristics which contribute to a higher level of congruence between intentions and actions. There is already first empirical evidence suggesting direct effects of the household composition and age on the IBG in other contexts (Chai et al. 2015, Nickerson and Rogers 2010). In contrast, in our data in the context of climate adaptation, it is hardly possible to find such variables – especially the IBG for heat adaptation is unrelated to most household characteristics observable in our data. For flood adaptation, we again find a strong effect of damage experience – hence households with concrete flood experience rather follow-up on their adaptation intentions than unaffected households.

Finally, we link our empirical insights on the IBG across different subgroups to the concept of regret theory (Loomes and Sugden 1982; Bell 1982; Fishburn 1982) to better understand if the lack of realizing intentions can be explained by an anticipated regret. According to this concept, individuals tend to avoid situations where they feel to have "overinvested" in adaptation, which in turn might be expressed by a lower degree of life satisfaction. Our analysis on self-reported life satisfaction indeed uncovers a potential and so far unexplored role of anticipated regret in the context of private climate change adaptation measures: While survey participants who have successfully implemented their intentions and were also damaged by a natural disaster show the highest level of life satisfaction in our data, individuals are least satisfied if they have realized their intentions but so far did not experience any situations where these measures reduced the damages.

Conceptual Framework and Hypotheses

An important finding of the psychological literature on values and action is that behavior being related to the environment is ultimately a result of a long causal chain involving a variety of personal and contextual factors (e.g. Stern 2000). While attitudes, motivations and norms play a decisive role in the decision process, and in particular on the intention to act, there are numerous other relevant constraining factors, which limit actual behavior. This is in line with earlier psychological research being grounded in *The Theory of planned behavior* by Ajzen (1991), which postulates that decisions about whether and how much to act, despite being positively correlated, may be caused and explained by different psychological motivations. As a result, we frequently observe differences between stated intentions and realized actions in a broad set of decisions – the IBG. In this respect, understanding the underlying decision processes with respect to disaster preparedness and climate change adaptation are important to gain a better understanding on why some individuals prepare well for natural disaster risks, while many others living in disaster-prone areas do not engage in preventive behaviors (Meyer and Kunreuther 2017).

We start our conceptual approach by quantifying the size of the IBG for a large set of specific flood-proofing and heat stress reduction measures. For the case of flood proofing measures, Bubeck et al. (2020) shows a significant gap between stated intentions and implemented actions. They also provide a link between the intensity of planning and the likelihood to actually act on the intentions: The share of intentions being realized is highest for high-cost structural measures which need substantially more planning, and hence the reported intention may be more reliable than in case of low-cost measures which can be taken more spontaneously.[4] This is also in line with a large strand of related literature suggesting the IBG to be smaller when vague intentions are substantiated by concrete plans (for a review see Rogers et al. 2015). These effects are found in the context of physical exercises (Reuter et al. 2010, Sniehotta et al. 2005), saving (Rabinovich and Webley 2007), vaccination (Milkman et al. 2011), voting

[4] However, these results are based on a relative low number of observations. For example, the number of households reporting their intentions of installing specific high-cost measures varies between 7 and 12, which is why the authors aggregated these numbers for the statistical analyses.

(Nickerson and Rogers 2010) and job searching (Abel et al. 2019). Based on these empirical findings we have two research hypotheses with respect to the *presence* and the *size* of the IBG.

We first hypothesize that there is a positive IBG in the context of private climate adaptation for the average individual i:

H1a (Presence of IBG): $IBG_i > 0$

Furthermore, we can assess the existence of an IBG by comparing the goodness-of-fit of implementation models with and without intentions as a predictor. In this regard, we hypothesize – following our expectations based on the available empirical evidence that there is a large IBG – that the model with intentions does not outperform a similar model without intentions:

H1b (Goodness-of-fit with intentions): $M_{int,X} = M_X$

where $M_{int,X}$ is the goodness-of-fit of a model including intentions and covariates X as explanatory variables, and M_X is the corresponding measure for a model with only X as explanatory variables.

With respect to the *size* the IBG, we postulate that it negatively correlates with the cost C (i.e. monetary and time cost for planning and implementation of the measure):

H1c (Size of IBG): $\frac{\partial IBG_i}{\partial C} < 0$

If there is a sizeable IBG, it is questionable whether data on intentions and implemented actions can be used equivalently to analyze household behavior. Richert et al. (2017) argue that Protection Motivation Theory explains the willingness to take precautionary measures better than the presence of already implemented actions. Other studies estimate adaptation models based on reported intentions and deduct policy implications aiming at increasing the implementation (e.g., Maidl and Buchecker 2015; Murtagh et al. 2019; Noll et al. forthcoming), hence they explicitly or implicitly assume that the drivers for intentions and actions are at least qualitatively identical. Given this literature, we formulate the second main research question, and test the hypothesis that intentions and actions may be explained by the same set of explanatory variables, and their effect sizes are similar:

H2 (Congruence of explanatory variables for intentions and actions): $\beta_{int} = \beta_{act}$

where β is a vector of estimated coefficients for an identical set of explanatory variables regarding intentions and actions, respectively.

Our third research question refers to the explanation of the IBG itself. Other studies have found that actions are better aligned to intentions (hence there is a lower IBG) when the perceived behavioral control is high. Heath and Gifford (2002) explain the use of public transport by a model including an interaction term of perceived behavioral control and intentions, finding that individuals with high values of perceived behavioral control showed a high level of congruence between intentions and actions. Sniehotta et al. (2005) find similar results in the context of physical exercises, also showing that self-efficacy contributes to a reduction of the IBG. In the context of pro-environmental consumption behavior, Grimmer and Miles (2017) and Nguyen et al. (2019) report smaller IBGs for people with high behavioral control and high perceived effectiveness of the own consumption behavior on the environment. In contrast, some studies find no or mixed results regarding the role of perceived behavioral control or related constructs (Rabinovich and Webley (2007) on saving decisions and Collins and Chamber (2005) in the public transport context). In addition, there is already first empirical evidence suggesting direct effects of the household composition and age on the IBG (Chai et al. 2015, Nickerson and Rogers 2010). As a third step, we therefore analyze whether the IBG itself may be explained by similar factors as adaptation implementation or intentions, hence whether we can identify observable household characteristics, which contribute to a higher level of congruence between intentions and actions.

Finally, we examine whether or not our empirical insights into the IBG across different subgroups are consistent with regret, following the concept of regret theory (Loomes and Sugden 1982, Bell 1982, Fishburn 1982). Anticipated and experienced regret may relate with adaptation decisions in the following ways, depending on the occurrence of a natural disaster. On the one hand, not taking an adaptation measure while experiencing a disaster and resulting damage, may trigger regret of being unprotected. On the other hand, taking an adaptation measure while not experiencing a disaster, may trigger regret of being protected due to incurred adaptation costs that do not result in a return in the form of avoided damages.

Experimental evidence provided for anticipatory regret of being unprotected influencing investments in flood damage mitigation measures through flood-proofing of buildings is given by Mol et al. (2020). Moreover, Robinson and Botzen (2019b) observe that both types of anticipatory regret influence flood insurance demand: individuals who anticipate regret of being unprotected are more likely to demand flood insurance, while individuals who anticipate regret of protection are less likely to demand flood insurance. Krantz and Kunreuther (2007) argue that individuals who experience the latter type of regret view protection as an investment that should generate a return during a disaster. Analyses of flood insurance purchases over time show that experiencing a flood increases purchases (Bradt et al. 2021; Michel-Kerjan and Kousky 2010), while individuals are likely to drop their insurance coverage if they did not experience a flood for some time (Michel-Kerjan et al., 2012). The first behavior is consistent with experienced regret of being unprotected, while the decision to drop coverage is consistent with experienced regret of being protected.

Based on these concepts of regret we expect that individuals tend to avoid situations where they feel to have "overinvested" in adaptation, which in turn might be expressed by a lower degree of life satisfaction. This is expressed in the following two hypotheses:

H3a (Regret of feeling unprotected): Individuals with no adaptation protection measures and a sizeable IBG feel a considerable regret of being unprotected after a disaster experience. This feeling of regret is reflected in a lower degree of self-reported life satisfaction compared no non-affected unprotected individuals.

For those who have invested in adaptation protection measures, the hypothesis reads as follows:

H3b (Regret of feeling (over-)protected): Individuals with adaptation protection measures and a small IBG feel a considerable regret of being (over-)protected as long as they lack experiences with natural disaster losses. This feeling of regret is reflected in a lower degree of self-reported life satisfaction compared to unprotected individuals without disaster experiences.

Data and Methods

Data set

We base the empirical analysis on a large-scale household panel survey in Germany on natural disaster risk reduction and climate change adaptation (data set "Green SOEP", Osberghaus et al. 2020). In 2012, 2014 and 2020, the pollster Forsa approached a representative sample of households for participation in the online survey. Forsa deliberately invited household heads to participate in the survey, defined as the person who is normally responsible for financial decisions within the household. The household sample used in our analysis is slightly older and better educated than the average German population, and there are less single occupancy households in the data set than would be in a representative sample. As an incentive, Forsa rewards respondents by points, which can be exchanged for products. In the initial raw data set, there are data of 10,703 participating households which participated in at least one of the three waves. For our analysis, we drop 4,979 households that participated only in one survey wave. We further exclude 530 households that were moving between the participations to ensure that changes in intentions and implementations are not primarily due to the circumstances at the new location. Hence, the final data set contains 5,194 households that participated twice or thrice in 2012, 2014 and 2020. In total, we have 12,879 observations. Table 1 depicts the participation patterns of responding households over the three survey waves.

Table 1: Survey participation pattern

Participation in waves…			Number of households	Percentage
2012	2014	2020		
X	X	X	2,491	48.0
X	X		1,740	33.5
	X	X	798	15.4
X		X	165	3.2
Total			5,194	100.0

Households that were moving between survey waves or participated only once are omitted.

In all three waves, the participants reported the actual implementation of flood and heat adaptation measures. In terms of flood, we collected data on one behavioral measure (moving valuable assets to higher floors) and five technical measures: Installing sewer backflow preventers, water barriers in the basement, water-resistant indoor painting, water-resistant exterior painting, and water-resistant flooring. While the behavioral measure can be implemented without significant financial costs, backflow preventers may be defined as a medium cost measure, and the remaining measures can imply major and costly changes in the structure of the building. For heat adaptation measures, respondents provided information on having a fan, air-conditioning, heat protection window films, and green roofs. As all elicited measures are typically not de-installed once they are implemented, we may identify a specific form of erroneous reporting by checking whether a specific measure is reported to be implemented in one wave and absent in a later wave. In such a case, we assume erroneous reporting in at least one wave and omit the data on that measure of the respective respondent for all waves. For the sake of brevity, for some analyses we combine the separate adaptation measures to aggregate measures of adaptation behavior. All four heat measures are aggregated to one heat adaptation variable which takes the value of one if at least one heat measure was implemented. Similarly, we construct a binary variable for structural flood adaptation, which combines the relatively costly flood measures (water barriers in the basement, water-resistant indoor painting, exterior painting, and flooring), and an aggregate binary variable for flood adaptation in general.

Beside data on realized implementations, in 2012 and 2014, we collected data that captures the stated intentions to implement the respective adaptation measures in the near future. Hence, the data allow us to identify households that state they intend to implement a certain measure, and to check whether the respective measure was indeed implemented some years later. Likewise, we can also assess whether households that newly implemented a measure have reported respective intentions in one of the previous survey waves or not.

The Green-SOEP data set contains a number of variables that may serve as potentially important covariates in the analysis of flood and heat adaptation decisions. Beside some basic socio-economic variables such as age, gender, education, income, household size, and homeownership, we use data on flood- and heat-related perceptions, exposure and insurance. For the analysis of the IBG, we also include data on perceived self-efficacy. For the life satisfaction analyses, we use self-reported levels of life satisfaction (based on a standardized questionnaire item with an 11-point scale).

Table 2 provides a summary of the variable definitions and descriptive statistics. English translations of the most relevant questionnaire items are included in Appendix A1. More information on the data set, including descriptive statistics and trends is available in Osberghaus et al. (2020).

Table 2: Variable definitions and scales, descriptive statistics.

Variable	Description	Min	Max	Mean	N
Flood adaptation					
FlMov	moving valuable assets to higher floors implemented	0	1	0.07	8,460
FlMov_I	*FlMov* intended	0	1	0.03	8,065
FlSew	sewer backflow preventers implemented	0	1	0.33	6,515
FlSew_I	*FlSew* intended	0	1	0.06	4,684
FlBar	water barriers in the basement implemented	0	1	0.03	9,421
FlBar_I	*FlBar* intended	0	1	0.02	9,285
FlWip	water-resistant indoor painting implemented	0	1	0.02	10,277
FlWip_I	*FlWip* intended	0	1	0.01	10,228
FlWep	water-resistant exterior painting implemented	0	1	0.12	6,394
FlWep_I	*FlWep* intended	0	1	0.02	6,021
FlFlo	water-resistant flooring implemented	0	1	0.16	6,655
FlFlo_I	*FlFlo* intended	0	1	0.01	5,963
FlStr	any structural (high cost) flood measure implemented	0	1	0.16	10,900
FlStr_I	*FlStr* intended	0	1	0.04	10,796
FlAdapt	any flood measure implemented	0	1	0.31	10,992
FlAdapt_I	*FlAdapt* intended	0	1	0.07	10,880
Heat adaptation					
HeatFan	Fan implemented	0	1	0.12	11,446
HeatFan_I	*HeatFan* intended	0	1	0.04	7,915
HeatAC	air-conditioning implemented	0	1	0.03	12,128
HeatAC_I	*HeatAC* intended	0	1	0.04	8,530
HeatSun	heat protection window films implemented	0	1	0.04	11,868
HeatSun_I	*HeatSun* intended	0	1	0.03	8,489
HeatGre	green roof implemented	0	1	0.01	7,599
HeatGre_I	*HeatGre* intended	0	1	0.00	8,293
HeatAdapt	any heat measure implemented	0	1	0.15	12,517
HeatAdapt_I	*HeatAdapt* intended	0	1	0.11	8,717
Socio-Economics					
Female	Gender female	0	1	0.30	12,879
Age	Age in years	19	92	55.92	12,879
Homeowner	Homeownership	0	1	0.63	12,537
Educ	High education (Abitur or higher)	0	1	0.41	12,298
HHSize	Household size in persons, truncated at 5	1	5	2.17	12,225
Income	Monthly household income in 1000 €	0.75	5.75	3.05	10,731
Flood-related variables					
FlZone	Residing in a flood zone (recurrence interval at least 200 years in flood hazard map)	0	1	0.07	12,719
FlProb	Subjectively expected recurrence interval of flooding, ranging from 1 (less often than every 200 years) to 4 (every 10 years or more often)	1	4	2.03	6,695
FlDam	Self-reported experience of financial flood damage	0	1	0.13	8,306
FlInsHome	Home is flood insured	0	1	0.59	7,546
FlInsCont	Contents are flood insured	0	1	0.47	12,368
Heat-related variables					
Temp	Average minimum temperature in summer months in °C	7.8	14.8	12.54	12,668
Wind	Average wind speed in m/s	15	71	32.43	12,683
BMI	Body-Mass-Index	11.8	220.4	27.26	11,756
HeatDam	Self-reported experience of health-related heat damage	0	1	0.05	12,573
Further variables					
SelfEff	Index of self-efficacy	7	49	36.47	3,346
LifeSat	Self-reported level of life satisfaction, ranging from 0 (completely dissatisfied) to 10 (completely satisfied)	0	10	7.25	12,843
Riskseek	Self-reported level of risk seeking, ranging from 0 (not at all willing to take risks) to 10 (very willing to take risks)	0	10	4.75	12,852
Patience	Self-reported level of patience, ranging from 0 (very impatient) to 10 (very patient)	0	10	5.90	12,850

Binary variables are coded as 1 if the condition in the description is met, and 0 if it is not met. Don't know answers are omitted. Based on the pooled sample of all available observations of all three survey waves. The number of observations varies because not all variables were included in every wave, due to filter questions, and because missing and don't know answers are omitted.

Methods

We base our empirical analysis on various statistical methods. Following the four research questions outlined in the introduction, the analysis consists of four sections that build upon each other. In the first section, we present descriptive statistics such as the percentage of intentions that are transferred into actions, and thereby address Hypothesis H1a (on the existence of an IBG in climate change adaptation) and Hypothesis H1c (its relation to measure costs). In this section we also employ multivariate logistic regressions of the implementation of specific measures, and compare goodness-of-fit statistics (Akaike information criterion, AIC, and Bayesian information criterion, BIC) of model specifications with and without prior intentions as an explanatory variable, to address Hypothesis H1b. The set of explaining variables is based on the empirical literature on intended or implemented adaptation behavior and respective review studies (e.g., Osberghaus 2021 and van Valkengoed and Steg 2019 for flood, Kussel 2018 and Osberghaus and Abeling 2022 for heat). In this section, we analyze the data for each of the six flood measures and four heat measures separately, and we focus on the measure-specific IBG. Moreover, we have to restrict the analysis to those households, which have not implemented the respective measure at the time of their first participation – otherwise there is no data on whether they intend to implement it or not.

In the subsequent section, we turn to research question #2 and estimate logistic regression models of adaptation intentions and actual behaviors as dependent variables, using the same sets of explaining variables as in Section 1. After estimating the implementation and intention models simultaneously as seemingly unrelated regressions, we derive the differences of the estimated coefficients, and assess the statistical significance of these differences (for each coefficient separately by the z-statistic and for the overall model by a joint F-test). We thereby assess the question whether intentions and implementations relate to the same explanatory variables in similar ways. If that was the case, multivariate analyses of intentions may still yield results relevant for implementation – despite an eventually large IBG. In this and the subsequent sections, we focus on the aggregate measures (flood and heat adaptation) for keeping the analyses brief and concise. Results for the specific adaptation measures, however, are reported in the Appendices.

In section 3, we assess how the resulting IBGs in the flood and heat adaptation contexts can be explained by observable characteristics of households (research question #3). For this analysis, we calculate for both domains (flood and heat) a respondent-specific share of stated intentions that are implemented subsequently, aggregating all time periods and measures within the domain. As these two variables vary between zero (no intention implemented) and one (all intentions implemented) and have only few distinct values in between, we opt for treating these variables as ordinal data. Hence, we use spearman correlation coefficients (and ordered probit regression models) for assessing univariate (and multivariate) correlations of these measures with potentially relevant variables. We thereby relate our analysis to prior studies from the psychological literature, which analyzed the IBG in other contexts.

Finally, inspired by regret theory, in section 4 we assess the question whether the IBG in the context of flooding may partly be explained by the regret caused by the experience that a costly investment in flood adaptation measures may proof to be unnecessary if no flood damage is occurring. For this analysis, we use self-reported data on life satisfaction (ranging from zero to ten) and assess the effect of experiencing flood damage interacted with the implementation status of prior flood adaptation intentions. Thereby we can approach the question how the perceived utility of implementing flood adaptation intentions depends on the occurrence of flood damage. Following the literature (e.g., Frey et al. 2010; Haushofer and Fehr 2014), these interaction regressions are implemented as linear, ordinary least squares regressions with a typical set of covariates for life satisfaction regressions.

Results and Discussion

Section 1: Is there an intention-behavior gap, and is it related to costs?

As an approach to analyzing hypotheses H1a and H1c, we present data describing how well stated intentions of survey respondents align to implementations in a later survey wave – hence the size of the IBG in general and for different kinds of adaptation measures. In Table 3, we report for each of the ten specific measures and for the aggregate adaptation measures the percentages of intentions that are indeed implemented later on. While this metric is central for assessing the actual IBG, it is silent about spontaneous (unintended) implementation of adaptation. Therefore, we also report the share of implementations that were "announced" by stated intentions in the preceding survey wave. We also report the number of households in four categories: (a) no implementation and no prior intention, (b) implementation but no prior intention, (c) no implementation despite prior respective intention, and (d) implementation after stating the intention.

Table 3: Percentage of adaptation intentions that are implemented, and number of households categorized by intentions and implementations.

Adaptation measure	Stated intentions that are imple-mented	Implementations that were intended	No prior intention, no imple-mentation	No prior intention, but imple-mentation	Prior intention, but no imple-mentation	Prior intention and imple-mentation
	(percentage)		(Number of observations)			
Flood (low cost)						
moving valuable assets to higher floors (*FlMov*)	23.6	5.6	3607	286	55	17
Flood (medium cost)						
sewer backflow preventers (*FlSew*)	25.0	11.3	2030	260	99	33
Flood (high cost)						
water barriers in the basement (*FlBar*)	21.0	9.4	4286	125	49	13
water-resistant indoor painting (*FlWip*)	16.2	4.5	5083	128	31	6
water-resistant exterior painting (*FlWep*)	15.6	2.6	2762	267	38	7
water-resistant flooring (*FlFlo*)	30.0	2.2	2759	400	21	9
any high cost flood measure (*FlStr*) [a]	22.0	5.5				
Flood (aggregate)						
any flood measure (*FlAdapt*) [a]	24.8	6.8				
Heat						
Fan (*HeatFan*)	24.3	12.1	5231	385	165	43
air-conditioning (*HeatAC*)	5.6	20.3	6286	55	238	14
heat protection window films (*HeatSun*)	8.2	9.9	6076	155	191	17
green roofs (*HeatGre*)	4.0	5.9	4260	16	24	1
any heat measure (*HeatAdapt*) [a]	12.8	12.8				

Pooled sample of 2014 and 2020 data on implementations. These data on implementations are combined with the same household's data on intentions from a prior survey wave (e.g., implementations reported in 2014 are combined with intentions reported in 2012). Based only on households, which have provided data on their intentions in a prior survey wave and which have not implemented the respective measure at the time of their first survey participation.

[a] For the aggregated adaptation measures, a clear-cut categorization of households is not possible as a household may fall in different categories for different measures.

As a first insight of Table 3, the gap between intentions and subsequent behavior in the adaptation context is substantial. For all analyzed adaptation measures in both the flood and heat domains, only a minority of stated intentions proof to be realized some years later. The percentage of implemented intentions never exceeds 30 percent. In other words, between 70 and 96 percent of the intentions reported by the survey respondents have not been implemented during the survey period (which is, depending on the participation patterns, between two and eight years). Some respondents may report the intention to implement a specific measure, but instead implement another measure in the same domain. In this case, we count this intention as not realized. If we allow that a specific intention may be realized by another newly implemented measure, the share of implemented intentions in the flood domain (*FlAdapt*) rises from 24.8 to 37.3%, and in the heat domain (*HeatAdapt*) from 12.8 to 19.0%, but still there is a sizeable IBG.

We can also assess the question whether asking for intentions is a good indicator for subsequent behavior. By comparing the number of households that have implemented a measure with and without prior intentions, we clearly see that the vast majority of observed implementations were done "unscheduled", hence without the household head reporting on a respective intention in an earlier survey wave (the share of implementations with prior plans varies between 2.2 and 20.3 percent). One potential reason is related to the structure of the panel survey: Given the long time period between the survey waves, it is well possible that some respondents formed an intention after their last survey participation, and implemented it already before the next wave. The presented data is therefore rather a lower bound for the shares of implementations that were intended. However, these figures give some initial hints that reported adaptation intentions may not align well with adaptation behavior posing some severe challenges on both researchers and policy makers: Data on stated private intentions to adapt to climate change has to be interpreted with great care as intentions are an insufficient predictor for realized actions. Analogously, it is also challenging to infer future "passive" behavior from a low level of stated intentions. Hence, we find strong support for **H1a**: There is a considerable IBG in the context of private climate adaptation.

As another way of assessing the IBG, we ask whether prior intentions are informative for modelling implementation behavior. More concretely, we employ multivariate binary regression models of implementation decisions of specific and aggregate adaptation measures. For testing H1b, we compare the goodness-of-fit statistics of regression models with and without including prior intentions as an explanatory variable. In Table 4, we present for each adaptation measure the average marginal effects of intentions and the differences of AICs and BICs from models without prior intentions and models including prior intentions. Negative differences mean lower information criterions for models with prior intentions, hence these models are to be preferred. The full underlying regression results are presented in Table 9 and Table 10 in Appendix A2.[5]

[5] Although self-efficacy may be a relevant predictor of adaptation, the variable *SelfEff* is not included in the regression models. The reason is data availability – self efficacy was only elicited in the survey wave of 2020, hence its inclusion in the regression would drastically reduce the number of usable observations.

Table 4: AIC and BIC differences of multivariate logit regression models of adaptation implementation, with and without including prior intentions.

Adaptation measure group	Adaptation measure	Average marginal effect of intention	AIC (model with intention) minus AIC (model without intention)	BIC (model with intention) minus BIC (model without intention)
Flood (low cost)	moving valuable assets to higher floors	0.070**	-2.6	3.0
Flood (medium cost)	sewer backflow preventers	0.062*	-0.8	4.3
Flood (high cost)	water barriers in the basement	0.046**	-2.4	3.3
	water-resistant indoor painting	0.066***	-7.7	-1.9
	water-resistant exterior painting	0.046	1.7	7.0
	water-resistant flooring	0.122*	-0.6	4.8
	any high cost flood measure	0.062	-0.4	5.5
Flood	any flood measure	0.023	1.6	7.2
Heat	Fan	0.089***	-18.1	-12.1
	air-conditioning	0.033***	-19.5	-13.4
	heat protection window films,	0.042***	-10.6	-4.5
	green roofs	0.022**	-1.3	3.8
	any heat measure	0.063***	-13.1	-7.0

Based on multivariate logistic regression models presented in Table 9 and Table 10 in Appendix A2. The regression models include only households, which have not implemented the measure in the prior survey wave. AIC is multiplied by the number of observations to obtain the same dimension as for BIC. The stars *, **, *** indicate significance levels of 10, 5, and 1 percent.

Both criterions penalize the inclusion of additional model parameters, but the BIC does more so than the AIC. This explains why in some cases the AIC difference is negative (i.e., the model with intentions should be preferred) while the BIC difference is positive (the model without intentions is preferred).

In general, we find negative differences to be more likely in the heat domain, suggesting that in this context models including prior intentions as an additional regressor are to be preferred, rather than in the flood context where especially the BIC often suggests models without intentions to be equally informative. However, differences in AIC and BIC depend also on the explanatory power of the other explaining variables, and here flood and heat models differ considerably: The pseudo-R2 of flood models is substantially higher than the respective statistics of heat models (see Table 9 and Table 10 in Appendix A2). Hence, the contribution of an additional parameter to the goodness-of-fit may be higher in heat models just because the other parameters have less explanatory power than in the flood models.[6]

While we focus here on the goodness-of-fit of the estimated models, we acknowledge that the estimated average marginal effects of intentions are positive in all models and significant at the 10 percent level

[6] The regression framework used in this section also allows for an ancillary analysis on the role of damage experience for adaptation implementation. One may speculate that experiencing a damaging event may have a more substantial effect if no adaptation was intended. Therefore, we repeat the estimations of newly implemented adaptation measures for both adaptation domains, including interaction terms of prior intentions and damage experience. The results (reported in Table 11 in Appendix A2) confirm positive effects of damage experience on implementations – however, these effects do not differ between individuals who intended or did not intend the behavior beforehand.

in most cases, which is at least reassuring for the internal validity of the intention variable.[7] Moreover, the effect sizes are relatively large. However, the differences in the models are relatively minor: the information criterions do not clearly prefer one model to the other. This may be surprising, given the fact that the additional parameter indicates the intention of exactly the same household to implement exactly the measure in question. If there was no intention-behavior gap, the models with intentions should predict the implementation behavior perfectly (or at least to a very large extent, allowing for some measurement error). However, the goodness-of-fit of standard models (without intentions as regressor) is hardly improved by the inclusion of intention variables. Therefore, we conclude that stated intentions to implement adaptation rarely provide additional information on implementation decisions, compared to models with a standard set of explaining variables, hence the results support **H1b.**

Finally, we focus on the size of the IBG for different adaptation domains and specific measures, thereby addressing hypothesis H1c. Comparing the aggregate adaptation measures for flood versus heat, it seems that intentions regarding flood adaptation are slightly more often implemented than in the heat context. This difference is driven by a large number of households intending to install air-conditioning or sun protection films, but not implementing them. One speculative interpretation of this result is the following: when presented, these measures seem attractive and some respondents rather spontaneously pledge that they intend to install such measures. Afterwards, when confronted with unexpected costs or practical challenges, the intentions are not followed up. In contrast, the proposed flood measures may not have the same appeal to the uninformed respondent, or the related costs and difficulties are assessed more realistically, which results in lower numbers of "spontaneously" reported intentions in this domain. Hence, the difference in the IBG between the flood and heat domains may be related to higher levels of deliberate and concrete planning in the context of more costly and complex flood measures.[8] We interpret this finding as support for **H1c**: The probability that intentions are realized increases with measure complexity and costs, hence the IBG is lower in these cases. This interpretation is backed by prior literature on the implementation of flood adaptation plans: Bubeck et al. (2020) find lower IBGs for measures incurring considerable investments and planning. In addition, studies from other contexts repeatedly found that deliberate planning effectively reduces the IBG (Abel et al. 2019, Milkman et al. 2011, Nickerson and Rogers 2010, Rabinovich and Webley 2007, Reuter et al. 2010, Rogers et al. 2015, Sniehotta et al. 2005).

Section 2: Are intentions and implementations related to similar explaining variables?

Next, we turn to the second research question and compare regression results of estimating intentions versus models of implementations, hence we use both intentions and implementations as dependent variables. Given the substantial size of the IBG and the low level of explanatory power of intentions in terms of behavior, it is an open and relevant question whether it is possible to identify a joint set of explanatory variables, which are able to explain both – intentions and subsequent actions. If that is the case, we can at least have confidence in regression model results that estimate factors of influence on adaptation intentions, even though the levels of outcomes may differ considerably, given the existence of a substantial IBG. For the multivariate logistic regression models, we use again the same set of explaining variables, and only use households, which have not implemented the respective measure in the prior survey wave, to have a similar set of households in both regression models. Figure 1 depicts the estimated coefficients for flood adaptation, and Figure 2 for heat adaptation. Appendix A3 contains the respective figures for specific measures.

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[7] Note that the effects are insignificant for the aggregate measures *FlStr* and *FlAdapt*. This may be reasoned by the fact that implementation and intentions may refer to different measures. For example, the intention of installing a water barrier may have little explanatory power for the implementation of water-resistant flooring.

[8] At least in the heat domain, there may also be seasonal effects: in summer time, there may be more "spontaneous" intention statements in the heat domain, which are not followed up when it gets cooler. However, the descriptive data do not support this interpretation. Intentions reported in the 2014 wave (collected in June and July) are more often followed up than intentions reported in the 2012 wave (collected in October and November). In order to control for potential seasonal effects, we include survey wave dummies in the multivariate analyses.

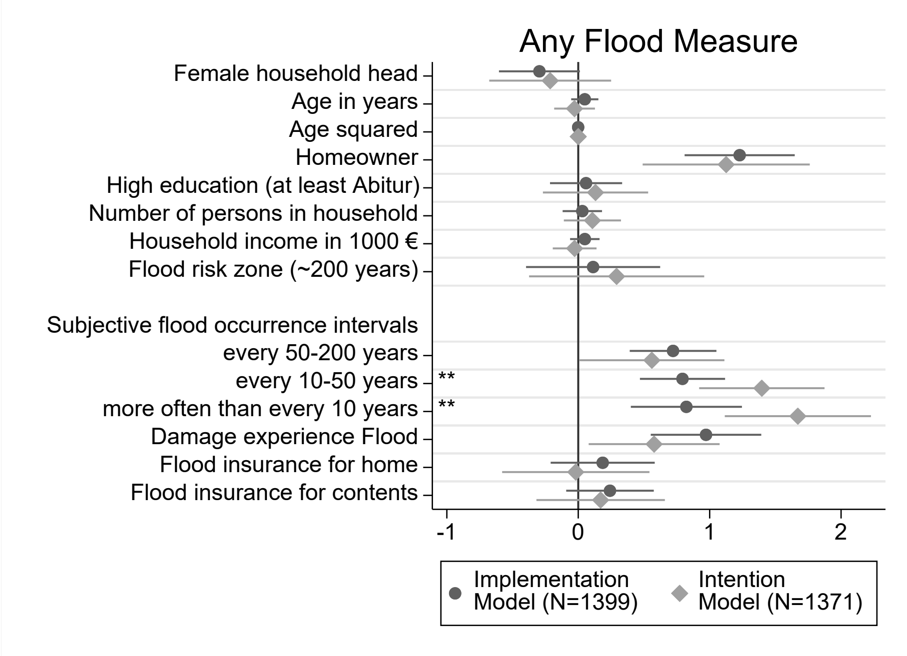

*Figure 1: Estimated coefficients (and 95% confidence intervals) of logistic regression models for implementing and intending any flood adaptation measure. The estimation samples includes only observations of 2020, and only households, which have not implemented a measure in the prior survey wave. The stars indicate significantly different coefficients for the two models. *, **, *** indicate significance levels of 10, 5, and 1 percent.*

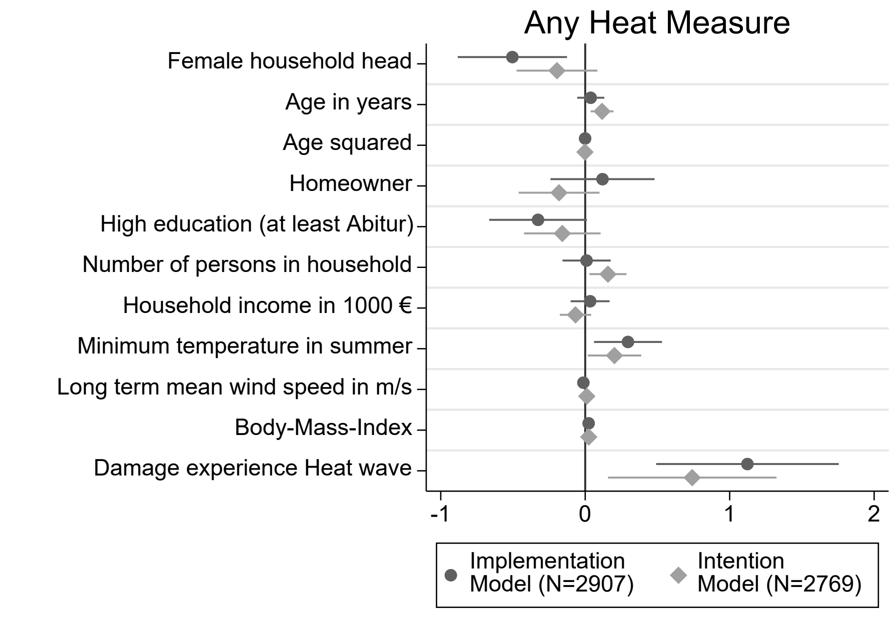

Figure 2: Estimated coefficients (and 95% confidence intervals) of logistic regression models for implementing and intending any heat adaptation measure. The estimation samples includes only observations of 2014, and only households, which have not implemented a measure in the prior survey wave. None of the differences between the coefficients is significant at the 10 percent level.

At first sight, the estimated coefficients seem to relate quite well for models on implementation and intentions. For the aggregated flood adaptation variable *FlAdapt*, a joint F-test of all coefficients being identical across the two models suggests only insignificant differences of the overall model (p=0.16). Some nuanced differences can be detected regarding the effect of expected flood probabilities: They show a strong and increasing positive effect on adaptation intentions, but a somewhat lower and nonlinear effect on actual behavior. The same pattern is visible in respective analyses of more specific measures in Appendix A3, and may well be explained by negative feedback-effects of measure implementation on risk perceptions, which are absent for intentions (Bubeck et al. 2012). This result is also in line with cross-sectional data from France reported by Richert et al. (2017), who find substantially stronger effects of risk perceptions on flood adaptation planning than on implementing measures. Other differences in the estimated coefficients are not statistically significant – at least in the models of aggregated adaptation measures. Another noteworthy result is obtained from the analysis of relatively costly measures in the heat domain (air-conditioning, sun protection films, in Appendix A3): household income has a significantly positive effect on implementation, but not on intentions. This result may be related to affordability issues: Poor households may intend to adapt to heat, but face liquidity constraints when it comes to the implementation, as also discussed by Doremus et al. (2022).[9] In the heat domain, the joint F-test also yields insignificant differences between coefficients explaining the aggregate heat adaptation (p=0.35). However, some models of specific heat adaptation measures differ substantially, partly due to the mentioned differences in income effects.

We perceive these insights as partly encouraging for the use of adaptation intention models for deducting relevant factors of behavior. While there are certain differences in the set of variables, which proof to be significant, and certainly in their effect sizes, the overall pattern of explanatory variables does not change dramatically, and intention models may be used at least as proxies for estimating relevant factors of actual behavior, though the predicted levels of intentions will be of limited use regarding implemented actions. Hence, the results broadly confirm our Hypothesis 2. As a caveat, we found some differences in the estimated effect sizes and significance of damage experience (larger effects for implementation) of our measure for flood risk perceptions (larger effects for intentions), and of the effect of income for costly heat measures (larger effects for implementation). This finding suggests people may not well consider their budget constraints when answering intentions to adapt in surveys.

Section 3: Explaining the intention-behavior gap

One core result of our analysis so far is that the IBG in climate adaptation at the household level is considerable, and intentions do not well align with subsequent actions. In the next step, we assess whether part of the variation of this gap may be explained by observable household characteristics. For this section, we calculate a household- and domain-specific share of intentions that are implemented, including all adaptation measures and time steps of the survey. This indicator of implemented intentions is inversely related to the IBG, and takes values of zero for respondents not realizing any of their stated intentions, of one for those who have implemented all of their intentions, and some values in between when some intentions were realized, and some not. Table 5 depicts the values of this indicator for the flood and heat domain.

[9] In contrast to this finding from the heat domain, income effects in the flood domain do not differ between intention and implementation models. This corroborates our interpretation that flood measures are more deliberately planned than heat measures, and potential liquidity constraints are already taken into account in the intention stage.

Table 5: Indicators of implemented intentions

Share of implemented intentions	Number of households	Percentage of households
For all flood measures		
0	555	72.2
0.33	5	0.7
0.5	30	3.9
0.67	3	0.4
1	176	22.9
Total	769	100.0
For all heat measures		
0	1310	86.2
0.33	9	0.6
0.5	35	2.3
1	165	10.9
Total	1519	100.0

Only households included which report intentions and provide data on later implementation in any specific adaptation measure.

First, we calculate univariate spearman correlation coefficients of these two indicators with all available variables reported in Table 2. In Table 6, we report only those coefficients, which are statistically distinguishable from zero at the 10 percent level.

Table 6: Spearman correlation coefficients of implementation indicators

Variables	Correlation with implementation indicator in flood domain	Correlation with implementation indicator in heat domain
Socio-Economics		
Female		
Age		
Homeowner	0.125	
Educ		
HHSize		-0.084
Income		
Flood-related variables		
FlZone		
FlProb	0.154	
FlDam	0.173	
FlInsHome		
FlInsCont		
Heat-related variables		
Temp		
Wind		
BMI		
HeatDam		
Further variables		
SelfEff		
LifeSat		
Riskseek		
Patience		

Only coefficients reported which are significant at the 10 percent level. We are using the last available observation per household. Hence, we correlate all implementations of intentions realized in the course of the panel survey to all damage experience happening in the same time period. Thus, there is temporal congruence between the implementation indicators and the other variables.

Table 6 shows that there is hardly any statistically significant relationship between the share of implemented adaptation intentions and observable household characteristics. The highest correlations are found for flood risk perceptions (*FlProb*) and flood damage experience (*FlDam*). For households scoring high on these variables, the IBG in the flood domain tends to be lower. Notably, we do not find significant correlations with perceived self-efficacy, which is in contrast to some prior psychological literature on the IBG (Grimmer and Miles 2017, Heath and Gifford 2002, Nguyen et al. 2019, Sniehotta et al. 2005). In Table 7, we expand this analysis to the multivariate setting and estimate ordered probit regression models of the implementation indicators. Again, flood experience and risk perceptions are significant factors of the realization of adaptation intentions, but objective flood risk (living in a flood zone) seems to contribute to the implementation as well. In the heat domain, there are only marginally significant correlations of income and BMI with the implementation indicator. In another model specification, we also control for the fact that the IBG differs between specific measures (see descriptive results in Section 1), and add the number of plans for each specific measure. The results regarding personal characteristics – which is our focus here – do not change, therefore we report these regressions in the appendix (Table 12 in Appendix 2). Other modelling approaches, such as dichotomizing the indicators and using logistic regressions, or using ordinary least squares regressions, yield very similar results (Table 12 in Appendix A2).

Table 7: Ordered probit regressions of the implementation indicators, reported vales are coefficients.

	Implementation indicator in flood domain	**Implementation indicator in heat domain**
Socio-Economics		
Female	0.11	-0.14
Age	-0.056	0.03
Age^2	0.00	-0.00
Homeowner	1.23**	0.01
Educ	0.30	-0.07
HHSize	-0.21	-0.14
Income	-0.12	0.12*
Flood-related variables		
FlZone	0.68**	
FlProb		
- category 2	0.72**	
- category 3	0.26	
- category 4	0.42	
FlDam	0.73***	
FlInsHome	0.17	
FlInsCont	0.07	
Heat-related variables		
Temp		0.08
Wind		0.03
BMI		0.02*
HeatDam		0.23
N	216	465
Pseudo-R2	0.161	0.079

Federal state- and time-fixed effects are always included. The stars *, **, *** indicate significance levels of 10, 5, and 1 percent. We are using the last available observation per household. Hence, we correlate all implementations of intentions realized in the course of the panel survey to all damage experience happening in the same time period (and before). Thus, there is temporal congruence between the implementation indicators and the other variables.

In general, we conclude that it is difficult to explain the considerable IBG in the adaptation context by data, which are typically observable in household surveys. If at all, we can learn from the analysis that households at risk, with high flood risk perceptions and damage experience may have a slightly higher propensity to follow up on their stated intentions in terms of flood adaptation. This may also explain why the implementation rates reported by Bubeck et al. (2020), using exclusively data of flood-affected households, are somewhat higher than in our context.

Section 4: Intention-behavior gap and regret theory: Impacts on life satisfaction

In this final section, we approach the IBG in climate adaptation from a regret theory angle. Decisions such as the implementation of adaptation intentions are always subject to uncertainty, as adaptation is predominantly beneficial if an uncertain event realizes, such as an extreme weather event. Regret theory postulates that the utility of some specific decision does not only depend on the outcome given the chosen decision, but also on the best alternative outcome given the uncertainty resolution (Loomes and Sugden 1982, Bell 1982, Fishburn 1982). Applied to the context of flood adaptation intentions and implementations, it means that the utility of the implementation of an adaptation intention depends on whether the measure proofs to be beneficial – hence, whether a flood occurs or not. In the cases when the adaptation intention is not implemented and a flood occurs, or when the intention is followed up and no flood occurs, there may be feelings of regret that the decision was either delayed until it was too late ("regret of being unprotected") or proofed to be in vain ("regret of being (over-)protected"), respectively. Both types of these regret feelings may be anticipated beforehand and thereby influence the decision whether to realize adaptation intentions or not. Especially an anticipation of the "in vain" investment may contribute to a large IBG.

In the following, we attempt to tease out these feelings of regret in a life satisfaction framework. Following the empirical literature on life satisfaction data (e.g., Frey et al. 2010; Haushofer and Fehr 2014), we use these self-reported data as a rough proxy for utility. We include as explanatory variables the self-reported flood damage experience and an indicator variable indicating whether the household has implemented the intention of a flood adaptation measure, and the interaction of these two binary variables. We expand the model by a set of typical explanatory variables for life satisfaction models. The results of the OLS regression are summarized in Table 8.

Table 8: Ordinary least squares regression results of life satisfaction.

	Life satisfaction	**Life satisfaction**
FlDam	-0.135*	-0.157**
FlAdapt_II (intention of *FlAdapt* implemented)	-0.157	-0.629*
(FlDam)(FlAdapt_II)*		1.054**
Control variables		
Female	0.223***	0.223***
Age	-0.029*	-0.029*
Age²	$0.41e^{-3}$***	$0.41e^{-3}$***
Homeowner	0.276***	0.277***
Educ	0.114**	0.116**
HHSize	0.011	0.011
Income	0.237***	0.236***
Patience	0.081***	0.081***
RiskSeek	0.134***	0.134***
N	6938	6938
R2	0.089	0.089

FlAdapt_II equals one for respondents who followed up on their intentions to implement any flood adaptation measure, and zero for all other respondents (including those without stated intentions). Based on a pooled sample of all available observations. Federal state- and time-fixed effects are always included. The stars *, **, *** indicate significance levels of 10, 5, and 1 percent.

The life satisfaction regression in column 1 shows the expected effects of control variables, and a meaningful share of explained variance. Moreover, there is a negative correlation of self-reported damage experience with life satisfaction, and no significant effect of having followed the own intentions of implementing a flood adaptation measure. In column 2 we add the interaction of damage experience and implementation, and find that the implementation indicator indeed correlates with life satisfaction, but the direction depends on flood damage experience, which is in support of both **H3a** and **H3b**. Those respondents who may feel they have implemented the adaptation measure in vain (because no flood damage occurred) (indicated by the simple *FlAdapt_II* coefficient), exhibit the lowest levels of life satisfaction – this supports the hypothesis that there is regret of being (over-)protected (**H3b**). There is also regret of being unprotected amongst those who have not implemented adaptation and were flood affected (**H3a**), indicated by the negative coefficient of *FlDam*. Those who have followed up on their intentions and indeed experience a flood event (*FlDam* * *FlAdapt_II*), show the statistically highest levels of life satisfaction, which are considerably higher than those who have neither experienced a flood, nor implemented any intentions (reference group in the regression). Although these results should not strictly be interpreted as causal effects, they do show clear patterns, which are in line with what regret theory would predict. If household heads expect a relatively high level of regret caused by the perceived level of over-investment into an adaptation measure, they might take this into account by adjusting their level of investment.

The pattern of life satisfaction levels for the four categories of households is also illustrated by plotting the mean values and confidence intervals in Figure 3. Note that amongst the group of not-implementing households, flood damage correlates negatively with life satisfaction. In contrast, for the group of households implementing their intentions, the correlation of life satisfaction and damage experience tends to be positive.

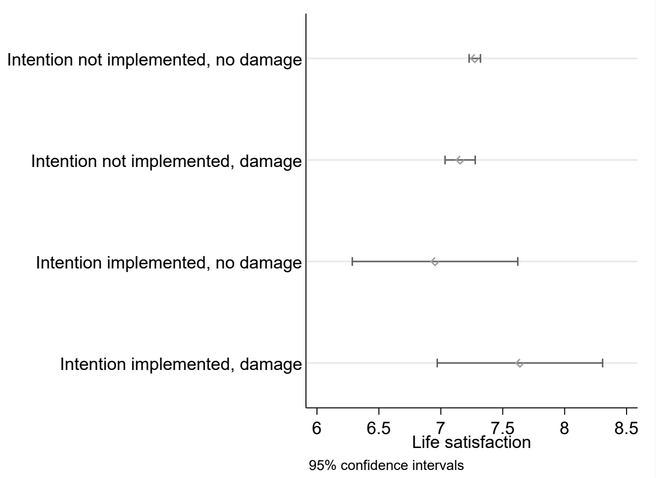

Figure 3: Mean values and 95% confidence intervals of life satisfaction for four categories of households.

Conclusion

In this study, we focus on the intention-behavior gap (IBG) in the context of private climate adaptation. Insights on this gap are particularly important in the emerging field of studies on climate adaptation and disaster risk mitigation at the household level, as much of this literature relies on self-reported adaptation intentions, to avoid the empirical challenge of potential feedback effects of implemented adaptation on risk perceptions. However, in how far stated intentions are followed up by actual implementation is so far an open question. Moreover, it is not clear which determinants contribute to the size IBG, hence, which types of households are prone to act on their intentions, and which specific measure characteristics are important for the rate of implementation. Based on a unique longitudinal data set on household adaptation over the period of eight years, we contribute to filling these gaps in the literature. As the first study, we are able to track reported adaptation intentions and behavior of a significant number of households over time. The periods between the survey waves are generally sufficient for implementing the analyzed measures.

We address four research questions and obtain four main results: First, we find there is indeed a substantial IBG in the context of adaptation to flood and heat hazards. In our data, we see that only a share of 25% of all stated intentions in the flood domain and 13% of intentions in the heat domain are implemented after two to eight years. We find that despite a significant positive correlation between intentions and implementation, the contribution of intentions to the goodness-of-fit of implementation models is limited. The descriptive data also suggest that the IBG may be lower in cases where deliberate planning is necessary because the specific measure seems complex or costly.

This first result may raise concerns about the external validity of studies which use stated intentions as a proxy for the implementation of adaptation measures. However, in the second section we find that estimated coefficients for the determinants of intentions broadly align with the respective coefficients in implementation models. These findings imply that conclusions regarding the effects of household characteristics, environmental factors, individual preferences etc. on adaptation intentions may still provide relevant insights for subsequent behavior, even though actual levels of adaptation intentions and behavior are likely to deviate and, consequently, can only imprecisely assessed as a consequences of the IBG. Hence studies focused on intentions can give relevant insights into factors that contribute to the implementation of adaptation measures, which may be useful information for policymakers who are interested to know which population sub-groups are likely to adapt or not. However, if policymakers would be interested in forecasting levels of implemented adaptation measures then studies on intentions may not be a good guide. This conclusion is also relevant for an emerging literature on future climate risk assessments that integrate human adaptation decisions in natural disaster risk models, and calibrate these decisions using survey data (Aerts et al. 2018, De Ruig et al. 2022), for which we learn that survey results on intentions levels should not be equated with implementation levels.

Third, we attempt to explain the IBG in the climate adaptation context by observable data on the household and individual characteristics of the respondent, such as perceived self-efficacy. We find only a few statistically significant effects, but one important result is that damage experience contributes to a closing of the IBG, hence intentions are rather followed up if the household is affected by some extreme weather event. Other potential explanatory factors, such as perceived self-efficacy, hardly correlate with the size of the IBG in climate adaptation.

Finally, we interpret the effects of intention realization and damage experience in a regret theory framework. Based on a life satisfaction regression, we show that stated life satisfaction significantly varies with damage experience and the realization of prior adaptation intentions. There is a "regret to be unprotected". Hence, life satisfaction drops for unprotected and flood-affected respondents – in particular compared to their protected and flood-affected counterparts. However, there is also a significant "regret of being (over-)protected" for adapted, but unaffected respondents, which show significantly lower levels of life satisfaction than unprotected and unaffected respondents do. This latter finding may be interpreted as one potential explanation for the existence of the IBG in climate adaptation.

Based on these findings, we conclude that it may be problematic to derive policy-relevant conclusions by the use of surveyed data on adaptation intentions only, especially when it comes to the general protection level within a population. Wherever possible, empirical research should make use of data on actually implemented adaptation. These data may be self-reported or measured more objectively, e.g. one may use sales data or external/professional observations of structural measures. The usage of implementation data raises the challenge of possible feedback effects of adaptation determinants and behavior. For solving this issue, the strategy of using longitudinal data on implementations and motivational factors may be a more promising approach than employing cross-sectional data on intentions.

In terms of policy conclusions, we see from our study that there is a window-of-opportunity for strengthening adaptation behavior in the aftermath of extreme weather events – not just because the intention to engage in adaptation rises (as many studies have shown) but also because pre-event intentions have a higher chance to be realized after an event. This insight may be used in adaptation-related communication campaigns and interventions, especially in the aftermath of natural disasters.

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Appendix

Appendix A1: Questionnaire Items

Implementation and intention of flood adaptation

Please indicate which of the following flood protection measures you have already carried out in your house or flat or are planning to do so in the near future:

Display in random order

	No, neither implemen-ted nor planned	**Yes, planned**	**Yes, already carried out**	**Don't know / Prefer not to say**
Relocation of valuable furnishings to a higher floor *(only if several floors are used).*	O	O	O	O
Water barriers in the basement *(only if basement is used)*	O	O	O	O
Sewer backflow preventers *(only for homeowners)*	O	O	O	O
Water-resistant exterior painting *(only for homeowners)*	O	O	O	O
Water-resistant indoor painting	O	O	O	O
Water-resistant flooring (e.g. tiles, granite) due to risk of flooding *(only for homeowners).*	O	O	O	O
Flood-proof heating system (e.g. secured oil tank) *(only for homeowners)*	O	O	O	O

Implementation of heat adaptation

Please indicate which of these items of equipment you have purchased yourself to make the indoor climate in your flat more comfortable.

Please note: This question only refers to purchases that you yourself have consciously made (with the primary aim of making the indoor climate in your flat more pleasant). Equipment that was already present in your flat when you moved in is not included.

O Table or ceiling fan

O Sun protection films or sun protection glass for the windows

O Air conditioning

O Green roof

O None of these features *(single choice, always in last place)*

O Don’t know

Intention of heat adaptation

Please indicate which of these items of equipment you

Please indicate which of the following equipment you expect to purchase in the near future to make the indoor environment in your home more comfortable.

(only options that were not selected in implementation question)

O Table or ceiling fan

O Sun protection films or sun protection glass for the windows

O Air conditioning

O Green roof

O None of these features *(single choice, always in last place)*

O Don't know

Self-efficacy (*SelfEff*)

In the following section, we would like you to indicate to what degree you agree with the statements on a scale from 1 (do not agree at all) to 7 (agree fully).

Show in random order

	Do not agree at all						Agree fully	Don't know / Prefer not to say
	1	2	3	4	5	6	7	
I have little control over the things that happen to me.	O	O	O	O	O	O	O	O
There is no solution at all to some of my problems.	O	O	O	O	O	O	O	O
There is little I can do to change the many important things in my life.	O	O	O	O	O	O	O	O
I often feel helpless in coping with life's problems.	O	O	O	O	O	O	O	O
Sometimes I feel that I am being ordered around in life.	O	O	O	O	O	O	O	O
What happens to me in the future is largely up to me.	O	O	O	O	O	O	O	O
I can do everything I really set out to do.	O	O	O	O	O	O	O	O

Life Satisfaction (*LifeSat*)

First of all, what would you say: How satisfied are you currently, all in all, with your life?

How would you rate yourself on a scale from 0 ("completely dissatisfied") to 10 ("completely satisfied")?

Completely dissatisfied										**Completely satisfied**
0	1	2	3	4	5	6	7	8	9	10
O	O	O	O	O	O	O	O	O	O	O

plus Don't know / Prefer not to say

Appendix A2: Additional Tables

Table of logit regressions with and without prior intentions, for all specific and aggregate measures

Table 9: Multivariate logit regression models of flood adaptation implementation, with and without including prior intentions.

Dependent variable	FlMov		FlSew		FlBar		FlWip	
Intentions		0.84**		0.52*		1.16**		1.92***
Female	-0.39*	-0.38*	-0.13	-0.12	0.30	0.34	-0.12	-0.12
Age	0.13*	0.13*	0.02	0.02	0.19**	0.19**	0.00	-0.01
Age squared (in 0.001)	-1.26**	-1.23**	-0.12	-0.09	-1.22*	-1.23*	-0.06	0.04
Homeowner	0.34	0.34			0.17	0.12	-0.57	-0.57
Educ	0.19	0.18	-0.25	-0.25	0.05	0.08	0.05	0.05
HHSize	-0.03	-0.03	0.00	0.00	0.07	0.09	-0.13	-0.14
Income	0.04	0.04	0.13*	0.12	0.09	0.08	0.06	0.06
FlZone	-0.29	-0.32	0.26	0.26	-0.09	-0.08	-0.65	-0.60
FlProb: 1	reference	reference	reference	reference	reference	reference	reference	reference
FlProb: 2	0.97***	0.95***	0.38*	0.35	0.38	0.36	0.35	0.31
FlProb: 3	1.19***	1.16***	0.35	0.32	1.05***	1.00***	0.53*	0.49
FlProb: 4	1.23***	1.19***	0.31	0.26	1.02***	0.98***	1.06***	1.05***
FlDam	1.21***	1.18***	0.37	0.33	0.81***	0.80***	1.21***	1.15***
FlInsHome	-0.43*	-0.43*	0.57**	0.57**	0.27	0.28	0.90**	0.91**
FlInsCont	0.47**	0.49**	-0.03	-0.02	0.31	0.31	0.41	0.40
Pseudo-R2	0.13	0.14	0.05	0.06	0.10	0.11	0.12	0.13
N	2024	2024	1174	1174	2162	2162	2552	2552

Dependent variable	FlWep		FlFlo		FlStr		FlAdapt	
Intentions		0.46		0.92*		0.47		0.15
Female	-0.37	-0.38	0.22	0.24	-0.06	-0.06	-0.22*	-0.22*
Age	0.02	0.02	-0.03	-0.03	-0.01	-0.01	0.05	0.04
Age squared (in 0.001)	-0.09	-0.09	0.23	0.23	0.10	0.12	-0.47	-0.46
Homeowner					1.63***	1.62***	1.39***	1.39***
Educ	-0.32*	-0.32*	0.19	0.18	0.05	0.05	-0.03	-0.03
HHSize	-0.11	-0.11	0.03	0.03	0.05	0.05	-0.02	-0.02
Income	0.03	0.03	0.06	0.07	-0.01	-0.01	0.08	0.08
FlZone	-0.42	-0.43	-0.06	-0.09	-0.10	-0.11	0.10	0.10
FlProb: 1	reference	reference	reference	reference	reference	reference	reference	reference
FlProb: 2	0.23	0.23	0.61***	0.60***	0.49***	0.48***	0.73***	0.72***
FlProb: 3	-0.08	-0.09	0.70***	0.71***	0.66***	0.65***	0.87***	0.86***
FlProb: 4	0.42*	0.42*	0.96***	0.94***	0.74***	0.73***	0.93***	0.92***
FlDam	-0.07	-0.08	0.46**	0.44**	0.65***	0.65***	0.87***	0.86***
FlInsHome	0.59**	0.59**	-0.07	-0.09	0.20	0.21	-0.06	-0.05
FlInsCont	0.22	0.22	0.47**	0.48**	0.42***	0.42***	0.38***	0.38***
Pseudo-R2	0.05	0.05	0.07	0.07	0.13	0.14	0.15	0.15
N	1469	1469	1520	1520	2496	2496	2127	2127

Based on the most recent observation of each respondent. The regression models include only households, which have not implemented the measure in the prior survey wave. Reported values are logit coefficients. Year- and federal-state fixed effects are always included. The stars *, **, *** indicate significance levels of 10, 5, and 1 percent.

Table 10: Multivariate logit regression models of heat adaptation implementation, with and without including prior intentions.

Dependent variable	HeatFan		HeatAC		HeatSun		HeatGre		HeatAdapt	
Intentions		1.11***		1.95***		1.35***		3.09***		0.63***
Female	-0.07	-0.08	-0.28	-0.18	-0.07	-0.09	-0.15	-0.25	-0.05	-0.05
Age	0.09**	0.08**	-0.04	-0.05	0.05	0.05	-0.22*	-0.23*	0.03	0.02
Age squared (in 0.001)	-0.97***	-0.89**	0.15	0.33	-0.30	-0.24	1.97*	2.02*	-0.39	-0.29
Homeowner	0.19	0.27*	0.59	0.59	0.44*	0.44*			0.31**	0.33**
Educ	-0.08	-0.06	-0.39	-0.46	-0.20	-0.18	0.45	0.31	-0.12	-0.11
HHSize	-0.04	-0.04	-0.18	-0.16	-0.06	-0.08	0.32	0.13	-0.03	-0.04
Income	0.04	0.04	0.44***	0.43***	0.29***	0.29***	0.63**	0.67**	0.13**	0.12**
Temp	0.25***	0.25**	0.49**	0.45**	-0.07	-0.07	1.35***	1.32**	0.24***	0.24***
Wind	-0.01	-0.01	-0.01	-0.03	-0.01	-0.01	-0.16**	-0.17**	-0.01	-0.01
BMI	0.03*	0.03*	0.02**	0.02*	0.00	0.00	-0.22**	-0.24**	0.02*	0.02*
HeatDam	0.90***	0.85***	0.28	0.15	1.06***	1.04***			0.72***	0.67***
Pseudo-R2	0.05	0.06	0.10	0.13	0.05	0.06	0.26	0.28	0.03	0.04
N	3050	3050	3114	3114	3351	3351	1299	1299	3220	3220

Based on the most recent observation of each respondent. The regression models include only households, which have not implemented the measure in the prior survey wave. Reported values are logit coefficients. Year- and federal-state fixed effects are always included. The stars *, **, *** indicate significance levels of 10, 5, and 1 percent.

Table 11: Multivariate logit regression models of flood and heat adaptation implementation, testing for different effects of damage experience for intended versus unintended implementations.

Dependent variable	*FlAdapt*	*HeatAdapt*
Intentions	0.04	0.66***
FlDam	0.81***	
Intentions**FlDam*	0.47	
HeatDam		0.73***
Intentions**HeatDam*		-0.29
Female	-0.22	-0.05
Age	0.05	0.02
Age squared (in 0.001)	-0.46	-0.30
Homeowner	1.39***	0.33**
Educ	-0.03	-0.11
HHSize	-0.02	-0.04
Income	0.08	0.12**
FlZone	0.10	
FlProb: 1	Reference	
FlProb: 2	0.73***	
FlProb: 3	0.87***	
FlProb: 4	0.93***	
FlInsHome	-0.06	
FlInsCont	0.38***	
Temp		0.24***
Wind		0.01
BMI		0.02*
Pseudo-R2	0.15	0.04
N	2127	3220

Based on the most recent observation of each respondent. The regression models include only households, which have not implemented the measure in the prior survey wave. Reported values are logit coefficients. Year- and federal-state fixed effects are always included. The stars *, **, *** indicate significance levels of 10, 5, and 1 percent.

Table 12: Alternative regressions of the implementation indicators, reported vales are coefficients.

	Implementation indicator in flood domain			Implementation indicator in heat domain		
Dependent variable	At least one intention implemented	Share of implemented intentions	Share of implemented intentions	At least one intention implemented	Share of implemented intentions	Share of implemented intentions
Estimation Method	Logit	OLS	Ordered probit	Logit	OLS	Ordered probit
Socio-Economics						
Female	0.10	0.04	0.24	-0.31	-0.03	-0.16
Age	-0.047	-0.10	-0.04	0.06	0.01	0.03
Age²	0.00	0.00	0.00	-0.00	-0.00	-0.00
Homeowner	2.14**	0.20**	1.60***	0.05	-0.01	0.15
Educ	0.54	0.07	0.30	-0.13	-0.01	-0.02
HHSize	-0.35	-0.04	-0.21	-0.24	-0.03*	-0.13
Income	-0.21	-0.03	-0.11	0.19	0.02*	0.15**
Flood-related variables						
FlZone	0.68**	0.15	0.62*			
FlProb						
- category 2	1.38**	0.16**	0.78**			
- category 3	0.54	0.05	0.23			
- category 4	1.02	0.09	0.59			
FlDam	1.28***	0.20***	0.70***			
FlInsHome	0.15	0.05	0.14			
FlInsCont	0.26	0.01	0.15			
Heat-related variables						
Temp				0.19	0.01	0.14
Wind				-0.05	-0.00	-0.02
BMI				0.04*	0.00	0.03**
HeatDam				0.42	0.04	0.24
Number of prior plans for specific measures						
FlMov			-0.16			
FlSew			-0.51***			
FlBar			-0.61**			
FlWip			-0.23			
FlWep			-1.01***			
FlFlo			-0.25			
HeatFan						0.43**
HeatAC						-0.34*
HeatSun						-0.08
HeatGre						-0.52
N	204	216	216	438	465	465
(Pseudo-)R2	0.192	0.194	0.195	0.076	0.071	0.124

One observation per household included. Federal state- and time-fixed effects are always included. The stars *, **, *** indicate significance levels of 10, 5, and 1 percent.

Appendix A3: Additional Figures

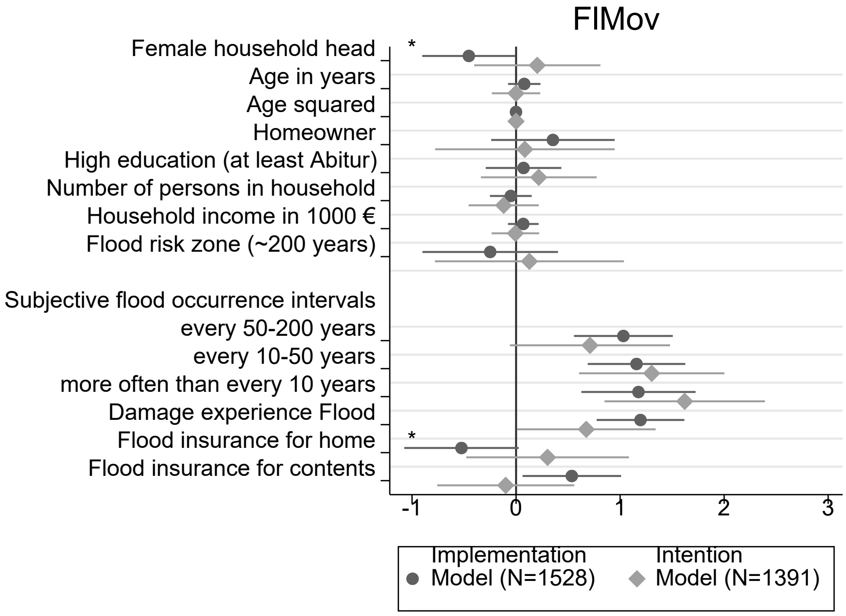

*Figure 4: Estimated coefficients (and 95% confidence intervals) of logistic regression models for implementing and intending FlMov. The estimation samples includes only observations of 2020, and only households, which have not implemented the measure in the prior survey wave. The stars indicate significantly different coefficients for the two models. *, **, *** indicate significance levels of 10, 5, and 1 percent. The joint F-test of all coefficients being identical across the two models suggests that the models overall yield similar coefficients (p=0.14).*

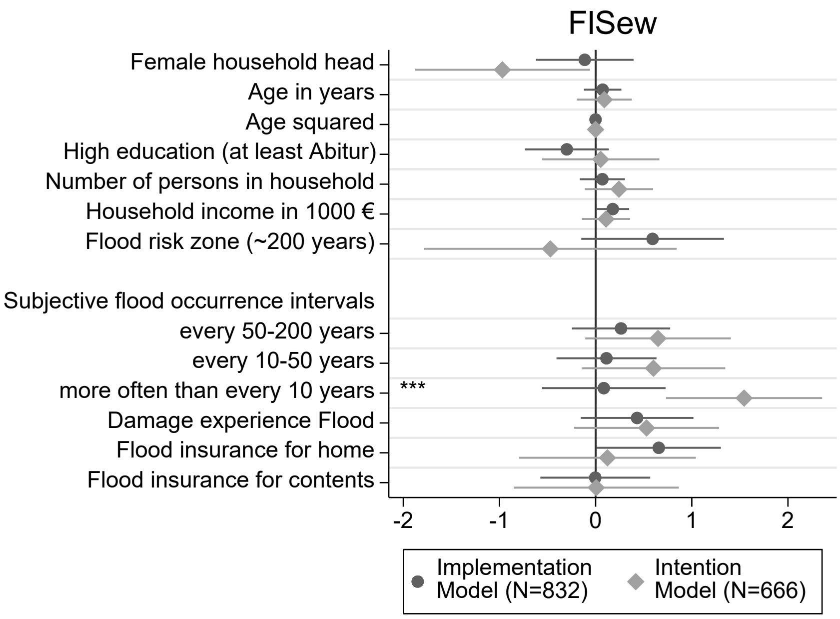

*Figure 5: Estimated coefficients (and 95% confidence intervals) of logistic regression models for implementing and intending FlSew. The estimation samples includes only observations of 2020, and only households, which have not implemented the measure in the prior survey wave. The stars indicate significantly different coefficients for the two models. *, **, *** indicate significance levels of 10, 5, and 1 percent. The joint F-test of all coefficients being identical across the two models suggests that the models overall yield similar coefficients (p=0.11).*

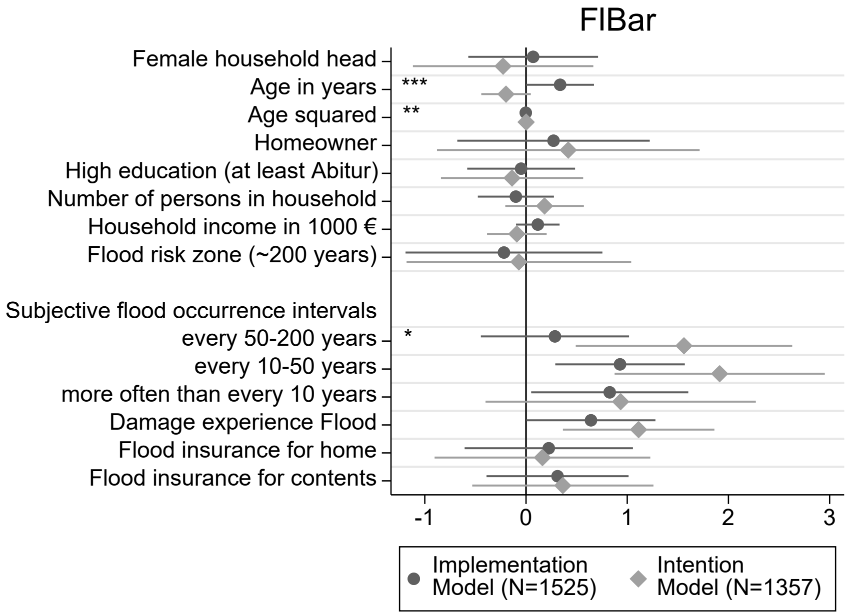

*Figure 6: Estimated coefficients (and 95% confidence intervals) of logistic regression models for implementing and intending FlBar. The estimation samples includes only observations of 2020, and only households, which have not implemented the measure in the prior survey wave. The stars indicate significantly different coefficients for the two models. *, **, *** indicate significance levels of 10, 5, and 1 percent. The joint F-test of all coefficients being identical across the two models suggests that the models overall yield similar coefficients (p=0.20).*

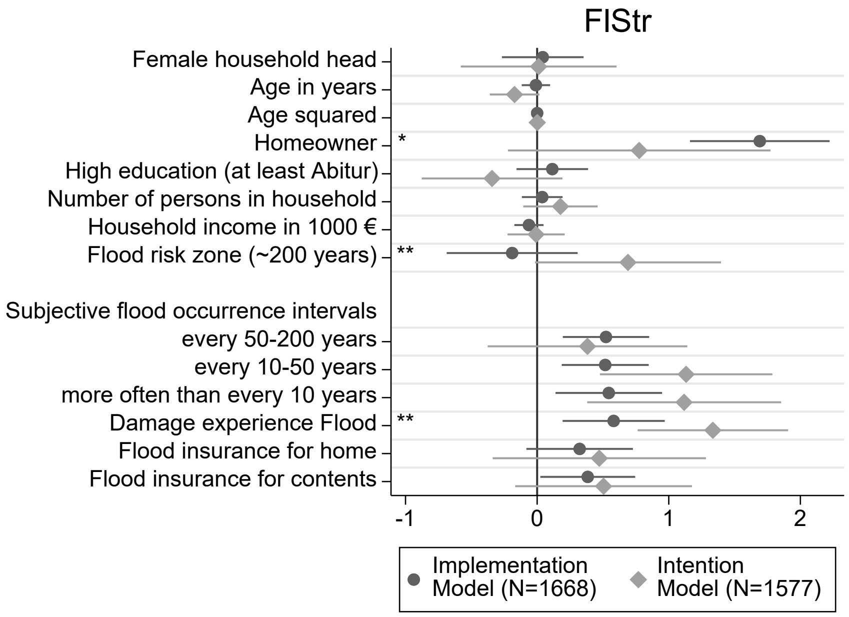

*Figure 7: Estimated coefficients (and 95% confidence intervals) of logistic regression models for implementing and intending FlStr. The estimation samples includes only observations of 2020, and only households, which have not implemented the measure in the prior survey wave. The stars indicate significantly different coefficients for the two models. *, **, *** indicate significance levels of 10, 5, and 1 percent. The joint F-test of all coefficients being identical across the two models suggests that the models overall yield different coefficients (p=0.04).*

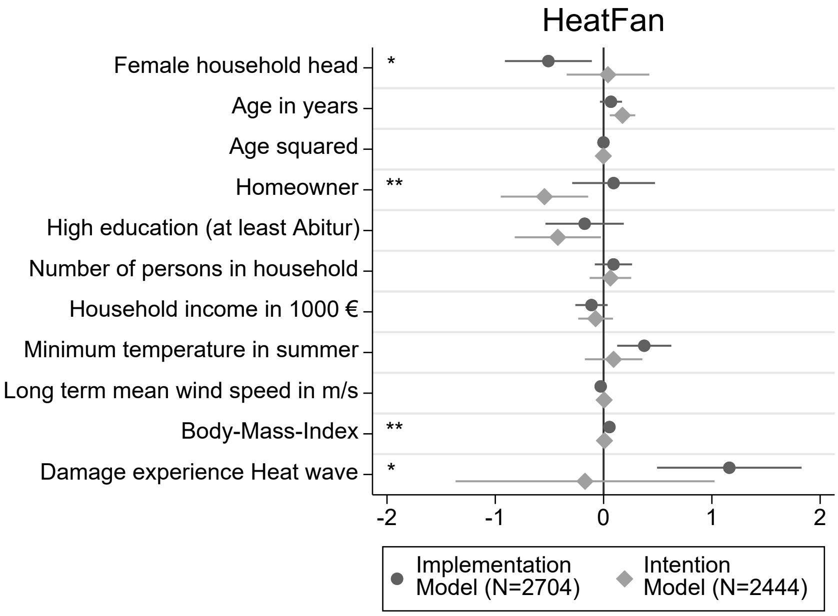

*Figure 8: Estimated coefficients (and 95% confidence intervals) of logistic regression models for implementing and intending HeatFan. The estimation samples includes only observations of 2014, and only households, which have not implemented the measure in the prior survey wave. The stars indicate significantly different coefficients for the two models. *, **, *** indicate significance levels of 10, 5, and 1 percent. The joint F-test of all coefficients being identical across the two models suggests that the models overall yield different coefficients (p<0.01).*

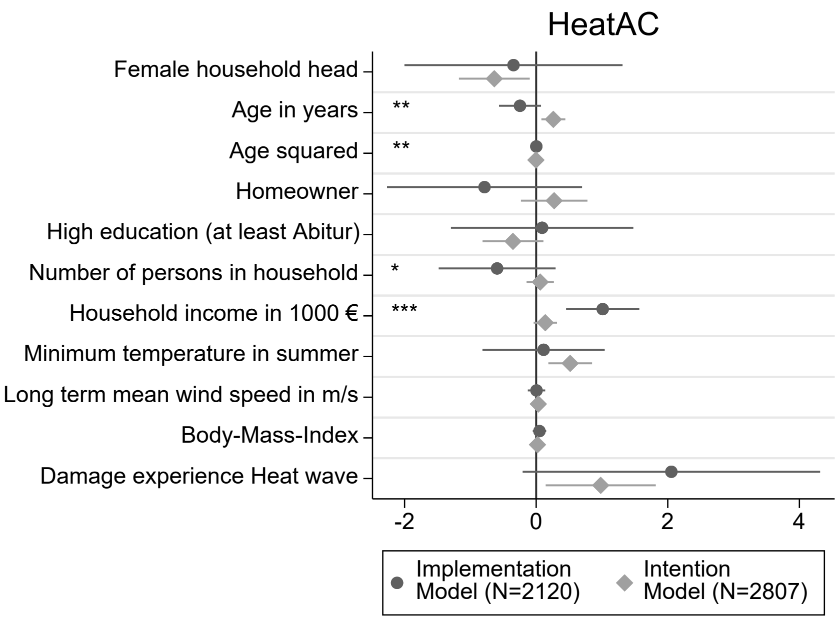

*Figure 9: Estimated coefficients (and 95% confidence intervals) of logistic regression models for implementing and intending HeatAC. The estimation samples includes only observations of 2014, and only households, which have not implemented the measure in the prior survey wave. The stars indicate significantly different coefficients for the two models. *, **, *** indicate significance levels of 10, 5, and 1 percent. The joint F-test of all coefficients being identical across the two models suggests that the models overall yield different coefficients (p<0.01).*

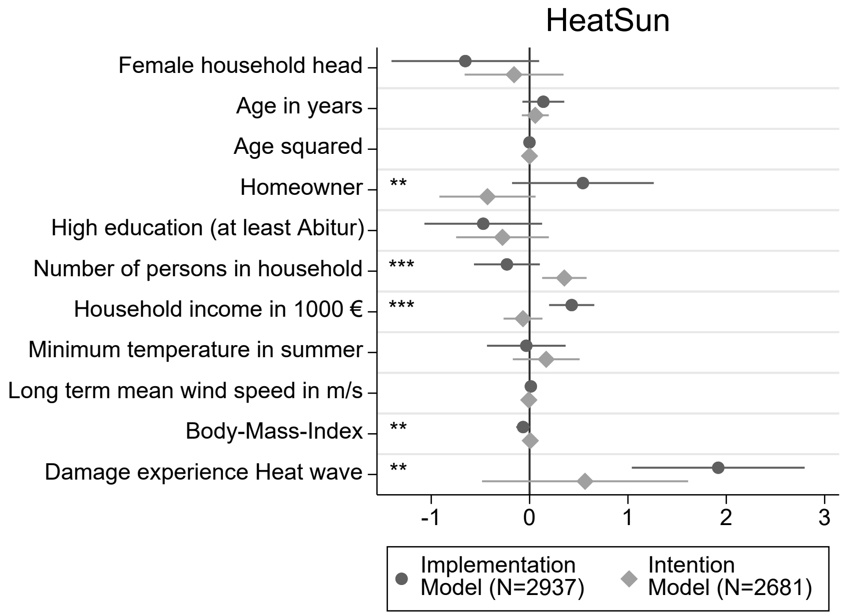

*Figure 10: Estimated coefficients (and 95% confidence intervals) of logistic regression models for implementing and intending HeatSun. The estimation samples includes only observations of 2014, and only households, which have not implemented the measure in the prior survey wave. The stars indicate significantly different coefficients for the two models. *, **, *** indicate significance levels of 10, 5, and 1 percent. The joint F-test of all coefficients being identical across the two models suggests that the models overall yield different coefficients (p<0.01).*

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