More Talk, No Action? The Effect of Exposure to Extreme Weather Events on Climate Change Concern and Pro-Environmental Behaviour

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Abstract

Previous research has shown a link between extreme weather events and people's concern about climate change and their pro-environmental behaviour. This indicates that people may become more environmentally friendly amid increasing extreme weather events. Still, the influence of experiencing extreme weather events on actual behaviour has rarely been tested with large-scale individual-level data and longitudinal methods. This study links panel data from 35,678 individuals to floods across England and heatwaves across the UK, and applies within-person estimators to account for pre-existing differences between affected and unaffected individuals. Results reveal that individuals are more likely to be concerned about climate change after being affected by a geographically proximate flood or a temporally proximate heatwave. These effects are stronger among initially right-leaning partisans and those initially more sceptic about the existence of climate change, thereby indicating attitudinal updating due to experiential learning. However, those exposed to extreme weather events do not change their environmental behaviour such as energy saving, sustainable shopping or mode of transportation. Even among those who become more concerned, people's behaviour does not react to extreme weather events.

Keywords: Climate Change; Climate Change Concern; Pro-Environmental Behaviour; Extreme Weather Events; Floods; Heatwaves; Individual Panel Data

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1 Introduction

Continued severe droughts and record temperatures throughout 2022 have once again underscored the tremendous impact of the climate crisis on societies across the globe. Most nations have not dramatically changed polluting behaviors and therefore greenhouse gas emissions continued to increase over the past decade (IPCC 2022). Climate projections predict that the frequency of natural disasters will substantially increase above current levels in the foreseeable future (Roudier et al. 2016)), and affect a substantial amount of people (Mora et al. 2017).

Mitigation of climate change and its impacts thus lists among the most pressing challenges of our time (Dietz, Shwom, and Whitley 2020; IPCC 2022). Yet, many societal and political actions critically hinge on the support of individual actors (Brügger, Morton, and Dessai 2015; van Valkengoed and Steg 2019). It is therefore important to understand the drivers of people’s attitudes towards climate change and relevant behavioural patterns. Several studies have shown that individual experiences of climate-related events – like floods, extreme precipitation, or heatwaves – are linked to stronger beliefs in climate change (Howe et al. 2019; Hornsey et al. 2016; Larcom, She, and van Gevelt 2019; Myers et al. 2013; Osberghaus and Fugger 2022; Spence et al. 2011) and green voting (Baccini and Leemann 2020; Hazlett and Mildemberger 2020; Hoffmann et al. 2022), thereby indicating that climate change itself may change people’s attitudes and behaviour. Still, many empirical findings are based on cross-sectional comparisons (Demske et al. 2017; Howe 2018; Howe et al. 2019) or use spatially aggregated data only (Howe et al. 2019).

This study investigates how the exposure to extreme weather events – floods and heatwaves – influences people’s concern about climate change and their pro-environmental behaviour based on large-scale individual-level data in the UK. The study also investigates several theoretical mechanisms. First, it uses the

57 natural variation in spatial and temporal distance of extreme weather events to
58 investigate the role of experiential learning. Second, we compare the effect across
59 several subgroups, such as political partisans and initial sceptics to contrast
60 experiential learning against motivated reasoning patterns.

61 The study contributes to the existing literature in several ways. First, we
62 use individual-level panel data of nearly 36,000 individuals, and link those to
63 recorded flood outlines in England and weather data across the UK based on
64 participants' place of residence. Second, we apply panel-data methods and
65 within-person estimators to rule out person-specific confounding. Third, the
66 study investigates two types of extreme weather events – floods and heatwaves
67 – increasing the robustness and generalisability of results. Fourth, it tests effects
68 on climate change concern and various forms of behaviour, which allows to test
69 if attitudinal changes translate into more sustainable behaviour. Fifth, it differ-
70 entiates the impact of extreme weather events by spatial and temporal distance
71 to the respective events. Finally, we explore heterogeneous effects according to
72 partisanship and initial climate scepticism, which provides additional insights
73 on the psychological pathways of the relation.

74 Results reveal that floods and heatwaves indeed increase the concern about
75 climate change. The magnitude of this effect increases with spatial and tem-
76 poral proximity, which is in line with experiential learning. Moreover, right-
77 leaning partisans and those initially more sceptic about climate change show
78 the strongest impact on climate change concern after being affected by an ex-
79 treme weather event. This indicates that extreme weather events can actually
80 update people's attitudes. However, updating attitudes does not change people's
81 pro-environmental behaviour. Extreme weather events have negligible effect on
82 people's behaviour, and this finding is consistent across floods and heatwaves,
83 across different behavioural measures, as well as across several subgroups.

84 **2 Theory**

85 There are several pathways in which extreme weather events can influence peo-
86 ple’s beliefs and attitudes, which are all related to the concept of experiential
87 learning. This section will briefly outline the theoretical idea of experiential
88 learning, and subsequently argue that it is hard to predict how changes in atti-
89 tudes will translate into individual behaviour.

90 **Attitudinal updating**

91 It is often argued that this effects is based on experiential learning. Processing
92 scientific information and making an informed risk assessment of an abstract
93 construct like climate change requires motivation and cognitive effort (Myers
94 et al. 2013). However, people often avoid spending cognitive resources, but in-
95 stead rely on subconscious cognitive processes when forming opinions or making
96 decisions (Dietz 2020; Kahneman 2011; Myers et al. 2013). Providing (more)
97 statistical evidence is therefore unlikely to convince people who do not believe
98 in the existence of climate change or to increase their concern. Experiential
99 learning – personally experiencing climate change – can be more influential for
100 several reasons. First, personal experience increases the mental accessibility of
101 concrete events related to the abstract concept of climate change (Demski et
102 al. 2017; Howe 2018; Taylor, Bruine de Bruin, and Dessai 2014; Pryce, Chen,
103 and Galster 2011; Adger et al. 2013; Grothmann and Patt 2005; Spence et al.
104 2011). Second, experiencing extreme weather events can induce strong emo-
105 tional feelings attached to environmental issues (Whitmarsh 2008; Zaalberg et
106 al. 2009; Leiserowitz 2006; McAdam 2017). Third, directly experiencing ex-
107 treme weather events reduces the perceived spatial and temporal distance of
108 climate change (Brügger, Morton, and Dessai 2015; Brügger et al. 2015; Evans,
109 Milfont, and Lawrence 2014; Mildenerger, Lubell, and Hummel 2019; Spence,

110 Poortinga, and Pidgeon 2012). Affected people adjust their prior belief that cli-
111 mate change only happens in far geographical and temporal distance (Druckman
112 and McGrath 2019; Howe 2018).

113 Following this last strand of argumentation, more proximate events – in space
114 and time – should have stronger impacts on prior climate change concerns. As
115 personal exposure also elevates the perceived risk of experiencing more adverse
116 impacts and provides more specific goals of mitigating action (Howe and Leis-
117 erowitz 2013; Myers et al. 2013; Spence et al. 2011), it should increase the
118 propensity of engaging in mitigating behaviour (Brügger, Morton, and Dessai
119 2015; Demski et al. 2017). *We thus expect extreme weather events to have a*
120 *stronger impact on climate change concern and pro-environmental behaviour,*
121 *the closer these events are in time and space.*

122 Nevertheless, if and especially how extreme weather events influence atti-
123 tudes towards climate change has been subject of debate (Brügger, Demski,
124 and Capstick 2021), and many theories hinge on critical assumptions. For in-
125 stance, people need to accurately attribute local events to long-term climate
126 change (Howe 2018; Ogunbode et al. 2019). Moreover, from a motivated rea-
127 soning perspective, a person could consider past experiences as invalid evidence
128 if these experiences are not congruent with their prior beliefs (Druckman and
129 McGrath 2019; Howe and Leiserowitz 2013; Howe 2018; Myers et al. 2013). Peo-
130 ple who initially are not concerned about climate change may not use personal
131 experiences to update their existing opinions. For instance, previous research
132 (Hazlett and Mildemberger 2020) has found that wildfire exposure affects vot-
133 ing behaviour for green policies among Democrats but not among Republicans.
134 Still, it is debated if this results from partisanship itself or whether it is a re-
135 sult of general scepticism about climate change (Ogunbode et al. 2019). Recent
136 research in Germany (Osberghaus and Fugger 2022) has found that proximate

137 floods increased climate change concern especially among those who were ini-
138 tially more likely to be concerned about climate change. People might thus
139 interpret personal experiences in a way that reinforces their existing beliefs in-
140 stead of updating their prior beliefs and concerns.

141 **Behavioural changes**

142 Overall, the previous literature on attitudinal changes provides some hope for
143 climate change mitigation in the sense that more frequent extreme weather
144 events will nudge peoples' behaviour into a more sustainable direction. Still,
145 there is a substantial gap between attitudes and behaviour: regarding individual
146 pro-environmental behaviour, additional barriers need to be taken into account
147 (Ajzen 1991; Best and Kneip 2011; Diekmann and Preisendörfer 2003).

148 For instance, affected people need to project the experience of extreme
149 weather events on their motivation to prevent potential future impacts (Brügger
150 et al. 2015; Pryce, Chen, and Galster 2011; Mildenerger, Lubell, and Hummel
151 2019). However, personal experience could also induce the opposite behaviour
152 because people doubt the effectiveness of mitigation strategies, thus lacking a
153 feeling of efficacy (Brügger et al. 2015; Mildenerger, Lubell, and Hummel 2019;
154 Zhou 2016). If people feel incapable of dealing with climate change, they may
155 cope with the uncomfortable situation by denying their individual responsiveness
156 or contribution (Brügger et al. 2015). Moreover, construal level theory predicts
157 that immediate needs and short-term cost-benefit calculations become more im-
158 portant for behavioural intentions in face of proximate threats, in turn lowering
159 the likelihood of engaging in costly pro-environmental behaviour (Brügger et al.
160 2015; Spence, Poortinga, and Pidgeon 2012).

161 While the above mentioned barriers affect individual as well as collective re-
162 sponses, the dilemma of collective action (Olson 1971; Ostrom 1998) constitutes

163 another well-known barrier for changes in long-term collective behaviour or mit-
 164 igation of climate change. Although small changes among all individuals of a
 165 society would greatly benefit global climate change mitigation, the contribution
 166 of a single person to global climate change is objectively close to zero (Lubell et
 167 al. 2006; Olson 1971). Even if the perceived risk is high, every single person has
 168 an incentive to free-ride – avoiding the behavioural costs of pro-environmental
 169 actions – and to rely on others providing the collective good (Lubell et al. 2006;
 170 Ostrom 1998). In other words, everyone profits from successful global mitiga-
 171 tion and no one can be excluded from using the common good (Ostrom 1998).
 172 Also in the face of direct extreme weather experiences it might thus still be
 173 the ‘rational’ (in the sense of maximizing self-interests) response to not change
 174 behavioural patterns.

175 Although several studies have documented a positive link between extreme
 176 weather events and pro-environmental behaviour (Adger et al. 2013; Grothmann
 177 and Patt 2005; Spence et al. 2011; van Valkengoed and Steg 2019; Zaalberg et al.
 178 2009), it has previously been criticized (Demskei et al. 2017; Howe 2018; Howe et
 179 al. 2019) that many studies rely on cross-sectional data. This makes it difficult
 180 to establish causal relations. The risk of experiencing an extreme weather event
 181 often may correlate with spatial patterns in attitudes and behaviour (Betz,
 182 Cook, and Hollenbach 2020; Howe et al. 2019), thereby affecting estimates in
 183 cross-sectional studies. Recent longitudinal studies have confirmed previous
 184 findings by identifying impacts of extreme weather events on voting behaviour
 185 (Baccini and Leemann 2020; Hazlett and Mildemberger 2020; Hoffmann et al.
 186 2022) and environmental attitudes (Osberghaus and Fugger 2022). Still, it is
 187 not clear if those impacts also translate into changes of individual behaviour
 188 which would help mitigating long-term climate change. *We thus hypothesize*

189 *that the effect of extreme weather events on behaviour is weaker than the effect*
190 *on attitudes.*

191 **3 Materials and Methods**

192 **3.1 Data and variables**

193 This study uses individual-level panel data of the harmonized British House-
194 hold Panel Study (BHPS, 1991 - 2008) and UK Household Longitudinal Study
195 (UKHLS, 2009 - 2020), a nationally representative panel study with annual
196 information from 1991 to 2020 (University of Essex, Institute for Social and
197 Economic Research 2020). The special access version includes information on
198 the current place of residence down to the level of Lower Layer Super Output Ar-
199 eas (LSOA). On average, an LSOA includes 1,400 individuals (600 households)
200 and thus provides a very fine-grained spatial resolution, especially in densely
201 populated areas. This geographical information was matched to 1) the Envi-
202 ronment Agency’s Recorded Flood Outlines data in England ¹, which contains
203 the date and geographic information on floods from rivers, the sea, groundwater
204 and surface water; and to 2) the HadUK-Grid climate observations (Hollis et al.
205 2019), which provide UK-wide information on daily temperature. The residen-
206 tial history of respondents and population weighted centroids of LSOAs were
207 used to match flood events and maximum daily temperature.

208 To measure the experience of flood events in England, we first created a
209 series of buffers around the population-weighted centroid of each LSOA. Buffer
210 widths of 1km, 2km, and 5km radius were used to measure floods in varying
211 spatial proximity. As exemplarily shown in Figure 1, we then calculated the
212 spatial overlap between the buffers and all flood outlines for each single day. An

¹The dataset is publicly available at <https://data.gov.uk/dataset/16e32c53-35a6-4d54-a111-ca09031eaaaf/recorded-flood-outlines#licence-info> (last access: October 28, 2020).

Figure 1: Merging strategy between 1km buffer around the population-weighted centroid of each LSOA and flood outlines using the example of Oxford 2007. Flooded areas are indicated in blue.

LSOA was classified as experiencing a flood, if – on a given day – one hectare (10,000m²) of the respective buffer area was covered by floodings. The area of one hectare is close to approximately 1.5 soccer fields in size. This cut-off point was chosen to exclude very small (potentially unrecognisable) floods. Following previous literature (Hazlett and Mildemberger 2020), only floods within the previous two years before the interview date were included to construct the flood-exposure indicator (see Figures S5 for alternative specifications). Based on the available data, we can however not identify if an individual has directly experienced harm to health or property due to the flood.

As noted earlier (Howe et al. 2019), extreme weather events like heatwaves do not happen on a local scale, but usually affect a very large area (see Figure

Figure 2: Heatwave classification based on the example of August 1, 2013. Left panel shows the daily maximum temperature on that specific day. Right panel shows the LSOAs which were classified as experiencing a heatwave on the respective day. The marked areas have experienced a daily maximum temperature of $\geq 29^{\circ}\text{C}$ for at least three consecutive days (2 days before date + respective date).

224 2). High temperatures or heatwaves are thus not suited to explore the role of
 225 spatial proximity. However, given the higher number of respondents affected,
 226 heatwaves provide a setting to investigate the role of temporal proximity. To
 227 measure the exposure to extreme temperatures or heatwaves, LSOA outlines
 228 were intersected with the $5 \times 5\text{km}$ grid of the HadUK-Grid climate observations,
 229 including information on the daily maximum temperature. Subsequently, an
 230 LSOA was coded as experiencing a heatwave if the daily maximum temperature
 231 equals or exceeds 29°C for at least three consecutive days. The threshold of 29°C
 232 has been used in previous research on the effect of heatwaves (Larcom, She, and
 233 van Gevelt 2019). To avoid classifying single hot days as ‘heatwave’, we coded

only instances as an event in which the high temperature remained at 29°C for at least three consecutive days up to the respective date. This information is available for the entire UK, including Northern Ireland, Scotland, and Wales. To examine the role of temporal proximity, we constructed the heatwave indicator for being affected within the past 14 days, within the past month, and within the past 4 months before the interview date.

This study tests the effect of extreme weather experience on two outcome measures: concern about climate change, and pro-environmental behaviour. Concern about climate change was measured by the question ‘Please select whether, on the whole, you personally believe or do not believe each of the following statements. People in the UK will be affected by climate change in the next 30 years’ with response options ‘Yes, I do believe this’ or ‘No, I do not believe this’. Pro-environmental behaviour was measured by an average index of seven (recoded) questions on how often respondents do the following: ‘Leave your TV on standby for the night’; ‘Switch off lights in rooms that aren’t being used’; ‘Keep the tap running while you brush your teeth’; ‘Put more clothes on when you feel cold rather than putting the heating on or turning it up’; ‘Decide not to buy something because you feel it has too much packaging’; ‘Buy recycled paper products such as toilet paper or tissues’; ‘Take your own shopping bag when shopping’. All questions were answered on a 5-point scale from ‘always’ to ‘never’, and were recoded in the way that larger numbers refer to more environmentally friendly behaviour. These two measures – climate change belief and pro-environmental behaviour – are available for three BHPS/UKHLS waves (survey years 2008-11, 2012-14, and 2018-2020). Sample descriptives can be found in Section A of the Supplementary Material.

To test heterogeneous treatment effects, we used the following questions. For partisanship, we used the party support and preference. Right-leaning parties

are ‘Conservatives’, ‘Ulster Unionist’, ‘Democratic unionist’, ‘UK Independence Party’, and ‘The Brexit Party’. Left-leaning parties are ‘Labour’, ‘Liberal Democrat’, ‘Scottish National Party’, ‘Plaid Cymru’, ‘Green Party’, ‘Alliance Party’, ‘SDLP’, and ‘Sinn Fein’. Those not stating a party preference or indicating that their party support is ‘not very strong’ are coded as no partisanship. To measure scepticism, we used the following three questions: a) ‘The so-called ‘environmental crisis’ facing humanity has been greatly exaggerated’, b) ‘The effects of climate change are too far in the future to really worry me’, and c) ‘If things continue on their current course, we will soon experience a major environmental disaster’ (reversed). Any person agreeing (‘Yes, I believe this’) on one of those statements was coded as sceptic, everyone not agreeing as not sceptic.

3.2 Analytical Strategy

Cross-sectional methods rely on the main identification assumption that the indicator of interest is the strictly exogenous conditional on the observed controls: $E(\epsilon_{it}|\tau_{it}, \mathbf{x}_{it}) = 0$, where τ_{it} is the extreme weather indicator, $\mathbf{x}_{it}$ a row-vector of time-constant and time-varying control variables, and ϵ_{it} the error term. This assumption, for instance, would be violated if a person-specific trait – say affinity to nature – influences the likelihood of being affected by a weather event and the belief in climate change or pro-environmental behaviour respectively. It would also be violated by regional differences in the likelihood of extreme weather events and environmental attitudes (see for instance placebo tests, Figures S6 and S7 in the Supplement).

To tackle these issues, we use twoways person-fixed effects (FE) estimators with group-specific time trends in the main analysis. The FE estimator calculates if becoming affected by a flood is correlated to within-person changes of

attitudes and behaviour. This rules out any bias due to time-constant person-specific confounders (Wooldridge 2010). Formally, we estimated the following FE model:

$$y_{it} = \tau_{it}\beta + \mathbf{z}_{it}\boldsymbol{\theta} + \alpha_i + \eta_s * \delta_i + \epsilon_{it}, \quad (1)$$

where α_i are individual-specific fixed effects, and $\mathbf{z}_{it}$ is a subset of time-varying control variables in $\mathbf{x}_{it}$. This relaxes the main identification assumption to $E(\epsilon_{it}|\tau_{it}, \mathbf{z}_{it}, \alpha_i, \eta_s, \delta_i) = 0$. While the indicator for extreme weather events still needs to be unrelated to idiosyncratic variation in ϵ_{it} , we account for all time-constant between-person differences. Yet, in the conventional two-ways FE specification, we still need the assumption of parallel trends between ‘treatment’ and ‘control’ group $E(\eta_{si}|\tau_{it}, \mathbf{z}_{it}) = 0$, i.e. those affected by an event would have had the same temporal trend in the outcome than the unaffected if they would not have been affected (Goodman-Bacon 2021; Rüttenauer and Ludwig 2020). This assumption is further relaxed here by interacting the seasonal fixed effects η_s with δ_i , an indicator of whether an individual ever received or will receive ‘treatment’ (ever affected by flood or heatwave respectively), thereby accounting for group-specific temporal trends. This δ_i indicator is constructed using the full observed residential history of each individual, which in the most informative cases ranges from 1991 to 2020 (UKHLS respondents are only observed from 2009 onwards).

All models were estimated as linear probability (climate change belief) or linear (environmental behaviour) models via least squares methods for the sake of simplicity. However, supplementary robustness checks using probit models for the binary indicator of climate change belief fully support the main results (see Figure S4). All models control for the year-season, and additional estimates include individual-level controls which have been shown to influence environ-

mental attitudes and behaviour (Hornsey et al. 2016; van Valkengoed and Steg 2019): age (5 year intervals), highest education, child(ren) in the household, marital status, and household income (decile intervals). Supplementary pooled OLS models (Figure S2) also include the time-constant controls sex, ethnicity and migration background. Standard errors are clustered at the individual and the LSOA level. The *R* package *sf* (Pebesma 2018) were used for spatial operations, *lfe* (Gaure 2013) and *plm* (Croissant and Millo 2008) for estimation of FE models, and *ggplot2* (Wickham 2016) and *texreg* (Leifeld 2013) for presentation of results.

To test the interaction between past experience and partisanship or scepticism respectively, the entire right-hand side of Equation (1) was interacted with the respective time-constant group indicator, thereby accounting for potential interactions with other controls and the time trends. Note that we used first wave information only to measure initial partisanship and initial scepticism. This is important as partisanship and scepticism could be subject of attitudinal updating due to experiencing an extreme weather event themselves.

4 Results

Figure 3 descriptively shows the average level of pro-environmental behaviour for observations ever affected by a heatwave and observations never affected along the temporal proximity to the actual event. The distance to the event for the control group is calculated by matching never affected observations to affected observations based on the interview date – we are thus comparing affected individuals to unaffected individuals who answered on similar dates. Although observations exposed to a heatwave more often engage in pro-environmental behaviour (see also Figure S2), a substantial part of the behavioural difference between affected and unaffected individuals already existed prior to the actual

Figure 3: Average pro-environmental behaviour before and after experiencing a heatwave. Triangles and squares are the averages within 15 days interval bins. Trend lines and respective 95% confidence intervals are based on thin plate splines smoothness estimates of the original continuous data (not shown). The treatment group contains respondents who were affected in the past (after heatwave), or will be affected in the future (before heatwave). Distance to the event for the control group is constructed by using nearest neighbours matching – solely based on the interview date – with maximum 5 days distance and 1-3 matches per treated unit.

event. This indicates that the spatial patterns of pro-environmental behaviour correlate with the likelihood of experiencing an extreme weather event. The treated and control group likely differ on various dimensions.

Similarly, cross-sectional models based on placebo outcomes indicate a significant relation between extreme weather events and theoretically unrelated outcomes like religiosity or the satisfaction with income (Figures S6 and S6). Obviously this is not because floods and heatwaves affect religiosity or satisfaction with income, but because the spatial patterns of extreme weather events are not random (Betz, Cook, and Hollenbach 2020; Howe et al. 2019) and correlate with the spatial patterns of other covariates. These spurious associations

Figure 4: Coefficient of past flood / heatwave experience for different spatial distances to floods and temporal distances to the heatwave incidences, respectively. Linear individual fixed effects (FE) estimator. Error bars represent 95% confidence interval (** $p < 0.01$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.1$). Two-sided test with cluster robust standard errors (clustered by person and LSOA). Basic controls: year-season of interview. Additional controls: age (5 year intervals), highest education, child(ren), marital status, household income (decile intervals). N describes the number of observations in each estimation sample (constant across spatial and temporal distances).

vanish once we rely on person-fixed effects (FE) estimators with group specific time trends (Figures S6 and S6). This strategy eliminates all time-constant person-specific differences, and additionally accounts for potentially non-parallel trends between treatment and control group. The within-person estimates are hence to be preferred when aiming to identify a causal relation between extreme weather events and attitudes or behaviour, although we cannot completely rule out time-varying unobserved confounding.

Figure 4 depicts how climate change concern and pro-environmental behaviour changes when individuals are exposed to floods (upper panel) and heat-waves (lower panel) compared to periods in which they are not exposed. If individuals are exposed to floods within 2km or 1km of their homes, they are more likely to be concerned about climate change than they are in unaffected periods. This holds no matter of additional socio-demographic controls. Net of controls, being exposed within 2km changes the likelihood of being concerned about climate change by 3.0%-points ($p < 0.01$), and being exposed within 1km by 3.6%-points ($p < 0.05$). In relative terms, exposing a randomly drawn individual to a flood within 1km would increase the expected likelihood of this individual to believe in climate change by 4.5% (from the overall sample probability of 79.5%). For floods occurring within 5km, the effect size essentially drops to zero ($\beta = 0.008$, $p > 0.1$), thereby implying a strong distance decay. This finding is in line with the assumption that proximate events have a stronger effect on risk perception and attitudinal updating (Brügger, Morton, and Dessai 2015; Brügger et al. 2015; Evans, Milfont, and Lawrence 2014; Mildemberger, Lubell, and Hummel 2019; Spence, Poortinga, and Pidgeon 2012). However, the strong distance decay also implies that the societal significance of the flood effect is limited: only 3.6% of the observations experienced a flood within 2km of their residence (Table S1). Even if flood incidences were to double during the next decade, this would only marginally affect the overall share of people believing in climate change (increase by 0.26%-points in total).

More importantly, this change in belief does not translate into changes in behaviour. For all geographical distances, being affected by a flood exhibits only minor and non-significant effects on changes in pro-environmental behaviour (β from -0.016 to -0.001, all $p > 0.05$). By trend, the estimates even point into an unexpected direction, indicating a slight decrease in pro-environmental

behaviour. This might be explained by adverse reactions to proximate threats (Brügger et al. 2015; Spence, Poortinga, and Pidgeon 2012). The pattern looks strikingly similar with transportation behaviour: being affected by an extreme weather event exerts a null-effect on the frequency of travelling by car and the frequency of using a bicycle (see Figure S3).

For heatwaves (bottom panel of Figure 4), again we find that temporally proximate events significantly change an individual’s concern about climate change. Experiencing a heatwave within the past month prior to the interview increases the probability of climate change concern by 2.8%-points ($p < 0.01$). Similarly, being exposed within 14 days increases the probability by 2.8%-points ($p < 0.01$). The effect is however undetectable for a temporal distance of four months ($\beta = 0.012$, $p > 0.05$). This pattern according to temporal proximity is strikingly similar to the geographical pattern of floods. Both extreme weather events exhibit a positive effect on climate change concern, and this effect increases in magnitude with temporal and spatial proximity. Again, the distance decay is relatively strong with effects being non-significant for 4 months temporal distance. Yet, the positive effect of heatwaves on climate change concern does not translate into changes in pro-environmental behaviour. None of the temporal bandwidths indicates a significant effect of past heatwave exposure on pro-environmental behaviour (β from 0.001 to 0.010, all $p > 0.1$). Moreover, the point estimates are negligible in magnitude: based on an effect of 0.01 points (on a 5-point scale), we would expect a randomly drawn individual to increase their pro-environmental behaviour by only 0.31% when being exposed to a heatwave. Again, supplementary analyses corroborate these results regarding mobility behaviour: individuals do not adjust their frequency of travelling by car or bicycle after experiencing an extreme weather event (see Figure S3).

408 **Updating vs Motivated Reasoning**

409 A matter of debate in the previous literature is *how* extreme weather events af-
410 fect attitudes (Brügger et al. 2015; Brügger, Demski, and Capstick 2021; Ogun-
411 bode et al. 2019). In the following, we thus test if extreme weather events indeed
412 work through the updating of prior beliefs or rather the reinforcement of exist-
413 ing views. We differentiate between groups with different initial characteristics:
414 a) people who initially state a strong political partisanship (left-leaning or right
415 leaning), and b) those who initially express higher scepticisms about the exis-
416 tence of climate change. Note that the groups are formed based on information
417 from the first wave only, as these dimensions in later waves may be subject to
418 updating themselves.

419 We find that right-leaning partisans are more responsive to extreme weather
420 events (Figure 5, upper panel). Being exposed to a flood within 1km increases
421 the likelihood of being concerned about climate change by 8.4 %-points among
422 people with a strong support for right-leaning parties. Similarly, being exposed
423 to a recent heatwave elevates climate change concern among right-leaning par-
424 tisans by 10 %-points or 13.9% from the group-specific mean ($p < 0.01$). This is
425 a substantially higher effect than what we observe among left-leaning partisans
426 and those without any partisanship, and the differences are statistically signifi-
427 cant at the 5% level (see Supplement C). Although those who initially support
428 a right-leaning party have a lower likelihood of being concerned about climate
429 change at the beginning, we predict that being exposed to a temporally close
430 heatwave elevates their likelihood onto a level similar to those who initially sup-
431 port a left-leaning party. A strikingly similar picture emerges when we compare
432 those who initially expressed a higher scepticism about climate change (Fig-
433 ure 5, lower panel). Those who were initially more sceptic experience stronger
434 effects due to being exposed to extreme weather events. Being exposed to a spa-

435 tially close flood increases the likelihood by 7.9%-points and being exposed to a
436 temporally close heatwave by 3.8%-points. Those who are initially less sceptic
437 about climate change, however, do not significantly change their concern after
438 experiencing an extreme weather event. Again, those differences are statistically
439 significant (see Supplement C).

440 These additional results indicate that people indeed update their prior views
441 due to personal experiences; they rather contradict the idea of motivated rea-
442 soning. If motivated reasoning were the dominant reaction to extreme weather
443 events, we would expect lower responsiveness among right-leaning partisans and
444 those who are initially more sceptic about climate change. The observed pat-
445 terns are strikingly similar across the two measures of extreme weather events
446 – floods and heatwaves. Moreover, the distance decay is only visible among
447 right-leaning partisans and initial sceptics. This is in line with the idea that
448 experiential learning and updating that works through reducing the perceived
449 temporal and spatial distance of extreme weather events.

450 An alternative explanation for this finding could be potential ceiling effects
451 on the (dichotomous) dependent variable: those initially more concerned about
452 climate change just have a lower likelihood to be influenced by extreme weather
453 events. Supplementary results based on a subset of individuals who express
454 no concern in the first wave are less pronounced but point into the same di-
455 rection (Figure S8). Moreover, ceiling seems to be inherent in the theoretical
456 discussion of experimental learning vs motivated reasoning: it is plausible that
457 environmental cues will not heavily influence those who are already very con-
458 cerned about climate change. The already concerned individuals may expect
459 such events, and thus react less sensitive just because they are already at a high
460 level of concern.

Figure 5: Coefficient of past flood / heatwave experience on climate change belief for different spatial distances to floods and temporal distances to the heatwave incidences, respectively. Separated by respondents initially indicating strong partisanship and high scepticism about climate change, respectively. Linear individual fixed effects (FE) estimator. Error bars represent 95% confidence interval (** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.1$). Two-sided test with cluster robust standard errors (clustered by person and LSOA). Controls: year-season of interview, age (5 year intervals), highest education, child(ren), marital status, household income (decile intervals). All controls are interacted with partisanship and scepticism respectively. N describes the number of observations in each estimation sample (constant across spatial and temporal distances).

461 Nevertheless, these conclusions only apply to climate change concern, and
 462 not to behavioural changes. Supplementary analyses (Figure S9) do identify dif-
 463 ferences in behavioural responsiveness along partisanship and initial scepticism.
 464 Apparently, attitudinal updating does not translate into behavioural changes.
 465 This might also explain why other studies measuring voting behaviour (Hazlett
 466 and Mildenberger 2020) or behavioural intentions (Ogunbode, Liu, and Tausch
 467 2017) derive at different conclusions according to partisanship. However, the
 468 political landscape in the UK is also less divided along climate related issues,
 469 potentially increasing the tendency for belief updating on this specific topic.

470 Given the absence of any behavioural responses to extreme weather events
 471 across the entire sample, we tested two additional explanations, namely a) that
 472 people feel incapable of preventing climate change, thus lacking a subjective feel-
 473 ing of efficacy (Brügger et al. 2015; Mildenberger, Lubell, and Hummel 2019;
 474 Zhou 2016), and b) that they are aware of the social dilemma / the low con-
 475 tribution of their own individual behaviour (Lubell et al. 2006; Ostrom 1998).
 476 Although we observe slight positive reactions to heatwaves among those who
 477 do not think that climate change is beyond control and those less aware of
 478 the dilemma situation (Figure S10), the effects of extreme weather events on
 479 behaviour remain small and statistically insignificant. Moreover, patterns are
 480 inconsistent across floods and heatwaves.

481 5 Discussion

482 Previous studies have documented a link between extreme weather events and
 483 concern about climate change. The present study confirms that experiencing
 484 floods or heatwaves in the immediate surrounding triggers changes in the likeli-
 485 hood of being concerned about climate change. In line with experiential learning,
 486 effect sizes increase with spatial and temporal proximity to the event, with a

487 strikingly consistent picture across floods and heatwaves. Based on individual-
488 level data in the UK, the magnitude of the updating process is stronger among
489 initially right-leaning partisans and those initially more sceptic about climate
490 change. Overall, this supports the idea of attitudinal updating due to a re-
491 duction in perceived spatial and temporal distance of climate change. This
492 conclusion is somewhat add odds with previous studies reporting stronger ef-
493 fects among left-leaning (Hazlett and Mildemberger 2020; Ogunbode, Liu, and
494 Tausch 2017) and less sceptic respondents (Osberghaus and Fugger 2022). Fur-
495 ther research is necessary to investigate if those differences in conclusions emerge
496 due to country-specific differences, whether they are owed to different processes
497 applying to voting decisions as compares to climate change attitudes, or if they
498 are a product of different measures and methods.

499 Nonetheless, the positive effect of extreme weather events on attitudes does
500 not translate into more pro-environmental behaviour such as saving electricity,
501 turning down the heating, buying sustainable products, or switching to more
502 sustainable modes of transportation. Also transportation behaviour is unaf-
503 fected by extreme weather events. The reason for the hesitance to change be-
504 haviours contributing to long-term climate change mitigation remains unclear in
505 this study. We tested different possibilities like motivated reasoning, perceived
506 efficacy for mitigation, and awareness of the behavioural dilemma. However,
507 along all the lines tested here, behavioural reactions to extreme weather events
508 remain negligible. Overall, it seems unlikely that the problem of environmentally
509 harmful behaviour will ‘solve itself’ due to increasing extreme weather events
510 and a more local framing of these events. Although the increasing concern about
511 climate change can help to boost the support for green policies (Baccini and Lee-
512 mann 2020; Hazlett and Mildemberger 2020; Hoffmann et al. 2022), wisely de-
513 signed political instruments (Beiser-McGrath and Bernauer 2019; Liebe, Gewin-

ner, and Diekmann 2021) are needed to steer individual behaviour into a more sustainable direction.

This study comes with several limitations. First, the outcome measures are not ideal. Using an existing panel study comes with the advantage of large scale representative data, but environmental behaviour outcomes are relatively specific. They only measure collective behaviour and lack information about private mitigation or adaptation strategies. For instance, people might increasingly buy insurances against extreme weather events or protect themselves by better insulation. Second, the behavioural indicators are based on self-reported behaviour, and further research should aim for measures of the actual ecological footprint (Bruderer Enzler and Diekmann 2019). Still, supplementary results based on transportation behaviour support the main findings (Figure S3). Lastly, we cannot identify personal damages experienced by respondents based on the flood data. Personally experiencing flooded basements or homes is likely to exert stronger (and more long-lasting) impacts than purely observing floods in the residential area. However, this would require an even larger sample given the comparably low incidence rate of such events.

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Supplementary material

A Descriptives

Table S1: Estimation sample 1 (Floods - Climate change concern)

Statistic	N	Mean	St. Dev.	Min	Max
Climate change concern	65,270	0.795	0.404	0	1
Flood affected (1km)	65,270	0.018	0.132	0	1
Flood affected (2km)	65,270	0.036	0.187	0	1
Flood affected (5km)	65,270	0.088	0.283	0	1
Age	65,270	49.271	16.976	16	103
Sex (female)	65,270	0.563	0.496	0	1
Migration background	65,270	0.120	0.325	0	1
Child(ren) in household	65,270	0.324	0.468	0	1
Household income (in thousand)	65,270	3.889	3.374	0	89.712
High scepticism	46,400	0.593	0.491	0	1
Ethnic background					
Any White	65,270	0.867	0.339	0	1
Mixed	65,270	0.017	0.130	0	1
Asian	65,270	0.076	0.266	0	1
Black	65,270	0.033	0.179	0	1
Other	65,270	0.006	0.076	0	1
Highest education					
GCSE etc	65,270	0.207	0.405	0	1
Degree	65,270	0.272	0.445	0	1
Other higher degree	65,270	0.124	0.330	0	1
A-level etc	65,270	0.197	0.398	0	1
Other qualification	65,270	0.097	0.297	0	1
No qualification	65,270	0.101	0.302	0	1
Marital status					
Married/Civil partner	65,270	0.567	0.495	0	1
Living as couple	65,270	0.116	0.320	0	1
Widowed/surviving civil partner	65,270	0.053	0.224	0	1
Divorced/dissolved civil partner	65,270	0.073	0.261	0	1
Separated (incl. from civil partner)	65,270	0.018	0.132	0	1
Never married	65,270	0.173	0.378	0	1
Partisanship					
Left-leaning partisanship	61,431	0.126	0.332	0	1
No partisanship	61,431	0.779	0.415	0	1
Right-leaning partisanship	61,431	0.095	0.293	0	1

Table S2: Estimation sample 2 (Floods - Behaviour)

Statistic	N	Mean	St. Dev.	Min	Max
Pro-environmental behaviour	68,134	3.264	0.655	1	5
Flood affected (1km)	68,134	0.017	0.130	0	1
Flood affected (2km)	68,134	0.036	0.185	0	1
Flood affected (5km)	68,134	0.089	0.285	0	1
Age	68,134	49.687	16.695	16	103
Sex (female)	68,134	0.585	0.493	0	1
Migration background	68,134	0.144	0.351	0	1
Child(ren) in household	68,134	0.334	0.472	0	1
Household income (in thousand)	68,134	3.822	3.360	0	89.712
High scepticism	44,581	0.594	0.491	0	1
Ethnic background					
Any White	68,134	0.842	0.365	0	1
Mixed	68,134	0.017	0.130	0	1
Asian	68,134	0.093	0.290	0	1
Black	68,134	0.041	0.199	0	1
Other	68,134	0.007	0.083	0	1
Highest education					
GCSE etc	68,134	0.206	0.404	0	1
Degree	68,134	0.267	0.442	0	1
Other higher degree	68,134	0.124	0.329	0	1
A-level etc	68,134	0.188	0.391	0	1
Other qualification	68,134	0.099	0.298	0	1
No qualification	68,134	0.117	0.322	0	1
Marital status					
Married/Civil partner	68,134	0.575	0.494	0	1
Living as couple	68,134	0.113	0.316	0	1
Widowed/surviving civil partner	68,134	0.057	0.232	0	1
Divorced/dissolved civil partner	68,134	0.076	0.264	0	1
Separated (incl. from civil partner)	68,134	0.019	0.138	0	1
Never married	68,134	0.161	0.367	0	1
Partisanship					
Left-leaning partisanship	64,401	0.128	0.334	0	1
No partisanship	64,401	0.779	0.415	0	1
Right-leaning partisanship	64,401	0.093	0.290	0	1

Table S3: Estimation sample 3 (Heatwaves - Climate change concern)

Statistic	N	Mean	St. Dev.	Min	Max
Climate change concern	85,182	0.798	0.402	0	1
Heatwave affected (14 days)	85,182	0.027	0.162	0	1
Heatwave affected (1 month)	85,182	0.045	0.208	0	1
Heatwave affected (4 months)	85,182	0.104	0.305	0	1
Age	85,182	49.550	16.969	16	103
Sex (female)	85,182	0.566	0.496	0	1
Migration background	85,182	0.103	0.304	0	1
Child(ren) in household	85,182	0.320	0.467	0	1
Household income (in thousand)	85,182	3.794	3.249	0	89.712
High scepticism	55,425	0.591	0.492	0	1
Ethnic background					
Any White	85,182	0.894	0.308	0	1
Mixed	85,182	0.014	0.118	0	1
Asian	85,182	0.061	0.240	0	1
Black	85,182	0.026	0.159	0	1
Other	85,182	0.005	0.071	0	1
Highest education					
GCSE etc	85,182	0.205	0.403	0	1
Degree	85,182	0.262	0.440	0	1
Other higher degree	85,182	0.126	0.332	0	1
A-level etc	85,182	0.201	0.401	0	1
Other qualification	85,182	0.095	0.293	0	1
No qualification	85,182	0.111	0.314	0	1
Marital status					
Married/Civil partner	85,182	0.566	0.496	0	1
Living as couple	85,182	0.113	0.316	0	1
Widowed/surviving civil partner	85,182	0.057	0.231	0	1
Divorced/dissolved civil partner	85,182	0.073	0.260	0	1
Separated (incl. from civil partner)	85,182	0.019	0.135	0	1
Never married	85,182	0.173	0.378	0	1
Partisanship					
Left-leaning partisanship	80,398	0.132	0.338	0	1
No partisanship	80,398	0.781	0.414	0	1
Right-leaning partisanship	80,398	0.088	0.283	0	1

Table S4: Estimation sample 4 (Heatwaves - Behaviour)

Statistic	N	Mean	St. Dev.	Min	Max
Pro-environmental behaviour	88,983	3.245	0.654	1	5
Heatwave affected (14 days)	88,983	0.027	0.163	0	1
Heatwave affected (1 month)	88,983	0.045	0.208	0	1
Heatwave affected (4 months)	88,983	0.105	0.307	0	1
Age	88,983	50.041	16.713	16	103
Sex (female)	88,983	0.587	0.492	0	1
Migration background	88,983	0.121	0.326	0	1
Child(ren) in household	88,983	0.328	0.469	0	1
Household income (in thousand)	88,983	3.730	3.239	0	89.712
High scepticism	53,349	0.591	0.492	0	1
Ethnic background					
Any White	88,983	0.874	0.331	0	1
Mixed	88,983	0.014	0.118	0	1
Asian	88,983	0.074	0.261	0	1
Black	88,983	0.032	0.176	0	1
Other	88,983	0.006	0.076	0	1
Highest education					
GCSE etc	88,983	0.203	0.402	0	1
Degree	88,983	0.256	0.436	0	1
Other higher degree	88,983	0.126	0.332	0	1
A-level etc	88,983	0.192	0.394	0	1
Other qualification	88,983	0.096	0.295	0	1
No qualification	88,983	0.128	0.334	0	1
Marital status					
Married/Civil partner	88,983	0.573	0.495	0	1
Living as couple	88,983	0.110	0.313	0	1
Widowed/surviving civil partner	88,983	0.061	0.240	0	1
Divorced/dissolved civil partner	88,983	0.075	0.263	0	1
Separated (incl. from civil partner)	88,983	0.020	0.139	0	1
Never married	88,983	0.161	0.367	0	1
Partisanship					
Left-leaning partisanship	84,326	0.133	0.339	0	1
No partisanship	84,326	0.781	0.413	0	1
Right-leaning partisanship	84,326	0.086	0.280	0	1

Figure S1: Average belief in climate change, and environmental friendly behaviour before and after experiencing a flood (top) or a heatwave (bottom). The top panel is based on the 2km spatial buffer for floods. Triangles and squares are the averages within each 2-months (top) or 15 days (bottom) interval bins. Trend lines and respective 95% confidence intervals are based on thin plate splines smoothness estimates of the original continuous data (not shown). Treatment contains respondents who were affected in the past (after flood/heatwave), or will be affected in the future (before flood/heatwave). Synthetic control group is a matched sample, using nearest neighbours matching on the interview date with maximum 5 days distance and 1-3 matches per treated unit.

B Result tables

Table S5: Individual fixed effects model. Dep. var.: Concern about climate change.

	Flood 5km		Flood 2km		Flood 1km	
	(1)	(2)	(3)	(4)	(5)	(6)
Flood affected	0.009 (0.007)	0.008 (0.007)	0.031** (0.010)	0.030** (0.010)	0.038** (0.014)	0.036* (0.014)
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	No	Yes	No	Yes	No	Yes
R ²	0.587	0.588	0.587	0.589	0.587	0.588
Adj. R ²	0.311	0.312	0.311	0.313	0.311	0.312
Num. obs.	65270	65270	65270	65270	65270	65270
Num. groups: Person-ID	26101	26101	26101	26101	26101	26101
Num. groups: season_index	32	32	32	32	32	32
Num. groups: interaction	33	33	32	32	32	32

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, [†] $p < 0.1$. Two-sided test. Cluster robust standard errors in parentheses (clustered by person and LSOA). Basic controls: year-season of interview. Additional controls: age (5 year intervals), sex, UK-born, ethnic group, highest education, child(ren), marital status, household income, household income squared.

Table S6: Individual fixed effects model. Dep. var.: Pro-environmental behaviour.

	Flood 5km		Flood 2km		Flood 1km	
	(1)	(2)	(3)	(4)	(5)	(6)
Flood affected	-0.013 (0.009)	-0.016 [†] (0.009)	-0.006 (0.014)	-0.012 (0.013)	-0.001 (0.020)	-0.013 (0.019)
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	No	Yes	No	Yes	No	Yes
R ²	0.733	0.736	0.732	0.736	0.732	0.735
Adj. R ²	0.553	0.558	0.553	0.558	0.553	0.557
Num. obs.	68134	68134	68134	68134	68134	68134
Num. groups: Person-ID	27303	27303	27303	27303	27303	27303
Num. groups: season_index	32	32	32	32	32	32
Num. groups: interaction	33	33	32	32	32	32

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, [†] $p < 0.1$. Two-sided test. Cluster robust standard errors in parentheses (clustered by person and LSOA). Basic controls: year-season of interview. Additional controls: age (5 year intervals), sex, UK-born, ethnic group, highest education, child(ren), marital status, household income, household income squared.

Table S7: Individual fixed effects model. Dep. var.: Concern about climate change.

	Heatwave 4 months		Heatwave 1 month		Heatwave 14 days	
	(1)	(2)	(3)	(4)	(5)	(6)
Heatwave affected	0.013 [†] (0.007)	0.012 [†] (0.007)	0.028** (0.009)	0.028** (0.009)	0.028** (0.011)	0.028* (0.011)
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	No	Yes	No	Yes	No	Yes
R ²	0.584	0.585	0.585	0.585	0.584	0.585
Adj. R ²	0.306	0.307	0.306	0.308	0.306	0.307
Num. obs.	85182	85182	85182	85182	85182	85182
Num. groups: Person-ID	34085	34085	34085	34085	34085	34085
Num. groups: season_index	32	32	32	32	32	32
Num. groups: interaction	33	33	33	33	33	33

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, [†] $p < 0.1$. Two-sided test. Cluster robust standard errors in parentheses (clustered by person and LSOA). Basic controls: year-season of interview. Additional controls: age (5 year intervals), sex, UK-born, ethnic group, highest education, child(ren), marital status, household income, household income squared.

Table S8: Individual fixed effects model. Dep. var.: Environmental behaviour.

	Heatwave 4 months		Heatwave 1 month		Heatwave 14 days	
	(1)	(2)	(3)	(4)	(5)	(6)
Heatwave affected	0.009 (0.009)	0.010 (0.009)	0.000 (0.013)	−0.001 (0.013)	0.008 (0.015)	0.005 (0.015)
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	No	Yes	No	Yes	No	Yes
R ²	0.730	0.733	0.730	0.733	0.730	0.733
Adj. R ²	0.549	0.554	0.549	0.554	0.549	0.554
Num. obs.	88983	88983	88983	88983	88983	88983
Num. groups: Person-ID	35678	35678	35678	35678	35678	35678
Num. groups: season_index	32	32	32	32	32	32
Num. groups: interaction	33	33	33	33	33	33

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, [†] $p < 0.1$. Two-sided test. Cluster robust standard errors in parentheses (clustered by person and LSOA). Basic controls: year-season of interview. Additional controls: age (5 year intervals), sex, UK-born, ethnic group, highest education, child(ren), marital status, household income, household income squared.

C Partisanship and scepticism

Table S9: Individual fixed effects model. Dep. var.: Concern about climate change.

	Flood 5km	Flood 2km	Flood 1km
	(1)	(2)	(3)
Flood affected	0.006 (0.018)	0.017 (0.026)	0.033 (0.034)
Flood affected $\times$ no partisan	0.001 (0.020)	0.010 (0.028)	0.001 (0.038)
Flood affected $\times$ right partisan	0.011 (0.030)	0.046 (0.045)	0.051 (0.061)
Basic controls	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes
R ²	0.590	0.590	0.590
Adj. R ²	0.318	0.319	0.318
Num. obs.	61431	61431	61431
Num. groups: Person-ID	24221	24221	24221

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $^{\dagger}p < 0.1$. Two-sided test. Cluster robust standard errors in parentheses (clustered by person and LSOA). Basic controls: year-season of interview. Additional controls: age (5 year intervals), sex, UK-born, ethnic group, highest education, child(ren), marital status, household income, household income squared. All controls are interacted with the time-constant parti level.

Table S10: Individual fixed effects model. Dep. var.: Concern about climate change.

	Heatwave 4 months	Heatwave 1 month	Heatwave 14 days
	(1)	(2)	(3)
Heatwave affected	-0.016 (0.017)	0.013 (0.024)	0.005 (0.025)
Heatwave affected $\times$ no partisan	0.025 (0.019)	0.010 (0.026)	0.017 (0.029)
Heatwave affected $\times$ right partisan	0.063* (0.030)	0.070 † (0.039)	0.095* (0.044)
Basic controls	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes
R ²	0.586	0.586	0.586
Adj. R ²	0.312	0.312	0.312
Num. obs.	80398	80398	80398
Num. groups: Person-ID	31745	31745	31745

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $^{\dagger}p < 0.1$. Two-sided test. Cluster robust standard errors in parentheses (clustered by person and LSOA). Basic controls: year-season of interview. Additional controls: age (5 year intervals), sex, UK-born, ethnic group, highest education, child(ren), marital status, household income, household income squared. All controls are interacted with the initial partisanship.

Table S11: Individual fixed effects model. Dep. var.: Concern about climate change.

	Flood 5km	Flood 2km	Flood 1km
	(1)	(2)	(3)
Flood affected	0.002 (0.009)	−0.001 (0.014)	−0.019 (0.020)
Flood affected × sceptic	0.009 (0.015)	0.049* (0.022)	0.098** (0.032)
Basic controls	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes
R ²	0.593	0.594	0.594
Adj. R ²	0.328	0.328	0.329
Num. obs.	46400	46400	46400
Num. groups: Person-ID	18131	18131	18131

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $^{\dagger}p < 0.1$. Two-sided test. Cluster robust standard errors in parentheses (clustered by person and LSOA). Basic controls: year-season of interview. Additional controls: age (5 year intervals), sex, UK-born, ethnic group, highest education, child(ren), marital status, household income, household income squared. All controls are interacted with the initial scepticism.

Table S12: Individual fixed effects model. Dep. var.: Concern about climate change.

	Heatwave 4 months	Heatwave 1 month	Heatwave 14 days
	(1)	(2)	(3)
Heatwave affected	−0.007 (0.009)	0.000 (0.013)	−0.007 (0.014)
Heatwave affected × sceptic	0.027 † (0.015)	0.045* (0.020)	0.046* (0.023)
Basic controls	Yes	Yes	Yes
Additional controls	Yes	Yes	Yes
R ²	0.592	0.592	0.592
Adj. R ²	0.326	0.327	0.326
Num. obs.	55425	55425	55425
Num. groups: Person-ID	21697	21697	21697

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $^{\dagger}p < 0.1$. Two-sided test. Cluster robust standard errors in parentheses (clustered by person and LSOA). Basic controls: year-season of interview. Additional controls: age (5 year intervals), sex, UK-born, ethnic group, highest education, child(ren), marital status, household income, household income squared. All controls are interacted with the initial scepticism.

691 **D Pooled OLS results**

Figure S2: Coefficient of past flood / heatwave experience for different spatial distances to floods and temporal distances to the heatwave incidences, respectively. Linear Pooled OLS (POLS) estimator. Error bars represent 95% confidence interval (** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.1$). Two-sided test with cluster robust standard errors (clustered by person and LSOA). Basic controls: year-season of interview. Additional controls: age (5 year intervals), sex, UK-born, ethnic group, highest education, child(ren), marital status, household income (decile intervals). N describes the number of observations in each estimation sample (constant across spatial and temporal distances).

692 E Transportation behavioural

Figure S3: Frequency of travels by car and bicycle: coefficient of past flood / heatwave experience for different spatial distances to floods and temporal distances to the heatwave incidences, respectively. Linear individual fixed effects (FE) estimator. Error bars represent 95% confidence interval (** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $^{\dagger}p < 0.1$). Two-sided test with cluster robust standard errors (clustered by person and LSOA). Controls: year-season of interview, age (5 year intervals), highest education, child(ren), marital status, household income (decile intervals). All controls are interacted with trust level. N describes the number of observations in each estimation sample (constant across spatial and temporal distances).

693 The results in this supplement replicate the main analysis using a self-
694 reported measure for the frequency of travels by car/van and bicycle instead
695 of the composite index of pro-environmental behaviour. This was measured by
696 the question ‘How frequently do you travel by private car or van - whether as a
697 driver or passenger? Please count a single trip as one journey and each return

698 trip as two.’ and ‘How frequently do you use a bicycle? Please count a single
699 trip as one journey and each return trip as two.’, with (reverted) response op-
700 tions ranging from one to eight (1 - ‘Less than that or never’, ‘Once or twice
701 a year’, ‘Less than that but more than twice a year’, ‘Once or twice a month’,
702 ‘Less than that but more than twice a month’, ‘Once or twice a week’, ‘Less
703 than once a day but at least 3 times a week’, 8 - ‘At least once a day’). The
704 question is available for UKHLS waves 4, 6, 8, and 10 (survey years 2012-2014,
705 2014-2016, 2016-2018, and 2018-2020).

706 **F Climate change belief: probit models**

Figure S4: Coefficient of past flood / heatwave experience for different spatial distances to floods and temporal distances to the heatwave incidences, respectively. Non-linear probit models, Pooled: Pooled probit model, FE: Individual fixed effects probit model (estimated via correlated random effects probit). Error bars represent 95% confidence interval (** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $^{\dagger}p < 0.1$). Two-sided test with approximate standard errors. Basic controls: year-season of interview. Additional controls: age (5 year intervals), sex, UK-born, ethnic group, highest education, child(ren), marital status, household income (decile intervals). N describes the number of observations in each estimation sample (constant across spatial and temporal distances).

707 **G FE floods with varying temporal distances**

Figure S5: Coefficient of past flood / heatwave experience for different spatial distances to floods according to temporal distance to the incidence. Linear individual fixed effects (FE) model. Error bars represent 95% confidence interval (** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.1$). Two-sided test with cluster robust standard errors (clustered by person and LSOA). Controls: year-season of interview, age (5 year intervals), sex, UK-born, ethnic group, highest education, child(ren), marital status, household income (decile intervals). N describes the number of observations in each estimation sample (constant across spatial and temporal distances).

H Placebo outcomes

Figure S6: Placebo test (floods) with religious belief and satisfaction with household income. Coefficient of past flood experience as in main analysis. Linear (probability) models, POLS: Pooled OLS estimator, FE: Individual fixed effects estimator. Error bars represent 95% confidence interval (** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $^{\dagger}p < 0.1$). Two-sided test with cluster robust standard errors (clustered by person and LSOA). Basic controls: year-season of interview. Additional controls: age (5 year intervals), sex, UK-born, ethnic group, highest education, child(ren), marital status, household income (decile intervals). N describes the number of observations in each estimation sample (constant across spatial and temporal distances).

Figure S7: Placebo test (heatwaves) with religious belief and satisfaction with household income. Coefficient of past heatwave experience as in main analysis. Linear (probability) models, POLS: Pooled OLS estimator, FE: Individual fixed effects estimator. Error bars represent 95% confidence interval (** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $^{\dagger}p < 0.1$). Two-sided test with cluster robust standard errors (clustered by person and LSOA). Basic controls: year-season of interview. Additional controls: age (5 year intervals), sex, UK-born, ethnic group, highest education, child(ren), marital status, household income (decile intervals). N describes the number of observations in each estimation sample (constant across spatial and temporal distances).

709 **I Effect heterogeneity - Conditional on starting value**

Figure S8: Coefficient of past flood / heatwave experience on pro-environmental behaviour for different spatial distances to floods and temporal distances to the heatwave incidences, respectively. The sample is reduced to those who report that they are not concerned about climate change in the first wave. Separated by respondents initially indicating strong partisanship and high scepticism about climate change, respectively. Linear individual fixed effects (FE) estimator. Error bars represent 95% confidence interval (** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $^{\dagger}p < 0.1$). Two-sided test with cluster robust standard errors (clustered by person and LSOA). Controls: year-season of interview, age (5 year intervals), highest education, child(ren), marital status, household income (decile intervals). All controls are interacted with partisanship and scepticism respectively. N describes the number of observations in each estimation sample.

710 **J Effect heterogeneity - Pro-environmental Behaviour**

Figure S9: Coefficient of past flood / heatwave experience on pro-environmental behaviour for different spatial distances to floods and temporal distances to the heatwave incidences, respectively. Separated by respondents initially indicating strong partisanship and high scepticism about climate change, respectively. Linear individual fixed effects (FE) estimator. Error bars represent 95% confidence interval (*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.1$). Two-sided test with cluster robust standard errors (clustered by person and LSOA). Controls: year-season of interview, age (5 year intervals), highest education, child(ren), marital status, household income (decile intervals). All controls are interacted with partisanship and scepticism respectively. N describes the number of observations in each estimation sample (constant across spatial and temporal distances).

Figure S10: Coefficient of past flood / heatwave experience on pro-environmental behaviour for different spatial distances to floods and temporal distances to the heatwave incidences, respectively. Separated by respondents indicating that climate change is beyond control and that their contribution does not matter if others do not contribute, respectively. Linear individual fixed effects (FE) estimator. Error bars represent 95% confidence interval (** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.1$). Two-sided test with cluster robust standard errors (clustered by person and LSOA). Controls: year-season of interview, age (5 year intervals), highest education, child(ren), marital status, household income (decile intervals). All controls are interacted with beyond control and dilemma awareness respectively. N describes the number of observations in each estimation sample (constant across spatial and temporal distances).