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

Derrick Xu *

Abstract

Does exposure to climate shocks make people behave more pro-environmentally? I use precise residential locations to identify people exposed to floods and analyze a decade of real-world donation records from around 90,000 donors in England, along with longitudinal surveys. I show that people become more likely to donate to environmental charities and support the Green Party, after experiencing a flood that directly affects their own postcode. I also find that they are more likely to reassess their own environmental efforts as not enough following such an experience. However, exposure to floods affecting close neighbors does not lead to similar changes, indicating an "only in my backyard" phenomenon: on average, people become more pro-environment only when personally affected. Further, I show that people with strong universalist values do increase their green donations following neighboring floods. This suggests that the lack of response is driven by those with weak universalist values, who typically care less about global challenges.

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

*Department of Economics, University of Southampton; derrick.xu@soton.ac.uk I am grateful for the advice and support from my PhD supervisors, Sarah Smith and Yanos Zylberberg. I would also like to thank Uta Bolt, Adam Gill, Teresa Harrison, Daniel Hungerman, Michel Serafinelli, Rachel Tan and other conference and seminar participants at the Bristol PhD Seminar, Essex PhD Conference in Applied Economics, and 2025 ASSA Annual Meeting for their comments. I acknowledge the help from Charities Aid Foundation, especially Kate Hammond, for making their donation data available, Oliver Wing and Jeffrey Neal from Fathom UK for making the flood risk data available. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

1 Introduction

The consequences of climate change are intensifying (UNEP, 2022; IPCC, 2023), posing substantial threats to both natural ecosystems and human societies. However, the "principal margin of action" rests largely with high-income countries (Duflo, 2024), as they produce twice the carbon emissions relative to their share of the global population (Ritchie, 2024). Understanding what drives pro-environmental behavior in developed economies is therefore essential for mitigating the climate crises.

Public responses, ranging from charitable giving to climate policy support, require widespread awareness of climate change (Deryugina, 2013; Frondel et al., 2017). In societies like the UK, awareness is already very high, with 70 percent of people viewing climate change as a serious threat. However, public actions remain insufficient to meet climate targets.[1] One possible explanation is that fewer people in these countries are actually affected by climate change, given that only 10 percent of the UK population has experienced severe weather events or knows someone who has (World Risk Poll, 2021). To investigate this, I look at whether experiencing climate shocks motivates pro-environmental actions.

Floods serve as a focal point in this paper because they are among the major impacts of climate change affecting the UK and are often associated with climate change by the public.[2] I use flood records in England from 2009 to 2022, collected by the Environment Agency, which provide detailed data on the timing and spatial extent of each flood event. Although floods in England affect fewer people and cause fewer deaths than some extreme global incidents, these small-scale floods occur more frequently around the world. Floods create visible damage within clear geographic boundaries, allowing for precise measurement of exposure based on proximity to flooded areas. This makes them ideal for studying local responses to climate events.

Estimating the effects of flood exposure is often limited by the lack of precise location data, essential for identifying directly affected people, and by the difficulty of observing real-world individual behaviors. Instead, researchers typically use aggregated outcomes or collect data through surveys and experiments. These methods, however, carry the risk that participants may report socially desirable behaviors (Brownback and Novotny, 2018; Reisinger, 2022) or adjust their actions according to what they believe the researcher

[1] Climate Action Tracker (2024) "rates the UK's climate targets, policies, and finance as insufficient", stating that "substantial improvements are needed for alignment with the Paris Agreement's 1.5°C temperature limit." Further, Climate Change Committee (2020) reports that "the 2050 net zero target would be unattainable without changes in people's behaviors." The committee shows that 32% of emission reductions by 2035 depend on individuals and households adopting low-carbon technologies and sustainable products, and reducing carbon-intensive consumption.

[2] Capstick et al. (2015) show that, following the major floods in 2013/2014, 72% of the British public agreed that these floods "showed us what we can expect in the future from climate change." Further, in Appendix A.3, using data from Google Trends throughout the research period, I show that Google searches for climate change increase during weeks with floods.

expects (Ekström, 2012; De Quidt et al., 2019).[3]

The Charities Aid Foundation (CAF) has granted access to a unique dataset that addresses both challenges. The data includes donation records from 91,665 regular donors to about 55,000 charities from 2011 to 2022. For each donor-year, I classify donations by cause and use a binary indicator for giving to environmental charities as the primary measure of pro-environmental behavior. Surveys often measure green behavior through willingness to donate, with evidence showing that green donations strongly correlate with support for climate policies (Andre et al., 2024; Dechezleprêtre et al., 2023). The CAF data, however, captures actual financial commitments and enables tracking changes in donations across multiple causes. Notably, CAF donors are likely among the richer people in the population, a group particularly influential in shaping climate outcomes.[4] To evaluate whether these effects generalize, I also use data from the UK Household Longitudinal Study (UKHLS), which covers a more representative sample.

Both CAF and UKHLS provide individuals' postcodes at the most granular level, with each postcode covering around 15 households.[5] This detailed location enables the precise assignment of people to treatment based on their proximity to floods. People are classified as directly flooded if their postcode is affected by a flood, and as indirectly flooded if their postcode is within 200 meters of a flood but not directly affected.

Exploiting geographic and temporal variations in flood incidents, I compare the change in green outcomes before and after a flood between those directly (or indirectly) affected and others from the same region whose postcodes have the same flood risk but are not flooded. The identifying assumption is that whether an individual's postcode is flooded in a given year is uncorrelated with other determinants of their green actions, conditional on individual fixed effects, region-by-year and risk-by-year fixed effects. This assumption is plausible given the unpredictability of floods among places of the same level of flood risk. To validate this assumption, I test for pre-flood trends in green donations between affected and control groups and find no statistically significant differences. I further support my estimation by showing largely consistent results using estimators that address limitations of the two-way fixed effects model in a staggered treatment setting (De Chaisemartin and d'Haultfoeuille, 2023; Roth et al., 2023) and a randomization test (Bertrand et al., 2004).

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

[3] Research also shows that people may make different decisions in the lab. For example, they are less generous with earned income than with windfall (Carlsson et al., 2013; Li et al., 2019) and less generous with out-of-pocket cash than with cash promised on a screen (Reinstein and Riener, 2012).

[4] Baltruszewicz et al. (2023) highlights significant inequalities in carbon emissions within the UK. In 2019, the wealthiest 10% of the population consumed around three times more energy for driving and five times more for recreational activities compared to the bottom 10%.

[5] According to Office for National Statistics (2023), there are 1.79 million live postcodes in the UK, with an average area of 0.14 square kilometers per postcode.

is substantial, given that only six percent of donors in the control group contribute to environmental charities. It remains statistically significant for up to three years after the flood and continues to be positive in size even six years after exposure. Repeated direct exposures further amplify this effect, with an additional flood experience leading to an even greater increase in green giving. This increase is driven specifically by donations to charities working on climate change, with no significant effect on giving to other causes, suggesting that the change is specific to climate-friendly behavior rather than a general rise in pro-sociality. 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 the highly localized response also extends to increased support for the Green Party among a broader sample of people.

My headline results indicate an "only in my backyard" phenomenon, emphasizing the role of personal consequences of climate shocks in motivating green action. The effect is consistent with the idea that mitigating climate change is a public good, where people may have less incentive to act, especially when they do not personally bear the costs. However, directly experiencing climate shocks could make these issues feel more personally relevant, shifting climate change from a problem mainly affecting others to one affecting oneself. This relevance can operate through two broad channels: *information* (Andre et al., 2024; Deryugina and Shurchkov, 2016; Dechezleprêtre et al., 2023) and *salience* (Bordalo et al., 2020, 2022; Allcott and Rogers, 2014). Direct exposure to floods might provide firsthand information about climate change, such as the personal costs of such events.[6] Floods can also increase the salience of personal climate risks through "availability bias", as flood threats feel immediate and emotionally urgent for those directly affected, while remaining abstract for others (Kahneman and Tversky, 1982; Deryugina, 2013; Gallagher, 2014). These channels, taken together, could explain why people with firsthand flood experience are more likely to engage in green actions.

Interestingly, I find evidence suggesting that direct flood exposure makes people less likely to see themselves as environmentally friendly. The drop in self-assessment, without a corresponding decrease in actual efforts, is consistent with people raising their expected standard of being pro-environment. This suggests a potential mechanism for the behavioral change: direct experience raises people's expectations of the environmental actions required, leading them to lower their self-evaluation and modify their actions to meet these revised expectations (Akerlof and Kranton, 2000, 2005).

To better understand the highly localized response, I show that people with strong universalist values increase green giving when their neighbors are affected. This pattern suggests that the limited response is driven by those with weaker universalist—or more

[6]Moreover, floods often attract media coverage (Eisensee and Strömberg, 2007; Beattie, 2022), shaping beliefs and behaviors. For example, Gallagher (2014) shows that flood insurance take-up increases among unaffected neighbors in the same media market but not among those merely spatially close.

communitarian—values. Universalists prioritize the welfare of all people over group-based interests and thus care about both global and local problems equally (Schwartz, 2007, 2012; Cappelen et al., 2022; Enke et al., 2023). They may interpret floods affecting their neighbors as part of a global climate challenge, which aligns with my finding that the increased donations go to non-local, climate-related charities. By contrast, communitarians tend to place less weight on global problems such as climate change.

The central contribution of this paper is the finding that people behave more pro-environmentally only when personally affected by climate shocks. Previously, Dechezleprêtre et al. (2023) provide global survey evidence showing that public support for climate policies hinges on self-interest. My results suggest that those affected by floods 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). A growing body of research focuses on aggregated political outcomes, showing that extreme weather events make politicians more likely to endorse green legislation and policy reforms (Herrnstadt and Muehlegger, 2014; Gagliarducci et al., 2019). Similarly, the public tends to show greater 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).[7]

My paper differs from these literature in two key ways. First, I use precise locations to determine individual exposure to climate events, while previous work mostly uses broader administrative units like counties or census blocks. Studying regional responses is useful when aggregated outcomes matter, such as voting for legislation (Herrnstadt and Muehlegger, 2014; Coury, 2023). Yet, the broader definition can introduce measurement errors when the focus is on individuals. For instance, people living in non-flooded areas within a county would be misclassified as treated if flood exposure is determined at the county level. I show that using precise locations to identify households 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

[7]While most research focuses on disaster-hit areas, Goebel et al. (2015) find that people in the UK, Germany and Switzerland increase support for the Green Party after Japan' Fukushima nuclear disaster.

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. I focus on a setting where people have more choices in directing their money and flexibility to adjust their choices (Andreoni, 2006), unlike political decisions. I can also 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 does not reduce support for other social causes, and is relatively long-lasting.

This paper also relates to research on how climate events affect beliefs and preferences. To the best of my knowledge, I am the first to look at their effects on self-assessment. Previous work shows that self-assessment is important in driving green actions (Sonenshein et al., 2014; Binder and Blankenberg, 2017), but people may overestimate their efforts (Biais et al., 2005; Burks et al., 2013; Leviston and Uren, 2020). My results suggest that direct flood experiences might lead people to adjust their self-evaluation, recognizing their efforts as insufficient. This can further motivate their actions to align with the updated beliefs (Festinger, 1957; Bandura, 1991). Most research 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), showing context-dependent evidence. Gao et al. (2020) show that the impact of disasters on risk perception depends on whether the actual damage exceeds or falls short of expectations. I show that flood exposure does not change perceptions of climate change as a threat to the UK. This aligns with other research showing that people with initially high risk perception are less likely to update their beliefs (Deryugina, 2013), given the broad climate awareness in the UK.

More broadly, this paper is related to studies on how adverse experiences affect prosocial behaviors. Previous research shows that natural disasters increase donations to victims (Deryugina and Marx, 2021; Scharf et al., 2022; Jayaraman et al., 2023), and health shocks lead people to reallocate their donations toward health charities (Black et al., 2021). Unlike most of these studies, I focus on a group of people who are typically wealthier and donate more. Méon and Verwimp (2022) find that a damaging storm in Belgium makes affected people more prosocial, increasing their donations to an unrelated famine relief campaign in Africa. In contrast, I show that people view flooding as climate shocks, increasing donations to charities addressing climate change, but I do not observe a general increase in prosociality, as donations to non-climate charities remain unchanged.

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. 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.[8] However, this strong perception does not translate into adequate public actions (Climate Change Committee, 2020). One conjecture is that the insufficient effort is partly 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.

The remainder of this section discusses the distribution of flood risk and incidents in England, whether people associate floods with climate change, and how they insure against flood risk and receive post-flood aid.

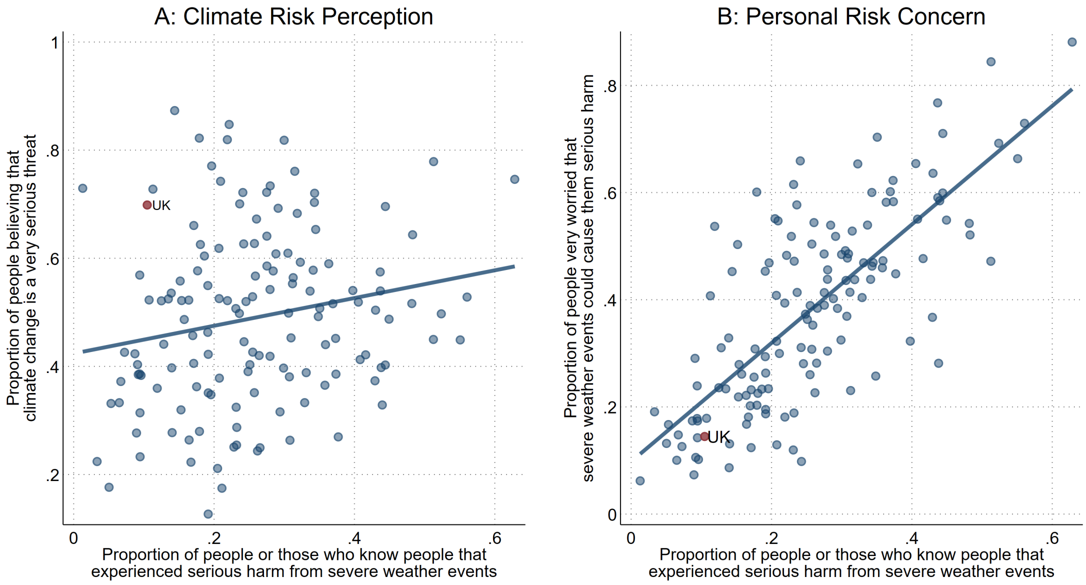


Figure 1: Risk Perception and Severe Weather Experiences across Countries

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.

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

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 flooding risk is also common in property valuations. I use flood risk data provided by Fathom UK, an organization known for its leading scientists and advanced flood modeling services. Their model incorporates high-resolution terrain data, comprehensive flood defenses, and channel drainage systems (Fathom, 2021). I define flood risk as the annual probability that flood depth exceeds 10 centimeters at a given location.[9] Postcode-level flood risk is calculated as the mean flood risk across all places within the postcode. Appendix B provides details on the construction of the flood risk variable. Appendix Figure B.1 shows that the main flood risk measure is positively correlated with alternative measures, including flood risk at depths above 25 centimeters and the flood risk published by the Department for Environment, Food & Rural Affairs (Defra). I use the flood risk map from Fathom as the main measure because it is more granular, with a 10-meter resolution, and better captures the risks that directly affect individuals, which people tend to care more about.[10] Figure 2a shows that areas along rivers, coastlines, and rural regions are more prone to flooding.

2.2 Flood Occurrences

Floods in the UK have lower intensity and affect fewer people compared with other countries. Although the UK lacks catastrophic flood disasters, it does encounter smaller-scale floods, which are the most common form of flooding worldwide.[11]

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.

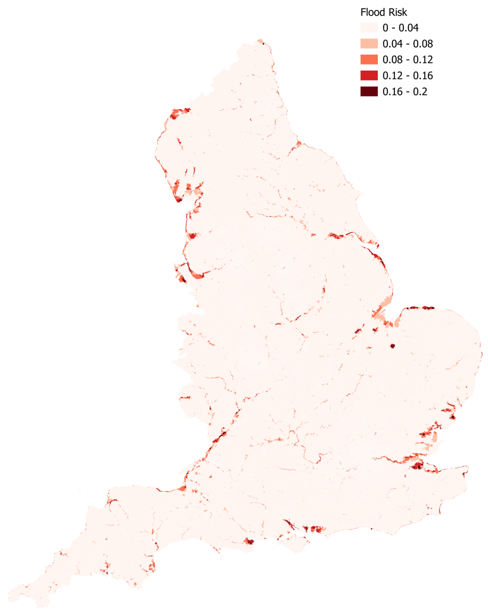
[9] A flood depth of 10 cm is unlikely to pose a direct risk to people but can cause significant damage to buildings and their contents (Landmark Information Group, 2022).

[10] The flood risk provided by Defra is at 50-meter resolution.

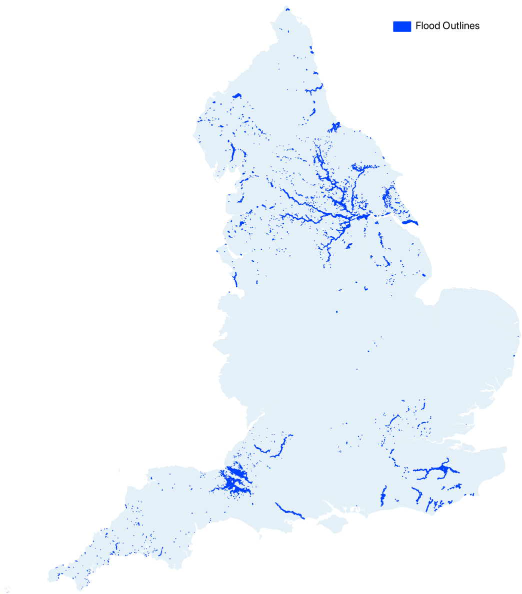
[11] In the Appendix Table A.2, I compare floods in the UK with those in other regions, using flood and storm records between 2009 and 2022 from EM-DAT. I show that: (1) the average fatality per flood event in the UK is about half that in other European countries and a fifth of that in the US; (2) the 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 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 when and where floods occur provides a plausible natural experiment. I leverage the geographic and temporal variations in flood occurrences. First, Figure 2b illustrates the distribution of flood incidents across England, showing that floods mainly occur in high-risk areas. However, some high-risk areas have remained unaffected since 2009, highlighting the randomness of flood locations within high-risk zones. Second, the yearly fluctuation in the number of flood events, shown in Appendix Figure A.2, makes it difficult to anticipate floods—especially when 80% of people in my data experience them only once.



(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.

2.3 Do People Associate Floods with 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 factors may affect how people experience floods, making the link between flood events and climate change tenuous. Whether floods are perceived as climate shocks depends on whether people link flood incidents with climate change. To investigate this, I collect weekly Google Trends indices for the search terms "climate change" and "flood", separately for each year from 2009 to 2022. For each search term and year, the week with the highest search volume is normalized to one, and the indices for all other weeks are scaled proportionally relative to that peak. Comparing weeks with floods to those without within the same year and month, I show that searches for climate change increase by 0.23 standard deviations during flooded weeks. The result is robust to a randomization test, with details reported in Appendix A.3. This finding aligns with another research in the US showing that extreme weather events increase searches about climate change (Herrnstadt and Muehlegger, 2014).[12]

2.4 Flood Insurance and Post-Flood Aid

Over 95% of properties in England are insured against flood risk, a rate comparable to some European countries like France and Switzerland but much higher than in the US (Hu, 2022). The UK public reinsurance scheme, Flood Re, 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). Therefore, the high uptake of home insurance reduces the likelihood of households facing significant financial losses from flood recovery. Alongside these insurance measures, the UK government has introduced various schemes to support households impacted by flooding. These initiatives include cash subsidies and tax discounts, provided either as general flood relief or tailored to specific flood events, helping to mitigate the immediate disruptions to the lives of those affected (Department for Communities and Local Government, 2014).

[12] This result is suggestive rather than definitive. The increase in searches indicates that people generally connect floods with climate change, but it does not reveal whether those who refrain from changing their behavior fail to make this connection, or recognize it but choose not to act.

3 Empirical Approach

3.1 Data

3.1.1 Environmental Donation

The data come from the Charities Aid Foundation (CAF), which provides a platform for people to manage their donations. I observe all transactions made by personal donors through their CAF accounts between 2011 and 2022. This dataset has two main advantages. First, people can donate to any UK-registered charity at any time. The data avoid biases that may exist in experimental settings, such as experimenter demand bias, where participants may adjust their behavior to align with perceived expectations, and social desirability bias, where individuals report desirable actions. Unlike experiments, which often involve a limited set of charities and hypothetical choices, this dataset captures real-world giving decisions involving actual financial costs. Second, the data allow me to examine changes in donations across a wide range of causes, including potential shifts in the composition of charities people choose to support.

I focus on the 91,665 donors in England who have been active for more than seven years (the 75th percentile), as it is difficult to assess whether people who are less active on CAF stopped donating entirely or donated through other channels. Donors are considered active from the year of their first donation until the year of their most recent donation, regardless of whether they donated in the intervening years.[13] I construct a panel dataset in which each donor appears from the year of their first donation through to the end of the dataset in 2022. If a donor does not make any donation in a given year after their first, they remain in the dataset with their donation coded as zero.

These CAF donors include individuals across the entire wealth distribution, while they are more concentrated in wealthier postcodes. Figure D.1 illustrates this by comparing the wealth distribution of active CAF donors with that of the general population using postcode-level property prices. I also compare annual donation size between active CAF donors and those surveyed by UKHLS, showing that 80% of CAF donors fall within the top 60% of UKHLS donors ranked by donation size (see Appendix Tables D.1 and D.2). These high-value donors are especially relevant for this study. First, they account for a large share of total giving: in the UKHLS data, the top 60% of donors account for 95% of donations. Second, richer people contribute disproportionately more to carbon emissions through their consumption (Baltruszewicz et al., 2023), meaning their behavior

[13] For example, if a donor gave in 2011 and 2013, they are considered active for three years, even if they made no donation in 2012. The median active period across all donors is four years, while the 75th percentile is seven years. This suggests that many donors appear in the data only briefly, making it hard to assess whether they stopped donating or switched channels. Therefore, I focus on the top 25% of donors whose active span exceeds seven years. I also conduct a robustness check using donors who actually donated in more than seven calendar years, and the results remain consistent and significant.

has greater implications for climate change.

For each donor-year, I aggregate donations by sector using the International Classification of Non-profit Organizations (ICNPO).[14] Environmental charities are active in advocating for policy reform and addressing environmental issues.[15] The top ten environmental charities, based on CAF donations, are listed in Appendix Table C.1, accounting for over 70% of all donations to environmental causes. Nine of them work on issues relevant to climate change. Figure 3 shows that environmental charities represent 2.5% of all charities receiving CAF donations but receive less than 2% of total donations. This indicates that individual environmental charities receive fewer donations than other charities. Given the small share of donors supporting environmental causes, I use a dummy variable to indicate support for environmental charities: *Green Donation* equals one if an individual donates to any environmental charity in a given year and zero otherwise.

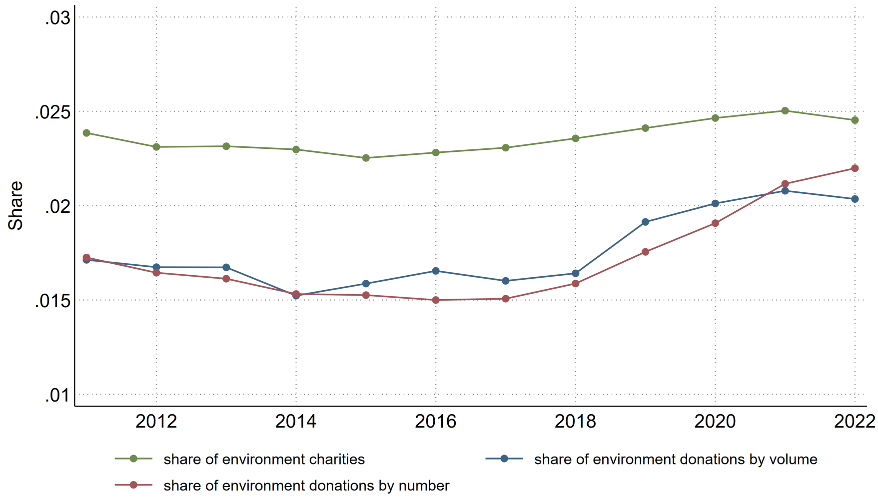


Figure 3: Share of Environmental Charities and Environmental Donations

Notes: 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 to support political parties that prioritize environmental issues. The UK Household Longitudinal Study has surveyed 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 equal to one if an individual identifies as a supporter of, or feels closer to, the Green Party, and zero otherwise.

[14]The "5100 Environment" category in ICNPO includes charities focused on pollution control and prevention, environmental education and health, and environmental conservation (Salamon and Anheier, 1996). The classification is provided by the National Council for Voluntary Organizations.

[15]For example, the Woodland Trust has planted over 50 million trees, contributing to carbon sequestration (Woodland Trust, 2024).

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 surveyed behaviors and the PCA loadings are reported in Appendix Table C.2. The overall index has positive loadings on all dimensions and accounts for 45 percent of the variance in the subindices.

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

3.1.3 Environmental Beliefs

Environmental actions often stem from deeply held beliefs. UKHLS asked 11 questions about these beliefs in Waves 4 and 10.[16] 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).[17]

Retaining factors with an eigenvalue above one results in four factors, closely related to what sociologists have considered important in driving green behaviors (Stern, 2000; van Valkengoed et al., 2022). I assign names to each factor accordingly.[18] 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

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

[17] The distinction in constructing behavioural and belief indices reflects a conceptual difference between survey questions in behaviour and beliefs rather than a mechanical difference in the PCA procedure. For behaviours, the survey questions are designed to capture three clearly defined and ex ante distinct domains: energy consumption, recycling, and transport. To ensure that each domain contributes equally to the overall behavioural index, I first construct three sub-indices, one for each domain, and then aggregate them into a final behavioural index. This two-step approach prevents domains with more items or higher variance from mechanically receiving greater weight. By contrast, the underlying dimensions of environmental beliefs are not clearly defined ex ante, so I rely on a single PCA with varimax rotation to let the data identify the relevant belief dimensions, with the rotation used to obtain components that are as interpretable and orthogonal as possible by construction. The varimax rotation assumes orthogonal latent factors, enabling each variable to load more strongly on a specific factor.

[18] 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)

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.

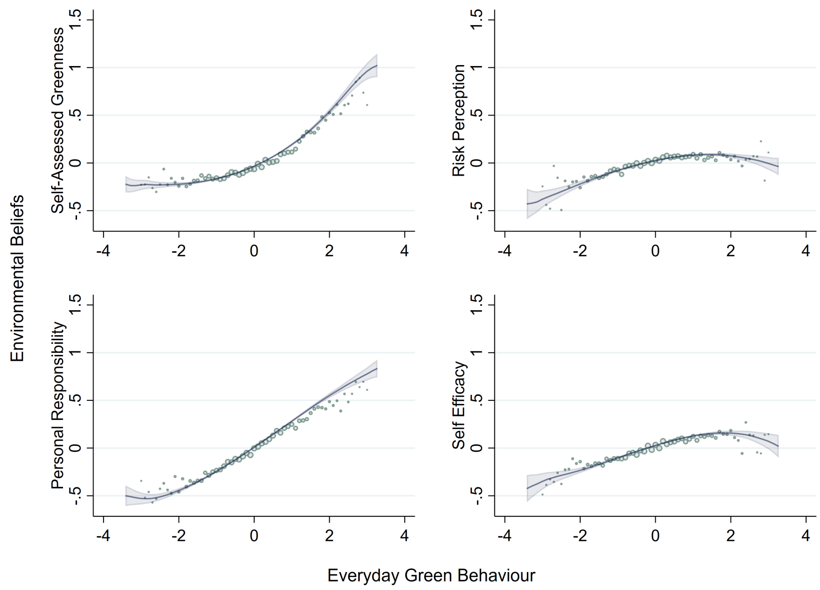


Figure 4: Correlation between Environmental Beliefs and Everyday Green behavior

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.

3.1.4 Moral Values

To examine the role of moral values in shaping responses, I use data from British Election Study (BES), a survey designed to be cross-sectionally representative of the UK public, with around 30,000 respondents in each wave. I focus on two variables related to universalist values: respondents' views on globalisation ("Do you think globalisation is a good or a bad thing?") and their sense of local attachment ("Do you feel a sense of belonging to your community?"). The smallest geographical unit available for respondents' addresses is the parliamentary constituency. In England, there are around 540 such constituencies. I therefore average responses at that level and apply PCA to capture universalist versus communitarian values. The details of the measure are discussed in Section 4.4.

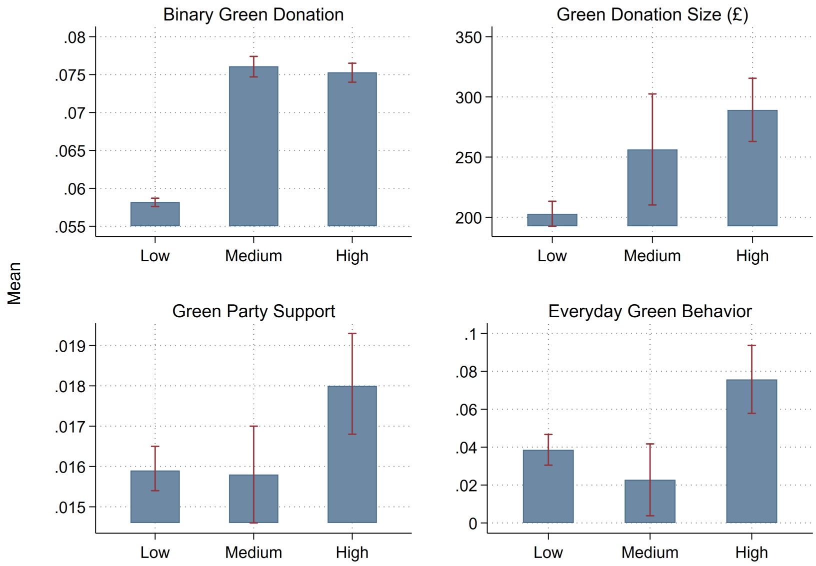


Figure 5: Mean of Environmental behaviors by Flood Risk

Notes: The figures are based on non-flooded observations. *Binary Green Donation* indicates whether an individual gives to environmental charities in a year. The sub-figure 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.

3.2 Descriptive Statistics

People living in high versus low flood-risk areas exhibit differences in pro-environmental actions and social characteristics. Figure 5 shows that individuals in high flood-risk areas are more likely to support environmental charities, vote for the Green Party, and adopt a green lifestyle. These observed associations suggest that living in high-risk areas may influence pro-environmental attitudes, or reversely that pro-environmental people may self-select into these areas. Table 1 shows socio-demographic differences across these groups, using UKHLS data. Residents in high-risk postcodes have slightly higher monthly incomes (£1,910 versus £1,766) and are more likely to hold university degrees (27% versus 25%). Additionally, Conservative Party supporters are more concentrated in high-risk areas. These differences underscore the need for within-individual comparisons to control for these time-invariant characteristics that might affect giving decisions.

3.3 Estimation Strategy

I use a difference-in-differences design to estimate the effect of flood exposure. Treatment depends on the proximity of floods to the postcodes where people live. I classify people as *directly* affected if a flood affects their postcode and as *indirectly* affected if a flood

Table 1: Descriptive Statistics on 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. 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: Low (flood risk = 0) , Medium (0 < flood risk ≤ 0.001), and High (flood risk > 0.001).

affects neighboring postcodes within a 200-meter radius but not their own postcode.[19] I compare changes in environmental outcomes before and after a flood between people affected (directly or indirectly) and those from the same region whose postcodes have the same flood risk but are unaffected. I extend the radius to examine the effect of varying distances from the flood.

Both CAF and UKHLS provide personal addresses at the smallest postcode level, with each postcode containing, on average, only about 15 households.[20] This granularity allows for a more precise identification of people affected by floods, marking an improvement over previous work. By definition, 734 CAF donors (around 1%) were directly treated between 2011 and 2022, while 1,685 donors (around 2%), who were located within 200 meters of flooded areas, were indirectly treated. Appendix Table E.1 reports the number of people who switched their treatment status to directly or indirectly flooded by year.

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's postcode is directly

[19] Keep the definitions for *direct* and *indirect* exposure in mind when interpreting the results, as I use these terms for simplicity when discussing the estimation strategies. While I use a very small unit to define flood exposure, it is still possible that individuals in a flooded postcode are not personally affected. But, if only neighboring postcodes are flooded, their properties are certainly not directly affected.

[20] 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.

flooded in year t and remains one for all subsequent years; otherwise, it equals zero. $F_{it}^{indirect}$ is defined similarly for individuals whose neighboring postcodes within 200 meters were flooded, but not their own postcode. Once people experience a flood, they remain treated from the year of their first exposure onward. β_1 and β_2 capture the effects of direct and indirect flood exposure.[21] Standard errors are clustered at the postcode level in the baseline specification. As robustness checks, I also report results clustering at the postcode area level and using Conley standard errors, which adjust for spatial correlation within 100 kilometers. I discuss these standard errors in the robustness checks section.

To make within-individual comparisons, I include individual fixed effects (α_i) to account for time-invariant differences across individuals. To compare people from the same region who face the same flood risk, I include region-by-year fixed effects (γ_{rt}) and flood risk-by-year fixed effects ($\delta_t R_i$). The region-by-year fixed effects control for time-varying region-specific trends common to all people within a region, such as evolving economic conditions. For instance, economic trajectories vary across regions and may shape environmental awareness differently.[22] While it may absorb region-level responses to floods, such as increased environmental campaigns, my goal is to identify the effect of personal flood exposure, conditional on these regional responses. I exploit variation in the precise distance between where people live and where floods occur to achieve this. The flood risk-by-year fixed effects control for trends in environmental outcomes and flood exposure that are common across people facing the same flood risk. I use a continuous measure of flood risk in the main analysis and consider alternative measures in robustness checks.

The identifying assumption is that flood exposure is random within areas that face the same level of flood risk. Under this assumption, flood exposure is unrelated to other determinants of green behaviors, conditional on individual, region-by-year, and flood risk-by-year fixed effects. This implies that, absent flood exposure, people who were flooded would have followed the same trend as those from the same region with the same flood risk but who were not flooded.

To support this assumption, I compare the trends in green donations across three groups: directly treated, indirectly treated, and the control group. Since the comparison is made within regions and flood risk areas, I first remove year-specific effects shared by people from the same region and facing the same level of flood risk, by regressing green donation on region-by-year and flood risk-by-year fixed effects, and retain the residuals. I then calculate the yearly average residual green donation separately for each group,

[21] I choose the absorbing specification to ensure a consistent estimation framework across all outcomes, including those observed too sparsely to estimate an event-study specification. For instance, environmental beliefs are measured only in two waves six years apart. The specification should be interpreted as capturing the average change in behavior before and after one's first flood exposure within the observed period, rather than as assuming strictly permanent effects.

[22] For example, previous research suggests that people are more likely to prioritize the environment under good economic conditions (Gagliarducci et al., 2019; Hoffmann et al., 2022).

excluding observations when treated individuals were actually exposed to a flood. Figure D.3 shows that, without flooding, the three groups follow roughly similar trends. As a more rigorous test, I find no statistically significant differences in pre-flood changes between the treatment and control groups, as shown in Figure 9.

To ensure the robustness of the estimation, I do two additional sets of checks. First, recognizing the small size of treatment group and potential serial or spatial correlation, I conduct a nonparametric randomization test, whose inference does not rely on asymptotic assumptions. The results support my main estimation. Second, I use more restrictive control groups for comparison.[23] Specifically, I make comparisons among people from the same postcode area with the same level of flood risk, by including postcode-area-by-year fixed effects to account for year effects specific to an area.[24] I also narrow the sample by only including those residing 200 to 400 meters from the floods as the control group, as they are more likely to share similar characteristics if living in places with similar flood risk. I discuss the results in detail in the robustness section.

The two-way fixed effects regression can produce biased estimates, as it involves using people treated earlier as controls for those treated later (Goodman-Bacon, 2021; De Chaisemartin and d'Haultfoeuille, 2023; Roth et al., 2023). This issue arises when treatment effects vary across individuals and over time, as those treated earlier may follow different trends in their post-treatment periods compared to those treated later, making them unsuitable as a comparison group. Additionally, the common trend assumption might not hold because I define treatment status based only on floods occurring after 2009. If someone in the control group experienced a flood before 2009 and treatment effects vary over time, their trends may differ from those who were treated later. To address these concerns, I show in Figure 6 and Appendix Figure F.1 that the two-way fixed effects estimates align with alternative heterogeneity-robust estimators.

Finally, I address the problem of movers and sample attrition. Unlike most studies that make comparisons at the administrative unit level, I compare individuals directly and hence avoid the issue of changing population compositions within a 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. Relatedly, for survey responses, moving could lead to sample attrition, potentially biasing the results if those who stay

[23]I cannot directly test whether flooded and non-flooded people are comparable in their demographics, since I do not observe donor characteristics.

[24]In the UK, postcodes are hierarchical. A full postcode (e.g. `BS8 1TU`) identifies a small group of addresses—the smallest geographic unit in the system. The first one or two letters form the *postcode area*, which is the largest unit in the system and typically corresponds to a major city or region. For example, `BS` denotes the Bristol postcode area. There are 124 postcode areas in the UK. These areas are nested within broader administrative regions. In England, these are the nine standard regions: North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, East of England, London, South East, and South West.

respond differently from those who move after a flood. To address these concerns, I show in Appendix Table F.12 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 F.13.

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 F.1.

4.1.1 Environmental Donations

Figure 6 shows that people are two percentage points (ppt) more likely to give to environmental charities after exposure to a flood directly affecting their own postcode. However, there is no effect on green giving after indirect exposure to a flood affecting their neighbors. Figure 6a shows the results from the baseline two-way fixed effects model. Despite its flexibility, the method has limitations in designs where people are exposed to floods at different times. To address the concern, I show consistent results in Figure 6b using an imputation-based estimator proposed by Borusyak et al. (2024),[25] and in Appendix Figure F.1 using estimators by others.[26]

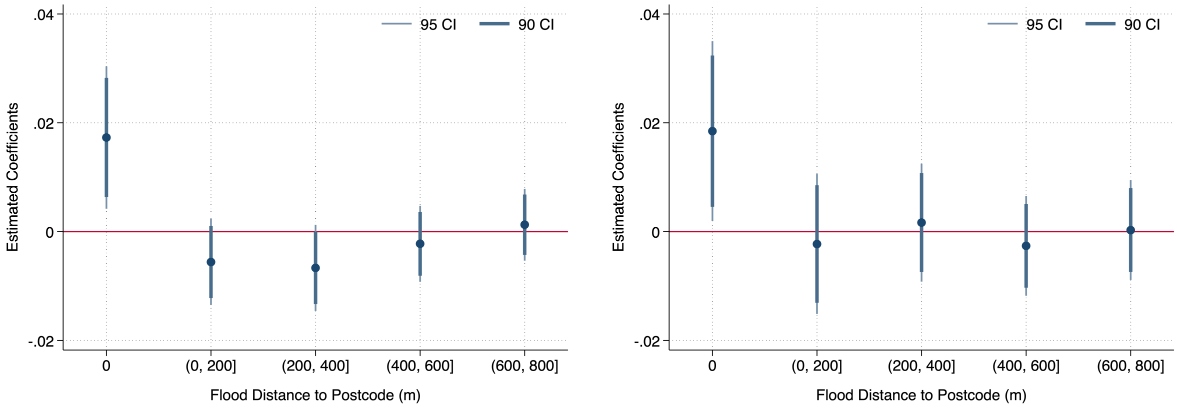
Given that only six percent of people in the control group give to environmental causes, the effect of direct exposure on the probability of green giving is substantial.[27] In contrast, Figure 6 shows no significant impact from floods occurring at distances of 200, 400, 600, and 800 meters. I also cannot reject the hypothesis that all coefficients of exposure to a flood between 200 and 800 meters are equal to zero, given the F-statistic of 1.26, reported in Appendix Table F.1. This suggests an "only-in-my-backyard" phenomenon, where people act only when their immediate interests are threatened. This might explain

[25] This method uses data from untreated observations—both untreated individuals and untreated time periods for treated individuals—to predict counterfactual outcomes for each treated individual-year observations. The actual outcomes are then compared with the predicted counterfactuals to estimate the treatment effects. This approach is equivalent to fitting a regression of the outcome on individual and time fixed effects using only untreated observations, and then using that regression to predict the counterfactual outcomes for treated observations. When the parallel trends assumption holds across all periods, it has greater efficiency compared to other heterogeneity-robust estimators (Roth et al., 2023).

[26] Callaway and Sant'Anna (2021) propose an estimator using the never or not-treated as the control group for each treated group. The method is designed for staggered, absorbing treatment settings. 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 unchanged.

[27] I also report the effect on the size of green donation conditional on giving to environmental charities in Appendix Table F.2. I do not find systematic changes at the intensive margin.

the paradox of widespread recognition of climate change as a severe threat in the UK, yet insufficient action towards tackling climate change.

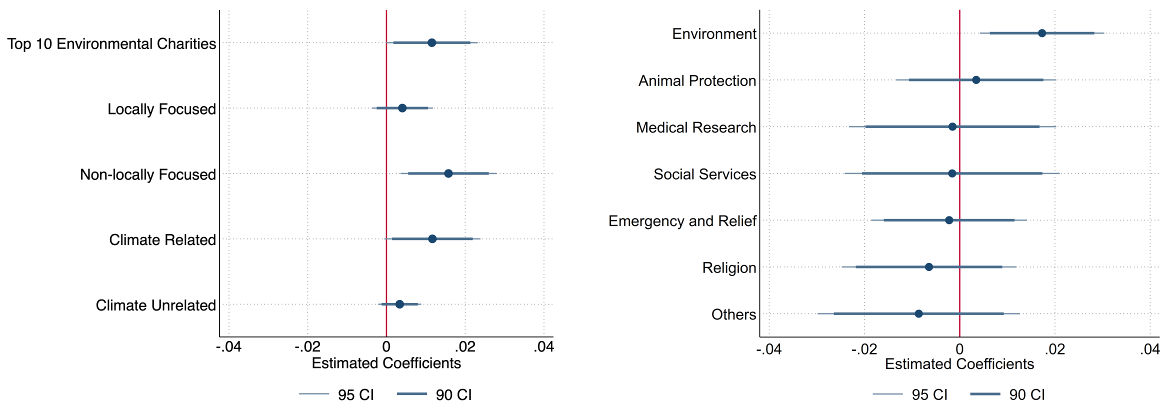


(a) Baseline (Two-way Fixed Effects)

(b) Borusyak, Jaravel & Spiess (2024)

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% and 95% confidence intervals, with standard errors clustered at the postcode level.



(a) By Environmental Charity Type

(b) By Charitable Cause

Figure 7: The Effect of Direct Flood Exposure on the Probability of Giving

Notes: I plot the coefficients of direct flood exposure on giving to different groups of environmental charities and to charities working in various cause areas, along with confidence intervals. Standard errors are clustered at the postcode level. Specifically, panels (a) and (b) plot coefficients from separate regressions that share the same specification format but use different outcome variables. The outcomes for panel (a) include: whether the donor gave to the top ten environmental charities; whether the donor gave to environmental charities that primarily benefit local or non-local areas, based on classifications from the National Council of Voluntary Organizations; and whether the donor gave to climate-related or non-climate-related charities. I manually classify the top 100 environmental charities based on whether their missions, activities, or campaigns explicitly mention climate change. In panel (b), charities are mapped to their cause areas according to the International Classification of Non-Profit Organizations.

Figure 7a shows that the increase in donations is primarily directed toward charities addressing broader, non-local environmental issues related to climate change. Focusing on the ten largest environmental charities, none of which address specific local concerns such as floods, and most of which have missions or activities linked to climate change, I find that people are more likely to support these organizations following exposure to a flood affecting their postcode. In addition, using the National Council for Voluntary Organizations' classification of charities that primarily benefit local areas, I show that the rise in donations is not directed toward local charities, such as those focused on waterway conservation. Finally, due to the lack of a refined classification system for environmental 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 reference climate change. The results show that donations to these climate-focused organizations increase, while donations to other environmental charities remain largely unchanged.[28]

In addition, Figure 7b shows that direct flood exposure increases support for climate change without reducing support for other cause areas. First, people are not more likely to donate to charities involved in post-flood aid, such as social service or emergency relief organizations, perhaps because these services in the UK are typically provided by the government. Second, contrary to Sinding Bentzen (2019), who argues that people may turn to religion to make sense of unexpected events, I do not find significant changes in donations to religious charities. This suggests that if people link floods to climate change, they may not turn to religiosity for explanation. Finally, donations to charities less likely connected to floods, such as those focused on animal protection or medical research, remain unaffected, which also validates my results through placebo outcomes. This pattern differs from the case of health shocks: Black et al. (2021) show that experiencing one leads people to shift their donations from other causes to health charities.

Are people as responsive to additional flood experiences as they are to their first? Repeated exposure can amplify concerns about the severity of floods affecting themselves, increasing environmental actions. On the other hand, it may feel less shocking and undermine belief in the effectiveness of individual actions, reducing their effort. Among CAF donors, 149 people experienced floods more than once over the decade (20% of those directly affected). I compare their donations following the first and second exposures to their donations prior to the first exposure. Figure 8 shows that the second exposure increases green giving by 3.8 percentage points, in addition to the effect of first exposure. It is nearly double the first exposure effect. In contrast, seeing neighbors being flooded multiple times does not have a significant effect. This suggests that people become more pro-environment, the more they are personally affected by environmental disasters.

[28] There is also the possibility that charities focusing on climate change are larger and more established organizations and therefore more visible to the public, with greater fundraising capacity. Such organizational capacity may itself shape public responses to environmental disasters.

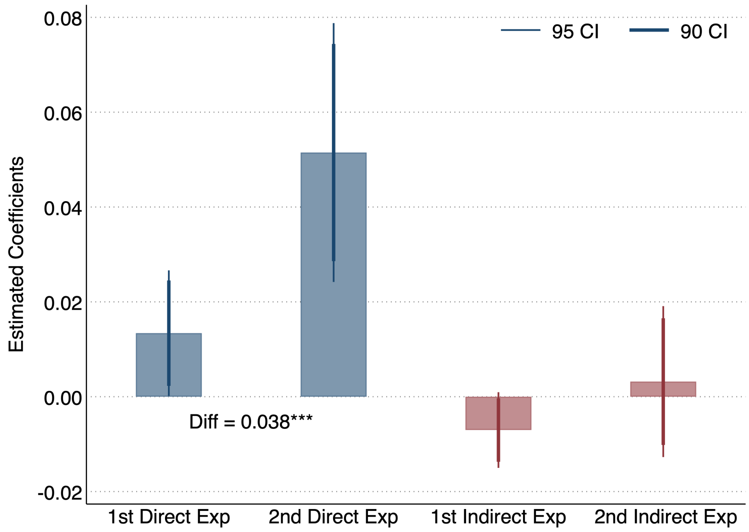


Figure 8: The Effect of Multiple Flood Exposures on Green Donation

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. Around 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 E.1. The estimation is to compare behaviors post first and post second flood experience 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% and 95% confidence intervals.

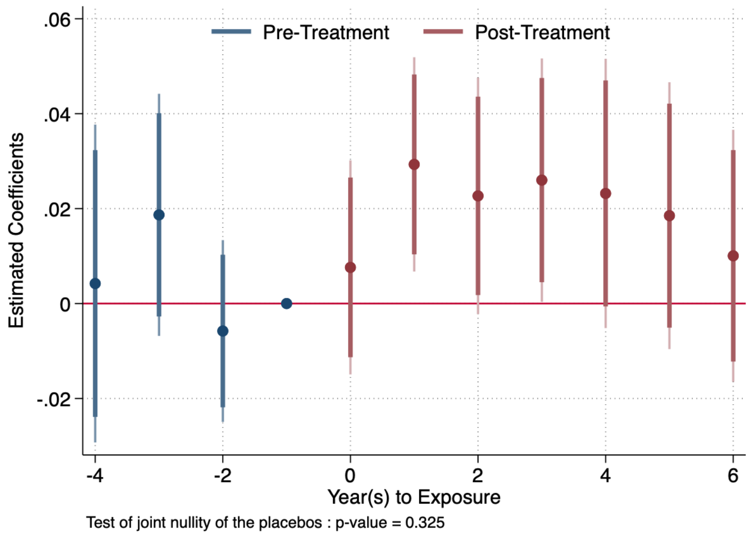


Figure 9: Event Study of Direct Flood Exposure on Green Donations

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% and 95% 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.

Finally, I examine the persistence of the effect, using the estimator from De Chaisemartin and d'Haultfoeuille (2024). This method uses the last untreated period for treated individuals as the baseline. It then compares the evolution of outcomes from the baseline period to a given year t between treated individuals (treatment group) and those who were untreated both at the baseline and in year t (control group). The estimator aggregates treatment effects across groups by the number of years since their initial treatment. When estimating the effects of direct exposure, people exposed to floods indirectly are excluded from the sample to ensure they are not part of the control group. Similarly, when estimating the effects of indirect exposure, those directly flooded are excluded.

Figure 9 shows that the treatment effect remains positive in magnitude six years after the flood, while the pattern suggests that the effect is diminishing over time. Within two years after direct flood exposure, the average yearly probability of giving to environmental charities increases by 1.7 percentage points (reported in Appendix Table F.6). The rise in green giving is statistically significant during the first three years following exposure; In the fourth year, the effect becomes insignificant, with a p-value close to 10%. The loss of significance reflects both a decaying effect and the limited sample size, as donors exposed in later years are less likely to be observed four years post-treatment. I show that most donors, once they give to a specific charity, do so for only one consecutive year, with 70% giving to the same charity for two or fewer consecutive years (Appendix Figure D.2). This suggests that the persistence in green giving is less likely to be driven by the inherent tendency of highly engaged donors to give continuously. Additionally, Appendix Figure F.2 shows no significant difference in green donations over time between individuals living 200 to 800 meters from flood zones and those living farther away. This provides further support for the main result: people do not become more pro-environmental in their giving behavior after floods that affect nearby neighbors but not themselves.

Direct flood exposure has a more lasting effect on green donations, compared with existing literature. Previous studies show that donations to fundraising appeals for major disaster reliefs last only up to 15 weeks (Jayaraman et al., 2023; Scharf et al., 2022). The transient response likely reflects the temporary and immediate need for post-disaster aid. By contrast, the more persistent effect in my setting may reflect the fact that climate change is an enduring challenge, in the sense that flood exposure can heighten concerns about the personal consequences of climate change for a longer period. 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 more sustained pro-environmental actions.

4.1.2 Green Party Support and Everyday Green Behavior

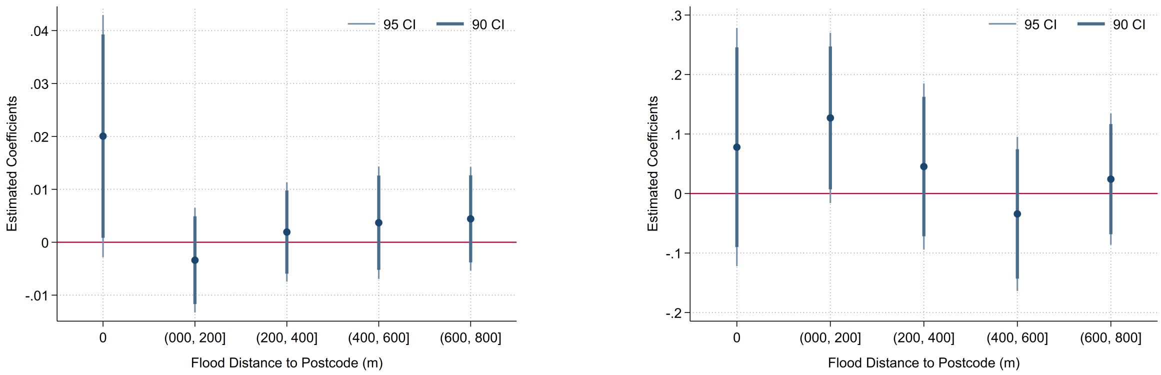
Figure 10a shows that direct flood exposure increases support for the Green Party by two ppt, which is a large effect considering only 1.6% of people support the Green Party. However, indirect exposure has no effect. Moreover, in Appendix Table F.3, I show that people are three ppt (p-value = 0.16) more 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. Additionally, I show that flooded people do not become more interested in politics, implying that flood exposure heightens public awareness of environmental issues. It is worth noting that the UKHLS sample is more representative of the UK population, and the result suggests that the localized response is likely a more general pattern rather than one specifically driven by donors.

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 a flood affects one's own postcode. 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 F.1. Furthermore, in Table F.16, 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 after a flood. Therefore, I caution against interpreting the indirect exposure effect as definitive evidence.

4.1.3 Discussion

First, I consider whether economic constraints might explain the results. If floods negatively affected household income, standard economic theory would predict a decline in charitable giving. However, using UKHLS data, I find no significant impact of either



(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% and 95% confidence interval. Standard errors are clustered at the postcode level.

direct or indirect flood exposure on self-reported income (Appendix Table F.5) or on the amount of total giving (Appendix Table F.10). This is consistent with the UK context, where flood insurance coverage is high and premiums are tied to property values rather than flood risk, as the risk component of insurance is subsidized by the government.

A second set of possible channels relates to how charities and the media respond to floods. Their actions may influence giving behavior, but these mechanisms are less likely to fully explain the highly localized responses observed in the data.

Floods may prompt charities to step up fundraising and target households in affected areas. An analysis of tweets from major environmental organizations between 2017 and 2022 indicates that charities are more likely to mention floods and climate change in weeks when floods occur, relative to other weeks in the same month and year (see Appendix Table F.4). This suggests that charities use social media to raise climate awareness. Yet while such messaging is broadly visible, my data show behavioral responses only among those directly affected by flooding. This contrast provides suggestive evidence that social media messaging may increase general awareness, but only those directly affected translate it into action. Regarding targeted fundraising, charities may adjust campaigns based on observable characteristics such as location or wealth, but such strategies are unlikely to selectively reach donors on the basis of personal traits or moral values.

Local media coverage can also raise awareness of flood events and may influence public environmental behavior. However, such effects are unlikely to be the main driver of my results. Local media typically span entire cities or regions, so broad responses to such reporting would likely be absorbed by region-by-year or city-by-year fixed effects. The fact that the rise in donations is concentrated only among those living directly within the flooded postcode—even compared with nearby residents within 400 metres—suggests that the effect primarily reflects direct exposure to floods rather than media spillovers.

4.2 The Effect of Flood Exposure on Beliefs and Preferences

I explore mechanisms behind the green reaction, presenting the effect on environmental beliefs and preferences in Figure 11, with full results in Appendix Section F.2.

4.2.1 Self-Assessed Greenness

I show that people whose postcodes are affected by floods are 0.305 standard deviations less likely to view themselves as mostly environmentally friendly, whereas neighboring floods do not have a statistically significant effect on self-evaluation. Self-assessment depends on both individuals' actual efforts and their expectations of what they should do. Since their green behavior did not decrease, the lower self-assessment likely reflects a rise in expectations about the range of activities considered sufficient. In other words, experiencing environmental shocks with personal consequences may prompt people to update their expectations of environmental behavior. Appendix Table F.7 shows that the result loses significance at the 10% level (p-value = 0.12) when standard errors are clustered at the postcode area level, but remains statistically significant when using Conley standard errors adjusted for spatial correlation. The coefficient is robust when adjusting for multiple hypothesis testing.[29] The result is robust to two alternative measures of self-assessed greenness: one based on the simple average of the two relevant variables, and the other constructed using principal component analysis of only the two questions, retaining the first component (see Appendix Table F.8). Considering the small number of treated individuals, I perform a randomization test (Roth et al., 2023), which does not rely on asymptotic assumptions about data correlation, also shows the result statistically significant (p-value = 0.088).[30]

4.2.2 Risk Perception and Risk Preferences

Figure 11B shows that flood exposure does not change perceptions of general climate threat affecting the UK, as the effects of both direct and indirect exposure are close to zero. The precise null effect suggests that failing to reject the null hypothesis is not due to weak statistical power from the small sample size. This finding aligns with the fact that a large portion of the UK population already acknowledges the threat of climate

[29] I apply Bonferroni corrections across the four main environmental belief outcomes, constructed from the 11 belief questions in the UKHLS survey and shown in Figure 4. The effect on self-assessed greenness remains statistically significant (p = 0.020) when using Conley standard errors.

[30] The analyses also suggest that the effect on self-assessed greenness is less likely to be a random coefficient. First, this measure is constructed as a meaningful component that underlies multiple variables. Second, the randomization test suggests that the observed effect is less likely driven by chance.

change (as shown in Figure 1) and that climate change denial is minimal in the UK (as shown in Appendix Table A.1). These results are consistent with Deryugina (2013), who shows that updates in risk perception may depend on the initial level of risk perception.

I also do not find changes in financial behaviors that are indicative of risk preference. I look at the purchase of household contents insurance as a proxy, following what is common in the literature (Gao et al., 2020; Shai, 2022). In the UK, insurance premiums are not expected to change significantly after floods, as the effect of flood incidents on insurance premiums is transferred to the government. Therefore, change in insurance purchases, if any, is unlikely due to a price effect. 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 F.9 shows that none of these measures change in a statistically significant way after flood exposure.

4.2.3 Personal Responsibility, Self-efficacy and Prosociality

Subfigures D and E in Figure 11 show that neither direct nor indirect flood exposure within 200 meters alters people's beliefs about their contribution to climate change or the efficacy of their actions in influencing its trajectory. Specifically, 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 flood exposure within 200 to 800 meters, I cannot reject the hypothesis that they are all zero. Therefore, I advise caution in interpreting this as consistent evidence of a change in personal responsibility. Similarly, I find little evidence that flood exposure affects self-efficacy perceptions.

Another possible explanation is that disasters enhance prosociality by fostering solidarity, empathy, and cooperative recovery efforts (Douty, 1972; Rao et al., 2011). However, Figure 7b shows no statistically significant change in giving to non-environmental causes. Similarly, self-reported UKHLS data shows no increase in the probability of giving or donation size, as reported in Appendix Table F.10. While UKHLS provides a representative sample for assessing general prosocial behavior, it does not specify donation recipients. These findings suggest the observed increase in green giving reflects a specific rise in environmentally prosocial behavior rather than an increase in broader prosociality.

4.3 Robustness Checks

This section discusses results from robustness checks.

Adjusted Standard Errors. I report standard errors clustered at the postcode area level and Conley standard errors adjusted for spatial correlation when estimating the effect on main environmental outcomes (see Tables F.1 and F.7). Clustering at higher

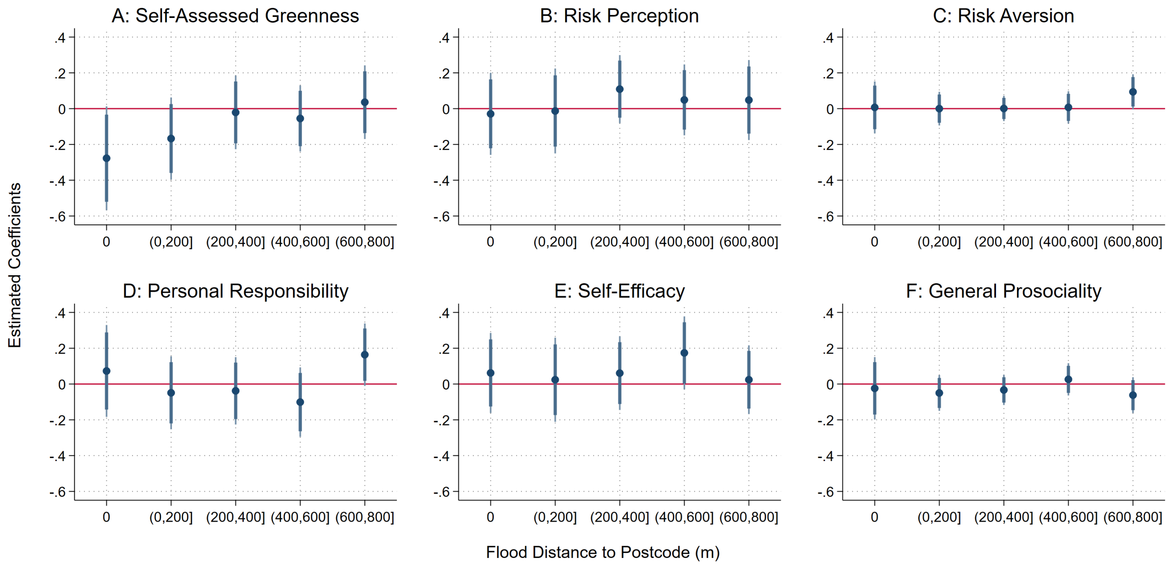


Figure 11: The Effect of Flood Exposure on Environmental Beliefs and Preferences

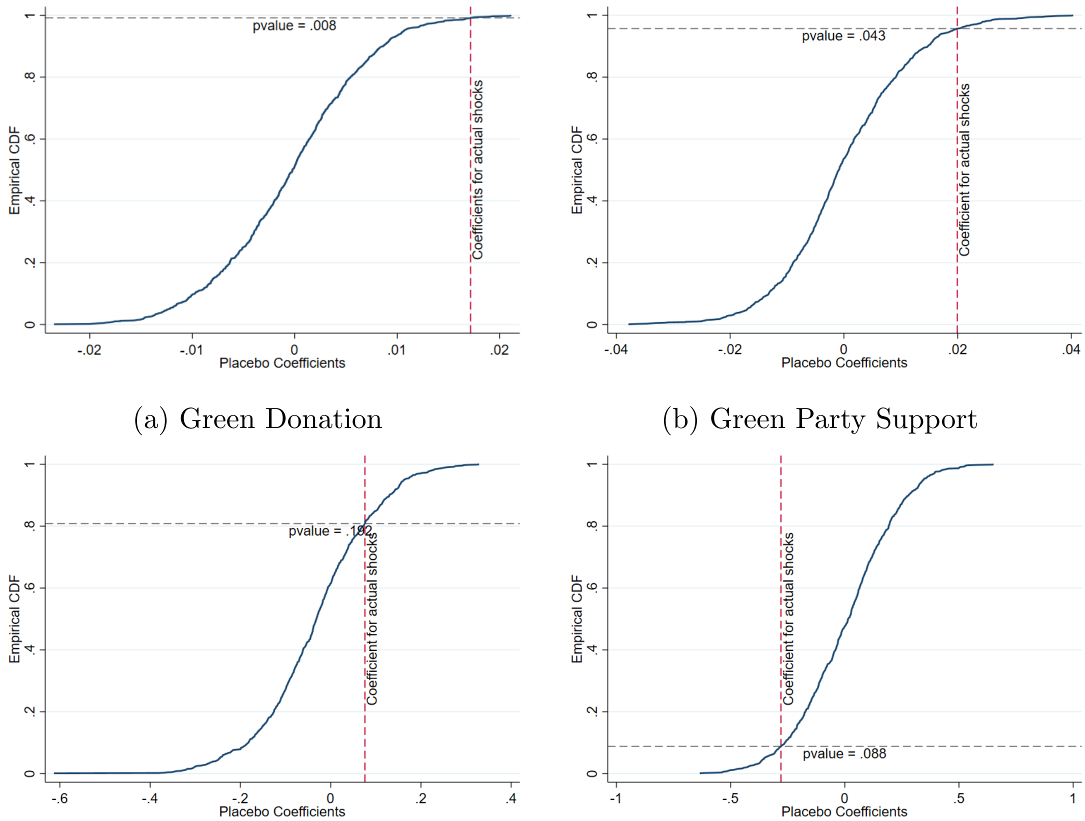
Notes: I plot coefficients and 90% and 95% confidence level from estimating Equation 1 on beliefs and preferences. All outcome variables are standardized, and from the UKHLS. *Self-Assessed Greenness* indicates whether one considers oneself environmentally friendly enough; *Risk Perception* refers to 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.

geographic levels often accounts for within-area correlation but may reduce efficiency due to the smaller number of clusters. A further limitation is that this approach does not capture spatial correlation across geographic boundaries. This is particularly relevant in England, where geographic boundaries, such as those for NHS regions, local authorities, and parliamentary constituencies, often do not align. Conley standard errors help address this by accounting for spatial dependence based on geographic proximity. I adjust for spatial correlation within 100 kilometers, a threshold that is likely sufficient given that the distance between the northernmost and southernmost points of England is approximately 850 kilometers. For the main outcomes, green donations, green politics, and self-assessed greenness, Conley standard errors are smaller than those clustered at either the postcode or postcode area level. For other outcomes, the results remain statistically insignificant.[31]

Randomization Test. I have a small number of people exposed to floods, indicating that the asymptotic inference that works in large samples may not work here (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 preserving the number of flooded individuals for each year and 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 asymptotic distribution of the data, which additionally addresses the concern that standard errors might be biased if the variables are serially correlated (Bertrand et al., 2004).

Alternative Measures of Flood Risk. My identification strategy relies on the assumption that flood exposure is random within areas of the same flood risk. To account for this, I include flood risk-by-year fixed effects to ensure comparisons are made among individuals facing the same risk level. The main analysis defines flood risk as the annual probability that flood depth exceeds 10 centimeters at a given location. First, I examine the sensitivity of the results to the functional form of flood risk. Instead of using a continuous measure, I group individuals into three bins based on their flood risk levels and include risk-bin-by-year fixed effects to relax the linearity assumption. Results reported in Appendix Table F.14 show that the coefficients on green donations, support for Green Party, and self-evaluated greenness remain statistically significant. Second, I explore alternative flood risk measures, including a higher flood depth threshold of 25 centimeters

[31] I also check Conley standard errors using distance cut-offs of 50 km, 100 km, and 150 km. The corresponding p-values for the effect of direct flood exposure are reported in Appendix Table F.11. The results are largely consistent with the baseline. In particular, when using the larger cut-offs (100 km and 150 km), for which residual spatial correlation is less likely to be a concern, the estimated effects on green donations, green party support, everyday green behavior, and self-assessed greenness remain statistically significant or close to the 10% level.



(a) Green Donation

(b) Green Party Support

(c) Everyday Green Behavior

(d) Self-Assessed Greenness

Figure 12: The Randomization 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.

and a publicly available measure from the government based on river and sea flood risk. As shown in Appendix Table F.15, the results remain consistent with the baseline.

Alternative Comparison Groups. First, I compare people within the same postcode areas by including postcode-area-by-year fixed effects. This addresses the concern that region-by-year fixed effects may not fully capture differences in trends or shocks experienced by people living in the same local area. Appendix Table F.16 presents the results, showing that the effects of flood exposure on green donations, support for the Green Party, and self-assessed greenness remain robust.

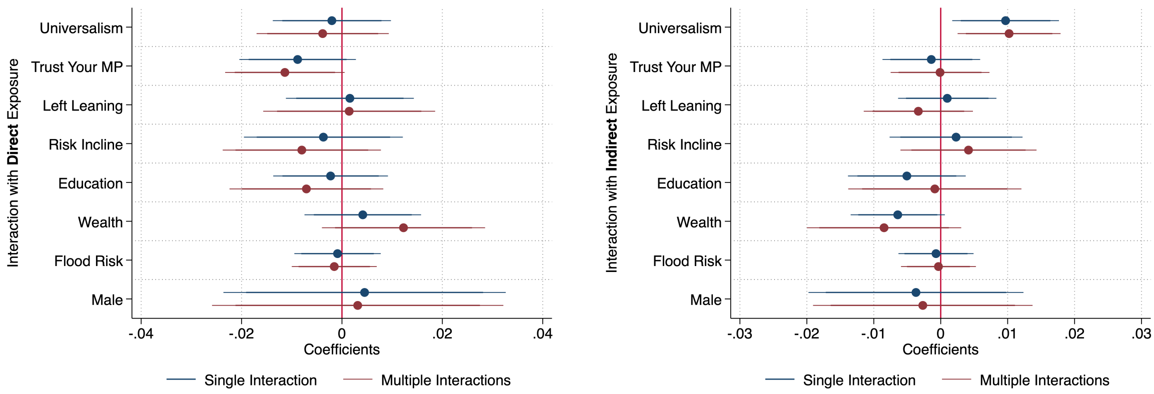
Second, the main figures show that flood exposure has no significant effect on people living 200 to 400 meters away from a flood site, with effect sizes close to zero. People living in such close proximity to flooded areas are likely to share similar demographic characteristics with those directly or indirectly affected, provided they face similar flood risk. I therefore re-estimate the main specification using only people in the 200-400 metre range as the control group. The results, reported in Appendix Table F.17, remain robust for green donations and Green Party support. However, the effect on self-assessed greenness is no longer significant (p-value = 0.174). This is likely due to limited statistical power and the fact that the outcome is observed only twice, in surveys conducted six years apart. Nonetheless, I interpret the result as suggestive evidence.

4.4 Heterogeneous Responses by Moral Value

I further explore the lack of pro-environmental responses to neighboring floods, focusing on the role of moral values. Individuals with universalist values, who prioritize the well-being of all people equally (Schwartz, 2007, 2012), often show greater concern for global challenges, whereas those with communitarian values tend to focus on local issues. Previous research has highlighted a strong correlation between moral universalism and support for environmental protection (Cappelen et al., 2022; Enke et al., 2023).

The degree of universalism shapes whom people direct their altruism toward. Neighboring floods may elicit two types of altruistic responses: communitarian altruism, where individuals provide direct help to their in-groups (e.g., close neighbors), or universalist altruism, where floods are viewed as part of a broader global challenge requiring collective action. I hypothesize that individuals with universal moral values are more likely to engage in pro-environmental activities in response to neighboring floods compared to those with communitarian values.

To measure universalism, I construct a constituency-level indicator using PCA on two variables: belief in globalization as a positive force and sense of belonging to the local community. They tend to represent opposing ends of the universalist-communitarian spectrum. The first principal component captures stronger globalization beliefs alongside weaker local attachment. I validate this measure by showing its alignment with universalist (as opposed to communitarian) behaviors. Specifically, it correlates positively with support for EU integration, immigration, and equality, and negatively with local identity, national defense, and opposition to overseas aid and minority rights. Details on the PCA and correlations are provided in Appendix Table F.18 and Figure F.3.



(a) Direct Flood Exposure

(b) Indirect Flood Exposure

Figure 13: Heterogeneous Effect of Flood Exposure on Environmental Donations

Notes: The figure plots coefficients with 90% and 95% confidence intervals for interaction terms. In the "single interaction" models, each regression includes interactions of both direct and indirect flood exposure with a single variable. In the "multiple interactions" 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, except for gender.

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 regression estimating heterogeneous responses, I interact direct and indirect flood exposure from equation 1 with individual potential moderating factors in separate regressions and with all factors in a single regression. The results show that the moderating role of universalism on indirect flood exposure remains significant, even when controlling for political orientation and socio-economic variables such as wealth and education.

These findings are in line with the idea that universalists apply moral values broadly, extending beyond self or group interests, to address global challenges like environmental protection. For instance, Figure F.3 shows that universalism is positively associated with agreement that governments should prioritize environmental protection over economic growth and negatively associated with the belief that environmental protection has gone too far. This aligns with research showing that universal moral values, but not in-group-focused benevolence, are linked to stronger climate action commitments (Andre et al., 2024), greater recognition of climate change's consequences, and lower levels of climate skepticism (Prati et al., 2018). As Andre et al. (2024) highlight, climate action represents a global cooperation challenge, disproportionately affecting lower-income countries and spanning present and future generations, which makes universalist individuals more likely to advocate for environmental protection irrespective of direct personal impact.

5 Conclusion

This paper presents new insights into the relationship between experiences of climate disasters and green behaviors. By precisely identifying the distance between a person's postcode code and flooded areas, I show that the effect of floods on environmental behaviors is highly localized, suggesting that personal experience plays a crucial role in catalyzing behavioral 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. Framing and communication strategies that make these consequences vivid and personally relatable could therefore be important. At the same time, it remains unclear whether belief in personal consequences, absent direct exposure, would be equally effective, a question that remains open for future research.

The study also finds that the increase in green behaviors following flood exposure does not coincide with changes in general perceptions of climate risk or in overall prosociality. There is, however, suggestive evidence that flood exposure may affect how people evaluate their own lifestyles, lowering their self-assessments even as they engage in more green actions. This points to a potential channel through which climate shocks shape behavior: by prompting people to reflect more critically on their own actions. Future research could examine whether similar patterns arise in response to more severe events or in different social contexts, and whether such introspection leads to longer-term behavioral change.

I find that the effect of direct flood exposure on green donations are broadly consistent across subgroups: there are no systematic differences by flood risk, risk preferences, trust in government, political ideology, education, wealth, or gender. By contrast, while most people do not respond to neighboring floods, individuals with stronger moral universalist values, those who care about the welfare of all people equally, are more likely to increase their green donations. This suggests that people with greater moral universalism may interpret their neighbors' floods as part of a wider, global climate issue, whereas others are motivated to act only when climate change is perceived as a personal threat.

These findings are robust across multiple checks, but three points help to contextualize their interpretation. First, the analysis focuses on CAF donors, who are wealthier and more active in charitable giving than the general population; future work should examine whether similar patterns hold among people who typically do not donate. Second, the floods studied here are modest in scale compared with major natural disasters; research is needed to study how the severity of such events shapes media and public responses—for example, whether attention is directed more toward immediate economic losses rather than links to climate change. Finally, the UK context, characterized by high recognition of climate change but relatively infrequent severe climate shocks, may resemble other high-income countries but not necessarily lower-income or more disaster-prone settings, and comparative research is needed to understand how institutional and cultural contexts shape heterogeneous responses to climate shocks.

References

Akerlof, G. A. and Kranton, R. E. (2000). Economics and identity. *The Quarterly Journal of Economics*, 115(3):715–753.

Akerlof, G. A. and Kranton, R. E. (2005). Identity and the economics of organizations. *Journal of Economic Perspectives*, 19(1):9–32.

Allcott, H. and Rogers, T. (2014). The short-run and long-run effects of behavioral interventions: Experimental evidence from energy conservation. *American Economic Review*, 104(10):3003–3037.

Andre, P., Boneva, T., Chopra, F., and Falk, A. (2024). Misperceived social norms and willingness to act against climate change. *Review of Economics and Statistics*, pages 1–46.

Andreoni, J. (2006). Philanthropy. *Handbook of the economics of giving, altruism and reciprocity*, 2:1201–1269.

Baccini, L. and Leemann, L. (2021). Do natural disasters help the environment? how voters respond and what that means. *Political Science Research and Methods*, 9(3):468–484.

Baltruszewicz, M., Steinberger, J. K., Paavola, J., Ivanova, D., Brand-Correa, L. I., and Owen, A. (2023). Social outcomes of energy use in the united kingdom: Household energy footprints and their links to well-being. *Ecological Economics*, 205:107686.

Bandura, A. (1982). Self-efficacy mechanism in human agency. *American Psychologist*, 37(2):122.

Bandura, A. (1991). Social cognitive theory of self-regulation. *Organizational behavior and human decision processes*, 50(2):248–287.

Beattie, G. (2022). Measuring social benefits of media coverage: How coverage of climate change affects behavior. *Available at SSRN 4211879.*

Berkowitz, L. (1984). *Advances in Experimental Social Psychology.* Academic Press.

Bertrand, M., Duflo, E., and Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *The Quarterly journal of economics*, 119(1):249–275.

Betts, R. A. and Brown, K. (2021). Introduction. In Betts, R. A., Haward, A. B., and Pearson, K. V., editors, *The Third UK Climate Change Risk Assessment Technical Report.* Climate Change Committee, London.

Biais, B., Hilton, D., Mazurier, K., and Pouget, S. (2005). Judgemental overconfidence, self-monitoring, and trading performance in an experimental financial market. *The Review of economic studies*, 72(2):287–312.

Binder, M. and Blankenberg, A.-K. (2017). Green lifestyles and subjective well-being: More about self-image than actual behavior? *Journal of Economic Behavior & Organization*, 137:304–323.

Black, N., De Gruyter, E., Petrie, D., and Smith, S. (2021). Altruism born of suffering? the impact of an adverse health shock on pro-social behaviour. *Journal of Economic Behavior & Organization*, 191:902–915.

Bordalo, P., Gennaioli, N., and Shleifer, A. (2020). Memory, attention, and choice. *The Quarterly journal of economics*, 135(3):1399–1442.

Bordalo, P., Gennaioli, N., and Shleifer, A. (2022). Salience. *Annual Review of Economics*, 14:521–544.

Borusyak, K., Jaravel, X., and Spiess, J. (2024). Revisiting Event-Study Designs: Robust and Efficient Estimation. *The Review of Economic Studies*, page rdae007.

Botzen, W. W. and van den Bergh, J. C. (2012). Risk attitudes to low-probability climate change risks: Wtp for flood insurance. *Journal of Economic Behavior & Organization*, 82(1):151–166.

Bourdeau-Brien, M. and Kryzanowski, L. (2020). Natural disasters and risk aversion. *Journal of Economic Behavior & Organization*, 177:818–835.

Brown, P., Daigneault, A. J., Tjernström, E., and Zou, W. (2018). Natural disasters, social protection, and risk perceptions. *World development*, 104:310–325.

Brownback, A. and Novotny, A. (2018). Social desirability bias and polling errors in the 2016 presidential election. *Journal of Behavioral and Experimental Economics*, 74:38–56.

Bulut, H. and Samuel, R. (2024). The influence of the 2021 european flooding on pro-environmental attitudes and partial behaviour transition. *npj Climate Action*, 3(1):22.

Burks, S. V., Carpenter, J. P., Goette, L., and Rustichini, A. (2013). Overconfidence and social signalling. *Review of Economic Studies*, 80(3):949–983.

Callaway, B. and Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of econometrics*, 225(2):200–230.

Cameron, L. and Shah, M. (2015). Risk-taking behavior in the wake of natural disasters. *Journal of human resources*, 50(2):484–515.

Cappelen, A. W., Enke, B., and Tungodden, B. (2022). Universalism: Global evidence. Technical report, CESifo Working Paper.

Capstick, S. B., Demski, C. C., Sposato, R. G., Pidgeon, N. F., Spence, A., and Corner, A. J. (2015). Public perception of climate change in britain following the winter 2013/2014 flooding. Unpublished report, Cardiff University.

Carlsson, F., He, H., and Martinsson, P. (2013). Easy come, easy go: The role of windfall money in lab and field experiments. *Experimental Economics*, 16:190–207.

Climate Action Tracker (2024). United kingdom. Accessed: 2024-07-03.

Climate Change Committee (2020). The sixth carbon budget: The uk's path to net zero. Accessed: [2024-05-12].

Coury, M. (2023). Climate risk and preferences over the size of government: Evidence from california wildfires. *The Review of Economics and Statistics*, pages 1–46.

De Chaisemartin, C. and d'Haultfoeuille, X. (2024). Difference-in-differences estimators of intertemporal treatment effects. *Review of Economics and Statistics*, pages 1–45.

De Chaisemartin, C. and d'Haultfoeuille, X. (2023). Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: A survey. *The Econometrics Journal*, 26(3):C1–C30.

De Quidt, J., Vesterlund, L., and Wilson, A. J. (2019). Experimenter demand effects. In *Handbook of research methods and applications in experimental economics*, pages 384–400. Edward Elgar Publishing.

Dechezleprêtre, A., Fabre, A., Kruse, T., Planterose, B., Chico, A. S., and Stantcheva, S. (2023). Fighting climate change: International attitudes toward climate policies. Technical report, National Bureau of Economic Research.

Department for Communities and Local Government (2014). Flood support schemes - revised guidance. Accessed: 2024-01-05.

Deryugina, T. (2013). How do people update? the effects of local weather fluctuations on beliefs about global warming. *Climatic Change*, 118:397–416.

Deryugina, T. and Marx, B. M. (2021). Is the supply of charitable donations fixed? evidence from deadly tornadoes. *American Economic Review: Insights*, 3(3):383–98.

Deryugina, T. and Shurchkov, O. (2016). The effect of information provision on public consensus about climate change. *PloS One*, 11(4):e0151469.

Djourelova, M., Durante, R., Motte, E., and Patacchini, E. (2024). Experience, narratives, and climate change beliefs. *Working Paper*.

Douty, C. M. (1972). Disasters and charity: some aspects of cooperative economic behavior. *The American Economic Review*, 62(4):580–590.

Duflo, E. (2024). Keynote lecture 2: Climate change compensation. Video Lecture. Accessed: 2024-10-31.

Eisensee, T. and Strömberg, D. (2007). News droughts, news floods, and us disaster relief. *The Quarterly Journal of Economics*, 122(2):693–728.

Ekström, M. (2012). Do watching eyes affect charitable giving? evidence from a field experiment. *Experimental Economics*, 15:530–546.

Enke, B., Rodríguez-Padilla, R., and Zimmermann, F. (2023). Moral universalism and the structure of ideology. *The Review of economic studies*, 90(4):1934–1962.

Fathom (2021). Fathom-uk: Methodological documentation. Available from: https://www.fathom.global/product/global-flood-map/uk-flood-map/.

Festinger, L. (1957). *A Theory of Cognitive Dissonance*. Stanford University Press, Stanford, CA.

Flood Re (2023). A flood re-insurance scheme. https://www.floodre.co.uk. Accessed: 2023-12-26.

Frondel, M., Simora, M., and Sommer, S. (2017). Risk perception of climate change: Empirical evidence for germany. *Ecological Economics*, 137:173–183.

Gagliarducci, S., Paserman, M. D., and Patacchini, E. (2019). Hurricanes, climate change policies and electoral accountability. *NBER Working Paper*.

Gallagher, J. (2014). Learning about an infrequent event: Evidence from flood insurance take-up in the united states. *American Economic Journal: Applied Economics*, pages 206–233.

Gao, M., Liu, Y.-J., and Shi, Y. (2020). Do people feel less at risk? evidence from disaster experience. *Journal of Financial Economics*, 138(3):866–888.

Garbarino, N., Guin, B., et al. (2022). The effects of subsidized flood insurance on real estate markets. *Bank of England Working Paper*.

Goebel, J., Krekel, C., Tiefenbach, T., and Ziebarth, N. R. (2015). How natural disasters can affect environmental concerns, risk aversion, and even politics: evidence from fukushima and three european countries. *Journal of Population Economics*, 28:1137–1180.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2):254–277.

Grothmann, T. and Patt, A. (2005). Adaptive capacity and human cognition: the process of individual adaptation to climate change. *Global Environmental Change*, 15(3):199–213.

Hazlett, C. and Mildenberger, M. (2020). Wildfire exposure increases pro-environment voting within democratic but not republican areas. *American Political Science Review*, 114(4):1359–1365.

Herrnstadt, E. and Muehlegger, E. (2014). Weather, salience of climate change and congressional voting. *Journal of Environmental Economics and Management*, 68(3):435–448.

Hoffmann, R., Muttarak, R., Peisker, J., and Stanig, P. (2022). Climate change experiences raise environmental concerns and promote green voting. *Nature Climate Change*, 12(2):148–155.

Hu, Z. (2022). Social interactions and households' flood insurance decisions. *Journal of Financial Economics*, 144(2):414–432.

IPCC (2023). Climate change 2023: Synthesis report. https://www.ipcc.ch/report/ar6/syr/.

Ito, K., Ida, T., and Tanaka, M. (2018). Moral suasion and economic incentives: Field experimental evidence from energy demand. *American Economic Journal: Economic Policy*, 10(1):240–267.

Jayaraman, R., Kaiser, M., and Teirlinck, M. (2023). Charitable donations to natural disasters: evidence from an online platform. *Oxford Economic Papers*, 75(4):902–922.

Jolliffe, I. T. (1995). Rotation of principal components: choice of normalization constraints. *Journal of Applied Statistics*, 22(1):29–35.

Kahneman, D. and Tversky, A. (1982). The psychology of preferences. *Scientific american*, 246(1):160–173.

Kew, S. F., McCarthy, M., Ryan, C., Pirret, J. S., Murtagh, E., Vahlberg, M., Amankona, A., Pope, J. O., Lott, F., Claydon, O., Coonan, B., Pinto, I., Barnes, C., and Philip, S. (2024). Scientific report on uk storms: Autumn and winter storms over uk and ireland are becoming wetter due to climate change. Technical report, Royal Netherlands Meteorological Institute (KNMI), Met Office, Met Éireann, British Red Cross, Red Cross Red Crescent Climate Centre, Grantham Institute, Imperial College London.

Koletsou, A. and Mancy, R. (2011). Which efficacy constructs for large-scale social dilemma problems? individual and collective forms of efficacy and outcome expectancies in the context of climate change mitigation. *Risk Management*, 13:184–208.

Landmark Information Group (2022). Sample flood report. Accessed: 2024-05-29.

Leviston, Z. and Uren, H. V. (2020). Overestimating one's "green" behavior: Better-than-average bias may function to reduce perceived personal threat from climate change. *Journal of Social Issues*, 76(1):70–85.

Li, H., Liang, J., Xu, H., and Liu, Y. (2019). Does windfall money encourage charitable giving? an experimental study. *VOLUNTAS: International Journal of Voluntary and Nonprofit Organizations*, 30:841–848.

Li, Y., Johnson, E. J., and Zaval, L. (2011). Local warming: Daily temperature change influences belief in global warming. *Psychological science*, 22(4):454–459.

Liao, Y. and Junco, P. R. (2022). Extreme weather and the politics of climate change: A study of campaign finance and elections. *Journal of Environmental Economics and*

Management, 111:102550.

Lohmann, P. M. and Kontoleon, A. (2023). Do flood and heatwave experiences shape climate opinion? causal evidence from flooding and heatwaves in england and wales. *Environmental and Resource Economics*, pages 1–42.

Méon, P.-G. and Verwimp, P. (2022). Pro-social behavior after a disaster: Evidence from a storm hitting an open-air festival. *Journal of Economic Behavior & Organization*, 198:493–510.

Office for National Statistics (2023). Postal geographies. Accessed: 2024-05-29.

Poortinga, W. (2022). Review of environmental attitudes and behaviour questions in the understanding society survey.

Prati, G., Pietrantoni, L., and Albanesi, C. (2018). Human values and beliefs and concern about climate change: A bayesian longitudinal analysis. *Quality & Quantity*, 52:1613–1625.

Rao, L.-L., Han, R., Ren, X.-P., Bai, X.-W., Zheng, R., Liu, H., Wang, Z.-J., Li, J.-Z., Zhang, K., and Li, S. (2011). Disadvantage and prosocial behavior: The effects of the wenchuan earthquake. *Evolution and Human Behavior*, 32(1):63–69.

Reinstein, D. and Riener, G. (2012). Decomposing desert and tangibility effects in a charitable giving experiment. *Experimental Economics*, 15:229–240.

Reisinger, J. (2022). Subjective well-being and social desirability. *Journal of Public Economics*, 214:104745.

Ritchie, H. (2024). There are huge inequalities in global co2 emissions. Our World in Data. Accessed: 2024-11-03.

Roth, J., Sant'Anna, P. H., Bilinski, A., and Poe, J. (2023). What's trending in difference-in-differences? a synthesis of the recent econometrics literature. *Journal of Econometrics*, 235(2):2218–2244.

Salamon, L. M. and Anheier, H. K. (1996). *The international classification of nonprofit organizations: ICNPO-Revision 1, 1996*. Johns Hopkins University Institute for Policy Studies Baltimore.

Scharf, K., Smith, S., and Ottoni-Wilhelm, M. (2022). Lift and shift: The effect of fundraising interventions in charity space and time. *American Economic Journal: Economic Policy*, 14(3):296–321.

Schwartz, S. H. (2007). Universalism values and the inclusiveness of our moral universe. *Journal of cross-cultural psychology*, 38(6):711–728.

Schwartz, S. H. (2012). An overview of the schwartz theory of basic values. *Online readings in Psychology and Culture*, 2(1):11.

Shai, O. (2022). Out of time? the effect of an infrequent traumatic event on individuals' time and risk preferences, beliefs, and insurance purchasing. *Journal of Health Economics*, 86:102678.

Shupp, R., Loveridge, S., Skidmore, M., Lim, J., and Rogers, C. (2017). Risk, loss, and ambiguity aversion after a natural disaster. *Economics of disasters and climate change*, 1:121–142.

Sinding Bentzen, J. (2019). Acts of god? religiosity and natural disasters across subnational world districts. *The Economic Journal*, 129(622):2295–2321.

Skouralis, A. and Lux, N. (2023). The impact of flood risk on england's property market. Real Estate Research Centre, Bayes Business School, City University of London.

Sonenshein, S., DeCelles, K. A., and Dutton, J. E. (2014). It's not easy being green: The role of self-evaluations in explaining support of environmental issues. *Academy of Management Journal*, 57(1):7–37.

Spence, A., Poortinga, W., Butler, C., and Pidgeon, N. F. (2011). Perceptions of climate change and willingness to save energy related to flood experience. *Nature climate change*, 1(1):46–49.

Stern, P. C. (2000). New environmental theories: toward a coherent theory of environmentally significant behavior. *Journal of Social Issues*, 56(3):407–424.

Stern, P. C., Dietz, T., Abel, T., Guagnano, G. A., and Kalof, L. (1999). A value-belief-norm theory of support for social movements: The case of environmentalism. *Human Ecology Review*, pages 81–97.

Thompson, V., Dunstone, N. J., Scaife, A. A., Smith, D. M., Slingo, J. M., Brown, S., and Belcher, S. E. (2017). High risk of unprecedented uk rainfall in the current climate. *Nature communications*, 8(1):1–6.

UKHLS (2022). Understanding society: Waves 1-12, 2009-2021. [data collection]. 17th Edition. SN: 6614, http://doi.org/10.5255/UKDA-SN-6614-18.

UNEP (2022). Climate change 2022: Mitigation of climate change. https://www.unep.org/resources/emissions-gap-report-2022.

van Valkengoed, A. M., Abrahamse, W., and Steg, L. (2022). To select effective interventions for pro-environmental behaviour change, we need to consider determinants of behaviour. *Nature Human Behaviour*, pages 1–11.

Whitmarsh, L. (2008). Are flood victims more concerned about climate change than other people? the role of direct experience in risk perception and behavioural response. *Journal of risk research*, 11(3):351–374.

Woodland Trust (2024). The northern forest. Accessed: 2024-05-29.

World Risk Poll (2021). 2021 lloyd's register foundation world risk poll methodology.

Accessed: 2024-05-15.

Appendices

A Additional Contexts

A.1 Risk Perception of Climate Change

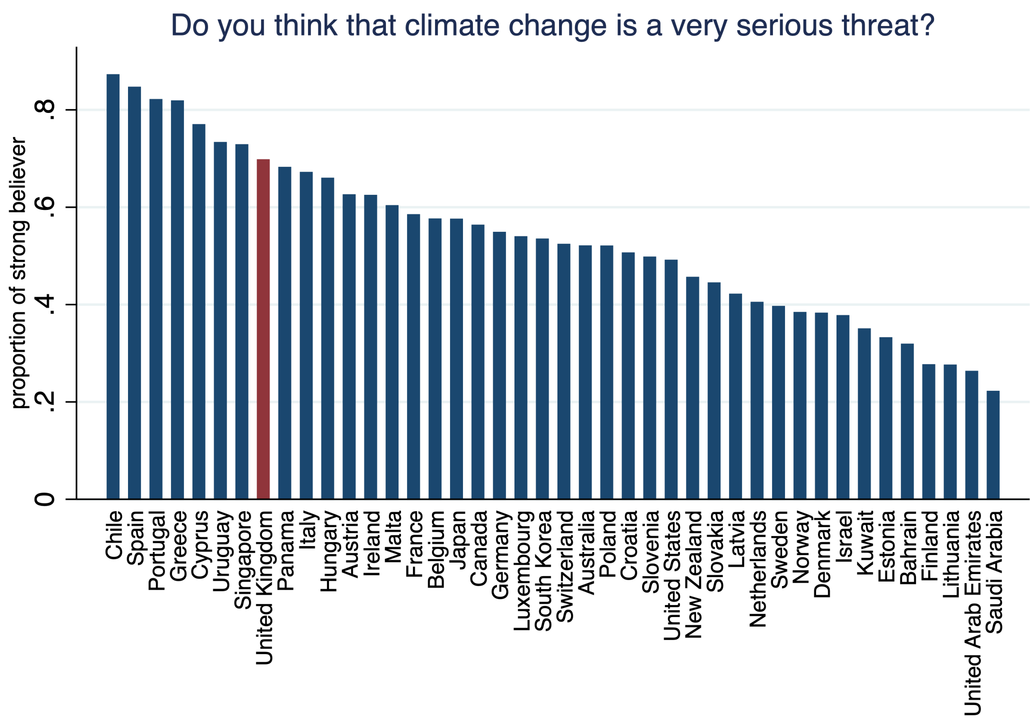


Figure A.1: Proportion of Strong Believers in Climate Change by High-Income Country

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.

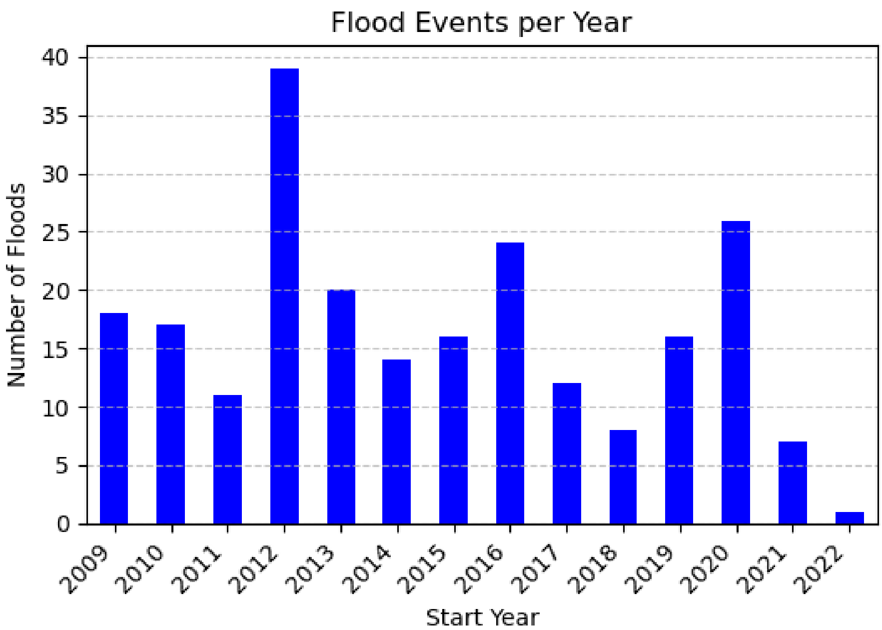


Figure A.2: Number of Floods by the Year of Start

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 Flood Risk Measure

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.

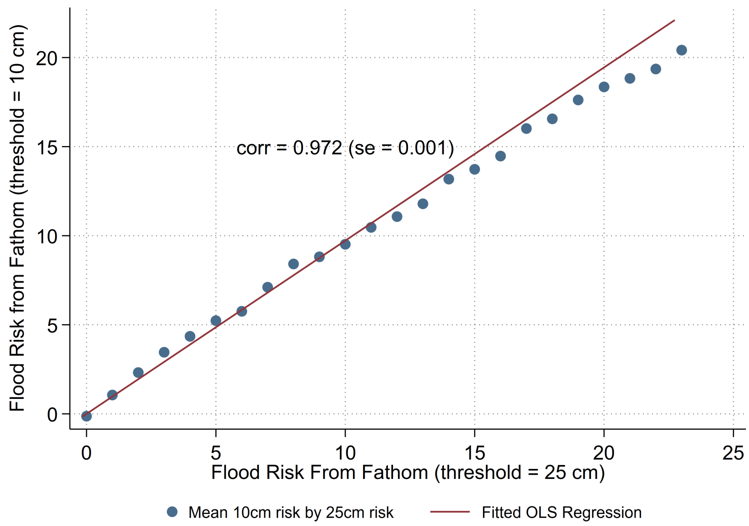
In summary, for every 10 m x 10 m square in the UK, I have data on the water depth for a flood event specific to a given hazard type and magnitude.

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.

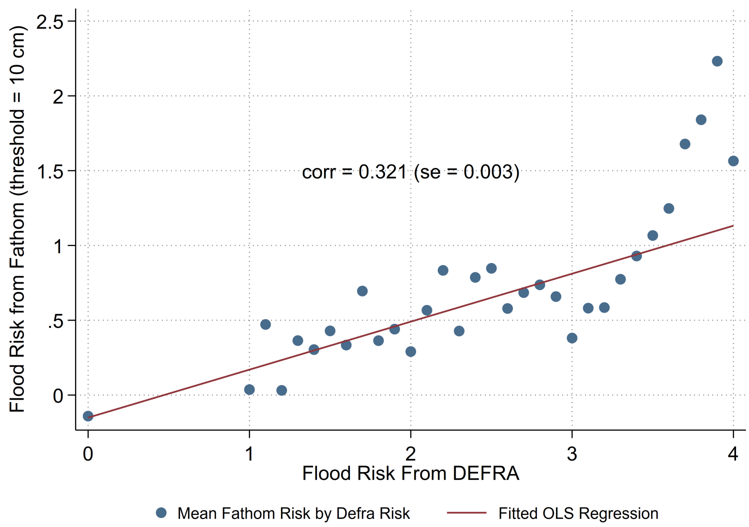
The algorithm initializes the flood risk for this location at 0. It starts by examining the flood depths beginning with the least frequent occurrences, i.e., the 1000-year flood. If simulated flood events of any hazard type result in a depth exceeding 10 centimeters, the initial flood risk of 0 is replaced 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.



(a) Fathom 10cm risk vs. Fathom 25cm risk



(b) Fathom 10cm risk vs. DEFRA risk

Figure B.1: Correlation between Different Flood Risk Measures

Notes: The observations consist of 80,254 unique postcodes of CAF donors with measures on flood risk in the main sample. In panel (a), I fit an OLS regression of the main flood risk measure, defined as the annual probability of floods exceeding 10 cm (the primary measure used in the paper), on the annual probability of floods exceeding 25 cm, using data from Fathom. The scatter plot shows the average 10 cm risk by bins of 25 cm risk. In panel (b), I regress the same 10 cm flood risk measure on flood risk levels (from rivers and seas) provided by the Department for Environment, Food and Rural Affairs (Defra). According to Defra, risk levels are coded as: 0 = no risk, 1 = very low risk, 2 = low risk, 3 = medium risk, 4 = high risk. The plot shows the mean Fathom 10 cm flood risk by Defra risk level. The Defra dataset is available here.

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.

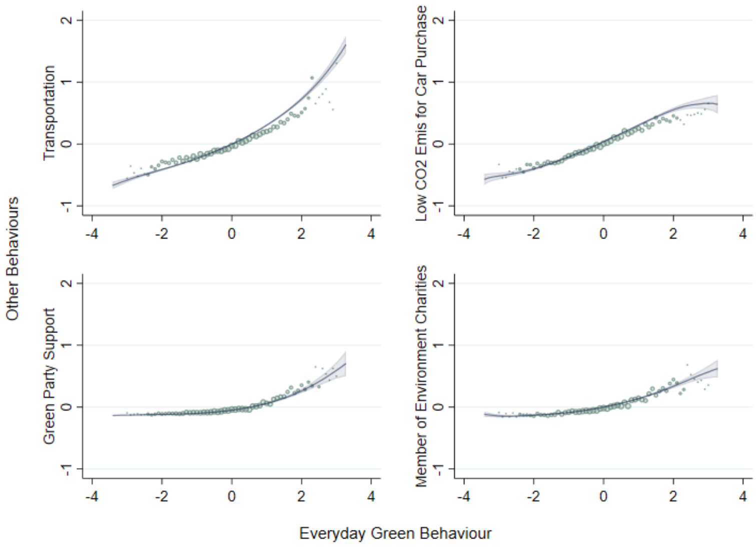


Figure C.1: Correlation between Everyday Green Behavior and Other Green Behaviors

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 choosing fewer flights, which are not used in the everyday green behavior index.

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

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 Descriptive Statistics on CAF Donors

Figure D.1: Wealth Distribution of CAF Donors' Postcodes

Notes: The wealth index is defined as the percentile rank of the average property price in each postcode, calculated from transactions between 2000 and 2022 using data from the UK Land Registry. The figure shows the distribution of postcodes in which CAF donors reside across this wealth index. While CAF donors are represented across the entire distribution, postcodes in higher wealth percentiles are overrepresented: each percentile above the 60th accounts for more than 1% of donor postcodes.

Table D.1: Comparison of donation distribution between UKHLS and CAF

	Yearly Donation Size	
	Donors from UKHLS	Active CAF Donors
Mean	203	858
P1	3	7
P5	7	22
P10	10	42
P25	25	55
P50	70	120
P75	200	537
P90	480	1,728
P95	800	3,285
P99	2,500	10,240
N	27,647	76,540

Notes: This table compares the distribution of annual donation amounts between two groups: (1) individuals who reported positive charitable giving in the UK Household Longitudinal Study (UKHLS) in the wave beginning in 2012, the first wave that includes donation-related questions overlapping with the CAF data period, and (2) active donors in the Charities Aid Foundation (CAF) transaction data. Active CAF donors are defined as individuals whose first and last recorded donations span more than seven years between 2011 and 2022. In the UKHLS, respondents report total donations made to charities in the past 12 months. For comparability, annual donation amounts for CAF donors are constructed based on their donations in 2012. The table reports selected percentiles of the donation distribution and sample sizes for each group.

Table D.2: CAF Donors against the distribution of donors surveyed by UKHLS

Donors Surveyed by UKHLS				Share of Active CAF Donors (%)
Decile of Giving	Share of Donors (%)	Minimum Donation (£)	Share of Total Giving (%)	
1	10	1	0.30	1.96
2	10	10	0.80	1.86
3	10	20	1.30	2.93
4	10	30	2.20	11.25
5	10	50	2.70	20.40
6	10	70	4.50	6.12
7	10	100	5.60	9.63
8	10	150	9.00	4.08
9	10	200	15.10	14.80
10	10	480	58.40	26.97

Notes: This table divides UKHLS respondents who reported positive donations into ten equal-sized groups (deciles) based on their annual donation amounts, using data from the 2012 wave. For each decile, the table reports the minimum annual donation amount in that group and the share of total donations accounted for by donors in that decile. The final column shows the distribution of active CAF donors across these same decile thresholds, based on their annual donation amounts. This comparison illustrates how CAF donors are positioned within the broader population of donors as captured in the UKHLS survey.

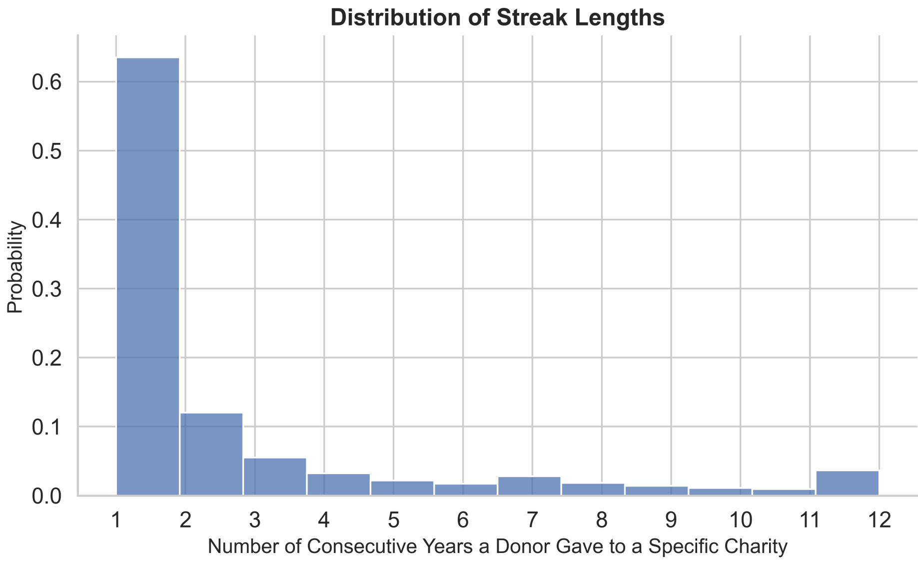


Figure D.2: Distribution of Streak Lengths for CAF Donors

Notes: This figure plots the distribution of streak lengths for CAF donors in my sample. A streak is defined as the number of consecutive years once an individual started giving to a charity. It shows that most donors give for only one year, and around 80% give for fewer than three consecutive years.

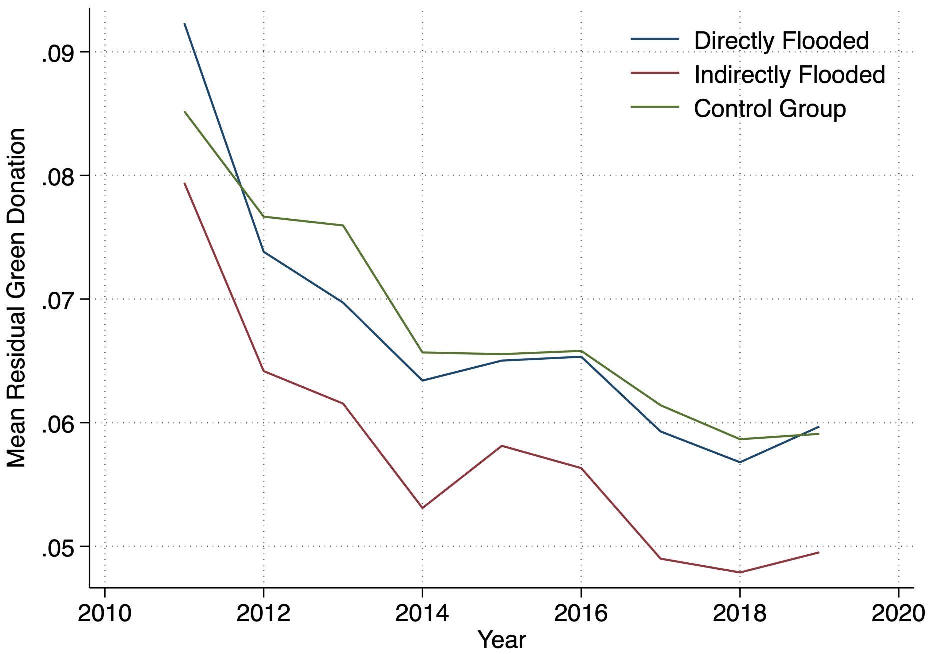


Figure D.3: Trends in green donations across directly flooded, indirectly flooded, and control groups within the same region and flood risk, excluding treated observations.

Notes: This figure shows the average donation behavior over time for three groups: (1) directly flooded individuals (those whose postcodes were flooded), (2) indirectly flooded individuals (those whose postcodes are within 200 meters of a flooded area), and (3) unaffected individuals who were not flooded but reside in the same region and face the same flood risk. Since I compare people within the same region and face the same flood risk, I first regress *Green Donation* on region-by-year and flood-risk-by-year fixed effects and retain residuals. The figure reports mean residuals by year after excluding treated observations (i.e. those exposed to flooding, directly or indirectly) to assess whether the groups follow similar trends in the absence of treatment. I exclude the years 2020-2022 due to an insufficient number of untreated observations among the treated groups (fewer than 10 per year).

E Statistics on Treatment Group

Table E.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	1,356	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 E.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	41,925	15	31
2010	40,685	-	26
2011	36,899	14	24
2012	35,114	17	39
2013	33,584	13	62
2014	34,182	29	34
2015	32,007	34	92
2016	29,956	42	86
2017	27,604	-	16
2018	26,511	-	-
2019	24,802	26	69
2020	22,624	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	191	84.9	528	92.0
≥ 2	34	15.1	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. The table is based on the first time an individual is observed as flooded, rather than the first time they were exposed to a flood.

F Additional Analyses and Robustness Checks

F.1 Results on Environmental Behaviors

Table F.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
	(0.007)***	(0.012)*	(0.102)
	[0.007]**	[0.011]*	[0.092]
	{0.003}***	{0.006}***	{0.040}*
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]
	{0.004}	{0.005}	{0.095}
200 < distance ≤ 400 m	-0.007	0.002	0.045
	(0.004)	(0.005)	(0.071)
	[0.003]*	[0.005]	[0.072]
	{0.006}	{0.005}	{0.062}
400 < distance ≤ 600 m	-0.002	0.004	-0.034
	(0.004)	(0.005)	(0.066)
	[0.004]	[0.006]	[0.073]
	{0.003}	{0.006}	{0.059}
600 < distance ≤ 800 m	0.001	0.004	0.024
	(0.003)	(0.005)	(0.056)
	[0.003]	[0.005]	[0.058]
	{0.005}	{0.003}	{0.043}
Mean Outcome	.063	.016	.047
F(All Coefs of Indirect Exposure = 0)	1.261	0.493	0.957
N	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. The baseline standard errors clustered at the postcode level are reported in parentheses; those clustered at the postcode area level are in square brackets; and Conley-adjusted standard errors, which account for spatial correlation within a 100 km radius, are in curly brackets. *** significant at 1%, ** significant at 5%, * significant at 10%.

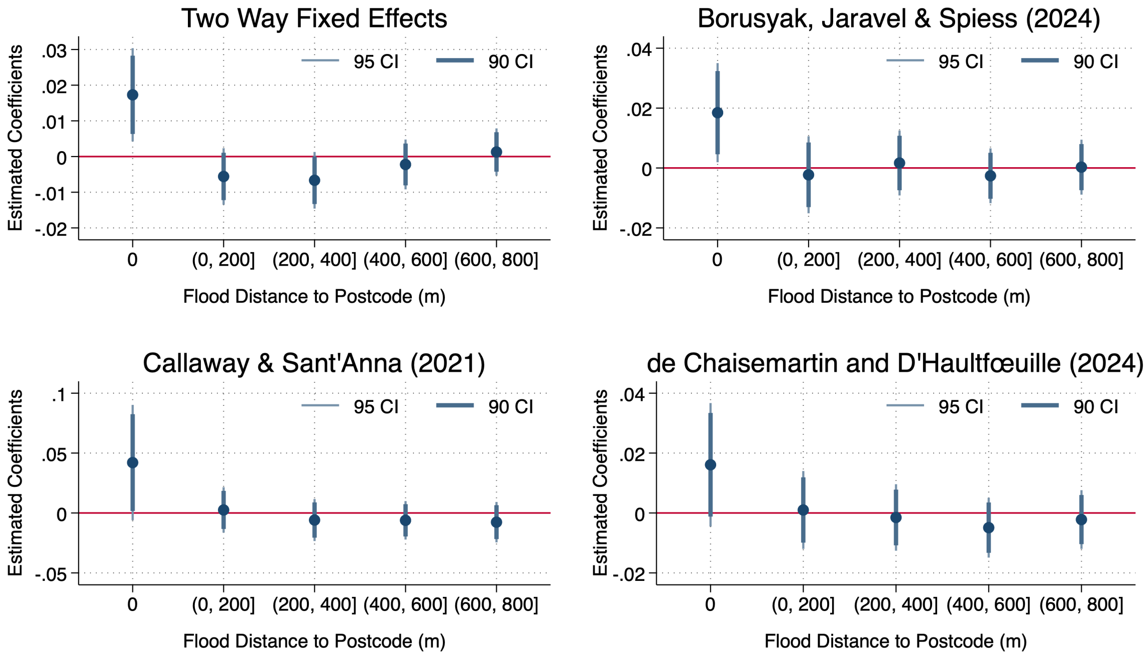


Figure F.1: The Effect of Flood Exposure on Green Donation

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.

Table F.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)	1.746
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 F.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%.

Table F.4: The Effect of Flood Occurrence on Tweets Count by Environmental Charities

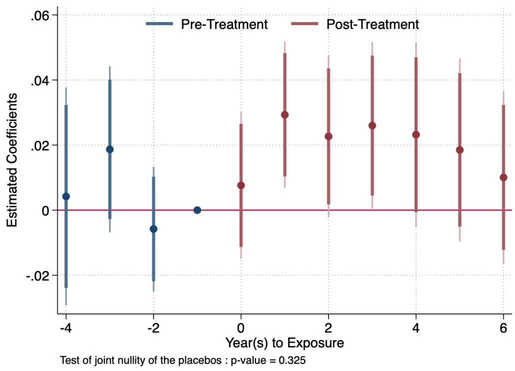
	Climate Change	Floods Only	Other Topics
	(1)	(2)	(3)
Flood Occurrence	1.195	0.106	-1.568
	(0.583)**	(0.052)**	(2.359)
	[0.040]**	[0.010]**	[0.780]
Observations	2,190	2,190	2,190
Mean Number of Tweets per Day	12.469	0.216	90.742
Year by Month Fixed Effects	Yes	Yes	Yes

Notes: I rank general charities by their mean annual donation income received through CAF. I then scrape all posts published on Twitter between 2017 and 2022 by charities ranked above 2,200. These charities together account for more than 90% of total donations made through CAF. This analysis relies only on charities classified as "Environmental" by the International Classification of Non-profit Organizations. The outcome variables include the number of tweets in a given week that mention climate change, mention floods without referencing climate change, and discuss other topics. 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 within each year-month. 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.

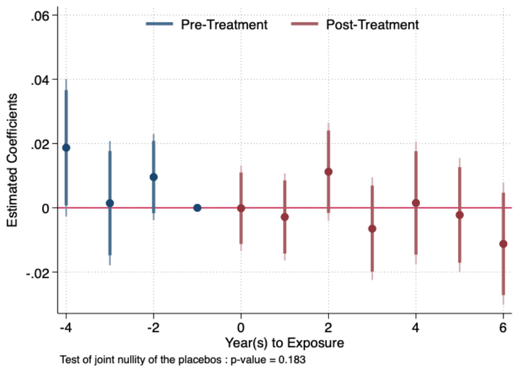
Table F.5: The Effect of Flood Exposure on Personal Income

	Personal Income		
	(1) Full Sample	(2) Winsorize p5 - p95	(3) Log Transformed
Direct Flood Exposure			
distance = 0 m	-51.814	-36.902	-0.097
	(82.995)	(44.563)	(0.073)
Indirect Flood Exposure			
$000 < \text{distance} \leq 200$ m	165.283	10.860	-0.005
	(102.862)	(27.479)	(0.033)
$200 < \text{distance} \leq 400$ m	52.752	9.306	0.005
	(46.537)	(21.974)	(0.030)
$400 < \text{distance} \leq 600$ m	-43.513	-38.794*	-0.055*
	(28.675)	(21.398)	(0.030)
$600 < \text{distance} \leq 800$ m	-1.797	-15.632	-0.001
	(36.393)	(20.425)	(0.027)
F(All Coefs of Indirect Exp = 0)	1.543	1.062	0.876
Observations	370,686	370,686	348,227
Individual FE	Yes	Yes	Yes
Flood Risk by Year FE	Yes	Yes	Yes
Region by Year FE	Yes	Yes	Yes

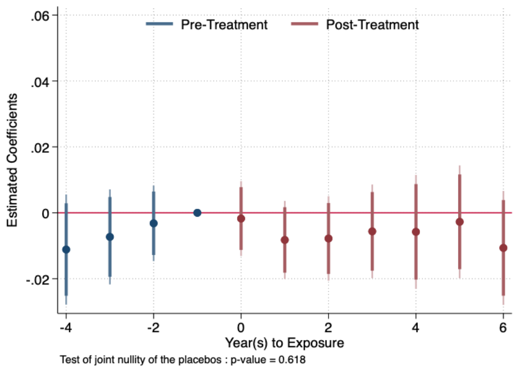
Notes: The outcome variable is total net monthly income, after taxes on earnings and National Insurance contributions. The treatment variable indicates whether an individual has experienced a flood that directly affected their postcode, or whether the flood impacted neighboring areas at varying distances from their postcode. The term *distance* represents the distance at which they were exposed to a flood. Column (1) reports the regression on the full sample; column (2) uses the same sample, but with the outcome winsorized between the 5th and 95th percentiles; and column (3) reports the regression with log-transformed personal income, using a sample with positive observations. Standard errors clustered at the postcode level are provided in round brackets. *** significant at 1%, ** significant at 5%, * significant at 10%.



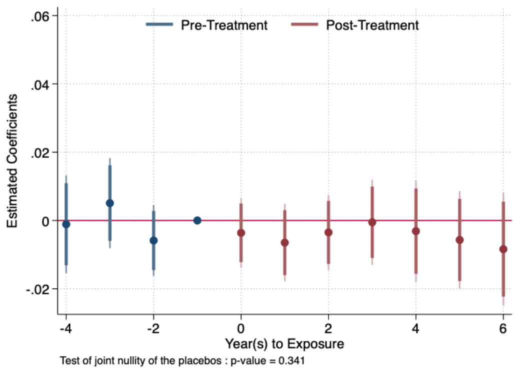
(a) Flood Distance: 0 m



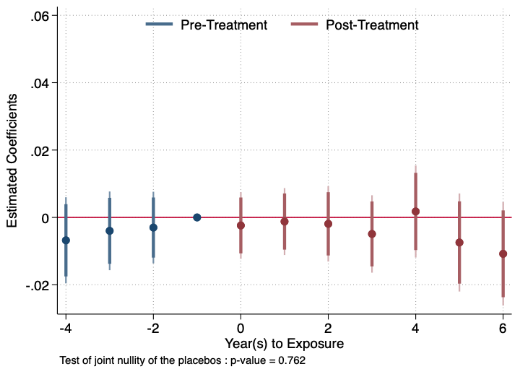
(b) Flood Distance: 0 – 200 m



(c) Flood Distance: 200 – 400 m



(d) Flood Distance: 400 – 600 m



(e) Flood Distance: 600 – 800 m

Figure F.2: 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% and 95%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.

Table F.6: The Effect of Flood Exposure on Green Donation (more restrictive sample)

	Green Donation		
	(1) Within-2-year Effect	(2) Registration Before First Flood Exposure	(3) Only Non-urban Residents
Direct Flood Exposure			
distance = 0 m	0.017**	0.017***	0.041***
	(0.007)	(0.007)	(0.010)
Indirect Flood Exposure			
$0 <$ distance ≤ 200 m	-0.005	-0.005	-0.001
	(0.004)	(0.004)	(0.010)
$200 <$ distance ≤ 400 m	-0.006	-0.006	0.001
	(0.004)	(0.004)	(0.010)
$400 <$ distance ≤ 600 m	-0.002	-0.002	0.011
	(0.004)	(0.004)	(0.010)
$600 <$ distance ≤ 800 m	0.001	0.001	-0.013
	(0.003)	(0.003)	(0.011)
Observations	1,021,210	1,023,973	202,038
Number of Directly Treated Obs.	1837	4600	3190
Flood Risk by Year FE	Yes	Yes	Yes
Region by Year FE	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes

Notes: The table presents the coefficients of flood exposure on green donation support. Column (1) drops treated observations more than two years after exposure, to estimate the effect within a two-year window; Column (2) includes only donors whose first donation predates their first direct flood experience by at least one year, ensuring that their registered address was in place before the flood; Column (3) includes only donors who live in non-urban postcodes. 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. The baseline standard errors clustered at the postcode level are reported in parentheses. *** significant at 1%, ** significant at 5%, * significant at 10%.

F.2 Results on Environmental Beliefs and Preferences

Table F.7: 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]
	{0.099}***	{0.132}	{0.090}	{0.157}
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]
	{0.125}	{0.127}	{0.077}	{0.139}
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]
	{0.119}	{0.059}*	{0.142}	{0.102}
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]*
	{0.100}	{0.198}	{0.121}	{0.091}*
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]
	{0.121}	{0.074}	{0.117}	{0.057}
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. The baseline standard errors clustered at the postcode level are reported in parentheses; those clustered at the postcode area level are in square brackets; and Conley-adjusted standard errors, which account for spatial correlation within a 100 km radius, are in curly brackets. *** significant at 1%, ** significant at 5%, * significant at 10%.

Table F.8: The Effect of Flood Exposure on Self-assessed Greenness

	Self-Assessed Greenness		
	(1) Original Index	(2) Simple Average	(3) Component Analysis
Direct Flood Exposure			
distance = 0 m	-0.277*	-0.068*	-0.213*
	(0.148)	(0.038)	(0.123)
Indirect Flood Exposure			
0 < distance ≤ 200 m	-0.167	-0.022	-0.079
	(0.117)	(0.026)	(0.083)
200 < distance ≤ 400 m	-0.021	-0.044*	-0.136*
	(0.105)	(0.025)	(0.080)
400 < distance ≤ 600 m	-0.055	0.026	0.085
	(0.094)	(0.023)	(0.075)
600 < distance ≤ 800 m	0.036	0.012	0.039
	(0.105)	(0.025)	(0.080)
F(All Coefs of Indirect Exp = 0)	0.631	1.340	1.338
Observations	32,098	61,526	61,526
Individual FE	Yes	Yes	Yes
Flood Risk by Year FE	Yes	Yes	Yes
Region by Year FE	Yes	Yes	Yes

Notes: All three columns report estimates for the same outcome, a measure of self-assessed greenness. Column (1) is the main index used in the paper. It is constructed using principal factor analysis on all environmental belief items, with varimax rotation, retaining the factor that loads most strongly on the two statements: "I am happy with what I do at the moment" and "I'm environmentally friendly in most things or everything I do." Column (2) uses a simple average of these two statements. Column (3) applies principal component analysis to the same two statements and retains the first component. The treatment variable indicates whether an individual experienced a flood after 2009 that directly affected their postcode (direct exposure) or affected neighboring areas (indirect exposure). *Distance* measures the distance from the flood to the individual's postcode. Standard errors, clustered at the postcode level, are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table F.9: 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 $\leq$ 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 $\leq$ 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 $\leq$ 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 $\leq$ 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 F.10: 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 $\leq$ 200 m	-0.023	-0.050	-7.510	-0.010
	(0.024)	(0.051)	(40.703)	(0.054)
200 $<$ distance $\leq$ 400 m	-0.015	-0.033	2.973	0.004
	(0.020)	(0.043)	(28.754)	(0.038)
400 $<$ distance $\leq$ 600 m	0.012	0.026	-36.615*	-0.049*
	(0.021)	(0.046)	(19.019)	(0.025)
600 $<$ distance $\leq$ 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. *Donation Dummy* indicates whether an individual donated any money to charities or other organizations. Conditional on those who gave, *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%.

F.3 Results of Robustness Checks

Table F.11: P-values (based on Conley Standard Error) for the effect of direct flood exposure

	(1) 50km	(2) 100km	(3) 150km
Green Donation	0.002	0.000	0.000
Everyday Green Behaviour	0.525	0.050	0.000
Green Party Support	0.092	0.000	0.109
Self-assessed Greenness	0.245	0.005	0.000
Risk Perception	0.744	0.827	0.650
Personal Responsibility	0.647	0.418	0.750
Self Efficacy	0.722	0.691	0.670

Notes: The table reports p-values for the estimated effect of direct flood exposure (i.e. when an individual's postcode is directly affected by a flood) on major environmental outcomes, following the same specifications as Tables F.1 and F.7. P-values are based on Conley standard errors with distance cut-offs of 50 km, 100 km, and 150 km.

Table F.12: 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 F.13: 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 F.14: 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							
$000 < \text{distance} \leq 200$ 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)
$200 < \text{distance} \leq 400$ 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)
$400 < \text{distance} \leq 600$ 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)
$600 < \text{distance} \leq 800$ 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 outcomes. *Green Donation* indicates if one donates to environmental charities. *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. *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 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 F.15: The Effect of Flood Exposure (with alternative measures for flood risk)

	Green Donation		Green Party Support		Everyday Green Behavior		Self-Assessed Greenness		Risk Perception		Personal Responsibility		Self-Efficacy	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Direct Flood Exposure														
distance = 0 m	0.017**	0.018***	0.021*	0.019*	0.078	0.082	-0.280*	-0.298**	-0.030	-0.006	0.077	0.088	0.062	0.062
	(0.007)	(0.007)	(0.012)	(0.012)	(0.102)	(0.101)	(0.149)	(0.147)	(0.117)	(0.118)	(0.132)	(0.131)	(0.115)	(0.115)
Indirect Flood Exposure														
000 < distance ≤ 200 m	-0.006	-0.005	-0.003	-0.003	0.127*	0.128*	-0.168	-0.167	-0.009	-0.000	-0.047	-0.050	0.026	0.022
	(0.004)	(0.004)	(0.005)	(0.005)	(0.073)	(0.073)	(0.117)	(0.117)	(0.120)	(0.120)	(0.104)	(0.104)	(0.120)	(0.120)
200 < distance ≤ 400 m	-0.007	-0.006	0.002	0.002	0.044	0.044	-0.019	-0.016	0.108	0.110	-0.038	-0.038	0.061	0.062
	(0.004)	(0.004)	(0.005)	(0.005)	(0.071)	(0.071)	(0.105)	(0.105)	(0.097)	(0.098)	(0.096)	(0.096)	(0.105)	(0.105)
400 < distance ≤ 600 m	-0.002	-0.002	0.004	0.003	-0.034	-0.035	-0.055	-0.046	0.049	0.053	-0.101	-0.092	0.174*	0.174*
	(0.004)	(0.004)	(0.005)	(0.005)	(0.066)	(0.066)	(0.094)	(0.094)	(0.101)	(0.101)	(0.099)	(0.099)	(0.104)	(0.103)
600 < distance ≤ 800 m	0.001	0.001	0.004	0.004	0.025	0.023	0.037	0.039	0.049	0.047	0.166*	0.164*	0.025	0.026
	(0.003)	(0.003)	(0.005)	(0.005)	(0.056)	(0.056)	(0.105)	(0.106)	(0.114)	(0.114)	(0.089)	(0.089)	(0.098)	(0.098)
F(All Coefs of Indirect Exposure = 0)	1.27	1.142	0.487	0.456	0.952	0.972	0.635	0.609	0.418	0.431	1.300	1.243	0.825	0.847
Observations	1,025,652	1,025,664	283,418	283,479	56,747	56,760	32,098	32,108	32,098	32,108	32,098	32,108	32,098	32,108
Alternative Flood Risk Measure	25cm	DEFRA	25cm	DEFRA	25cm	DEFRA	25cm	DEFRA	25cm	DEFRA	25cm	DEFRA	25cm	DEFRA
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Flood Risk by Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region by Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: I consider alternative measures of flood risk. The odd-numbered columns report regression results using flood risk defined as the annual probability of flood depth exceeding 25 cm, in contrast to the 10 cm threshold used in the main measure. The even-numbered columns report results using flood risk levels from the Department for Environment, Food and Rural Affairs (Defra). *Green Donation* indicates if one donates to environmental charities. *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. *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 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 F.16: 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)	1.041	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 outcomes. *Green Donation* indicates if one donates to environmental charities. *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. *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 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 F.17: The Effect of Flood Exposure (sample: only those who have lived within 400 meters of a flood)

	(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**	0.022*	0.083	-0.263	-0.111	0.093	0.020
	(0.012)	(0.012)	(0.125)	(0.194)	(0.156)	(0.164)	(0.140)
Indirect Flood Exposure							
000 < distance ≤ 200 m	-0.005	-0.005	0.094	-0.161	0.022	-0.029	-0.052
	(0.005)	(0.005)	(0.086)	(0.147)	(0.144)	(0.132)	(0.136)
Observations	48,210	10,338	2,307	1,458	1,458	1,458	1,458
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region by Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Flood Risk by Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents regression results based on a sample of individuals who have ever lived within 400 meters of a flood. The comparison group includes those living between 200 and 400 meters, excluding individuals who live farther away. *Green Donation* indicates if one donates to environmental charities. *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. *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. Standard errors, clustered at the postcode level, are provided in brackets. *** indicates significance at 1%, ** at 5%, and * at 10%.

F.4 Measure of Moral Universalism

Table F.18: 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 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.

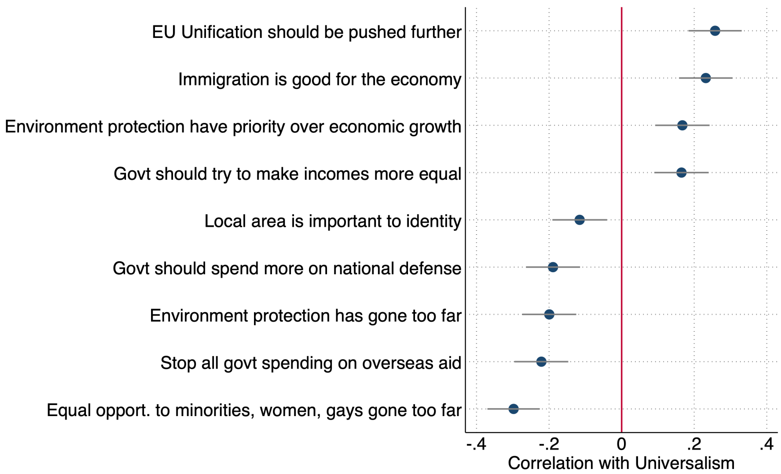


Figure F.3: Correlation with the Measure of Universalism

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.