Only In My Backyard: The Effect of Flood Exposure on Environmental Behavior

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Abstract

How directly do people need to experience climate change to change their actions? I analyse a decade of real-world donation records from 90,000 donors in England and data from longitudinal surveys. By observing the precise locations of these individuals, I show that, after being directly affected by floods, people are more likely to view their environmental efforts as insufficient and to increase their support for environmental charities and the Green Party. However, this effect does not occur when floods only affect their neighbours, even those living within 200 metres. The results suggest an "only in my backyard" phenomenon, where people act only when personally affected by climate consequences. Further analysis reveals that individuals with strong universalist values do respond to neighbouring floods, indicating that the broader lack of responses stems primarily from those less concerned with global issues like climate change.

Keywords: flood; climate change; environmental behavior; environmental belief
JEL Codes: D64; D72; D91; H41; Q54

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1 Introduction

Climate change poses severe and unevenly distributed risks, with low-income countries facing the greatest impacts (Carleton et al., 2022). However, the "principal margin of action" largely rests with high-income countries (Duflo, 2024), whose carbon emissions are twice their share of the global population (Ritchie, 2024). This disparity underscores the need to understand what drives green actions especially in developed economies.[1]

Active public responses to this global challenge, from voluntary efforts to supporting climate policies, require broad acceptance of climate risks (Deryugina, 2013; Frondel et al., 2017). In some affluent societies, like the UK, this awareness is already high, with 70 percent of people viewing climate change as a serious threat, yet public actions remain insufficient (Climate Change Committee, 2020).[2] One possible explanation is that people may not feel climate consequences are personally relevant, given that only 10 percent of the UK population have experienced extreme weather events or know someone who has (World Risk Poll, 2021).

To explore this explanation, I look at how directly people need to experience climate change to act more pro-environmentally. In this research, floods serve as a focal point, as they are among the major climate impacts affecting the UK (Met Office, 2024), and are often connected to climate change by the public.[3] While floods in England affect fewer people and cause fewer deaths than some extreme global incidents, they represent the scale of floods that occur most frequently worldwide. I use flood records collected by the Environment Agency in England, covering the period from 2009 to 2022, which provide detailed data on the timing and spatial extent of each flood event at its peak. Floods create visible damage within clear geographic boundaries, allowing for precise measurement of exposure based on proximity to affected areas. This makes them ideal for studying the localized effects of climate impacts.

Floods could influence green behavior through two general channels: information

[1] The following data highlights the contrast. First, IEA (2023) reports that the top ten percent of global emitters, mostly in high-income economies, produce per capita emissions over 200 times those of the bottom ten percent, who are mainly in developing countries. Second, Carleton et al. (2022) project that continued high growth in emissions could raise death rates in low-income countries to 107 per 100,000 people by 2099, compared to 25 per 100,000 in high-income countries.

[2] Climate Action Tracker (2024) "rates the UK's climate targets, policies and finance insufficient", indicating that "the UK's climate policies and commitments need substantial improvements to be consistent with the Paris Agreement's 1.5°C temperature limit." Public support is crucial for implementing climate policies, especially true in some areas. For example, regarding building decarbonization, "the UK is significantly off-track in both the uptake of low-carbon heating and energy efficiency measures."

[3] In Appendix A.3, I show that Google search interest in climate change increases during weeks with floods compared to other weeks within the same month, covering the period of my research. Capstick et al. (2015) also show that, following the major floods of the 2013/2014 winter, 72 percent of the British public agreed that these floods "showed us what we can expect in the future from climate change". While attributing specific weather events to climate change is difficult, these results suggest that the public does link flood incidents with climate change.

(Deryugina and Shurchkov, 2016; Dechezleprêtre et al., 2023; Andre et al., 2024) and salience (Bordalo et al., 2020, 2022; Allcott and Rogers, 2014). First, floods cause disruptions to daily life, and often receive extensive media coverage (Eisensee and Strömberg, 2007; Beattie, 2022), offering new information that people may use to update their beliefs about climate risk and costs of climate events.[4] This information can lead people to reassess and re-optimize their choices. Moreover, even with high climate awareness, people may not prioritize climate change in their everyday decisions. Floods act as salient reminders, bringing these concerns to the forefront and encouraging green actions in response.[5] While, theoretically, floods can influence behavior, the extent to which proximity to climate events drives pro-environmental response requires empirical investigation.

Estimating the local effects of floods is often constrained by limited access to precise address data — critical for identifying directly affected people — and by challenges in observing real-world behaviors at the individual level. Researchers instead rely on aggregated outcomes or collect data through surveys and experiments, which carry the risk that people may report socially desirable behaviors (Brownback and Novotny, 2018; Reisinger, 2022) or align their actions with perceived researcher expectations (Ekström, 2012; De Quidt et al., 2019).[6]

The Charities Aid Foundation (CAF) has granted unique access to a comprehensive dataset that addresses these challenges. This dataset includes donation records from 90,000 regular donors to about 55,000 charities from 2011 to 2022. For each donor by year, I match donations to their causes and use a binary indicator for giving to environmental charities as the main measure of pro-environmental behavior. Surveys commonly measure green behavior through willingness to donate, showing that green donations are strongly correlated with support for climate policies (Andre et al., 2024; Dechezleprêtre et al., 2023). Moreover, the CAF data reflects real financial commitments and allows me to track changes in each donor's giving across various causes. Importantly, CAF donors are likely among the richer people in the population, as 70 percent of them fall within the top 20 percent of the general population in terms of donation size (Scharf et al., 2022). This group is particularly relevant for the study, given their influence on climate outcomes. To assess whether these effects extend more broadly, I also use data from the UK Household Longitudinal Study (UKHLS), which covers a more representative sample.

[4] Media coverage of flood events is an important channel in driving beliefs and behaviors. Gallagher (2014) shows an increase in insurance take-up after a flood among unaffected neighbors who share the same media market, but not among those who are merely geographically close.

[5] A salient event can also make people seek information on climate change, as Herrnstadt and Muehlegger (2014) show that internet searches for climate change increase following unusual weather events.

[6] Research also suggests that people may make different decisions with earned income. For example, individuals tend to be less generous with earned endowments than with windfall gains (Carlsson et al., 2013; Li et al., 2019) and less generous with out-of-pocket money than with cash promised on a screen (Reinstein and Riener, 2012).

Both CAF and UKHLS provide postcodes of individuals at the most granular level, with each postcode typically covering around 15 households.[7] This granularity allows me to allocate people into treatment (either directly or indirectly flooded) or control groups, based on their proximity to flood incidents. Specifically, people are considered directly flooded if their postcode was affected by a flood, and indirectly flooded if the surrounding area within 200 meters outside their postcode was affected but not their own postcode.

Exploiting geographic and temporal variations in flood occurrences, I compare green outcomes before and after a flood, between those directly (or indirectly) affected and those not affected but living in postcodes with the same flood risk from the same region. The identifying assumption is that whether an individual is flooded in a given year is uncorrelated with other determinants of their green actions, conditional on individual fixed effects, region-by-year fixed effects, and varying trends in flood exposure and behavior across places with different flood risks. This assumption is plausible given the unpredictability of floods, especially among postcodes with the same flood risk in the same region. Testing whether those affected are comparable to those unaffected, I find no significant differential trend in green donations between these groups before actual flood occurrences. Moreover, I find robust evidence through a randomization test, as well as estimators that address potential issues with the two-way fixed effects model in a staggered treatment setting (De Chaisemartin and d'Haultfoeuille, 2023; Roth et al., 2023; Borusyak et al., 2024).

I find that people are two percentage points more likely to donate to environmental charities after experiencing a flood that directly affects their own postcode. This effect is substantial, given that only six percent of donors in the control group give to environmental charities, and it lasts for up to five years before returning to baseline. Repeated direct exposures further amplify this effect, with an additional flood experience leading to an even greater increase in green activities. This increase is driven specifically by donations to climate-related charities, with no significant effect on giving to other causes, suggesting that the change is specific to pro-environmental behavior rather than a general rise in prosociality. In contrast, people do not change their green donations after a flood affecting their neighbors, even if they live within 200 meters, regardless of whether the exposure occurs once or multiple times. Finally, I show that this highly localized effect also extends to increased support for the Green Party among a broader sample of people.

In addition to influencing behavior, I find that direct flood exposure makes people less likely to view themselves as environmentally friendly enough. However, there is no significant shift in self-evaluation after indirect exposure. Neither direct nor indirect exposure appears to affect people's perception of climate risk in general, risk attitudes, perceived

[7] According to Office for National Statistics (2023), there are 1.79 million live postcodes in the UK, and hence the average area per postcode is 0.14 square kilometers.

efficacy of personal actions in addressing climate change, or sense of responsibility as contributors to climate change. Self-assessment depends on what people actually do and what they believe they should do. Since their real efforts do not decrease, the drop in self-assessment implies a rise in their expectations. This points to a possible mechanism for observed behavior change: direct experience raises people's expectations of what constitutes a sufficient level of green activities, leading them to view their efforts as not enough. As a result, they adjust their behaviors to align with these revised expectations (Akerlof and Kranton, 2000, 2005).

The results illustrate an "only in my backyard" phenomenon, highlighting the importance of personal impacts of climate change in motivating green behavior. This effect aligns with the model of internalizing social costs. Climate change mitigation is a public good, and people may have an incentive to free-ride, particularly when they do not bear the costs personally. However, direct experience makes climate issues personally relevant, leading people to view climate inaction as having direct consequences and motivating them to reassess their current efforts and adopt further behavioral changes to prevent future harm. The sense of personal relevance may be reinforced through the two channels: first, direct exposure provides firsthand information on the costs and disruptions of climate events, prompting people to update their beliefs about personal risks. Second, it increases the salience of climate risks through "availability bias", as flood threats feel immediate and emotionally urgent for those directly affected, while remaining distant for others (Kahneman and Tversky, 1982; Deryugina, 2013; Gallagher, 2014).

Building on the observed lack of response to floods affecting neighbors, I find that people with strong universalism values are more likely to support environmental charities, even when they are not directly affected. Universalists prioritize the welfare of all people and the environment over group-based or self interests (Schwartz, 2007, 2012; Cappelen et al., 2022; Enke et al., 2023). For people with a universalist orientation, who may already feel a deep connection to environmental issues, indirect exposure — such as witnessing a neighbor's flood damage — can be enough to inspire further green actions. In contrast, those with weaker universalism may be more motivated by direct, personal consequences of climate events. The results suggest that moral universalism might drive broader green activities, even among those less affected by environmental problems. In Section X, I will discuss in detail how universalism might promote such behaviors and the feasibility of fostering these values to encourage pro-climate activities.

The central contribution of this paper is the finding that people behave more pro-environmentally only when personally affected by climate consequence. The localized effect highlights the potential role of personal climate exposure in shaping behaviors. Dechezleprêtre et al. (2023) provide global survey evidence showing that public support for climate policies hinges on self-interest. My results suggest that those more likely to be flooded might see greater personal benefits in reversing climate change, hence behaving more actively. This finding has an important implication: efforts to encourage green behaviors may be more effective if people are made more aware of the personal impact of climate change rather than just recognizing it as a global problem. Therefore, this paper relates to studies examining the effect of extreme climate events on green activities. Previous research often uses surveys to measure activities or elicit willingness to act (Whitmarsh, 2008; Spence et al., 2011; Bulut and Samuel, 2024). Using real political outcomes, a growing body of research shows that, after extreme weather events, politicians are more likely to endorse green legislation and policy reforms (Herrnstadt and Muehlegger, 2014; Gagliarducci et al., 2019), and the public tends to increase support for climate policies (Hazlett and Mildenberger, 2020; Baccini and Leemann, 2021; Coury, 2023) and vote for the Green Party (Goebel et al., 2015; Hoffmann et al., 2022).[8]

My paper differs in two key ways. First, I use precise locations to determine individual exposure to climate events, while previous work often uses broader administrative units like counties or census blocks. Studying responses at the regional level is suitable when aggregated outcomes matter, such as voting for green legislation (Herrnstadt and Muehlegger, 2014; Coury, 2023). However, the broader definition can introduce measurement errors when the focus is on individuals. For example, people living in non-inundated areas within a county would be misclassified as treated if flood exposure is determined at the county level. My results show that using precise locations to identify those directly affected is crucial for detecting behavioral nuances that broader definitions might miss.

Second, I am the first to use real-world donations to measure environmental outcomes. Liao and Junco (2022) show that extreme temperatures increase donations to Democratic candidates, who are typically pro-environment. In a lab study, Li et al. (2011) find that people are more likely to donate to an environmental charity if they perceive the previous day's temperature as unusual. Experiments and surveys are suitable for measuring one-off responses. Scharf et al. (2022) find that a fundraising appeal might simply bring forward donations despite an immediate increase for those non-fundraising charities, showing the importance of using data rich in timing and charity space to capture full responses. Unlike political decisions, I focus on a setting where people have more choices in directing their money and flexibility to adjust their choices (Andreoni, 2006). I can track people on where their donation goes for more than ten years. With these strengths, I provide novel evidence that the sizable increase in green donations due to direct climate exposure is long-lasting and does not reduce support for other social causes.

[8] While most papers focus on the effect in disaster-hit areas, Goebel et al. (2015) documents that people in the UK, Germany, and Switzerland showed stronger support for the Green Party in their own countries in response to the Fukushima nuclear disaster in Japan.

This paper also relates to research on how climate experiences affect beliefs and preferences that underlie green behaviors. I am the first to look at the effect on self-assessment. Previous work shows that self-assessment is important in driving green behavior (Sonenshein et al., 2014; Binder and Blankenberg, 2017), but people often overestimate their efforts (Biais et al., 2005; Burks et al., 2013; Leviston and Uren, 2020). I provide a causal relationship that direct flood experiences make people adjust their self-evaluation and realize their efforts are insufficient. This realization can motivate them to align their actions with their beliefs (Festinger, 1957; Bandura, 1991). Most research in this area focuses on risk perception (Gallagher, 2014; Frondel et al., 2017; Brown et al., 2018; Lohmann and Kontoleon, 2023; Djourelova et al., 2024) and risk attitudes (Botzen and van den Bergh, 2012; Cameron and Shah, 2015; Shupp et al., 2017; Bourdeau-Brien and Kryzanowski, 2020), suggesting context-dependent evidence. Gao et al. (2020) show that the impact of unexpected disasters on risk perception depends on whether the actual damage exceeds or falls short of expectations. I do not find that flood exposure changes perceptions of climate change as a threat to the UK. This aligns with existing research showing that people with initially low risk perception are more likely to update their beliefs (Deryugina, 2013), given the widespread perception of climate risk in the UK. My research suggests that highlighting behavioral insufficiency might be an effective way to drive more sustainable actions in a context where climate threats are widely recognized.

This research is more broadly related to studies of how adverse experiences affect prosocial behaviors. Previous work shows that natural disasters can lead more donations to those affected (Deryugina and Marx, 2021; Scharf et al., 2022; Jayaraman et al., 2023), and health shocks can lead people to reallocate their donations to health charities (Black et al., 2021). Méon and Verwimp (2022) find that a damaging storm in Belgium makes affected people more prosocial, increasing their contributions to an unrelated famine relief campaign for Africa. In contrast, I do not observe a general increase in prosociality, as donations to non-environmental charities do not rise. This research altogether suggests that the effect on altruism may depend on the extent of damage caused by these events.

The rest of the paper is structured as follows. Section 2 describes the context and flooding in England. Section 3 discusses data and empirical strategy. Section 4 presents the results, and Section 5 concludes.

2 Flooding in England

Compared with other countries, awareness about climate change is notably high but extreme weather events are actually rare in the UK. Figure 1 shows that 70% of UK residents view climate change as a very serious threat.[9] This level of risk perception is substantial, given that only 10% have experienced extreme weather or know someone who has (World Risk Poll, 2021). Google search also suggests that there is no growing trend in the denial of climate change in the UK, unlike what is common in the US.[10]

However, this strong perception does not translate into adequate actions towards combating climate challenges (Climate Change Committee, 2020). One conjecture is that the insufficient effort is due to minimal concern about the personal impact of global warming. Figure 1B shows that only 15% of UK residents are worried about suffering serious harm from extreme weather, which correlates more strongly with their personal experiences.

The remainder of this section discusses the distribution of flood risk and incidents in England, and how people insure against flood risk and receive post-flood aid.

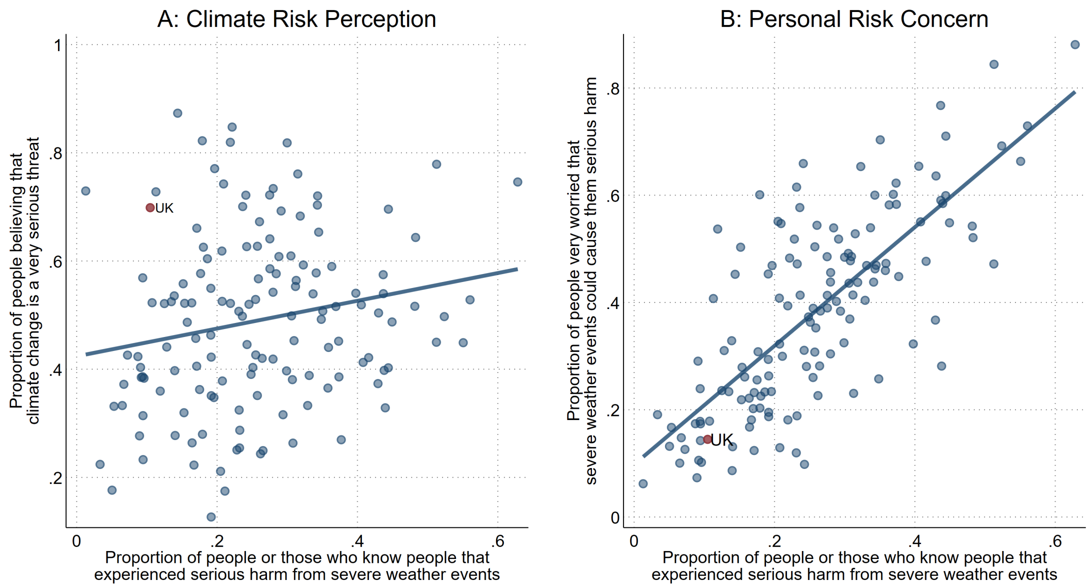
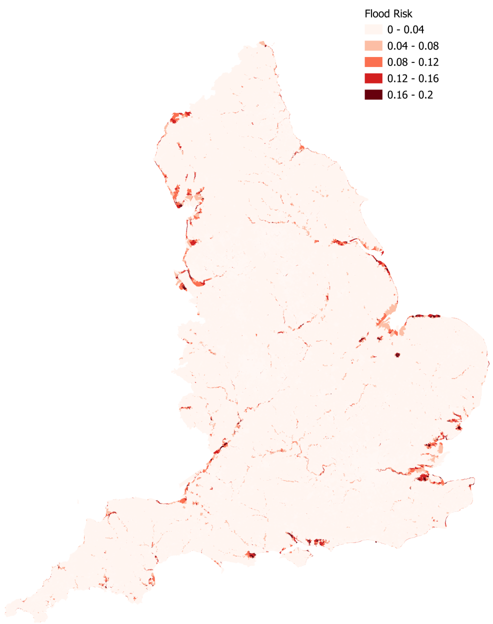


Figure 1: Risk Perception and Severe Weather Experiences across Countries

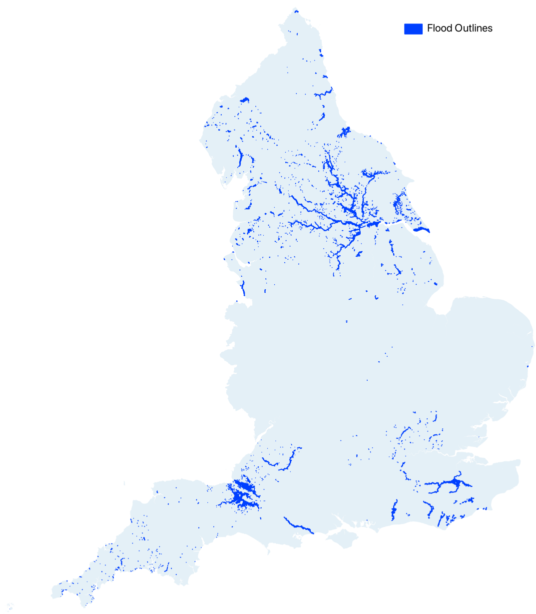
Notes: This figure presents scatter plots comparing the proportion of people who believe in climate risk and those worried about their personal risk from severe weather to the proportion of people exposed to severe weather events, in Figures A and B respectively. Each dot represents a country. The line indicates the fitted OLS line. The data are from the Lloyd's Register Foundation World Risk Poll, which conducted around 125,000 interviews across 121 countries in 2021.

[9]Appendix Figure A.1 shows that the UK ranks among the top 10 high-income countries for recognising climate risk.

[10]Appendix Table A.1 shows the top five rising search queries related to "global warming" and "climate change" in the UK and the US. It shows that the low-level climate change denial in the UK pairs with a heightened concern about its impact on future generations, in contrast to the US, which has witnessed rising queries casting doubt on the reality of climate change.



(a) Postcode-level Flood Risk



(b) Flood Incidents

Figure 2: Flood Risk and Flood Incidents (2009-2022) in England

Notes: Flood risk in figure a is defined as the probability that the flood depth at a specific location exceeds 10 cm in any given year. The map presents the risk averaged across all 10-meter by 10-meter squares within each postcode. The high-resolution outlines of floods that have occurred since 2009 in figure b are primarily derived from aerial photographs captured during peak flooding.

2.1 Flood Risk

One out of six properties in England is at risk of flooding (Skouralis and Lux, 2023). Flood risk information is widely available, as the government publishes detailed flood maps and long-term risk assessments. Assessing such risk is also common in property valuations. I use a refined flood risk map modeled at a granular 10-meter resolution to account for the awareness individuals have of risks that directly affect themselves. The data is provided by Fathom UK, an organization renowned for its leading scientists and flood modeling services. Their model incorporates an accurate terrain dataset, comprehensive defenses, and channel drainage (Fathom, 2021). I define flood risk as the probability of flood depth exceeding 10 centimeters at a specific location in any given year. Postcode-level risk is the mean of flood risk across all 10-by-10 meter locations within each postcode.[11] Appendix Table E.11 shows that my results are not sensitive to this threshold. In Appendix B, I elaborate on the methodology of constructing the flood risk variable. The plot of flood risk in England in Figure 2a shows that areas along rivers, coastlines, and rural regions are more prone to flooding.

2.2 Flood Occurrences

Extreme weather events in the UK, such as floods, generally have lower intensity and affect fewer people compared to other global incidents. Although the UK does not experience the catastrophic nature of flood disasters seen globally, it does encounter smaller-scale floods, which are the most common form of flooding worldwide.[12]

I focus on floods that occurred from 2009 to 2022 in England, a period that aligns with the data on environmental behaviors observed in this study. Flood records collected by the Environment Agency through aerial photography, satellite imagery, and surveys precisely outline the affected areas at the time of peak flooding and provide clear timing for each event. The flood extent rarely aligns with the border of administrative units, highlighting the importance of defining flood exposure using the precise location of individuals. I refine the sample by excluding potentially erroneous records. Specifically, I drop duplicate flood entries, invalid floods as determined by the Environment Agency, floods with the same event ID but conflicting start years, and floods that persisted for more than a year. This sample ensures a set of floods with accurate timing, at least at the year level.

[11] A flood depth of 10 cm is unlikely to pose a risk to people but can significantly damage buildings and their contents (Landmark Information Group, 2022).

[12] In the appendix table A.2, I compare floods in the UK with those in other regions, using flood and storm records between 2009 and 2022 from EM-DAT. I show that: (1) the average fatality per flood event in the UK is about half that in other European countries and a fifth of that in the US; (2) the most severe floods in the UK are less deadly than those in other countries; (3) the scale of floods in the UK is similar to those that occur around half the time in the US and more frequently than half the time in Europe.

Appendix Table A.3 shows that these flood events are typically small, affecting an average of 90 postcodes. Given that the average postcode in England covers 15 households, this amounts to around 1,350 households affected per flood event. A median flood is even more localized, affecting only 12 postcodes. These floods are short-lived, with an average duration of four days, although the majority last merely a single day. The data records the detailed extent of flooded areas but lacks intensity information for each event.

Within areas of the same flood risk, the unpredictability of where and when floods strike provides a plausible natural experiment. I exploit the geographic and temporal variations in flood occurrences. Firstly, Figure 2b shows the widespread distribution of flood incidents across England, noting that floods mostly occur in areas associated with high flood risks. However, some high-risk areas have remained unaffected since 2009, suggesting the randomness of flood locations within the high-risk area. Secondly, the fluctuation in the number of flood events from year to year, as shown in Appendix Figure A.2, makes it challenging to discern a trend of global warming over such a short period.

2.3 Flood Insurance and Post-Flood Aid

Over 95% of properties in England are insured against flood risk — a rate comparable to some European countries, such as France and Switzerland, but much higher than that in the US (Hu, 2022). The UK public reinsurance scheme, Flood Re, launched in April 2016, allows insurers to transfer the flood risk component of their policies to a reinsurer at a reduced cost, regardless of the property's specific risk. This ensures the availability and affordability of flood insurance, particularly in flood-prone areas (Flood Re, 2023). Given that the risk component is subsidized by the government, specific flood incidents are unlikely to affect current or future insurance premiums (Garbarino et al., 2022). Moreover, the high uptake of home insurance suggests that households are less likely to face significant financial losses from flood recovery.

The UK government has rolled out various schemes to support households, businesses, and farmers impacted by flooding. These initiatives include cash subsidies and tax discounts, either as general flood relief or tailored to specific flood events. Such measures are crucial in reducing the immediate disruptions to the lives of affected individuals (Department for Communities and Local Government, 2014).

3 Empirical Approach

3.1 Data

3.1.1 Environmental Donation

The data is provided by the Charities Aid Foundation (CAF), which offers a platform for people to manage their donations. I observe all donations made by personal donors through their CAF accounts between 2011 and 2022. I focus on the 91,665 donors in England who have been active for more than seven years.[13] This data has two main strengths. First, people can donate to any UK charity across a wide range of causes. The data consist of naturally occurring observations, eliminating experimenter demand bias that may exist in experimental studies, where participants are often asked to donate to a limited set of charities. Second, I can track donors to examine whether increased donations to environmental causes are accompanied by a decrease in donations to other causes. However, it is important to note that CAF donors tend to represent high net-worth individuals, who typically give larger amounts than the average person in the UK.

I classify each charity by the International Classification of Non-profit Organizations (ICNPO).[14] Then for each donor, I aggregate their donations by year and cause. Figure 3 shows that environmental charities make up 2.5% of the total charities receiving donations from CAF, yet they receive less than 2% of the total donations. This suggests that individual charities working on environmental causes receive fewer donations from CAF than those in other sectors. Environmental charities, however, play a crucial role in advocating for policy change and investing in solutions to environmental issues. For instance, the Woodland Trust has planted over 50 million trees since its inception, contributing directly to carbon sequestration (Woodland Trust, 2024). The 10 largest environmental charities, based on donations received from CAF donors, are summarized in Appendix Table C.1, accounting for more than 70% of all donations to environmental

[13] I focus on donors in England because I can identify whether they were exposed to a flood. I count the number of years donors are active in their CAF accounts, defining a donor as active from the year of their first donation until the year of their most recent donation. For example, if a donor made their first donation in 2011 and their last in 2013, they would be considered active for three years, regardless of whether they donated in 2012. The median number of active years across all donors is 4, while the 75th percentile is 7. This suggests that many donors are only present in the dataset for a short period, making it difficult to determine whether they stopped donating entirely or donated through other channels. To address this, I focus on the 25% of donors who have been active for more than seven years. I construct a panel dataset where each donor appears from the year of their first donation through to the end of the dataset in 2022. In any year where a donor makes no donations, they remain in the dataset, but their donations to all causes are recorded as zero. Additionally, I consider a sample where donors have made donations for more than seven years. The results remain similar and statistically significant.

[14] According to ICNPO, charities in the "5100 Environment" category provide services related to pollution control and prevention, environmental education and health, and environmental conservation (Salamon and Anheier, 1996). The classification of UK charities is maintained and provided by the National Council for Voluntary Organisations.

causes. Notably, nine of these charities address issues relevant to climate change. Given the small share of donors supporting environmental causes, I use a dummy variable to indicate individual support for environmental charities. *Green Donation* equals 1 if an individual donates to any environmental charity in a given year and 0 otherwise.

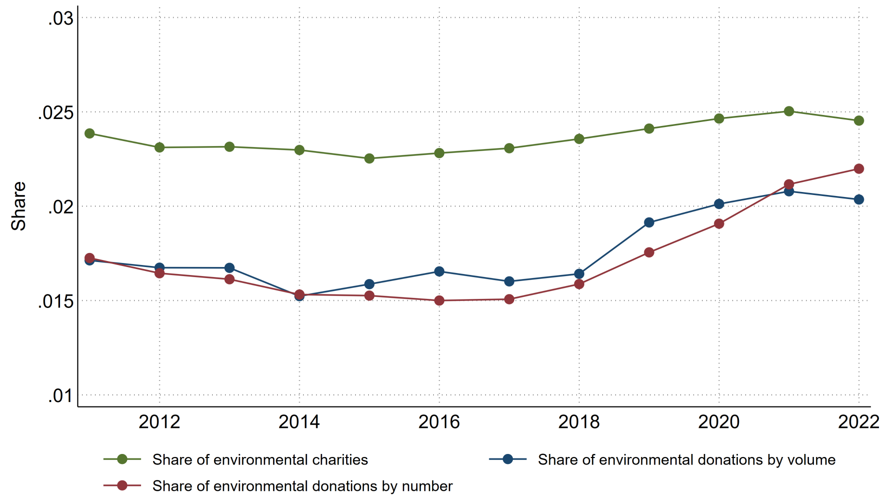


Figure 3: Share of Environmental Charities and Environmental Donations

Notes: I aggregate all donations in CAF by cause and year. I plot the share of environmental charities that have received donations through CAF, the share of donations going to environmental charities by volume and by number of donations. In total, 55,447 unique charities have received donations through CAF, including 1,297 environmental charities.

3.1.2 Green Party Support and Everyday Green behavior

Another way to engage is by supporting political parties that prioritize environmental issues. The UK Household Longitudinal Survey Study has been surveying people's political support since its inception in 2009, covering Waves 1 through 12, with the exception of Wave 8 (UKHLS, 2022). I define *Green Party Support* as one if an individual identifies as a supporter of or feels closer to the Green Party, and zero otherwise.

I also look at *Everyday Green behavior*. UKHLS surveyed nine specific activities related to energy usage, recycling, and transportation in Waves 1, 4, and 10. I use a two-step principal component analysis (PCA) to construct a behavioral index. Initially, I build a subindex for each behavioral dimension by retaining its first component. Then, I create an overall index using the first principal component derived from these three subindices. This two-step method avoids overemphasizing any dimension simply because it has more questions in the survey. The specific behaviors surveyed and the PCA loadings are reported in Appendix Table C.2. The overall index has positive loadings on all behavioral dimensions and accounts for 45% of the variance in the subindices.

The UKHLS is designed to be representative of the UK population. However, among the 48,000 individuals who participated in at least two waves where political support was surveyed, and the 23,500 individuals who were present in at least two waves where everyday green activities were surveyed, fewer than 200 were directly flooded. This small sample of affected people limits the statistical power to explore heterogeneous responses.

3.1.3 Environmental Beliefs

Environmental actions often stem from deeply held environmental beliefs. UKHLS asked 11 questions about these beliefs in Waves 4 and 10.[15] Unlike the behavioral questions aimed at measuring environmental friendliness, the factors shaping the design of belief questions are initially unclear (Poortinga, 2022). I apply PCA with varimax rotation to combine these questions into a set of latent factors, following Jolliffe (1995).[16]

Retaining factors with an eigenvalue above one results in four factors, closely related to what sociologists have considered important in driving pro-environmental behaviors (Stern, 2000; van Valkengoed et al., 2022). I assign names to each factor accordingly.[17] The factor loadings, presented in Appendix Table C.3, show that the retained factors explain around half of the variation in the original variables. Factor 1 captures the belief in an individual's capacity to impact climate change (Self-Efficacy); Factor 2 reflects whether respondents attribute responsibility for the climate crisis to themselves (Personal Responsibility); Factor 3 captures the perception of whether people in the UK will be affected by climate change (Risk Perception); and Factor 4 reflects the extent to which a respondent perceives their lifestyle as sufficiently green (Self-Assessed Greenness).

Figure 4 shows a strong correlation between these four environmental beliefs and green behaviors, which motivates me to investigate changes in beliefs as potential drivers of behavioral responses.

3.2 Descriptive Statistics

Using data from UKHLS, I summarize the characteristics of people living in high and low flood-risk postcodes in Table 1. People in high-risk postcodes typically earn more, with an average of monthly income of £1,910 compared to £1,766 in low-risk zones. Regarding education, 27% of residents in high-risk postcodes have university degrees, slightly higher than the 25% in low-risk areas. In addition, Conservative Party supporters are 5% more likely to live in high-risk areas than in low-risk areas. This might indicate a difference in

[15] Some questions were asked in Wave 1 as well, but constructing a belief index using PCA requires observations with all variables.

[16] The varimax rotation assumes the latent factors are orthogonal, enabling each variable to be strongly associated with a specific factor.

[17] Here are articles mostly in social psychology that discuss these four factors. Self-efficacy: Bandura (1982), Koletsou and Mancy (2011); personal responsibility: Berkowitz (1984), Stern et al. (1999); risk perception: Grothmann and Patt (2005); self-assessed greenness: Binder and Blankenberg (2017)

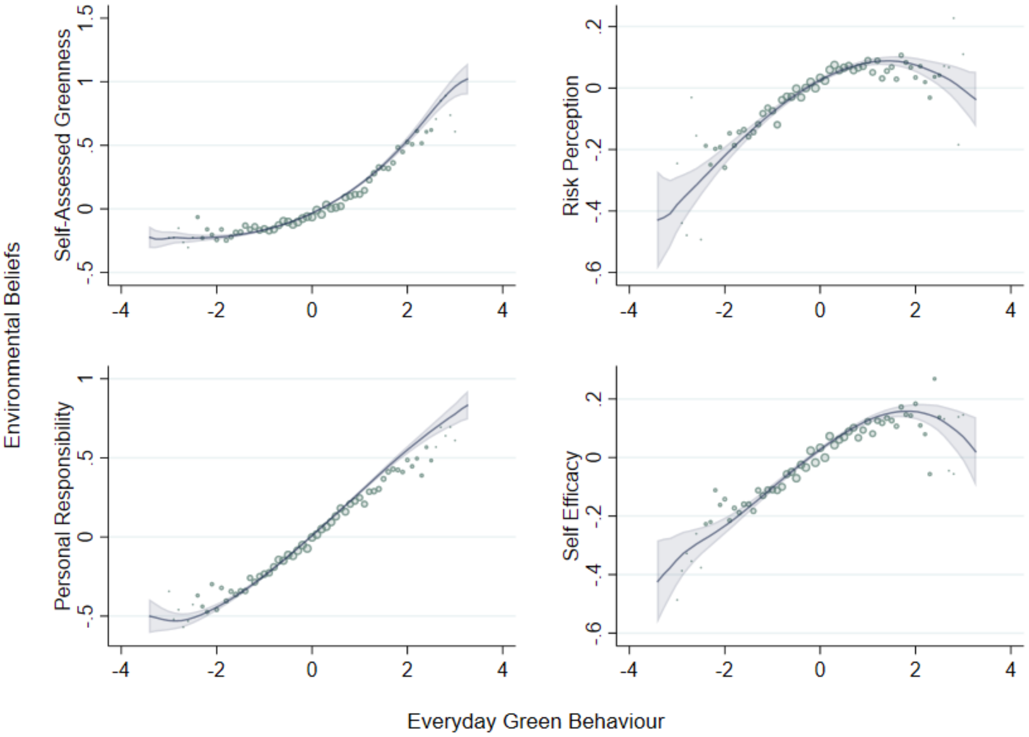


Figure 4: Correlation between Environmental Beliefs and Everyday Green behavior

Notes: *Everyday Green behavior* indicates the level of environmental friendliness of everyday activities. Individuals are binned in increments of 0.1 based on the value of *Everyday Green behavior*. The x-axis represents these bins, while the y-axis represents the mean value of each variable across individuals within each bin. *Self-efficacy* refers to one's belief in their own capacity to behave in ways necessary to attenuate climate change; *personal responsibility* refers to the belief that one ascribes the responsibility for climate change to themselves; *risk perception* refers to the belief in the risk of climate change; *self-assessed greenness* refers to whether one considers oneself environmentally friendly enough.

Table 1: Descriptive Statistics on Individual Demographics by Flood Risk

	All	Low Risk	Medium Risk	High Risk
Monthly Gross Income (£)	1,806.16	1,765.92	1,868.01	1,948.99
	(4,381.59)	(4,417.14)	(2,598.59)	(5,387.97)
Age	47.74	47.41	48.78	48.43
	(18.57)	(18.57)	(18.55)	(18.56)
Female	0.54	0.54	0.54	0.54
	(0.50)	(0.50)	(0.50)	(0.50)
University Degree	0.26	0.25	0.26	0.28
	(0.44)	(0.43)	(0.44)	(0.45)
Urban Address	0.81	0.85	0.71	0.71
	(0.39)	(0.36)	(0.46)	(0.45)
Conservative Party Support	0.21	0.19	0.24	0.24
	(0.40)	(0.40)	(0.42)	(0.43)
Obs.	385,893	278,299	51,468	56,126

Notes: UKHLS provides demographic information of their respondents. Conservative Party Supporter indicates if a respondent considers himself a strong supporter of or feels closer to the Conservative Party. I define Flood Risk as the probability that the flood depth at a specific location exceeds 10 centimeters in any given year. Individuals are grouped into three categories based on the flood risk of their postcode: Low (flood risk $= 0$) , Medium ($0 <$ flood risk ≤ 0.001), and High (flood risk > 0.001).

climate risk perception or attitudes among people holding opposite political ideologies.

Figure 5 shows that people living in high flood-risk areas tend to care more about the environment. Specifically, they are more likely to support the environmental charities and the Green Party, and to adopt a green lifestyle. This suggests that individuals living in high-risk areas are aware of the risk they face and environmental problems in general. However, the descriptive statistics tells us little about whether high flood risk exposure makes people more pro-environment or if pro-environmental people choose to live in high-risk areas. Therefore, I exploit unanticipated flood exposure to estimate its causal effect on environmental behaviors and underlying beliefs.

3.3 Estimation Strategy

I use a difference-in-differences (DiD) design to estimate the impact of flood exposure on environmental behaviors. This approach compares the change in individual behavior before and after flood exposure relative to those who were not exposed. I classify people into three groups based on their flood exposure. Individuals are *directly* flooded if a flood affects their postcode; individuals are *indirectly* flooded if a flood affects neighboring postcodes within a 200-meter radius but not their own postcode; individuals are in the *control* group if they are neither directly nor indirectly flooded. I will extend the radius to examine the impact of varying distances of exposure. Once individuals are exposed to

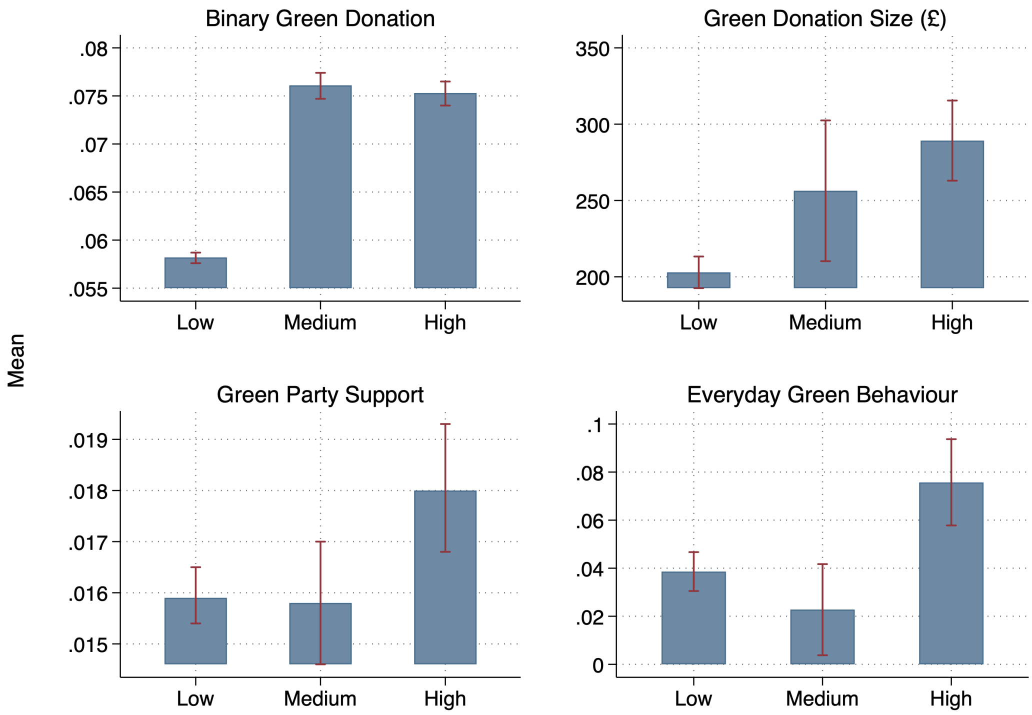


Figure 5: Mean of Environmental behaviors by Flood Risk

Notes: The figures are based on non-flooded observations. *Binary Green Donation* indicates whether an individual gives to environmental charities in a year. The subfigure on *Green Donation Size* is conditional on positive donations that have been made to environmental charities. *Everyday Green behavior* indicates the level of environmental friendliness of everyday activities. *Green Party Support* indicates whether an individual considers himself a supporter or feels closer to the Green Party. Flood risk is defined as the probability that the flood depth at a specific location exceeds 10 centimeters in any given year. Individuals are grouped into three categories based on the flood risk of their postcode.

a flood, they remain in the treated group from the year of their first exposure.

Both CAF and UKHLS provide personal addresses at the smallest postcode level, with each postcode containing, on average, only about 15 households.[18] This granularity allows for precise identification of individuals' direct or indirect exposure to floods, representing a notable improvement over previous work. By definition, 734 CAF donors (around 1%) were directly treated between 2011 and 2022, and 1,685 (around 2%) were indirectly treated within 200 meters of their postcode. Appendix Table D.1 reports the number of individuals who switched their treatment status from unflooded to directly or indirectly flooded by year. It shows that floods mostly affect people living in high-risk areas.

The main specification is:

$$Y_{it} = \beta_1 F_{it}^{direct} + \beta_2 F_{it}^{indirect} + \alpha_i + \gamma_{rt} + \delta_t R_i + u_{it}, \tag{1}$$

where Y_{it} is the outcome variable. F_{it}^{direct} equals one if individual i directly experienced a flood in year t; it remains one for every subsequent year following their first flood exposure. Otherwise, it is zero. $F_{it}^{indirect}$ is defined similarly for individuals who experienced a flood indirectly. Standard errors are clustered at the postcode level and also at the postcode area level. β_1 and β_2 capture the effect of direct and indirect flood exposure, respectively.

The regression includes three types of fixed effects. Firstly, the individual fixed effects α_i account for the constant behavioral differences across individuals. Secondly, the region-by-year fixed effects γ_{rt} control for common trends or shocks affecting all individuals within the same region. There is a chance that a flood event triggers a regional response, which would be absorbed by the region-by-year fixed effects. Nonetheless, the assumption is that the flood effect should be stronger for those in close proximity to the floods. Economic conditions across different regions in England are evolving in different directions and can influence environmental awareness in distinct ways. Previous research suggests that people are more likely to prioritize the environment under good economic conditions (Gagliarducci et al., 2019; Hoffmann et al., 2022). However, the region-by-year fixed effects may not fully account for shocks common to individual cities. Therefore, I include postcode area-by-year fixed effects as an alternative, with more than 100 postcode areas in England.[19] I present the results in Appendix Table E.10.

Thirdly, I include flood risk-specific year fixed effects $\delta_t R_i$. It captures the trend of

[18]CAF directly provides donor postcodes. The UKHLS offers a proxy for household location, where all households within a given postcode share the same proxy location. I match this proxy household location with its corresponding postcode boundary using the ONS postcode directory.

[19]A postcode area in the UK is the largest geographic unit used in the postal address coding system, identified by one or two letters corresponding to a specific city or town. For instance, the "BS" in the postcode "BS8 1TU" denotes Bristol. There are 124 postcode areas in use. In parallel, England is divided into nine regions: North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, East of England, London, South East, and South West.

environmental outcomes and flood exposures shared by individuals facing different level of flood risk. Including $\delta_t R_i$ is key for causal estimation. As shown in Figure 2, floods are more likely to strike high-risk areas, but flood exposure is plausibly random within areas of the same flood risk. In the main results, I use a continuous measure of flood risk, assuming a linear correlation between yearly fixed effects and flood risks. I also report results of specifications including discrete risk level by year fixed effects, by grouping people into three categories. The results, shown in Appendix Table E.9, indicate that the estimation is not sensitive to the form of flood risk.

The identification relies on the assumption that flood exposure is unrelated to other determinants of environmental behaviors, conditional on individual, region-by-year, and flood risk-specific year fixed effects. The unpredictability of flood timing and affected locations, conditional on flood risk, makes the assumption plausible.

The DiD design assumes that the outcome for the treated group would evolve in the same way as the control group if they were not treated. The two-way fixed effects model might yield biased estimates, as it uses people treated earlier as controls for those treated later (Goodman-Bacon, 2021; De Chaisemartin and d'Haultfoeuille, 2023; Roth et al., 2023). If the treatment effects are heterogeneous across individuals and over time, the post-treatment periods of those treated earlier might follow trends different from those treated later, making them an invalid comparison group. The common trend assumption might also be violated since I only use post-2009 floods to determine treatment status. If someone in the control group was treated before 2009 and the treatment effects vary over time, they may not follow the same trend as those not treated before 2009.

To address these concerns, I show that the two-way fixed effects model yields estimates consistent with alternative heterogeneity-robust estimators in Figure 6. Given that I have a large control group, it is expected that the two-way fixed effects model functions well in my setting, because the average behavior in the control group, used for comparison, is predominantly influenced by those never treated. Therefore, individuals who were treated before 2009 and those treated earlier in the sample have minimal impact on the outcomes in the control group. Additionally, Figure 7 shows no significant differential trend in outcomes before actual flood occurrences.

Finally, I address the problem of movers and sample attrition. Unlike most studies that make comparisons at the geographic unit level, I compare individuals directly and hence avoid the issue of changing population compositions within a geographic unit. However, for CAF donors, I only have addresses at the time of registration. If an individual moved to a postcode after it was affected by a flood, or left a postcode before a flood occurred, they would be incorrectly allocated to the treatment group. For survey responses, moving could lead to sample attrition, potentially biasing the results if those who stay respond differently from those who move after a flood. To address these concerns, I show in Appendix Table E.7 that flood exposure does not affect relocation by looking at those who changed their address but remained in the survey. I also show that flood exposure is not correlated with survey attrition in Appendix Table E.8.

4 Results

4.1 The Effect of Flood Exposure on Environmental behaviors

This section reports the results of the effect of flood exposure on environmental behaviors. I visualize the main estimates below and report them in full in Appendix Section E.1.

4.1.1 Environmental Donations

Figure 6 shows that people are two percentage points (ppt) more likely to give to environmental charities after direct exposure to a flood affecting their own postcode. However, there is no effect on green giving after indirect exposure to a flood affecting their neighbors. Considering that only 6% of people in the control group give to environmental causes, the effect of direct exposure on the extensive margin is substantial. I also report the effect on the size of green giving conditional on positive donations to environmental charities in Appendix Table E.2. I do not find a significant change on green giving at the intensive margin. Therefore, I focus on the extensive margin results. In contrast, Figure 6 shows no significant impact from floods occurring at distances of 200, 400, 600, and 800 meters. Also, I cannot reject the hypothesis that all coefficients of indirect exposure are equal to zero, given the F-statistic of 1.26, reported in Appendix Table E.1. I report estimation with all alternative estimators in Appendix Figure E.1, showing that the effects estimated with the two-way fixed-effects model are consistent with alternative diff-in-diff estimators.[20] This observation suggests an "only-in-my-backyard" phenomenon, where people act only when their immediate interests are threatened. This might explain the paradox of widespread recognition of climate change as a severe threat in the UK, yet insufficient action towards tackling climate change.

Direct flood exposure tends to have a long-lasting effect on environmental giving. I use the last untreated period before flood exposure as the baseline and estimate the temporal

[20] Borusyak et al. (2024) propose an imputation-based estimator, which is equivalent to fitting a regression of the outcome on individual and time fixed effects in the sample of untreated observations, and using that regression to predict the counterfactual outcome of treated observations. Callaway and Sant'Anna (2021) propose an estimator using the never or not-treated as the control group for each treated group, which is only suitable for a binary treatment in a staggered absorbing setting. Similar but applicable to a wider setting, the estimator proposed by De Chaisemartin and d'Haultfoeuille (2024) compares the evolution of outcomes for treated individuals from the last untreated period to those whose treatment status was the same as the treated group but remained constant. Estimation results with all heterogeneity-robust estimators are presented in Appendix Figure E.1.

effects using the estimator proposed by De Chaisemartin and d'Haultfoeuille (2024). This approach compares the evolution of outcomes from the baseline period between those treated and those not-yet-treated. I exclude individuals exposed to floods multiple times from the event study. Figure 7 shows that the probability of green giving is higher than the baseline period five years after initial flood exposure. This increase is statistically significant in the two years following the exposure. The loss of significance from the third year onwards is likely due to insufficient sample sizes, as later treated donors might not be observed three years after their exposure. Hence, this provides strong evidence of a long-lived effect. In contrast, there is no clear difference in green donations before and after an indirect exposure, as plotted in Appendix Figure 7.

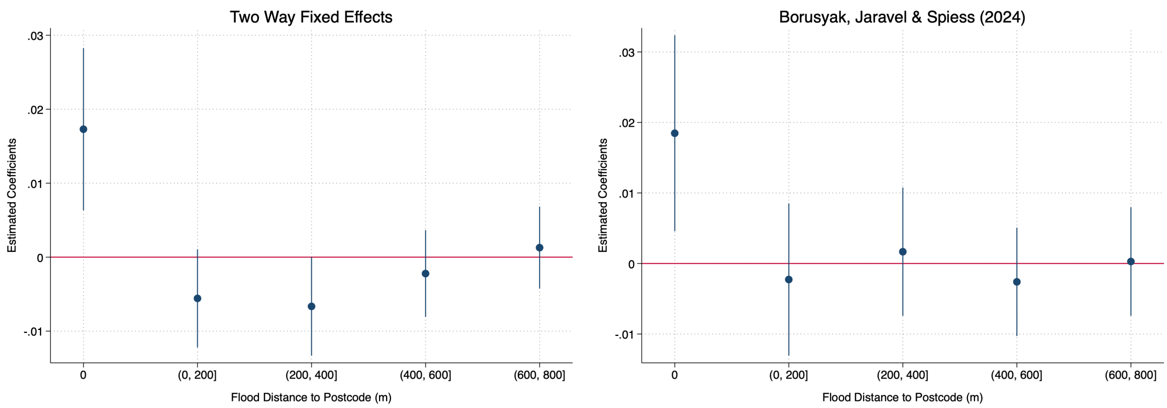
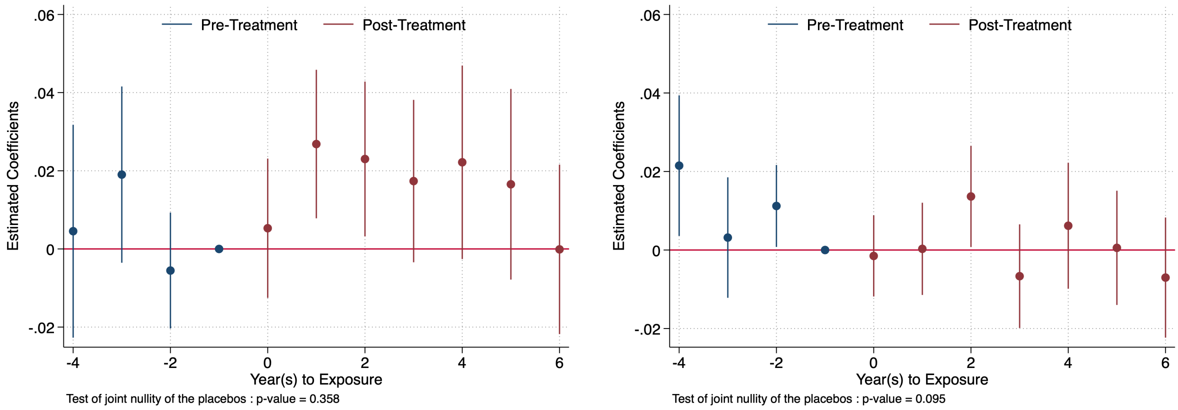


Figure 6: The Effect of Flood Exposure on Green Donation

Notes: This figure plots the estimated effects of flood exposure at various distances on the probability of giving to environmental charities. The subfigures plots the coefficients obtained using the two-way fixed effects model, and the imputation-based approach proposed by Borusyak et al. (2024) with the Stata command `did_imputation`. The figure presents point estimates along with their corresponding 90% confidence intervals, with standard errors clustered at the postcode level.

Are people equally responsive to additional flood experiences as they are to their first experience? Repeated exposure can heighten concerns about future impacts and increase support for environmental actions. Conversely, it might undermine belief in the effectiveness of their actions, leading to reduced donations. I show that green giving increases with the number of direct experiences. Specifically, 149 CAF donors (20% of those directly treated) experienced two or more floods. I compare their donations post-first and post-second flood exposure against their donations pre-first exposure. Figure 8 shows that the second exposure increases the probability of giving to an environmental charity by 3.8 ppt, relative to the first exposure. In contrast, an additional indirect exposure does not affect green donations, same as the first indirect exposure. This suggests that multiple personal experiences might intensify people's concerns about the personal consequences.

As shown in Figure 9a, the increase in green donations is driven by charities working on broader issues related to climate change. By looking at donations to the ten largest



(a) Direct Flood Exposure (b) Indirect Flood Exposure

Figure 7: Event Study of Flood Exposure on Green Donations

Notes: I use the estimator proposed by De Chaisemartin and d'Haultfoeuille (2024). The year before flood exposure is set as the baseline period. I then compare the changes in outcomes from the baseline period to l years later between those who were treated and those who remain untreated by l years after the baseline. I plot the point estimates and the 90% confidence intervals, with standard errors clustered at the postcode level. The three years before the baseline are chosen as the placebo period, and the p-value for the joint test that all placebo coefficients are equal to zero is reported at the bottom.

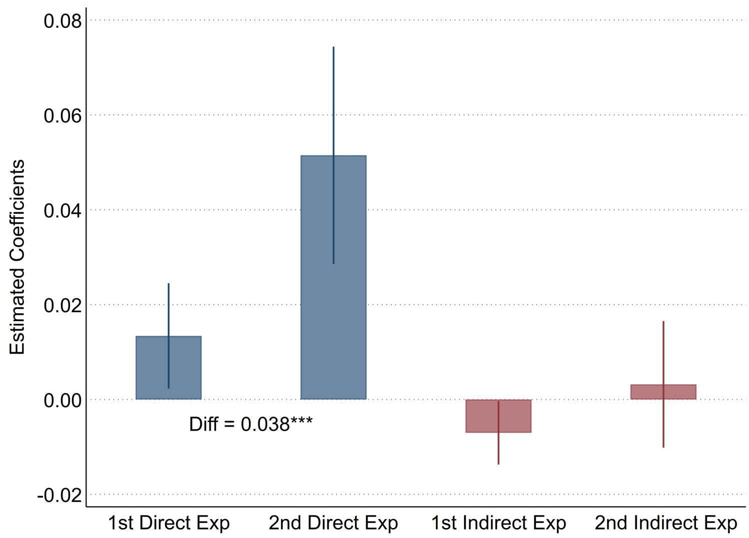
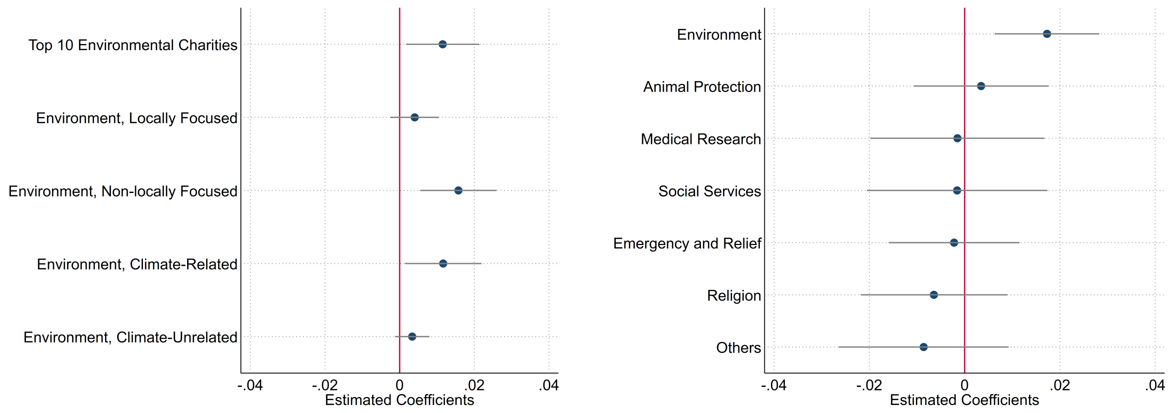


Figure 8: The Effect of Multiple Flood Exposures on Green Donation

Notes: First Flood Exposure (1st Exp) indicates the period following an individual's first exposure to a flood but before their second experience. Second Flood Exposure ($\geq$ 2nd Exp) denotes the period after their second flood experience. Approximately 80% of people are exposed to floods directly only once, while 20% are exposed more than once. I report the number of people by the number of times they have been exposed to floods in Appendix Table D.1.The estimation strategy is to compare behaviors after both the first and second flood exposures to behaviors before the first exposure, controlling for individual fixed effects, year-specific flood risk effects, and region-by-year fixed effects. Standard errors are clustered at the postcode level. The vertical line plots the 90% confidence interval.



(a) By Environmental Charity Type

(b) By Charitable Cause

Figure 9: The Effect of Direct Flood Exposure on the Probability of Giving

Notes: This figure presents the effects of direct flood exposure on the probability of giving to specific types of charities. I plot the point estimates along with the 90% confidence intervals, with standard errors clustered at the postcode level. In Figure a, brief descriptions of the top ten environmental charities are provided in Appendix Table C.1. I further categorize environmental charities based on whether they primarily benefit local areas, following the classification provided by the National Council of Voluntary Organisations. Additionally, I classify the top 100 environmental charities based on whether their mission, activities, or campaigns explicitly mention climate change. In Figure b, charities are mapped to their cause area according to the International Classification of Non-Profit Organizations (ICNPO).

environmental charities — most of which have missions or activities linked to climate change but do not address specific local issues like floods — I find that people are more likely to support these charities after directly experiencing a flood. In addition, using the National Council for Voluntary Organisations' classification of charities benefiting local areas, I show that this rise in donations is not directed toward local charities, such as those focused on waterway conservation. Finally, lacking a detailed classification system for climate-related charities, I manually reviewed the mission statements, programs, and campaigns of the top 100 environmental charities, which account for 95% of all environmental donations. I classify a charity as climate-related if its materials explicitly address climate change. I show that donations to these climate-focused organizations increase, while donations to other environmental charities (e.g., wildlife trusts) remain stable.

Previous research suggests that major disruptive events may lead people to change their consumption habits, including the types of charities they support (Black et al., 2021). I show that direct flood exposure heightens attention specifically toward climate change without reducing support for other social causes. Notably, people are not more likely to donate to charities involved in post-flood aid, such as social service or emergency relief organizations, possibly because these services in the UK are typically provided or funded by the government. Second, there is suggestive evidence that people affected by floods are less likely to give to religious charities. This contrasts with Sinding Bentzen (2019), who argues that people may turn to religion to make sense of unexpected events.

My findings, however, suggest that if people link floods to climate change, they may not turn to religiosity for explanation. Finally, donations to causes unrelated to climate change show no significant change.

4.1.2 Green Party Support and Everyday Green Behavior

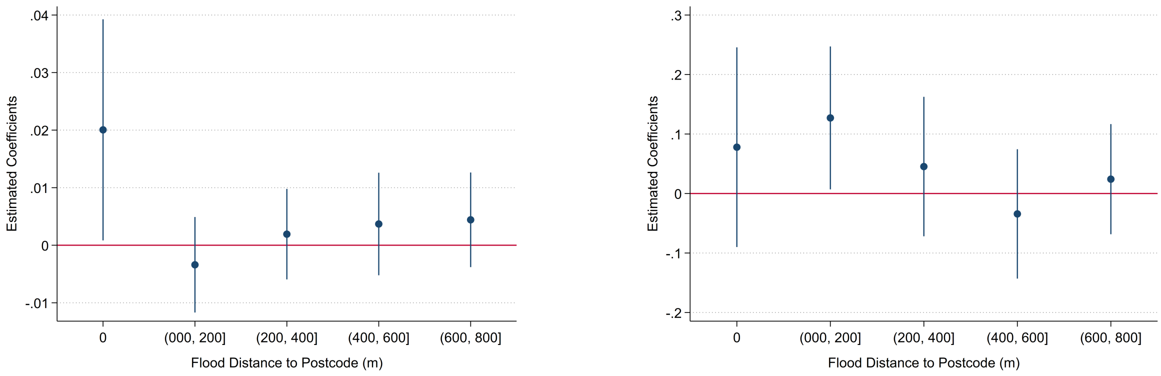
Figure 10a shows that direct flood exposure increases support for the Green Party by two percentage points (ppt), which is a large effect considering only 1.6% of people support the Green Party. However, indirect exposure has no effect. The UKHLS sample is more representative of the UK population. This suggests that the localized response is likely to be a general pattern rather than one driven solely by donors. Meanwhile, in Appendix Table E.3, I show that people are three ppt (p-value = 0.16) more likely to support the Labour Party, with no obvious change for the Conservative Party. This aligns with the Labour Party's greener stance on environmental policies compared to the Conservative Party. This implies that the observed increase in Green Party support might come from people in other political segments. Additionally, I show that flooded people do not become more interested in politics, implying that flood exposure heightens public awareness of the need for political efforts to address environmental issues.

Using data from all three waves (2009, 2012, and 2018) that survey everyday green activities, Figure 10b shows an increase in daily green activities after direct exposure. However, this increase is not statistically significant, which could be due to the large gap between waves when people are surveyed. For instance, among the mere 200 people who were directly flooded during this period, I only observe later outcomes at the time of the survey for those who were treated earlier. If the treatment effect decays over time, I might not observe changes in everyday behavior despite its presence.

Figure 10b shows that exposure to a flood affecting neighbors within 200 meters might increase everyday green behavior. However, when testing the null hypothesis that all coefficients of indirect exposure within 800 meters are equal to zero, I cannot reject this hypothesis, as indicated by an F-statistic of 0.957, reported in Table E.1. Furthermore, in Table E.10, when controlling for postcode area-by-year fixed effects, the effect of indirect exposure within 200 meters loses its statistical significance. This suggests that when comparing people living in the same city, there is no differential trend of everyday activities between those indirectly flooded and those not flooded following a flood. Therefore, I caution against interpreting the indirect exposure effect as strong causal evidence.

4.2 Flood Exposure, Beliefs and Preferences

This section explores the mechanisms driving the pro-environmental reaction. I present the effect on main measures of environmental beliefs in Figure 11 and report the coeffi-



(a) Green Party Support

(b) Everyday Green Behavior

Figure 10: The Effect of Flood Exposure on other Green Behaviors

Notes: Green Party Support indicates if one considers himself a supporter of the Green Party. *Everyday Green Behavior* is a standardized outcome, measuring the overall environmental friendliness of people's everyday activities related to transportation, recycling, and energy consumption. The x-axis represents the distance at which they were exposed to a flood. I plot the coefficients from estimating Equation 1 and the 90% confidence interval. Standard errors are clustered at the postcode level.

cients in Appendix Section E.2.

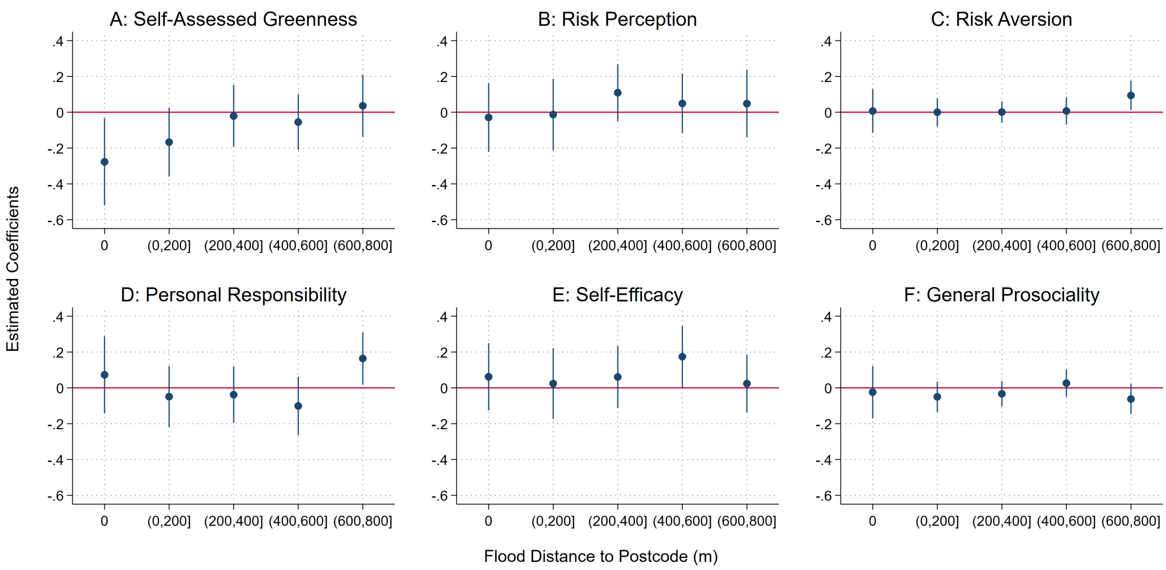


Figure 11: The Effect of Flood Exposure on Environmental Beliefs and Preferences

Notes: I plot coefficients and 90% confidence level from estimating Equation 1 on environmental beliefs and preferences. All outcome variables are standardized, and from the UKHLS. *Self-Assessed Greenness* indicates whether one considers oneself environmentally friendly enough; *Risk Perception* refers to the belief in whether people in the UK will be affected by climate change; *Personal Responsibility* relates to the belief that one ascribes the responsibility for climate change to themselves; *Self-efficacy* denotes one's belief in their own capacity to behave in ways necessary to attenuate climate change. *Risk Aversion* is proxied by the purchase of content insurance; *General Prosociality* is proxied by whether an individual makes a donation in the year. Standard errors are clustered at the postcode level.

4.2.1 Self-Assessed Greenness

I show that people directly affected by floods are 0.305 standard deviations less likely to view themselves as mostly environmentally friendly, whereas those indirectly affected do not change their self-perceptions. Change in self-evaluation depends on their actual efforts and their expectations of what they should do. Since their green behavior did not decrease, this might occur because these affected people elevate their expectations about the range of activities considered sufficient for the environment. This leads them to consider themselves as less environmentally friendly. In other words, being exposed to climate change events that have personal consequences makes people update their expectations on environmental behavior. Not meeting this revised standard could lead to utility loss, such as guilt and discontent, which in turn motivates further green behaviors.

4.2.2 Risk Perception and Risk Preferences

Figure 11B shows that flood exposure does not change the perception of climate threat in the UK. Both direct and indirect exposure have effects close to zero. The precise zero suggests that not rejecting null effect is not due to weak statistical power from the small sample size. Further, I combine all instances of direct and indirect exposure and analyze their effect collectively. I report the results in Appendix Table E.12, and find no significant effect. Interestingly, an effect appears when region-by-year fixed effects are not included. This suggests that there might be a regional response. For example, media coverage are more likely to follow a flood, causing regional changes in risk perception. However, I cannot conclude whether these effects are due to floods or other concurrent events. My main coefficients capture the "exposure" effect — illustrating how risk perception varies in proximity to flood occurrences among people living in the same region. The null effect aligns with the fact that a significant portion of the UK population already acknowledges the threat of climate change (as shown in Figure 1), and there is little climate change denial in the UK (as shown in Appendix Table A.1). This suggests that a change in risk perception might depend on the initial level of risk perception (Deryugina, 2013).

I also do not find changes in financial behaviors that are indicative of risk preference. Observing risk preference is challenging, and I use the purchase of household contents insurance as a proxy, following what is common in the literature (Gao et al., 2020; Shai, 2022). The UK provides a suitable setting, where insurance premiums are not expected to change significantly after flood occurrences, as the effect of flood incidents on insurance premiums is transferred to the government. Additionally, I use the proportion of investments in high-risk assets, such as company stocks, and low-risk assets, like national savings, as alternative indicators for risk preference. Appendix Table E.5 shows that none of these measures change in a statistically significant way after flood exposure.

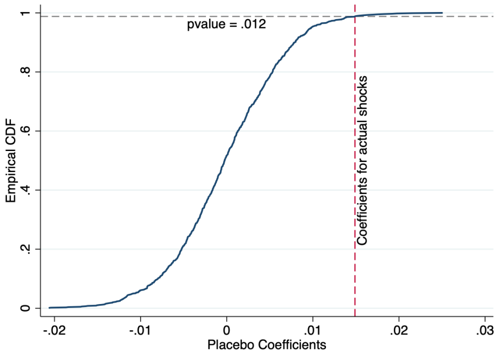
4.2.3 Prosociality, Self-Efficacy and Personal Responsibility

An alternative explanation for the behavioral change could be that disasters generally enhance prosociality due to heightened community feelings, empathy, and cooperative recovery efforts (Douty, 1972; Rao et al., 2011). However, using data from UKHLS, I do not find an increase in the probability that people give or in the size of their total donations. UKHLS includes a sample more representative of the population, making it useful for quantifying general prosocial behavior, even though it does not specify where the donations go. The results are reported in Appendix Table E.6. Overall, while direct flood exposure changes people's expectations about environmental activities and encourages environmental behaviors, it does not enhance prosocial behaviors more broadly.

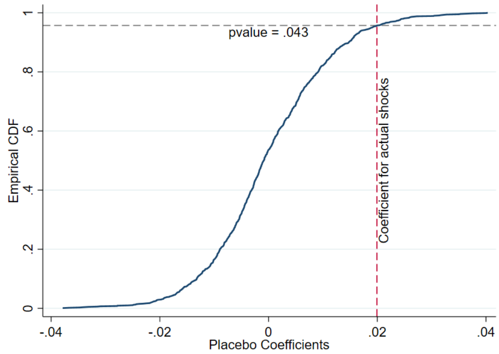
Recognizing personal responsibility and self-efficacy might also influence cooperative actions. However, Subfigures E and F in Figure 11 show no consistent effect of flood exposure on people's beliefs about their responsibility for climate change or the efficacy of their actions. Specifically, I find that exposure to a flood within 600 meters of one's postcode has no effect on the recognition of personal responsibility, despite a positive effect from floods occurring between 600 and 800 meters. When testing the joint coefficients for indirect flood exposure, I cannot reject that they are all equivalent to zero. Hence, I advise caution against interpreting this as strong evidence of a change in personal responsibility. Similarly, I conclude that flood exposure lacks an effect on self-efficacy perceptions.

4.3 Robustness Checks

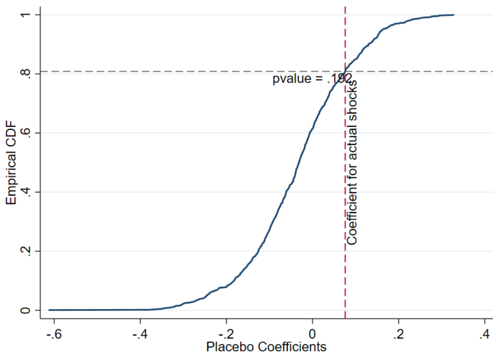
I have a small sample of individuals exposed to floods, which indicates that the asymptotic inference that work well in large samples might not work (Roth et al., 2023). I run a non-parametric permutation test on $\beta = 0$, which represents a null effect of flood exposure. I randomly select individuals affected by flooding, while maintaining the number of flooded individuals for each year and preserving the distribution of flood risk characteristics among those affected. This permutation is performed 1000 times, and I plot the empirical probability distribution of the coefficients estimated with placebo shocks in Figure 12. The p-value indicates the proportion of estimated coefficients extremer than the coefficient estimated with actual floods. The small p-values in the plots suggest that the treatment effect does not appear by chance. This test does not rely on the underlying distribution of the sample, which additionally addresses the concern that standard errors might be biased if the variables are serially correlated (Bertrand et al., 2004).



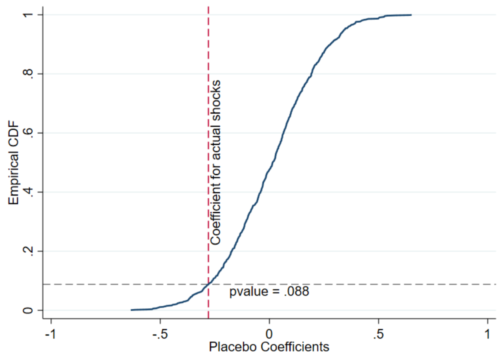
(a) Green Donation



(b) Green Party Support



(c) Everyday Green Behavior



(d) Self-Assessed Greenness

Figure 12: The Permutation Test

Notes: I run a non-parametric permutation test on $\beta = 0$, which represents a null effect of flood exposure. I randomly select individuals affected by flooding, while maintaining the number of flooded individuals for each year and preserving the distribution of flood risk characteristics among those affected. This permutation is performed 1000 times, and I plot the empirical probability distribution of the coefficients estimated with placebo shocks. The vertical line shows the coefficients estimated with actual floods, and the p-value is the proportion of placebo estimates that are more extreme than the real estimate.

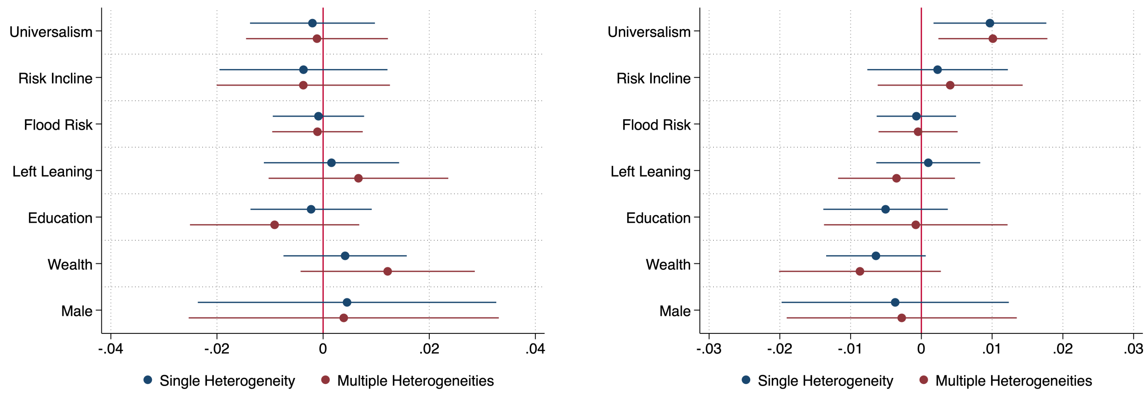
4.4 Further Analyses and Discussion

Compared to existing research, direct flood exposure has a more lasting effect, with an additional experience showing a striking, incremental impact on green activities. For example, prior studies find that donations to fundraising appeals for major natural disasters last only 2 to 15 weeks (Jayaraman et al., 2023; Scharf et al., 2022), likely because the need for post-disaster aid is temporary, while climate change presents a lasting challenge. Allcott and Rogers (2014) show that personalized energy feedback with social comparison information can reduce electricity usage within days, though these effects often fade after a few months. They also find that repeated interventions have effects five times smaller than the initial treatment — unlike the incremental effect of repeated flood exposures, which is greater than the first exposure. Both Scharf et al. (2022) and Allcott and Rogers (2014) attribute these short-lived effects to a cue-based mechanism, where behavior reverts to baseline once the salient cue is removed. Similarly, Ito et al. (2018) find that moral persuasion affects energy use for only three months beyond the treatment period, whereas economic incentives last longer. Much like the appeal of personal economic benefits, my findings suggest that climate-related experiences with personal stakes can be powerful motivators for sustained pro-environmental behavior.

I further investigate the limited response to climate events that lack direct personal impact. Since mitigating climate change is a global common good — and most people in the UK may not face its immediate costs — I examine whether people with universal moral values, who prioritize the well-being of all people and the environment, are more likely to respond to nearby floods.

To operationalize universalism, I construct a constituency-level measure using PCA on two variables: belief in globalization as a positive force and sense of belonging to the local community. The first factor loads positively on globalization and negatively on community attachment. I hypothesize that people with stronger globalization beliefs and weaker local attachment are more likely to hold inclusive values. I validate this measure by showing that it aligns with universalist values: it positively correlates with support for EU integration, immigration, and income equality, and negatively correlates with local identity, national defense support, and opposition to overseas aid and minority rights. Detailed PCA results and correlations are in Appendix Table E.13 and Figure E.2.

Figure 13 shows that a one-standard-deviation increase in universalism is associated with a one-percentage-point rise in green donations in response to nearby floods. In the heterogeneity analysis, I interact direct and indirect flood exposure with each variable individually, and then with all factors simultaneously. Results indicate that universalism's moderating effect on indirect flood exposure remains significant, even when controlling for socio-economic variables, including political orientation, wealth, and education.



(a) Direct Flood Exposure

(b) Indirect Flood Exposure

Figure 13: Heterogeneous Effect of Flood Exposure on Environmental Donations

Notes: The figure plots coefficients with 95% confidence intervals for interaction terms. In the "single heterogeneity" models, each regression includes interactions of both direct and indirect flood exposure with a single variable. In the "multiple heterogeneities" model, all interaction variables are included in a single regression. All variables, except for three, are at the constituency level and sourced from the British Election Study. Wealth and flood risk data are at the postcode level, while gender is at the individual level. All variables are standardized.

Universalists apply moral values broadly, extending beyond self or group interests (Schwartz, 2007, 2012; Enke et al., 2023), fostering a deep concern for environmental issues. In Figure E.2, I show that the universalism measure strongly correlates with agreement that governments should prioritize environmental protection over economic growth and with disagreement that environmental protection has gone too far. Supporting this, Andre et al. (2024) find that universal moral values are associated with a stronger commitment to climate action. Similarly, Prati et al. (2018) show that universalist values — but not in-group-focused benevolence — are linked to higher perceived consequences of climate change and lower climate skepticism. As Andre et al. (2024) argues, climate action is a global cooperation challenge affecting present and future generations worldwide, making it likely that people with universalist values will more strongly support climate protection. Universalist values foster a global sense of identity and empathy, motivating support for environmental actions that address global challenges and benefit distant or vulnerable communities, regardless of direct personal impact.

Previous research suggests that moral values can be influenced in two main ways: increasing value accessibility or shifting value importance (Russo et al., 2022). First, priming techniques make specific values more accessible in memory by activating related cues, promoting behaviors aligned with those values without changing their perceived importance (Russo et al., 2022). For example, Sagiv et al. (2011) show that participants with high benevolence values contribute more to a public goods game when these values are made accessible by completing a values survey before the game. Second, interventions can increase the relative importance of a value by fostering identification with influential individuals or groups. Döring and Hillbrink (2015) show that people randomly assigned to watch the movie *Into the Wild* perceive universalism values as more important. Similarly, Maio and Olson (1998) argue that prompting critical reflection on culturally accepted values can make people more open to value change. For instance, Bernard et al. (2003) show that reasoning about equality helped participants strengthen their endorsement of it, even when presented with opposing arguments. These findings indicate the potential for making universalism values more salient or prioritized to promote pro-environmental behaviors, but further research is needed in the context of climate change.

5 Conclusion

This paper presents new insights into the relationship between flood experiences and changes in pro-environmental behaviors. The key finding is a significant increase in green behaviors among individuals directly exposed to floods. This increase includes activities such as political engagement and financial support for environmental charities. It highlights the impact of personal experience with climate consequences on encouraging individual efforts to address environmental issues.

Additionally, this work highlights the localized impact of floods. By precisely identifying those directly or indirectly affected using postcodes, I show that the effect of floods on environmental behaviors is highly localized, suggesting that personal experience is crucial in catalyzing behavior change. The pronounced effect of direct experience indicates that efforts to encourage green behavior may be more effective if people are made aware of the personal consequences of climate change. Therefore, framing and communication strategies that make the consequences more vivid and relatable are important. While personal exposure to climate consequences drives actions, it remains unclear whether other factors could make people believe in their personal consequences, and whether such belief, without direct experience, would be as effective. This question opens a pathway for future research to explore how perceptions of personal risk influence environmental actions.

Interestingly, the study also finds that the increase in green behaviors following flood exposure does not coincide with a shift in risk perceptions or general prosociality. Instead, it suggests another factor at play: self-assessment. Specifically, I show that experiencing a flood lowers people's self-evaluations of their current environmental lifestyles despite increased efforts, indicating that individuals raise their expectations for these behaviors. The sense of guilt from not meeting these updated expectations could drive further behavioral responses. This finding implies that providing information on what constitutes a sufficient amount of green activities might be effective in driving further behavioral changes in contexts where risk perception is already high.

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Appendices

A Additional Contexts

A.1 Risk Perception of Climate Change

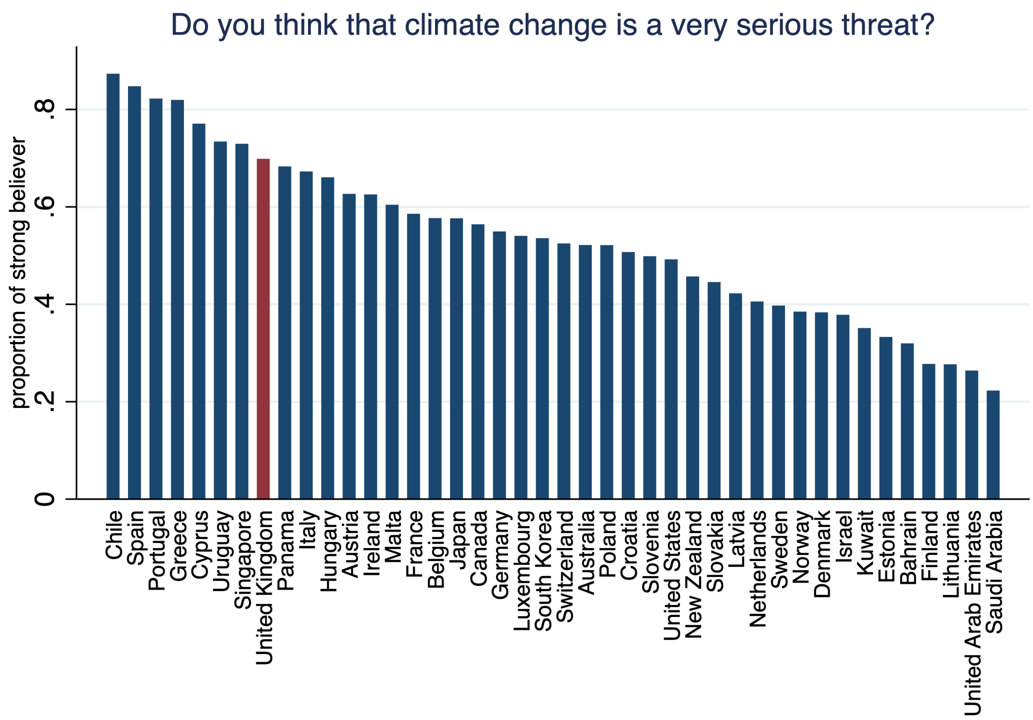

Figure A.1: Proportion of Strong Believers in Climate Change by High-Income Country

Notes: The data is from the 2021 World Risk Poll, available at https://wrp.lrfoundation.org.uk. The survey was conducted by Lloyd's Register Foundation, covering over 125,000 people in 121 countries. The figure is based on the question "Do you think that climate change is a very serious threat, a somewhat serious threat, or not a threat at all to the people in this country in the next 20 years? If you do not know, please just say so". The plot shows the proportion of respondents who answered "very serious threat" in each country. Only high-income countries are included in this figure.

Table A.1: Google Search Top Five Rising Queries from 2004 until 2023

Search Term	US	UK
Global Warming	what is climate change	climate change and global warming
	trump global warming	global warming bitesize
	global warming fake	what is climate change
	how to help global warming	global warming bbc bitesize
	climate change definition	global warming meaning
Climate Change	trump climate change	climate change news
	cause of climate change	climate definition
	climate change issues	climate change definition
	is climate change natural	climate change kids
	is climate change real	climate change for kids

Notes: For each search term, these queries are those with the biggest increase in search frequency since 2004 in each country. The data was collected from Google Trends on 16th Nov 2023.

A.2 Floods in England

In the UK, the average death toll per flood event is 3, compared to 7 in other European countries, and 16 in the US. Examining the distribution further, the 99th percentile of deaths per flood in the UK is 5, whereas it's significantly higher in the US at 168 and 52 in Europe. This indicates that even the largest floods in the UK are less deadly. However, considering the median death toll is 6 in the US and 3 in Europe, it appears that the scale of floods in the UK is comparable to those that occur around half the time in the US and more frequently than half the time in Europe. Statistics on the affected population suggests a similar pattern.

Table A.2: Comparison of Floods Collected by EM-DAT From 2009 to 2022

	Total Deaths				
	Mean	1st Perc.	Median	99th Perc.	No.
Asia	62	1	15	842	1,260
Africa	31	1	13	290	495
Americas (non-USA)	21	1	6	273	469
United States	16	1	6	168	234
Oceania	7	1	3	47	60
Europe (non-UK)	7	1	3	52	231
Great Britain	3	1	2	5	17

	Total Affected				
	Mean	1st Perc.	Median	99th Perc.	No.
Asia	827,224	6	20,445	15,730,534	1,335
Africa	106,784	14	14,823	1,104,229	600
Americas (non-USA)	109,755	18	8,103	2,412,734	602
United States	618,459	2	300	1,114,450	143
Oceania	28,058	106	5,500	199,040	109
Europe (non-UK)	18,132	2	670	362,536	256
Great Britain	6,364	13	600	43,800	15

Notes: The table presents summary statistics of flood events collected by EM-DAT from 2009 to 2022, available at https://www.emdat.be. EM-DAT gathers information from various sources, including governmental and non-governmental agencies. It is important to note that the floods in this dataset are likely a subset of the floods affecting England, as collected by the Environment Agency in England. The statistics are grouped by continents or countries. "Total Deaths" represents the number of total fatalities from each flood event, whereas "Total Affected" includes the number of people injured, rendered homeless, or in need of immediate assistance.

Table A.3: Statistics on Affected Postcodes and Flood Duration

Statistic	Number of Affected Postcodes	Duration (Days)
Count	229	229
Mean	90	4
Standard Deviation	292	11
Minimum	1	1
1st Percentile	1	1
25th Percentile	4	1
50th Percentile	12	1
75th Percentile	45	2
99th Percentile	1,431	62
Maximum	2,802	81
Total (N)	229	229

Notes: The flood data is from the Environment Agency. Statistics in the table represent floods that occurred between 2009 and 2022, after removing (1) duplicate flood entries, (2) floods deemed invalid by the Environment Agency, (3) floods with the same event ID but different start years, and (4) floods that persisted for over a year. The number of affected postcodes is the number of postcodes that experienced flooding during the flood event. To calculate the affected postcodes, I intersect all postcode polygons with the polygon for each flood event.

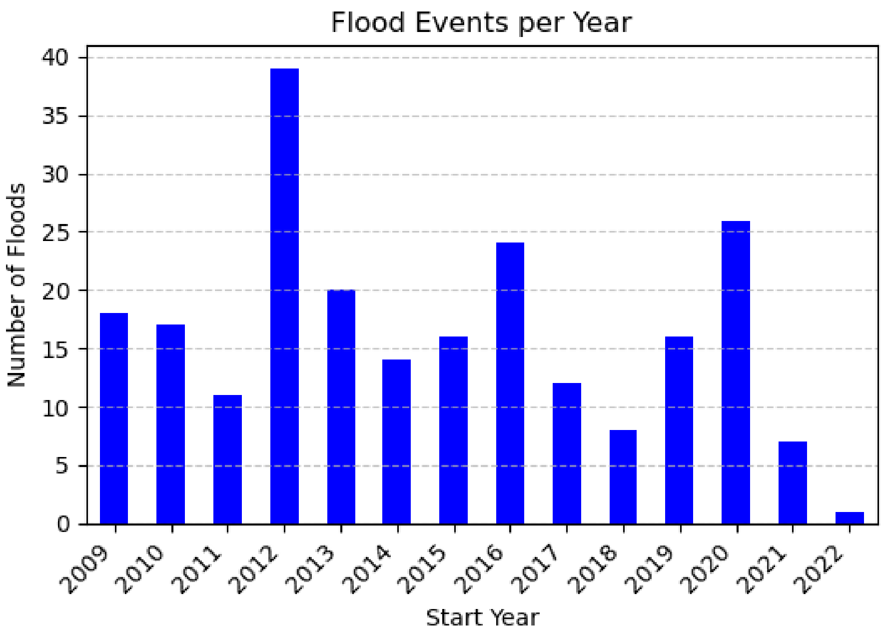

Figure A.2: Number of Floods by the Year of Start

Notes: The flood data is from the Environment Agency. The flood sample is the one used in my analysis. I refine the flood sample by removing (1) duplicate flood entries, (2) floods deemed invalid by the Environment Agency, (3) floods with the same event ID but different start years, and (4) floods that persisted for over a year.

A.3 The Association between Floods and Climate Change

Climate change has contributed to flooding in the UK and is increasing the risk of future floods (Thompson et al., 2017; Betts and Brown, 2021; Kew et al., 2024). However, various other factors may affect how people experience floods, making the connection between specific flood events and climate change tenuous. Whether floods are perceived as climate shocks depends on whether people link flood occurrences with climate change.

To explore this, I collect weekly Google Trends indices for climate change from 2009 to 2022 in the UK. Table A.4 shows that searches for climate change increase by 0.23 standard deviations during weeks with floods. The finding is consistent with previous research, showing extreme weather events in the US increase searches about climate change (Herrnstadt and Muehlegger, 2014). Specifically, I compare the index in weeks with floods to other weeks within the same year and month. While floods are more frequent in certain seasons, their timing within a given month is plausibly random.

To validate the results, I conduct a randomization test involving 100 permutations, where "placebo" flood weeks are randomly selected while preserving the original distribution of flood-affected weeks within the year (Columns 1 and 3) or month (Columns 2 and 4). The null hypothesis is that flood occurrences have no effect on Google searches. The p-value is derived from the proportion of times that coefficients from placebo floods exceed those from actual floods, as reported in square brackets in Table A.4. A p-value of 0 rejects the null hypothesis, suggesting a statistically significant effect and ruling out the possibility that the results are driven by chance. Moreover, the randomization test does not depend on the underlying data structure, such as serial correlation, which rules out the risk that the results are driven by mis-specification.

Table A.4: The Effect of Flood Occurrence on Google Search

	Flood Search		Climate Search	
	(1)	(2)	(3)	(4)
Flood Occurrence	0.939	0.861	0.240	0.227
	(0.170)***	(0.151)***	(0.110)**	(0.103)**
	[0.000]	[0.000]	[0.000]	[0.000]
Observations	808	808	808	808
Year Fixed Effects	Yes	No	Yes	No
Year by Month Fixed Effects	No	Yes	No	Yes

Notes: Google Trends indices are *weekly* time series that I collected separately for search interest in "climate change" and "flood" in the UK for each year from 2009 to 2022. For each topic, the index in a given week represents the proportion of searches relative to the peak week of that year (indexed as 1). I standardized the search indices by year. Flood occurrence indicates whether floods occurred in a specific week. I run the following specification: $y_t = \alpha + \beta \text{FloodOccur}_t + x_t + e_t$, where x_t represents either year fixed effects or year-by-month fixed effects. I report the coefficients in the table. Standard errors are clustered at the week level and reported in brackets. *** indicates significance at 1%, ** at 5%, and * at 10%. In addition, I perform a randomization test in which weeks are randomly selected to be labeled as weeks with flooding, rather than using the actual flood records. I repeat this permutation 100 times. This random assignment is done either within each year (for columns (1) and (3)) or within each month by year (for columns (2) and (4)). The p-value, reported in square brackets, shows the proportion of times that the coefficients estimated from these randomly assigned weeks with flooding are larger than those estimated using the actual weeks that experienced flooding.

B Construction of Flood Risks

Input Data. Fathom UK provides simulated flood depths at a 10-meter resolution across various flood hazard types and magnitudes. Specifically, it identifies three primary types of floods: fluvial, pluvial, and coastal. For each flood hazard type, simulations are conducted for 10 distinct magnitudes: 5-year, 10-year, 20-year, 50-year, 75-year, 100-year, 200-year, 250-year, 500-year, and 1000-year floods. A 5-year flood denotes a flood event that has, on average, a 1 in 5 chance of being equalled or exceeded in any given year. In simpler terms, it refers to floods with an average recurrence interval of 5 years. In contrast, the 1000-year flood signifies the most extreme magnitude, associated with a 1 in 1000 chance of occurring in any given year.

In summary, for every 10 m x 10 m square in the UK, I have data on the water depth for a flood event specific to a given hazard type and magnitude.

Construction of Flood Risk. Let's consider a specific 10 m by 10 m square location. Using the data available, the goal is to compute the approximate annual probability that a flood might exceed a depth of 10 centimeters in this location.

The algorithm initializes the flood risk for this location at 0. It starts by examining the flood depths beginning with the least frequent occurrences, i.e., the 1000-year flood. If simulated flood events of any hazard type result in a depth exceeding 10 centimeters, the initial flood risk of 0 is replaced with 1/1000. If not, the risk remains at 0 for this loop. Subsequently, the algorithm follows a similar process for the more frequent 500-year flood. If any flood hazard leads to an exceedance of 10 centimeters, the current flood risk (be it 0 or 1/1000) is updated to 1/500. If not, the risk retains its previous value. The procedure continues in this manner, working through each return period until it reaches the most frequent flood event, the 1 in 5-year flood.

In summary, the algorithm determines the return period of the most frequent flood that results in a depth exceeding 10 centimeters for the specified location. It then uses the inverse of this return period (1 over the return period) as a proxy for the flood risk. For example, a location with a flood risk of 0.2 indicates that the most frequent flood expected to exceed a depth of 10 centimeters is the 5-year flood.

Postcode Level Risk. In the end, I average flood risks across locations within a postcode to represent the flood risk each household in that postcode faces. This approach is adopted because I only have postcode-level information for each survey participant and individual donor.

C Environmental Behaviors and Beliefs

Table C.1: Top UK Environmental Charities

Charity Name (Share of Green Donation)	**Brief Intro**
Friends of the Earth (21%)	"Beat climate breakdown; protect nature and wildlife everywhere; fight for a fossil free future; put planet over profit; work out where to double trees."
The Woodland Trust (15%)	"to protect woods and trees; bring damaged ancient woods back to life, restoring irreplaceable ecosystems to improve landscape resilience; expand native woodland and create tree-rich habitats to benefit nature, climate ..."
Greenpeace Environmental Trust (12%)	"The Greenpeace Environmental Trust supports a range of projects in the UK and around the world. Our focus is on scientific research, investigations and education, all of which address the urgent environmental problems we face."
Whale and Dolphin Conservation (8%)	"... free from the threat of pollution, collisions with vessels and accidental entanglement in fishing gear; winning recognition of whales and dolphins as sentient socially complex beings, and our allies in the fight against climate and nature breakdown."
The National Trust (5%)	"Climate change is the biggest threat to nature and the historic environment. Find out how we're helping wildlife to thrive and working towards sustainability in a changing climate."
The Countryside Charity (4%)	"What we care about: nature and landscapes; better places to live; litter and recycling; farming; sustainable transport; climate change and energy"
Soil Association (2%)	"The Soil Association is the charity joining forces with nature for a better future: a world with good health, in balance with nature, and a safe climate."
World Land Trust (2%)	"Helping people across the world protect and restore their land to safeguard biodiversity and the climate"
Wildfowl and Wetlands Trust (2%)	"Our vision is a world where healthy wetland nature thrives and enriches lives. At WWT, we believe one of the best ways we can help meet the challenges of today's climate, biodiversity and wellbeing crises is by working with nature."
People's Trust for Endangered Species (2%)	"Some habitats contain such a richness of life that we need to protect them at all odds. We are working to preserve ancient woodlands, orchards and wood pastures and parklands, as well as the countless species they support."

Notes: These are the top 10 environmental charities in terms of the number of donations received from CAF donors. The "Share of Green Donation" refers to the proportion of donations to environmental charities that are made to each specific charity. The "Brief Intro" contains extracts from each charity's website, detailing what they do or their mission statements.

Table C.2: Principal Component Analysis on Environmental Behaviors

	Factor Loading	Unexplained Variance
A: Energy index		
Don't leave TV on standby for the night	0.433	0.812
Switch off lights in rooms that aren't being used	0.620	0.616
Don't keep the tap running while you brush your teeth	0.599	0.641
Wear more clothes rather than turning on heating when it's cold	0.594	0.648
Eigenvalue	1.283	
Proportion of variance explained	0.321	
B: Recycle index		
Decide not to buy something because of overpackaging	0.743	0.447
Buy recycled paper products such as toilet paper or tissues	0.759	0.424
Take your own shopping bag when shopping	0.582	0.661
Eigenvalue	1.467	
Proportion of variance explained	0.489	
C: Transport index		
Use public transport rather than travel by car	0.835	0.303
Walk or cycle for short journeys less than 2 or 3 miles	0.835	0.303
Eigenvalue	1.394	
Proportion of variance explained	0.697	
Overall: Everyday Green Behaviour		
Energy Index	0.718	0.485
Recycle Index	0.720	0.482
Transport Index	0.583	0.660
Eigenvalue	1.372	
Proportion of variance explained	0.457	
Obs.	104,702	

Notes: The table presents factor loadings from a two-step principal component analysis on environmental behaviors. First, I build a subindex for each behavioral category by retaining its first principal component, and the factor loadings are in Panel A – C. Second, I create an overall index of everyday green behavior using the first principal component of these subindices, and the factor loadings on subindices are in the last panel. Unexplained variance is the variance in the variable that is not accounted for by the associated factor.

Table C.3: Comparison of Environmental Behaviors by Flood Risk

Risk Level	Variable	Mean	Lower Bound	Upper Bound	Obs.
Low	Binary Green Donation	0.0582	0.0576	0.0587	699,363
Low	Green Donation Size	202.91	192.54	213.29	40,669
Low	Green Party Support	0.0159	0.0154	0.0165	214,490
Low	Everyday Green Behaviour	0.0386	0.0305	0.0467	59,098
Medium	Binary Green Donation	0.0761	0.0747	0.0774	150,379
Medium	Green Donation Size	256.34	210.24	302.45	11,441
Medium	Everyday Green Behaviour	0.0228	0.0038	0.0417	10,768
Medium	Green Party Support	0.0158	0.0146	0.0170	39,866
High	Binary Green Donation	0.0753	0.0740	0.0765	169,631
High	Green Donation Size	289.23	262.96	315.49	12,768
High	Everyday Green Behaviour	0.0757	0.0578	0.0937	11,764
High	Green Party Support	0.0180	0.0168	0.0193	42,955
All	Binary Green Donation	0.0636	0.0632	0.0641	1,019,373
All	Green Donation Size	229.32	217.69	240.95	64,878
All	Everyday Green Behaviour	0.0418	0.0350	0.0487	81,630
All	Green Party Support	0.0162	0.0158	0.0167	297,311

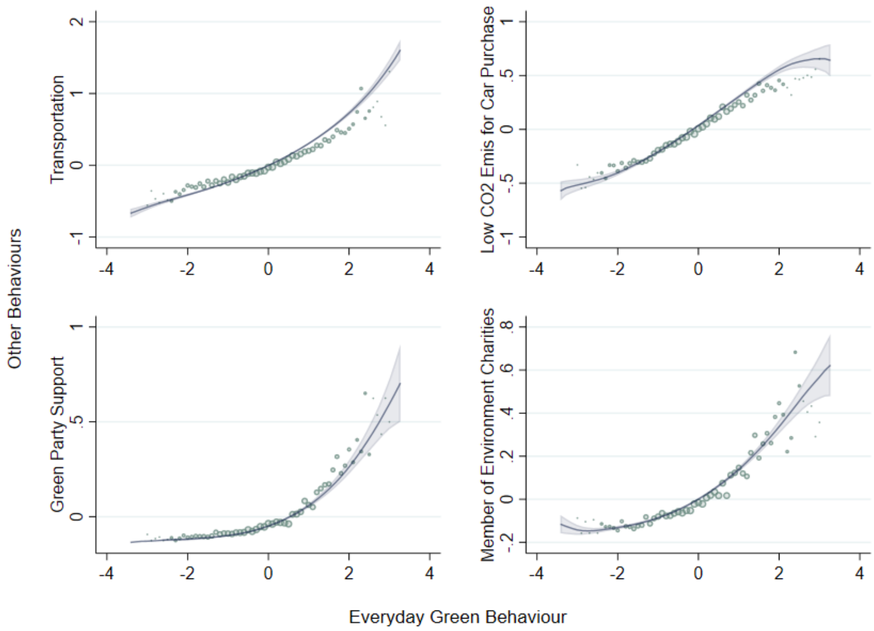

Figure C.1: Correlation between Everyday Green Behavior and Other Green Behaviors

Notes: *Everyday Green Behavior* indicates the level of environmental friendliness of everyday activities, which is a weighted average of behavioral scores related to personal transportation, recycling, and energy consumption. Individuals are binned in increments of 0.1 based on the value of *Everyday Green Behavior*. The x-axis represents these bins, while the y-axis represents the mean value of each variable across individuals within each bin. In the first subfigure, *Transportation* is the first principal component derived from car sharing and opting for fewer flights, which are not used in building the everyday green behavior index.

Table C.4: Principal Component Analysis on Environmental Beliefs

	Factor 1	Factor 2	Factor 3	Factor 4	Unexplained Variance
Unrotated factors					
Eigenvalues	2.863	2.072	1.172	1.078	
Proportion of explained variance	0.205	0.148	0.084	0.077	
Not worth UK to make changes because other countries will cancel out what we do	0.715	-0.131	-0.045	-0.056	0.467
Not worth me doing things to help the environment if others don't do the same	0.710	-0.054	0.002	-0.142	0.473
The effects of cliamte change are too far in the future to really worry me	0.659	0.032	-0.148	0.110	0.530
Climate change is beyond control - it's too late to do anything about it	0.573	0.122	0.029	0.189	0.620
Any changes I make to help the environment need to fit in with my lifestyle	0.547	0.110	0.019	-0.154	0.665
Environmental crisis facing humanity has been greatly exaggerated	0.532	-0.065	-0.291	0.083	0.621
Being green is an alternative lifestyle and it's not for the majority	0.358	-0.313	-0.051	0.178	0.740
I would be prepared to pay more for environmentally-friendly products	-0.027	0.712	0.061	0.219	0.440
My behaviour and everyday lifestyle contribute to climate change	0.029	0.666	0.137	-0.038	0.535
We will soon experience an environmental disaster if current course continues	0.040	0.644	0.325	0.134	0.461
I'm happy with what I do at the moment	0.160	-0.583	-0.039	0.369	0.497
People in the UK will be affected by climate change in the next 200 years	-0.011	0.028	0.855	-0.048	0.266
People in the UK will be affected by cliamte change in the next 30 years	-0.094	0.195	0.830	0.035	0.262
I'm environmentally friendly in most things or everthing I do	-0.040	0.069	-0.009	0.869	0.239
Obs.	69,002				

Notes: The table presents the results of the principal component analysis of environmental beliefs with a varimax rotation. I retain the first four factors with an eigenvalue above one. The four factors are closely related to the environmental beliefs that sociologists have considered important in determining pro-environmental behaviors. Specifically, Factor 1 captures self-efficacy; Factor 2 captures personal responsibility; Factor 3 captures risk perception; Factor 4 captures self-assessed greenness. The table presents the factor loadings for each variable, and the proportion of variance in each variable that remains unexplained by the four factors.

Table C.5: Co-movement between Environmental Behaviors and Environmental Beliefs

	Everyday Green Behaviour		
	(1)	(2)	(3)
Self Efficacy	0.103***	0.099***	0.033***
	(0.004)	(0.004)	(0.007)
Personal Responsibility	0.241***	0.235***	0.058***
	(0.004)	(0.004)	(0.007)
Risk Perception	0.076***	0.073***	0.014**
	(0.004)	(0.004)	(0.006)
Self-Assessed Greenness	0.174***	0.173***	0.052***
	(0.004)	(0.004)	(0.006)
Year Fixed Effects	No	Yes	Yes
Individual Fixed Effects	No	No	Yes
Adjusted R_squares	0.110	0.113	0.556
Observations	59595	59595	34164

Notes: Self-efficacy refers to one's belief in their own capacity to behave in ways necessary to attenuate climate change; personal responsibility refers to the belief that one ascribes the responsibility for climate change to themselves; risk perception refers to the belief in the risk of climate change; self-assessed greenness refers to whether one considers oneself environmentally friendly enough. Standard errors are clustered at the individual level and reported in the parentheses. *** significant at 1%, ** significant at 5%, * significant at 10%.

D Statistics on Treatment Group

Table D.1: Count of CAF Donors Flooded by Year and Flood Risk

Panel A: Number of Individuals Exposed to Floods by Year

	Low and Medium Flood Risk			High Flood Risk		
Year	Obs.	Direct Exp.	Indirect Exp.	Obs.	Direct Exp.	Indirect Exp.
2011	73,974	19	233	15,135	92	95
2012	73,974	29	171	15,135	80	65
2013	73,974	30	133	15,135	108	70
2014	73,974	1	8	15,135	5	2
2015	73,974	54	318	15,135	169	79
2016	73,974	10	95	15,135	17	16
2017	73,974	7	12	15,135	5	5
2018	73,974	1	1	15,135	1	4
2019	73,974	7	87	15,135	23	43
2020	73,974	14	123	15,135	49	59
2021	73,974	3	26	15,135	7	18
2022	73,974	2	18	15,135	1	4
Total	-	177	1,225	-	557	460

Panel B: Count of Individuals by Number of Flood Exposures

	Direct Flood Exposure		Indirect Flood Exposure	
Number of Exposures	Count	Percent	Count	Percent
1	585	79.7	1,357	80.5
2	112	15.3	258	15.3
3	31	4.2	52	3.1
$\geq$4	6	0.8	19	1.1

Notes: Direct Flood Exposure means the individual's postcode was directly affected by a flood in that survey year. Indirect Flood Exposure refers to situations where floods affected areas within a 200-meter radius of the individual's postcode, but not the postcode itself. The number of directly and indirectly flooded people in year 2011 includes those who switched treatment status in previous years.

Table D.2: Count of UKHLS Respondents Flooded by Year

Panel A: Count of Flooded Individuals by Year

Wave	Observations	Direct Flood Exposure	Indirect Flood Exposure
2009	41925	15	31
2010	40685	-	26
2011	36899	14	24
2012	35114	17	39
2013	33584	13	62
2014	34182	29	34
2015	32007	34	92
2016	29956	42	86
2017	27604	-	16
2018	26511	-	-
2019	24802	26	69
2020	22624	12	86
Total	-	202	565

Panel B: Count of Individuals by Number of Direct Exposure

	Direct Flood Exposure		Indirect Flood Exposure	
Number of Exposures	Count	Percent	Count	Percent
1	170	83.3	528	92.0
≥ 2	34	16.7	46	8.0

Notes: Direct Flood Exposure means the individual's postcode was directly affected by a flood within that survey year. Indirect Flood Exposure refers to situations where floods affected areas within a 200-meter radius of the individual's postcode, but not the postcode itself. The observations record the number of survey respondents in each wave. Missing observations indicate the number is fewer than 10, and the total does not include years when the observation is fewer than 10.

E Additional Analyses and Robustness Checks

E.1 Results on Environmental Behaviors

Table E.1: The Effect of Flood Exposure on Environmental Behaviors

	(1) Green Donation	(2) Green Party Support	(3) Everyday Green Behaviour
Direct Flood Exposure			
distance = 0 m	0.017	0.020	0.078
	(0.006)***	(0.012)*	(0.102)
	[0.007]**	[0.011]*	[0.092]
Indirect Flood Exposure			
000 < distance ≤ 200 m	-0.006	-0.003	0.127
	(0.004)	(0.005)	(0.073)*
	[0.004]	[0.005]	[0.080]*
200 < distance ≤ 400 m	-0.006	0.002	0.045
	(0.004)	(0.005)	(0.071)
	[0.003]*	[0.005]	[0.072]
400 < distance ≤ 600 m	-0.002	0.004	-0.034
	(0.004)	(0.005)	(0.066)
	[0.004]	[0.006]	[0.073]
600 < distance ≤ 800 m	0.001	0.004	0.024
	(0.003)	(0.005)	(0.056)
	[0.003]	[0.005]	[0.058]
Mean Outcome	.063	.016	.042
F(All Coefs of Indirect Exposure = 0)	1.26	0.493	0.957
Observations	1,025,652	283,418	56,747
Individual FE	Yes	Yes	Yes
Flood Risk by Year FE	Yes	Yes	Yes
Region by Year FE	Yes	Yes	Yes

Notes: The table presents the coefficients of flood exposure on environmental behaviors. *Green Donation* is a binary variable that indicates if an individual donates to environmental charities. *Green Party Support* indicates if one considers himself a supporter of the Green Party. *Everyday Green Behavior* indicates individual-level environmental friendliness of their everyday activities, a weighted average of behavioral scores related to transportation, recycling, and energy consumption. The treatment variables indicate whether the observation occurs after an individual's first exposure to a flood. Since individuals are considered "treated" from the year they were exposed to their first exposure, the analysis involves comparing individuals before and after this initial exposure. The term *distance* represents the distance at which they were exposed to a flood. The regression controls for individual fixed effects, year-specific flood risk effects, and region-by-year fixed effects. Standard errors, clustered at the postcode level, are provided in round brackets, while those clustered at the postcode area level are reported in square brackets. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table E.2: The Effect of Flood Exposure on Green Donation Size

	Green Donation Size
	(1)
Direct Flood Exposure	
distance = 0 m	-0.032
	(0.110)
Indirect Flood Exposure	
0 < distance ≤ 200 m	-0.129*
	(0.067)
200 < distance ≤ 400 m	0.006
	(0.045)
400 < distance ≤ 600 m	-0.097*
	(0.058)
600 < distance ≤ 800 m	-0.036
	(0.054)
Observations	59,100
F(All Coefs of Indirect Exposure = 0)	1.635
Flood Risk by Year FE	Yes
Region by Year FE	Yes
Individual FE	Yes

Notes: Green Donation Size is the size of donations made to an environmental charity in a year. The sample consists of observations with positive green donations. The treatment variables indicate whether the observation occurs after an individual's first exposure to a flood. Since individuals are considered "treated" from the year they were exposed to their first exposure, the analysis involves comparing individuals before and after this initial exposure. The term *distance* represents the distance at which they were exposed to a flood. Standard errors are clustered at the postcode level, reported in the brackets. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table E.3: The Effect of Flood Exposure on Political Behaviors

	(1) Labour Party Support	(2) Conservative Party Support	(3) Political Interest
Direct Flood Exposure			
distance = 0 m	0.032	0.018	-0.018
	(0.023)	(0.024)	(0.039)
Indirect Flood Exposure			
000 < distance ≤ 200 m	0.006	0.004	0.008
	(0.015)	(0.013)	(0.028)
200 < distance ≤ 400 m	0.005	-0.010	0.029
	(0.014)	(0.014)	(0.024)
400 < distance ≤ 600 m	0.005	0.004	0.012
	(0.013)	(0.013)	(0.021)
600 < distance ≤ 800 m	0.003	-0.002	0.002
	(0.012)	(0.011)	(0.023)
Observations	283,418	283,418	287,443
Individual FE	Yes	Yes	Yes
Flood Risk by Year FE	Yes	Yes	Yes
Region by Year FE	Yes	Yes	Yes

Notes: *Labour Party Support* and *Conservative Party Support* are both binary, indicating whether an individual considers themselves a supporter of the Labour Party or the Conservative Party, respectively. *Political Interest* is personal interest in politics. The treatment variables indicate whether the observation occurs after an individual's first exposure to a flood. Since individuals are considered "treated" from the year they were exposed to a flood, the analysis involves comparing individuals before and after this initial exposure. The term *distance* represents the distance at which they were exposed to a flood. The regression controls for individual fixed effects, year-specific flood risk effects, and region by year fixed effects. Standard errors clustered at the postcode level are provided in round brackets. *** significant at 1%, ** significant at 5%, * significant at 10%.

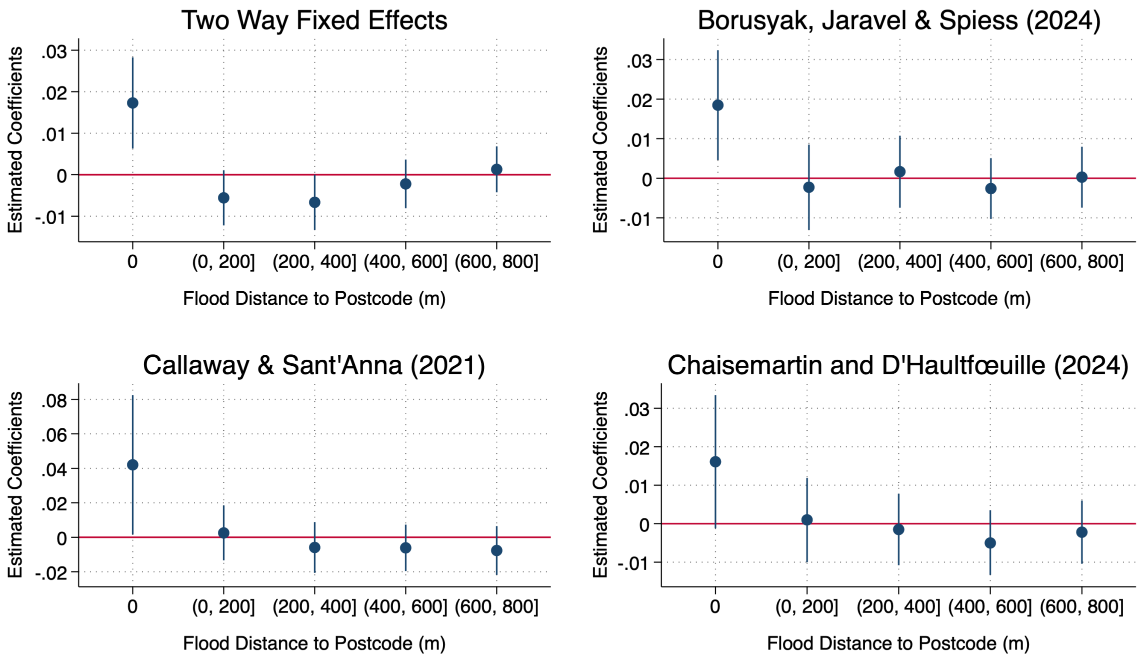

Figure E.1: The Effect of Flood Exposure on Green Donation

Notes: This figure plots the estimated effects of flood exposure at various distances on the probability of giving to environmental charities. The subfigures plots the coefficients obtained using the two-way fixed effects model, the estimator proposed by Borusyak et al. (2024) with the Stata command `did_imputation`, the one proposed by Callaway and Sant'Anna (2021) with the command `csdid`, and the one proposed by De Chaisemartin and d'Haultfoeuille (2024) with the command `did_multiplegt_dyn` respectively. The figure presents point estimates along with their corresponding 90% confidence intervals, with standard errors clustered at the postcode level.

E.2 Results on Environmental Beliefs and Preferences

Table E.4: The Effect of Flood Exposure on Environmental Beliefs

	(1) Self-Assessed Greenness	(2) Risk Perception	(3) Personal Responsibility	(4) Self Efficacy
Direct Flood Exposure				
distance = 0 m	-0.277	-0.029	0.073	0.062
	(0.148)*	(0.117)	(0.131)	(0.114)
	[0.179]*	[0.105]	[0.153]	[0.117]
Indirect Flood Exposure				
000 < distance ≤ 200 m	-0.167	-0.013	-0.049	0.024
	(0.117)	(0.121)	(0.104)	(0.120)
	[0.114]	[0.101]	[0.098]	[0.116]
200 < distance ≤ 400 m	-0.021	0.109	-0.038	0.061
	(0.105)	(0.097)	(0.096)	(0.105)
	[0.086]	[0.089]	[0.107]	[0.093]
400 < distance ≤ 600 m	-0.055	0.049	-0.101	0.174
	(0.094)	(0.101)	(0.099)	(0.104)*
	[0.135]	[0.132]	[0.127]	[0.094]*
600 < distance ≤ 800 m	0.036	0.048	0.164	0.024
	(0.105)	(0.114)	(0.089)*	(0.098)
	[0.086]	[0.105]	[0.095]*	[0.094]
F(All Coefs of Indirect Exposure = 0)	0.631	0.423	1.288	0.826
Observations	32,098	32,098	32,098	32,098
Individual FE	Yes	Yes	Yes	Yes
Flood Risk by Year FE	Yes	Yes	Yes	Yes
Region by Year FE	Yes	Yes	Yes	Yes

Notes: The table presents the coefficients of flood exposure on environmental beliefs. *Self-Assessed Greenness* indicates whether one considers oneself environmentally friendly enough; *Risk Perception* refers to the belief in whether people in the UK will be affected by climate change; *Personal Responsibility* relates to the belief that one ascribes the responsibility for climate change to themselves; *Self-efficacy* denotes one's belief in their own capacity to behave in ways necessary to attenuate climate change. The treatment variables indicate whether the observation occurs after an individual's first exposure to a flood. Since individuals are considered "treated" from the year they were exposed to their first exposure, the analysis involves comparing individuals before and after this initial exposure. The term *distance* represents the distance at which they were exposed to a flood. The regression controls for individual fixed effects, year-specific flood risk effects, and region-by-year fixed effects. Standard errors, clustered at the postcode level, are provided in round brackets, while those clustered at the postcode area level are reported in square brackets. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table E.5: The Effect of Flood Exposure on Financial Behaviors Indicative of Risk Preferences

	(1) Content Insurance	(2) Standardised Content Insurance	(3) National Savings	(4) Company Stocks	(5) National Savings Share	(6) Company Stocks Share
Direct Flood Exposure						
distance = 0 m	0.003	0.007	0.058	-0.045	0.231	-0.078
	(0.030)	(0.074)	(0.087)	(0.110)	(0.260)	(0.083)
Indirect Flood Exposure						
000 < distance ≤ 200 m	-0.000	-0.000	-0.013	0.006	0.001	-0.037
	(0.020)	(0.048)	(0.040)	(0.055)	(0.216)	(0.149)
200 < distance ≤ 400 m	0.000	0.001	0.000	0.014	-0.256	-0.057
	(0.015)	(0.036)	(0.058)	(0.058)	(0.273)	(0.103)
400 < distance ≤ 600 m	0.003	0.007	-0.018	-0.005	0.083	0.136
	(0.019)	(0.046)	(0.047)	(0.048)	(0.257)	(0.252)
600 < distance ≤ 800 m	0.038*	0.094*	0.040	-0.001	0.102	-0.087
	(0.021)	(0.050)	(0.046)	(0.041)	(0.130)	(0.150)
F(All Coefs of Ind Exp = 0)	0.893	0.893	0.249	0.019	0.414	0.237
Observations	158,162	158,162	42,936	42,936	2,148	3,734
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Flood Risk by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region by Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table presents the coefficients of flood exposure on measures of risk preferences. *Content Insurance* indicates whether an individual's household has purchased contents insurance; *National Saving* and *Company Stocks* indicate whether an individual's household has investments in national savings or company stocks, respectively; *National Saving Share* and *Company Stocks Share* represent the share of household investment in national savings or company stocks, respectively, conditional on those with investment in the relevant category. *Log AllInvest Amt* is the logarithmically transformed total amount of an individual's household investments, regardless of the types of investment. The treatment variables indicate whether the observation occurs after an individual's first exposure to a flood. Since individuals are considered "treated" from the year they were exposed to their first exposure, the analysis involves comparing individuals before and after this initial exposure. The term *distance* represents the distance at which they were exposed to a flood. The regression controls for individual fixed effects, year-specific flood risk effects, and region by year fixed effects. Standard errors, clustered at the postcode level, are provided in brackets. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table E.6: The Effect of Flood Exposure on General Prosocialilty

	(1) Donation Dummy	(2) Standardised Donation Dummy	(3) Donation Amount	(4) Standardised Donation Amount
Direct Flood Exposure				
distance = 0 m	-0.011	-0.024	-20.563	-0.027
	(0.042)	(0.089)	(45.323)	(0.060)
Indirect Flood Exposure				
000 < distance ≤ 200 m	-0.023	-0.050	-7.510	-0.010
	(0.024)	(0.051)	(40.703)	(0.054)
200 < distance ≤ 400 m	-0.015	-0.033	2.973	0.004
	(0.020)	(0.043)	(28.754)	(0.038)
400 < distance ≤ 600 m	0.012	0.026	-36.615*	-0.049*
	(0.021)	(0.046)	(19.019)	(0.025)
600 < distance ≤ 800 m	-0.029	-0.062	-16.178	-0.021
	(0.024)	(0.051)	(29.994)	(0.040)
F(All Coefs of Indirect Exp = 0)	0.820	0.820	1.052	1.052
Observations	136,136	136,136	80,435	80,435
Individual FE	Yes	Yes	Yes	Yes
Flood Risk by Year FE	Yes	Yes	Yes	Yes
Region by Year FE	Yes	Yes	Yes	Yes

Notes: The table presents the coefficients of flood exposure on measures of general prosocial preference, proxied by donations. The data is from UKHLS. *Whether Donated* indicates whether an individual donated any money to charities or other organizations. Conditional on those who gave, *Donation Frequency* indicates the frequency with which one made donations in that year, and *Donation Amount* is the amount of donations an individual made in the last 12 months. The treatment variables indicate whether the observation occurs after an individual's first exposure to a flood. Since individuals are considered "treated" from the year they were exposed to their first exposure, the analysis involves comparing individuals before and after this initial exposure. The term *distance* represents the distance at which they were exposed to a flood. The regression controls for individual fixed effects, year-specific flood risk effects, and region by year fixed effects. Standard errors, clustered at the postcode level, are provided in round brackets, while those clustered at the postcode area level are reported in square brackets. *** significant at 1%, ** significant at 5%, * significant at 10%.

E.3 Results of Robustness Checks

Table E.7: The Effect of Flood Exposure on Moving

	Change in Address	
	(1)	(2)
Direct Flood Exposure		
distance = 0 m	-0.014	-0.014
	(0.022)	(0.023)
Indirect Flood Exposure		
000 < distance ≤ 200 m	-0.003	0.001
	(0.012)	(0.012)
200 < distance ≤ 400 m	0.003	0.004
	(0.010)	(0.010)
400 < distance ≤ 600 m	-0.006	-0.006
	(0.010)	(0.010)
600 < distance ≤ 800 m	-0.018*	-0.015
	(0.010)	(0.010)
F(All Coefs of Indirect Exposure = 0)	1.060	0.817
Observations	262,067	259,820
Individual FE	Yes	Yes
Flood Risk ($t-1$) by Year FE	No	Yes
Region by Year FE	Yes	Yes

Notes: Change in Address indicates whether an individual has changed address since the previous wave. The treatment variables indicate whether the observation occurs after an individual's first exposure to a flood. Since individuals are considered "treated" from the year they were exposed to a flood, the analysis involves comparing individuals before and after this initial exposure. The term *distance* represents the distance at which they were exposed to a flood. The regression controls for individual fixed effects, previous year's flood risk by year fixed effects, and region by year fixed effects. Standard errors clustered at the postcode level are provided in round brackets. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table E.8: Correlation between Flood Exposure and Survey Attrition

	Attrition	
	(1)	(2)
Direct Flood Exposure		
distance = 0 m	0.017	0.016
	(0.017)	(0.017)
Indirect Flood Exposure		
000 < distance ≤ 200 m	-0.003	-0.004
	(0.011)	(0.011)
200 < distance ≤ 400 m	0.004	0.003
	(0.008)	(0.008)
400 < distance ≤ 600 m	-0.007	-0.008
	(0.008)	(0.008)
600 < distance ≤ 800 m	-0.002	-0.002
	(0.008)	(0.008)
F(All Coefs of Indirect Exposure = 0)	0.275	0.328
Observations	273,980	273,980
Flood Risk by Year FE	Yes	Yes
Region by Year FE	No	Yes

Notes: Attrition indicates the year when an individual exited the UKHLS survey. In this analysis, I have included only those participants who remained in the survey for at least three waves and never changed their address. I then assume that the attritors (those who left the survey) remained in the same location in the year they exited the study. The treatment variable indicates whether an individual has experienced a flood that directly affected their postcode, or whether the flood impacted neighboring areas at varying distances from their postcode. The term *distance* represents the distance at which they were exposed to a flood. The regression controls for flood risk specific year fixed effects, and region by year fixed effects. Standard errors clustered at the postcode level are provided in round brackets. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table E.9: The Effect of Flood Exposure (discrete risk level by year fixed effects)

	(1) Green Donation	(2) Green Party Support	(3) Everyday Green Behaviour	(4) Self-Assessed Greenness	(5) Risk Perception	(6) Personal Responsibility	(7) Self Efficacy
Direct Flood Exposure							
distance = 0 m	0.017**	0.020*	0.080	-0.287*	-0.005	0.079	0.084
	(0.007)	(0.012)	(0.101)	(0.147)	(0.116)	(0.130)	(0.113)
Indirect Flood Exposure							
000 < distance ≤ 200 m	-0.005	-0.003	0.126*	-0.175	-0.005	-0.047	0.025
	(0.004)	(0.005)	(0.074)	(0.117)	(0.121)	(0.104)	(0.120)
200 < distance ≤ 400 m	-0.007	0.002	0.043	-0.018	0.112	-0.042	0.056
	(0.004)	(0.005)	(0.071)	(0.105)	(0.098)	(0.096)	(0.105)
400 < distance ≤ 600 m	-0.002	0.004	-0.037	-0.061	0.047	-0.097	0.172*
	(0.004)	(0.005)	(0.066)	(0.094)	(0.101)	(0.099)	(0.104)
600 < distance ≤ 800 m	0.001	0.004	0.025	0.042	0.048	0.165*	0.028
	(0.003)	(0.005)	(0.056)	(0.105)	(0.114)	(0.089)	(0.098)
F(All Coefs of Indirect Exposure = 0)	1.240	0.486	0.929	0.699	0.428	1.281	0.801
Observations	1,025,652	283,418	56,747	32,098	32,098	32,098	32,098
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Flood Risk Level by Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region by Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table presents the coefficients of flood exposure on environmental behaviors. *Everyday Green Behavior* indicates individual-level environmental friendliness of their everyday activities, a weighted average of behavioral scores related to personal transportation, recycling, and energy consumption. *Green Party Support* is binary, indicating if an individual considers himself a supporter of the Green Party. *Green Donation* indicates if one donates to environmental charities. The treatment variables indicate whether the observation occurs after an individual's first exposure to a flood. Since individuals are considered "treated" from the year they were exposed to a flood, the analysis involves comparing individuals before and after this initial flood exposure. The term *distance* represents the distance at which they were exposed to a flood. The regression controls for individual fixed effects, discrete flood risk by year fixed effects, and region by year fixed effects. Standard errors, clustered at the postcode level, are provided in brackets. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table E.10: The Effect of Flood Exposure (postcode area by year fixed effects)

	(1) Green Donation	(2) Green Party Support	(3) Everyday Green Behaviour	(4) Self-Assessed Greenness	(5) Risk Perception	(6) Personal Responsibility	(7) Self Efficacy
Direct Flood Exposure							
distance = 0 m	0.019***	0.021*	0.041	-0.267*	-0.076	0.024	0.140
	(0.007)	(0.012)	(0.107)	(0.159)	(0.128)	(0.134)	(0.120)
Indirect Flood Exposure							
000 < distance ≤ 200 m	-0.005	-0.003	0.104	-0.117	-0.009	-0.110	0.034
	(0.004)	(0.005)	(0.074)	(0.121)	(0.122)	(0.117)	(0.124)
200 < distance ≤ 400 m	-0.006	0.002	0.035	0.014	0.095	-0.068	0.070
	(0.004)	(0.005)	(0.074)	(0.116)	(0.107)	(0.105)	(0.113)
400 < distance ≤ 600 m	-0.002	0.004	-0.049	-0.064	0.071	-0.111	0.184*
	(0.004)	(0.005)	(0.063)	(0.099)	(0.103)	(0.099)	(0.105)
600 < distance ≤ 800 m	0.001	0.005	0.003	0.047	0.088	0.197**	0.052
	(0.003)	(0.005)	(0.058)	(0.106)	(0.116)	(0.092)	(0.100)
F(All Coefs of Indirect Exposure = 0)	1.04	0.606	0.705	0.376	0.446	1.932	0.962
Observations	1,025,652	283,395	56,699	32,054	32,054	32,054	32,054
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Flood Risk by Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Postcode Area by Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table presents the coefficients of flood exposure on environmental behaviors. *Everyday Green Behavior* indicates individual-level environmental friendliness of their everyday activities, a weighted average of behavioral scores related to personal transportation, recycling, and energy consumption. *Green Party Support* is binary, indicating if an individual considers himself supporter of the Green Party. *Green Donation* indicates if one donates to environmental charities. The treatment variables indicate whether the observation occurs after an individual's first exposure to a flood. Since individuals are considered "treated" from the year they were exposed to a flood, the analysis involves comparing individuals before and after this initial flood exposure. The term *distance* represents the distance at which they were exposed to a flood. The regression controls for individual fixed effects, year-specific flood risk effects, and postcode-area by year fixed effects. Standard errors, clustered at the postcode level, are provided in brackets. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table E.11: The Effect of Flood Exposure on Green Donation (varying threshold for flood risk definition)

	Green Donation			
	(1)	(2)	(3)	(4)
Direct Flood Exposure				
distance = 0 m	0.017***	0.017**	0.017**	0.016**
	(0.007)	(0.007)	(0.007)	(0.007)
Indirect Flood Exposure				
$0 < \text{distance} \leq 200$ m	-0.006	-0.006	-0.006	-0.006
	(0.004)	(0.004)	(0.004)	(0.004)
$200 < \text{distance} \leq 400$ m	-0.007	-0.007	-0.007*	-0.007*
	(0.004)	(0.004)	(0.004)	(0.004)
$400 < \text{distance} \leq 600$ m	-0.002	-0.002	-0.002	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)
$600 < \text{distance} \leq 800$ m	0.001	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Observations	1,025,652	1,025,652	1,025,652	1,025,652
F(All Coefs of Indirect Exposure = 0)	1.261	1.270	1.286	1.306
Threshold of Flood Depth to Define Flood Risk (cm)	10	25	50	100
Flood Risk by Year FE	Yes	Yes	Yes	Yes
Region by Year FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes

Notes: Each column includes a regression with different definitions of flood risk — the probability that flood depth at a specific location exceeds x centimeters in a given year. *Green Donation* indicates if one donates to environmental charities. The treatment variables indicate whether the observation occurs after an individual's first exposure to a flood. Since individuals are considered "treated" from the year they were exposed to a flood, the analysis involves comparing individuals before and after this initial flood exposure. The term *distance* represents the distance at which they were exposed to a flood. Standard errors, clustered at the postcode level, are provided in brackets. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table E.12: The Effect of Flood Exposure on Green Behavior and Risk Perception

	(1) Everyday Green Behaviour	(2) Everyday Green Behaviour	(3) Risk Perception	(4) Risk Perception
Flood Exposure	0.075**	0.042	0.159***	0.047
	(0.033)	(0.035)	(0.052)	(0.055)
Observations	56,747	56,747	32,098	32,098
Individual FE	Yes	Yes	Yes	Yes
Flood Risk by Year FE	Yes	Yes	Yes	Yes
Region by Year FE	No	Yes	No	Yes

Notes: The term *Everyday Green Behavior* indicates the individual-level environmental friendliness of everyday activities. It is a weighted average of behavioral scores related to personal transportation, recycling, and energy consumption. *Risk Perception* refers to the belief about whether people in the UK will be affected by climate change. The treatment variable *Flood Exposure* indicates whether an individual has been exposed to a flood in an area within a range of 800 meters of their postcode. Since individuals are considered "treated" from the year they were first exposed, the analysis involves comparing individuals before and after this initial exposure. Standard errors, clustered at the postcode level, are provided in brackets. *** indicates significance at 1%, ** at 5%, and * at 10%.

E.4 Further Analyses

E.4.1 Measuring Universalism

Table E.13: Measuring Universalism Using Principal Component Analysis

	Component 1	**Component 2**
Eigenvalue	1.06	0.94
Proportion of Variance	0.53	0.47
Factor Loadings		
Sense of belonging to local community.	-0.71	0.71
Globalisation is a good or bad thing.	0.71	0.71

Notes: The two variables are from the British Election Study and averaged at the constituency level. There are a total of 632 constituencies with record.

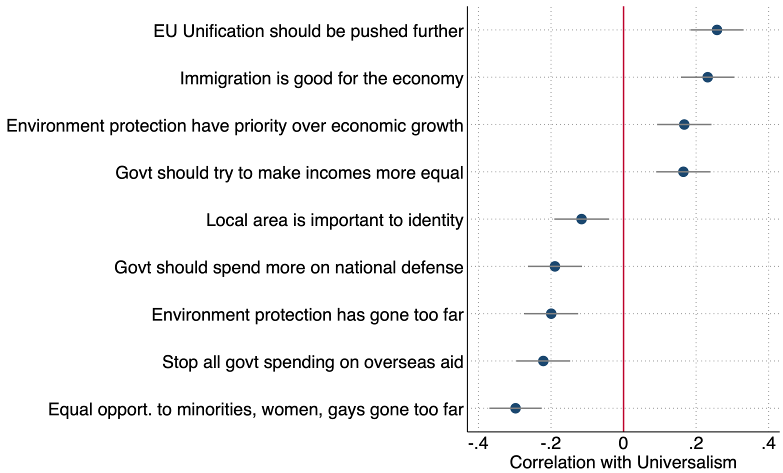

Figure E.2: Correlation with the Measure of Universalism

Notes: I plot the correlation between the constructed universalism measure and other variables related to political or policy views. All variables are measured at the constituency level, sourced from the British Election Study, and standardized.

E.4.2 Response From Charities

Table E.14: The Effect of Flood Occurrence on Tweets Count by Environmental Charities

	Climate Change	Floods Only	Other Topics
	(1)	(2)	(3)
Flood Occurrence	1.195	0.106	-1.561
	(0.583)**	(0.052)**	(2.359)
	[0.040]	[0.010]	[0.780]
Observations	2,190	2,190	2,190
Mean Number of Tweets per Day	12.469	0.216	90.743
Year by Month Fixed Effects	Yes	Yes	Yes