Supplementary materials for: “Does personal experience of climate change influence climate-change beliefs? The case of the 2019–2020 Australian bushfires”

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1 Methods

1.1 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.

1.2 Counterbalancing of materials

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. The Q-sort always preceded the auxiliary psychological scales. Study 3 maintained this approach to administering materials, to facilitate comparison between studies. The additional materials (Fire Perception Scale and Policy direction preferences) were always administered together, and randomly preceded or proceeded the block of Q-sort and auxiliary psychological scales. Policy direction preferences always immediately followed the Fire Perception Scale.

2 Results

2.1 Segment membership replication

See Table 1.

Table 1: 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

(continued)

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 2: Estimated effects of study on segment membership using a multinomial logistic regression model.

Predictors	Categories	Ratio of Acceptor odds and Fencesitter odds		Ratio of Sceptics odds and Fencesitter odds	
		Estimate (p value)	95% Confidence interval	Estimate (p value)	95% Confidence interval
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. 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 2. Coefficient p values were estimated using the Wald Z-test.

Table 3: Difference in means of auxiliary psychological characteristics over time.

	Study 1	Study 3			
Psychological characteristics	*M* (*SD*)	*M* (*SD*)	*t*	*p*	$p_{adjusted}$
Cognitive style					
Orientation to Immediate Goals	2.57 (0.91)	2.74 (0.87)	2.36	.019	.08
Conspiracist Ideation	2.32 (1.02)	2.45 (1.11)	1.41	.158	.47
Need for Cognition	3.36 (0.78)	3.37 (0.76)	0.12	.901	1.00
Orientation to Future Goals	3.74 (0.68)	3.74 (0.73)	-0.07	.943	1.00
Ideology, worldviews, and values					
Environment-as-Elastic Worldview	2.44 (0.92)	2.62 (0.92)	2.37	.018	.11
Political Ideology	3.62 (1.59)	3.89 (1.39)	2.21	.028	.14
System Justification	5.00 (1.58)	5.20 (1.44)	1.59	.113	.45
Self-Transcendence Values	-0.34 (0.97)	-0.44 (0.95)	-1.27	.204	.61
Conservation Values	1.31 (0.91)	1.36 (0.91)	0.61	.539	1.00
Environment-as-Ductile Worldview	3.76 (0.75)	3.76 (0.71)	-0.01	.994	1.00
Personality					
Conscientiousness	3.76 (0.89)	3.71 (0.84)	-0.72	.469	1.00
Agreeableness	3.62 (0.84)	3.58 (0.87)	-0.57	.571	1.00
Extraversion	2.85 (0.96)	2.83 (0.97)	-0.28	.776	1.00
Openness	3.32 (0.84)	3.33 (0.80)	0.13	.893	1.00
Neuroticism	2.77 (1.06)	2.77 (1.00)	-0.02	.987	1.00

Note:

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

2.3 Auxiliary psychological characteristics

See Table 3 for the difference in means of auxiliary psychological characteristics between Study 1 and Study 3, for: cognitive style; ideology, worldviews, and values; and personality.

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

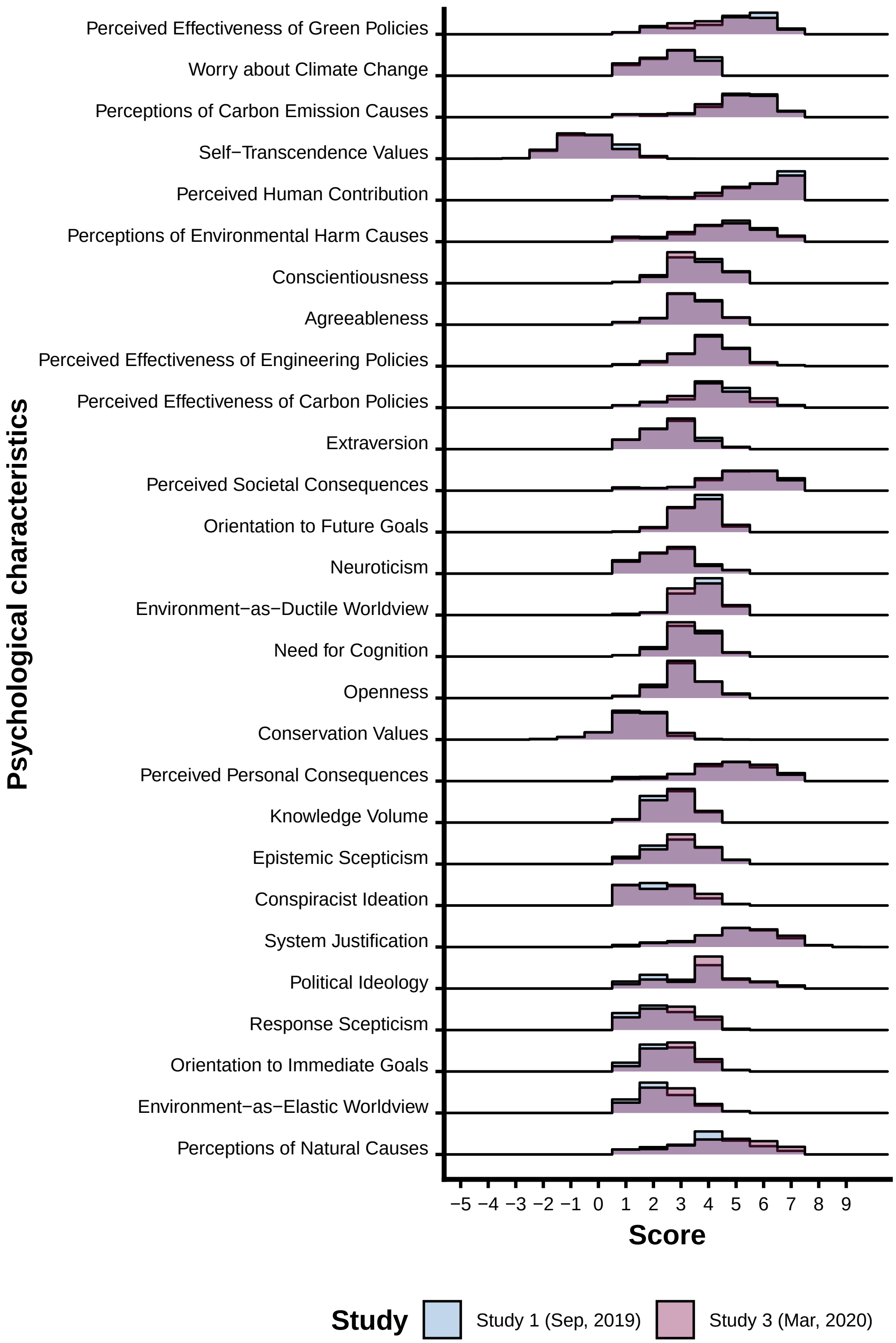

Figure 1: Density estimates for auxiliary psychological variables in Study 1 (blue) and Study 3 (purple).

2.4 Fire Perception Scale

2.4.1 Scree plot

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

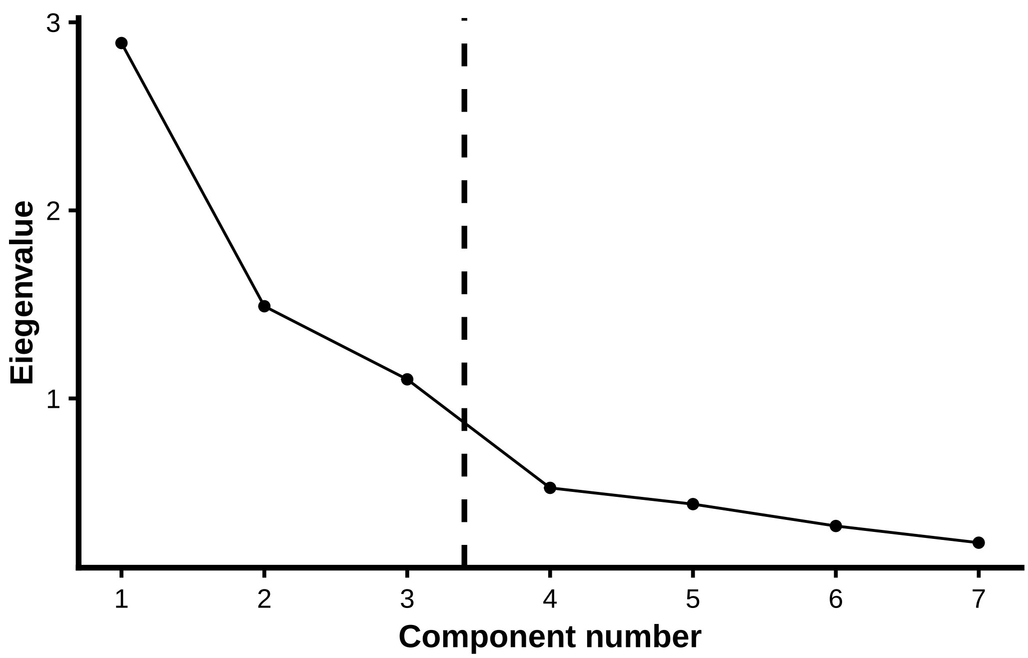

Figure 2: Scree plot for the Fire Perception Scale. Vertical dashed line indicates a break in the scree.

2.4.2 Segment differences

For each Fire Perception Scale subscale (climate processes, fire realities, 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 4).

2.4.3 Correlations

The correlations between the Fire Perception Scale subscale scores and auxiliary psychological characteristics are shown in Table 5.

Table 4: 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 Realities			
Intercept	-	3.66 (.000)***	[3.50, 3.83]
Segment	Acceptors	0.84 (.000)***	[0.63, 1.06]
	Fencesitters	-	-
	Sceptics	0.36 (.064)	[-0.02, 0.75]
(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 5: Pearson correlations between the Fire Perception Scale subscale scores and auxiliary psychological characteristics.

Psychological characteristics	Fire Perception Scale		
	(A) Climate Processes	(B) Fire Realities	(C) Arson Causes
Climate change cognition and affect			
Epistemic Scepticism	-0.48***	-0.31***	0.41***
Response Scepticism	-0.41***	-0.43***	0.30***
Perceptions of Natural Causes	0.07	-0.28***	0.25***
Perceived Societal Consequences	0.62***	0.16*	-0.22**
Perceived Human Contribution	0.64***	0.22**	-0.18**
Perceived Effectiveness of Engineering Policies	-0.21**	0.30***	-0.11
Perceived Personal Consequences	0.64***	0.01	-0.16*
Perceptions of Carbon Emission Causes	0.66***	0.04	-0.15*
Perceived Effectiveness of Green Policies	-0.07	0.35***	-0.13
Perceived Effectiveness of Carbon Policies	-0.12	0.33***	-0.09
Worry about Climate Change	0.64***	0.00	-0.11
Knowledge Volume	0.14*	0.10	0.07
Perceptions of Environmental Harm Causes	0.54***	-0.10	-0.07
Cognitive style			
Conspiracist Ideation	0.07	-0.28***	0.26***
Orientation to Future Goals	0.35***	0.16*	-0.05
Orientation to Immediate Goals	0.04	-0.36***	0.15*
Need for Cognition	0.10	0.16*	-0.04
Ideology, worldviews, or values			
Environment-as-Elastic Worldview	-0.32***	-0.45***	0.22**
Self-Transcendence Values	-0.30***	0.29***	-0.06
Conservation Values	-0.22**	-0.28***	0.27***
Environment-as-Ductile Worldview	0.49***	0.24***	-0.13
Political Ideology	-0.24***	-0.23***	0.28***
System Justification	0.05	-0.16*	0.24***
Personality			
Conscientiousness	-0.11	0.10	0.04
Neuroticism	0.12	-0.10	0.05
Openness	0.01	0.10	-0.06
Extraversion	-0.02	-0.06	0.03
Agreeableness	-0.01	0.10	-0.02

Note:

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Colour indicates the magnitude and direction of the correlation.

Table 6: 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 6). 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 7.

To explore segment differences in the use of emotional language, we created a binomial logistic regression model (Table 8). 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] Table 9 with a Holm [1979] p value adjustment for multiple comparisons.

Table 8: 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]
Segment	Acceptors	1.47 (.309)	[0.71, 3.14]

(continued)

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	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 7: 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 9: Pairwise comparisons of segment membership on fear content in justification of policy direction preferences, estimated using a binomial logistic regression model.

Contrasts	Estimate	95% Confidence interval	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 values for the likelihood-ratio test were adjusted using the Holm [1979] method. Model estimates of coefficients were exponentiated to odds ratios.

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