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Multidimensional partisanship shapes climate policy support and behaviours

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Partisanship is one of the largest and most studied social barriers to climate change mitigation in the United States. Here we expand conceptualizations of 'left-right' or 'Democrat-Republican' towards understanding partisanship as a multidimensional social identity with both negative and positive elements. Partisan support or opposition for climate action can be driven by identification with the partisan in-group (positive or 'expressive' partisanship), as well as perceived threats from the 'out-group' (negative partisanship). Using original survey data, we show that when negative and expressive partisanship is low, climate policy support is similar for Republicans and Democrats. However, differences in policy support increase when partisan identification amplifies. Yet, for climate behaviours, we find more limited partisan effects. The proposed multidimensional partisanship framework revisits the role of partisan polarization in shaping climate change action and points to alternative ways to transcend partisan barriers.

Although there is a high degree of consensus among climate scientists about the anthropogenic origin of climate change[1], global emissions have yet to peak, leaving the climate system increasingly vulnerable to irreversible and abrupt changes[2]. The reasons for the failure to respond are complex. Fossil fuel technologies are deeply entrenched in industrial societies and transitioning to renewable energy is no simple task[3,4]. Yet, the United States has lagged behind peer nations in CO_2 emissions reductions and implementation of effective climate policy[5].

There are undoubtedly technical challenges to rapid decarbonization, but much of the problem in the United States remains political. Partisan polarization surrounding climate change is a substantial barrier to federal climate change policy, creating a loose patchwork of mostly state and local efforts towards decarbonization. Starting in the late 1980s and intensifying in the 1990s, the climate change counter-movement successfully fomented disbelief in climate science, amplifying opposition to climate policy among political conservatives[6,7]. Republicans are less supportive of policies to mitigate climate change and are more likely to question the validity of climate science[8,9]. Yet, it remains unclear to which extent partisan polarization affects climate-relevant behaviours, a form of the 'attitudes-behaviour' gap[10]. Partisanship has been found to have a limited effect across a wide range of climate and energy behaviours[11,12]. Households that install solar panels are politically diverse[13], but Democrats are more likely to purchase electric vehicles[14].

Climate change polarization research often draws upon social identity frameworks, wherein partisanship is conceptualized as a group identity or social affiliation[15,16]. People are assumed to be socialized into a partisan identity at a young age, which often remains stable over their life course[17,18]. One major implication of adopting an identity framework is that many partisans will shift their attitudes (and possibly behaviours) to match what they consider to be appropriate for their social in-group. This often occurs via a cue-taking process, wherein partisan elites (for example politicians, media figures) frame salient issues, which are subsequently adopted by their co-partisans[19,20]. While some partisans will update their opinions rather abruptly when presented with an elite cue, partisan responses to elite cues are not uniform[21,22]. The social identity perspective on partisanship helps explain why there is intense polarization surrounding high-profile issues: partisans change what they think to match their group, creating a uniformity of opinion within a partisan social group.

Multidimensional partisan social identities

Drawing upon social identity theory[23], partisans have been found to differ across two key dimensions: positive ('expressive') and negative partisanship[24]. Individuals typically have multiple social identities, which are hierarchically categorized by the salience of group affiliation. Expressive partisans strongly identify with a political party and

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their supporters as a primary social 'in-group'[25,26]. Partisan identity forms a central component of how they define and think of themselves[27]. Salient expressive partisanship encompasses both strong in-group affect, but also draws distinctions and sets boundaries against out-group members[28].

Negative partisanship is less driven by the desire to maintain in-group status, and rather towards opposition and minimization of the out-group[29]. Group formation necessitates boundary setting and differentiation from the out-group[30], but negative identities privilege the desire for distinctiveness over those for inclusion[28]. Negative partisanship has increased substantially in the last decade, with Democrats and Republicans increasingly reporting dislike for opposing partisans, finding them untrustworthy, or even in some extreme cases, not supporting their children marrying a member of the other party[31,32]. Yet, expressive partisan identities remain more prevalent than negative ones[30,33].

Expressive partisan identities are associated with an increased likelihood of volunteering for campaigns and donating money to a political candidate[26], as well as willingness to participate in boycotts[34]. Negative partisan identities draw upon political disagreements, often around salient issues among those that are more politically engaged[35]. For example, negative partisan identities can increase engagement in Occupy Wall Street protests or the anti-nuclear movement[29], as well as opposition to climate change and COVID-19 restrictions and behavioural compliance.

Some debates contrast expressive with instrumental accounts of partisanship. In the instrumental account, voters choose parties on the basis of their policy platform and will quickly change their loyalties if a party does not align with their individual policy preferences[36]. Expressive partisans adopt identities affiliated with the in-group rather than instrumentally aligning themselves with a party that best represents a set of policy preferences.

Expressive and negative partisanship are sub-dimensions of partisanship. Expressive and negative partisanship are not particularly strongly related ($r = 0.15$) (Fig. 1), and are similarly held across Republicans and Democrats ($r \leq 0.10$). Expressive and negative partisanship are best understood as moderators, differentially shaping climate change support and behaviours within party affiliations.

Partisan differences are particularly salient for societal problems requiring collective actions such as climate change, as such dilemmas can only be resolved by participation of population majorities. However, the consequences of expressive and negative partisanship for policy support and climate behavioural intentions remain largely unknown. For instance, negative Republicans may oppose climate change actions, seeing such as a victory over Democratic policies, while non-negative Republicans may not necessarily be in opposition. Expressive partisanship moderates partisan support for coal industry subsidies[37], where at low levels of expressive partisanship, Republicans and Democrats do not substantially differ—indeed, they both are mostly opposed. However, at heightened levels of expressive partisanship, Republicans are much more likely to support coal industry subsidies. In terms of negative partisanship, Democrats who are distrustful of Republicans are more supportive of renewable energy policies, while distrusting Republicans are more likely to be opposed[38].

We hypothesize that partisan identification could be modified by expressive and negative partisanship. We expect that negative partisanship will drive partisans to oppose climate actions (policies and behaviours) that they associate with the opposition party (for example, carbon taxes or eating less meat). However, at the same time, negative partisanship is less likely to encourage support for the climate actions originating from their own partisan group. For example, negative partisanship probably creates resistance to restrictive forms of climate policy among Republicans, but may not further entrench policy support among Democrats, as negative partisanship is primarily motivated by the desire to defeat the partisan out-group. On the other hand, expressive partisanship might intensify partisan support for climate actions associated with the partisan in-group. For Democrats, this means that expressive partisanship might engender more support for policy priorities or behaviours associated with Democrats, but it may not intensify opposition from Republicans.

Research design

We use survey data from the United States ($n = 1{,}604$, Summer 2021) to evaluate the role of partisan social identities in shaping climate change policy support and behavioural intentions. We identify how expressive and negative partisanship moderate the effect of party affiliation across three measures of policy support (increases to fossil fuel taxes, support for renewable energies, banning old household appliances) and four measures of climate behavioural intentions (buying $C0_2$ offsets, reducing car usage, eating less meat, reducing warm water usage; Fig. 2). These measures of policy support encompass a range of 'push' and 'pull' instruments[39], while behavioural intentions vary across dimensions of perceived costs associated with behavioural changes[40]. We adopt ordinal logistic regression to model the measures of policy support and behavioural intentions independently, where party affiliation interacts (product term) with negative and expressive partisanship to identify moderating effects. All regression models control for respondents' climate change concern, social, institutional and scientific trust, gender identification, age, income, educational attainment, racial/ethnic identification, region and rural/urban residence.

We rely upon predicted probabilities to interpret the practical implications of these nonlinear interaction regression models[41], predicting the likelihood that respondents will have the highest response outcome of support for each policy measure ('strongly support') and climate change behaviours ('very willing/I already do this'). Predictive margins are calculated for different categories of party affiliation ('strong Republican' and 'strong Democrat') and scores of the expressive/negative partisanship scales (−2 s.d., −1 s.d., mean, +1 s.d. and +2 s.d.)[42].

Accordingly, predicted probabilities can be interpreted as the likelihood of strongly supporting climate policy measures or a high level of willingness to voluntarily engage in climate behaviours at the combination of each level of expressive or negative partisanship and affiliation (Figs. 3 and 4). For example, strongly affiliated Republicans that have heightened negative partisanship (+2 s.d.) are predicted to have a probability of 0.05 to be strongly in favour of increases to fossil fuels taxes (Fig. 3a,), while we estimate that 0.38 (or 38%) of strongly affiliated Democrats with heightened expressive partisanship (+2 s.d.) are strongly in support of renewable energy subsidies (Fig. 3b).

Climate change policy support

In terms of support for climate change policies, we find greatest support for renewable energy subsidies (56% in favour and only 20% opposed), followed by support for policies banning old appliances (46% in favour and only 28% opposed) and those that increase fossil fuel taxes (43% in favour, 34% opposed) (Fig. 2). The sample mean for responding 'strongly in favour' is plotted as a dashed grey line in all of the predicted probabilities (Fig. 3).

The effect of partisan affiliation on climate policy support is moderated by expressive and negative partisanship (Fig. 3). For 'Increasing fossil fuel taxes' (Fig. 3a), there is a powerful interaction between negative partisanship and party affiliation. At low levels of negative partisanship, we observe minimal differences between strong Republicans and Democrats (both having a predicted probability of ~0.20). However, negative partisanship amplifies the effects of party affiliation. Democratic support for fossil fuel taxes increases moderately at heightened levels of negative partisanship (a roughly 5% difference in support in comparison with low levels of negative partisanship). Yet, the predicted probability of a Republican being strongly in favour of increased fossil fuel taxes substantially decreases from 0.23 at low

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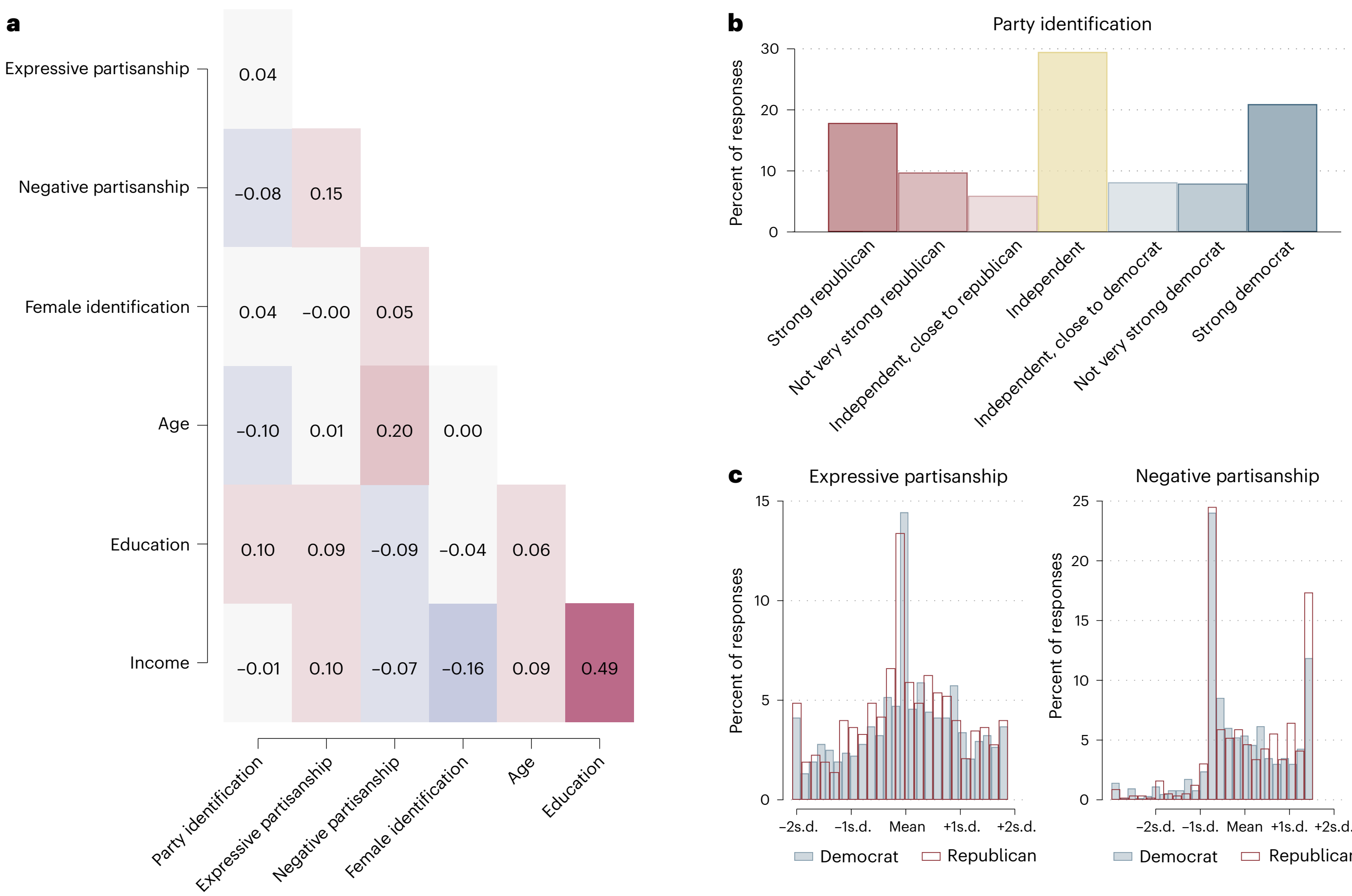

Fig. 1 | Descriptive statistics of key partisan predictors. a–**c**, Pairwise correlation matrix of party affiliation, expressive and negative partisanship, and socio-demographic characteristics (**a**), percent distribution of valid (non-missing) responses for party affiliation (**b**), and histogram for the expressive and negative partisanship scales by Republican (red) and Democratic (blue) affiliation (**c**).

levels of negative partisanship to 0.05 at high levels. However, for expressive partisanship, there is comparatively less evidence of moderation, where Democrats remain roughly 0.10 more likely to support increasing fossil fuel taxes across all levels of expressive partisanship. We find similar patterns for 'Support for renewable energy subsidies' (Fig. 3b). Democratic support for renewable energy subsidies is strongly moderated by expressive partisanship. Democrats with high expressive partisanship are substantially more likely (0.38) to support such policies than those with lower levels of expressive partisanship (0.19). Yet among Republicans, we find a small decrease in predicted support for renewable energy subsidies at greater levels of expressive partisanship (0.25 versus 0.17). Further, at low levels of negative partisanship, Republicans and Democrats have a similar likelihood of supporting renewable energy subsidies. But again, support decreases quite substantially for Republicans with heightened levels of negative partisanship, having a 0.11 predicted probability of being strongly in favour of supporting renewable energy subsidies. Alternatively, support for renewable energy subsidies increases moderately for Democrats with heightened levels of negative partisanship.

Turning to support for 'Banning old appliances' (Fig. 3c), we observe more complex patterns of moderation. At low levels of expressive partisanship, we find minimal differences between Republican (0.15) and Democratic support (0.13) for banning old appliances. Yet, support increases more substantially for Democrats (0.29) than for Republicans (0.16) at heightened levels of expressive partisanship. For negative partisanship, there is a smaller observed moderation by party affiliation, where Democrats become slightly more likely to support banning old appliances with heightened negative partisanship, while Republicans become slightly less supportive.

Climate change behaviours

Regarding willingness to engage in climate mitigation behaviours, 49% are 'very willing' or 'already do' use warm water more sparingly, compared with 35% for willingness to reduce the number of times a week that they eat meat, 33% for reducing how often they use their car, and 28% for willingness to purchase CO_2 offsets (Fig. 2).

The likelihood of being 'very willing/I already do this' to engage in four climate mitigation behaviours for respondents at varied levels of party affiliation is moderated by expressive and negative partisanship (Fig. 4). Compared with the observed moderation of climate policy support measures, expressive and negative partisanship do not strongly moderate the effect of party affiliation. Rather, somewhat surprisingly, we mostly find evidence of direct effects of expressive and negative partisanship, and comparatively smaller effects of party affiliation.

High levels of expressive partisanship are positively associated with willingness to purchase CO_2 offsets and reduce car usage for both Democrats and Republicans, while heightened levels of negative partisanship are associated with decreased willingness to eat less meat for both partisan groups. For using warm water more sparingly, we do find some evidence of moderation, where Republicans with high levels of negative partisanship (0.51) are less likely to change their behaviours than those with lower levels (0.44), while Democrats with heightened levels of negative partisanship (0.53) are more likely to use less warm water than those with lower levels (0.43).

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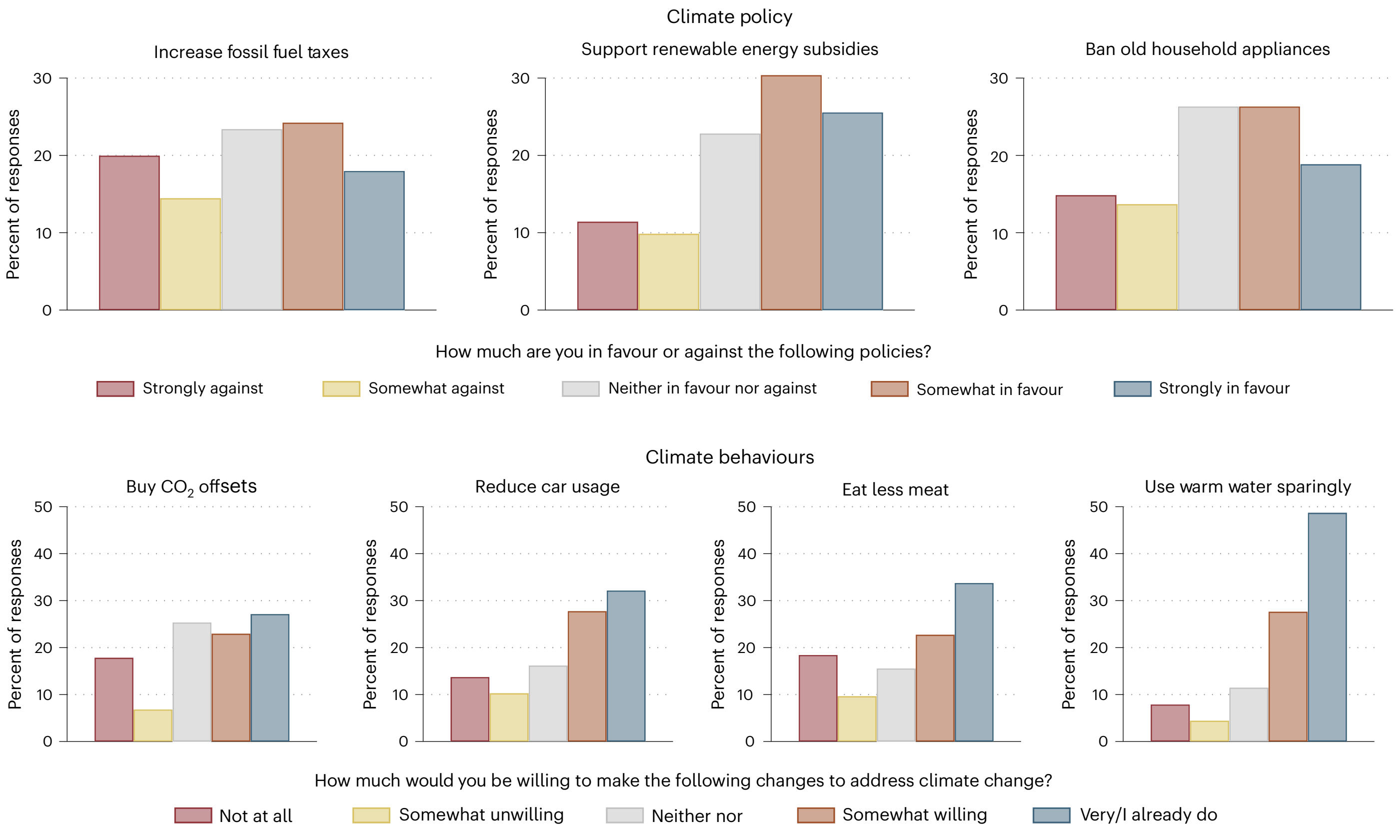

Fig. 2 | Distribution of responses to dependent variables. Percent of valid (non-missing) responses by response for each climate policy and climate behaviour variables.

In sum, these findings suggest comparatively smaller differences between Republicans and Democrats in willingness to voluntarily engage in behaviours that can mitigate climate change.

Discussion

Partisanship is one of the most well-documented predictors of climate change policy support and remains one of (if not the) largest barriers to comprehensive federal policies in the United States. We find that partisan polarization around climate change policy is largely driven by expressive and negative aspects of partisanship, with negative partisanship having an especially pronounced effect. While previous research has focused mainly on inter-party polarization[9,43–45], we find a key source of intra-party divergence and differentiation among Republican partisans. Republican resistance to climate change policy emerges primarily among Republicans with high levels of negative partisanship. We find fewer differences among Republicans based on levels of expressive partisanship.

A key implication of our analysis is that Republican resistance to climate change policies is for many, less about promoting the goals of the in-group and more about defeating those of Democrats. Figuring out why some Republicans become negative Republicans is an important future task, warranting further analytic attention from researchers. Although there is a large literature on political socialization[18], comparatively less is known about the forces that drive partisans towards negative partisanship. This is an important knowledge gap, as understanding how negative partisanship develops might open new avenues for transcending partisan polarization. Indeed, our analysis implies that simple Republican affiliation is not a major barrier to policy support or behavioural change—Republicans are, in fact, quite supportive of climate change policy if they are highly not negative partisans. Solving this social identity puzzle should be a central task of future research and may require qualitative data, longitudinal data and media analysis.

A promising finding of this study is that there is little polarization surrounding voluntary engagement in climate change mitigation behaviours. Particularly, expressive partisanship does not appear to be a barrier to willingness to engage in climate change behaviours for either Republicans or Democrats. Notably, at high levels of expressive partisanship, Republicans are found to be more likely than Democrats to purchase CO_2 offsets. These findings suggest that partisan polarization may be more limited to climate change policy and attitudinal realms, while behavioural intentions may be a product of other motivating factors, such as perceptions of costs, risk and efficacy[46]. Although there are limits to the extent to which individual or household-level behavioural change can reduce societal-level emissions, we suggest that further research should attend to how to engender behavioural adaptation[47] and encourage behaviours in a non-partisan way. For example, recent research has focused on identifying social tipping (or positive tipping) mechanisms[48] which can be further expanded to explore how minimizing partisan differences can remove barriers to action, and creating more 'critical conditions' for rapid societal transformations[49]. Furthermore, future research could further explore the limited partisan differences in climate mitigating behaviours, as this could be a manifestation of the well-known attitude-behaviour gap[10].

Some theoretical perspectives have assumed that conservatives are less likely to be concerned about environmental problems caused by deregulated markets ('antireflexivity')[50] and more likely to reject environmental policies, as they inherently involve government intervention ('solution aversion')[51]. Yet, our findings suggest that Republican opposition is largely among those preferring to impede Democratic goals (negative), as opposed to promoting those of their own party

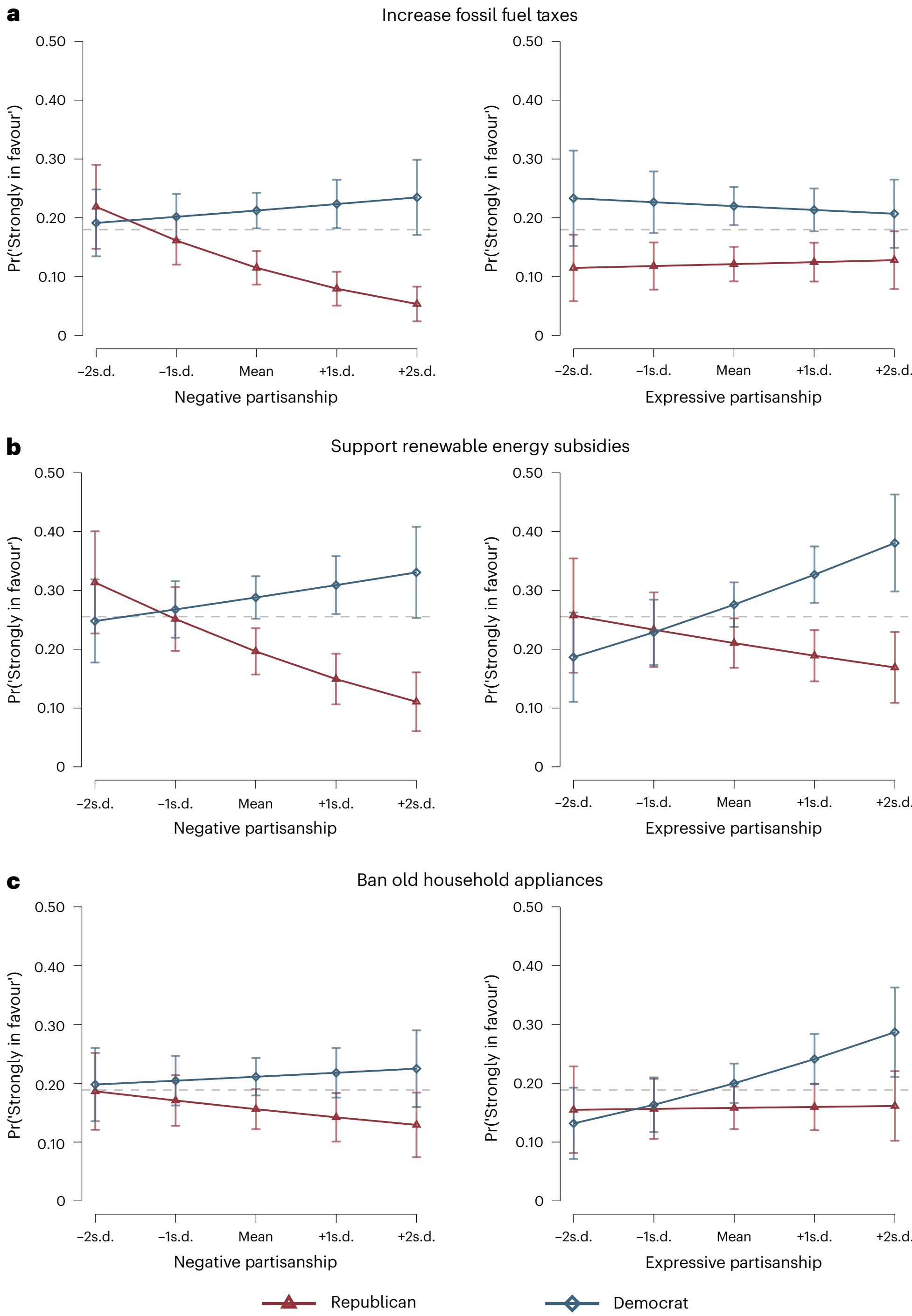

Fig. 3 | Interaction effect of partisan social identities by party affiliation for climate change policy support. Probabilities are calculated from ordered logistic regression estimates (Supplementary Table 1) of climate change policies on expressive and negative partisanship by partisan affiliation interaction product term, controlling for climate change concerns, social, institutional and scientific trust, gender identification, age, income, educational attainment, racial/ethnic identification, region and rural/urban residence. Predicted probabilities are calculated at the highest value of climate change behaviours ('strongly in favour'), at the polar level of party affiliation 1 'strong Republican' and 7 'strong Democrat', and expressive and negative partisanship scales at −2 s.d., −1 s.d., mean, +1 s.d. and +2 s.d. for the interaction product terms, holding all other predictors at their means (marginal effects[42]). Error bars are 95% confidence intervals around the predicted probabilities. Dashed grey lines indicate sample mean responses for outcome 'Strongly in favour'. Analytical sample sizes: $n = 1{,}151$ ('increase fossil fuel taxes', **a**), $n = 1{,}142$ ('support renewable energy subsidies', **b**), $n = 1{,}137$ ('ban old household appliances', **c**).

(expressive). Accordingly, the barrier of polarization may be less a product of ideological differences, but rather out of a desire to limit victories of the perceived 'out-group'. Additionally, these findings further lend credence to the research on the moderating effects on party affiliation, such as by education[52] and income[53], as well as emerging research on how individual values and polarization interact to shape climate change policy support[54].

The sheer power of negative and expressive partisanship could also allow for additional interventions to shift public opinion. Recall that a well-funded campaign to derail climate action is one of the primary

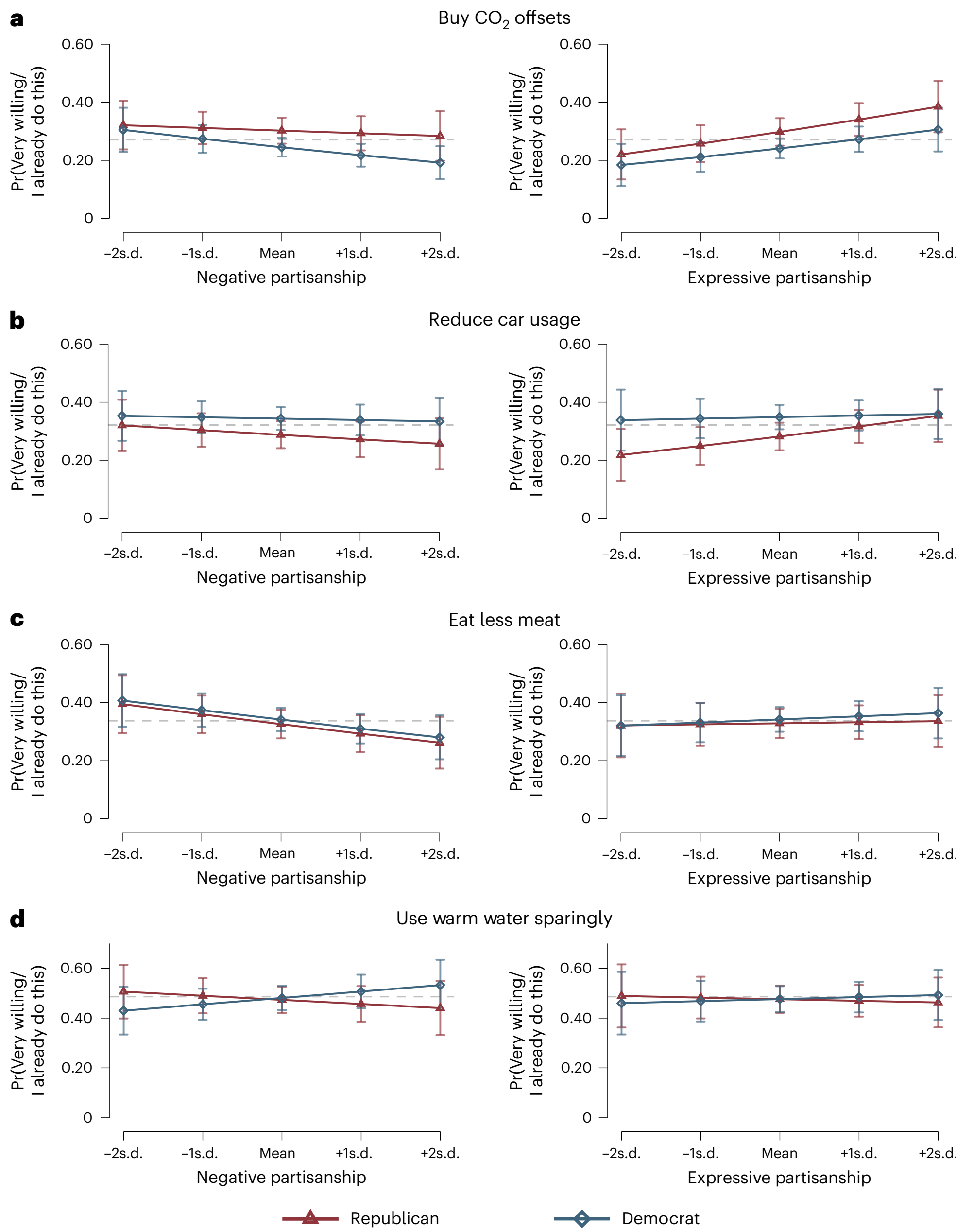

Fig. 4 | Interaction effect of partisan social identities by party affiliation for 'Willingness to engage in climate change behaviours'. Probabilities are calculated from ordered logistic regression estimates (Supplementary Table 2) of climate change behaviours on expressive and negative partisanship by partisan affiliation interaction product term, controlling for climate change concerns, social, institutional and scientific trust, gender identification, age, income, educational attainment, racial/ethnic identification, region and rural/urban residence. Predicted probabilities are calculated at the highest value of climate change behaviours ('very willing/I already do this'), at the polar level of party affiliation 1 'strong Republican' and 7 'strong Democrat', and expressive and negative partisanship scales at −2 s.d., −1 s.d., mean, +1 s.d. and +2 s.d. for the interaction product terms, holding all other predictors at their means. Error bars are 95% confidence intervals around the predicted probabilities. Dashed grey lines indicate sample mean responses for outcome 'I already do this/very willing' Analytical sample sizes: $n = 1{,}146$ ('buy CO_2 offsets', **a**), $n = 1{,}170$ ('reduce car usage', **b**), $n = 1{,}171$ ('eat less meat', **c**) and $n = 1{,}172$ ('use warm water sparingly', **d**).

causes of entrenched partisan polarization surrounding climate change[6,55]. The current work reveals some additional complexities: negative Democrats are much more supportive of climate policies, presumably because they seek to 'defeat' or 'win' against Republicans in policy struggles. Partisan animus may be a driving force for negative partisans towards policies like carbon taxes. The implications of negative partisanship are therefore complex—to some degree, our work implies that negative feelings toward Republicans could be harnessed to encourage climate policy support among Democrats. Indeed, one interpretation of our results is that it is advantageous, from a climate policy perspective, for Democrats to become more negative, and alternatively, when climate policy is framed as a component of Republican social identity, opportunities are presented towards overcoming barriers to support.

Online content

Any methods, additional references, Nature Portfolio reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at https://doi.org/10.1038/s41558-022-01548-6.

References

1. Cook, J. et al. Consensus on consensus: a synthesis of consensus estimates on human-caused global warming. *Environ. Res. Lett.* **11**, 048002 (2016).
2. Steffen, W. et al. Trajectories of the earth system in the anthropocene. *Proc. Natl Acad. Sci. USA* **115**, 8252–8259 (2018).
3. Unruh, G. C. Escaping carbon lock-in. *Energy Policy* **30**, 317–325 (2002).
4. Sovacool, B. K., Hess, D. J. & Cantoni, R. Energy transitions from the cradle to the grave: a meta-theoretical framework integrating responsible innovation, social practices, and energy justice. *Energy Res. Soc. Sci.* **75**, 102027 (2021).
5. Compston, H. & Bailey, I. Climate policy strength compared: China, the US, the EU, India, Russia, and Japan. *Climate Policy* **16**, 145–164 (2016).
6. Farrell, J. Corporate funding and ideological polarization about climate change. *Proc. Natl Acad. Sci. USA* **113**, 92–97 (2016).
7. Oreskes, N. & Conway, E. M. *Merchants of Doubt: How a Handful of Scientists Obscured the Truth on Issues from Tobacco Smoke to Global Warming* (Bloomsbury Publishing, 2011).
8. Hornsey, M. J., Harris, E. A., Bain, P. G. & Fielding, K. S. Meta-analyses of the determinants and outcomes of belief in climate change. *Nat. Clim. Change* **6**, 622–626 (2016).
9. McCright, A. M., Marquart-Pyatt, S. T., Shwom, R. L., Brechin, S. R. & Allen, S. Ideology, capitalism, and climate: explaining public views about climate change in the United States. *Energy Res. Soc. Sci.* **21**, 180–189 (2016).
10. Kollmuss, A. & Agyeman, J. Mind the gap: why do people act environmentally and what are the barriers to pro-environmental behavior? *Environ. Educ. Res.* **8**, 239–260 (2002).
11. Allen, S., Dietz, T. & McCright, A. M. Measuring household energy efficiency behaviors with attention to behavioral plasticity in the United States. *Energy Res. Soc. Sci.* **10**, 133–140 (2015).
12. O'Connor, R. E., Bord, R. J., Yarnal, B. & Wiefek, N. Who wants to reduce greenhouse gas emissions? *Soc. Sci. Q.* **83**, 1–17 (2002).
13. Mildenberger, M., Howe, P. D. & Miljanich, C. Households with solar installations are ideologically diverse and more politically active than their neighbours. *Nat. Energy* **4**, 1033–1039 (2019).
14. Sintov, N. D., Abou-Ghalioum, V. & White, L. V. The partisan politics of low-carbon transport: why Democrats are more likely to adopt electric vehicles than Republicans in the United States. *Energy Res. Soc. Sci.* **68**, 101576 (2020).
15. Greene, S. Social identity theory and party identification. *Soc. Sci. Q.* **85**, 136–153 (2004).
16. Iyengar, S., Sood, G. & Lelkes, Y. Affect, not ideology: a social identity perspective on polarization. *Public Opin. Q.* **76**, 405–431 (2012).
17. Lyons, J. The family and partisan socialization in red and blue america. *Polit. Psychol.* **38**, 297–312 (2017).
18. Sapiro, V. Not your parents' political socialization: introduction for a new generation. *Annu. Rev. Polit. Sci.* **7**, 1–23 (2004).
19. Bisgaard, M. & Slothuus, R. Partisan elites as culprits? how party cues shape partisan perceptual gaps. *Am. J. Polit. Sci.* **62**, 456–469 (2018).
20. Carmichael, J. T. & Brulle, R. J. Elite cues, media coverage, and public concern: an integrated path analysis of public opinion on climate change, 2001–2013. *Environ. Polit.* **26**, 232–252 (2017).
21. Cohen, G. L. Party over policy: the dominating impact of group influence on political beliefs. *J. Pers. Soc. Psychol.* **85**, 808 (2003).
22. Mayer, A. National energy transition, local partisanship? Elite cues, community identity, and support for clean power in the United States'. *Energy Res. Soc.Sci.* **50**, 143–150 (2019).
23. Tajfel, H. & Turner, J. C. in *The Social Psychology of Intergroup Relations* (eds Austin, W. G. & Worchel, S.) 33–47 (Brooks/Cole, 1979).
24. Bankert, A. Negative and positive partisanship in the 2016 US presidential elections. *Polit. Behav.* **43**, 1467–1485 (2021).
25. Green, D., Palmquist, B. & Schickler, E. *Partisan Hearts and Minds: Political Parties and the Social Identities of Voters*. (Yale Univ. Press, 2002).
26. Huddy, L., Mason, L. & Aarøe, L. Expressive partisanship: campaign involvement, political emotion, and partisan identity. *Am. Pol. Sci. Rev.* **109**, 1–17 (2015).
27. Huddy, L., Bankert, A. & Davies, C. Expressive versus instrumental partisanship in multiparty European systems. *Polit. Psychol.* **39**, 173–199 (2018).
28. Zhong, Chen-Bo, Dijksterhuis, A. & Galinsky, A. D. The merits of unconscious thought in creativity. *Psychol. Sci.* **19**, 912–918 (2008).
29. Bankert, A. in *Research Handbook on Political Partisanship* (eds Oscarsson, H. & Holmberg, S.) 89–101 (Edward Elgar Publishing, 2020).
30. Brewer, M. B. The psychology of prejudice: ingroup love and outgroup hate? *J. Soc. Issues* **55**, 429–444 (1999).
31. Abramowitz, A. I. & Webster, S. The rise of negative partisanship and the nationalization of US elections in the 21st century. *Elect. Stud.* **41**, 12–22 (2016).
32. Abramowitz, A. I. & Webster, S. W. Negative partisanship: why Americans dislike parties but behave like rabid partisans. *Polit. Psychol.* **39**, 119–135 (2018).
33. Lee, A. H., Lelkes, Y., Hawkins, C. B. & Theodoridis, A. G. Negative partisanship is not more prevalent than positive partisanship. *Nat. Hum. Behav.* **6**, 951–963 (2022).
34. Endres, K. & Panagopoulos, C. Boycotts, buycotts, and political consumerism in America. *Res. Polit.* https://doi.org/10.1177/2053168017738632 (2017).
35. Webster, S. W. & Abramowitz, A. I. The ideological foundations of affective polarization in the US electorate. *Am. Polit. Res.* **45**, 621–647 (2017).
36. Brennan, G. & Hamlin, A. Expressive voting and electoral equilibrium. *Public Choice* **95**, 149–175 (1998).
37. Mayer, A. Support for displaced coal workers is popular and bipartisan in the United States: evidence from western Colorado. *Energy Res. Soc. Sci.* **90**, 102593 (2022).
38. Hazboun, S. O. The politics of decarbonization: examining conservative partisanship and differential support for climate change science and renewable energy in Utah. *Energy Res. Soc. Sci.* **70**, 101769 (2020).
39. Stadelmann-Steffen, I. & Dermont, C. The unpopularity of incentive-based instruments: what improves the cost–benefit ratio? *Public Choice* **175**, 37–62 (2018).
40. Tobler, C., Visschers, V. H. M. & Siegrist, M. Addressing climate change: determinants of consumers' willingness to act and to support policy measures. *J. Environ. Psychol.* **32**, 197–207 (2012).
41. Mize, T. D. Best practices for estimating, interpreting, and presenting nonlinear interaction effects. *Sociol. Sci.* **6**, 81–117 (2019).
42. Williams, R. Using the margins command to estimate and interpret adjusted predictions and marginal effects. *Stata J.* **12**, 308–331 (2012).
43. Gustafson, A. The development of partisan polarization over the green new deal. *Nat. Clim. Change* **9**, 940–944 (2019).
44. Jenkins-Smith, H. C. Partisan asymmetry in temporal stability of climate change beliefs. *Nat. Clim. Change* **10**, 322–328 (2020).
45. Goldberg, M. H. Shifting Republican views on climate change through targeted advertising. *Nat. Clim. Change* **11**, 573–577 (2021).
46. Valkengoed, A. M. & Steg, L. Meta-analyses of factors motivating climate change adaptation behaviour. *Nat. Clim. Change* **9**, 158–163 (2019).
47. Steg, L. Limiting climate change requires research on climate action. *Nat. Clim. Change* **8**, 759–761 (2018).

https://doi.org/10.1038/s41558-022-01548-6

48. Otto, I. M. et al. Social tipping dynamics for stabilizing Earth's climate by 2050. *Proc. Natl Acad. Sci. USA* **117**, 2354–2365 (2020).
49. Winkelmann, R. Social tipping processes towards climate action: a conceptual framework'. *Ecol. Econ.* **192**, 107242 (2022).
50. McCright, A. M. & Dunlap, R. E. Anti-reflexivity. *Theory Cult. Soc.* **27**, 100–133 (2010).
51. Campbell, T. H. & Kay, A. C. Solution aversion: on the relation between ideology and motivated disbelief. *J. Pers. Soc. Psychol.* **107**, 809 (2014).
52. Hamilton, L. C. Education, politics and opinions about climate change evidence for interaction effects. *Climatic Change* **104**, 231–242 (2011).
53. Ballew, M. T., Pearson, A. R., Goldberg, M. H., Rosenthal, S. A. & Leiserowitz, A. Does socioeconomic status moderate the political divide on climate change? The roles of education, income, and individualism. *Glob. Environ. Change* **60**, 102024 (2020).
54. Smith, E. K. & Hempel, L. M. Alignment of values and political orientations amplifies climate change attitudes and behaviors. *Climatic Change* **172**, 1–28 (2022).
55. McCright, A. M. & Dunlap, R. E. Defeating Kyoto: the conservative movement's impact on US climate change policy. *Soc. Probl.* **50**, 348–373 (2003).

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Methods

Data collection

This study adheres to principles of ethical research on human research subjects: the survey instrument, data collection and storage for this project were approved by the ETH Zurich's Ethics Committee (EK-2021-N-94). We partnered with Dynata (formerly known as Survey Sampling International) to sample adult residents of the United States (n = 1,604). We used quota samples for gender identification, education, age, race and region of the country. We compared the sample demographic statistics and population parameters (Supplementary Table 3). Following their agreement with Dynata, respondents were compensated (typically with rewards points) for their completion of the survey. We excluded respondents who completed the survey in less than half the median completion time. Our survey further includes two attention checks, and respondents who failed either check were removed from the analytical sample. In total, 181 out of the original 1,785 respondents were removed for not passing the attention checks or for completing the survey too quickly (Supplementary Table 4).

Our questionnaire was presented in English. At the start of the survey, respondents read information about the scope, purpose and possible risks associated with participation, and were asked to provide their consent. Some 9% did not provide consent and were directed to the end of the survey. Respondents were allowed to end their participation at any point and were able to skip questions. We did not collect information that could directly identify respondents. Online panels have grown increasingly more common in the academic literature, particularly for preliminary or exploratory research, but we remind the reader that our data are not a true probability sample although online panels typically provide relatively high-quality data [56,57].

Outcomes

We employed seven separate measures to capture two broader constructs: climate change policy preferences and climate change behaviours (Fig. 2). For climate policy preferences, we adopted three items from the European Social Survey, Wave 8[58] special module on 'public attitudes to climate change', each measuring support for distinct climate policies: increase fossil fuel taxes, support renewable energy subsidies and ban old household appliances. For each of the policy preferences, the respondents were asked how much they are in favour of or are against the policy, with outcomes ranging on a Likert-scale from (1) strongly against to (5) strongly in favour.

Next, we used four separate items adopted from Tobler et al.[40] measuring voluntary engagement in climate behaviours: buying CO_2 offsets, reducing car usage, eating less meat and using warm water more sparingly. As perceived costs present a substantial barrier to climate behavioural adaptation[59], these items were designed to measure voluntary engagement in behaviours that are each associated with different forms of perceived adaptation costs: financial, time, inconvenience and discomfort, respectively.

For each behaviour, respondents were asked to evaluate how willing, or not willing, they would be to make the behavioural change to address climate change, with responses ranging from (1) not at all willing to (5) very willing. Further, another response category was also presented: (6) 'I already do this' to account for respondents who have already made these behavioural adaptations. For parsimony and analytical purposes, we combined the responses 'very willing' and 'I already do this' into a single response item for our evaluations. We believe that people who are 'very willing' are not substantively different from those who responded that they 'already do this'. Furthermore, we provided supplementary analyses, with these behavioural dependent variables coded either as 5-item or 6-item (including 'I already do this' as the top response category) scales, finding non-substantive differences between these results (Supplementary Fig. 1). Such an approach reduces the variability of the outcome measures, which could reduce the power of these analyses. We weighed such concerns with the benefits of parsimony offered by the 5-item scale. Given that we find non-substantive differences between 5- and 6-item scales, we used the parsimonious coding, which has the added advantage of being more appropriate for ordinal logistic regression modelling techniques.

Partisanship predictors

Our focal predictors are indicators of party affiliation, expressive partisanship and negative partisanship. We used a seven-category variable for party affiliation (Fig. 1). For expressive partisanship, we employed an established 8-item scale[26] and performed factor analysis to determine dimensionality, which strongly suggested that a single factor underlies these items (Supplementary Table 5). From here, we estimated a factor score with a mean of zero and standard deviation of one. For negative partisanship, we reproduced a scale developed by the Pew Research Center[60]. Again, we conducted a factor analysis to determine the dimensionality of these items, which provided strong evidence of a single-factor solution (Supplementary Table 6). Furthermore, internal reliability analyses suggest validity across items included in both scales (Supplementary Table 7). We then calculated a factor score, again with a mean of zero and standard deviation of one. The distribution of responses to each form of partisanship is displayed in Fig. 1.

Control variables

To avoid potential confounding variables, we included a range of controls in our regression analyses. One of the most consistent predictors of climate change support and policy support is risk perception or concern—simply put, people who view climate change as a more serious problem are more likely to change their behaviours or support policies towards mitigation. Trust is also associated with increased climate change behaviours and policy support, albeit in complex ways[61]. Accordingly, we controlled for social trust (for example, trust in other people), institutional trust (for example, trust in governmental institutions) and trust in scientists as a source of information about climate change, vaccines, nuclear power and evolution (Supplementary Tables 8–10). We followed well-established practices to further control for socio-demographic characteristics: gender identification, education, age, income, racial identification, respondent geographical region and urban/rural inhabitance. We provide descriptive statistics, variable coding and the original scale source (when appropriate) for all the predictor and control variables in Supplementary Table 11.

Analytic strategy

As the dependent variables are all scored on an ordinal scale, we adopted ordinal logistic regression as the modelling choice. Ordinal logistic regression models have well-documented challenges of interpretation[62]. In particular, within non-linear models, the coefficients of interaction product terms cannot be interpreted with regards to their significance or effect magnitude[41]. Accordingly, we adopt predicted probabilities (margins[42]) as the primary analytical approach, exploring the substantive effects of the interactive product terms. For each outcome dependent variable, we first estimated ordinal logistic regression models for the direct and interactive effects of partisanship (Supplementary Tables 1 and 2). All models were estimated with the control variables. We then calculated predicted probabilities for the likelihood to respond to the highest value of the outcome variable (for example, 'strongly in favour' for the measure of climate policy support, and 'very willing/I already do this' for climate behaviours) at substantive levels of party affiliation (1 'strongly Republican' and 7 'strongly Democrat'), and expressive and negative partisanship scales (−2 s.d., −1 s.d., mean, +1 s.d. and +2 s.d.), holding all other predictors at their means.

Accordingly, predicted probabilities could be interpreted as the likelihood of supporting the climate policy measures or willingness to engage in climate behaviours at the combination of each level of partisanship and affiliation (Figs. 3 and 4).

Robustness checks

We performed a series of robustness checks on these findings (see Supplementary Materials). In sum, we find that these results are robust against several potential forms of systematic biases, including potential confounding effects (Supplementary Tables 12 and 13) via potential omitted variables or spurious interaction effects (Supplementary Figs. 2 and 3). Further, we note that the effects for behavioural willingness measures do not substantively vary across coding schemes—either 'very willing' or 'I already do this' (Supplementary Fig. 1).

Furthermore, we explored potential sources of error via collinearity analyses, finding no single variable to have a variance inflation factor of over 2.3, with a mean of 1.45 across all items (Supplementary Table 14).

All data analyses were performed using Stata SE 16.1.

Ethics

The survey instrument, data collection and storage for this project were approved by the ETH Zurich's Ethics Committee (EK-2021-N-94). The authors declare that they have adhered to all ethical regulations for research involving human subjects.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

Full original survey data are available on the Harvard Dataverse[63] with the identifier https://doi.org/10.7910/DVN/8V9FDH.

Code availability

Analytical replication materials are available on the Harvard Dataverse[63] with the identifier https://doi.org/10.7910/DVN/8V9FDH.

References

56. Roulin, N. Don't throw the baby out with the bathwater: comparing data quality of crowdsourcing, online panels, and student samples. *Ind. Organ. Psychol.* **8**, 190–196 (2015).
57. Walter, S. L. A tale of two sample sources: do results from online panel data and conventional data converge? *J. Bus. Psychol.* **34**, 425–452 (2019).
58. European Social Survey. *European Social Survey Round 8 Data: Edition 2.0*. (Norwegian Centre for Research Data, 2016).
59. Diekmann, A. & Preisendörfer, P. Green and greenback: the behavioral effects of environmental attitudes in low-cost and high-cost situations. *Ration. Soc.* **15**, 441–472 (2003).
60. Pew Research Center. *Partisanship and Political Animosity in 2016* (Pew Research Center, 2016).
61. Smith, E. K. & Mayer, A. A social trap for the climate? Collective action, trust and climate change risk perception in 35 countries. *Glob. Environ. Change* **49**, 140–153 (2018).
62. Mood, C. Logistic regression: why we cannot do what we think we can do, and what we can do about it. *Eur. Sociol. Rev.* **26**, 67–82 (2010).
63. Smith, E. K. & Mayer, A. *Replication Data for: Multi-dimensional Partisanship Shapes Climate Policy Support and Behaviors* (Harvard Dataverse, 2022); https://doi.org/10.7910/DVN/8V9FDH

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Author contributions

A.P.M and E.K.S. designed the research, developed and analysed the results, and co-wrote the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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Reporting Summary

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Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	Survey data was collected using Qualtrics survey software.
Data analysis	All data analyses were performed using Stata 16.1.

For manuscripts utilizing custom algorithms or software that are central to the research but not yet described in published literature, software must be made available to editors and reviewers. We strongly encourage code deposition in a community repository (e.g. GitHub). See the Nature Research guidelines for submitting code & software for further information.

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Full survey data and replication materials are available on the Harvard Dataverse: https://doi.org/10.7910/DVN/8V9FDH

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Behavioural & social sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	Quantitative analyses adopting ordered logistic regression estimates of climate change policy support and behaviors on multidimensional forms of partisanship.
Research sample	We adopt non-probability, online panel (convenience) as the sample for these analyses. We sample adult residents of the U.S. (n=1,604) provided by an online panel service (Dynata). We used quota samples for gender identification, education, age, race, and region of the country. Comparison of sample statistics and population parameters are presented in Table S11 in the supplementary materials.
Sampling strategy	Respondents were recruited via a commerical panel provider, Dynata. Dynata provide access to online panel and ensured sampling quotas were met. No personal information was collected from respondents (confidential data collection), and respondents were compensated for their participation according to their agreement with Dynata. The sample size (n=1,604) was chosen to maximize respondents with the available project funding. The full sample is used for these analyses (adopting list-wise deletion methodologies common to regression techniques), and is broadly considered large enough for national US samples.
Data collection	The survey design, data collection and analyses were all conducted by the project team, only access to the sample panel was granted via Dynata. We fielded the survey in English. The survey instrument was approved by the ETH Zurich's Ethics Committee (EK-2021-N-94).
Timing	Data were collected from July 22 to August 3, 2021.
Data exclusions	Respondents under 18 years old were excluded from the study. Respondents that failed at least 2 of 3 attention checks were excluded from the analyses (~10.1% of responses).
Non-participation	Upon entering the survey, respondents are asked to provide their consent to participate in the study. 9% of those entering the survey chose to not provide consent.
Randomization	There were no randomizations and experimental designs utilized for the data used in these analyses. Attitudinal climate change concerns, social, institutional, and scientific trust) and socio-demographic (gender identification, age, income, educational attainment, racial/ethnic identification, region and rural/urban residence) controls are included in all regression analyses to adjust for potential confounding effects.

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Policy information about studies involving human research participants

Population characteristics	We sample adult residents of the U.S. (n=1,604) provided by an online panel service (Dynata). We used quota samples for

Population characteristics	gender identification, education, age, race, and region of the country. Full comparisons of sample statistics and population parameters for the quotas are presented in Table S11 in the supplementary materials.
Recruitment	Respondents were recruited in contracted partnership with Dynata, an online panel provider. Dynata provided access to their proprietary online panel and ensured sampling quotas were met. No personal information was collected from respondents (confidential data collection), and respondents were compensated for their participation according to their agreement with Dynata.
Ethics oversight	The survey instrument , data collection and storage for this project was approved by the ETH Zurich's Ethics Committee (EK-2021-N-94)

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