Supplementary materials for: "Does extreme climate event exposure influence climate-related opinions? The case of the 2019–2020 Australian Black Summer bushfires?"

1 Methods

1.1 Gender differences across studies

We created a multinomial logistic regression model to predict gender as a function of study, using the *multinom* function from the *nnet* package [Venables and Ripley, 2002]. Specifically, we modelled the log odds ratio of female to male participants (male was entered as the reference category) with study entered as a categorical predictor (Study 2 was entered as the reference category). For the purposes of this model, we excluded participants who did not identify their gender as either female or male. Coefficients were exponentiated to estimate odds ratios, and are presented in Table 1. A Wald Z-test was used to estimate the (unadjusted) p values of model coefficients.

Numerically, the ratio of female to male participants was stable across studies. A log likelihood ratio test did not indicate an improvement in model fit when study was included as a predictor, compared to a model with only an intercept term (χ^2 (2) = 0.28, p = 0.868, ω = 0.02). Furthermore, no model coeffecients were statistically significant (Table 1), indicating a lack of evidence that gender differed across studies.

1.2 Age differences across studies

To determine whether age differed across studies, we built a linear regression model. The model predicted age as a function of study, using the *lm* function from the *stats* package [R

Table 1: Estimated effects of study on participant gender, estimated using a multinomial logistic regression model.

		Ratio of female odds and male odds	
Predictors	Categories	Estimate (p value)	95% CI
Intercept	-	0.96 (.691)	[0.79, 1.17]
Study	Study 1	1.07 (.626)	[0.82, 1.40]
	Study 2	-	-
	Study 3	1.00 (.993)	[0.72, 1.40]

Note:
Each study was entered as a categorical predictor, with Study 2 as the reference category. Male was entered as the reference category of gender. Model estimates of coefficients were exponentiated to odds ratios.

Table 2: Linear regression models predicting participant age (years) as a function of study.

Predictors	Categories	Estimate (p value)	95% CI
Intercept	-	46.82 (.000)***	[45.10, 48.54]
Study	Study 1	-0.11 (.927)	[-2.51, 2.28]
	Study 2	-	-
	Study 3	0.31 (.835)	[-2.63, 3.26]

Note:
$^{***}p < .001$.
Each study was entered as a categorical predictor, with Study 2 as the reference category.

Core Team, 2023]. Study was entered as a categorical predictor (Study 2 was entered as the reference category), and a Wald Z-test was used to estimate p values (Table 2).

Numerically, participant age was stable across studies. The linear regression model did not accounted for a significant amount of variance in compared to intercept-only models (F (2, 1058) = 0.04, p = 0.960, R^2 = 0.00, $R^2_{adjusted}$ = 0.00), indicating a lack of evidence that study was a significant predictor of age. Furthermore, no model coeffecients were statistically significant (Table 2), indicating a lack of evidence that gender differed across studies.

1.3 Fast responders

For each study, a pilot study of approximately fifty people was conducted to identify fast responders. Fast responders were identified as those who completed the survey in less than half of the median time taken by participants in the pilot study, which was 873 seconds for Study 1, 664 seconds for Study 2, and 509 seconds for Study 3. The data of fast responders was not collected, and therefore, not included in the analysis.

1.4 Counterbalancing of auxiliary psychological scales

For Study 1, auxiliary psychological scales were counterbalanced using a digram-balanced Latin square design. However, there is a slight discrepancy in the number of each Latin squares completed (range = 25 to 44) due to non-completions and the nature of randomisation. Study 3 maintained this approach to administering materials, to facilitate comparison between studies.

2 Results

2.1 Segment membership replication

See Table 3.

Table 3: Segment membership factor scores for each study and Q-sort statement

Statement	Acceptor				Sceptic			
	Study 1	Study 2	Study 3	Maximum difference	Study 1	Study 2	Study 3	Maximum difference
1. It is important to vote for leaders who will combat climate change.	4	4	4	0	-4	-3	-4	1
2. Scientists should stop falsely claiming that climate change is a settled science.	-2	-2	-2	0	4	4	4	0
3. Climate change is a hoax perpetrated by the United Nations.	-4	-4	-4	0	3	3	3	0
4. Poor people will be impacted the worst by climate change.	1	0	1	1	0	0	1	1
5. They changed the name from ”global warming” to ”climate change” because the planet isn’t warming.	-2	-2	-2	0	3	3	3	0
6. The concept of global warming was created by and for the Chinese in order to make U.S. manufacturing non-competitive.	-3	-3	-3	0	2	1	2	1
7. Cow farts cause more ’climate change’ than human activity.	-2	-2	-2	0	1	2	1	1
8. Climate change is a threat to the health and safety of our children.	3	3	3	0	-3	-4	-3	1

(continued)

Statement	Acceptor				Sceptic			
	Study 1	Study 2	Study 3	Maximum difference	Study 1	Study 2	Study 3	Maximum difference
9. Politicians and the mass media are ignorant about the risks of climate change.	0	0	0	0	-1	-1	-1	0
10. Climate change sceptics ignore basic climate science facts.	1	1	1	0	-1	-2	-2	1
11. Through cutting science funding, we damage Australia's ability to respond to climate change.	1	2	2	1	-2	-1	-1	1
12. The Great Barrier Reef is at risk from climate change.	3	3	3	0	-2	-2	-2	0
13. The threat of climate change is much worse than climate scientists originally thought.	2	1	1	1	-3	-3	-3	0
14. Politicians who refuse to tackle climate change are just as bad as those who deny climate science.	1	1	1	0	-1	-2	-2	1
15. The increased occurrence of extreme weather events is a clear sign that climate change is real.	2	2	2	0	-2	-2	-2	0
16. Australian agriculture is thriving so climate change can't be real.	-3	-3	-3	0	2	2	2	0
17. Australia is experiencing more extreme weather and hotter days due to climate change.	2	2	2	0	-2	-1	-1	1
18. Those who demand climate action are the usual "torch-and-pitchfork" crowd.	-2	-2	-2	0	2	2	2	0

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Statement	Acceptor				Sceptic			
	Study 1	Study 2	Study 3	Maximum difference	Study 1	Study 2	Study 3	Maximum difference
19. Climate change policy and renewable energy (e.g., solar power) should be a major focus of Australian political elections.	2	2	2	0	-1	0	-1	1
20. Climate sceptics, with no genuine expertise, cannot know better than climate scientists.	0	0	0	0	0	0	1	1
21. Climate change and human burning of fossil fuels are strongly linked.	0	1	0	1	0	-1	-1	1
22. People who deny the science of climate change should not hold public office.	0	0	-1	1	-1	-1	0	1
23. We need to keep coal, oil, and gas in the ground and adopt more renewable energy sources, like solar and wind power.	0	0	0	0	0	0	0	0
24. No political party can say they have a climate change action plan when they favour coal, oil, and gas companies.	-1	0	-1	1	1	1	1	0
25. We must start working together for real solutions on climate change.	1	1	1	0	1	1	0	1
26. It is shameful that climate change, the greatest problem of our time, is barely discussed in the media.	-1	-1	-1	0	0	0	0	0
27. Countries must fulfil their Paris Climate Agreement goals.	-1	-1	0	1	1	1	0	1

(continued)

Statement	Acceptor				Sceptic			
	Study 1	Study 2	Study 3	Maximum difference	Study 1	Study 2	Study 3	Maximum difference
28. Regardless of who is elected, the reality is that climate change is going to destroy everything.	-1	-1	-1	0	0	0	0	0
29. Oil and gas companies could not care less about climate change.	-1	-1	-1	0	2	2	2	0
30. Australian politicians need to wake up to the emergency of tackling climate change.	0	-1	0	1	1	1	1	0

Table 4: Estimated effects of study on segment membership, estimated using a multinomial logistic regression model.

		Ratio of Acceptors odds and Fencesitters odds		Ratio of Sceptics odds and Fencesitters odds	
Predictors	Categories	Estimate (p value)	95% CI	Estimate (p value)	95% CI
Intercept	-	2.25 (.000)***	[1.80, 2.80]	0.38 (.000)***	[0.27, 0.54]
Study	Study 1	1.06 (.709)	[0.78, 1.44]	0.81 (.417)	[0.48, 1.35]
	Study 2	-	-	-	-
	Study 3	0.65 (.021)*	[0.46, 0.94]	0.60 (.111)	[0.32, 1.12]

Note:
$^{*}p < .05$; $^{***}p < .001$.
Each study was entered as a categorical predictor, with Study 2 as the reference category. Fencesitter was entered as the reference category of segment. Model estimates of coefficients were exponentiated to odds ratios.

2.2 Change in segment membership over time

2.2.1 Multinomial regression model

We created a multinomial logistic regression model to predict segment membership as a function of study, using the *multinom* function from the *nnet* package [Venables and Ripley, 2002]. Segment membership was entered as the dependent variable, with the Fencesitter segment as the reference category. Study was entered as a categorical predictor, with Study 2 as the reference category. Coefficients were exponentiated to estimate odds ratios, and are presented in Table 4. A Wald Z-test was used to estimate the (unadjusted) p values of model coefficients.

2.3 Auxiliary psychological characteristics

See Table 5 for the difference in means of auxiliary psychological characteristics between Study 1 and Study 3, for: cognitive style; ideology, worldviews, and values; and personality. To guard against Type I errors, we applied a [1979] p value adjustment to four families of tests for changes in psychological characteristics: climate change cognition and affect; cognitive styles; ideology, worldviews, and values; and personality. The results for mean differences of climate change cognition and affect are not presented here, as these are reported in the main text.

See Figure 1 for density estimates of auxiliary psychological characteristics in Study 1 and Study 3.

```
Warning: There was 1 warning in `mutate()`.
i In argument: `across(where(is.double), specify_decimal, )`.
Caused by warning:
! The `...` argument of `across()` is deprecated as of dplyr 1.1.0.
Supply arguments directly to `.fns` through an anonymous function instead.

  # Previously
  across(a:b, mean, na.rm = TRUE)

  # Now
  across(a:b, \(x) mean(x, na.rm = TRUE))
```

Table 5: Difference in means of auxiliary psychological characteristics between Study 1 and Study 3.

	$M_{Study\ 3} - M_{Study\ 1}$				
Psychological characteristics	Estimate	95% *CI*	*t*	*p*	$p_{adjusted}$
Cognitive style					
Orientation to Immediate Goals	0.17	[0.03, 0.32]	2.36	.019	.076
Conspiracist Ideation	0.13	[-0.05, 0.31]	1.41	.158	.475
Need for Cognition	0.01	[-0.12, 0.13]	0.12	.901	1.000
Orientation to Future Goals	0.00	[-0.12, 0.11]	-0.07	.943	1.000
Ideology, worldviews, and values					
Environment-as-Elastic Worldview	0.18	[0.03, 0.34]	2.37	.018	.108
Political Ideology	0.27	[0.03, 0.51]	2.21	.028	.139
System Justification	0.20	[-0.05, 0.44]	1.59	.113	.452
Self-Transcendence Values	-0.10	[-0.26, 0.06]	-1.27	.204	.611
Conservation Values	0.05	[-0.10, 0.20]	0.61	.539	1.000
Environment-as-Ductile Worldview	0.00	[-0.12, 0.12]	-0.01	.994	1.000
Personality					
Conscientiousness	-0.05	[-0.19, 0.09]	-0.72	.469	1.000
Agreeableness	-0.04	[-0.18, 0.10]	-0.57	.571	1.000
Extraversion	-0.02	[-0.18, 0.14]	-0.28	.776	1.000
Openness	0.01	[-0.12, 0.14]	0.13	.893	1.000
Neuroticism	0.00	[-0.17, 0.17]	-0.02	.987	1.000

Note:

p values were adjusted using the Holm [1979] method.

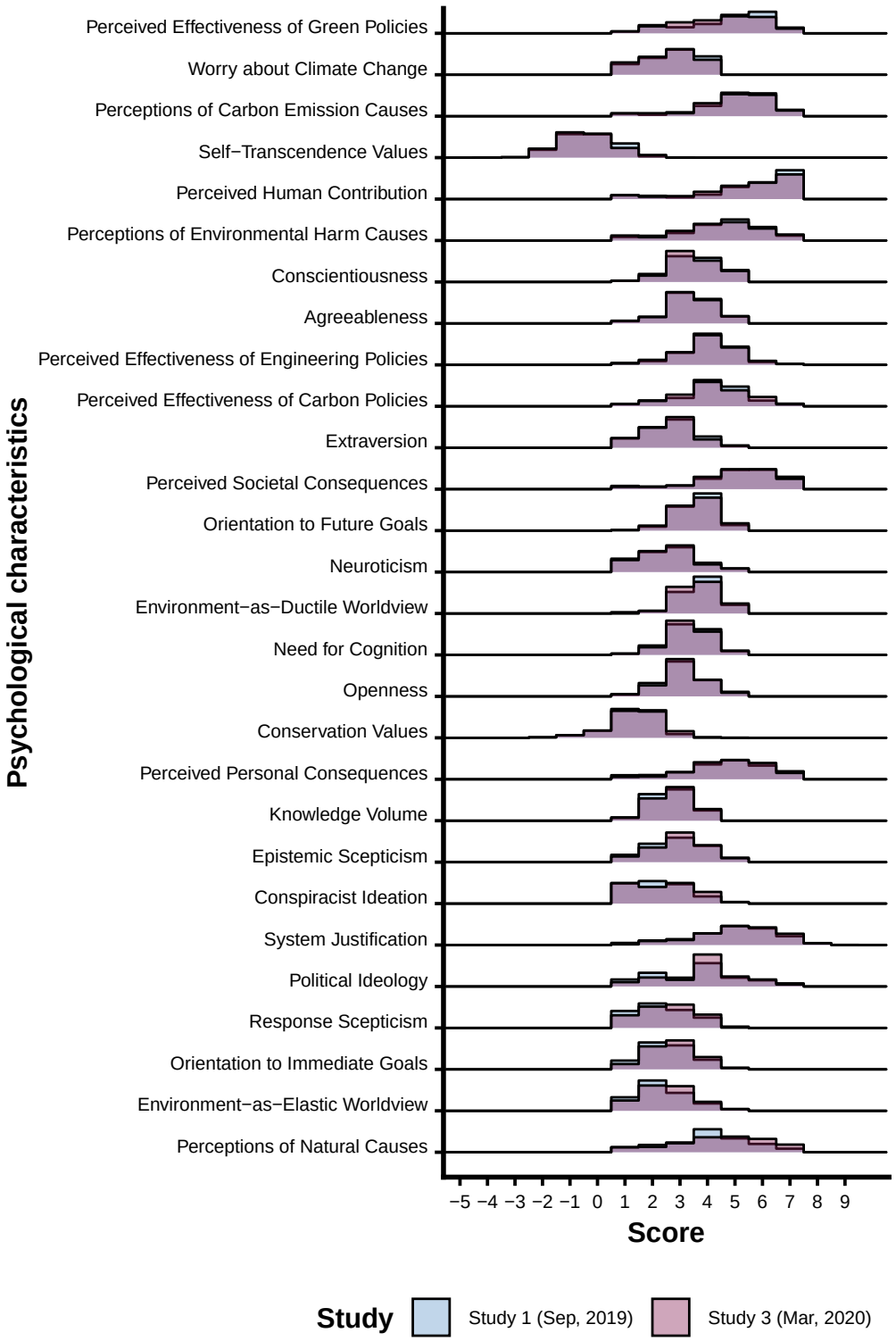

Figure 1: Density estimates for auxiliary psychological variables in Study 1 (blue) and Study 3 (purple).

2.4 Fire Perception Scale

2.4.1 Scree plot

The scree plot for the Fire Perception Scale is shown in Figure 2.

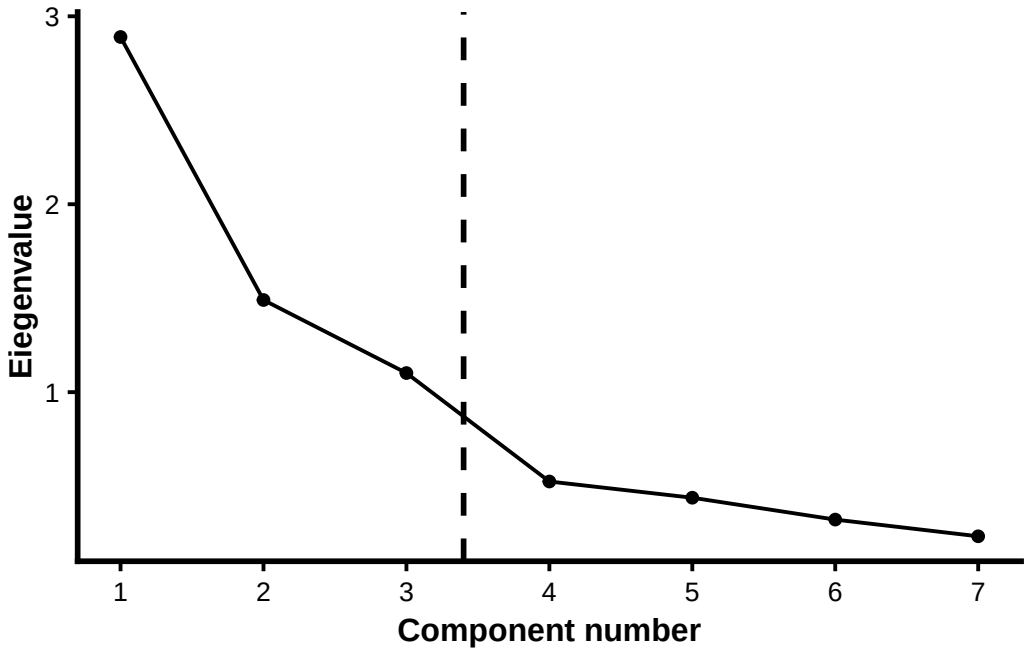

Figure 2: Scree plot for the Fire Perception Scale. Vertical dashed line indicates a break in the scree.

2.4.2 Segment differences

For each Fire Perception Scale subscale (Climate Processes, Fire Appraisal, and Arson Causes), we built a linear regression model to predict subscale score as a function of segment, using the *lm* function from the *stats* package [R Core Team, 2023]. Segment was entered as a categorical predictor, and a Wald Z-test was used to estimate p values (Table 6).

2.4.3 Correlations

The correlations between the Fire Perception Scale subscale scores and auxiliary psychological characteristics are shown in Table 7. In Table 8, we present the correlations of auxiliary psychological characteristics with two Fire Perception Scale items concerning perceived causes for the bushfires—climate change (item 1) and arson (item 7).

Table 6: Linear regression models predicting Fire Perception Scale subscale scores (bolded) as a function of segment.

Models and predictors	Categories	Estimate (p value)	95% Confidence interval
(A) Climate Processes			
Intercept	-	2.95 (.000)***	[2.74, 3.16]
Segment	Acceptors	0.53 (.000)***	[0.26, 0.80]
	Fencesitters	-	-
	Sceptics	-1.76 (.000)***	[-2.24, -1.27]
(B) Fire Appraisal: Climate change made bushfires less likely			
Intercept	-	2.81 (.000)***	[2.55, 3.07]
Segment	Acceptors	-1.04 (.000)***	[-1.38, -0.70]
	Fencesitters	-	-
	Sceptics	-0.64 (.038)*	[-1.25, -0.03]
(B) Fire Appraisal: Bushfires were severe			
Intercept	-	4.14 (.000)***	[3.98, 4.30]
Segment	Acceptors	0.65 (.000)***	[0.44, 0.86]
	Fencesitters	-	-
	Sceptics	0.08 (.664)	[-0.29, 0.46]
(C) Arson Causes			
Intercept	-	3.71 (.000)***	[3.46, 3.96]
Segment	Acceptors	-0.55 (.001)**	[-0.88, -0.23]
	Fencesitters	-	-
	Sceptics	0.74 (.014)*	[0.15, 1.32]

Note:
$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.
Each segment was entered as a categorical predictor, with Fencesitter as the reference category.

Table 7: Pearson correlations between the Fire Perception Scale subscale scores and auxiliary psychological characteristics.

Psychological characteristics	Fire Perception Scale			
	(A) Climate Processes	(B) Fire Appraisal: Climate change made bushfires less likely	(B) Fire Appraisal: Bushfires were severe	(C) Arson Causes
Climate change cognition and affect				
Epistemic Scepticism	-0.48***	0.32***	-0.16*	0.41***
Response Scepticism	-0.41***	0.34***	-0.36***	0.30***
Perceived Societal Consequences	0.62***	-0.06	0.25***	-0.22**
Perceptions of Natural Causes	0.07	0.25***	-0.19**	0.25***
Perceived Human Contribution	0.64***	-0.14*	0.24***	-0.18**
Perceived Effectiveness of Engineering Policies	-0.21**	-0.32***	0.12	-0.11
Perceived Personal Consequences	0.64***	0.09	0.16*	-0.16*
Perceived Effectiveness of Green Policies	-0.07	-0.34***	0.18**	-0.13
Worry about Climate Change	0.64***	0.11	0.17*	-0.11
Perceived Effectiveness of Carbon Policies	-0.12	-0.35***	0.15*	-0.09
Perceptions of Carbon Emission Causes	0.66***	0.02	0.13	-0.15*
Perceptions of Environmental Harm Causes	0.54***	0.15*	0.03	-0.07
Knowledge Volume	0.14*	-0.02	0.18**	0.07
Cognitive style				
Conspiracist Ideation	0.07	0.25***	-0.18**	0.26***
Orientation to Immediate Goals	0.04	0.33***	-0.24***	0.15*
Orientation to Future Goals	0.35***	-0.03	0.28***	-0.05
Need for Cognition	0.10	-0.09	0.19**	-0.04
Ideology, worldviews, and values				
Environment-as-Elastic Worldview	-0.32***	0.36***	-0.37***	0.22**
Conservation Values	-0.22**	0.29***	-0.14*	0.27***
Political Ideology	-0.24***	0.23***	-0.12	0.28***
Self-Transcendence Values	-0.30***	-0.27***	0.17*	-0.06
Environment-as-Ductile Worldview	0.49***	-0.13	0.31***	-0.13
System Justification	0.05	0.26***	0.08	0.24***
Personality				
Neuroticism	0.12	0.05	-0.13	0.05
Conscientiousness	-0.11	-0.08	0.09	0.04

(continued)

Psychological characteristics	(A) Climate Processes	(B) Fire Appraisal: Climate change made bushfires less likely	(B) Fire Appraisal: Bushfires were severe	(C) Arson Causes
Openness	0.01	-0.06	0.12	-0.06
Extraversion	-0.02	0.08	0.00	0.03
Agreeableness	-0.01	0.00	0.21**	-0.02

Note:
$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.
Colour indicates the magnitude and direction of the correlation.

Table 8: Pearson correlations between the Fire Perception Scale causal items and auxiliary psychological characteristics.

Psychological characteristics	Fire Perception casual items	
	1. Climate change causes	7. Arson causes
Climate change cognition and affect		
Epistemic Scepticism	-0.61***	0.41***
Perceived Human Contribution	0.73***	-0.18**
Perceived Societal Consequences	0.68***	-0.22**
Response Scepticism	-0.57***	0.30***
Perceptions of Carbon Emission Causes	0.64***	-0.15*
Perceived Personal Consequences	0.58***	-0.16*
Worry about Climate Change	0.57***	-0.11
Perceptions of Environmental Harm Causes	0.44***	-0.07
Perceptions of Natural Causes	-0.05	0.25***
Perceived Effectiveness of Green Policies	0.13	-0.13
Knowledge Volume	0.12	0.07
Perceived Effectiveness of Engineering Policies	-0.08	-0.11
Perceived Effectiveness of Carbon Policies	0.04	-0.09
Cognitive style		
Orientation to Future Goals	0.34***	-0.05
Conspiracist Ideation	-0.09	0.26***
Orientation to Immediate Goals	-0.12	0.15*
Need for Cognition	0.14*	-0.04
Ideology, worldviews, and values		
Environment-as-Elastic Worldview	-0.47***	0.22**
Environment-as-Ductile Worldview	0.54***	-0.13
Political Ideology	-0.34***	0.28***
Conservation Values	-0.31***	0.27***
System Justification	-0.04	0.24***
Self-Transcendence Values	-0.17*	-0.06
Personality		
Neuroticism	0.11	0.05
Openness	0.09	-0.06
Conscientiousness	-0.09	0.04
Extraversion	-0.07	0.03
Agreeableness	0.04	-0.02

Note:
$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.
Colour indicates the magnitude and direction of the correlation.

Table 9: Estimated effects of segment membership on policy direction preferences using a binomial logistic regression model.

		Ratio of the odds of a preference for more action and the odds of an alternative preference	
Predictors	Categories	Estimate (p value)	95% Confidence interval
Intercept	-	1.08 (.736)	[0.69, 1.68]
Segment	Acceptors	8.03 (.000)***	[3.92, 17.49]
	Fencesitters	-	-

Note:
$^{***}p < .001$.
Each segment was entered as a categorical predictor, with Fencesitter as the reference category. Sceptics were excluded from the model, as none indicated a preference for more action. Model estimates of coefficients were exponentiated to odds ratios.

2.5 Policy direction preferences

2.5.1 Policy direction preferences as a function of segment membership

To assess the association between segment membership and policy direction preferences, we used a binomial logistic regression model (see Table 9). Policy direction preferences were coded as a binary variable, with 1 indicating a preference for more action and 0 indicating an alternative preference (e.g., a preference for no change, less action, or no action). The model estimated the log odds ratio of a preference for more action as a function of segment membership, using the *glm* function with a logit link function. Association between segment membership and the use of emotional words was assessed with a likelihood-ratio test that compared the regression model with and without segment membership as a predictor (χ^2 (1) = 35.45, $p < .001$). A Wald Z-test was used to estimate p values of model coefficients. As no Sceptic indicated a preference for more action, we could not estimate the effect of segment membership on policy direction preferences for Sceptic and therefore excluded Sceptic from the model.

2.5.2 Emotion analysis

To explore the relationship between segment membership and policy direction preferences, we conducted an emotion analysis of participants' justifications for their policy direction preferences. First, we prepared the data by segmenting each participant's text response into individual words (known as tokenisation), via the *unnest_tokens* function of the *tidytext* package

[Silge and Robinson, 2016]. Then, we removed words that were not relevant to the analysis, such as numbers, hyperlinks, and hashtags. Additionally, we removed words with a unique meaning in the context of the study, including "climate", "change", "global", "warming", "bushfire", "bushfires", "fires", "fire", "barrier" and "bark". Next, we identified the words present in the NRC Word-Emotion Association Lexicon [Mohammad and Turney, 2013]. Due to the infrequent use of emotional language by participants, we examine whether a participant used one or more words associated with a particular emotion. The resulting prevalence of emotions in participants' justifications is shown in Table 10.

To explore segment differences in the use of emotional language, we created a binomial logistic regression model (Table 11). The model estimated the log odds ratio of using an emotion, using the *glm* function with a logit link function. Segment membership was entered as a categorical predictor, with Fencesitter as the reference category. Association between segment membership and the use of emotional words was assessed with a likelihood-ratio test that compared the regression model with and without segment membership as a predictor. To control for multiple comparisons, the p values of likelihood-ratio tests were adjusted using the Holm [1979] method. A Wald Z-test was used to estimate the (unadjusted) p values of model coefficients. We followed up significant results with pairwise comparisons between segments, using the *marginaleffects* package [Arel-Bundock, Greifer, and Heiss, Forthcoming]. We controlled for multiple comparisons using the Holm method [1979] to adjust p values. The multiple comparisons are shown in Table 12.

Table 11: Effects of segment membership on emotion content in justification of policy direction preferences, estimated using a binomial logistic regression model.

		Ratio of the odds of an emotion word present and the odds of an emotion word absent	
Predictors	Categories	Estimate (p value)	95% Confidence interval
Anger (χ^2 (2) = 8.73, p = .013, $p_{adjusted}$ = .056)			
Intercept	-	0.10 (.000)***	[0.04, 0.20]
Segment	Acceptors	1.77 (.231)	[0.72, 4.77]
Segment	Fencesitters	-	-
Segment	Sceptics	6.55 (.003)**	[1.91, 22.94]
Fear (χ^2 (2) = 11.93, p = .003, $p_{adjusted}$ = .015*)			
Intercept	-	0.22 (.000)***	[0.12, 0.37]
Segment	Acceptors	3.16 (.001)**	[1.63, 6.46]
Segment	Fencesitters	-	-
Segment	Sceptics	2.32 (.147)	[0.71, 7.13]
Anticipation (χ^2 (2) = 1.18, p = .554, $p_{adjusted}$ = 1.000)			
Intercept	-	0.20 (.000)***	[0.10, 0.34]

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Predictors	Categories	Ratio of the odds of an emotion word present and the odds of an emotion word absent	
		Estimate (p value)	95% Confidence interval
Segment	Acceptors	1.47 (.309)	[0.71, 3.14]
Segment	Fencesitters	-	-
Segment	Sceptics	1.02 (.983)	[0.21, 3.65]
Joy (χ^2 (2) = 1.65, p = .437, $p_{adjusted}$ = 1.000)			
Intercept	-	0.08 (.000)***	[0.03, 0.17]
Segment	Acceptors	0.90 (.853)	[0.30, 2.84]
Segment	Fencesitters	-	-
Segment	Sceptics	2.43 (.243)	[0.47, 10.37]
Surprise (χ^2 (2) = 8.99, p = .011, $p_{adjusted}$ = .056)			
Intercept	-	0.04 (.000)***	[0.01, 0.11]
Segment	Acceptors	3.20 (.077)	[0.99, 14.30]
Segment	Fencesitters	-	-
Segment	Sceptics	9.74 (.004)**	[2.14, 52.42]
Trust (χ^2 (2) = 2.01, p = .366, $p_{adjusted}$ = 1.000)			
Intercept	-	0.25 (.000)***	[0.14, 0.43]
Segment	Acceptors	1.50 (.245)	[0.77, 3.03]
Segment	Fencesitters	-	-
Segment	Sceptics	1.97 (.237)	[0.61, 5.94]

Note:
$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.
Each segment was entered as a categorical predictor, with Fencesitter as the reference category. The χ^2 statistic is the likelihood-ratio test comparing the model with segment as a predictor to the null model without the predictor. The likelihood-ratio test p values were adjusted using the Holm [1979] method. Model estimates of coefficients were exponentiated to odds ratios.

Table 10: Frequency and proportion of participants' emotions in justification of policy direction preferences.

Emotion	n	Proportion of sample (%)	Example response
Fear	67	31.46	"the recent bushfire is a wakeup call. how much more **worse** do we want to experience?"
Trust	54	25.35	"they keep stating that they in front Paris **agreement,** but this **agreement** isn't enough, the way the world is going these environment issue will get worse"
Anticipation	42	19.72	"It is **expected** of them, and facing re election they need to show they are doing something"
Sadness	41	19.25	"because forest fires has causing **negative** consequences"
Anger	31	14.55	"We are **destroying** our home and recent weather patterns confirm we are going to **lose** our home"
Disgust	23	10.80	"i dont think the climate change has much to do with the fires thats all up to the **nasty** people thats started them"
Surprise	21	9.86	"No such thing as climate change. Ever since God created the Earth it has heated and cooled. And Jesus shall return soon.What is coming those who do not believe are in for a **shock**"
Joy	17	7.98	"few steps are taken, but there is a big **journey** ahead of us"

Note:
Bolded words reflect the exemplified emotion.

Table 12: Pairwise comparisons of segment membership on fear content in justification of policy direction preferences, estimated using a binomial logistic regression model.

Contrasts	Estimate	95% CI	p value	$p_{adjusted}$ value
ln(odds(Acceptors) / odds(Fencesitters))	3.16	[1.59, 6.28]	.001**	.003**
ln(odds(Sceptics) / odds(Acceptors))	0.73	[0.26, 2.09]	.563	.563
ln(odds(Sceptics) / odds(Fencesitters))	2.32	[0.74, 7.24]	.147	.293

Note:
$^{**}p < .01$; $^{***}p < .001$.
p values for contrasts were adjusted using the Holm [1979] method. Estimates were exponentiated.

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