Does concern regarding climate change impact subsequent mental health? A longitudinal analysis using data from the Avon Longitudinal Study of Parents and Children (ALSPAC)

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Abstract

Climate change is having a substantial – and increasingly severe – impact on our planet, affecting people's health, security and livelihoods. As a consequence, the concept of 'climate anxiety' has recently been developed to characterise the psychological and emotional impact of concern over climate change. However, whether climate anxiety – or less extreme manifestations such as climate concern – impacts subsequent mental health is uncertain. Numerous studies have identified an association between climate anxiety and worse mental health, but as most of this research is cross-sectional it is impossible to infer the direction of causation (e.g., does climate anxiety cause broader mental health, or do broader mental health problems cause climate anxiety, or is there bidirectional causation?). In this paper, we will use longitudinal data from young adults (aged approx. 30 years old) in the Avon Longitudinal Study of Parents and Children (ALSPAC) based in the UK. ~~As climate concern (our proxy for climate anxiety) was measured prior to later mental health in ALSPAC, w~~We first aim to answer the following ~~primary~~ research question: Does concern regarding climate change cause subsequent mental health? Our outcomes will be a range of validated mental health scales for depression, anxiety and well-being, and analyses will adjust for a range of baseline confounders and prior mental health to try and estimate an unbiased causal effect. As a second~~ary~~ research question, we will explore whether the association between climate concern and mental health is moderated by whether participants engage in climate action and whether they believe that individual actions can mitigate the impacts of climate change. The results of this study will help us understand the causal relations between climate concern~~/anxiety~~ and subsequent mental health, which could inform efforts to support individuals with climate concern and anxiety.

Keywords: ALSPAC; Climate Anxiety; Climate Concern; Mental Health; Longitudinal; Causal Inference

Introduction

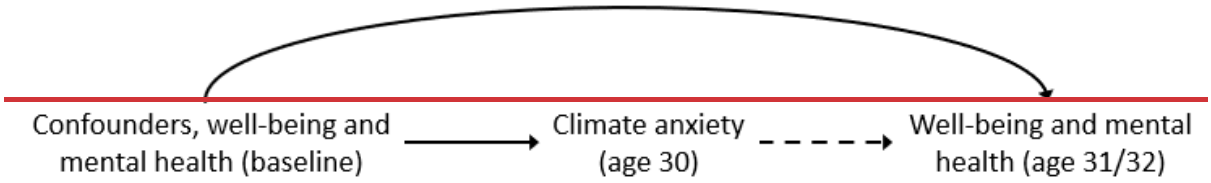
Climate change is increasingly affecting our planet, impacting people's health, security and livelihood, as well as wider biodiversity (IPCC, 2023). At current rates of greenhouse gas emissions, our planet's climate is expected to get more extreme and more volatile, increasingly affecting both people and the environment. The consequences of inactivity and 'business-as-usual' are therefore predicted to be dire, including increased displacement of people, famine, catastrophic weather events, biodiversity loss and the disappearance of countries and communities close to sea-level (IPCC, 2023).

Given these devastating predictions – especially when coupled with the slow progress and frequent lack of political will to reach net-zero greenhouse gas emissions (Hickman et al., 2021) – it is perhaps not surprising that many studies have identified 'climate anxiety' (or 'eco-anxiety') as an emotional response to these events, even in individuals not yet directly affected by climate change (Clayton, 2020; Dodds, 2021). Although various definitions have been proposed (Coffey et al., 2021), climate anxiety has been broadly defined as a "heightened emotional, mental or somatic distress in response to dangerous changes in the climate system" (Climate Psychology Alliance, 2020); or, perhaps more starkly, as "a chronic fear of environmental doom" (Clayton et al., 2017). Climate anxiety has been associated with a range of symptoms including panic attacks, helplessness, anger, sadness, sleeplessness and irritability (Climate Psychology Alliance, 2020; Coffey et al., 2021), and may particularly affect children and young adults (Hickman et al., 2021; Léger-Goodes et al., 2022).

Over the past 5 or so years, public awareness of climate anxiety has increased, with celebrities and high-profile names such as Greta Thunberg reporting to suffer from climate anxiety (e.g., these news articles: ~~(~~McGinn, 2019; Vaughan, 2019; Young, 2020) ~~https://grist.org/politics/2019s-biggest-pop-culture-trend-was-climate-anxiety/, https://www.newscientist.com/article/mg24432613-000-the-world-started-to-wake-up-to-climate-change-in-2019-now-what/ and https://www.independent.co.uk/life-style/children-climate-change-sleep-nightmares-eco-anxiety-greta-thunberg-a9371191.html)~~. Numerous studies have found that anxiety regarding climate change is associated with worse mental health, such as higher rates of depressive and anxiety symptoms (Clayton & Karazsia, 2020; Helm et al., 2018; Searle & Gow, 2010; Stanley et al., 2021), as summarised ~~in~~ by Clayton and Coffey (Clayton, 2020; Coffey et al., 2021). However, climate anxiety may not always be pathological, as it can also lead to positive and adaptive responses such as increased climate action (Clayton, 2020). This includes performing a greater number of pro-environmental behaviours and engaging in environmental activism (Ogunbode et al., 2022); such adaptive behavioural responses – and in particular collective, as opposed to individual, climate actions – have been suggested to mitigate the negative aspects of climate anxiety (e.g., ~~(~~Schwartz et al., 2023)~~)~~. Given these relationships, there have been a number of reports claiming that climate anxiety is a potential mental health crisis and offering advice to help minimise the impact of climate anxiety, by groups such as the Climate Psychology Alliance (Climate Psychology Alliance, 2020) and the American Psychological Association (Clayton et al., 2017).

However, much of this work is cross-sectional (for a rare exception, see ~~(~~Sciberras & Fernando, 2022)~~)~~ and on small and non-representative samples. This makes it difficult to know whether climate anxiety does in fact cause subsequent mental health ~~issues~~, and – if so – how best to support those with climate anxiety (note that, following standard practice in causal inference literature (Hernán & Robins, 2020), throughout this paper our use of 'cause' is agnostic regarding the direction of effect). For instance, it is plausible that prior mental health may cause both climate anxiety and subsequent mental health ~~(Figure 1)~~, meaning that longitudinal data are needed to adjust for prior mental health in order to remove this bias due to reverse causality and try to estimate an unbiased causal effect (VanderWeele, 2021); given this, there have been calls for longitudinal work to try and tease apart

these complex causal relations (Sampaio & Sequeira, 2022). Furthermore, the lack of large-scale population-based studies with representative samples may limit the generalisability of previous results, be unable to detect relatively small effect sizes, and potentially be biased due to selection (e.g., if participants with an interest or belief in climate change were more likely to take part; ~~(~~Hernán & Robins, 2020; Lu et al., 2022)~~)~~. There is therefore a need to explore these questions using data from a large-scale longitudinal population-based study; this is what we intend to do here, using data from the Avon Longitudinal Study of Parents and Children (ALSPAC) based in the UK.



~~*Figure 1:* Directed Acyclic Graph (DAG) showing the assumed relations between climate anxiety, well-being/mental health variables and confounding variables in the present study. Arrows represent the direction of causality. Our causal effect of interest is the dashed arrow between 'Climate anxiety (age 30)' and 'Well-being and mental health (age 31/32)'. Given the assumptions embedded in this DAG, even if climate anxiety does not cause subsequent mental health, in cross-sectional research we would still expect to observe an association between these variables due to confounding between the baseline variables (confounders and/or prior well-being/mental health) and both the exposure (climate anxiety) and the outcome (later well-being and mental health). By using longitudinal data, we can control for both baseline confounders and prior well-being/mental health, allowing us to close this back-door path between the exposure and outcome, and estimate an unbiased causal effect of interest (assuming the assumptions embedded in the DAG are correct). Note that baseline confounders (e.g., sex, socioeconomic position, etc.) and baseline well-being/mental health variables have been grouped together here for ease of presentation.~~

Note that throughout the rest of this paper we predominantly focus on concern regarding climate change ('climate concern') rather than 'climate anxiety' specifically. As we discuss in more detail below, while climate concern and climate anxiety are correlated they are not synonymous, with climate concern reflecting the less-severe manifestations of climate anxiety (Lutz et al., 2023). However, we focus on climate concern here for several reasons. First, climate concern is much more common than climate anxiety in the population, with approximately 60% of 16-25 year-olds worldwide 'extremely' or 'very' worried about climate change (Hickman et al., 2021); for similar results, see (Clayton, 2020; Major-Smith, Halstead, Major-Smith, et al., 2024). Understanding the causal relationships between climate concern and mental health/well-being could therefore have important public health implications beyond focusing on more extreme manifestations of climate anxiety. Second, it is possible that the concept of climate anxiety – often characterised by clinical symptoms of depression and anxiety disorder (e.g., panic attacks, helplessness, sadness, sleeplessness; ~~(~~Climate Psychology Alliance, 2020; Coffey et al., 2021) – conceptually overlaps with our mental health outcomes, and hence measure the same (or very similar) constructs. While not all scales of climate anxiety focus on these clinically-relevant symptoms (e.g., ~~(~~Clayton & Karazsia, 2020), we side-step this potential complication in our study by focussing on climate concern, rather than climate anxiety. Finally, from a practical perspective, we are also constrained by our secondary dataset, which only contains information on climate concern, not climate anxiety.

Our primary aim is therefore to use ALSPAC's longitudinal data to explore whether climate concern ~~regarding climate change (our proxy for climate anxiety, as discussed in more detail below)~~ may

cause later mental health, adjusting for prior mental health status and a range of baseline confounders to rule out both confounding bias and reverse causality (Figure 1). As a secondary aim, we will investigate whether this association is moderated by engagement in individual climate actions and/or belief that individual actions can impact climate change (i.e., whether participants who are concerned about climate change but do little to act on this/don't believe that their actions will have any impact have worse mental health outcomes; ~~(~~Schwartz et al., 2023)~~)~~. Our research questions are therefore (note that as our aim is causal effect estimation rather than statistical hypothesis testing, these are phrased as broad research questions rather than specific hypotheses; see ~~(~~Hernán & Greenland, 2024)~~)~~:

1) Does concern regarding climate change cause subsequent mental health?

2) Does engaging in climate action, or belief that individual climate action is effective, moderate the relationship between climate concern and mental health?

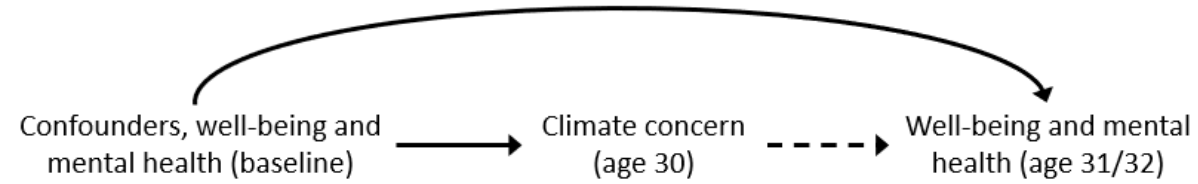


Figure 1: Directed Acyclic Graph (DAG) showing the assumed relations between climate concern, well-being/mental health variables and confounding variables in the present study. Arrows represent the direction of causality. Our causal effect of interest is the dashed arrow between 'Climate concern (age 30)' and 'Well-being and mental health (age 31/32)'. Given the assumptions embedded in this DAG, even if climate concern does not cause subsequent mental health, in cross-sectional research we would still expect to observe an association between these variables due to confounding between the baseline variables (confounders and/or prior well-being/mental health) and both the exposure (climate concern) and the outcome (later well-being and mental health). By using longitudinal data, we can control for both baseline confounders and prior well-being/mental health, allowing us to close this back-door path between the exposure and outcome, and estimate an unbiased causal effect of interest (assuming the assumptions embedded in the DAG are correct). Note that baseline confounders (e.g., sex, socioeconomic position, etc.) and baseline well-being/mental health variables have been grouped together here for ease of presentation.

Methods

Study Description

The current research focuses on the ALSPAC offspring generation. Pregnant women resident in Avon, UK with expected dates of delivery between 1st April 1991 to 31st December 1992 were invited to take part in the study. The initial number of pregnancies enrolled was 14,541, of which there were a total of 14,676 foetuses, resulting in 14,062 live births and 13,988 children who were alive at 1 year of age (Boyd et al., 2013; Fraser et al., 2013). When the oldest children were approximately 7 years of age, an attempt was made to bolster the initial sample with eligible cases who had failed to join the study originally, resulting in an additional 913 children being enrolled. The total sample size for analyses using any data collected after the age of seven is therefore 15,447 pregnancies, resulting in 15,658 foetuses, of which 14,901 were alive at 1 year of age (Northstone et al., 2019). ~~The current research focuses on the ALSPAC offspring generation.~~

The final sample size will consist of all eligible offspring alive at 1 year of age who had not withdrawn consent for their data to be used, and who have data for either the exposure (climate concern~~/anxiety~~) or any of the outcomes (mental health and well-being); based on our experiences with ALSPAC data, we expect this final sample size to be approximately 5,000 participants. Note that combined we have extensive experience with ALSPAC data, including on climate change and mental health topics (e.g., ~~(~~Freminot et al., 2024; Halstead et al., 2023; Major-Smith, Halstead, Golding, et al., 2024; Major-Smith, Halstead, Major-Smith, et al., 2024; Major-Smith, Morgan, Golding, & Halstead, 2024)~~)~~; however, we have not yet analysed ALSPAC data for the specific research questions above as we have not yet accessed the mental health and well-being outcome data, and therefore do not know in advance the results of these proposed analyses.

Please note that the study website contains details of all the data that is available through a fully searchable data dictionary and variable search tool: http://www.bristol.ac.uk/alspac/researchers/our-data/. Study data gathered since the study offspring were aged 22 were collected and managed using REDCap electronic data capture tools hosted at the University of Bristol (Harris et al., 2009).

Data

Climate Concern Exposure~~s~~

Our main exposure of interest to indicate climate ~~anxiety~~ concern will be the question "How concerned are you about the impact of climate change?", with answers 'Not at all concerned' (2% of participants), 'Not very concerned' (9% of participants), 'Somewhat concerned' (48% of participants) and 'Very concerned' (41% of participants). As relatively few participants answered 'Not at all concerned', to boost sample sizes and power for the analyses in this paper we will combine these answers with 'Not very concerned', resulting in a three-level categorical variable. A small number of participants (<50) did not answer this climate concern question because they answered that they 'did not believe in climate change' to a previous question; as individuals who do not believe in climate change presumably cannot be concerned about climate change, we will code these individuals as 'Not at all concerned'. This question was asked as part of a questionnaire containing a larger section on 'climate change' between November 2021 and May 2022 when the study offspring were approximately 30 years of age (Major-Smith, Halstead, Major-Smith, et al., 2024).

While previous studies have used similar measures to assess climate anxiety and concern (Hickman et al., 2021; Ogunbode et al., 2022; Poortinga et al., 2019; Sciberras & Fernando, 2022), we note that this measure of 'climate concern' may not fully capture all aspects of 'climate anxiety', especially when compared against validated climate anxiety scales (e.g., the 'climate change anxiety scale'; ~~(~~Clayton & Karazsia, 2020)~~)~~. Although similar measures of climate concern are moderately-to-strongly correlated with validated climate anxiety scales (Lutz et al., 2023; Whitmarsh et al., 2022), it is possible for individuals to be highly concerned about climate change yet not anxious (although logically the inverse – low climate concern but high climate anxiety – would appear impossible). Nonetheless, previous studies investigating climate anxiety have used similar questions regarding climate concern or worry to explore climate anxiety (Sciberras & Fernando, 2022), with these responses having high internal validity with related questions such as feeling 'tense', 'anxious' and 'terrified' regarding climate change (Ogunbode et al., 2022). ~~We therefore acknowledge that although~~While our measure of climate concern ~~may~~ is not ~~be~~ synonymous with climate anxiety, ~~we believe it is a reasonable proxy~~there is conceptual overlap, with recent research confirming that climate concern appears to capture the less-severe end of the climate anxiety spectrum (Lutz et al., 2023). ~~Additionally, from a practical perspective, as we are using secondary data we are limited to the climate change questions that were collected within ALSPAC; while perhaps suffering from measurement error (as we discuss in more detail below), we hope that the other strengths of our study – i.e., longitudinal data on a large-scale broadly-representative longitudinal population-based sample – mean that the insights from this study will still be valuable. For clarity, from now on we will refer to this measure as 'climate concern'.~~

Individual Climate Actions and Efficacy Effect Modifiers

We will also use two further variables from this 'climate change' questionnaire as effect modifiers in ~~secondary~~ follow-up analyses: engagement in individual climate actions and belief that individual actions can impact climate change. For engagement in individual climate actions, participants were given a list of 17 pro-environmental actions (including 'reduced air travel', 'eaten less/no meat and/or dairy' and 'reduced household waste'; see Supplementary Table S1 for a full list), and for each action asked whether they had 'Not done this', 'Done due to climate change' or 'Done for other reasons'. The total number of actions performed for climate change reasons (max = 17; mean = 5.2) will be used as our measure of engagement in climate action. For belief that individual actions can impact climate change, we used the question "Do you think that what you do, however small, will make a difference to the long-term effects of changes to our climate?". The original response options to this question were 'No' (21%), 'Not sure' (27%) and 'Yes' (52%); for this study, to minimise the number of interaction terms and boost power we will combine the 'No' and 'Not sure' response to create a binary variable with the levels 'No/Not sure' and 'Yes'.

Mental Health and Well-being Outcomes

We will use a range of psychometrically validated well-being and mental health outcomes assessed after the climate questions. This will include (scales summarised in Table 1):

i) The 10-item Edinburgh Postnatal Depression Scale (EPDS) to assess depressive symptoms (note that this scale is valid for measuring depression more generally, as well as during the postnatal period; ~~(~~Cox et al., 1987)~~)~~. Total scores range from 0 to 30, with higher scores indicating more severe depressive symptomatology. In the ALSPAC mothers, the EPDS had high internal validity (Cronbach's alpha > 0.80) and construct validity when compared to other validated depression scales, such as the Centre for Epidemiologic Studies Depression Scale (Heron et al., 2004). This EPDS was asked

between June 2023 and January 2024, when the study offspring were approximately 32 years of age.

ii) The 7-item Generalised Anxiety Disorder-7 (GAD7) scale to assess anxiety (Spitzer et al., 2006). Total scores range from 0 to 21, with higher scores indicating more severe anxiety symptoms. Internal consistency of the GAD7 is high (Cronbach's alpha = 0.92) and demonstrated construct validity when compared against other anxiety scales and clinical diagnoses of anxiety (Spitzer et al., 2006). The GAD7 was asked at the same time as the EPDS, above.

iii) The 14-item Warwick-Edinburgh Mental Well-Being Scale (WEMWBS) to assess well-being (Tennant et al., 2007). Total scores range from 14 to 70, with higher scores indicating greater well-being. The scale has high internal validity in population samples (Cronbach's alpha = 0.91) and construct validity when compared against other well-being scales (Tennant et al., 2007). This WEMWBS was asked between December 2022 and May 2023, when the study children were approximately 31 years of age.

Confounders

We will adjust for a range of confounders which, based on plausible assumptions and/or previous literature, may cause both the exposure (climate concern) and the outcomes (well-being, depression and anxiety). These confounders are summarised in Table 2, and include: prior well-being and mental health measures, offspring sex, ethnicity, relationship status, having children, various measures of socioeconomic position (e.g., highest education level, area-level deprivation quintiles, and income), personality traits (here we focus on 'openness to experience', as it is associated with both climate beliefs and mental health in ALSPAC, and 'neuroticism', given its known associations with mental health; (Bhardwaj et al., 2024; Freminot et al., 2024), as well as parental measures of depression, anxiety and socioeconomic position (Hornsey et al., 2016; Joinson et al., 2017; Leach et al., 2008; Moreno-Peral et al., 2014; Poortinga et al., 2019; Reiss, 2013). Note that we have not included 'age' here, as all study offspring are approximately the same age, meaning that age is unlikely to be a confounder.

All confounders were measured prior to the exposure and outcome, with most measured in early adulthood (between 21 and 28 years of age), other than personality assessed at age 13 and parental variables assessed during the pregnancy of the study offspring or shortly afterwards (Table 2). and – il If the assumptions in Figure 1 are met, – adjusting for these confounders should result in an unbiased causal estimate of the exposure-outcome relationship (Hernán & Robins, 2020). However, whether these assumptions are met is impossible to verify empirically, and we will discuss sources of bias which may limit a causal interpretation – such as unmeasured confounding, selection bias and measurement error – in more detail below and in the discussion section of our final paper.

Table 1: Summary of the well-being, depression and anxiety scales used as outcomes in the present study. For the EPDS all items refer to 'in the past week', while for GAD7 and WEMWBS all items refer to 'in the past two weeks'.

Measure	Scale	Items	Responses (scoring)
Depressive symptoms	Edinburgh Postnatal Depression Scale (EPDS; ~~(~~Cox et al., 1987)~~)~~	I have been able to laugh and see the funny side of things	As much as I always could (0); Not quite so much now (1); Definitely not so much now (2); Not at all (3)
		I have looked forward with enjoyment to things	As much as I ever did (0); Rather less than I used to (1); Definitely less than I used to (2); Hardly at all (3)
		I have blamed myself unnecessarily when things went wrong	Yes, most of the time (3); Yes, some of the time (2); Not very often (1); No, never (0)
		I have been anxious or worried for no good reason	No, not at all (0); Hardly ever (1); Yes, sometimes (2); Yes, often (3)
		I have felt scared or panicky for no very good reason	Yes, quite a lot (3); Yes, sometimes (2); No, not much (1); No, not at all (0)
		Things have been getting on top of me	Yes, most of the time (3); Yes, sometimes (2); No, hardly ever (1); No, not at all (0)
		I have been so unhappy that I have had difficulty sleeping	Yes, most of the time (3); Yes, sometimes (2); Not very often (1); No, not at all (0)
		I have felt sad or miserable	Yes, most of the time (3); Yes, sometimes (2); Not very often (1); No, not at all (0)
		I have been so unhappy that I have been crying	Yes, most of the time (3); Yes, quite often (2); Only occasionally (1); No, never (0)
		The thought of harming myself has occurred to me	Yes, quite often (3); Sometimes (2); Hardly ever (1); Never (0)
Anxiety symptoms	Generalised Anxiety Disorder-7 (GAD7; ~~(~~Spitzer et al., 2006)~~)~~	How often have you been bothered by feeling nervous, anxious or on edge?	Not at all (0); Less than half the days (1); More than half the days (2); Nearly every day (3)
		How often have you been bothered by not being able to stop or control worrying?	
		How often have you been bothered by worrying too much about different things?	
		How often have you been bothered by trouble relaxing?	
		How often have you been bothered by being so restless that it is hard to sit still?	

		How often have you been bothered by becoming easily annoyed or irritable?	
		How often have you been bothered by feeling afraid as though something awful might happen?	
Well-being	Warwick-Edinburgh Mental Well-Being Scale (WEMWBS; ~~(~~Tennant et al., 2007)~~)~~	I've been feeling optimistic about the future	None of the time (1); Rarely (2); Sometimes (3); Often (4); All the time (5)
		I've been feeling useful	
		I've been feeling relaxed	
		I've been feeling interested in other people	
		I've had energy to spare	
		I've been dealing with problems well	
		I've been thinking clearly	
		I've been feeling good about myself	
		I've been feeling close to other people	
		I've been feeling confident	
		I've been able to make up my own mind about things	
		I've been feeling loved	
		I've been interested in new things	
		I've been feeling cheerful	

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Table 2: The ALSPAC variables used as confounders in the present study.

Variable	Variable coding	When measured
Prior depressive symptoms	Continuous (Short Moods and Feelings Questionnaire [SMFQ] total score; Angold et al., 1995)	Approx. age 25 years
Prior ICD-10 depression diagnosis	Binary (Yes vs No; based on Clinical Interview Schedule – Revised [CIS-R]; Lewis et al., 1992)	Approx. age 24 years
Prior anxiety symptoms	Continuous (Generalised Anxiety Disorder-7 [GAD7] total score; Spitzer et al., 2006)	Approx. age 21 years
Prior ICD-10 anxiety diagnosis	Binary (Yes vs No; based on CIS-R)	Approx. age 24 years
Prior well-being	Continuous (Warwick-Edinburgh Mental Well-Being Scale [WEMWBS] total score; Tennant et al., 2007)	Approx. age 23 years
Sex	Binary (Female vs Male)	At birth
Ethnicity	Binary (White vs other than White)	In pregnancy (with more recent information to fill in missing data)
Relationship status (living with a partner)	Binary (No vs Yes)	Approx. age 28 years
Have children	Binary (No vs Yes)	Approx. age 28 years
Highest educational qualification	Ordered category (GCSE/none vs vocational vs A-level vs degree) [a]	Approx. age 27 years
Occupational social class	Ordered category (Managerial, administrative and professional vs Intermediate vs Small employers vs Lower supervisory and technical vs [Semi-]routine) [b]	Approx. age 23 years
Monthly income after tax	Ordered category (£0-£499 vs £500-£999 vs £1000-£1499 vs £1500-£1999 vs £2000 and above)	Approx. age 26 years
Index of multiple deprivation	Ordered category (1st quintile [least deprived] vs 2nd quintile vs 3rd quintile vs 4th quintile vs 5th quintile [most deprived])	January 2021
Housing status	Unordered category (owned/mortgaged vs renting vs council/housing association vs other)	Approx. age 28 years
'Openness' personality trait	Continuous (Big-5 personality measure) (Goldberg, 1992)	Approx. age 13 years
'Neuroticism' personality trait	Continuous (Big-5 personality measure) (Goldberg, 1992)	Approx. age 13 years
Maternal depressive symptoms	Continuous (Edinburgh Postnatal Depression Scale [EPDS] total score; Cox et al., 1987)	In pregnancy
Paternal depressive symptoms	Continuous (EPDS total score)	In pregnancy
Maternal anxiety symptoms	Continuous (Crown-Crisp Experiential Index – Anxiety subscale [CCEI-A] total score; Crown & Crisp, 1979)	In pregnancy

Paternal anxiety symptoms	Continuous (CCEI-A total score)	In pregnancy
Mother's age at birth	Continuous (years)	At birth
Mother's highest educational qualification	Ordered category (CSE/none vs vocational vs O-level vs A-level vs degree) [a]	In pregnancy
Parental occupational social class	Ordered category (I vs II vs III non-manual vs III manual vs IV/I) [c]	In pregnancy
Parental weekly household income after tax	Ordered category (£0-£100 vs £100-£199 vs £200-£299 vs £300-£399 vs £400 and above)	When study child approx. age 3 years
Maternal index of multiple deprivation	Ordered category (1st quintile [least deprived] vs 2nd quintile vs 3rd quintile vs 4th quintile vs 5th quintile [most deprived])	In pregnancy
Maternal housing status	Unordered category (owned/mortgaged vs renting vs council/housing association vs other)	In pregnancy

[a] GCSE = General Certificate of Secondary Education qualification (compulsory examinations sat at the end of secondary school at approx. age 16; introduced in 1986 to replace CSE and O-levels); CSE = Certificate of Secondary Education qualification (examinations sat at the end of secondary school at approx. age 16; compulsory from the early 1970s, unless completing O-level qualifications instead; replaced in 1986 by GCSEs); O-level = Ordinary level qualifications (examinations sat at the end of secondary school, often for more academically-able pupils at approx. age 16; replaced in 1986 by GCSEs); A-level = Advanced level qualification (non-compulsory examinations sat at the end of college or sixth form at approx. age 18).

[b] For more information on these National Statistics Socio-Economic Classification categories, see: https://www.ons.gov.uk/methodology/classificationsandstandards/otherclassifications/thenationalstatisticssocioeconomicclassificationnssecrebasedonsoc2010.

[c] For more information on these occupational social classes, see: https://sru.soc.surrey.ac.uk/SRU9.html.

Analysis

~~*Primary analyses*~~*Research question 1* – *Main effect of climate concern*

We will investigate the relationship between our climate concern exposure with each of the outcomes in turn (depressive symptoms, anxiety symptoms, and well-being) using linear regression models. Analyses will be repeated first in unadjusted (univariable) models, followed by adjusted (multivariable) models adjusting for all confounders detailed above. As 'not at all/not very concerned' will be the baseline exposure level for analyses, post-estimation tests will also be used to assess whether the association with mental health outcomes differ between 'somewhat concerned' and 'very concerned' levels of the exposure. Sensitivity analysis to assess the levels of unmeasured confounding necessary to alter the study's conclusions (e.g., making a result null, no longer reaching a given alpha level threshold, or how results would change if the level of unmeasured confounding was the same as the level of measured confounding) will also be applied (Cinelli & Hazlett, 2020).

~~*Secondary analyses*~~*Research question 2* – *Effect modification*

To explore whether the above main effects are moderated by engagement in climate actions and/or belief in individual efforts, we will repeat the above analyses, this time including an interaction

between climate concern with either 'total number of individual climate actions' or 'belief in efficacy of individual actions'.

Missing data

As is common with longitudinal population-based studies, as data were collected in multiple waves there are missing data in many of our variables. When focusing on our analytic sample – i.e., those with exposure or outcome data (estimated approx. 5,000 participants) – levels of missing data in each variable are likely to be small (estimated 10-20%). Despite the low amount of missing data in each variable, as there are lots of confounding variables this could add up to a large degree of missingness in the final complete-case analysis; of the approximately 5,000 participants estimated to be in the analytic sample, based on our experience with the ALSPAC data we estimate that there will likely be approximately 1,000 participants in the final complete-case analysis.

Due to the large amount of missing data, these analyses are likely to be inefficient (i.e., wider standard errors/confidence intervals). Missing data can also result in selection bias if missingness is related to the outcome (Hernán, 2017; Hernán & Robins, 2020; Lu et al., 2022). However, as we will adjust for a range of variables known to relate to continued ALSPAC participation - such as maternal age, socioeconomic position, prior mental health and offspring sex (Cornish et al., 2020; Fernández-Sanlés et al., 2021; Fraser et al., 2013) – this should minimise the extent of selection bias and we would expect complete-case analyses to be relatively unbiased (Hughes et al., 2019). Despite the inclusion of these predictors of selection, we cannot rule out the risk of selection bias, as we discuss in more detail below.

Although we expect the complete-case analyses to be largely unbiased, we will impute missing data via multiple imputation using chained equations to boost sample size and increase power (van Buuren, 2018; White et al., 2011). The scenario described here – small amounts of missing data in a large number of variables – is ideally-suited for multiple imputation as observed data from the other variables can be used to inform missing data in the other variables. We will impute up to the ~5,000 participants expected in the analytic sample, and use these multiply-imputed results as our main analyses. We will also compare these multiply-imputed results against the complete-case results; as detailed above, we do not expect these complete-case results to be less biased than to those from multiple imputation, but do expect multiple imputation to increase efficiency. For all multiple imputation analyses, we will generate 50 imputed datasets with a burn-in of 10 iterations (this will be checked to ensure convergence), with the imputation model specific to the variable of interest (e.g., logistic regression for binary variables, linear regression or predictive-mean matching for continuous variables, etc.).

For ~~our primary analysis~~research question 1 – the main effect of climate anxiety on mental health and well-being – we will perform multiple imputation including all outcomes in the same imputation model. All of the exposure, outcome and confounder variables described above will be included in this imputation model.

For ~~our secondary analyses~~research question 2 exploring potential effect modification, as there are additional complexities when imputing data with interactions to ensure that the imputation model is compatible with the substantive analysis model (Bartlett et al., 2015; Tilling et al., 2016; White et al., 2011), we will perform multiple imputation separately for these analyses. To simplify the process of including interaction terms in our imputation models, we will also conduct multiple imputation separately for each outcome-effect modifier combination (rather than including all interaction terms in the imputation model). We will first perform imputations using the 'all interactions' approach,

which is necessary to ensure the imputation model is compatible with the analysis model and returns unbiased estimates (assuming the 'missing-at-random' assumption is met, which we assume it is here; ~~(~~Tilling et al., 2016)~~)~~. That is, when imputing the mental health or well-being outcome we will include the exposure-effect modifier interaction in the imputation model; when imputing the climate anxiety exposure we will include the outcome-effect modifier interaction in the imputation model; and when imputing the effect modifier we will include the outcome-exposure interaction in the imputation model. Because best practice for the inclusion of interaction terms in multiple imputation is still a young and evolving field, we will also include an additional multiple imputation method for interactions as a sensitivity analysis, known as multiple imputation by 'substantive model compatible fully conditional specification' (SMCFCS; ~~(~~Bartlett et al., 2015). This approach is similar to standard multiple imputation, but uses rejection sampling to ensure that the results of the imputation models are compatible with the substantive analysis model. As with the ~~primary~~ multiple imputation analysis for research question 1, for both approaches all other covariates in addition to the exposure, outcome and effect modifier will be included in all imputation models. If both the 'all interactions' and SMCFCS approaches provide similar answers, this will increase confidence that our results are robust. We will also estimate the main effect of the exposure on the outcome to check that different imputation models provide similar results to those of the ~~primary~~ research question 1 analysis above.

All analyses will be conducted in R version 4.3.1 (R Development Core Team, 2021), with standard multiple imputation and the 'all interactions' approach performed using the 'mice' package (van Buuren, 2018), SMCFCS performed using the 'smcfcs' package (Bartlett et al., 2015), and unmeasured confounding sensitivity analyses performed using the 'sensemakr' package (Cinelli & Hazlett, 2020). As noted above, as our study focuses on causal effect estimation rather than hypothesis testing, the main focus of our results will be on the range of plausible effect sizes (i.e., point estimates and 95% confidence intervals); *p*-values (interpreted as continuous measures of evidence against – on incompatibility with – the null hypothesis of no association) will be interpreted alongside these effect estimates, in addition to R^2 statistics and predicted values/marginal effects from these models, to help interpret and contextualise results (Sterne & Davey Smith, 2001). For example analysis code using simulated data, see the 'ClimateConcernAndMH_ExampleAnalysisCode.r' script (https://osf.io/9zpyn/).

Power Analyses

Given the complexities of the dataset and analyses – many confounding variables, variables with missing data, the use of multiple imputation methods and uncertainty regarding the causes of missingness – all of which impact power, it is difficult to estimate an accurate minimum effect size ~~of interest for~~ this study would be capable of detecting ~~given the sample size available~~. Nonetheless, we have conducted a relatively simple simulation-based power analysis to estimate our power to detect a range of plausible minimum effect sizes for our ~~primary~~ research question 1 analysis (whether climate concern causes subsequent well-being and mental health), based on an expected complete-case sample of 1,000 participants. For the purposes of this power analysis we use an alpha level of 0.05, based on 1,000 simulated datasets (see the 'ClimateConcernAndMH_PowerAnalysis.r' script: https://osf.io/9zpyn/). Our plausible minimum effect size estimates were based on a range of effect sizes for a per-standard deviation (SD) increase in the mental health outcome, using the same effect size for both levels of the exposure ('somewhat concerned' and 'very concerned'), with 'not at all/not very concerned' as the baseline; the effect sizes explored were 0.1, 0.2 and 0.3 (followed by 0.25) SD unit differences. As these effect sizes are on the standardised mean difference scale, they are comparable to Cohen's *d* effect sizes.

Based on this power analysis using plausible parameter values, there was little power to reliably detect effect sizes of 0.1 SD difference (power for 'somewhat concerned' = 0.192; power for 'very concerned' = 0.176), or of 0.2 SD difference (power for 'somewhat concerned' = 0.603; power for 'very concerned' = 0.545). There was sufficient power to reliably detect an effect size of 0.3 SD difference over 90% of the time (power for 'somewhat concerned' = 0.939; power for 'very concerned' = 0.901), with moderate power to detect an effect size of 0.25 SD difference (power for 'somewhat concerned' = 0.798; power for 'very concerned' = 0.749). Given these assumptions, this suggests that our ~~primary~~ analysei~~s~~ for research question 1 likely haves~~s~~ sufficient power to detect effect sizes of 0.25 SD unit differences~~s~~ or greater, and definitely above 0.3. However, given the complications mentioned above, this estimate may not be wholly accurate; for instance, if the confounders explain more or less variability in the outcome than our simulations assume then power may be either higher or lower, while using multiple imputation to boost the sample size may improve power (although it is unclear by how much as this will depend on the amount and patterning of missing data and how accurately the imputation models impute missing data values). Nonetheless, the results of this power analysis provide a useful benchmark regarding the minimum effect size of interest we can expect to reliably observe.

We also conducted power analyses for our ~~secondary~~ research question 2 analyses~~s~~, regarding potential effect modification of the above associations by both engagement in climate action (continuous variable) and belief in the efficacy of climate change efforts (binary variable). For engagement in climate action, our power analyses indicated moderate power to detect an interaction effect when a one-unit increase in climate actions was associated with a 0.05 SD improvement in mental health scores among those concerned about the climate (power for 'somewhat concerned' interaction = 0.794; power for 'very concerned' interaction = 0.692); to help contextualise this, we simulated climate action to have a standard deviation of 2, so a 2 ~~standard deviation~~SD increase in climate action would lower mental health scores by approximately 0.2 of a ~~standard deviation~~SD among individuals concerned about climate change. Power was substantially weaker when the interaction effects were set to 0.025 SD units (power for 'somewhat concerned' interaction = 0.291; power for 'very concerned' interaction = 0.242). For the power analyses with 'climate efficacy' as the effect measure modifier, there was sufficient power to detect an effect if belief in climate efficacy lowered mental health scores by 0.2 SD units among those concerned about the climate (power for 'somewhat concerned' interaction = 0.827; power for 'very concerned' interaction = 0.714), but not if the interaction effect size was 0.1 (power for 'somewhat concerned' interaction = 0.313; power for 'very concerned' interaction = 0.256).

See table 3 below for a study design template summarising the proposed study.

Threats to causality and generalisability

We will now briefly discuss the three main threats to causal inference – confounding, selection bias and measurement error (Hernán & Robins, 2020) – and whether we believe they may cause bias in our proposed analyses. We note here that these are just our assumptions, and it is possible that they may be incorrect; further work will be required to explore this in more depth and see whether our results replicate. We will also end with a brief discussion on generalisability.

Confounding. Confounding bias has been discussed in detail above, and we believe that inclusion of the wide range of baseline confounders detailed above (Table 2) is sufficient to reduce the risk of confounding bias, particularly the inclusion of baseline mental health and well-being variables. While it is of course possible that other unmeasured confounders which we have not considered may bias these associations, mental health/well-being and sociodemographic factors are known to have

strong associations with both climate anxiety and mental health (Clayton, 2020) and so are key confounders to adjust for which will hopefully minimise the possibility of unmeasured confounding. As ALSPAC has currently only asked the climate questions once, we are not able to adjust for prior climate concern, which could perhaps be a relevant confounder if it impacts both climate concern at age 30 and subsequent mental health (independent of prior mental health; ~~(~~VanderWeele, 2021). A related source of confounding bias is due to 'residual confounding'; that is, if the confounders are measured with error, then their inclusion as covariates may not be sufficient to fully remove confounding bias (Greenland, 1980; Hernán & Robins, 2020). While possible, many of the prior mental health confounders are based on validated scales, while the inclusion of a wide-range of socioeconomic confounders should increase the probability of capturing socioeconomic position accurately, hopefully reducing the risk of residual confounding. Even if unmeasured or residual confounding is a possibility, the use of sensitivity analyses for unmeasured confounding will allow us to explore the levels of unmeasured confounding necessary to alter our interpretations and whether these are plausible or not.

Selection bias. This bias has been discussed above in the 'missing data' section, which we will expand upon here. One main concern is that that our intended imputation procedure is only to ~5,000 participants in the analytic sample with exposure and/or outcome data, which is around one-third of the full ALSPAC sample size. While this selected sample could theoretically result in bias, we have made this decision for both practical and theoretical reasons. From a practical perspective, as only ~30% of the ALSPAC sample have exposure or outcome data, there is a greater chance of model misspecification and resulting error in the imputation model when imputing this large a proportion of missing data for the full ~15,000 sample, especially given the lack of valid auxiliary variables to help predict this missing data (Cornish et al., 2015). From a theoretical perspective, as discussed above the inclusion of factors known to relate to continued ALSPAC participation – such as maternal age, socioeconomic position, prior mental health and offspring sex – in our substantive analysis model is likely to reduce the risk of selection bias by making the 'missing-at-random' assumption more plausible. While it is possible that the exposure and outcome may cause selection directly – which would not be corrected by the covariate adjustment method described above – we believe that this is unlikely to result in substantial bias as we feel that participation in ALSPAC is unlikely to be strongly influenced by the exposure climate concern, independent of the other covariates included in our model. This is because ALSPAC is predominantly a health study, with the climate questions embedded within a larger questionnaire, meaning that completion is unlikely to be strongly associated with climate awareness and concerns. While this is an assumption, if the exposure has little relation to selection then collider stratification selection bias is unlikely to strongly bias results (Hughes et al., 2019), although we cannot rule out effect modification selection bias if variables which moderate the exposure-outcome relationship themselves cause selection (Lu et al., 2022).

Measurement error. As our outcomes have been assessed using well-validated scales, we anticipate little measurement error in our outcomes, minimising the risk of bias. Prior ALSPAC research has shown that self-reported responses to potentially-sensitive topics, such as mental health and medical records, are comparable to 'gold-standard' measures (Golding et al., 2001), providing some assurance against bias due to measurement error. However, as discussed above it is possible that our measure of climate concern may not fully capture all relevant aspects of climate anxiety; that is, our exposure may be measured with error if climate concern is intended as a proxy for climate anxiety. Although climate concern is certainly an important aspect of climate anxiety, and previous studies have shown that climate concern and climate anxiety are related and may measure similar constructs (Lutz et al., 2023; Ogunbode et al., 2022; Whitmarsh et al., 2022), this study likely overlooks many of the specific thoughts and behaviours related to climate anxiety which may be captured by more detailed and validated scales (e.g., ~~(~~Clayton & Karazsia, 2020~~)~~. As noted above,

while this is to some extent unavoidable given our use of secondary ALSPAC data, it is an important limitation to consider. For instance, the focus on climate concern could perhaps result in an underestimate of the true effect size of the impact of climate anxiety on mental health, as only those suffering from severe climate anxiety – and not merely those very concerned about climate change – may have worse subsequent mental health. We hope that future research can combine the strengths of our study – large-scale broadly-representative longitudinal data – with well-validated measures of climate anxiety to explore if/how they differ from our results using just climate concern. We also note that our 'individual climate actions' effect modifier could be measured with error as the question asked whether participants had performed any of these actions, regardless of frequency (Table S1). This could lead to a dilution of any potential effect modification if, for instance, engaging repeatedly in these climate actions moderated the relationship between climate concern and mental health/well-being more compared to only performing these actions once; yet in these analyses both situations are impossible to separate and would be grouped together.

Generalisability: As this sample is based on ALSPAC offspring born in the early 1990s in the Bristol/Avon area of south-west England, the extent to which results may be generalisable to the wider UK population – or beyond – is unclear. For instance, ALSPAC offspring are more ethnically homogenous compared to the wider UK population (~4% of ALSPAC offspring have an ethnicity other than White vs ~14% in the wider UK population) and are less likely to come from low income households (Boyd et al., 2013; Fraser et al., 2013). The extent to which results would generalise to ages beyond those studied here (early 30s) is also unknown. Finally, we note that the city of Bristol is a very 'green' city, being the first in the UK to declare a Climate and Ecological Emergency (Bristol City Council, 2023) and one of the first to elect a Green Party member of parliament. It is possible that this could alter the relationship between climate concern and mental health, compared to other less 'green' areas; for instance, those concerned about climate change might have a larger social support network of like-minded individuals, potentially mitigating any impacts on mental health or well-being.

Table 3: Study design template summarising the proposed study. R scripts for the power analyses and demonstrating the proposed analyses can be found on the OSF (https://osf.io/9zpyn/).

Question	Hypothesis	Sampling plan	Analysis Plan	Rationale for deciding the sensitivity of the test for confirming or disconfirming the hypothesis	Interpretation given different outcomes	Theory that could be shown wrong by the outcomes
~~Primary analysis~~Research question 1: Does concern regarding climate change cause subsequent mental health?	N/A (as interested in causal effect estimation, rather than hypothesis testing; although based on previous research on may expect that climate concern would cause worse subsequent mental health)	Secondary data from UK longitudinal birth cohort study (Avon Longitudinal Study of Parents and Children; ALSPAC), with expected analytic sample sizes of ~1,000 (in complete-case analyses) and ~5,000 (for multiple imputation analyses, including all participants with exposure or outcome data). See main text for simplified (but plausible) simulation-based power analyses for detecting minimum effect sizes.	We will investigate the relationship between our climate concern exposure with each of the outcomes in turn (depressive symptoms, anxiety symptoms, and well-being) using linear regression models. To account for missing data and increase sample size of analyses, we will use multiple imputation, as described in the main text, and compare results from the multiply-imputed and complete-case analyses.	N/A (as interested in causal effect estimation, rather than hypothesis testing; will use effect sizes, 95% confidence intervals, *p*-values, R^2 statistics and predicted values/marginal effects from these models used to help interpret and contextualise results. Sensitivity analyses will also be conducted to explore the extent of unmeasured confounding necessary to alter interpretation of results).	These analyses could find that climate concern may cause worse mental health and well-being. If so, discussion of whether the assumptions for a causal interpretation from observational data are met (i.e., no confounding, selection bias or measurement error) would be needed, in addition to whether the observed effect size is of practical significance. Alternatively, perhaps no effect would be observed, suggesting that climate concern may not cause mental health/well-being (again, assuming a causal interpretation is warranted). We would not anticipate climate concern to cause *better* mental health or well-being.~~As per 'rationale'~~	While not a specific theory as such, by using longitudinal data and applying a causal inference approach these results will help to understand the extent to which concern regarding climate change may cause subsequent mental health and well-being (if at all). These results could help inform interventions to promote mental health and well-being in relation to climate concern.

					~~box, will use a range of statistics to aid interpretation of direction and magnitude of plausible effect sizes.~~	
~~Secondary analyses~~Research question 2: Does engaging in individual climate action~~s~~, or belief that individual climate action is effective, moderate the relationship between climate concern and mental health?	N/A (as interested in causal effect estimation, rather than hypothesis testing; although based on previous research may expect that engaging in climate actions and belief in efficacy of individual climate actions could buffer any negative relationship between climate concern and subsequent mental health)	As above, using secondary ALSPAC data. Using similar power analyses to above, but now including interaction terms. See main text for simplified (but plausible) simulation-based power analyses for detecting minimum effect sizes.	We will repeat the above analyses, this time including an interaction between climate concern with either 'total number of climate actions' or 'belief in efficacy of individual actions'. Multiple imputation will again be used to impute missing data (using both the 'all-interactions' and 'substantive model compatible' approach~~es~~ to include interaction effects).	As above (with exception of no sensitivity analyses for unmeasured confounding).	~~As above, but with a specific focus on predicted values from the models to aid interpretation of the magnitude of potential effect modification.~~ It is plausible that individuals concerned about climate change may have better mental health/well-being if they engage in individual climate actions and/or believe in the efficacy of climate actions. Alternatively, perhaps these variables do not moderate the relationship between climate concern and mental health. We believe it is unlikely for these variables to cause *worse* mental health/well-being among those concerned about the climate. As above, interpretation of whether these results	As above, but with a specific focus on whether engaging in climate action or belief in the efficacy of individual climate actions moderate the above relationship, again with possible practical applications regarding potential interventions to aid individuals concerned and distressed about climate change.

					may be causal, and the practical implications of any observed effect sizes, would again be needed.	

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Competing interests

None.

Ethics

Ethical approval for the study was obtained from the ALSPAC Ethics and Law Committee and the Local Research Ethics Committees. Informed consent for the use of data collected via questionnaires and clinics was obtained from participants following the recommendations of the ALSPAC Ethics and Law Committee at the time.

Data and Code Availability

ALSPAC data access is through a system of managed open access. Information about access to ALSPAC data is given on the ALSPAC website (http://www.bristol.ac.uk/alspac/researchers/access/) and in the ALSPAC data management plan (http://www.bristol.ac.uk/alspac/researchers/data-access/documents/alspac-data-management-plan.pdf). Data used for this submission will be made available on request to the Executive (alspac-exec@bristol.ac.uk). The datasets presented in this article are linked to ALSPAC project number B4572, please quote this project number during your application.

Analysis code and synthetic ALSPAC datasets (created using the 'synthpop' R package; ~~(~~Nowok et al., 2016)~~)~~ will be openly-available on DM-S's GitHub page once the analyses have been conducted: https://github.com/djsmith-90. As raw ALSPAC data cannot be released, these synthesised datasets will be modelled on the original data, thus maintaining variable distributions and relations among variables (albeit not perfectly), while at the same time preserving participant anonymity and confidentiality, thus allowing this research to be 'quasi-reproducible' (Major-Smith, Kwong, Heron, Northstone, et al., 2024). Please note that while these synthetic datasets can be used to follow the analysis scripts, as data are simulated they should not be used for research purposes; only the

actual, observed, ALSPAC data should be used for formal research and analyses reported in published work. For this analysis plan, scripts demonstrating the proposed analyses using simulated data, and for the power analyses, can be found on the following OSF page: https://osf.io/9zpyn/.

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Supplementary Information

Supplementary Table S1: List of the 17 pro-environmental actions asked to participants. For each action, participants were asked to tick the response options that applied, from "Action taken due to climate change", "Action taken for other reasons" or "I have not done this". Note that the question "taken action to eat less or not meat and/or dairy products" contained the additional responses "I have always been vegan" and "I have always been vegetarian".

Pro-environmental behaviour
1) Changed the way I travel locally
2) Reduced my household waste
3) Reduced energy use at home
4) Changed what I buy
5) Reduced air travel
6) Bought or hired an electric of hybrid vehicle
7) Bought food produced locally
8) Recycled/Upcycled more
9) Reduced amount of plastic I used
10) Chosen sustainably sourced items
11) Improved insulation in the home
12) Installed solar panels
13) Started growing vegetables
14) Planted tree(s)
15) Avoided organisations that support fossil fuels
16) Not had children, or reduced number of children that I had planned
17) Taken action to eat less or no meat and/or dairy