Come Rain or Shine: Extreme Weather, Climate Attitudes and Behaviour *

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Abstract

Whether personal experience with extreme weather translates into climate action remains unclear. This paper estimates the short- and long-run effects of local temperature anomalies on climate beliefs and carbon-related behaviour, by leveraging the UK Household Longitudinal Study merged with high-resolution temperature anomalies. Using quasi-random interview timing around these shocks, I find that extreme heat increases climate concern in the short run (by about 3% of the mean in beliefs), but the effect fades within 2-3 months. Exploiting variation in cumulative anomaly exposure over multiple years, I then show that sustained exposure works in the opposite direction: while pro-environmental beliefs trend upward over the sample period, the most exposed individuals gain about 2 points less on a 0-100 belief scale than comparable unexposed households, with the attenuation concentrated among those with higher baseline concern and greater material stakes. Behavioural responses show a persistent belief-action gap and only small long-run adjustment. Overall, the results suggest that experience with extreme temperatures is an unreliable driver of climate action.

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1 Introduction

Climate change is accelerating, leading to more extreme events, including heatwaves, cold spells, floods, and droughts (IPCC, 2022). As these events become more common, individuals are increasingly exposed to the direct consequences of a changing climate. A central question is how such exposure shapes beliefs and behaviour: do individuals update their views about climate change in response to what they experience, do those responses persist, and do they translate into changes in how people act? Answering these questions is not straightforward. Climate change is not directly observable; individuals must form beliefs about a global, long-run phenomenon from noisy and local signals, and the same experience can be interpreted in very different ways depending on context and prior views.

I study these dynamics in the United Kingdom, exploiting geo-referenced data from the UK Household Longitudinal Study. The survey provides repeated measures of climate-related attitudes and of self-reported pro-environmental behaviour for the same individuals over time, which I merge with high-frequency, high-resolution climate data. I measure temperature anomalies as standardized deviations from a 30-year local moving baseline, capturing how far an observed temperature departs from what is historically normal in a given place and season, rather than how warm or cold it is in absolute terms. Within this framework, I distinguish between moderate and extreme anomalies, and between hot and cold shocks. Moreover, the analysis involves two complementary outcomes: a climate beliefs index summarising individuals' views on the causes, severity, and urgency of climate change; a pro-environmental behaviour index capturing self-reported actions related to energy use, transport, and consumption. Taken together, these outcomes allow me to assess not only whether beliefs update in response to climate shocks, but whether such updating translates into behavioural change.

In the short run, identification exploits quasi-random variation in interview timing around local temperature anomalies; the analysis includes individual fixed effects, so belief and behavioural responses are identified from within-individual variation. Exposure to extreme heat increases climate concern, while cold anomalies have little effect on beliefs but reduce pro-environmental behaviour. Belief responses to heat are strongest shortly after exposure, increase with the persistence of the heat event, and fade within a few months.

The long-run analysis uses long differences in cumulative exposure to temperature anomaly events between survey waves. While pro-environmental beliefs trend upward over the sample period, cumulative exposure to positive anomaly events attenuates this growth. This negative effect on beliefs is stronger when exposure consists of longer-lasting anomaly spells, and increases monotonically with the number of heat events experienced. These long-run results are robust to concerns about endogenous residential sorting: anomaly exposure does not predict mobility, and the association persists when restricting to stayers only or to movers whose relocation is attributable to observable life events. Strikingly, this long-run negative effect on beliefs is opposite in sign to the short-run response, suggesting that repeated exposure to warm anomalies does not reinforce but, on the contrary, gradually erodes climate concern.

The evidence points to two different groups updating over time. In the short run, the increase in climate concern following extreme heat is concentrated among individuals with lower baseline concern (e.g., those consuming right-leaning media and those aligned with the more conservative parties). This pattern is aligned with standard updating: heat temporarily raises attention to climate change among more skeptical groups, i.e. those with lower priors. Similarly, repeated exposure to heat anomalies is consistent with evidence of a changing climate and should apriori reinforce concern. That it instead erodes beliefs is counterintuitive. A long-run negative belief response to repeated heat exposure can be then rationalized by motivated interpretation: individuals with the most psychological or material stakes may selectively reinterpret negative signals to dampen perceived long-run risk and alleviate anxiety (Bénabou and Tirole, 2016). Suggestive evidence is consistent with this interpretation, given that the negative effect on beliefs is strongest among individuals with higher baseline climate concern and among homeowners (a different set of individuals from those who exhibit short-run belief increases). These findings connect to a growing body of work on experience-based belief formation and the role of motivated reasoning in how individuals process climate-related information (e.g. Zappalà (2023)).

A large economics literature has studied the effects of weather and climate on economic outcomes (such as growth, productivity, health, migration, and conflict), yet comparatively little work examines how such shocks affect individual beliefs and preferences (Dell et al., 2014). This matters because climate change is not directly observable: individuals must infer its severity from noisy, localized signals. A literature in psychology documents that personal experience with unusual weather shifts perceptions of climate risk (see, among others, Sambrook et al. (2021); Dai et al. (2015); Spence et al. (2011); Demski et al. (2017)). These studies nonetheless face common limitations: they rely on cross-sectional designs and self-reported exposure, making it difficult to separate causal learning from recall bias; indeed, perceived weather conditions can diverge from objective measurements. Evidence using survey data on belief updating in response to climate shocks is more recent. Some studies find that affected individuals report higher climate concern following extreme events, but that these effects are short-lived (Arias and Blair, 2024) and strongly heterogeneous. Political affiliation and media framing explain much of the variation in belief responses (Djourelova et al., 2025), and subjective attribution of events to climate change, rather than exposure alone, drives policy support (Cologna et al., 2025). This heterogeneity is consistent with motivated reasoning: individuals often process climate-related information in ways that protect prior beliefs or identity (Druckman and McGrath, 2019), as documented in drought recollection in Bangladesh (Zappalà, 2023), such identity protection extends to economic identities, with long-run exposure to fossil-fuel extraction depressing climate beliefs (Dewitte, 2025). A related strand examines how extreme events interact with political environments: a heat wave in Sweden led to divergent belief updating across regions depending on local political context (Anderson and Robinson, 2024); disasters can increase support for incumbents when government responses are perceived as effective (Healy and Malhotra, 2009; Hilbig and Riaz, 2024); unusual local weather shifts online attention and pro-environmental congressional votes (Herrnstadt and Muehlegger, 2014); and climate disasters affect legislative behaviour, though effects are short-lived and concentrated among moderate legislators (Elliott et al., 2023). Together, these studies suggest that experienced climate shocks shape beliefs and evaluations without necessarily producing persistent changes in preferences or behaviour. A growing body of work documents a persistent gap between climate beliefs and climate-relevant actions. While many individuals acknowledge the reality and risks of climate change (Dechezleprêtre et al., 2025), stated concern responds more strongly to extreme events than actual behaviour does (Lohmann and Kontoleon, 2023; Xu, 2026), and interventions aimed at reinforcing climate beliefs have limited effects on behaviour (Vlasceanu et al., 2024; Galdikiene et al., 2026). The belief-action gap remains a central challenge for climate policy. The broader question of whether personal experience shapes beliefs in domains where rational agents should instead rely on aggregate information also connects this paper to a wider economics literature on experience effects. Malmendier and Nagel (2011) show that individuals who lived through macroeconomic downturns persistently take less financial risk, overweighting their own experience relative to long-run historical data; Malmendier and Nagel (2016) find that inflation expectations track personal price histories more closely than official statistics. The same logic applies here: a locally experienced heat wave is nearly uninformative about global climate trends (a fully informed agent should read the IPCC report rather than infer from this week's temperature) yet personal experience shapes beliefs and behaviour. This paper documents the conditions under which such experience-based updating occurs, and whether its effects persist.

This paper contributes to these literatures in several ways. First, it focuses on *temperature anomalies* rather than large-scale disasters, isolating effects from confounding local damages and institutional responses. Unlike disasters, temperature anomalies are frequent, locally salient, and increasingly common, yet particularly open to interpretation. I construct daily temperature anomalies at the neighbourhood level, standardized relative to a 30-year local baseline, capturing deviations from what is considered normal in a given place and season. This approach aligns with experience-based learning models emphasizing abnormal realizations as the psychologically relevant signal (Deryugina, 2013). Second, the availability of long individual-level panels from the UK Household Longitudinal Study allows me to trace both immediate and long-run responses to repeated climate exposure. Most existing studies rely on repeated cross-sections, limiting the ability to distinguish transient effects from persistent updating. By relating cumulative exposure to changes in beliefs and behaviour over several years, this paper provides some of the first evidence on whether repeated contact with climate anomalies leads to durable adaptation. Moreover, the rich complementary data in the survey (including media consumption habits, political affiliation, voting intentions, and housing tenure) further allow me to speak to mechanisms in a comprehensive way.

The remainder of the paper proceeds as follows. Section 2 describes the data, including the construction of high-resolution local temperature anomalies and the measures of climate beliefs and green behaviours drawn from the UK Household Longitudinal Study. Section 3 presents the short-run empirical design and evidence on belief updating around the timing of local temperature shocks, including identification validity checks. Section 4 studies longer-run belief dynamics using cumulative exposure to extreme temperature events, including tests for endogenous sorting. Section 5 discusses the mechanisms underlying these patterns. Section 6 examines how belief changes translate into behavioural outcomes, focusing on self-reported pro-environmental behaviour. Section 7 concludes.

2 Data

The analysis focuses on the United Kingdom, a setting characterized by accelerating climate change. Recent years have been unprecedented in the UK's climate history: the all-time highest temperature of 40.3°C was recorded on July 19, 2022, in Coningsby, Lincolnshire; 2022 was the warmest year on record, followed by 2023; and all ten of the warmest years have occurred within the past two decades (Kendon et al., 2020). More concerning still, the frequency and severity of extreme temperature events are increasing at a much faster pace than average temperature levels (Kendon et al., 2023). Constructing a high-frequency measure of temperature anomalies, this paper confirms these patterns, especially the increase in heatwaves intensity. In particular, the average extreme heat event increased from around 7 standard deviations above the local mean in 2009 to nearly 8.3 standard deviations in 2022. Beyond their physical consequences, these repeated shocks raise the question of how individuals interpret and adapt to climate experiences when exposure becomes frequent rather than exceptional.

To study the impact of weather shocks on beliefs and behaviour, I construct temperature anomalies using weather data, and match them with survey data on beliefs about climate change and green preferences. The level of granularity, for all observations, is at the Lower Layer Super Output Area (LSOA) level (2001 Census), which are small geographical statistical areas with a population between 1,000 and 3,000 residents.

2.1 Temperature Data

Rather than estimating the average effect of temperature increases, this paper focuses on identifying discrete, salient weather shocks and treating them as a source of quasi-random variation in local climate exposure. To this end, I construct a high-frequency measure of temperature anomalies using gridded daily data from the British Atmospheric Data Centre, which report maximum air temperatures at a 5km × 5km resolution[1]. An anomaly in LSOA j and day t is defined as:

$$\text{Anomaly}_{jt} = \frac{\text{Temperature}_{jt} - \text{Historical Temperature}_{mj}}{\sigma_{mj}}$$

where the numerator captures the deviation of the observed temperature on day t from the historical (climatological) average for that location and calendar month. The historical average is calculated using a 30-year moving window that updates annually to reflect the most recent three decades of temperature data[2]. This choice is to better capture the perceived extent of the anomaly, as individuals are more likely to make comparisons with relatively recent climatological patterns. Dividing by the local monthly standard deviation of historical temperatures, σ_{mj}, standardizes the anomaly, ensuring comparability across areas with different levels of baseline weather volatility[3]. In essence, this measure captures how many standard deviations the observed temperature deviates from the local historical mean.

While the standardized anomaly measure allows for continuous variation in climate exposure, my focus is on identifying discrete, high-salience weather events; events that are most likely to be perceived as meaningful departures from local climatic norms. Accordingly, I

[1] Such polygons often include more than one LSOA; LSOAs are assigned to each polygon based on where the majority of their territory stands.

[2] E.g. for temperature readings from 2009, the reference period is 1979-2008; for temperature readings from 2010, the reference period is 1980-2009; and so on.

[3] A temperature anomaly of 5 degree Celsius is more salient in a historically stable climate zone than in a location where large temperature swings are common.

restrict the analysis to the top 0.5% of positive and bottom 0.5% of negative anomalies in the distribution of daily LSOA-level temperature deviations, yielding a final sample of the most extreme 1% of temperature shocks. Within this set, I distinguish between *moderate* and *extreme* anomalies based on event intensity: moderate positive (negative) anomalies correspond to events between the 99.5th and 99.95th percentiles (between the 0.5th and 0.05th percentiles) of the local anomaly distribution, while extreme positive (negative) anomalies are those exceeding the 99.95th percentile (below the 0.05th percentile). This trimming strategy isolates events that are both rare and salient, and which are more likely to be cognitively registered as "climate events." Importantly, this approach captures relative deviations from local climate baselines rather than absolute temperature levels. Evidence from Google search behaviour seem to support this interpretation: in a case study of September 2020, relative searches for "*climate change*" spike on the day of an anomaly, even when absolute temperatures are not unusually high, suggesting that anomalous deviations, rather than temperature levels per se, may drive perceived salience of these events (Appendix A.1, Figure A.1).

Between 2009 and 2022, the maximum anomaly was 14.43 units of standard deviations larger than the local historical monthly temperature[4]; the lowest anomaly was 13.72 units of standard deviations smaller than the historical average[5]. On average, LSOAs experience 5 salient anomalies (positive or negative) per year. The overall intensity in positive extreme anomalies is increasing over time, as evident from Figure 2.1, while the intensity of negative extreme anomalies remained relatively stable, and both trends are consistent with recent climatological evidence (Kendon et al., 2023). In terms of spatial distribution (Appendix A.3, Figure A.3), coastal areas seem to have been disproportionally affected by positive anomalies, and northern regions, like Scotland and Northern Ireland, have also experienced more of these extremes.

2.2 Cumulative Exposure for the Long-Run Analysis

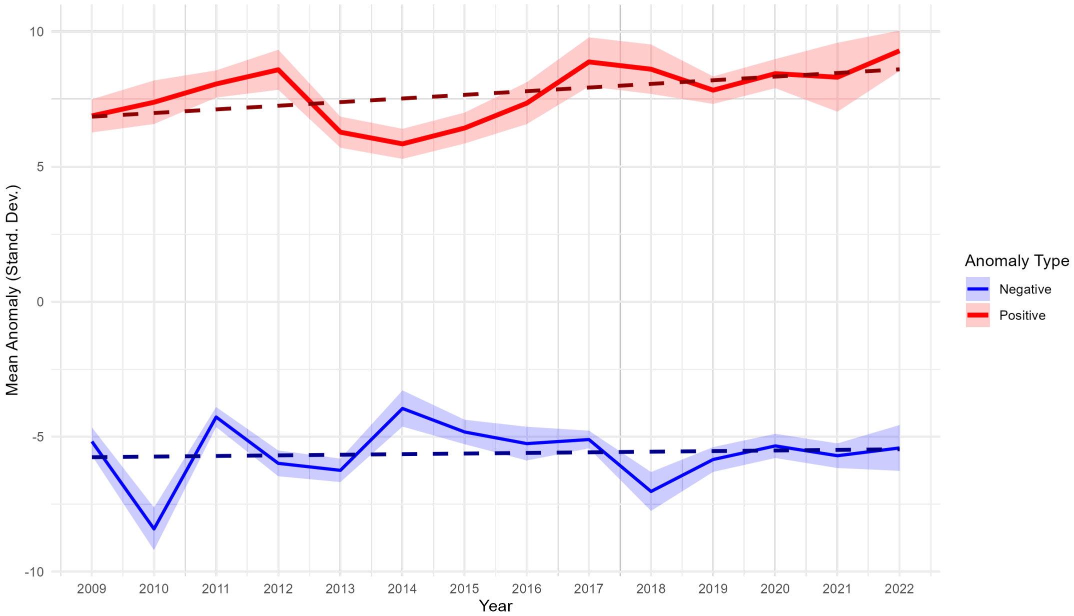
For the long-run analysis, I construct measures of cumulative exposure to temperature anomalies between Wave 4 and Wave 10 for respondents who do not change location between waves (on average six years separate the two waves)[6], the two waves in which belief and behaviour questions are asked. Table 2.1 summarizes these measures and the main characteristics of the underlying events. Exposure is measured both in terms of the total number of anomalous days and the number of distinct anomaly events (spells). On average, individuals experience about 22 anomalous days over the period, roughly evenly split between hot and cold anomalies. An anomaly event is defined as a contiguous spell of days during which daily temperature deviates from the local baseline beyond a given threshold (spells can be as short as one day). In the main long-run analysis, I focus on positive anomalies above the 99.5th percentile and negative anomalies below the 0.5th percentile of the local anomaly distribution, analogous to the thresholds used in the short-term analysis and chosen to isolate unusual deviations that are plausibly remembered

[4]A temperature of 25.62 degree Celsius was registered in South Harris, Scotland, the 27th of May 2012; the average temperature for that month is 11.69 degree Celsius and there is low historical variability (monthly standard deviation is 0.97).

[5]The 21st of December 2010, a maximum temperature of -13.17 degree Celsius was registered in Quilly Townland, Northern Ireland; the average maximum local temperature for that month is 7.59 degree Celsius, with historical variability of 1.87.

[6]Fieldwork dates for Wave 4: 03 January 2012–19 May 2014; for Wave 10: 09 Jan 2018–17 May 2020.

Figure 2.1: Temperature Anomalies - Trend Over Time



Notes: The figure displays average annual positive (red) and negative (blue) temperature anomalies in the UK between 2009 and 2022. Solid lines show yearly averages, while dashed lines indicate linear time trends for each anomaly type.

by respondents. The table also reports intensity and duration of anomaly spells. The main analysis treats all positive (negative) anomalies symmetrically, without differentiating into extremes. For each individual, cumulative exposure aggregates the number of events experienced between survey waves, and intensity and duration summarize the average severity and length of the spells.

2.3 Individual Survey Data

To construct the main outcome variables, I draw on data from Understanding Society (UKHLS), a longitudinal survey of approximately 45,000 households in the UK, conducted roughly annually since 2009 (University of Essex, Institute for Social and Economic Research, 2023). Crucially, the survey fieldwork is equally distributed throughout the calendar year[7], resulting in large variation in interview timing across households. This staggered structure allows me to exploit quasi-random variation in exposure to recent climate shocks, and to have a sufficient sample around the occurrence of extreme weather events within relatively short time windows. The survey includes detailed questions on climate-related beliefs, environmental attitudes, and self-reported behaviours. In addition, most waves contain modules eliciting political preferences, voting intentions and media consumption habits, including respondents' primary source of news and the specific outlet they rely on (whether through television, newspapers, or online platforms).

Outcome Variables. The empirical analysis considers multiple outcome variables, corresponding to both short- and long-term responses to climate shocks. For what regards

[7] Appendix Figure A.2 shows the distribution of interview dates in the analysis sample.

Table 2.1: Summary Stats of Anomaly Exposure and Event Characteristics (W4-W10)

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**	**N**
(A) Cumulative Days of Anomalies					
Any Anomalies	22.39	12.64	0	90	19,873
Hot Anomalies	11.07	7.71	0	51	19,873
Cold Anomalies	11.32	6.34	0	42	19,873
(B) Number of Events (Spells)					
Total Events	17.15	9.11	0	56	19,873
Hot Events	8.00	4.93	0	29	19,873
Cold Events	9.14	5.06	0	29	19,873
(C) Average Intensity (SD Anomaly)					
Hot Events	7.11	0.33	5.58	8.65	17,174
Cold Events	-5.26	0.33	-6.81	-3.72	17,182
(D) Average Duration (Days per Event)					
Hot Events	1.33	0.23	1	2.71	17,174
Cold Events	1.23	0.14	1	2.50	17,182

Notes: Panel A: count of days on which the respondent's LSOA experienced a temperature anomaly (deviation from local historical norm) in the given category, summed between the interview dates of Wave 4 and Wave 10. Panel B: number of distinct anomaly *events* (contiguous spells of anomalous days). "Hot Events" counts all positive-anomaly spells; "Cold Events" counts all negative-anomaly spells; "Total Events" is their sum. Panels C and D: average intensity (in standard deviations from local mean) and average duration (days per spell) among individuals with at least one event in that category.

individuals' environmental opinions, I construct index measures that summarize responses to a broad set of environment-related survey items. The dataset includes 21 relevant variables, 10 measuring environmental beliefs and 11 measuring self-reported *green* behaviour (see Appendix A.1 for a complete list), asked in waves 4 and 10 of the survey. Belief items include, for example, whether respondents agree that their behaviour contributes to climate change or whether the environmental crisis has been exaggerated. Behavioural items capture the frequency of specific actions, such as switching off lights in unused rooms or taking fewer flights when possible. To reduce dimensionality without imposing subjective weights, I build two separate indices: one for beliefs and one for behaviours. All items were recoded so that higher values correspond to more pro-environmental views. Variables where higher scores indicate weaker environmental concern were reverse coded. The *Beliefs Index* aggregates a set of binary variables capturing agreement with statements about climate change causes, consequences, and human responsibility. Given the binary nature of these items, I construct the beliefs index by taking the unweighted average across non-missing responses, yielding a measure on the [0,1] interval. This approach assigns equal importance to each belief item. The *Behaviour Index* is instead based on categorical variables measured on a Likert scale from 1 ("never") to 5 ("always"), representing the frequency of environmentally friendly behaviours (e.g., recycling, use of public transport). To preserve sample size, some missing values were imputed using the nearest integer to the mean response for each item. I then apply Principal Component Analysis (PCA) to the full set of behaviour variables and use the loadings from the first principal component, which captures the largest share of common variance, to construct a weighted index. The final behaviour index is a linear combination of standardized responses, with weights proportional to their PCA loadings[8], and normalized to range from 0 (least environmentally friendly) to 1 (most environmentally friendly). This approach follows established methods for constructing optimal indices when many related measures are available (Acemoglu et al., 2014; Bruhn et al., 2018; Dasgupta and Kapur, 2020; Sánchez de la Sierra, 2020). To assess robustness, I also construct a simple average-based behaviour index (equally weighted and normalized). The correlation between the PCA-based and the unweighted index is high (87%), although the PCA-based index is more left-skewed and may be viewed as a conservative measure (see Appendix A.5 for full PCA results).

3 Short Term Evidence on Belief Updating

The first part of the empirical analysis focuses on the immediate reactions (within one month) to temperature anomalies. To identify these effects, I exploit quasi-random variation in the timing of the survey implementation, relative to the occurrence of extreme local weather anomalies. Crucially, survey interviews are conducted continuously throughout the calendar year and independently of local weather conditions. Moreover, the precision of the climate data allows me to exploit geographic proximity to the event.

Because interview dates are staggered throughout the year and are not scheduled in response to local weather, some respondents are interviewed shortly before a temperature anomaly occurs in their LSOA while others are interviewed shortly after. Conditional on individual, region-by-season, and year fixed effects, this variation in timing is plausibly quasi-random. The estimates are identified from within-person variation: the same individual is observed in different waves, sometimes in the 30 days following a local anomaly and sometimes when no recent anomaly has occurred. Restricting the analysis to a 30-day window around each event limits confounding from other contemporaneous shocks, and the within-person comparison via individual fixed effects further absorbs time-invariant confounders. The short-run estimating equation is:

$$Y_{it} = \alpha_i + \delta_{r\times s} + \eta_y + \beta_1 Post_{it}^{pos,mod} + \beta_2 Post_{it}^{pos,ext} + \beta_3 Post_{it}^{neg,mod} + \beta_4 Post_{it}^{neg,ext} + X_{it}'\gamma + \varepsilon_{it}$$

where Y_{it} corresponds to one of the two outcomes described above (indexes of climate beliefs and individual self-reported green behaviours) for respondent i at interview t. Temperature anomalies and the distinction between moderate and extreme categories are defined in Section 2. Each indicator $Post_{it}^{k}$ equals one if respondent i's interview falls within the 30 days *following* a local anomaly of type k in their LSOA, and zero otherwise. Because all four indicators enter the equation simultaneously, each β_k captures the effect of type-k exposure conditional on any concurrent exposure to the other types. The comparison group comprises observations in which all four post-event indicators are simultaneously zero, i.e. respondents not interviewed within 30 days after any anomaly of any type[9]. The coefficients β_k thus capture the within-individual effect of being interviewed in the 30-day post-event window for anomaly type k, identified from quasi-random variation in interview timing relative to anomaly occurrence.

[8] For details, check Appendix A.5.

[9] A single indicator for observations outside all four event windows simultaneously is included in all specifications; dropping it leaves estimates unchanged.

Individual fixed effects α_i additionally absorb all time-invariant unobserved heterogeneity across respondents, such as baseline environmental preferences or stable political orientation. Region-by-season fixed effects $\delta_{r\times s}$ control for seasonal shocks common to broader geographic areas (there are in total twelve regions in the UK), while year fixed effects η_y capture aggregate time trends and nationwide shocks. The vector X_{it} includes time-varying respondent characteristics, namely age and age squared, income, marital status and presence of children, and occupation type. Standard errors are clustered at the local authority level.[10] Many climate events tend to affect multiple Lower Layer Super Output Areas (LSOAs) simultaneously within the same local authority. Moreover, local authorities are also the primary administrative bodies responsible for delivering public services and potentially managing the response to climate events within their jurisdiction; unlike LSOAs, which are primarily statistical units. The way a local authority's government body reacts to a climate event can shape the beliefs' updates of residents across the affected area.

Identification relies on one assumption: the timing of survey interviews relative to the anomaly events must be as good as random. This assumption is, by definition, untestable, but credible given the continuous and independent nature of fieldwork scheduling and the exogeneity of weather events. Moreover, to assess the plausibility of this identifying assumption, I conduct a set of balancing tests comparing pre-determined individual characteristics for respondents interviewed before and after the event (see Appendix B.5). The absence of systematic differences in observables provides evidence that treatment status is not driven by selection.

3.1 Short-Term Results

Table 3.1 presents the short-term effects of local temperature anomalies on environmental beliefs. Only exposure to extreme positive temperature anomalies (i.e. the most salient heatwaves[11]) increases the overall belief index by 0.016–0.017 points (on a normalized 0–1 scale). These are non-trivial effects, amounting to approximately 3% of the mean in beliefs. In contrast, exposure to extreme negative anomalies is associated with a negative point estimate, but the effect is imprecisely estimated. One possible interpretation is that cold shocks do not convey a clear signal about climate change, and may even reduce perceived relevance of climate risks. I return to this mechanism when examining short-run behavioural responses. More moderate temperature deviations, both positive and negative, yield small and statistically insignificant coefficients, suggesting that not all deviations from seasonal norms are perceived as meaningful or informative signals. Results for individual belief items are reported in Appendix B.1, where no single component drives the aggregate effect. Instead, the estimates point to a coherent shift in a latent belief construct related to pro-environmental attitudes.

Figure 3.1 explores heterogeneity in the short-run belief response to extreme positive temperature anomalies along two dimensions: the duration of the heat event and its timing relative to the interview date. The estimates are obtained by interacting the extreme positive anomaly indicator from the baseline specification with indicators for anomaly

[10] In the UK, a local authority is a government body responsible for the administration of local public services within a defined geographic area. Local Authorities are responsible for functions such as education, social services, housing, local planning, transport, and environmental regulation, and they represent the primary level of local government below the national level.

[11] They represent the highest 0.05% of all positive anomalies

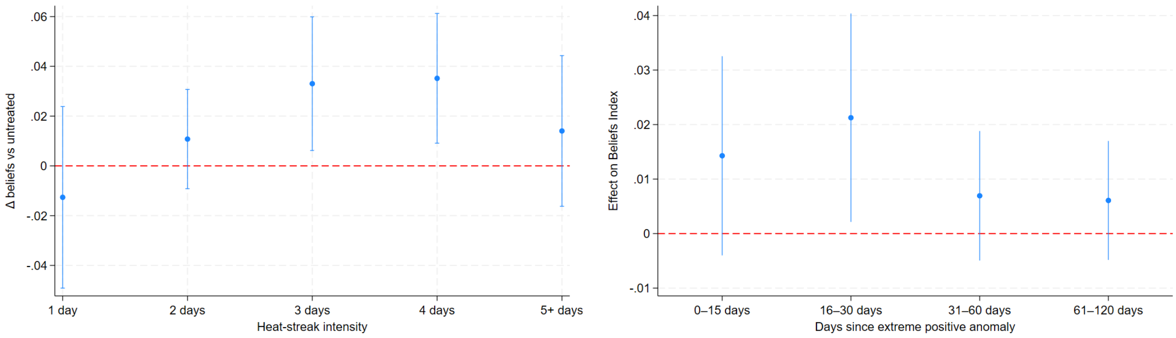
Table 3.1: Short-Term Effect of Temperature Anomalies on Beliefs Index

	Beliefs Index (AVG)	
Post Moderate +	-0.0045	-0.0045
	(0.0030)	(0.0031)
Post Extreme +	0.0165**	0.0170**
	(0.0084)	(0.0084)
Post Moderate −	0.0021	0.0021
	(0.0033)	(0.0034)
Post Extreme −	-0.0077	-0.0077
	(0.0070)	(0.0070)
Control Mean	0.5445	0.5445
N	36,144	36,144
R^2	0.7726	0.7728
Individual FE	✓	✓
Region × Season FE	✓	✓
Controls	—	✓

Notes: Standard errors clustered at the Local Authority level in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Estimates show the effect of being interviewed within 30 days after a temperature anomaly. The control mean is the average outcome for observations not in the 30-day post-event window, within the regression sample.

duration (left panel) and with bins for the time passed between the anomaly and the interview (right panel). For details on the specifications, refer to Appendix B.2 and B.3. The left panel shows that belief updating increases with the persistence of the heat event: short heat streaks are associated with small and imprecise effects, while anomalies lasting three or more consecutive days generate substantially larger and statistically significant increases in the beliefs index. Hence sustained exposure, rather than isolated temperature spikes, is more likely to be perceived as a meaningful climate signal. Moreover, the right panel documents a clear temporal decay in the effect. The belief response is strongest when interviews occur shortly after the anomaly and gradually attenuates as the time since exposure increases, becoming statistically indistinguishable from zero beyond 30 days (validating the choice of a 30-day window in the baseline specification).

Figure 3.1: Effects by Anomaly Duration & Anomaly Timing



Notes: The left panel plots estimated effects of extreme positive temperature anomalies on the beliefs index by the duration of the heat streak (number of consecutive days above the extreme threshold). Estimates for the longest streaks are imprecise owing to the small number of such events in the sample. The right panel plots coefficients on four mutually exclusive indicators for the time elapsed since the extreme positive anomaly (0–15, 16–30, 31–60, and 61–120 days). Vertical bars denote 90% confidence intervals. The dashed horizontal line indicates zero effect.

Moreover, Appendix B.1, Table B.2, examines whether temperature anomalies generate short-run changes in a broad set of well-being outcomes, including health satisfaction, happiness, optimism, sleep quality, and emotional states. In principle, temperature could affect beliefs through a direct channel: heat or cold might alter mood, well-being (Feddersen et al., 2016) and decision-making (Escobar Carias et al., 2024), which could in turn shift reported climate concern even in the absence of any climate-specific updating. Across the well-being outcomes, however, the estimated effects of both moderate and extreme temperature anomalies are generally statistically insignificant. This lack of response suggests that extreme temperature shocks do not operate primarily through broad changes in mood or general well-being.

Appendix B.7 probes the temporal persistence of the short-run effects by progressively extending the treatment window from 1 to 12 months. For beliefs, the extreme heat coefficient declines monotonically, from 0.017 within one month to 0.009 within six months, and becomes statistically indistinguishable from zero at twelve months. This rapid decay is consistent with the attention-based interpretation proposed earlier: anomaly exposure generates a short-lived increase in salience rather than persistent belief revision. Finally, Appendix B.8 verifies that the main short-run findings are not sensitive to the exact intensity threshold used to classify extreme anomalies.

3.2 Short-Run Heterogeneity by Political Alignment and Media

This subsection examines heterogeneity in the short-term belief response to extreme positive temperature anomalies. Table B.6 reports heterogeneous short-term effects of extreme positive temperature anomalies on the beliefs index by political alignment and media orientation[12]. Despite a strong scientific consensus, public opinion on climate change remains polarized, particularly with respect to preferred policy responses (Gounaridis and Newell, 2024), fueling an ideological backlash against climate policy (Bosetti et al., 2025). In this context, the media environment plays a central role in shaping how environmental

[12]For details on the categorization of these two variables, please refer to Appendix B.4.

signals are perceived. Partisan media outlets have been shown to selectively report or frame weather anomalies in ways that align with ideological narratives (Beattie, 2025; Mastrorocco et al., 2023; Ash et al., 2023), implying that extreme weather may function as an attention shock whose impact depends on pre-existing beliefs and information filters.

I find that the short-run belief response to extreme heat is concentrated among groups with lower baseline levels of climate concern[13]. Among media consumers, individuals exposed to right-leaning media exhibit the largest and most precisely estimated increase in the beliefs index (0.031, $p < 0.05$), followed by centrist media consumers (0.024, $p < 0.10$); responses among left-leaning media consumers, who display the highest baseline concern, are negative and statistically indistinguishable from zero. The political alignment results point in the same direction: right-aligned respondents show a statistically significant increase (0.027, $p < 0.10$), while left-aligned respondents do not. This asymmetry suggests a short-run catch-up effect: extreme temperature realizations temporarily narrow pre-existing belief gaps by increasing attention among more skeptical individuals. The absence of strong responses among already concerned groups thus implies diminishing marginal effects of additional climate-related information. This is consistent with standard updating logic: individuals with lower priors respond more strongly to informative signals about the state of the world, while those with already high concern do not need to revise their priors. This pattern also suggests that even among those exposed to more skeptical media narratives, sufficiently extreme climatic events can still induce belief updating, even if temporary.

3.3 Identification Validity

The short-run strategy relies on interview timing being quasi-random with respect to local temperature anomalies. Appendix B.5 provides direct evidence through balancing tests comparing pre-determined individual characteristics between respondents interviewed before and after a temperature anomaly. Across most demographic and socioeconomic variables (including age, income, gender, employment status, education, marital status, and presence of children) treated and control respondents are statistically indistinguishable, supporting the plausibility of the identifying assumption. The one exception is maximum temperature on the interview day, which is mechanically related to anomaly occurrence.

A complementary check exploits the temporal structure of the design. Appendix B.6 replaces the treatment variables with *lead* anomaly indicators, temperature events occurring 1–30 days *after* the interview date, which should have no effect on current beliefs if interview timing is exogenous. Consistent with this, lead coefficients are mostly small and statistically insignificant.

4 Long Term Evidence on Belief Updating

This section examines whether and how repeated exposure to temperature anomalies shapes climate beliefs and behaviours over longer horizons. Figure C.1 in Appendix C.1 documents two simple patterns. First, between Wave 4 and Wave 10 respondents become,

[13] Unconditional means of the beliefs index differ across groups. By media orientation, the average beliefs index equals 0.557 among left-leaning media consumers, 0.549 among centrist media consumers, and 0.522 among right-leaning media consumers. By political affiliation, the corresponding means are 0.559 for left-wing respondents, 0.572 for centrist respondents, and 0.517 for right-wing respondents.

on average, more pro-environmental in their beliefs, and climate anxiety and expectations about future impacts also rise[14]. Second, aggregate behavioural changes are mixed, with some actions increasing and others remaining stable. These unconditional trends, however, are not informative about the role of cumulative heat exposure. In particular, belief changes between Wave 4 and Wave 10 are positive across all exposure groups and show no clear gradient with exposure (Table 4.1), despite sizeable differences in baseline belief levels. This is consistent with a common time trend in beliefs that can mask heterogeneity in how beliefs evolve relative to baseline. At the same time, the dispersion of belief changes increases with the number of heat events, suggesting more heterogeneous updating under repeated exposure. Motivated by this pattern, the remainder of this section uses a within-individual long-difference specification to net out common trends and baseline heterogeneity and assess whether repeated exposure to temperature anomalies affects belief updating over time.

Table 4.1: Belief Levels, Changes, and Dispersion by Cumulative Heat Exposure

Heat Exposure	Bel. (Wave 4)	Bel. (Wave 10)	Δ Bel. (W10–W4)	SD(Δ Bel.)
No Events	0.598	0.651	0.054	0.206
Low (Q1)	0.581	0.636	0.055	0.208
Moderate (Q2)	0.583	0.634	0.053	0.217
High (Q3)	0.566	0.615	0.051	0.219
Extreme (Q4)	0.565	0.618	0.053	0.224

Notes: The table reports unconditional mean values of the beliefs index at Wave 4 and Wave 10, the corresponding mean change, and the standard deviation of changes in the belief index between waves, by quartiles of cumulative exposure to heat anomalies.

Cumulative exposure to temperature anomalies between Wave 4 and Wave 10 and the definition of anomaly events (spells) are described in Section 2; summary statistics are reported in Table 2.1. I estimate long-run effects using a long-difference specification that relates changes in individual outcomes to cumulative exposure to local temperature anomalies between the two waves, following a similar approach to Burke and Emerick (2016) (in agriculture).

Let y_{ij} denote the belief or behavioural outcome of individual i residing in location j. The main estimating equation is obtained by first differencing outcomes across waves:

$$\Delta y_{ij} \equiv y_{ij}^{W10} - y_{ij}^{W4}.$$

This transformation removes all time-invariant individual and location-specific confounders. Let C_{ij}^{Wt} denote cumulative exposure to temperature anomalies between the start of the panel and wave t. The long-difference specification can then be written as

$$\Delta y_{ij} = \beta_1 \Big(C_{ij}^{W10} - C_{ij}^{W4} \Big) + \Delta \varepsilon_{ij} = \beta_1 \Delta C_{ij} + \Delta \varepsilon_{ij},$$

where ΔC_{ij} captures the change in cumulative exposure to temperature anomalies between the two waves. Differently from the short-run specification, I decompose exposure only by

[14] Respondents are 15% more afraid of soon experiencing an environmental disaster, for instance, 23% more convinced that climate change is not an exaggeration, 12% more likely to say that the effects of climate change will be in the near future.

positive and negative events, without focusing specifically on extremes. The estimating equation therefore takes the following form:

$$\Delta y_{ij} = \beta_1 \, \Delta C_{ij}^{\text{Pos}} + \beta_2 \, \Delta C_{ij}^{\text{Neg}} + X_{ij}' \theta + \gamma_{\text{LA}} + \delta_m + \varepsilon_{ij},$$

where ΔC_{ij}^{k} denotes the number of events (i.e. continuous spells of an anomaly) individual i in location j is exposed to anomaly type k between Wave 4 and Wave 10. The dependent variable Δy_{ij} is the long difference in the beliefs index between Wave 4 and Wave 10, defined as the change in the beliefs measure multiplied by 100. The vector X_{ij} includes controls for changes in individual characteristics across waves, as well as interview conditions, including the number of days between the Wave 4 and Wave 10 interviews.[15] To ensure that the long-run estimates are not contaminated by the short-run responses documented above, X_{ij} also includes the counts of positive and negative anomaly events experienced in the twelve months prior to the second interview, as well as interview-day maximum temperature at both waves. Local Authority fixed effects γ_{LA} absorb common shocks at a more granular level than the regional one, while month-of-interview fixed effects δ_m account for seasonality in survey timing (in both waves). Standard errors are clustered at the Local Authority level.

This long-difference design leverages variation in climate exposure to study medium- to long-run responses, while differencing out all time-invariant individual and location-specific confounders. A remaining challenge for identification, however, is the possibility of non-random sorting across locations over time. If individuals systematically select into areas experiencing different climate trajectories based on unobserved preferences or constraints correlated with beliefs or behaviours, estimates of β_1 and β_2 may partially reflect compositional changes rather than pure exposure effects. While such sorting is likely limited over the relatively short horizon considered here and the non-disruptive and widespread nature of these events, it cannot be ruled out a priori. This concern is addressed in Section 4.2. A further limitation is that the design cannot rule out time-varying confounders correlated with geographic anomaly exposure over the 2012-2020 period. Shifts in the UK political and media environment, including the Brexit referendum, may have differentially affected areas with higher anomaly exposure through channels unrelated to temperature, and this remains a caveat to the long-run estimates.

4.1 Long-Term Results

Table 4.2 reports these long-difference estimates, pointing to a small but precisely estimated negative effect of repeated exposure to hot anomaly events on pro-environmental belief growth. Each additional hot event experienced over the period is associated with a statistically significant reduction in the belief index relative to unexposed individuals, while no corresponding effect is detected for cold events. The bottom panel of the table replaces the continuous exposure measure with indicators for quartiles of cumulative positive anomaly exposure, defined over the distribution of the number of distinct events experienced between Waves 4 and 10, with individuals experiencing no hot events as the reference group. The magnitude of this attenuation of belief growth[16] increases

[15] The distance between interviews is slightly heterogeneous across respondents: in the estimation sample, the mean is 2,188 days (approximately six years), with the 10th and 90th percentiles at 2,122 and 2,256 days, respectively (min 1,625; max 2,403).

[16] Remember that, over these six years, beliefs become greener on average; hence a negative effect should be interepreted as a reduction of this growth.

almost monotonically with the cumulative number of positive anomaly events individuals experience between Wave 4 and Wave 10. Moving from low to extreme exposure quartiles is associated with a steadily larger negative effect in the beliefs index. Appendix C.8 reports a robustness check that additionally includes interview-year fixed effects for both waves; the estimates are virtually unchanged. The results are also robust to replacing Local Authority fixed effects with region-level fixed effects or to omitting geographic controls entirely; estimated effects are slightly attenuated in magnitude but remain precisely estimated. Appendix C.2 confirms that the result is not driven by the choice to count distinct anomaly events rather than cumulative anomaly days.

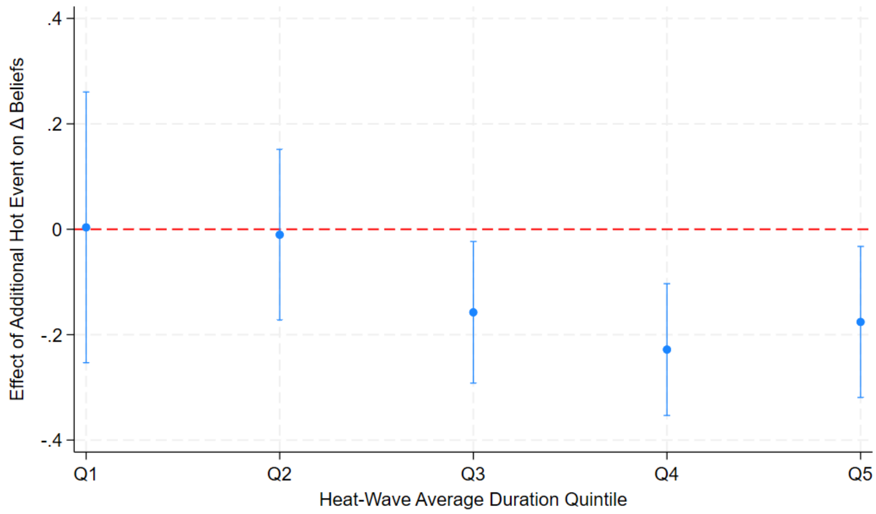
Table 4.2: Long-Difference Effect of Temperature Anomalies on Beliefs

	Δ Beliefs (0–100)
Δ *Hot Events*	-0.127***
	(0.0424)
Δ *Cold Events*	0.0591
	(0.0443)
Differences by quartile of cumulative positive anomaly exposure (ref. no hot events)	
Low exposure (Q1)	-0.744
	(0.615)
Moderate exposure (Q2)	-1.084*
	(0.640)
High exposure (Q3)	-1.362**
	(0.643)
Extreme exposure (Q4)	-2.085***
	(0.708)
N	12,833
R^2	0.0790
Local Authority FE	✓
Month FE	✓
Controls	✓

Notes: Standard errors clustered at the Local Authority level in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. The outcome is the long difference in the beliefs index between Waves 4 and 10 (scaled 0–100). The two panels correspond to separate specifications. The top panel reports coefficients from a long-difference regression relating changes in beliefs to changes in the cumulative count of positive and negative anomaly events. The bottom panel reports estimated coefficients by quartile of cumulative exposure to positive anomaly events between Waves 4 and 10, controlling for changes in cold event counts. Quartiles are defined over the distribution of the cumulative number of positive anomaly events in the estimation sample. The omitted category corresponds to respondents experiencing no hot anomaly events over the period. All specifications include Local Authority fixed effects and month-of-interview fixed effects for Wave 4 and Wave 10, as well as the full set of controls.

I then allow the effect of cumulative anomaly exposure to depend on the average duration of the anomaly spells experienced between waves. Figure 4.1 plots estimates from a specification in which cumulative positive anomaly exposure is interacted with quintiles of average anomaly spell duration, defined as the mean number of consecutive days above the extreme threshold during each positive anomaly spell. Negative belief updating is concentrated among individuals exposed to longer-lasting heat spells: effects are significant for the upper quintiles (Q3–Q5) while shorter-lived events show no detectable long-run impact (Q1–Q2). For details on this regression, refer to Appendix C.3.[17]

Figure 4.1: Long-Difference Effects by Anomaly Spell Duration



Notes: The figure plots estimated long-difference effects of positive temperature anomalies on the beliefs index by quintiles of average anomaly spell duration, measured as the mean number of consecutive days above the extreme threshold during each event. Each point represents the estimated marginal effect of one additional positive anomaly event on Δ beliefs, computed via the delta method from an interacted long-difference specification, including Local Authority fixed effects, month-of-interview fixed effects, and the full set of controls. Vertical bars denote 90% confidence intervals.

Appendix Table C.2 decomposes the aggregate effect across individual belief items. The dominant driver is EXAG (the belief that the environmental crisis has *not* been exaggerated) which is significant at all four exposure quartiles and grows monotonically from -0.039 (Q1) to -0.068 (Q4): more exposed individuals become progressively more likely to view climate risks as overstated. Also perceived disaster risk (DIS) shows a consistently negative pattern that intensifies with exposure, reaching significance at the highest quartile (-0.047). Two further items exhibit negative patterns, though less precisely estimated: whether it is worth the UK taking action on climate change (BRIT) and willingness to pay more for environmentally friendly products (PAYMORE). This is suggestive of motivated reasoning: what declines is individuals' assessment of the urgency and severity of climate risks, and the implied policy and spending responses that follow from it, while beliefs about causal mechanisms and personal values remain largely stable. We return to this interpretation in Section 5.1.

Appendix C.9 further replaces the anomaly-event counts with cumulative Cooling Degree Days (CDD) and Heating Degree Days (HDD), measures of total absolute thermal burden accumulated over the period, rather than deviations from local historical norms. Conditional on Local Authority fixed effects, neither variable is statistically significant. As discussed in that appendix, cumulative degree days largely reflect stable local climate and are therefore mostly absorbed by geographic fixed effects, leaving limited residual

[17] We also explored heterogeneity by average spell intensity but found no systematic pattern; see Appendix C.3.

identifying variation. The null is nonetheless consistent with the main interpretation: it is unexpected deviations from familiar temperatures, not total thermal exposure, that shapes how beliefs evolve.

4.2 Sorting Concerns in the Long-Run

A key identification concern for the long-run analysis is endogenous sorting: if individuals who are more (or less) climate-concerned systematically relocate to areas with different anomaly exposure between the two waves, the estimated effects could reflect selection into treatment. This section provides two complementary tests to address this threat.

I begin by testing whether anomaly exposure predicts residential mobility. If temperature anomalies do not affect the probability of moving, then sorting on anomaly exposure is less likely a concern. Table C.10 in Appendix C.7 reports two specifications. Column (1) tests whether cumulative pre-Wave 10 anomaly exposure predicts moving, controlling for Wave 4 socioeconomic characteristics and absorbing Local Authority fixed effects. Column (2) tests whether the change in treatment variables (the same Δ hot and Δ cold event counts used in the main long-difference specification) predicts mover status, conditional on the full set of controls and both LA and interview-month fixed effects. The results suggest that neither cumulative anomaly exposure (column 1) nor the change in treatment variables (column 2) significantly predicts mobility. All exposure coefficients are small in magnitude and not significant. Individuals exposed to more or fewer temperature anomalies are not differentially more likely to relocate between the two survey waves.

Even in the absence of selective migration on observables, one might worry that movers differ from stayers along unobserved dimensions that correlate with both anomaly exposure and belief trajectories. To address this, I estimate the main long-difference beliefs regression across four progressively restricted subsamples: (1) the full sample including both movers and stayers; (2) stayers only; (3) movers only; and (4) movers whose relocation can be attributed to observable life events (job changes, family formation, change in housing tenure etc.). The results in Table C.11 are consistent across subsamples. The negative association between cumulative hot events and belief growth is present in the full sample when including movers (column 1), among stayers only (column 2, analogous to the main specification), and among movers (column 3). The point estimate is qualitatively similar even when restricting to the subset of movers whose relocation can be explained by life events (column 4), though precision decreases with sample size.

5 Potential Mechanisms

The long-run findings present a puzzle. Repeated exposure should either raise climate concern among the under-informed or leave it unchanged among the well-informed (as it in the short-run). Two candidate mechanisms may account for a departure from the general upward trend. The first is motivated reasoning: when repeated heat raises the salience of climate risk, individuals for whom acknowledging that risk is psychologically or materially costly may selectively reinterpret the experience to preserve prior beliefs, implying negative updating concentrated among high-concern individuals and homeowners. The second is an economic channel: if temperature anomalies directly caused economic disruption, any observed link between anomaly exposure and the outcomes measured in the survey could reflect anomalies worsening the economy, which in turn may depress beliefs[18]. We test both explanations below. The evidence provides suggestive support for motivated reasoning, and no systematic support for an economic channel.

5.1 Motivated Reasoning

Table 5.1 tests whether the long-run negative effect of cumulative heat exposure on belief growth is stronger among individuals with higher baseline climate concern. Concern is measured via the Wave 4 item on whether the dangers of climate change have *not* been exaggerated (EXAG). I argue that this can be one of the most direct test of motivated reasoning: if individuals selectively reinterpret heat experiences to protect prior beliefs, exposure should be most dissonant for those most invested in the view that climate change is a genuine threat, giving them the greatest psychological incentive to reinterpret the signal. The results show a gradient in the predicted direction, though the joint test across concern levels does not reach conventional significance ($p = 0.19$). Among low-concern individuals, the effect is -0.083 ($p = 0.12$). The differential for high-concern individuals is -0.082^{*}, yielding an implied total effect of -0.165^{***}, roughly twice as large.

Table 5.1: Long-Run Heterogeneity in Belief Updating by Baseline Climate Skepticism

	Δ Beliefs (0–100)
Δ *Hot Events* (Low concern)	-0.083
	(0.054)
Δ *Hot Events* × Medium concern	-0.030
	(0.049)
Δ *Hot Events* × High concern	-0.082*
	(0.047)
Observations	12,833
Local Authority FE	✓
Month FE (W4 & W10)	✓
Controls	✓
Cold Events	✓

Notes: The dependent variable is the long-run change in the beliefs index between Waves 4 and 10. Concern is measured using Wave 4 responses to whether the dangers of climate change have *not* been exaggerated (EXAG): *low concern* (disagrees or neutral, omitted category), *medium concern* (agrees), *high concern* (strongly agrees). The first row reports the base effect for the low-concern group; the × Medium and × High rows are interaction coefficients reporting the differential effect relative to low concern. Implied total effects: -0.083 (low), -0.113^{**} (medium), -0.165^{***} (high). All specifications include Local Authority fixed effects, month-of-interview fixed effects for Wave 4 and Wave 10, controls, and cumulative cold events. Standard errors clustered at the Local Authority level. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Additional evidence comes from heterogeneity by material stakes. Table 5.2 shows that the negative association between heat exposure and beliefs is concentrated among homeowners, while it is small and statistically insignificant for non-owners. Homeownership is a channel through which climate change can affect long-term economic welfare, given that property

[18] A large literature in political economy documents that economic hardship may shift political preferences in a conservative or anti-establishment direction (Funke et al., 2016; Fetzer, 2019), for instance.

values, insurance costs, and exposure to environmental risks are directly tied to climatic conditions, as documented by a growing literature linking climate risk to housing markets (Bernstein et al., 2019; Baldauf et al., 2020). One possible interpretation is that homeowners face stronger incentives to discount or reinterpret signals of climate change that would otherwise imply future losses. The stronger negative updating observed among homeowners is thus consistent with motivated reasoning linked to material self-interest, complementing the anxiety-based pattern above. As reported in the table footnote, the formal test of equality between owner and non-owner marginal effects yields $p = 0.24$; this result should therefore be read as suggestive rather than conclusive.

Table 5.2: Long-Run Heterogeneity by Homeownership Status

	Δ Beliefs (0–100)
Δ *Hot Events* - Non-owner	-0.080
	(0.052)
Δ *Hot Events* - Homeowner	-0.142***
	(0.046)
Observations	12,833
Local Authority FE	✓
Month FE (W4 & W10)	✓
Controls	✓
Cold Events	✓

Notes: The dependent variable is the long-run change in the beliefs index between Waves 4 and 10. Each row reports the average marginal effect of cumulative heat exposure estimated separately for non-owners and homeowners (homeownership measured at Wave 4), from a single regression with the full set of controls and fixed effects. Standard errors clustered at the Local Authority level. A formal test of equality between the two marginal effects yields $p = 0.24$; the homeowner effect is nonetheless precisely estimated ($p = 0.002$). $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

One may worry that the heterogeneity by baseline concern reflects a ceiling effect rather than motivated reasoning: high-concern individuals already score near the top of the beliefs index at Wave 4, leaving mechanically less room to grow, regardless of what they experience. A direct ceiling test using EXAG is not feasible, however, since EXAG is itself one of the ten items composing the beliefs index. To address this, Table C.8 in Appendix C.5 exploits an alternative concern measure whose components are explicitly excluded from the beliefs index: a climate anxiety indicator (ANXIOUS) constructed from two questions in the survey, asking whether the respondent expects climate change to cause serious consequences within 200 years and within 30 years. Respondents are classified as *not anxious* (expects impacts on neither horizon), *moderately anxious* (expects long-term but not near-term impacts), and *highly anxious* (expects impacts on both horizons). The logic of the test is standard: under ceiling effects, the differential between anxious and non-anxious individuals should be negative and significant even in the zero-exposure group; under motivated reasoning, it should only emerge with heat. The results favour motivated reasoning: the coefficient on highly anxious in the no-events column is -0.005 ($p = 0.99$), indistinguishable from zero, and only turns significantly negative in columns 2-5. A ceiling effect cannot produce this pattern.

A separate concern is that positive temperature anomalies in the UK, particularly in summer, may be experienced as pleasant weather rather than as climate signals, which could confound the motivated-reasoning interpretation. If the negative effect on belief growth simply reflected individuals perceiving summer warmth as enjoyable rather than alarming, it should be concentrated in summer months. Table C.9 in Appendix C.6 tests this directly by re-estimating the main long-difference specification with separate exposure counts for summer (June-August) and non-summer hot moderate events. The negative effect is concentrated entirely in non-summer months (coefficient -0.161, $p = 0.012$), while summer events yield a small, insignificant estimate (-0.048, $p = 0.598$).

5.2 Economic Channels

A precondition for examining whether economic conditions moderate belief responses to climate signals is to establish whether anomalies themselves affect local economic outcomes. To test this hypothesis, I merge the individual-level survey data with Local Authority-level indicators of economic activity, specifically annual unemployment rates from the ONS Annual Population Survey and Gross Value Added from the ONS Regional Accounts. Table C.6 in Appendix C.4 reports the effect of temperature anomaly counts on four local economic indicators, estimated from a two-way fixed effects panel at the Local Authority-year level, covering the period 2009-2022. The specification includes both LA and year fixed effects. Standard errors are clustered at the Local Authority level. The results are in line with the idea of these events not being fundamentally disruptive. The majority of coefficients are small in magnitude and statistically insignificant. While hot anomaly days show a significant negative association with the unemployment rate, the magnitude is negligible: at the sample mean of roughly 11 hot anomaly days over the 13-year period, the implied cumulative effect on the local unemployment rate amounts to just 0.008 percentage points. In the UK context over this period, temperature anomalies do not seem to meaningfully disrupt local economic activity.

Building on this result, I now test whether long-run belief adjustment in response to cumulative anomaly exposure varies with local economic conditions. The results of this analysis, shown in Table C.7 of Appendix C.4, are clear: none of the interaction terms is statistically significant across any specification. Whether economic conditions are measured as average unemployment levels (column 2), changes in unemployment (columns 3 and 5), or GVA decline (column 4), there is no evidence that the belief response to cumulative anomaly exposure differs across areas with stronger or weaker local economies. This pattern is inconsistent with a competing mechanism, whereby individuals in economically struggling areas would exhibit a stronger belief decline in response to anomalies. Instead, the results suggest that the long-run attenuation of belief growth operates through channels that are independent of the local economic context and perhaps are more linked with the cognitive mechanisms described earlier, such as motivated reasoning.

6 From Beliefs to Behaviour

An important open question, however, is whether and how these belief updates translate into changes in individual behaviour. I begin by replicating the short-run analysis using the index of self-reported pro-environmental behaviours as the outcome. This is constructed from self-reported everyday environmental behaviours, such as energy conservation, consumption choices, transport habits, and travel decisions, that directly affect individual carbon footprints. Unlike the belief index, which captures perceptions, responsibility, urgency, and stated willingness to act, the behaviour index reflects realized (or at least reported) actions that may be subject to costs, habits, and constraints. As such, belief updating need not map one-to-one into behavioural change.

Table 6.1 reports the short-run effects of temperature anomalies on the *behaviour* index. In contrast to the belief responses, exposure to extreme positive temperature anomalies does not generate a statistically significant increase in pro-environmental behaviour in the short run. This suggests that salient heat events, while sufficient to update climate beliefs, are not immediately translated into behavioural adjustments. Strikingly, extreme negative temperature anomalies are associated instead with a statistically significant decline in pro-environmental behaviour, amounting to roughly 4–5% of the control mean. Two mechanisms are a priori plausible for this asymmetric response. The first is a purely physical channel: cold weather raises the direct cost of certain green behaviours, such as cycling, using public transport, or reducing heating, without involving any revision of climate-related beliefs. The second is a psychological channel: cold extremes undermine the perceived relevance or urgency of climate action under a "global warming" mental model, temporarily reducing motivation to act without shifting beliefs.

Table B.7 provides evidence consistent with this interpretation using contemporaneous measures of beliefs and perceived responsibility. The behavioural decline is concentrated among respondents with stronger pro-climate beliefs and among those who normally perceive their own behaviour as contributing to climate change. In contrast, individuals who already deny personal responsibility show little reaction. This pattern suggests that cold shocks relax behavioural effort primarily among those who are otherwise motivated to act. For these individuals, extreme cold may provide a "convenient" signal that can be used to down-weight the urgency of climate action, relaxing behavioural effort without requiring explicit revision of underlying beliefs.

In contrast to the negative belief responses documented above for the long-run analysis, temperature anomalies do not generate statistically significant adjustments in the behaviour index (see Table C.3), suggesting again that belief updating does not always translate into action.

7 Conclusions

This paper studies how individuals respond to local experiences of extreme weather by examining both short-run belief updating and longer-run behavioural responses to temperature anomalies. Leveraging high-frequency, high-resolution climate data merged with longitudinal survey data from the UK, the analysis exploits quasi-random variation in

Table 6.1: Short-Term Effect of Temperature Anomalies on Behaviour Index

	Behaviour Index		
	(PCA)	(PCA)	(Avg)
Post Moderate +	-0.0000	-0.0000	0.0036
	(0.0056)	(0.0056)	(0.0054)
Post Extreme +	0.0045	0.0043	-0.0081
	(0.0121)	(0.0122)	(0.0106)
Post Moderate −	-0.0039	-0.0033	-0.0030
	(0.0048)	(0.0047)	(0.0044)
Post Extreme −	-0.0197**	-0.0191*	-0.0172*
	(0.0099)	(0.0099)	(0.0094)
Control Mean	0.4291	0.4291	0.4697
N	27,950	27,944	27,944
R^2	0.7720	0.7730	0.7500
Individual FE	✓	✓	✓
Region × Season FE	✓	✓	✓
Controls	—	✓	✓

Notes: Standard errors clustered at the Local Authority level in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Estimates show the effect of being interviewed within 30 days after a temperature anomaly. The behaviour index is a normalized principal component of self-reported pro-environmental behaviours (PCA) or a simple average of standardized items (Avg). The control mean refers to observations not in the 30-day post-event window, within the regression sample.

interview timing around local temperature shocks and cumulative exposure over several years. This framework allows a direct comparison between immediate effects and longer-run adjustment.

Three main findings emerge. First, short-run responses are temporary: extreme heat raises climate-related beliefs, but these effects decay within a few months and are concentrated among individuals with lower baseline concern, consistent with a short-run catch-up in attention. Second, cumulative exposure over several years produces the opposite belief pattern: repeated positive anomaly exposure is associated with a negative effect on pro-environmental beliefs, a departure from the general upward trend, especially for longer-lasting episodes. This long-run attenuation is driven by different individuals; it is strongest among those with higher baseline climate concern and among homeowners, and is hard to reconcile with standard learning. Third, belief updating does not translate into action, and the two seem to move independently. In the short run, salient heat events that temporarily raise concern are not sufficient to shift behaviour; yet cold anomalies reduce pro-environmental action without any corresponding change in climate beliefs. In the long run, self-reported pro-environmental behaviour shows no significant change.

These results point to an important limitation of experience-based learning in the context of climate change. While extreme weather can momentarily increase concern, as documented in earlier literature, repeated exposure does not necessarily reinforce the general upward trend in pro-environmental beliefs and may even attenuate it. At the same time, behavioural responses are shaped by constraints and adaptation needs rather than by beliefs alone. This combination implies that relying on lived experience as a driver of climate concern or mitigation may be insufficient. These findings have also some implications for policy and communication. First, they suggest that climate communication strategies should not assume that repeated exposure to extreme weather will naturally translate into sustained concern or action. Instead, how climatic experiences are framed and interpreted appears central. Second, the divergence between beliefs and behaviour highlights the importance of policies that target constraints and infrastructure, rather than relying solely on changes in attitudes. Finally, the suggestive evidence that belief resistance is greatest among individuals with higher anxiety or material stakes, points to the role of psychological incentives in shaping climate perceptions.

This paper also opens several avenues for future research. One promising direction is to study how media narratives, social interactions, and local political discourse mediate the interpretation of extreme weather events, potentially reinforcing or counteracting motivated reasoning. Another is to examine whether similar dynamics arise in different climatic and institutional contexts, particularly in regions where heat exposure is more clearly associated with economic or health damages. More broadly, understanding how individuals process repeated, ambiguous signals about long-run risks remains a central challenge for climate economics, and one with implications well beyond the domain of environmental policy.

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Appendix

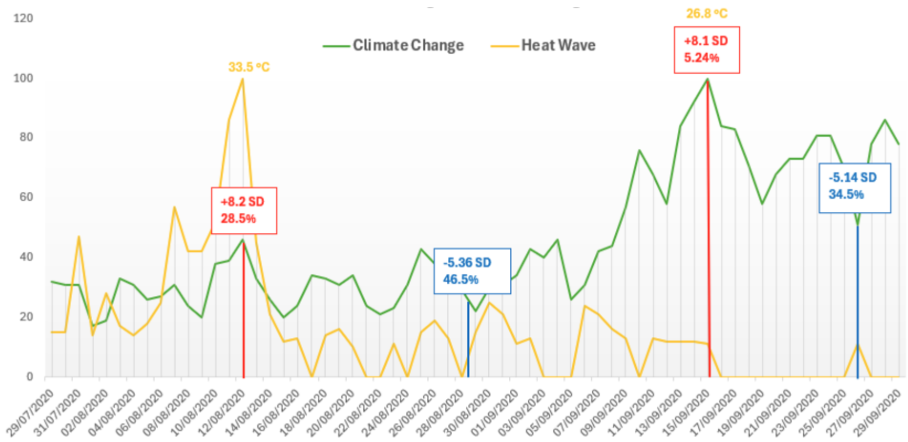
Appendix contents

A Data & Measurement

A.1 Google Searches

This appendix provides illustrative evidence on the salience of temperature anomalies using Google search data. I focus on a short case study covering August and September 2020. In this period two positive anomalies and two negative anomalies occurred within two months. At the same time, this is a single case study and should be interpreted with caution. Figure A.1 plots daily Google search intensity in the UK for the keywords "Climate Change" and "Heat Wave," together with the timing of local temperature anomalies. The figure highlights an important distinction. Searches for "Climate Change" spike precisely around positive temperature anomalies defined relative to local climatic norms, including episodes in which absolute temperatures are not particularly high (e.g., mid-September 2020). In contrast, searches for "Heat Wave" track absolute temperature levels more closely, rising primarily during periods of sustained heat rather than in response to relative deviations from the local mean. This pattern supports the interpretation that relative anomalies, rather than absolute temperatures, are more closely associated with attention to climate change.

Figure A.1: Relative Google Searches, August–September 2020

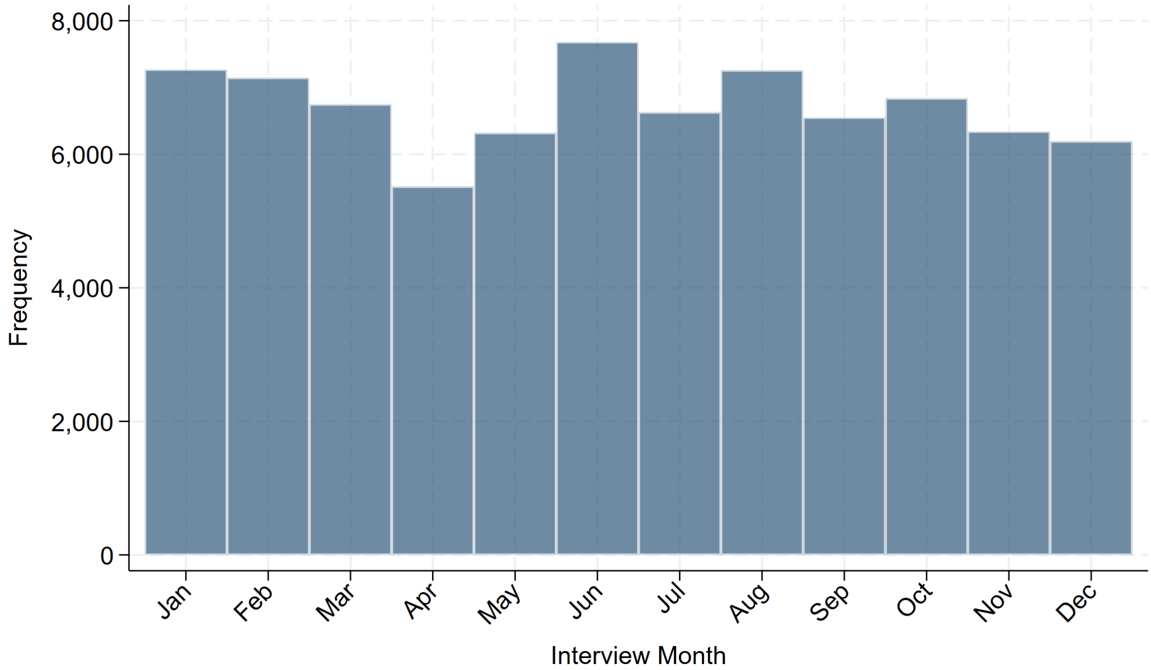


Notes: Vertical red (blue) lines indicate positive (negative) local temperature anomalies. Lines show the Google Search Index for "Climate Change" (green) and "Heat Wave" (yellow), normalized so that 100 corresponds to the maximum value within the period.

A.2 Interview Months

Figure A.2 shows the distribution of interview dates across calendar months. Interviews are conducted fairly evenly throughout the year, with a modest drop in December. Because positive temperature anomalies are concentrated in the summer months, while negative anomalies occur throughout the year, the distribution of interviews around anomaly dates is mechanically asymmetric across anomaly types. This reflects the seasonal nature of temperature extremes rather than differential survey timing.

Figure A.2: Distribution of Interviews across Months

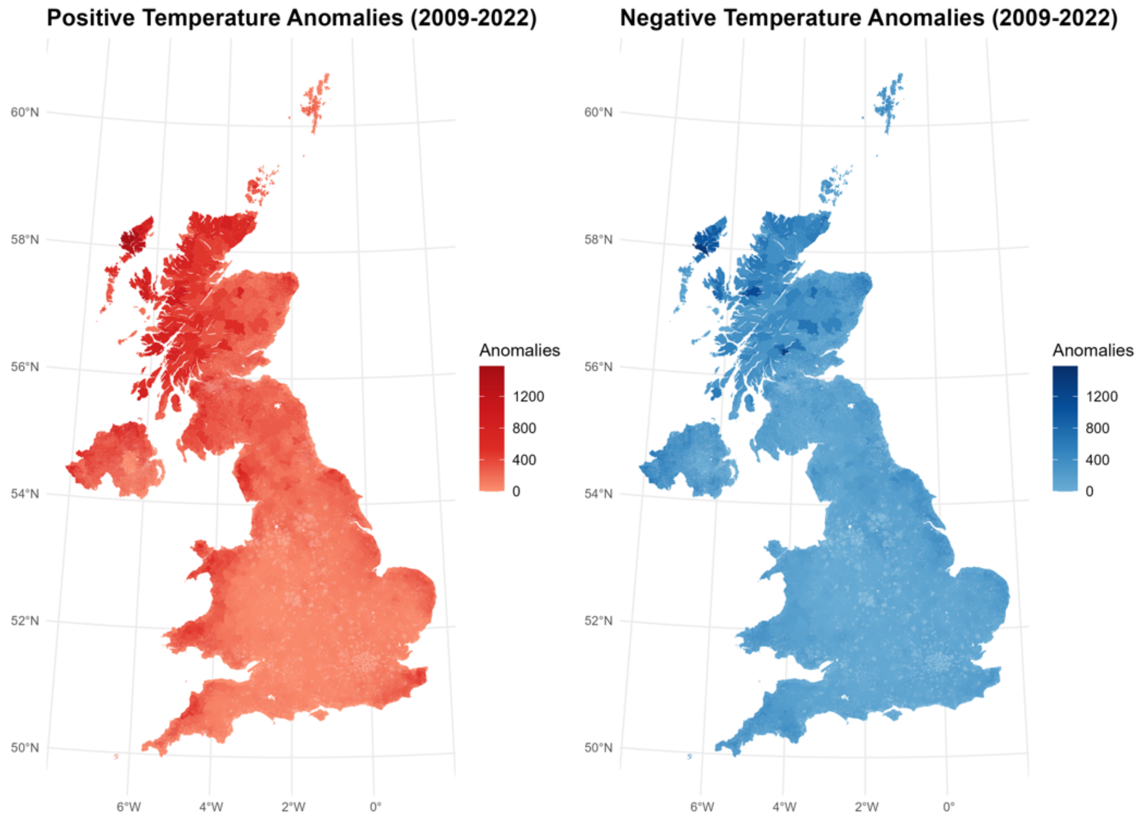


Notes: The graph shows the distribution of interviews by calendar month in the survey sample.

A.3 Spatial Distribution of Temperature Anomalies

Figure A.3 illustrates the spatial distribution of temperature anomalies across the UK. The maps report the cumulative number of positive and negative anomalies experienced at the LSOA level between 2009 and 2022. While both types of anomalies are widespread, positive anomalies exhibit stronger spatial concentration, particularly in coastal and northern areas, whereas negative anomalies are more evenly distributed across space.

Figure A.3: Spatial Distribution of Temperature Anomalies



Notes: The maps show the cumulative number of positive (left panel) and negative (right panel) temperature anomalies at the LSOA level over the period 2009-2022.

A.4 List of Beliefs & Self-Reported Behaviours

This appendix reports the full list of survey items used to construct the climate beliefs and pro-environmental behaviour indices. The first table documents the belief items. All items are harmonized so that higher values indicate stronger pro-environmental beliefs. The second table lists the self-reported behavioural items used to construct the behaviour index. These variables capture the frequency of everyday actions related to energy use, consumption, and mobility that directly affect individual carbon footprints. Behavioural items are coded so that higher values reflect more environmentally friendly behaviour.

Table A.1: Climate Belief Items

Code	Survey Item
BCON	My behaviour contributes to climate change
BEY	Climate change is beyond control
EXAG*	Environmental crisis has not been exaggerated
FUTR*	Effects of climate change are not too far in the future
DIS	Likely to experience a major environmental disaster soon
BRIT*	Worth the UK trying to combat climate change
WORTH*	Worth acting even if others do not
LIFEST	Current lifestyle is environmentally friendly
GRN*	Being green is not an alternative lifestyle
PAYMORE	Willing to pay more for environmentally friendly products
200YR	Climate change will have serious effects within the next 200 years
30YR	Climate change will have serious effects within the next 30 years

Notes: Items marked with * are reverse coded so that higher values consistently indicate stronger pro-environmental beliefs. 200YR and 30YR are the two component items used to construct the ANXIOUS indicator, but they are not included in the main index.

Table A.2: Self-Reported Pro-Environmental Behaviours

Code	Survey Item
TV	Leave the television on standby overnight
LIGHTS	Switch off lights in unused rooms
WATER	Turn off water while brushing teeth
CLOTHES	Wear more clothes instead of increasing heating
PACKAGING	Avoid buying products with excessive packaging
RECYCLED	Buy recycled paper products
OWNBAG	Bring own shopping bag when shopping
PUBTRANS	Use public transport instead of travelling by car
WALKCYCLE	Walk or cycle for short journeys (2–3 miles)
CARSHARE	Share car journeys with others
LESSFLIGHT	Take fewer flights when possible

Notes: All behaviour items are coded so that higher values correspond to more frequent engagement in pro-environmental behaviours.

A.5 PCA Behaviour Index

This appendix describes the construction of the pro-environmental behaviour index using principal component analysis (PCA). The PCA is conducted on eleven self-reported behavioural items. The loadings of the first principal component, reported in Table A.4, are used as weights to construct the main behaviour index, as this component captures the largest share of common variation across items. The first principal component explains approximately 19.6% of the total variance, with subsequent components accounting for substantially smaller shares. All items load positively on the first component, with the exception of the item measuring the frequency of leaving the television on standby overnight. The negative loading on this item reflects its ambiguous interpretation.

Table A.4: Results of the PCA and loadings of the first principal component

Component	Eigenvalue	Proportion
Comp1	2.15691	0.1961
Comp2	1.29772	0.1180
Comp3	1.10193	0.1002
Comp4	0.998344	0.0908
Comp5	0.944552	0.0859
Comp6	0.871352	0.0792
Comp7	0.831699	0.0756
Comp8	0.784114	0.0713
Comp9	0.754118	0.0686
Comp10	0.645199	0.0587
Comp11	0.614066	0.0558

Notes: Results from the PCA analysis run on self-reported green behaviours; only the loadings of component 1 were employed in the index's construction. The column "Proportion" represents the share of total variance explained by each component.

Variable	Comp1 Loadings
Behaviour 1	-0.1420
Behaviour 2	0.1773
Behaviour 3	0.2450
Behaviour 4	0.2789
Behaviour 5	0.3975
Behaviour 6	0.3908
Behaviour 7	0.2639
Behaviour 8	0.3241
Behaviour 9	0.3696
Behaviour 10	0.2532
Behaviour 11	0.3528

Notes: Loadings for the first principal component from the PCA analysis. Higher loadings indicate stronger associations with the component.

B Short-Run Supplementary Results

B.1 Additional Short-Run Results

This appendix reports additional short-term results that complement the main analysis by disaggregating the effects of temperature anomalies across individual belief items, specific pro-environmental behaviours, and a broad set of well-being outcomes. These results serve two purposes. First, they show that the aggregate short-run effects documented in the main text are not driven by a single survey item, but instead reflect small and diffuse movements across related dimensions. Second, they help rule out alternative channels, such as changes in general mood or well-being, through which temperature anomalies might mechanically affect beliefs or behaviour.

Table B.1: Short-Term Effect of Temperature Anomalies on Single Beliefs' Items

	(1) AVG	(2) BCON	(3) EXAG	(4) FUTR	(5) DIS	(6) BEY	(7) BRIT	(8) WORTH	(9) LIFEST	(10) GRN	(11) PAYMORE
Post Moderate +	-0.0045	0.0018	-0.0107	0.0038	-0.0145	-0.0021	-0.0138*	-0.0052	-0.0012	0.0124	-0.0109
	(0.0031)	(0.0079)	(0.0089)	(0.0087)	(0.0091)	(0.0084)	(0.0084)	(0.0088)	(0.0080)	(0.0087)	(0.0084)
Post Extreme +	0.0170**	0.0205	0.0218	-0.0025	0.0273	0.0104	0.0175	0.0374	0.0011	0.0249	0.0182
	(0.0084)	(0.0208)	(0.0206)	(0.0213)	(0.0258)	(0.0225)	(0.0239)	(0.0250)	(0.0180)	(0.0197)	(0.0222)
Post Moderate −	0.0021	-0.0045	-0.0046	0.0082	0.0078	0.0066	0.0006	0.0058	-0.0018	0.0005	0.0044
	(0.0033)	(0.0085)	(0.0084)	(0.0084)	(0.0079)	(0.0084)	(0.0088)	(0.0087)	(0.0069)	(0.0076)	(0.0088)
Post Extreme −	-0.0077	0.0135	-0.0241	-0.0069	-0.0091	-0.0160	-0.0158	-0.0312	0.0028	0.0065	0.0068
	(0.0070)	(0.0165)	(0.0174)	(0.0170)	(0.0167)	(0.0179)	(0.0194)	(0.0201)	(0.0119)	(0.0151)	(0.0157)
Observations	36,144										

Notes: Standard errors clustered at the Local Authority level in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. All regressions include individual fixed effects and season-by-region and interview-year fixed effects. Acronyms for single beliefs are explained in Appendix A.1.

Table B.2: Short-Term Effect of Temperature Anomalies on Well-Being Outcomes

	(1) HEALTH	(2) LEISURE	(3) SLEEP	(4) CONCENTR	(5) HAPPY	(6) OPTIM	(7) RELAXED	(8) CLEAR	(9) CLOSE
Post Moderate +	0.100	0.0224	-0.0123	-0.0173	0.00627	-0.00507	0.00381	0.00709	-0.00956
	(0.0661)	(0.0611)	(0.0254)	(0.0199)	(0.0211)	(0.0339)	(0.0298)	(0.0292)	(0.0332)
Post Extreme +	-0.0753	-0.0738	0.0347	-0.00338	0.0297	0.0332	0.0617	0.0792	0.0958
	(0.154)	(0.157)	(0.0616)	(0.0425)	(0.0574)	(0.0845)	(0.0749)	(0.0807)	(0.0731)
Post Moderate −	0.0172	0.0119	-0.0195	-0.00864	-0.00729	-0.00114	0.0269	0.0260	-0.00512
	(0.0627)	(0.0592)	(0.0284)	(0.0208)	(0.0219)	(0.0309)	(0.0277)	(0.0288)	(0.0313)
Post Extreme −	0.168	0.0790	0.0819*	0.0276	0.0149	-0.116	-0.0575	0.0225	0.0303
	(0.132)	(0.123)	(0.0478)	(0.0435)	(0.0480)	(0.0708)	(0.0634)	(0.0589)	(0.0628)
Observations	36,124	36,126	36,136	36,120	36,128	36,068	36,096	36,092	36,084
R^2	0.644	0.672	0.682	0.598	0.602	0.670	0.698	0.707	0.687

Notes: Standard errors clustered at the Local Authority level in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. All regressions include individual fixed effects and season-by-region and interview-year fixed effects, and the full set of controls. HEALTH: satisfaction with health; LEISURE: satisfaction with leisure; SLEEP: loss of sleep; CONCENTR: difficulty concentrating; HAPPY: happiness; OPTIM: optimism; RELAXED: feeling relaxed; CLEAR: thinking clearly; CLOSE: feeling close to others.

Table B.3: Short-Term Effect of Temperature Anomalies on Single Behaviour Items

	(1) AVG	(2) TV	(3) Lights	(4) Water	(5) Clothes	(6) Packaging	(7) Recycled	(8) Own Bag	(9) Public Tr.	(10) Walk/Cycle	(11) CarShare	(12) Less Flights
	Avg	**Energy**				**Consumption**			**Transport**			
Post Moderate +	-0.0000	0.0734	0.0565	0.0191	0.0768	0.0050	-0.0209	0.0282	-0.0182	-0.0240	0.0055	-0.0481
	(0.0056)	(0.0795)	(0.0430)	(0.0595)	(0.0548)	(0.0395)	(0.0509)	(0.0590)	(0.0424)	(0.0588)	(0.0526)	(0.0582)
Post Extreme +	0.0043	-0.298	-0.0340	-0.0048	0.0608	-0.0955	0.0717	-0.255*	0.0441	0.144	-0.0722	0.0975
	(0.0122)	(0.184)	(0.0899)	(0.146)	(0.142)	(0.0992)	(0.125)	(0.141)	(0.0918)	(0.132)	(0.136)	(0.115)
Post Moderate −	-0.0033	-0.0128	-0.0001	-0.0270	0.0205	-0.0049	-0.0257	-0.0372	-0.0164	0.0070	0.0271	-0.0636
	(0.0047)	(0.0720)	(0.0384)	(0.0561)	(0.0454)	(0.0403)	(0.0504)	(0.0515)	(0.0334)	(0.0547)	(0.0494)	(0.0540)
Post Extreme −	-0.0191*	-0.0025	-0.0056	0.0350	-0.0194	-0.0882	-0.0898	-0.278**	-0.164**	-0.0342	-0.0164	-0.0999
	(0.0099)	(0.152)	(0.0764)	(0.105)	(0.106)	(0.0914)	(0.0865)	(0.116)	(0.0820)	(0.120)	(0.109)	(0.107)
Observations	27,944	27,944	27,944	27,944	27,944	27,944	27,944	27,944	27,944	27,944	27,944	27,944

Notes: Standard errors clustered at the Local Authority level in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. All regressions include individual fixed effects and season-by-region and interview-year fixed effects. Behaviour items correspond to self-reported everyday environmental actions and are grouped by domain. Acronyms are explained in Appendix A.1.

B.2 Heterogeneity by Event Duration

This section reports the regression results underlying Figure 3.1, which studies heterogeneity in the short-run belief response to extreme positive temperature anomalies by event persistence. To do so, I interact the extreme positive anomaly indicator with indicators for the duration of the heat event, measured as the number of consecutive days above the extreme threshold within the 30-day event window. The estimating equation is

$$Y_{it} = \alpha_i + \delta_{r\times s} + \eta_y + \sum_{d=1}^{D} \beta_d \left(1\{\text{PosExtr}_{it} = 1\} \times 1\{\text{Duration}_{it} = d\}\right) + \theta' Z_{it} + \varepsilon_{it},$$

where $1\{\text{PosExtr}_{it} = 1\}$ is an indicator equal to one if respondent i is interviewed within 30 days after an extreme positive temperature anomaly (the same as the main analysis), and $1\{\text{Duration}_{it} = d\}$ denotes indicators for the length of the associated heat streak, measured in consecutive days above the extreme threshold. The vector Z_{it} includes indicators for non-extreme positive anomalies, negative anomalies (moderate and extreme), and the full set of time-varying controls used in the baseline specification. Individual fixed effects α_i, region-by-season fixed effects $\delta_{r\times s}$, and year fixed effects η_y are included throughout. Coefficients β_d therefore capture how the short-run belief response to extreme heat varies with event persistence, relative to the comparison group (observations not in the 30-day post-extreme-positive window). Table B.4 reports the corresponding estimates.

Table B.4: Heterogeneity by Duration of Extreme Positive Anomalies (Beliefs Index)

	(1) Beliefs Index (AVG)
Post Extreme + × 1 day	-0.0125
	(0.0222)
Post Extreme + × 2 days	0.0108
	(0.0121)
Post Extreme + × 3 days	0.0330**
	(0.0163)
Post Extreme + × 4 days	0.0352**
	(0.0158)
Post Extreme + × 5 days	0.0140
	(0.0184)
Observations	36,144
R^2	0.7729
Individual FE	✓
Region × Season FE	✓
Year FE	✓
Controls	✓

Notes: Standard errors clustered at the Local Authority level in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The table reports coefficients from a specification that replaces the baseline *Post Extreme +* indicator with interactions between *Post Extreme +* and indicators for the duration of the extreme heat streak (measured as consecutive days above the extreme threshold) within the 30-day post-event window. The omitted category comprises all observations not in the 30-day post-extreme-positive window, including pre-event observations, neutral periods, and observations near other anomaly types. All regressions include the baseline post-anomaly indicators for moderate positive, moderate negative, and extreme negative anomalies, the missing-anomaly indicator (flagging observations outside all four windows simultaneously), and the full set of time-varying controls.

B.3 Temporal Decay of the Short-Run Effect

To assess whether the short-run belief response to extreme positive anomalies fades over time, we replace the baseline $Post^{pos,ext}$ indicator with four separate indicators for the time elapsed between the anomaly and the interview: 0–15 days, 16–30 days, 31–60 days, and 61–120 days since the extreme positive event. The comparison group is identical to the baseline specification: observations not in the post-event window for extreme positive anomalies. The estimating equation is:

$$Y_{it} = \alpha_i + \delta_{r\times s} + \eta_y + \sum_{k=1}^{4} \beta_k \, \mathbf{1}\Big\{\text{Days}_{it}^{pos,ext} \in W_k\Big\} + X_{it}'\lambda + \varepsilon_{it},$$

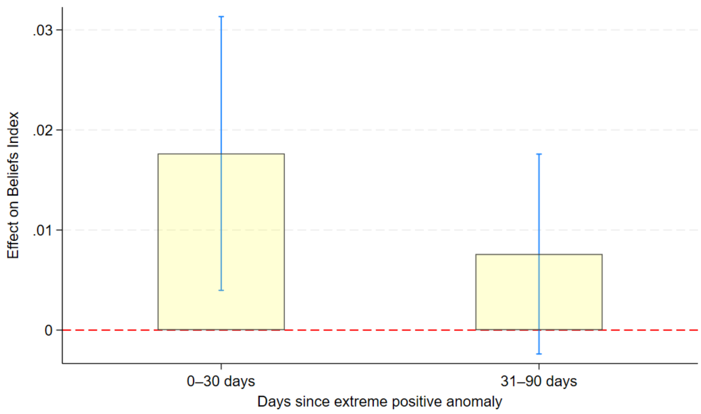
where $W_1 = [0, 15]$, $W_2 = [16, 30]$, $W_3 = [31, 60]$, and $W_4 = [61, 120]$ denote the four time windows in days since the most recent extreme positive anomaly. X_{it} includes indicators for moderate positive, moderate negative, and extreme negative anomaly exposure, a missing-anomaly indicator, the full set of time-varying controls, and individual, region-by-season, and year fixed effects. The omitted category is all observations not in any post-extreme-positive window, consistent with the baseline. Table B.5 reports the four coefficients. Figure 3.1 (right panel) plots them. Figure B.1 presents the collapsed two-bin version, contrasting the within-30-day estimate with the beyond-30-day estimate.

Table B.5: Temporal Decay of Extreme Positive Anomaly Effect on Beliefs

	Beliefs Index (AVG)
Post Extreme +: 0–15 days	0.0143
	(0.0111)
Post Extreme +: 16–30 days	0.0213*
	(0.0116)
Post Extreme +: 31–60 days	0.0069
	(0.0072)
Post Extreme +: 61–120 days	0.0061
	(0.0066)
Observations	36,144
R^2	0.7728
Individual FE	✓
Region × Season FE	✓
Year FE	✓
Controls	✓

Notes: Standard errors clustered at the Local Authority level in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The table replaces the baseline *Post Extreme* + indicator with four mutually exclusive indicators for the time elapsed since the extreme positive anomaly. The comparison group is all observations not in the post-event window for extreme positive anomalies, consistent with the baseline specification. All regressions include controls for moderate positive, moderate negative, and extreme negative anomaly exposure, a missing-anomaly indicator, and the full set of time-varying controls.

Figure B.1: Temporal Decay: Within vs. Beyond 30-Day Window



Notes: The figure collapses the four timing windows into two: 0–30 days (within the baseline event window) and 31–90 days (beyond it). The estimated effect within 30 days is 0.018 (s.e. 0.008, $p = 0.034$); the estimate beyond 30 days is 0.008 (s.e. 0.006, $p = 0.210$). Bars report OLS coefficients; capped spikes denote 90% confidence intervals. The comparison group and controls are identical to the baseline specification.

B.4 Short-Run Heterogeneity by Political Alignment and Media Orientation

I classify respondents into three political groups (*Left*, *Center*, and *Right*) based on the party they report *feeling closest to*[19]. To obtain a stable measure, I assign each individual a baseline political affiliation equal to the modal category observed in Waves 1–4, restricting attention to individuals whose reported affiliation is consistent in at least 80% of pre-treatment observations. Media readership orientation is constructed using respondents' main news sources in the survey, covering newspapers, television, and online news. Each outlet is classified as left-leaning, right-leaning, or centrist based on its typical editorial stance. Left-leaning sources include, among others, *The Guardian*, *The Independent*, *The Mirror*, ITV, and Channel 4; right-leaning sources include *The Daily Mail*, *The Telegraph*, *The Sun*, *The Express*, *The Star*, and Sky News; all remaining outlets, including the BBC, are classified as centrist. A respondent is assigned a left- or right-leaning media orientation if they report consuming at least one source in that category across any platform; respondents who consume only centrist outlets are classified as centrist.

The following equation estimates heterogeneous short-run belief responses to extreme positive temperature anomalies by political alignment. The coefficient β captures the effect of exposure for the omitted group (left-aligned respondents), while γ_g are interaction coefficients for centrist and right-aligned individuals. Table B.6 reports total subgroup effects, computed as $\beta + \gamma_g$ for each group. All specifications include individual fixed effects, region-by-season fixed effects, and year fixed effects. An equivalent specification is estimated when replacing political alignment with media orientation, using left-leaning media consumers as the omitted category.

$$Y_{it} = \alpha_i + \delta_{r\times s} + \eta_y + \beta\, Post_{it}^{pos,ext} + \sum_{g\in\{\text{Center},\text{Right}\}} \gamma_g \left(Post_{it}^{pos,ext} \times 1\{\text{Pol}_i = g\}\right) + \theta' Z_{it} + \varepsilon_{it},$$

[19] *Left*: Labour, Scottish National Party, Plaid Cymru, Green Party, SDLP, and Sinn Fein. *Center*: Liberal Democrat, Alliance Party, Change UK. *Right*: Conservatives, Ulster Unionist, Democratic Unionist, Brexit Party, or Reform UK.

Table B.6: Short-Run Heterogeneity in the Effect of Extreme Positive Anomalies

	Beliefs Index (AVG)
Political Alignment	
Post Extreme + Left	0.0128
	(0.0133)
Post Extreme + Center	0.0346
	(0.0317)
Post Extreme + Right	0.0269*
	(0.0139)
Media Orientation	
Post Extreme + Left Media	-0.0013
	(0.0148)
Post Extreme + Center Media	0.0235*
	(0.0141)
Post Extreme + Right Media	0.0311**
	(0.0152)
Control Mean	0.5445
Observations	36,144
Individual FE	✓
Region × Season FE	✓
Year FE	✓
Controls	✓

Notes: Entries report the total effect of exposure to extreme positive temperature anomalies for each subgroup, estimated as the sum of the main effect and the relevant interaction term from a single pooled specification. Standard errors clustered at the Local Authority level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B.7: Short-Run Effects of Cold Extremes on Behaviour by Beliefs in the Same Wave

	Post Extreme −
Panel A: Heterogeneity by baseline Beliefs (Index)	
Q1 (lowest)	-0.0142
	(0.0183)
Q2	-0.0040
	(0.0206)
Q3	-0.0327*
	(0.0178)
Q4 (highest)	-0.0233*
	(0.0139)
Panel B: Perceived Responsibility for CC	
My behaviour does not contribute to CC	-0.0082
	(0.0238)
Neither agree nor disagree	-0.0039
	(0.0151)
My behaviour does contribute to CC	-0.0365***
	(0.0128)

Notes: Entries report average marginal effects of exposure to an extreme negative temperature anomaly, computed after interacting the anomaly indicator with the heterogeneity variable listed in each panel. All specifications include individual fixed effects and season-by-region and interview-year fixed effects, the full set of controls, and standard errors clustered at the Local Authority level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

B.5 Balancing Tests

Table B.8: Balancing Table Across Anomaly Types

	Positive			Negative			Positive Extreme			Negative Extreme		
	Ctrl	Treat	Diff	Ctrl	Treat	Diff	Ctrl	Treat	Diff	Ctrl	Treat	Diff
Age	49.14	48.73	0.41	49.03	49.14	-0.11	49.46	49.71	-0.25	49.82	50.72	-0.90
HH Income	3880.05	3915.10	-35.04	4034.58	3888.81	145.77***	3798.03	3604.63	193.39	4047.90	3909.60	138.30
Female	0.56	0.56	0.00	0.55	0.56	-0.01	0.58	0.57	0.01	0.55	0.56	-0.01
Married	0.54	0.52	0.02	0.54	0.53	0.01	0.53	0.52	0.01	0.58	0.57	0.01
With children	0.04	0.04	-0.00	0.04	0.04	-0.00	0.03	0.05	-0.01	0.04	0.03	0.01
Univ. degree	0.37	0.37	0.00	0.38	0.38	0.00	0.34	0.34	-0.00	0.39	0.37	0.02
Max Temp.	16.21	18.40	-2.19***	11.23	13.31	-2.08***	16.02	17.90	-1.88***	9.50	10.28	-0.78***
Obs.	4838	5918		4907	6480		814	740		634	890	

Notes: Control (Ctrl) refers to respondents interviewed in the window before the anomaly; Treat to those interviewed after. Diff reports the difference in means from a two-sample t-test. Max Temp. is the maximum temperature on the day of interview. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B.8 reports balancing tests comparing pre-determined individual characteristics between respondents interviewed before and after a temperature anomaly, separately by anomaly type. For each subsample, the table displays mean values for the control and treatment groups, together with their differences. Across all demographic and socioeconomic characteristics (age, gender, income, education, marital status, and presence of children), the differences between treated and control individuals are generally small in magnitude and statistically insignificant. The only exception is household income in the negative anomaly subsample, where control individuals have somewhat higher income on average; household income is included as a control variable in all specifications. As expected, a significant difference emerges for the maximum temperature on the interview day, since contemporaneous temperature is mechanically related to the construction of the treatment and reflects the persistence of temperature conditions around anomaly events.

B.6 Placebo Test with Lead Anomalies

A potential threat to the identification strategy is that interview timing may not be exogenous to temperature conditions. To assess this concern, I conduct a placebo test by replacing the treatment variables with *lead* anomaly indicators, defined as temperature events occurring 1-30 days *after* the interview date. Under the identifying assumption that interview timing is quasi-random with respect to future temperature, these lead indicators should have no effect on current beliefs.

Table B.9: Placebo Test: Lead Anomalies on Beliefs

	(1) Beliefs	(2) Beliefs
Lead Moderate +	0.006**	0.006**
	(0.003)	(0.003)
Lead Extreme +	−0.007	−0.007
	(0.008)	(0.008)
Lead Moderate −	−0.000	−0.001
	(0.003)	(0.003)
Lead Extreme −	0.001	0.000
	(0.006)	(0.006)
N	36,144	36,144
R^2	0.773	0.773
Individual FE	✓	✓
Region × Season FE	✓	✓
Controls	—	✓

Notes: Standard errors clustered at the Local Authority level in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Lead anomalies are defined as temperature events occurring 1–30 days after the interview date.

Table B.9 reports the results. Most lead indicators are small in magnitude and statistically insignificant, broadly supporting the identifying assumption. The one exception is the lead for moderate positive anomalies, which carries a small but statistically significant coefficient of 0.006. This is consistent with the natural autocorrelation of temperature: a period that will produce a moderate positive anomaly within the next 30 days is likely already somewhat warm. Two features of the data support this interpretation. First, the coefficient is an order of magnitude smaller than the main effect of *extreme* positive anomalies ($\hat{\beta} = 0.017$), and of the opposite sign to what reverse causation would predict (if worried respondents sought re-interview dates that happened to precede warm spells, the lead should be negative, not positive). Second, the lead coefficient for extreme positive anomalies (the category driving the main result) is negative, small, and statistically insignificant ($\hat{\beta} = -0.007$). Extreme events are rare tail realisations that are, by construction, harder to anticipate from prevailing conditions, which is precisely what makes them informative for identification.

B.7 Short-Run Robustness: Treatment Window Length

Table B.10 assesses the sensitivity of the short-run results to the choice of treatment window. Each column redefines how long after a temperature anomaly an individual is classified as exposed (1, 3, 6, or 12 months)while keeping the pre-event control window fixed at 6 months for the one-, three-, and six-month windows, and at 12 months for the twelve-month window. The no-treatment buffer (the minimum number of days since the most recent anomaly required for an observation to serve as a clean control) is set to match the treatment window in each column, so that treatment and control groups remain mutually exclusive by construction. The results reveal a clear pattern of temporal decay. For beliefs (Panel A), the extreme heat coefficient declines monotonically from 0.017 within one month to 0.013 at three months and 0.009 at six months, remaining statistically significant throughout, before becoming indistinguishable from zero at twelve months ($\hat{\beta} = 0.003$). For behaviour (Panel B), the extreme cold effect of -0.019 is significant only within the one-month window and is negligible at all longer horizons. This rapid attenuation indicates that both effects are localised in time and do not persist beyond a few months.

Table B.10: Short-Run Robustness: Treatment Window Length

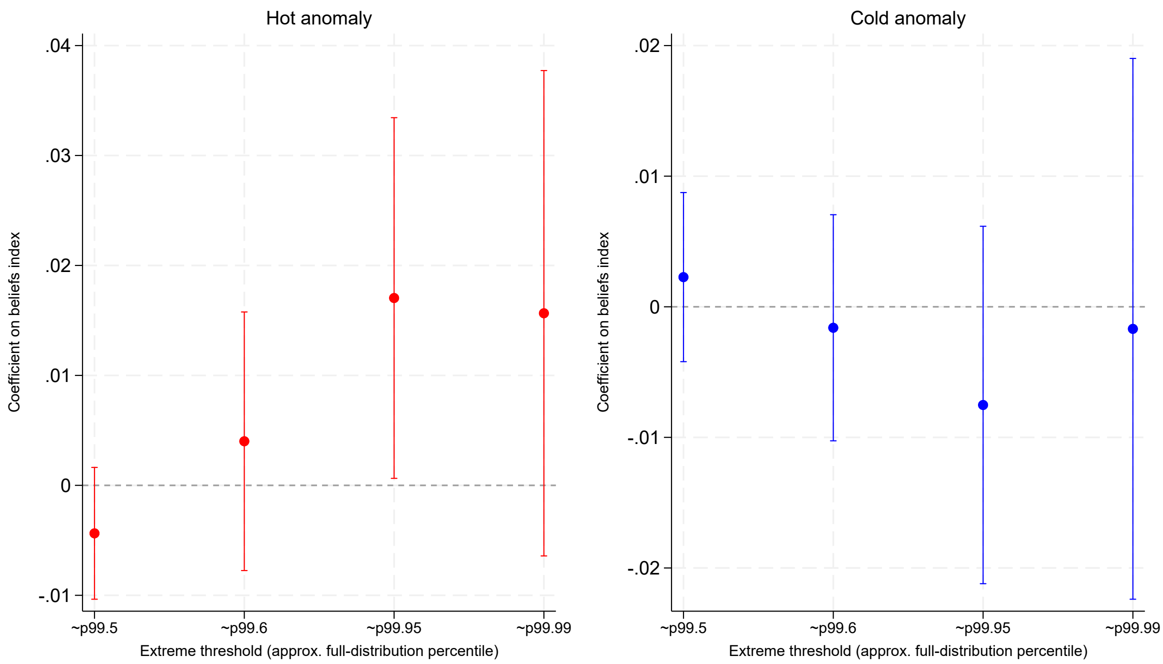
	(1) 1-month	(2) 3-month	(3) 6-month	(4) 12-month
Panel A: Climate Beliefs				
Post Moderate +	−0.004	−0.003	−0.001	−0.001
	(0.003)	(0.002)	(0.002)	(0.002)
Post Extreme +	0.017**	0.012**	0.008**	0.003
	(0.008)	(0.005)	(0.004)	(0.003)
Post Moderate −	0.002	0.001	0.002	0.003
	(0.003)	(0.002)	(0.002)	(0.002)
Post Extreme −	−0.008	−0.004	−0.003	0.003
	(0.007)	(0.011)	(0.007)	(0.006)
N	36,144	36,144	36,144	36,144
R^2	0.773	0.773	0.773	0.773
Panel B: Pro-Environmental Behaviour				
Post Moderate +	0.001	−0.000	−0.001	0.000
	(0.005)	(0.004)	(0.004)	(0.003)
Post Extreme +	0.005	0.003	−0.000	−0.001
	(0.012)	(0.007)	(0.006)	(0.005)
Post Moderate −	−0.002	−0.003	−0.003	0.001
	(0.004)	(0.003)	(0.003)	(0.003)
Post Extreme −	−0.019*	-0.005	−0.005	−0.003
	(0.010)	(0.007)	(0.006)	(0.004)
N	27,944	27,944	27,944	27,944
R^2	0.773	0.773	0.773	0.773
Individual FE	✓	✓	✓	✓
Region × Season FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓

Notes: Standard errors clustered at the Local Authority level in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Each column redefines the treatment window: an individual is classified as exposed if interviewed within 1, 3, 6, or 12 months of an anomaly event. The no-treatment buffer is set to match the treatment window in each column. The pre-event control window is fixed at 6 months for columns (1)-(3) and at 12 months for column (4).

B.8 Short-Run Robustness: Anomaly Intensity Threshold

Figure B.2 examines the sensitivity of the short-run belief results to the choice of intensity threshold used to classify a temperature anomaly as extreme. Each panel plots four coefficients from the baseline four-dummy specification, where the extreme threshold is varied across intensity levels. Moving left to right, the four points correspond to: the baseline moderate anomaly dummy (∼p99.5), an extreme definition set below the baseline cutoff (∼p99.6 of the full LSOA-day distribution), the baseline extreme anomaly dummy (∼p99.95, which replicates the main specification exactly), and a stricter extreme definition (∼p99.99). The left panel reports results for hot anomalies; the right panel for cold anomalies.

Figure B.2: Short-Run Robustness: Anomaly Intensity Threshold



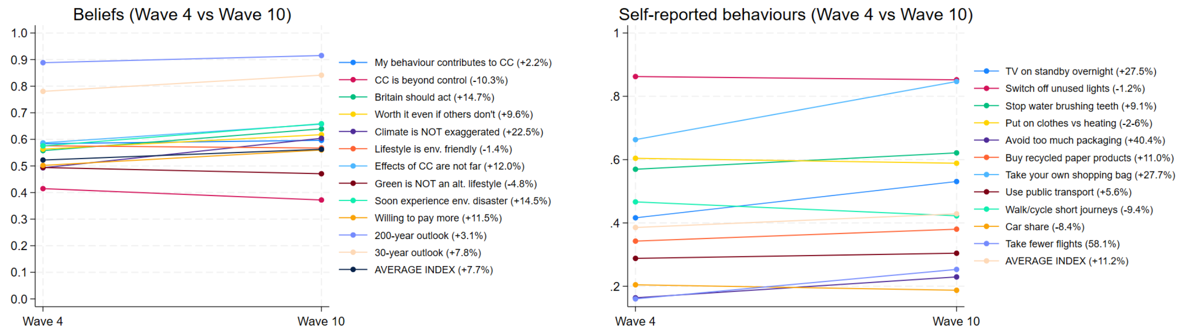
Notes: Each dot plots the coefficient on the anomaly dummy from the baseline short-run specification, varying the intensity threshold used to define an extreme anomaly. All four thresholds fall within the top 0.5% of the full LSOA-day temperature anomaly distribution. Bars denote 95% confidence intervals. Standard errors clustered at the Local Authority level.

C Long-Run Supplementary Results

C.1 Long-Run Descriptives

This appendix provides descriptive evidence on long-run changes in climate-related beliefs and behaviours between Wave 4 and Wave 10 of the UKHLS. Figure C.1 documents a broad-based increase in climate-related beliefs over time, consistent with a gradual rise in perceived climate risks and responsibility. In contrast, changes in self-reported pro-environmental behaviours are more heterogeneous: some behaviours increase, while others remain stable or decline.

Figure C.1: Long-Run Trends – Beliefs & Behaviours



Notes: The figure plots average levels of climate-related beliefs (left panel) and self-reported pro-environmental behaviours (right panel) in Wave 4 and Wave 10. Each series corresponds to a distinct survey item, normalized to lie between zero and one. Percent changes reported in the legend indicate relative changes over time.

C.2 Additional Long-Run Results

This appendix reports additional long-run results that complement the baseline analysis by exploring alternative measures of cumulative exposure and more granular outcome decompositions. First, I replace the number of anomaly events with the cumulative number of anomaly *days*, showing that the negative long-run association between heat exposure and climate beliefs is not driven by the event definition. Second, I disaggregate long-run belief effects across individual belief items and quartiles of positive anomaly exposure, documenting how negative updating intensifies with repeated exposure. Finally, I report additional specifications for the behaviour index, confirming that long-run behavioural adjustment remains limited even when beliefs respond significantly.

Table C.1: Long-Difference Effect of Temperature Anomalies (Days) on Beliefs and Behaviour

	Δ Beliefs (0–100)	Δ Behaviour (0–100)
Δ *Hot Anomaly Days*	-0.0723**	-0.0603
	(0.0303)	(0.0477)
Δ *Cold Anomaly Days*	0.0311	0.0486
	(0.0355)	(0.0525)
N	12,833	12,830
R^2	0.0785	0.0909
Local Authority FE	✓	✓
Month FE	✓	✓
Controls	✓	✓

Notes: Standard errors clustered at the Local Authority level in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Outcomes are long differences between Waves 4 and 10 (scaled 0–100). Explanatory variables are long differences in the cumulative number of hot and cold anomaly days experienced over the same period. All specifications include Local Authority fixed effects and month-of-interview fixed effects for Wave 4 and Wave 10.

Table C.2: Long-Difference Effects of Positive Anomaly Events on Single Belief Items

	(1) BEY	(2) BCON	(3) BRIT	(4) WORTH	(5) EXAG	(6) LIFEST	(7) FUTR	(8) GRN	(9) DIS	(10) PAYMORE	(11) 200YR	(12) 30YR
Low (Q1)	0.0053	-0.0027	-0.0256	0.0020	-0.0393**	0.0047	0.0048	0.0118	-0.0189	-0.0180	0.0326	-0.0123
	(0.0171)	(0.0167)	(0.0163)	(0.0177)	(0.0186)	(0.0148)	(0.0161)	(0.0155)	(0.0178)	(0.0147)	(0.0213)	(0.0273)
Moderate (Q2)	0.0090	-0.0074	-0.0254	-0.0181	-0.0334*	-0.0041	0.0106	0.0083	-0.0211	-0.0302*	0.0159	-0.0111
	(0.0181)	(0.0173)	(0.0177)	(0.0169)	(0.0183)	(0.0147)	(0.0163)	(0.0162)	(0.0188)	(0.0155)	(0.0221)	(0.0280)
High (Q3)	-0.0002	-0.0022	-0.0320*	-0.0127	-0.0589***	0.0117	0.0067	0.0094	-0.0309	-0.0251	0.0245	-0.0047
	(0.0179)	(0.0170)	(0.0185)	(0.0188)	(0.0194)	(0.0158)	(0.0161)	(0.0177)	(0.0194)	(0.0164)	(0.0224)	(0.0289)
Extreme (Q4)	-0.0090	-0.0094	-0.0269	-0.0191	-0.0679***	0.0008	0.0011	0.0020	-0.0465**	-0.0257	0.0223	0.0022
	(0.0211)	(0.0205)	(0.0215)	(0.0201)	(0.0209)	(0.0176)	(0.0186)	(0.0206)	(0.0234)	(0.0190)	(0.0253)	(0.0352)
Observations	12,758	12,744	12,752	12,772	12,754	12,788	12,765	12,479	12,741	12,780	12,498	12,555

Notes: Standard errors clustered at the Local Authority level in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Entries report long-difference estimates between Waves 4 and 10 (normalized outcomes). Quartiles refer to the distribution of cumulative exposure to hot anomaly events over the period; the omitted category is *Q0: no hot anomaly events.* All specifications include Local Authority fixed effects, month-of-interview fixed effects for Wave 4 and Wave 10, and the full set of controls. Acronyms for single beliefs are described in Appendix A.1.

Table C.3: Long-Difference Effect of Temperature Anomalies on Behaviour

	Δ Behaviour (0–100)
Δ *Hot Events*	-0.00399
	(0.0694)
Δ *Cold Events*	-0.00679
	(0.0672)
N	12,830
R^2	0.091
Local Authority FE	✓
Month FE	✓
Controls	✓

Notes: Standard errors clustered at the Local Authority level in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. The outcome is the long difference in the behaviour index between Waves 4 and 10 (scaled 0–100). Explanatory variables are long differences in cumulative exposure to positive and negative anomaly events over the same period. All specifications include Local Authority fixed effects and month-of-interview fixed effects for Wave 4 and Wave 10.

C.3 Long-Difference Heterogeneity by Anomaly Spell Intensity and Duration

This appendix provides additional details on the long-difference specifications underlying Figure 4.1, which examine how the long-run association between cumulative exposure to positive anomaly events and pro-environmental beliefs varies along two dimensions of event characteristics: intensity and duration. Starting from the baseline long-difference model described in Section 4, we allow the effect of cumulative exposure to hot anomaly events to vary with the average characteristics of the events experienced by each individual between Wave 4 and Wave 10. Let Δy_{ij} denote the long difference in the beliefs index for individual i residing in Local Authority j, and let $\Delta C_{ij}^{\text{Hot}}$ denote the long difference in the cumulative number of hot anomaly events over the same period. We first classify individuals into quintiles based on the distribution of the average intensity of hot anomaly events they experience, where intensity is measured as the mean temperature anomaly during each positive anomaly spell. Let $Q_{ij}^{\text{Int}} \in \{1, \dots, 5\}$ denote the corresponding intensity quintile, with the lowest quintile omitted. The estimating equation is:

$$\Delta y_{ij} = \beta\, \Delta C_{ij}^{\text{Hot}} + \sum_{q=2}^{5} \theta_q \left(\Delta C_{ij}^{\text{Hot}} \times 1\{Q_{ij}^{\text{Int}} = q\} \right) + \beta_c\, \Delta C_{ij}^{\text{Cold}} + X_{ij}'\gamma + \gamma_{\text{LA}} + \delta_m + \varepsilon_{ij}.$$

All specifications include Local Authority fixed effects γ_{LA}, month-of-interview fixed effects for Wave 4 and Wave 10 (δ_m), and the full set of controls described in the main text. Standard errors are clustered at the Local Authority level. Table C.4 reports the average marginal effects at each quintile of anomaly spell intensity. Table C.5 reports the analogous estimates across quintiles of average anomaly spell duration.

Table C.4: Long-Difference Effects by Anomaly Spell Intensity

	Δ Beliefs (0–100)
Δ *Hot Events* | *Intensity Q1*	-0.242***
	(0.093)
Δ *Hot Events* | *Intensity Q2*	-0.131*
	(0.080)
Δ *Hot Events* | *Intensity Q3*	-0.219**
	(0.086)
Δ *Hot Events* | *Intensity Q4*	-0.168*
	(0.089)
Δ *Hot Events* | *Intensity Q5*	-0.093
	(0.091)
Observations	11,181

Notes: Standard errors clustered at the Local Authority level in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Entries report average marginal effects of Δ Hot Events on Δ Beliefs, computed at each intensity quintile after interacting the hot events variable with quintile indicators. All specifications include LA, interview-month, and interview-year fixed effects and the full set of controls. Intensity quintiles are defined over the distribution of average anomaly spell intensity (mean anomaly during positive anomaly spells) in the estimation sample.

Table C.5: Long-Difference Effects by Anomaly Spell Duration

	Δ Beliefs (0–100)
Δ *Hot Events* | *Duration Q1*	0.004
	(0.156)
Δ *Hot Events* | *Duration Q2*	-0.010
	(0.098)
Δ *Hot Events* | *Duration Q3*	-0.158*
	(0.082)
Δ *Hot Events* | *Duration Q4*	-0.228***
	(0.076)
Δ *Hot Events* | *Duration Q5*	-0.176**
	(0.087)
Observations	11,181

Notes: Standard errors clustered at the Local Authority level in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Entries report average marginal effects of Δ Hot Events on Δ Beliefs, computed at each duration quintile after interacting the hot events variable with quintile indicators. All specifications include LA, interview-month, and interview-year fixed effects and the full set of controls. Duration quintiles are defined over the distribution of average anomaly spell duration (mean consecutive days above the threshold during positive anomaly spells) in the estimation sample.

C.4 Temperature Anomalies and Local Economic Activity

For each economic outcome Y_{it}, the estimated equation is

$$Y_{it} = \beta_1 \text{Hot}_{it} + \beta_2 \text{Cold}_{it} + \alpha_i + \gamma_t + \varepsilon_{it}, \tag{1}$$

where i indexes Local Authorities and t indexes years; Hot_{it} and Cold_{it} are the combined counts of moderate and extreme hot (respectively cold) anomaly events in LA i in year t, consistent with the main long-run analysis; α_i and γ_t are LA and year fixed effects; and ε_{it} is the error term, with standard errors clustered at the LA level. Each column of the table corresponds to a different choice of Y_{it} (unemployment rate, inactivity rate, log GVA, or GVA growth).

Table C.6: Effect of Temperature Anomalies on Local Economic Outcomes

	(1) Unemp. rate (%)	(2) Inactivity (%)	(3) Log GVA	(4) GVA growth
Hot anomaly days	-0.0007^{***}	0.0001	0.000001	0.0003
	(0.0002)	(0.0003)	(0.000007)	(0.0004)
Cold anomaly days	-0.0005^{***}	-0.0003	-0.000005	0.0001
	(0.0002)	(0.0002)	(0.000004)	(0.0002)
Observations	3,940	4,011	4,289	4,289
R^2	0.607	0.569	0.994	0.474
LA FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Notes: Each column reports a separate two-way FE regression at the Local Authority–year level. Standard errors clustered at the LA level in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. The sample covers approximately 300 Local Authorities over 2009–2022. Explanatory variables are counts of anomaly days per LA–year. Unemployment and inactivity rates are in percentage points; GVA growth is the year-on-year percentage change.

I now test whether long-run belief adjustment in response to cumulative anomaly exposure varies with local economic conditions. I consider four specifications: interactions with (i) a binary indicator for above-median average Local Authority unemployment; (ii) a binary indicator for whether unemployment *increased* between the two waves; (iii) a binary indicator for whether local GVA *declined*; and (iv) a continuous measure of the change in the local unemployment rate.

Table C.7: Long-Difference: Belief Changes Interacted with Local Economic Conditions

	(1)	(2)	(3)	(4)	(5)
Δ Hot events	-0.127***	-0.0981	-0.109*	-0.113**	-0.0973
	(0.0424)	(0.0860)	(0.0652)	(0.0524)	(0.0738)
Δ Cold events	0.0591	0.0493	0.0594	0.0307	0.0859
	(0.0443)	(0.0787)	(0.0623)	(0.0528)	(0.0813)
Δ Hot × High unemp.		0.00162			
		(0.111)			
Δ Cold × High unemp.		-0.00227			
		(0.112)			
Δ Hot × Unemp. increased			0.0909		
			(0.121)		
Δ Cold × Unemp. increased			-0.123		
			(0.151)		
Δ Hot × GVA declined				-0.412	
				(0.425)	
Δ Cold × GVA declined				0.615	
				(0.462)	
Δ Hot × Δ Unemp.					-0.000388
					(0.0167)
Δ Cold × Δ Unemp.					0.0111
					(0.0188)
Observations	12,833	8,371	8,371	9,878	8,371
R^2	0.079	0.050	0.050	0.046	0.050

Notes: Dependent variable: within-individual change in climate belief index (0–100) between Wave 4 and Wave 10 of Understanding Society. Δ Hot events and Δ Cold events are combined counts of moderate and extreme anomaly days over the inter-wave period. Standard errors clustered at the Local Authority level in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Column (2): interaction with above-median average LA unemployment. Column (3): interaction with whether LA unemployment increased between waves. Column (4): interaction with whether LA GVA declined. Column (5): continuous interaction with change in LA unemployment rate.

C.5 Ceiling Effect Test

Testing this concern directly using EXAG is not straightforward, EXAG is itself one of the ten items composing the beliefs index, so individuals with high concern on EXAG mechanically start closer to the ceiling of the outcome variable. To circumvent this, the test uses a concern measure whose components are explicitly excluded from the beliefs index. We construct a climate anxiety indicator (ANXIOUS) from two Wave 4 items: whether the respondent expects climate change to affect people seriously within 200 years (200YR) and within 30 years (30YR). As noted in Appendix A.1, these two items are not included in the beliefs index used throughout the paper. Respondents are classified as *not anxious* (expects impacts on neither horizon), *moderately anxious* (expects long-term but not near-term impacts), and *highly anxious* (expects impacts on both horizons). Because ANXIOUS is constructed from items outside the beliefs index, high-anxiety individuals carry no mechanical ceiling disadvantage on the outcome variable, making the test informative. The key observation is that a ceiling effect is a property of an individual's baseline level, not of their interaction with heat exposure. If limited headroom constrains belief growth, highly anxious individuals should gain less than non-anxious individuals *regardless* of heat exposure, i.e. the ceiling does not need heat to activate. Motivated reasoning instead predicts a specific interaction: the differential should be near zero without exposure and only emerge with cumulative heat.

Table C.8: Ceiling Effect Test: Belief Growth by Anxiety Level and Exposure Quartile

	(1) No events	(2) Q1	(3) Q2	(4) Q3	(5) Q4
Moderately anxious	2.698**	-1.285	-1.148	0.697	0.701
	(1.302)	(0.887)	(1.021)	(0.831)	(0.982)
Highly anxious	-0.00491	-2.639***	-3.291***	-2.169***	-1.678**
	(1.072)	(0.704)	(0.754)	(0.594)	(0.849)
Observations	1,559	3,347	2,517	2,955	2,279

Notes: Each column reports OLS estimates from a long-difference regression of the change in the beliefs index between Waves 4 and 10 (scaled 0–100) on anxiety-level indicators, estimated separately within the subsample of individuals with cumulative hot anomaly exposure in the indicated quartile (column 1: no events; columns 2–5: Q1–Q4 of the positive-exposure distribution). The omitted category is non-anxious individuals. Anxiety categories are defined as: *not anxious* (neither 30- nor 200-year impacts expected), *moderately anxious* (200-year but not 30-year impacts expected), and *highly anxious* (both horizons). All specifications include Local Authority fixed effects, month-of-interview fixed effects for Wave 4 and Wave 10, and the full set of individual controls. Standard errors clustered at the Local Authority level in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

C.6 Seasonal Split of Heat Exposure

A potential confound for the long-run result is that positive temperature anomalies in the UK, especially in summer months, may be perceived as pleasant weather rather than as signals of climate risk. If this were the dominant channel, the negative effect on belief growth would be concentrated in summer exposure, when warm anomalies are most likely to be experienced as enjoyable. To test this, the baseline long-difference specification is re-estimated with separate cumulative exposure counts for summer (June–August) and non-summer hot moderate events. These day-count measures are computed from the same LSOA-level anomaly data used in the main analysis, restricted to hot events, and matched to each respondent's location and interview window between Wave 4 and Wave 10. Day counts are used as a proxy for spell counts; the two are highly correlated and the day-count measure is sufficient to test whether the seasonal gradient is present. Table C.9 reports the results. Column 1 replicates the baseline specification using total hot moderate events. Column 2 replaces this with the two seasonal measures. The negative effect is entirely concentrated in non-summer months: the coefficient on non-summer hot days is -0.161 ($p = 0.012$), while summer events are small and statistically insignificant (-0.048, $p = 0.598$). This is the opposite of what a pleasant-weather confound would predict; under that story, the negative effect should be driven by summer events, which are precisely the ones with no effect here.

Table C.9: Seasonal Split of Long-Run Heat Exposure and Belief Growth

	(1) Baseline	(2) Seasonal split
Hot events (total)	-0.127***	
	(0.0424)	
Cold events	0.0591	-0.0281
	(0.0443)	(0.0290)
Hot days - summer (Jun–Aug)		-0.0423
		(0.0906)
Hot days - non-summer		-0.156**
		(0.0642)
Observations	12,833	12,833

Notes: Both columns report OLS estimates from the long-difference regression of the change in the beliefs index between Waves 4 and 10 (scaled 0–100) on cumulative anomaly exposure between waves. Column 1 replicates the baseline specification with total hot event counts. Column 2 replaces total exposure with separate day-count measures for summer (June-August) and non-summer months. Day counts of hot anomalies are matched to each respondent's LSOA between their Wave 4 and Wave 10 interview dates; day counts serve as a proxy for event/spell counts and are highly correlated with the spell-count measure used in the main analysis. All specifications include Local Authority fixed effects, month-of-interview fixed effects for Wave 4 and Wave 10, and the full set of individual controls. Standard errors clustered at the Local Authority level in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

C.7 Long-Differences including Movers

The first part of this appendix tests whether anomaly exposure predicts residential mobility. The corresponding linear probability equations are:

$$\begin{aligned}
\text{Mover}_i &= \beta_1\, C_i^{\text{pos, preW10}} + \beta_2\, C_i^{\text{cold, preW10}} + X_i^{W4\prime}\gamma + \alpha_{LA} + \varepsilon_i, \\
\text{Mover}_i &= \beta_1\, \Delta\text{Hot}_i + \beta_2\, \Delta\text{Cold}_i + X_i'\theta + \alpha_{LA} + \delta_{m(i)} + u_i,
\end{aligned}$$

where Mover_i is an indicator equal to 1 if individual i changes Local Authority between Wave 4 and Wave 10 (and 0 otherwise). $C_i^{\text{pos, preW10}}$ and $C_i^{\text{cold, preW10}}$ are cumulative counts of positive anomalies and cold anomalies measured prior to Wave 10. ΔHot_i and ΔCold_i are the long-difference exposure measures used in the main analysis (changes in cumulative counts of hot events and cold events between the two waves). X_i^{W4} denotes baseline (Wave 4) controls, while X_i denotes the full control set. α_{LA} are Local Authority fixed effects (absorbing time-invariant differences across baseline LAs), and $\delta_{m(i)}$ denotes interview-month fixed effects (Wave 4 and Wave 10). Standard errors are clustered at the Local Authority level.

Table C.10: Selection Equation: Does Anomaly Exposure Predict Moving?

	Dependent variable: Mover (0/1)	
Cumul. positive anomalies (pre-W10)	0.0043	
	(0.004)	
Cumul. cold anomalies (pre-W10)	-0.0026	
	(0.003)	
Δ Hot events		-0.0023
		(0.003)
Δ Cold events		0.0192
		(0.013)
Observations	21,892	21,318
R^2	0.079	0.055
LA FE	✓	✓
Month FE (W4 & W10)		✓
W4 controls	✓	
Full controls		✓

Notes: Each column reports a linear probability model for mover status (0/1). Standard errors clustered at the Local Authority level in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Column (1) tests whether cumulative pre-Wave 10 anomaly counts predict moving, with LA fixed effects and Wave 4 controls. Column (2) tests whether changes in treatment variables (same as the main long-difference specification) predict mover status, with LA and interview-month fixed effects and the full control set. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.11: Long-Difference Beliefs: Robustness Across Mover/Stayer Subsamples

	(1) Full sample	(2) Stayers	(3) Movers	(4) Explained movers
Δ Hot events	-0.132**	-0.084***	-0.100	-0.137
	(0.053)	(0.030)	(0.121)	(0.147)
Observations	16,216	12,833	3,294	2,052
R^2	0.066	0.078	0.137	0.173
LA FE	✓	✓	✓	✓
Month FE (W4 & W10)	✓	✓	✓	✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Dependent variable: within-individual change in climate belief index (0–100) between Wave 4 and Wave 10 of Understanding Society. Standard errors clustered at the Local Authority level in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. All columns include the full set of individual-level controls (age, income, marital status, dependent children, prior-year anomaly counts, interview-day temperature at both waves). Column (1): full sample. Column (2): individuals who did not change Local Authority between waves (same as main analysis). Column (3): individuals who moved. Column (4): movers whose relocation coincided with an observable life event (job change, family formation, etc.).

C.8 Calendar-Year Fixed Effects Robustness

As a robustness check addressing the concern that calendar-year confounders—such as shifts in the UK media or political environment between 2012 and 2020—may be correlated with anomaly exposure and belief trajectories, Table C.12 augments the baseline long-difference specification with interview-year fixed effects λ_y, included separately for Wave 4 and Wave 10. These absorb any national-level time-varying shocks specific to the calendar year in which each respondent was interviewed. The coefficients on heat and cold exposure are very close to the main estimates in Table 4.2, suggesting that calendar-year confounders do not drive the results. Note that this check absorbs national-level year effects only; geographically heterogeneous time trends (e.g. locally differential political or media salience) cannot be absorbed without collinearity with the long difference itself, and remain a caveat.

Table C.12: Long-Difference Robustness: Adding Interview-Year Fixed Effects

Δ Hot Events	-0.129***
	(0.0426)
Δ Cold Events	0.0600
	(0.0447)
Observations	12,833
R^2	0.079
LA FE	✓
Month FE (W4 & W10)	✓
Year FE (W4 & W10)	✓

Notes: Standard errors clustered at the Local Authority level in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. The specification augments the baseline long-difference model of Table 4.2 with interview-year fixed effects for Wave 4 and Wave 10, absorbing national-level time-varying shocks. All other controls and fixed effects are identical to the baseline.

C.9 Degree Day Robustness

Table C.13 replicates the long-difference beliefs regression of Table 4.2, replacing the anomaly-event treatment with cumulative Cooling Degree Days (CDD) and Heating Degree Days (HDD). CDD is the sum of annual degrees above 22°C at the respondent's Wave 4 LSOA across all calendar years spanned by their Wave 4 to Wave 10 interviews; HDD measures the analogous cumulative cold burden using a 15.5°C threshold. Both are constructed from HadUK-Grid 5 km daily data. Unlike the anomaly-event counts in the main specification, these variables capture absolute thermal exposure rather than deviations from the local historical norm. Panel B standardises each variable by its sample standard deviation.

Neither CDD nor HDD is statistically significant once Local Authority fixed effects are included. This is unsurprising on reflection: cumulative degree days largely reflect stable local climate, so much of their cross-sectional variation is absorbed by geographic fixed effects rather than identifying individual-level exposure. The contrast with the anomaly-event results—which survive Local Authority fixed effects—follows from the design of the anomaly measure: by normalising against local historical norms, anomaly counts carry genuine within-location variation that geographic controls cannot remove. The null on absolute heat burden is therefore consistent with the main finding: it is unexpected temperature shocks, not total thermal load, that shapes the trajectory of climate beliefs.

Table C.13: Long-Difference Robustness: Cooling and Heating Degree Days

	(1) Δ Beliefs (raw)	(2) Δ Beliefs (std.)
Cum. CDD	-0.00101	
	(0.00142)	
Cum. HDD	0.0000796	
	(0.000244)	
Cum. CDD (std.)		-0.440
		(0.617)
Cum. HDD (std.)		0.112
		(0.345)
N	12,833	12,833
R^2	0.078	0.078

Notes: Standard errors clustered at the Local Authority level in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Dependent variable: within-individual change in the climate beliefs index between Wave 4 and Wave 10, scaled 0–100. CDD (Cooling Degree Days) = cumulative sum of annual degrees above 22°C over all years between each respondent's Wave 4 and Wave 10 interview, computed at the Wave 4 LSOA; HDD analogously for degrees below 15.5°C. Both constructed from HadUK-Grid 5 km daily data. Column (1) uses raw cumulative values; column (2) standardises each by its sample standard deviation. All specifications absorb Local Authority and month-of-interview fixed effects for both waves and include the full set of individual-level controls.