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Mapping public support and polarization for U.S. climate policies and policy packages

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Mapping public support and polarization for U.S. climate policies and policy packages

Effective climate policy requires both public support and durable partisan consensus, yet little research has simultaneously mapped their predictors, including policy configuration, policy packaging, and socio-political context. Here, we use a discrete choice experiment (*N* = 5,463) to examine how these predictors affect support and polarization for 4,654 climate policy proposals across three domains in the United States. Applying multilevel regression and poststratification, we found that push policies, such as taxes, were less supported than pull policies, such as subsidies, without a systematic difference in polarization. On average, policy packaging reduced support, while its effect on polarization was heterogeneous, with a more pronounced reduction observed for less polarized policy packages. State-level predictors, including per-capita emissions, existing climate policies, and domain-specific predictors, such as meat price and registered electric vehicles, partly explained geographic variability in support. Our findings highlight the limits of policy packaging for improving political feasibility and the value of state-specific, evidence-based climate policy design.

Current policy action is insufficient to meet climate targets in most countries, reflecting both, limited implementation of ambitious policies and rollback of existing climate policies[1]. In contrast, international surveys show high public support for climate change mitigation and policies[2,3], including in the United States (US). There, recent studies found that 67% support a carbon tax targeting fossil fuel companies[4] and 59% support low-carbon technology subsidies[5]. This apparent disconnect between public support and governmental action raises the question whether public support fully captures the political feasibility of specific climate policies.

There are at least two explanations for the disconnect between public support and governmental policy action. First, the personal costs resulting from policies are less salient in stated-preference measures (i.e., inferring preferences from survey responses) compared to actual voting decisions[6,7], which can lead to an overestimation of policy support in surveys. Common limitations of such measures include vaguely framed policies (e.g., generating renewable energy on public land[4]), not explicitly communicating the personal costs and benefits of policies[8], and their hypothetical nature.

Second, public support does not necessarily lead to corresponding policy action. While policymakers tend to refrain from adopting unpopular policies[9], even policies with substantial average support may face political barriers[10], including lobbying from targeted industries, budgetary constraints, or dissent between legislative bodies (e.g., a Democratic president with a Republican-controlled Senate). Another important constraint is political polarization[10], which reflects the systematic divergence in attitudes, opinions, and behavior between (ideological) groups[11]. Consequently, assessing average public support alone may obscure differences in how support is distributed across partisan groups.

With political polarization becoming more pronounced globally and in the US[12], it can impede ambitious climate policymaking and make policies more vulnerable to rollback following changes in government[13]. Mechanisms underlying this pattern include public-elite feedback loops (party stance affects supporters, and supporters' opinions shape party[14–16]), electoral preselection (more extreme candidates win primaries[17]), and raised political costs of

cross-party collaboration (collaboration is less accepted among party supporters[18]), when policymakers perceive public polarization as pervasive[19,20]. Hence, partisan polarization constitutes an important dimension of political feasibility alongside overall public support, particularly where durable policy requires support that extends beyond a single political constituency (e.g., in swing states).

Whether climate policies receive broad and bipartisan support depends on their characteristics. Climate policies can be categorized along two dimensions[21]: push versus pull (e.g., making carbon-intensive options less attractive or making low-carbon options more attractive) and market-based versus non-market-based (e.g., changing prices or changing rules, infrastructure, or information around options). Pull policies tend to receive more support than push policies[22], while the evidence for non-market-based and market-based policies is mixed[21]. Climate policies also vary substantially in public polarization[23]. Some policies show large partisan gaps such as electric vehicle (EV) incentives, while others such as building efficiency standards receive comparably high cross-party support[24]. These differences may indicate the ideological associations attached to particular policies rather than their broader policy category. For example, strong Republican opposition to and Democratic support of EV subsidies may reflect their association with liberal political identities rather than stance on subsidies per se[25]. Based on this literature, there should be no clear link between polarization and support at the level of policy type. For example, subsidies may increase overall support but depending on the domain, they can either increase or decrease polarization in support.

Combining policies into packages has been proposed as a strategy for increasing public support, particularly by pairing less popular policies with more attractive policies[23,26,27]. For example, support for relatively unpopular policies, such as carbon taxes, may increase when they are combined with more popular measures, such as subsidies. However, packaging can also reduce support for otherwise popular policies when they are combined with less popular measures[22,28]. Packaging may likewise alter partisan differences in support, but whether it systematically reduces polarization remains unclear. Existing evidence suggests that effects

depend on package composition and may either reduce or increase differences between political groups[23,29]. Thus, although policy packaging has been proposed as a means of improving the political feasibility of climate policy, its consequences for both overall support and polarization remain uncertain.

Moreover, public support and polarization are shaped by the socio-political context in which policies are proposed. Prior research shows that climate policy support varies with economic conditions, infrastructure, and previous policy experience[30–32]. For example, support for more ambitious policies can be higher in countries where less restrictive climate policies have already been implemented, consistent with the policy sequencing hypothesis[32,33]. Conversely, support for climate policies tends to be lower in countries with larger fossil fuel sectors, where economic stakes of decarbonization are high, consistent with the vested-interest hypothesis[34,35]. While these contextual factors have been linked to climate policy support, considerably less is known about whether they also explain geographic variation in partisan polarization.

To address these gaps, our study pursues three research objectives. First, we jointly map two important drivers of policy adoption – support and polarization – across an extensive set of 4,654 policy proposals. Second, we systematically examine predictors of policy support and polarization at two levels: policy characteristics and geographic context. Third, we assess support and polarization for a large range of policies, individually (i.e., in isolation) and jointly in policy packages. Together, these objectives help to identify specific policies and policy packages with high support and low polarization at both the national and state level.

To this end, we conducted a preregistered survey with N = 5,463 US citizens from all 50 states and the District of Columbia (see Supplementary Table 1 for sample characteristics). The survey measured support for policies from three high-emission domains: food, transportation, and household energy[36]. For each policy, we provided detailed information on its concrete consequences, for instance on higher gasoline and meat prices resulting from a carbon tax. The policies spanned four categories: non-market-based pull policies comprising a *carbon label* for food, updated energy *label* on household appliances, and increased

federal funding for green infrastructure, non-market-based push policies comprising *mandates* on the share of vegetarian meals offered in public cafeterias, registered internal combustion engine vehicles, and fossil-fuel based heating systems, market-based pull policies comprising *subsidies* on plant-based food, public transportation fares, and energy efficiency upgrades, and a domain-general market-based push policy comprising *carbon taxes* with three attributes (tax level, tax dynamics, and revenue mechanism). Each policy had multiple levels. We tested our objectives using discrete choice experiments (DCE[26]) analyzed with multilevel regression and poststratification (MRP[37]), which allowed us to estimate policy support and polarization at the national and state levels.

Policy configuration as a driver of support and polarization

Climate policy support was low, and majority support was rare. Only 40.9% of isolated domain-specific policies ($M_{support}$ = 45.3%), 15% of carbon tax configurations ($M_{support}$ = 39.9%), and 1.4% of policy packages ($M_{support}$ = 37.3%) obtained majority support nationally (at least 50% support, see Supplementary Fig. 1). Support was bimodally distributed across all policy proposals (Supplementary Fig. 2). In line with previous research[23,29], average support was 18.2 percentage points (95% CI [16.7, 19.5]) higher for Democrats (M = 48.2%, SD = 7.9%) compared to Republicans (M = 30.0%, SD = 5.5%), which was particularly pronounced for isolated transportation policies ($M_{Dem\text{-}Rep}$ = 24.0 percentage points).

Policy type was systematically associated with support (Fig. 1; Supplementary Figs. 3 to 5). Push policies consistently received lower support than pull policies, confirming previous findings[21]. However, support for the least coercive mandate level exceeded support for no mandate in policy packages for food (B = 0.15, 95% CI [0.07, 0.23], p < .001) and household (B = 0.17, 95% CI [0.09, 0.25], p < .001), indicating a willingness to accept mild restrictions. In addition, Fig. 1 demonstrates that increasing policy intensity (e.g., higher taxes or subsidies) had a negative effect on support for carbon taxes and a positive effect for pull policies. Notably, participants showed limited sensitivity to some subsidy levels (e.g., subsidy on plant-based food in packages; 15% and 30% rebate: regression coefficient difference =

0.01, 95% CI [−0.07, 0.09], $z = 0.34$, $p = .73$). Among tax revenue-recycling mechanisms, income-insensitive redistribution and earmarked spending (for green projects and low-income programs) were preferred over income-sensitive redistribution and federal deficit reduction, which is also consistent with prior research[38–40].

The effects of carbon tax schemes on polarization (operationalized here as the interaction effect, ΔB, of a policy attribute and party affiliation on policy support) broadly mirrored our findings for policy support, indicating a support-polarization trade-off for tax revenue mechanisms: revenue mechanisms that increased support at the same time widened the support gap between Democrats and Republicans, namely funding low-income programs ($\Delta B = 0.98$, 95% CI [0.76, 1.21], $p < .001$), green spending ($\Delta B = 1.12$, 95% CI [0.89, 1.34], $p < .001$), and income-insensitive redistribution ($\Delta B = 0.32$, 95% CI [0.10, 0.55], $p = .004$). When evaluated in policy packages, higher carbon taxes tended to increase polarization (e.g., \$50/tCO_2e in household packages: $\Delta B = 0.58$, 95% CI [0.32, 0.85], $p < .001$).

Across domains, polarization was not linked to specific policy types, mirroring previous studies[24]. When evaluated in isolation, lower polarization was associated with a 75% vegetarian meal mandate ($\Delta B = -0.35$, 95% CI [−0.69, −0.01], $p = .046$) and carbon labels for food (only one mandate level decreased polarization), public transit fare subsidies (e.g., 15% reduction: $\Delta B = -0.73$, 95% CI [−1.07, −0.40], $p < .001$), and energy efficiency labels (all other household policies increased polarization), while fossil fuel-based heating system mandates were associated with higher polarization (e.g., phase-out by 2040: $\Delta B = 1.07$, 95% CI [0.76, 1.38], $p < .001$). In policy packages, domain-specific policies either did not affect the support gap between Democrats and Republicans or increased polarization (e.g., fossil fuel-based heating system phase-out by 2040: $\Delta B = 0.75$, 95% CI [0.57, 0.93], $p < .001$).

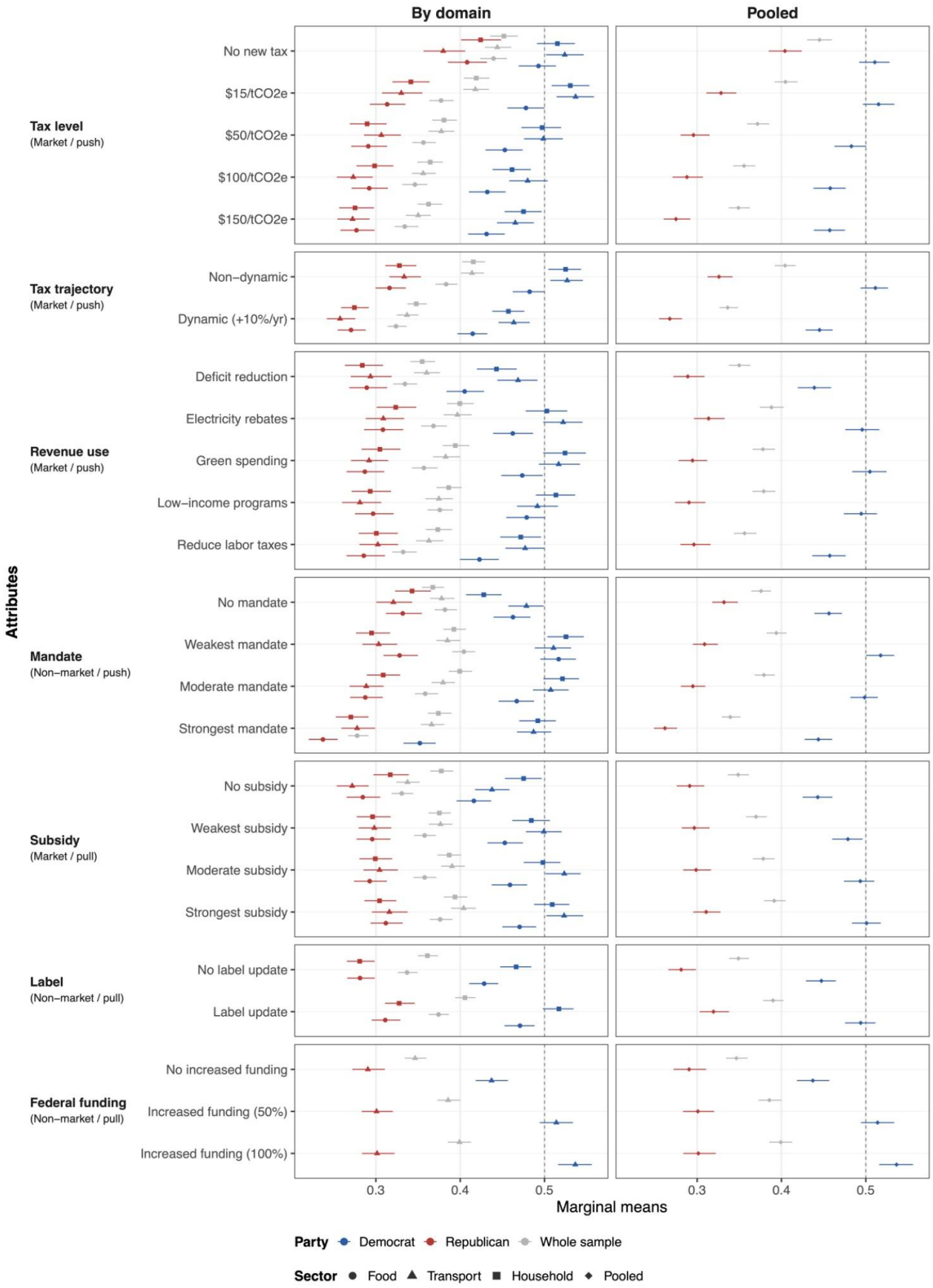


Fig. 1 | Partisan support marginal means for climate policy package attributes, by domain and pooled. N_{total} = 5,439, $N_{Democrats}$ = 2,107, $N_{Republicans}$ = 1,777. Marginal mean support for each policy attribute level based on the policy packages, shown separately by domain (left) and pooled across domains (right), for Democrats (blue) and Republicans (red), and the full sample (grey). Color encodes party and point shape encodes domain. Points are national poststratified (MRP) marginal means, the

average predicted support across all policy packages in which the attribute level is present, and horizontal lines are 95% confidence intervals from 1,000 bootstrap draws of the MRP models (the marginal mean was recomputed in every draw). Pooled estimates average the marginal means of the contributing domains: three domains for tax attributes, mandate and subsidy attributes; two for the labelling block (food and household); and one for federal funding (transport), for which the pooled point equals the single transport estimate. The dashed vertical line marks a marginal mean of 0.5.

The limits of policy packaging for support and polarization

To assess the policy packaging effect, we subtracted a counterfactual baseline, the mean support and polarization of a package's individual policies, from the package's actual estimated support and polarization[41]. This approach differs from most previous work, which tested whether pairing an unpopular with a popular policy increases support for the unpopular one[27,28]. In contrast to previous research[41], we find evidence that packaging multiple policies together generally decreased the support level as compared to this counterfactual baseline, while it has potential for reducing polarization.

On average, a package received 6.3 percentage points (*SD* = 3.3 percentage points) less support than expected from the counterfactual baseline (Fig. 2a). The negative effect of packaging on support was most pronounced for the least popular policy proposals, as indicated by a positive correlation between policy support (mean of counterfactual baseline and actual package support) and the packaging effect across domains ($r \geq .24$, see Supplementary Table 2). For example, a package including an annually increasing \$50/tCO_2e carbon tax with green spending, a 75% vegetarian meal mandate, a 30% plant-based food subsidy, and no label was only supported by 24.0%, whereas the mean of its individual parts was 37.3%. In contrast, a package including a fixed \$15/tCO_2e carbon tax with electricity bill rebates, no internal combustion engine vehicle phase-out, a 45% public transit subsidy, and 50% increase of green infrastructure federal funding was supported by 51.9%, which is only marginally lower than what would be expected by the mean of its individual parts, 52.5%. Policy packaging did not consistently affect polarization, reducing it by an average of 1.8 percentage points (*SD* = 4.5 percentage points). Relative to the counterfactual baseline of individual policies, packaging further increased polarization for more polarized packages and decreased polarization for less polarized ones ($r \geq .32$; Fig. 2b).

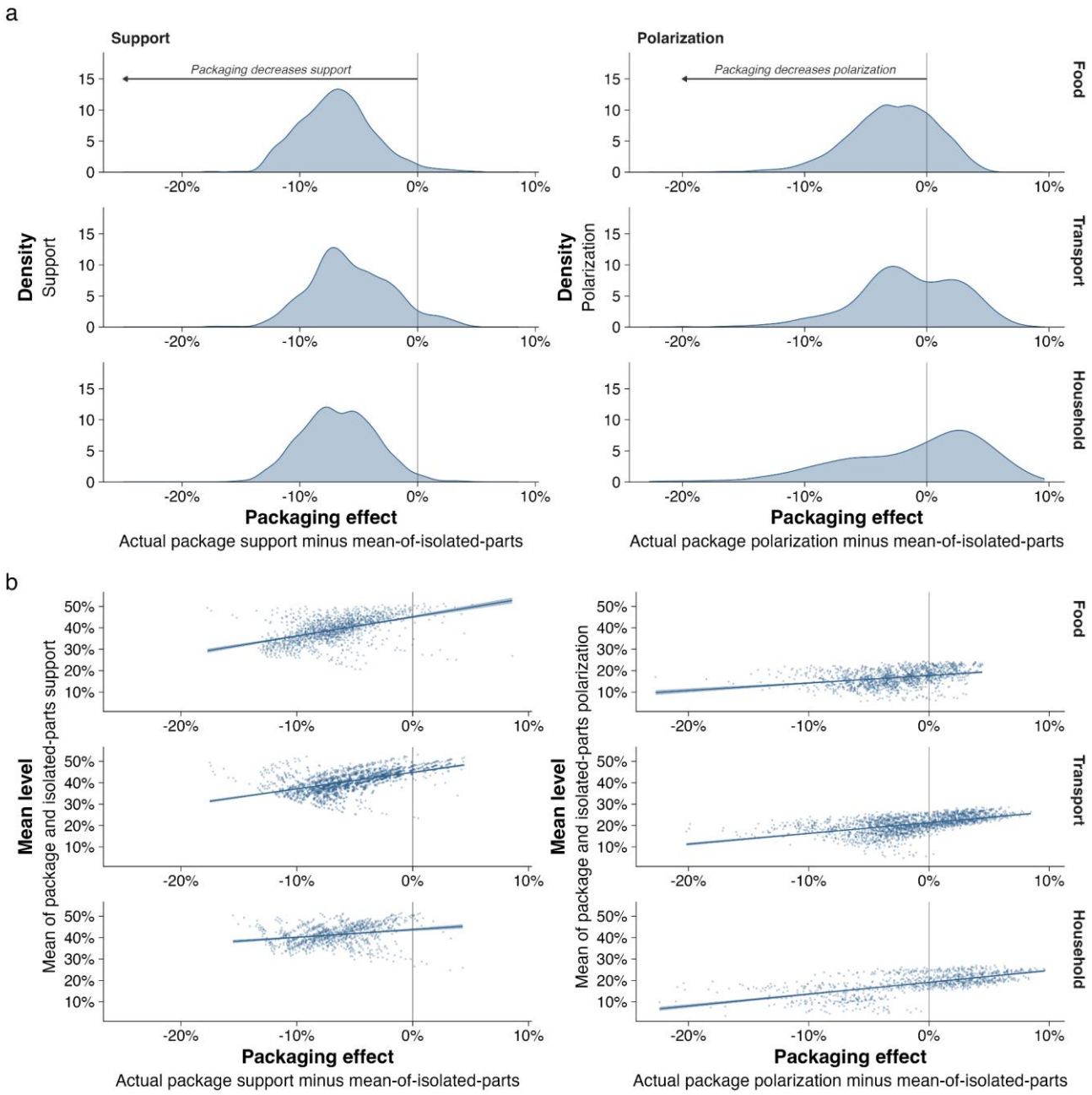


Fig. 2 | **Distribution of packaging effects on policy support and partisan polarization.** The packaging effect is defined as the deviation between a policy package's support or polarization estimate and the outcome predicted from averaging its individual, isolated policy components (actual package support/polarization minus the mean of its isolated parts). Negative values indicate that combining policies into a package yields lower support (or lower polarization) than would be expected from its parts alone; positive values indicate the package exceeds this additive baseline. The vertical grey line in every panel marks zero (actual package estimate equals mean of isolated parts). **a,** Density estimates of the packaging effect across all sampled policy packages within each domain and outcome. Horizontal arrows and annotations in the Food row illustrate the direction of below-additive effects. **b,** Relationship between each package's packaging effect (x-axis) and its mean support or polarization level (average of actual and counterfactual baseline package support or polarization, y-axis), with ordinary least-squares linear fits (shaded bands, 95% confidence intervals) summarizing the association within each domain and outcome. Points show individual sampled policy packages.

Policy packages per domain (one less policy than all possible policy combinations because there is no estimate for the combination without any policies): food: n = 1,311; transportation: n = 1,967; household: n = 983 (reduced number of household packages because of a mismatch in subsidy levels between packages and isolated policies, see Methods). Correlations between the packaging effect

and support and polarization (all *p*-values below .001): food (support: $r(1309) = .49$, 95% CI [.45, .53]; polarization: $r(1309) = .32$, 95% CI [.28, .37]), transport (support: $r(1965) = .55$, 95% CI [.52, .58]; polarization: $r(1965) = .54$, 95% CI [.51, .57]), household (support: $r(981) = .24$, 95% CI [.18, .30]; polarization: $r(981) = .64$, 95% CI [.60, .68]).

Consistent with prior evidence[28], attribute-level effects were systematically attenuated when policies were evaluated in packages compared to in isolation (37 of 42 attribute levels attenuated; Supplementary Fig. 6). That is, individual policy attributes had a stronger effect on support when policies were evaluated individually rather than in packages. However, there was no systematic difference in how strongly the effect was attenuated between push and pull policies (push minus pull = 0.06, 95% CI [−0.11, 0.23], $p = .52$; Supplementary Fig. 7).

State-level variation in policy support and polarization

Moving from policy characteristics to geographic context, we found large geographic variation in support across US states (Fig. 3), which was positively correlated with Democratic vote share ($r(45) = .76$, $p < .001$, 95% CI [.60, .86]), in line with previous research[42]. Polarization was more homogeneously distributed across states: average state-level polarization ranged from 12.2 to 17.4 percentage points for carbon taxes, with more restricted ranges for isolated policies (Min = 21.7, Max = 22.3 percentage points) and policy packages (Min = 17.1, Max = 18.8 percentage points).

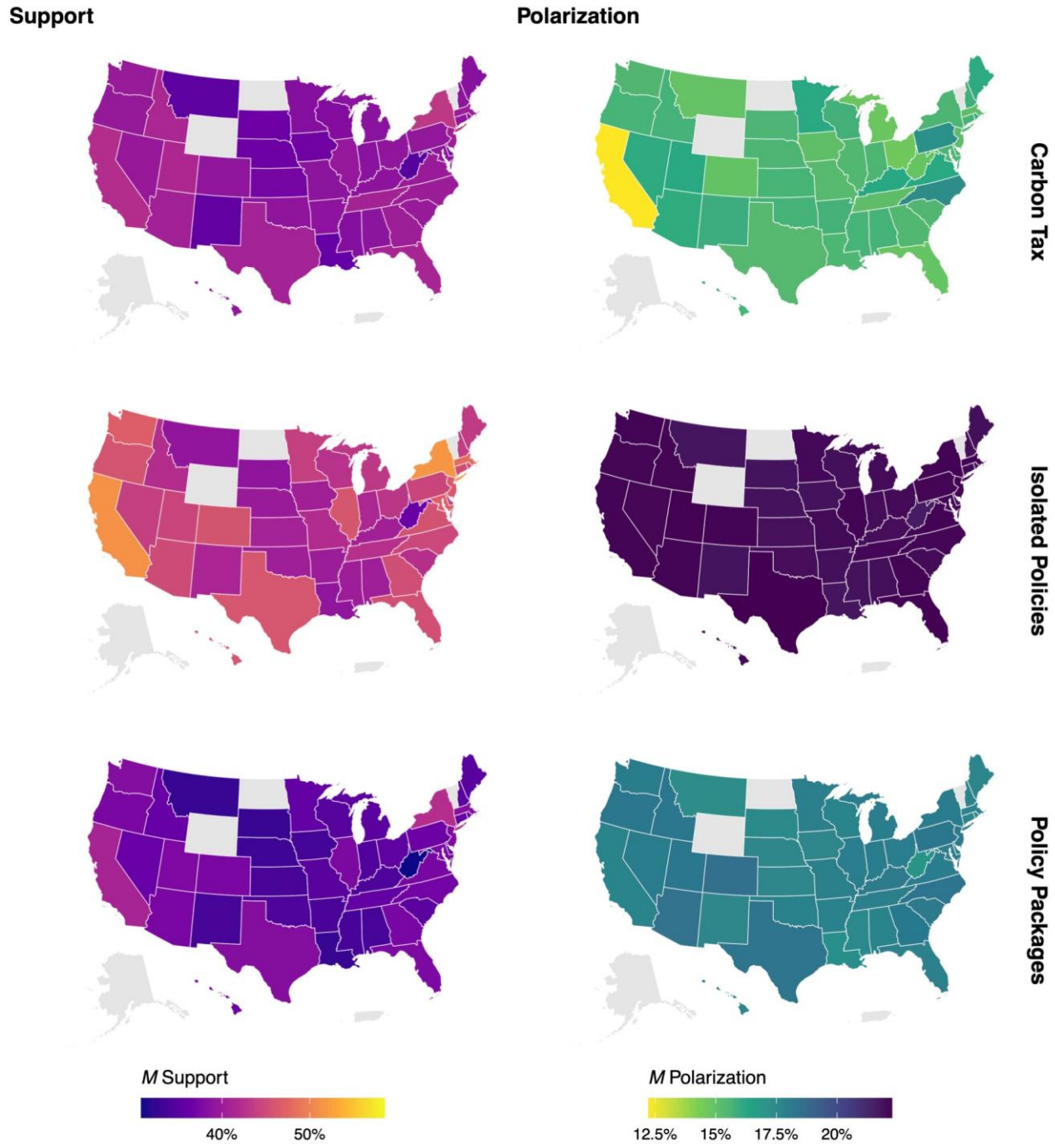


Fig. 3 | Climate policy support and polarization across states. $N_{support}$ = 5,439, $N_{polarization}$ = 3,884, number of policies: $N_{carbon\ tax}$ = 40, $N_{isolated\ policies}$ = 22, $N_{policy\ packages}$ = 4,592. Sample size for polarization is reduced as only participants who identified as either Republican or Democrat were included. Polarization is computed as the average difference in support between Democrats and Republicans for every policy proposal. The higher the polarization score is, the higher the support among Democrats compared to Republicans. Negative values would indicate higher support among Republicans. The underlying support estimates are based on the MRP approach. Grey states are not presented due to low sample size (fewer than ten Democrat or Republican participants: Alaska, North Dakota, Vermont, Wyoming). Across policy configurations (national estimates), average policy support and polarization are moderately to strongly correlated in most DCEs. More polarized policy proposals tended to receive higher average support, which we found for policy packages ($.25 \leq r \leq .65$, all $p < .001$). Correlations for isolated policies were more variable (carbon tax: $r(38) = .24$, $p = .13$, 95% CI [−.07, .51]; food: $r(5) = .93$, $p = .003$, 95% CI [.57, .99]; transportation: $r(6) = -.31$, $p = .45$, 95% CI [−.83, .50]; household: $r(5) = -.77$, $p = .04$, 95% CI [−.96, −.03]), but the small number of policies limits interpretability. See Supplementary Fig. 8 for the corresponding *SD* plots.

When investigating whether between-state variability in support can be attributed to specific state-level predictors, we find little systematic evidence. In the corresponding regression models with policy support as the criterion, we first used single state-level predictors, then added socio-demographic predictors, and finally included the other state-level predictors as controls (Fig. 4 and Supplementary Figs. 9 to 13). Most predictors became non-significant in the model including all control variables. For example, the number of implemented climate policies, both general and domain-specific, was a positive predictor of policy support in line with the policy sequencing hypothesis[32,33], when included as the only state-level predictor with socio-demographic predictors ($Max_{general}$: B = 0.15, 95% CI [0.08, 0.23], p < .001). In addition, higher per-capita carbon emissions were associated with lower average support (Min: B = −0.13, 95% CI [−0.20, −0.06], p < .001), consistent with the vested-interest hypothesis[34,35], and higher state-level GDP was positively associated with policy support (Max: B = 0.15, 95% CI [0.05, 0.24], p = .003).

Associations of domain-specific predictors with support were most pronounced for transportation. Better EV charging infrastructure (packages: B = 0.10, 95% CI [0.03, 0.17], p = .003), more registered EVs (packages: B = 0.10, 95% CI [0.01, 0.18], p = .03), and higher public transit use (packages: B = 0.10, 95% CI [0.05, 0.16], p < .001) positively predicted policy support, while greater automotive sector employment was negatively associated with support (packages: B = −0.13, 95% CI [−0.18, −0.07], p < .001). In the food domain, higher meat prices (packages: B = −0.15, 95% CI [−0.21, −0.10], p < .001) were related to lower support and more vegetarian restaurants (packages: B = 0.12, 95% CI [0.06, 0.17], p < .001) to higher support, while the share of installed heat pumps did not predict household policy support (packages: B = −0.02, 95% CI [−0.07, 0.04], p = .50).

Only few state-level variables significantly predicted polarization, based on the same hierarchical regression approach as for support (without individual-level covariates). Higher GDP (B = −0.18, 95% CI [−0.32, −0.04], p = .01), gasoline costs (B = −0.17, 95% CI [−0.30, −0.04], p = .01), and electricity costs (B = −0.16, 95% CI [−0.29, −0.03], p = .02) were associated with lower polarization in the carbon tax domain, but none of the predictors was

significant when controlling for other state-level predictors. In line with research showing that Republicans' views on climate change vary more across states than Democrats' views[42], these differences were driven by higher support among Republicans, whereas Democrats' support was similar across states. These associations of polarization with GDP and energy prices were also present for domain-specific policies (e.g., GDP household packages: B = −0.12, 95% CI [−0.24, −0.01], p = .03; electricity prices food packages: B = −0.15, 95% CI [−0.28, −0.02], p = .03; gasoline prices transportation packages: B = −0.18, 95% CI [−0.31, −0.05], p = .01).

The relation of implemented policies with polarization was inconclusive. In most models, the association was non-significant, while states with more implemented domain-specific climate policies tended to be less polarized on transportation policy packages (B = −0.15, 95% CI [−0.28, −0.02], p = .02) and more polarized on isolated food policies (B = 0.17, 95% CI [0.01, 0.33], p = .04; controlled for other state-level predictors).

When controlling for other state-level predictors, states with more fossil fuel jobs (isolated: B = 0.17, 95% CI [0.01, 0.32], p = .03) and higher fossil fuel revenue (isolated: B = 0.18, 95% CI [0.02, 0.34], p = .02) showed more polarization on isolated food policies. In states that depend economically on the fossil fuel industry, climate policy may be a more salient local issue on which political actors take clearer positions[43]. As citizens tend to follow the cues of their own party, particularly on contested issues[44,45], this may increase partisan polarization, potentially reinforced by industry campaigns against climate policy[46]. For transportation policies, better charging infrastructure (packages: B = −0.20, 95% CI [−0.33, −0.07], p = .002) and more registered EVs (packages: B = −0.18, 95% CI [−0.31, −0.05], p = .01) were associated with lower polarization, mainly because Republicans were more supportive in these states. Everyday exposure to the targeted technology may make it appear feasible and socially accepted, reducing the resistance of initially more skeptical groups[47,48].

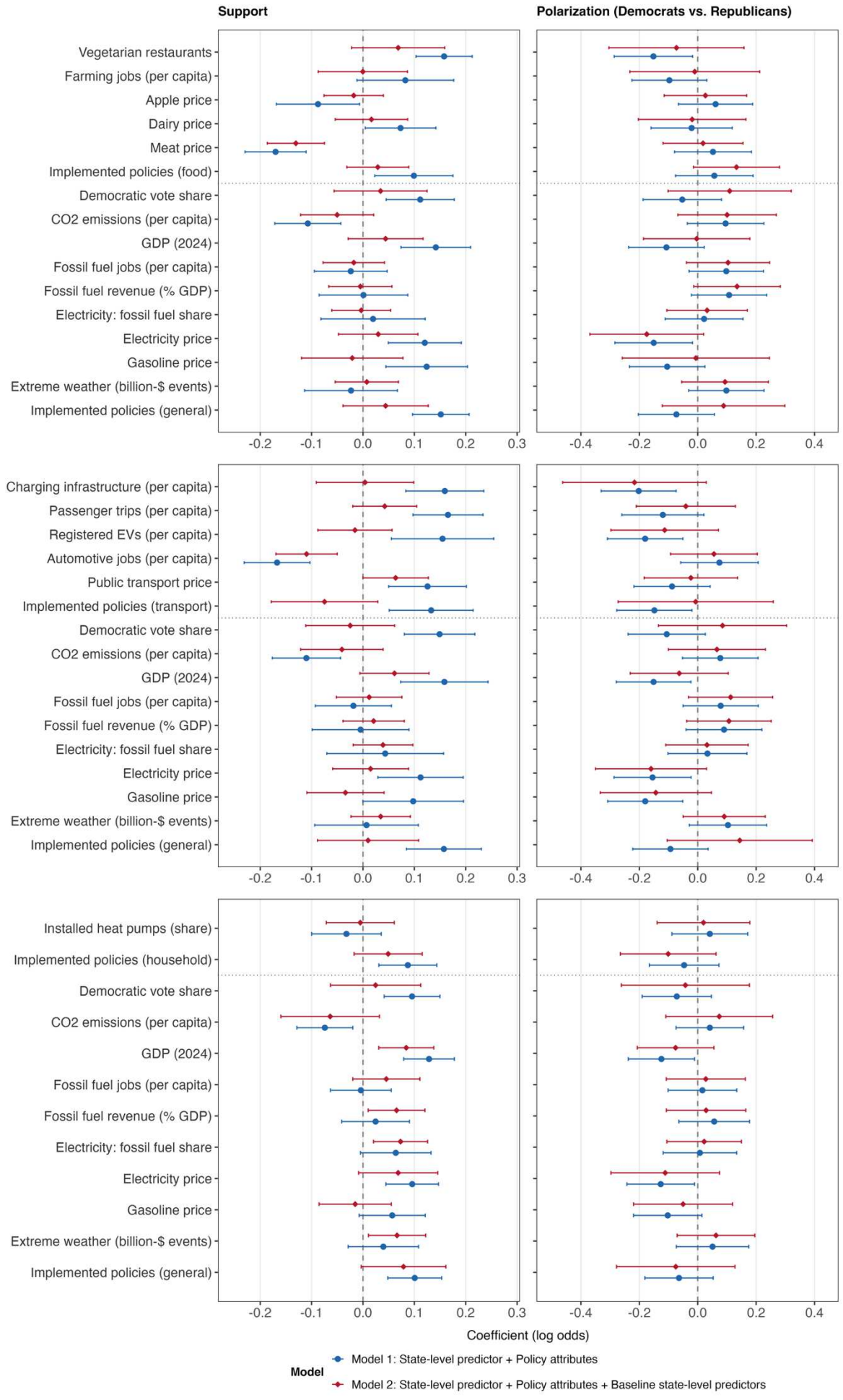

Support
Polarization (Democrats vs. Republicans)
Vegetarian restaurants
Farming jobs (per capita)
Apple price
Dairy price
Meat price
Implemented policies (food)
Democratic vote share
CO2 emissions (per capita)
GDP (2024)
Fossil fuel jobs (per capita)
Fossil fuel revenue (% GDP)
Electricity: fossil fuel share
Electricity price
Gasoline price
Extreme weather (billion-$ events)
Implemented policies (general)
Charging infrastructure (per capita)
Passenger trips (per capita)
Registered EVs (per capita)
Automotive jobs (per capita)
Public transport price
Implemented policies (transport)
Installed heat pumps (share)
Implemented policies (household)
-0.2
-0.1
0.0
0.1
0.2
0.3
-0.4
-0.2
0.0
0.2
0.4
Food
Transport
Household
Coefficient (log odds)
Model
Model 1: State-level predictor + Policy attributes
Model 2: State-level predictor + Policy attributes + Baseline state-level predictors

Fig. 4 | **State-level predictors of policy package support and polarization.** $N_{support}$ = 5,463 (Model 1; Model 2 excludes participants with missing socio-demographic data), $N_{polarization}$ = 3,899. Number of policies: N_{food} = 1,312, $N_{transportation}$ = 1,968, $N_{household}$ = 1,312. Error bars represent 95% confidence intervals. For support, we computed mixed-effects logit models for effect estimates, including a random intercept for person and state. We computed three models for each predictor: a model including policy attributes and the respective predictor alone (Model 1), a model additionally including socio-demographic control variables (political orientation, age, gender, education, income, and place of residency; Model 1.5), and a model additionally including a baseline state-level predictor set with low multicollinearity ($|r| < .60$; VIF < 5; Model 2). The figure shows Models 1 and 2; Model 1.5 estimates are reported in Supplementary Table 3. Given that we have multiple estimates for the baseline predictors, we present the estimate from the model including only the baseline predictors. The socio-demographic variables were standardized within states to mitigate multicollinearity between individual- and state-level predictors. For polarization, we estimated the interaction of party affiliation (Democrat vs. Republican) with the state-level predictor in mixed-effects logit models including the policy attributes, party affiliation and its interaction with the attributes, a random intercept for person, and a random intercept and random party slope for state. Estimates are the change in the Democrat − Republican gap per *SD* of the state-level predictor, with negative values indicating a smaller gap. We computed two models for each predictor: a model including the respective predictor alone (Model 1) and a model including the same baseline or swap-in state-level predictor set as Model 2 for support (Model 2).

Discussion

In most countries, current and planned climate policies are insufficient to meet climate targets. Effective climate policymaking can be obstructed by, among other barriers, weak public support and increasing polarization in the electorate[13]. Our findings provide empirical evidence for how policy design and context shape public support and polarization in the US. Across 4,654 climate policy proposals, effective instruments like carbon taxes were among the least supported ones. Only 1.4% of policy packages reached majority support, with support being bimodally distributed between Democrats and Republicans, indicating polarization[49].

The low overall climate policy support contrasts findings from previous studies[5,50]. This difference likely reflects differences in the level of detail in the presentation of policies, including their consequences for the general population. Corroborating this interpretation, our findings align with studies that similarly assessed policy support by using specific policies and providing information on their consequences[39]. Moreover, the US tends to be among the countries with lower public support for climate policies, which might further explain the difference[50]. However, public support is not stable and can shift over time. As a result policies that seem infeasible today may become feasible later[51,52].

Although these insights are rooted in the US context, they likely generalize to some degree. First, the effects of policy configuration on support mirror findings from other countries[5,21,26]. Second, ideological polarization over climate change, though most pronounced in the US, is increasingly evident in many other democracies[53,54]. In general, policy proposals associated with greater support also tended to be associated with greater polarization, indicating a support-polarization trade-off: high support was disproportionately driven by support from one political side while high bipartisan support was limited. However, some specific policies may offer useful starting points for policy design. Subsidies in the transportation domain and labels received relatively high support while being only moderately polarized, suggesting that some policy configurations can achieve high bipartisan support.

Policy support varied between states, indicating that political feasibility depends not only on policy design but also the socio-political context in which policies are proposed. This state-level variation is particularly relevant in the US, where subnational policymaking can partly compensate for rollback at the federal level. Several state-level factors could explain variance in policy support: states with higher per-capita emissions reported lower support, consistent with vested-interest accounts suggesting lower public support for climate policies where decarbonization is more expensive and vested interest contribute to a greater proliferation of disinformation[34,55]. Similar patterns emerged within specific domains. Greater employment in the automotive industry, reflecting a state's dependence on this sector, was associated with lower support for transportation policies that may contribute to a transition away from gasoline vehicles. Previous experience with climate policies also mattered: states with more already implemented climate policies tended to show higher support, consistent with prior evidence that existing policies can facilitate acceptance of subsequent proposals (i.e., policy sequencing[32,33]).

Associations of state-level predictors with polarization were weaker and less consistent, suggesting that contextual factors that shape overall policy support do not necessarily have parallel effects on partisan differences (i.e., implementing policies might have beneficial effects on support of more effective policies downstream without increasing polarization).

Together, these findings highlight that the political feasibility of climate policies varies systematically across states and depends on both economic exposure and existing policy conditions.

Previous work that investigated the effect of combining multiple policies into packages on support has demonstrated that support for unpopular policies such as carbon taxes increases when combined with more popular policies[26,27]. While we also found that popular policies increase policy support when combined with unpopular policies (as indicated by positive regression coefficients in the policy package models), our findings highlight that overall packaging decreased support for almost all proposals in comparison to a counterfactual baseline. This effect is contrary to the previously found additive effect[41] and was more pronounced for less popular policies. Thus, packaging does not appear to provide a general remedy for increasing support for climate policies (see also[29]). Our results suggest that for packaging to be successful, the combined policies may need to reach a sufficiently high level of support individually to avoid detrimental packaging effects on overall support.

A reason for the found negative effect of packaging on support could be that policy packages were perceived as more restrictive than individual policies in line with previous research[28]. Policies perceived as more restrictive tend to receive less support[56,57], which could explain the negative policy packaging effect in our study. An alternative explanation is that unpopular push policies are more salient in policy packages, so that people weigh them more heavily when evaluating the package[28]. However, our data do not support this mechanism. In packages, the effects of individual policy attributes (e.g., subsidy level) on support were weaker than for the same policies presented alone. If people overweighed push policies, the effects of popular pull policies should have attenuated more than those of push policies. Instead, the degree of attenuation did not differ systematically between push and pull policies but varied by policy domain. Such domain-specific patterns cannot account for a consistent negative packaging effect.

The effects of policy packaging on polarization were less uniform. Packaging further decreased polarization for less polarized policies but increased polarization for more

polarized ones. Thus, rather than systematically reducing partisan differences, packaging tended to reinforce polarization tendencies. Although the mechanisms underlying this pattern require further study, the findings suggest that whether packaging improves or worsens polarization depends strongly on the policies being combined.

Several limitations bound the interpretation of our findings. The analyses are US-specific, and the binary partisan structure we exploit does not transfer directly to multi-party systems, though the underlying logic – climate policy adoption requires minimizing polarization – applies wherever governmental change risks rollbacks. Our DCE captures stated preferences which differ from actual voting behavior[58]. Nonetheless, such preference data are widely used to inform the design and prioritization of policy proposals, making them a valuable input into policymaking even where they diverge from voting behavior. Relatedly, citizens are rarely able to vote on specific policies but indirectly shape policymaking by electing representatives or parties[59]. Such election decisions are more complex than evaluating single policies, as representatives and parties cover various political strategies. Finally, the estimated associations of state-level variables are correlational, sample sizes in some states are small, and representative quotas were implemented at the national, not the state-level. Because our state-level analyses are correlational, testing whether policy sequencing or vested-interest dynamics causally drive the observed patterns will require longitudinal or quasi-experimental designs.

Many countries are experiencing rising political polarization, insufficient adoption of ambitious climate policies, and climate policy rollbacks, widening the gap between the climate action required to minimize climate risks and what governments implement. Our results suggest that closing this gap requires navigating public support and polarization simultaneously. Contrary to more optimistic prior findings, our study shows that policy packaging is no silver bullet that automatically renders unpopular policies more popular or less polarized. Importantly, the political feasibility of such policies is not uniform: support and polarization vary across socio-political contexts, implying that policy strategies that are viable in one state may be less feasible in another. Effective climate policy design therefore

requires attention not only to which policies are combined, but also to the contexts in which they are implemented.

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Methods

Sample and preregistration

Part of the analyses and hypotheses were preregistered (https://osf.io/h5sm8/overview?view_only=d19989c20df9450180aafae5218f8412) before data collection including data exclusion criteria. Analyses on support were mostly preregistered and on polarization are exploratory and not preregistered. The study received ethical clearance from the ethics committee from the Faculty of Psychology from [hidden for double-blind review] (application number [hidden for double-blind review]).

The sample was drawn by the panel provider Dynata (https://www.dynata.com) and we implemented quotas for gender (male and female; not excluding participants that identified as neither), age (between 18 and 74 years; not excluding participants older than 74 years), and household income before taxes (under $25,000, $25,000 to $49,999, $50,000 to $74,999, $75,000 to $99,999, $100,000 to $149,999, over $150,000). Supplementary Table 1 gives an overview of how our sample maps onto the general US population in terms of

socio-demographic characteristics. Data was collected with an online questionnaire implemented in SoSci Survey[60]. Participants were financially compensated for their participation. Only participants who were at least 18 years old, US citizens, and gave informed consent were able to proceed with the survey. The survey included five attention checks and participants were screened out during the survey, when they failed to correctly answer at least two attention checks. Median response time in our final sample was 20 minutes and 25 seconds.

Of the 5,726 participants that finished the survey, 263 participants were identified as speeders (survey completion time under 10 minutes), AI bots or inattentive participants (i.e., straight-lining indicated by 0-variance in answers on item batteries). AI bot identification was based on an open answer item ("Please write 7 here.") that was programmed to be invisible to human participants and therefore "7"-responses were interpreted as non-human[61].

The final sample size of N = 5,463 suffices commonly applied rules-of-thumb for DCEs[62,63], is comparable to sample sizes in similar studies on policy support[26–28] and MRP applications[31,37].

Items and Measurement

Participants first answered various socio-demographic items including a first single-choice attention check ("To show that you are carefully reading the instructions of this survey, please select Toyota in this question."). Participants who answered this attention check incorrectly were presented with a warning ("Attention! One of your answers on the previous pages indicated that you did not read the instructions or texts carefully. Please read all instructions and texts carefully from now on. They are very important for answering this questionnaire. Answering an attention check incorrectly again will lead to exclusion from this study."). Participants were then introduced to the carbon tax DCE. We first explained the choice task and the different attributes of our carbon tax schemes including tangible consequences of different tax levels (i.e., changes in the prices of carbon-intensive products). Afterwards participants had to answer an attention check targeting the understanding of the basic concept of a carbon tax. Incorrect responses resulted in

participants seeing the warning and the carbon tax explanation page again. Participants who answered both attention checks incorrectly were screened out.

We then presented participants with three trials of the carbon tax DCE. The same procedure was repeated for the three domains food, transportation, and household, while randomizing the order of these domains. We presented two DCEs for each domain: two trials for the isolated domain-specific policies and three trials for the domain-specific packages including a general carbon tax. We then assessed participants' political orientation, party affiliation, importance of different political issues, governmental trust, and motivation to protect the environment. Participants were finally debriefed, had the opportunity to leave any comments or suggestions, and were forwarded to Dynata for compensation.

Dependent variables

We selected consumer behavior-focused policies as they might appear more relevant for participants (which can increase response quality) and applied a taxonomy which divides policies along two dimensions: market-based to non-market-based, and push to pull policies[21]. We defined policies for each of the four resulting categories based on policies that were implemented in the US at the time of data collection (e.g., the Inflation Reduction Act or Infrastructure Investment and Jobs Act). For the market-based-push policy we chose a general carbon tax independent of the domain as it is discussed as the most effective climate policy[64–66]. The attribute levels were defined based on previous studies and designs that are currently discussed as feasible in politics[67] and necessary in science[39,40,64–66]. We selected domain-specific subsidies as market-based-pull policies, mandates as non-market-based-push policies, and labels or federal spending as non-market-based-pull policies.

In addition, we investigated the effect of policy packaging in the three domains. Policy packaging refers to the idea of combining multiple policies into one package which is assumed to (i) have compensatory effects (i.e., popular measures compensating for unpopular measures) and (ii) affect the decision importance of attributes (i.e., single attributes affect support more strongly when policies are presented in isolation compared to in packages[26]).

The manipulated variables vary based on the specific policy DCE. For assessing the support of different carbon tax schemes, we manipulated three attributes of the carbon tax: the price of the tax (four levels: $15/tCO2e, $50/tCO2e, $100/tCO2e, $150/tCO2e), whether it is dynamic or not (two levels: no annual increase, annual increase by 10% with a cap at $300/tCO2e), and the mechanism how the revenue from the tax is used (five levels: green spending, deficit reduction, public programs for low-income households, reduce labor taxes inversely to income, reduce electricity prices equally for everyone).

For assessing the support of isolated food policies, we manipulated only one attribute with seven levels (specific policy and its level): vegetarian meal mandate (at least 25%, 50%, 75% vegetarian meals offered in public cafeterias), plant-based food subsidy (discount of 15%, 30%, 45%), carbon label on food products.

For assessing the support of isolated transportation policies, we manipulated only one attribute with eight levels (specific policy and its level): fleet emission standards (abandonment of new ICEVs by 2030, 2040, 2050), public transportation subsidy (discount on tickets of 15%, 30%, 45%), federal funding for green infrastructure programs (increase public funds by 50%, 100%).

For assessing the support of isolated household policies, we manipulated only one attribute with seven levels (specific policy and its level): fossil-fuel based heating systems phase-out (by 2030, 2040, 2050), household energy efficiency subsidy (increase current tax credit on investments from 30% to 40%, 50%, 60%), energy label for appliances.

For assessing the support of food policy packages, we manipulated six attributes: the price of the tax (five levels: no tax, $15/tCO2e, $50/tCO2e, $100/tCO2e, $150/tCO2e), whether it is dynamic or not (two levels: no annual increase, annual increase by 10% with a cap at $300/tCO2e), the mechanism how the revenue from the tax is used (five levels: green spending, deficit reduction, public programs for low-income households, reduce labor taxes inversely to income, reduce electricity prices equally for everyone), the vegetarian meal mandate level (four levels: no mandate, 25%, 50%, 75%), the plant-based food subsidy level

(four levels: no discount, 15%, 30%, 45%), and the carbon label on food products (two levels: no label, label).

The same policy package design principle was applied to the transportation and household domain, substituting the food domain policies with the corresponding policies from the transportation and household domain. Importantly, a coding error led to different levels of the household energy efficiency subsidy in packages (increase credit cap by 10%, 30%, 50%). Therefore, the first and second levels in the package condition map onto the first and third level of the isolated condition. In trials where the carbon tax price attribute level is "no tax" in the policy package tasks, the other two carbon tax attributes were omitted as they were not relevant then.

The main variable of interest in this study is the support of different climate policies and policy packages. The general structure of a policy support task was composed of two proposals (either carbon tax schemes, isolated domain-specific policies, or domain-specific policy packages). Support was assessed in two ways for an internal cross-validation of the findings. For every pair of policy proposals, each participant first evaluated which of the two they preferred (“If you had to choose between them, which of the two policy proposals would you prefer?”) and afterwards rated each proposal individually (“Would you approve of the policy proposals? Please rate each policy proposal separately now.”) on a five-point Likert-scale ranging from No to Yes (for a similar approach, see[28]).

The policy attributes of the seven DCEs yielded a total of 4,654 unique policy configurations. For carbon tax schemes and isolated policies, we presented participants with randomly drawn policy proposals, while ensuring that no participant saw any proposals twice. For policy packages, policy proposals were randomly drawn from a d-efficiency maximizing subset of 300 policy proposals per domain. Each participant evaluated three pairs of carbon tax proposals (total of 6 proposals), two pairs of isolated domain-specific policy proposals per domain (total of 12 proposals), and three pairs of domain-specific policy package proposals including a carbon tax scheme per domain (total of 18 proposals), resulting in between

21,852 and 32,778 observations per DCE. For an exemplary DCE trial for policy packages, see Supplementary Fig. 14.

We also computed a polarization score for each policy proposal by subtracting the average MRP-derived support of Republicans from the average support of Democrats for each policy proposal. More positive values indicate greater polarization based on higher support among Democrats and more negative values greater polarization based on higher support among Republicans[49].

Individual-level predictors

For the computation of the polarization score, we assessed party affiliation (Democratic, Republican, Independent, other). For the individual-level control variables, we assessed political orientation (from 1 = extremely liberal to 7 = extremely conservative), age, gender, annual household income before taxes, formal education, and place of residency. In addition, we assessed US citizenship, mother tongue, employment status, state of residency, household size, diet (e.g., vegan) and cafeteria usage (food domain), car ownership, owned car type, and public transportation usage (transportation domain), and home ownership and type of installed heating system (household domain). These variables, in addition to our measures of environmental attitude and governmental trust are not part of the analyses presented in this study.

Before the computation of multi-level models, all numerical variables were z-standardized (for the models investigating the effect of state-level predictors, we z-standardized continuous individual-level variables within states). Experimental conditions (i.e., the policy attributes) were dummy-coded in our analyses, defining the attribute level representing the lowest policy ambition as the reference level. In the isolated domain-specific DCEs, in which each level represents a different policy, the food carbon label, the 50% increase in federal funding (transportation), and the appliance energy label (household) served as reference levels. An overview of all items can be found in the preregistration.

State-level predictors

For the state-level factors, we used publicly accessible data. We accessed the corresponding data between May 15, 2025, and June 2, 2025, and acknowledge that some of the data may not be accessible anymore under the listed links. We clustered the predictors in eight categories (see Table 1). General predictors were tested in all seven DCEs and domain-specific predictors were tested in the DCEs of the respective domain. Six predictors were additionally used as state-level covariates in the MRP models.

Table 1

State-level predictors

Category	Domain	Predictor	Source
Existing climate policies	G	# implemented climate policies	https://www.climatepolicydashboard.org
	F, T, H	# implemented domain-specific climate policies	https://www.climatepolicydashboard.org
Extreme weather events	G	# billion $ disasters	https://www.ncdc.noaa.gov/stormevents/
Price for unsustainable option	F	Average price beef / dairy	https://www.ams.usda.gov/mnreports/ams_3228.pdf / https://www.ams.usda.gov/mnreports/dybretail.pdf
	G	Average price gasoline	https://gasprices.aaa.com/state-gas-price-averages/
	G, MRP	Average price electricity	https://www.eia.gov/electricity/monthly/epm_table_grapher.php
Price for sustainable option	F	Average price apples	https://www.ams.usda.gov/mnreports/fvwretail.pdf
	T	Average fares public transportation	https://www.apta.com/research-technical-resources/transit-statistics/fare-database/
Dependence on targeted industry	G	Electricity generated by fossil fuel / Revenue from fossil fuel industry	https://www.eia.gov/electricity/data/browser/ / https://www.journals.uchicago.edu/doi/epdf/10.1086/725250
	F	Jobs in farming (per capita)	https://www.bls.gov/oes/2023/may/oes450000.htm
	T	Jobs in automotive industry (per capita)	https://www.energy.gov/sites/default/files/2024-08/USEER%202024%20States%20Final.pdf
	G	Jobs in the fossil fuel industry	https://www.energy.gov/sites/default/files/2024-08/USEER%202024%20States%20Final.pdf
Current infrastructure	F	# vegetarian restaurants (per capita)	https://www.happycow.net/north_america/usa/?filters=vegan-vegetarian
	T	# EV chargers (per capita)	https://afdc.energy.gov/stations/states
Descriptive social norms	T	Share of registered EVs / Share of public transportation users	https://afdc.energy.gov/vehicle-registration / https://www.bts.gov/browse-statistical-products-and-data/state-transportation-statistics/state-transportation-numbers

Category	Domain	Predictor	Source
	H	Share of installed heat pumps	https://www.eia.gov/consumption/residential/data/2020/state/pdf / State%20Space%20Heating.pdf
Control (MRP)	G, MRP	GDP (2024)	https://www.bea.gov/sites/default/files/2025-03/stgdppi4q24-a2024.pdf
	G, MRP	Democratic Presidential vote share (2024)	https://edition.cnn.com/election/2024/results/president
	G, MRP	Level of point source carbon dioxide emissions	https://www.eia.gov/state/seds/data.php?incfile=/state/seds/sep_sum/html/rank_co2_capita.html
	MRP	Share of individuals who drive alone to work	https://data.census.gov/table/ACSST1Y2021.S0801
	MRP	Share of same-sex households	https://www.census.gov/data/tables/time-series/demo/same-sex-couples/ssc-house-characteristics.html

Note. G = general predictor, tested in all seven DCEs; F, T, H = domain-specific predictor, tested in the food, transportation, or household DCEs. MRP = state-level covariate of the MRP models. # = number of. All predictors were z-standardized.

Analyses

All socio-demographic variables were assessed through forced choice items although some had the option of “Prefer not to say”. Missing values on these socio-demographic variables such as employment status and formal education led to listwise deletion of the participant (complete-case analysis) in all models that included the corresponding variable (e.g., Models 1.5 and 2 of the state-level support analyses). All analysis R scripts, the post-stratification frame derived from the American Community Survey, the code to reproduce all main and supplementary figures, and the processed data are openly available (https://doi.org/10.5281/zenodo.23733282). All analyses were conducted in R (version 4.6.1)[68], and logit mixed-effects models were fitted with the lme4 package[69].

Preregistered

Following our preregistered analysis plan, we used logit mixed-effects models to regress dichotomized policy support on policy attributes, individual-level control variables, and state-level predictors. All analyses were conducted on both DV operationalizations: (i) the separate evaluation of each individual policy proposal (dichotomized: *no*, *probably not*, and *undecided* coded as not accepted [0] vs. *probably yes* and *yes* coded as accepted [1]) and (ii) the relative preference between two proposals presented in a trial (1 = preferred, 0 = not preferred). Because the conclusions that can be tested with both operationalizations did not

strongly differ, we report results based on the absolute evaluation in the main text and results based on the relative evaluation in the Supplementary Materials (see *Result robustness based on alternative outcome measurement*).

We determined the random-effect structure following the strategy outlined in the preregistration. Starting from a model with a random intercept for participants, we added a random intercept for states and then tested, separately for each attribute, whether uncorrelated random slopes of the attribute levels across states improved fit. All models were fitted by maximum likelihood (ML) and compared with likelihood-ratio tests, AIC, and BIC (Supplementary Table 4). The random intercept for states improved fit in six of seven DCEs (likelihood-ratio tests; carbon tax: $p = .77$) and was retained in all models. Uncorrelated random slopes of the attributes across states did not improve BIC for any of the attributes tested, and 21 of 24 of these models were singular or did not converge. Random slopes were therefore not retained. Adding the individual-level control variables (political orientation, age, gender, education, income, place of residency) improved fit (Supplementary Table 4). Intra-class correlations show that a large share of the variance in policy support resides at the participant level ($.42 \leq ICC \leq .49$) and very little at the state level ($.001 \leq ICC \leq .013$; Supplementary Table 4).

We then estimated, for each DCE separately, a logit mixed effects model regressing policy support on the dummy-coded policy attributes (for packages, all attributes entered jointly) with random intercepts for participants and states. To test the preregistered hypotheses on policy attributes, we compared all levels within each attribute with pairwise Wald contrasts (e.g., between revenue-recycling mechanisms or between subsidy levels); *p*-values were Holm-adjusted within attribute (Supplementary Table 5). We additionally estimated support for every possible policy (package) configuration with MRP (see below) to identify configurations that achieve majority support. Following[28], we evaluated the policy-packaging hypothesis by comparing attribute-level effects between the corresponding isolated and package DCEs (Supplementary Figs. 6 and 7). Package coefficients were recoded to the reference category of the isolated DCE (e.g., food label instead of the no

policy attribute for every food policy), and an attribute level was considered attenuated when the absolute value of its package coefficient was smaller than that of its isolated coefficient. Differences between isolated and package coefficients (with positive values indicating attenuation), were pooled by policy type (i.e., pull vs. push) and domain with random-effects models. Push and pull policies were compared with a random-effects meta-regression across the 30 domain-specific and carbon-tax attribute levels (excluding revenue-recycling mechanisms) with domain fixed effects (Supplementary Table 6).

To test the state-level hypotheses for policy support, we estimated three nested models with increasing complexity for each state-level predictor and DCE (Fig. 4 and Supplementary Figs. 9 to 13). Model 1 included the policy attributes and the focal state-level predictor (z-standardized). Model 1.5 additionally included the socio-demographic control variables (political orientation, age, gender, education, income, place of residency), with continuous individual-level variables being standardized within states to separate individual- from state-level variation. Model 2 additionally included a domain-specific baseline set of state-level predictors, based on a stepwise multicollinearity check (pairwise $|r| < .60$ and VIF < 5 in the corresponding mixed-effects model). The baseline sets comprised Democratic vote share, per-capita CO_2 emissions, as well as gasoline price, electricity price, and GDP (carbon tax); electricity, meat, and apple prices (food); electricity price, public-transportation fares, and automotive employment (transportation); and the share of heat pumps (household). Predictors that were not part of the baseline set were estimated in swap-in models, in which they replaced a baseline predictor (or were added to the baseline set if no baseline predictor had to be removed). For each predictor, we therefore report Model 1, Model 1.5, and either the baseline model (if the predictor is part of the baseline set) or the corresponding swap-in model (Model 2). Fig. 4 and Supplementary Figs. 9 and 10 show Models 1 and 2, Supplementary Figs. 11 to 13 all swap-in configurations, and Supplementary Table 3 all estimates. In the text, we summarize the estimates of general predictors across the seven DCEs by the Max of the Model 1.5 estimates.

To estimate national and state-specific support for each policy (package) configuration, we applied MRP[31,37]. For each DCE, we regressed policy support on (i) the policy attributes, (ii) gender (fixed effect), (iii) random intercepts for age group, education group, and income group, (iv) six z-standardized state-level covariates (share of individuals who drive alone to work, share of same-sex households, per-capita CO_2 emissions, 2024 Democratic presidential vote share, average electricity price, and state GDP), and (v) random intercepts for participants and states. Individual-level groups follow the US Census categories (age in seven groups, education in five groups, income in six groups, binary gender). Participants who identified as neither male nor female (n = 24) could not be poststratified and were excluded from the MRP models (N = 5,439). The poststratification frame was constructed from American Community Survey (ACS) data by summing the person weights of US citizens aged 18 or older in each state × gender × age × education × income cell (21,420 cells). For each configuration and cell, we computed the predicted support from the fixed effects and the estimated age, education, income, and state effects. Because the model is nonlinear, we integrated the participant random intercept out of the predictions, so that the estimates represent the share of the population supporting a policy rather than the support of a typical participant. Cell predictions were aggregated to national and state estimates by weighting them with the ACS cell counts. 95% confidence intervals were computed based on 1,000 draws from the joint approximate sampling distribution of the fixed and group-level effects (conditional on the estimated variance parameters). The MRP estimates form the basis of the shares of configurations above support thresholds (Supplementary Fig. 1), the maps (Fig. 3; Supplementary Fig. 8), the marginal means (Fig. 1), and the packaging effect analyses (Fig. 2).

Exploratory

Our analyses on partisan polarization in policy support were not preregistered. To estimate party-specific support, we re-fit the MRP models described above on participants who identified as Democrat or Republican (N = 3,884; 2,107 Democrats and 1,777 Republicans; binary gender), adding party affiliation and its interactions with all policy attributes as fixed

effects and allowing the state intercept to differ between parties (random intercept and random party slope by state). Predictions for Democrats and Republicans were generated with the same procedure as for the whole-sample MRP. For both parties, cells were weighted with the ACS counts of the whole state population, so that the party-specific estimates refer to the same demographic composition and differences in the demographic composition of Democrats and Republicans do not enter the polarization score. The polarization score of a configuration is the difference between the Democratic and Republican estimates (positive values indicate greater support among Democrats[49]). Both party estimates were computed from the same 1,000 draws, which yields percentile confidence intervals for the party-specific estimates, their mean, and the polarization score. The marginal means of the attribute levels of policy packages (Fig. 1) were computed in every draw as the average estimate across all package configurations containing the level.

To produce the maps of support and polarization across states (Fig. 3, Supplementary Fig. 8), we averaged the state-level estimates across all policy configurations within each state for each DCE family (carbon tax, isolated domain-specific policies, policy packages) and additionally mapped the within-state *SD* across configurations. Four states with fewer than 10 participants identifying as Democrat or Republican (Alaska, North Dakota, Vermont, Wyoming) are not shown on the maps but were retained in all model-based analyses. The same four states were excluded from the correlation between MRP-estimated average state-level support and Democratic vote share. Correlations between average support and polarization (Fig. 3) were computed across policy configurations from the national estimates. Density plots of support by party affiliation (Supplementary Fig. 2) are based on the national party-specific MRP estimates of all 4,654 configurations.

To investigate which policy attributes are associated with polarization, we fitted, for each DCE, a logistic mixed model on the Democrat and Republican subsample (N = 3,899) in which support was regressed on the policy attributes, party affiliation, and their interactions, with random intercepts for participants and states. The interaction terms give the difference between Democrats and Republicans in the effect of an attribute level (partisan gap, ΔB;

Supplementary Figs. 3 to 5, Supplementary Table 7), with positive values indicating that the attribute level widens the gap relative to the reference level. To investigate state-level drivers of polarization, we added interactions of party affiliation with a z-standardized state-level predictor (or predictor set) and allowed the intercept to differ between parties (random intercept and random party slope by state). The estimate of interest is the change in the Democrat - Republican gap (log-odds) per standard deviation of the predictor, with negative values indicating a smaller gap. As for support, we estimated a model with the focal predictor alone (Model 1) and a model with the baseline or swap-in set of state-level predictors (Model 2). Individual-level controls were not included (Fig. 4, Supplementary Figs. 9 and 10, Supplementary Table 8).

We conducted additional exploratory analyses of the policy packaging effect. For each package configuration, we computed the packaging effect as the difference between the national MRP estimate of the package (support or polarization score) and the mean of the national MRP estimates of its components evaluated in isolation: the carbon-tax scheme (carbon-tax DCE) and the mandate, subsidy, and label or funding levels (isolated domain-specific DCE). Components at the no-policy level (e.g., no carbon tax) were omitted from the mean, and the package with all attributes at the no-policy level was excluded. Household packages containing the 50% credit-cap increase were excluded because this subsidy level has no isolated counterpart (see Dependent variables), resulting in 1,311 food, 1,967 transportation, and 983 household packages (Fig. 2). To relate the packaging effect to the level of support or polarization, we correlated it with the mean of the actual and the baseline estimates (95% confidence intervals based on Fisher's z).

Finally, we tested whether the partisan gap differed between socio-demographic groups. For each DCE, we fitted a logistic mixed model on the Democrat and Republican subsample with the policy attributes, party affiliation, age, gender, education, income, and place of residency, and the interactions of party affiliation with the socio-demographic variables (random intercepts for participants and states) and compared it with the model without these interactions using likelihood-ratio tests (Supplementary Table 9). The interactions improved

fit in all seven DCEs (likelihood-ratio tests; N = 3,877). Most consistently, the partisan gap was smaller among participants living in urban than in rural areas (Δgap = −1.06 to −1.48, all $p < .001$) and larger among older participants (Δgap = 0.14 to 0.31 per *SD* of age). Differences by gender, education, and income were small and mostly not significant after Holm adjustment (Supplementary Table 9).

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SupplementaryMaterialsMappingpublicsupportandpolarizationforU.S.climatepoliciesandpolicypackages.pdf