Red state, blue state:

The polarizing influence of color in political maps

*Rémy A. Furrer¹, Karen Schloss², Gary Lupyan², Paula M. Niedenthal², & Adrienne Wood¹

¹ University of Virginia, ² University of Wisconsin - Madison

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Abstract

The media regularly visualizes the growing political polarization in the United States using a two-tone U.S. map, with Republican-leaning states in red and Democrat-leaning states in blue. However, such dichotomization conceals the true spectrum of political opinion and voting patterns. We asked whether dichotomizing maps into red and blue states leads people to overestimate polarization compared to maps that represent voting patterns continuously using hue and lightness gradients. And if so, is this polarizing effect due to partisan semantic associations with red and blue, or can any color mappings produce similar effects? Online U.S. participants estimated the hypothetical voting patterns of eight swing states depicted using dichotomous or continuous red/blue or orange/green color maps. The dichotomous red/blue maps produced more polarized predictions than the continuous red/blue maps, but there was no difference between dichotomous and continuous orange/green maps. This suggests the polarizing effect red/blue dichotomous maps have on predicted voting patterns can be mitigated by switching to novel colors. We conclude that the tribal associations and categorical nature of red/blue maps are not simply tools for illustrating political polarization in the U.S.—they may in fact be exacerbating them.

Red state, blue state: The polarizing influence of color in political maps

Intractable conflict over partisan issues such as healthcare, gun control, and immigration plagues contemporary U.S. politics^{1,2}. This conflict is in part due to increased polarization between Democratic and Republican voters and legislators³. Growing public awareness of polarization is reflected in Google search trends for the phrase “political polarization”, which have nearly quadrupled in interest over the last decade (see **Figure 1**). However, people slightly overestimate the true degree of polarization⁴. It turns out that the majority of people hold more moderate views than others attribute to them^{5,6,7}.

Expecting the rest of the population’s attitudes to be polarized, regardless of the true polarity of the population, leads to increased political action, such as attending political rallies and donating money to parties and candidates⁴. Polarized predictions can also escalate conflict^{8,9}. The concerning implications that stem from exaggerated public perceptions of polarization have attracted the attention of social scientists^{10,11,12,13}.

One simple and ubiquitous factor that captures and reflects people’s sense of polarization is how electoral maps are designed to visualize political outcomes. The ubiquity of dichotomously colored red and blue political maps, in particular, may lead constituents to think U.S. geographic regions are more politically segregated than they actually are. In fact, past research suggests that such polarization is exacerbated by the dichotomization and labeling of Republican-leaning districts as “red” and Democrat-leaning districts as “blue”¹⁴.

In current U.S. politics, the association between *Democrats* and *blue*, and *Republicans* and *red*, is so ubiquitous that it is easy to forget how recently this color mapping emerged. A person flipping through TV channels during a pre-2000 election season might have seen, on one

Figure 1. A plot of U.S. Google searches for “political polarization” over time fit with a quadratic trend line. Numbers on the Y-axis represent search interest relative to the highest point on the chart within the United States at the given time (X-axis). A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. A score of 0 means there was not enough data for this term.

news station, a political forecast map coded Republican-leaning districts or states as blue and Democrat-leaning ones as red, but then the next news station might use red-blue, or orange-green, or no colors at all^{15,16,17}. There was no agreement across news outlets or across election seasons, and if anything, left-leaning political parties had a stronger association with red (e.g., the Communist Party). The Republican-red and Democrat-blue mapping took hold in 2000, as the Bush v. Gore presidential election controversy and vote recounts unfolded over days and weeks and received extensive news coverage. Media outlets covering the election gradually settled on the current color scale, and the associations stuck.

In just two decades a color-coding system that began as a convenient visualization tool has become a symbol for—and, potentially, a contributor to—the increasing divide between liberals and conservatives. The symbolic dichotomization implies a lack of nuance in political

ideology, which in turn might exacerbate the bipartisan divide across political¹⁸, geographic¹⁹, and virtual²⁰ settings. The existence of “red states” and “blue states” is now taken for granted, though in actuality the U.S. is a quilt of different shades of purple as first demonstrated by Robert Vandervei, who coined the phrase *Purple America* after the 2000 presidential elections²¹. Red and blue have become such essential properties of people’s concepts for *Republican* and *Democrat* that on election days, when the parties are made particularly salient, people’s personal color preferences become more aligned with their party affiliation²². In other words, people’s preferences for their political in-group permeates their color preferences, underscoring the strength of the association between parties and colors.

Depicting the U.S. using a dichotomous color scale simplifies complex voting patterns (see **Figure 2A**), but it can also alter the ways in which people construe partisan politics, potentially further polarizing people’s estimates of voting outcomes. Color facilitates categorization²³ and grouping of objects^{24,25,26}, so people can look at a color-coded map and quickly extract information. But maps utilizing the red-blue categorization have a significant drawback. Prior work shows that dichotomizing a political map using two hues, red and blue, rather than a continuous hue gradient (from red to blue, through purple), leads people to overestimate within-state political homogeneity and nation-wide political polarization¹⁴. In other words, people assume “blue states” must be substantially more Democratic and liberal than “red states”, when in fact they could be just a few percentage points apart. This is because applying a categorical classification scale to a continuous feature, such as the percent of voters in a geographic region that hold a particular opinion, causes people to hold more categorical representations of the feature²⁷. People will then represent residents of “red states” and “blue states” as more different from each other than they actually are, potentially exacerbating harmful

stereotypes about “liberal bubble states” and conservative “flyover country.”

As depicted in **Figure 2**, there are multiple ways to continuously represent a variable of

Figure 2. Different approaches to red-blue maps representing the outcome of the 2016 election at the county level. *A*: Dichotomous solution. Red counties are those where Donald Trump received the greatest number of votes; blue, Hillary Clinton. *B*: A continuous hue solution. Counties are shaded according to winning candidate’s percentage of the vote, with purple counties being closer races and redder or bluer states having a larger margin in favor of Trump or Clinton, respectively. *C*: A continuous hue and lightness solution, where base hue indicates which candidate won the county, and saturation indicates the margin by which a candidate won a county. Prior work suggests judgments about polarization are reduced by solution B relative to solution A, but no work has compared solution C¹⁴. Furthermore, no work has compared the effect solution A relative to an absence of red-blue coding or to an arbitrary color mapping to isolate general effects of color on category representation from the effect of prior knowledge about the significance of red and blue in politics.

interest (which might be the percent of votes that went to a given candidate, or the percent of voters who endorse a position, for instance). Sticking with the red-blue representation, such a map could use a color gradient that passes from pure red, through purple (the result of combining red and blue), to pure blue¹⁴. This would result in a map of various hues of purple that capture the continuous distribution of voting patterns, as discussed in the previous paragraph (see **Figure 2B**). However, these purple maps make it challenging to interpret the outcome of a winner-takes-all electoral college system, where a single percentage point can decide whether an entire state

goes to the Republican or Democratic candidate. For such an election system, it is useful to represent the actual or likely *winner* of a district or state, as well as the *margin* by which they won or are expected to win. One way to maintain the continuous representation supported by red-purple-blue maps, while illustrating the categorical outcome of a winner-take-all system, is to use a divergent map with two hues interpolated through white (see **Figure 2C**). This visualization method avoids the muddiness of purple shades, but it is yet unknown whether they eliminate the categorical effects of hue on people's judgments of polarization.ⁱ

In this study, we asked whether dichotomizing maps into red and blue states leads people to overestimate polarization compared to maps that represent voting patterns continuously using red to white to blue hue and saturation color gradients. We also investigated the effects of prior color-concept associations by testing whether novel color scales (orange/green) decrease predicted voting polarization compared to the traditionally conditioned associations of red/blue colors with US political parties.

The present study also examined a second potential cognitive consequence of red-blue maps: the salience of information conveyed via color might cause people to underappreciate the value of accompanying numeric information in predicting electoral outcomes. Rutchick et al. (2009) showed that the addition of numeric information for each state (i.e., the percent of the Republican and Democratic votes cast in the state) reduces how divided and polarized participants expect the nation to be, compared to maps with no numeric information. We draw on research on base rate neglect^{29,30} to further elucidate the polarizing consequences of using dichotomous color-coded maps. Base rate neglect describes people's tendency to ignore important information about base-rate probabilities when presented with more salient, but

ⁱ The question of whether voting maps should depict land or people speaks is beyond the scope of this article, but see 28.

misleading, information^{31,32}. Considering base rate neglect in political judgments, we asked whether dichotomous color maps might lead participants to ignore numerically reported base rates. For instance, participants may ignore information that 51% of a county voted Republican, and guess instead, that a random voter in the county has a substantially higher likelihood of being Republican, simply because the district is colored pure red.

We preregistered four hypotheses, and tested them in two tasks. The first hypothesis was that stronger party color scale associations (red/blue) would increase voting polarization compared to previously non-associated colors scales (orange/green or uniform grey). The second hypothesis was that dichotomous color maps would increase voting polarization compared to continuous color maps. The third hypothesis was that the effect of dichotomous and continuous color maps would depend on whether the color scales had prior political associations (i.e., an interaction effect). The fourth hypothesis was that base rate neglect effects would be stronger for traditional color scale (red/blue) than for alternative color scales (orange/green or uniform grey). The Polarization Task tested hypotheses 1-3 and the Base Rate Task tested hypothesis 4

Methods

We preregistered the study design, target sample size, and exclusion criteria (<https://osf.io/tk7rq>). Any deviations from the preregistered plan are explicitly noted. This study was approved by the Institutional Review Board at the University of Virginia.

Participants

On October 30, 2020—four days before the 2020 presidential election—we recruited 550 participants via Amazon’s Mechanical Turk to participate in a 10-minute study about political judgments in exchange for \$1.50 (\$9/hr). We recruited participants who were 18 years or older, were American citizens, had lived in the United States for at least 10 years, and self-identified as

being fluent in English.

The preregistered sample size (500) was determined with a power analysis. Prior work examining the effect of color coding on political judgments, using a task similar to the Polarization Task of the present study¹⁴, found an effect size estimate of $\eta^2_p = .03$. The Base Rate Task is an adaptation of the classic base rate neglect paradigm, for which previous studies^{36,37} have found effect sizes ranging from $\eta^2_p = .046$ to $\eta^2_p = .068$. Based on these prior effect sizes, a power analysis using the `modelPower()` function from the `lmSupport` R package suggested 500 participants would give us 97.5% power to detect the Polarization Task effect (with $\alpha = .05$ and $\eta^2_p = .03$). The same sample size would give us over 99% power to detect the expected Base Rate Task effect.

We over-recruited by 50 participants to ensure we would have sufficient power even after excluding participants for failing our bot and attention checks. Initially 991 people started the survey, but 387 did not reach the consent form because they failed the initial bot check. Of the remaining 604, 99 failed to pass the mid-way attention check, leaving data from 505 participants for analysis. We had planned to eliminate data from any participants who left their browser during the tasks or reported color vision deficit, but we failed to record these pieces of information. Additionally, we decided not to eliminate participants who failed a final manipulation check because it was too stringent: in response to an open-ended debriefing question asking them what they thought the study was about, we planned to only keep data for participants who mentioned a relevant word stem (map*, politic*, color*, vot*, Democrat*, Republican*, u.s*, us*, or united states*). Within the 505 participants included, this criterion would have reduced our sample to 261.

The final sample of 505 participants included 173 women, 305 men (1 transgender man),

and 1 who identified as neither woman nor man. Participants had a median age bracket of 35-44 years (16 were ages 18-24, 215 were ages 25-34, 143 were ages 35-44, 60 were ages 45-54, 23 were ages 55-59, and 23 were ages 60+). Participants reported their ethnicities as follows: 362 White, 61 Black/African American, 29 Asian/Pacific Islander, 12 Hispanic/Latino/a, 12 Native American, and 4 “other”. 54 of the participants had a high school degree, 45 had a 2-year college degree, 279 had a 4-year college degree, 93 had a Master’s degree, and 9 had a PhD or professional degree.

In terms of the political leanings of the participants, 196 were registered Democrats, 192 registered Republicans, 43 Independent/Other, 39 unaffiliated, and 10 not registered. 214 were voting for Biden, 235 for Trump, and 19 were not voting.

Design

Materials for this study can be found on OSF (<https://osf.io/gq8f2/>). These include the informed consent sheet, a pdf containing the sample Polarization Task and Base Rate Task trials, the End of the Study Questionnaire, and the colormap stimuli sets from the Polarization Task and Base Rate Task.

Participants first encountered a consent information page inviting them to “participate in a research study about people’s understanding of political attitudes” and telling them “the purpose of the research is to gain a better understanding of how people think about American politics and the current political climate. This study will include a random sample of voting-age Americans.” Participants were then randomly assigned to one of five between-subject conditions: dichotomous red/blue, dichotomous orange/green, continuous red/blue, continuous orange/green, and uniform grey. The condition assignment in the Polarization Task also determined the stimuli they encountered in the Base Rate Task. After completing the two tasks they answered questions

about their knowledge of the 8 states included in the current study, their political opinions and activity level, and basic demographic information. We then debriefed them, thanked them for their time, and gave them their MTurk payment codes.

Polarization Task. In the Polarization Task, participants were asked to estimate the likely presidential voting pattern of 8 states for a “hypothetical” Republican or Democratic

Figure 3. Sample Polarization Task stimuli for each of the five between-subject conditions. Within the four color conditions, the color scales (1,3 – red/blue and 2,4 – orange/green) , the gradient steps (1,2 – dichotomous and 3,4 – continuous) assigned to each state was randomized across participants, but the states were always divided evenly across the two color categories. On each of the eight trials a participant completed, the position of the line with the arrow identified which of the 8 states the participant was judging. Note that the colors assigned to each state remained constant across a single participant’s trials.

candidate. The states were chosen because they have been classified as “swing states” in recent elections³³. The task involved a 2 x 2 between subjects design: Color Scale (red/blue color pair versus orange/green color pair) x Gradient Steps (dichotomous versus continuous). A fifth

condition with uniform gray maps was added to the 2x2 design and served as a baseline. The maps, as depicted in **Figure 3**, utilized either a) a dichotomized red-blue color scale, b) a dichotomized orange-green color scale (to determine whether the dichotomizing effects of red-blue maps are entirely due to prior associations people have between those colors and political parties), c) a hue and saturation gradient that passes from red to white to blue, d) a hue and saturation gradient that passes from orange to white to green, or e) uniform grey (to establish a baseline for how polarized participants judge the 8 states to be). Polarization was measured by having participants make voting predictions ranging from 0% to 100% of the state's voting percentages for a Democrat versus Republican candidate (see **Figure 4**). Higher polarization is quantified as greater absolute difference in the predicted voting breakdown (percent Democratic versus Republican) for states of different colors. For instance, predicting blue states will vote 60% Democrat and 40% Republican, and red states will vote 40% Democratic and 60% Republican, constitutes a more polarized estimate than predicting all states will go 50% Democrat and 50% Republican.

Figure 4. Sample Polarization Task trial.

The task consisted of 8 randomized trials (one trial for each of the 8 swing states) in which participants were asked to predict what percent of the state's voting population would vote Republican versus Democratic in an election with hypothetical candidates.

Map stimuli. We chose 8 U.S. states identified as “swing states” by FiveThirtyEight, a political and data analysis blog site that specializes in polling predictions based on analysis of big data³⁰. Swing states are those which either a Republican or a Democratic candidate has a reasonable chance of winning and which have been closely contested in recent elections. The FiveThirtyEight analysis identified 12 states as “swing states”: Colorado, Florida, Iowa, Michigan, Minnesota, Ohio, Nevada, New Hampshire, North Carolina, Pennsylvania, Virginia, and Wisconsin. We selected eight states from this list that were geographically dispersed and, as much as possible, non-contiguous: Colorado, Florida, Ohio, Nevada, New Hampshire, North Carolina, Pennsylvania, and Wisconsin.

The map is a vector drawing of the state borders of the continental United States with black lines on a white background. The dichotomous map included pairs of “base colors” (red/blue, orange/green), which were defined in CIE LCh space and converted to RGB values using the standard assumptions in the MATLAB `lab2rgb` function (see Table 1)ⁱⁱ. We generated the dichotomous red-blue and orange-green maps by filling the four of the swing states one color in the pair and four swing states with the other color the pair (see the left panels in Figure 2 and the color conversion table in supplementary materials). We balanced which of the 8 states were in which color category across participants by generating maps for all possible color-state

ⁱⁱ Participants completed the tasks online rather than on calibrated screens, so the colors produced by the RGB values were only estimates of the CIELCh coordinates. We reasoned that if we found systematic results across conditions, despite variation of color coordinates across participants' own screens, it would attest to the robustness of the results. This is similar to how participants view party colors in the media on their uncalibrated TVs/monitors/phones.

permutations (requiring four states per color). This resulted in 70 dichotomous red-blue and 70 dichotomous orange-green maps. The lightness (L^*) and chroma (C^*) were the same for all four base colors. We generated the uniform gray map by filling all of the eight swing states with gray. The gray in the uniform gray map had the same lightness as the base colors, but chroma was set to zero. We generated the continuous maps first defining a 4-step “color scale” for each base color, which included the base color and three steps interpolated between the base color and white (interpolation computed in CIELAB space with white set to $L^* = 100$, $a^* = 0$, $b^* = 0$). The gradation between the base color and white varied in lightness and chroma, we will subsequently refer to the steps in terms of lightness for simplicity.

Table 1. RGB, LCh and Lab coordinates for the base colors and grey

		RGB color space			CIElCh color space			CIElLab color space		
Blue		R	G	B	L	C	h	L	a	b
Base		50	103	210	46	64	-70	46	22	-60
C1		119	138	222	60	48	-70	60	16	-45
C2		168	175	234	73	32	-70	73	11	-30
C3		212	214	245	87	16	-70	87	5	-15
White		255	255	255	100	0	-70	100	0	0
Red		R	G	B	L	C	h	L	a	b
Base		200	54	60	46	64	30	46	55	32
C1		221	110	104	60	48	30	60	41	24
C2		238	159	152	73	32	30	73	28	16
C3		250	207	202	87	16	30	87	14	8
White		255	255	255	100	0	30	100	0	0
Orange		R	G	B	L	C	h	L	a	b
Base		175	83	3	46	64	60	46	32	55
C1		202	124	72	60	48	60	60	24	41
C2		225	167	130	73	32	60	73	16	27
C3		243	210	191	87	16	60	87	8	14
White		255	255	255	100	0	60	100	0	0
Green		R	G	B	L	C	h	L	a	b
Base		7	127	33	46	64	140	46	-49	41
C1		90	159	87	60	48	140	60	-36	31
C2		146	191	141	73	32	140	73	-24	21
C3		201	223	197	87	16	140	87	-12	10
White		255	255	255	100	0	140	100	0	0
Grey		R	G	B	L	C	h	L	a	b
Base		105	105	105	44	0	297	44	0	0

Table 1. RGB, LCh and LAB coordinates for the base colors and their scales (Blue, Red, Orange, Green) as well as grey.

Starting with the dichotomized maps described above, we filled the four states within each hue using the 4-step color scale, one color per state (see right panels, Figure 3). For instance, in a continuous red-blue map, one of the four states assigned to be red was filled with the base red and the other three with increasingly lighter reds (for color coordinates, see Table 1). We generated 70 maps for the red-blue gradient condition and 70 for orange-green gradient condition by randomly assigning one of the 8 colors to each of the 8 states. Note that we did not generate all possible permutations of lightness assignment because that would require generating $8!$, or 40,320, maps.

Procedure. Prior to providing informed consent and starting the actual study, participants completed a botcheck which required them to click on three circles in order to match the colors indicated in the instructions. Only 61% (604 out of 991) of participants passed this initial botcheck and were allowed to start the study, as preregistered. Before the task began, participants were told, “DO NOT refer to any sources (such as Google) while doing this task. We are interested in your general impressions of politics in the United States, not in your knowledge or accuracy”. On each trial, participants saw a vector line drawing of a political map of the continental United States with an arrow pointing to one of the eight swing states (see Figure 4). Below the map was a bimodal slider scale (Democrat – Republican) which displayed cumulative percentages for each political party with the prompt, “Estimate the percent of this state's population that would vote for a hypothetical Democratic candidate and a hypothetical Republican candidate.”

Importantly, the instructions did not explain the meaning or relevance of the color of the states, leaving participants to draw their own inferences about the color's meaning. Participants had unlimited time to make a response on each of the eight trials (one per state), which were

presented in random order. Following completion of the Polarization Task, participants saw an attention check that simply asked them to click the state of California on a labeled map. Of the 604 participants who made it to this point, 505 (84%) passed the attention check—the remaining 99 were excluded from analyses, as preregistered.

Base Rate Task. The Base Rate Task consisted of a modified base-rate neglect paradigm³⁰. Participants were told the percent of registered voters who voted Republican and Democrat in an unnamed U.S. county and then estimated the likelihood of a generic person voting Republican or Democratic. The target's views were represented in a vignette placed below a single state outline which has voting percentages depicted on it (see **Figure 5**). This task consisted of a single trial.

Figure 5. Base Rate Task conditions: grey map with Republican Majority (top left), grey map with Democrat Majority (bottom left), green map with Democrat Majority (top center), orange map for Republican majority (bottom-center), blue map with Democrat Majority (top right). red map for Republican Majority (bottom-right).

Map stimuli. We used a map of Loving County TX (see **Figure 5**) in order to minimize participants' prior knowledge compared to using any given state (the county shape remained

nameless when presented to participants). Participants were not told the name or location of the county. There were 6 between-subject conditions. Participants' color condition assignment from the eight states in the Polarization Task was the same as the color condition for the single county presented in the Base Rate Task. For example, participants who saw the orange/green colors during the Polarization Task were randomly assigned to a green or orange county for the Base Rate Task. The red-blue and orange-green maps were generated by filling the county with colors: red, blue, orange, green and grey (same values as in the Polarization Task).

Procedure. Before the Base Rate Task began, participants were told, "You will now see a map of a U.S. county. The numbers reported below the map indicate the percentage of the state's registered voters (excluding Independents) who are Democrats or Republicans." Below the map was a description of Chris, a hypothetical resident voter of the county. The description outlined Chris's views on 5 relatively non-partisan³⁵ political issues: "the government should implement new legislation to protect domestic animals", "The government should increase spending on support for veterans", "The government should update the aging infrastructure", "the government should simplify the tax system, allowing easier tax filing", "the government should focus on strengthening the economy".

Participants then estimated the resident's likelihood of being a registered Democrat or Republican on two slider scales ranging from 0% ("Likelihood of being Democrat") to 100% ("Likelihood of being a Republican). Subsequently, participants were asked to answer, "How influential will Chris' vote be in the upcoming county wide election?" on a slider scale ranging from 0% ("no influence") to 100% ("a great deal of influence"). This question was meant to capture the downstream effects of predicted polarization on perceived voting influence. If states are predicted to be more polarized (i.e., having a larger margin of difference) each individual

vote may be perceived as less influential.

End of study questionnaire. In the final phase, participants indicated which of the two political parties from the 2016 election won the majority of votes in each of the states from the Polarization Task. Participants also reported how familiar they were with each state on a 5-point Likert scale ranging from 1 (not familiar at all) to 5 (extremely familiar). These questions were included for possible follow-up exploratory analyses.

Once participants' prior knowledge about the 8 swing states was assessed, they reported their political attitudes and perceptions of political polarization. The following items were included as potential moderators in exploratory analyses. Political attitudes were measured using two items: "How do you feel about the Democratic party in general?" and "How do you feel about the Republican party in general?" ranging from "Dislike a great deal" to "Like a great deal" on a 100-point slider scale. Perceived polarization was measured on a 7-point Likert scale ranging from strongly agree to strongly disagree using four items: "Do you think the United States is more politically divided now than in the past?"; "Do you think political polarization is a problem in our country?"; "Do you think half of the country is being ignored by politicians?"; and "Do you think Red state Americans and Blue state Americans ultimately share the same values?" Participants were then asked the following open-ended questions: "What do you think this study is about?", "Did the colors on the maps make you think of anything?", and "Which colors did you see on the maps? Did you associate them with a particular political party?". They then reported who they voted for in the 2016 presidential election and who they intend on voting for in the 2020 election. Finally, participants answered a standard demographic questionnaire.

Results

All analysis were conducted using R. Any deviations from the preregistered analysis plan

(<https://osf.io/tk7rq>) are explicitly noted. See <https://github.com/adriennewood/red-state-blue-state> for both planned and final analysis syntax, output from analyses conducted on both simulated data and the real data. The data are also openly available (<https://osf.io/tk7rq>).

Polarization Task analyses

Estimating polarization. Participants were asked to judge 8 states (trials) while being randomly assigned to a color condition: dichotomous red-blue dichotomous orange-green, continuous red-blue, continuous orange-green, and uniform grey. We calculated how “polarized” each participant’s judgments were by calculating the relative variability in their predictions for the states depicted with the same hue versus the states depicted with the alternative hues. For each participant’s 8 trials, we calculated an F statistic. As part of the F statistic, we calculated the sum of squares between-group variation (SSB) and the sum of squares within-group variation (SSW) in their responses. The SSB for a participant describes how differently, on average, they expect states of a different color to vote. The SSW for a participant describes how differently, on average, a participant expects states of the same color to vote. This calculation was not initially possible for participants viewing the uniform grey condition so for each participant we randomly labeled each of their 8 trials as “color 1” or “color 2.” Thus, we could treat participants’ polarization scores in the uniform grey condition as baseline polarization scores that might be achieved by chance. We did not preregister this final step and originally planned to simply exclude the uniform grey participants from certain analyses.

We calculated secondary polarization scores with the aim of distinguishing between two different types of potential polarization: spread and clustering. The F statistic, our primary

measure of polarization, is influenced by both spread and clustering, which are two features of polarization. Spread (measured with SSB) describes how differently, on average, a participant judges different color states to vote. Clustering (measured with SSW) describes how similar a participant expects states of the same color to vote.

Based on simulated polarization data, we expected all three measures (F statistic, SSB, and SSW) to be positively skewed. We preregistered applying log transformations, which sufficiently corrected the skew of the SSB and SSW scores. However, the log-transformed F statistic polarization scores were still skewed, so we raised them to the $\frac{1}{4}$ power ($F^{1/4}$).

Preregistered analyses of the effect of color scales on polarization. In a series of models, we regressed our polarization estimates (transformed participant-level F, SSB, and SSW scores) on contrast-coded variables for Color Scale (red/blue=RB, orange/green=OG, and uniformly grey=UG) and Gradient Steps (dichotomous=D and continuous=C).

Model 1: The effect of color scale on perceived polarization. The first linear regressions tested hypothesis 1 by comparing participants in the dichotomous (Orange/Green and Red/Blue) or uniform grey conditions. We predicted that within the dichotomized colormap conditions, participants will make more polarized voting predictions for the colormap with strong party color associations (red/blue) than for the colormap without strong party color associations (orange/green). We also hypothesized that participants would make more polarized voting predictions for both dichotomous colormaps compared to a uniform grey map.

We regressed participant's polarization scores on two orthogonal contrast codes comparing the three-color conditions. The linear contrast variable (Uniform Grey = -.5, Dichotomous Orange/Green = 0, Dichotomous Red/Blue = .5) tested the hypothesized increase in polarization from Uniformly Grey, to Orange-Green, to Red-Blue. The quadratic contrast

variable (Uniform Grey = $-1/3$, Dichotomous Orange Green = $2/3$, Dichotomous Red/Blue = $-1/3$) tested the hypothesis that the Orange-Green polarization scores were different from the Uniformly-Grey and Red-Blue.

Polarization. As hypothesized, the linear contrast for participants' judgment polarization (participant-level F-values^{1/4}) was significant, $b = 0.278$, $SE = 0.085$, $t(300) = 3.26$, $p = .001$, $\eta_p^2 = .034$. However, the orthogonal contrast was also significant, $b = -0.251$, $SE = 0.073$, $t(300) = -3.43$, $p < .001$, $\eta_p^2 = .038$. In other words, participants made the most polarized political judgments when viewing the dichotomous red-blue maps (untransformed F-values, $M = 17.80$, $SD = 69.19$) compared to the grey ($M = 2.34$, $SD = 7.90$) and dichotomous orange-green maps ($M = 1.55$, $SD = 3.24$), but the grey maps were unexpectedly in between the red-blue and orange-green in terms of polarization (see **Figure 6**).

Figure 6. Polarization of judgments (participant-level F-values) in the Polarization Task across the 5 between-subject conditions are presented on the left. Estimates from Model 2 are presented on the right. The interaction between Gradient Steps and Color Scale was significant, as was the simple effect of Color Scale for Dichotomous maps. Note that the F-values depicted in these plots are untransformed for ease of interpretability but were raised to the $1/4$ power for the analyses to correct for positive skew.

Cluster and Spread. The participant-level SSW scores—how tightly clustered participants’ political judgments were within-color—were not significantly predicted by the two contrast variables, $|t's| < .95$, $p's > .34$. The overall effect of color on F-values thus seemed to be carried by differences in how spread out (SSB) participants the color-level state groupings to be: linear contrast code, $b = 0.521$, $SE = 0.290$, $t(300) = 1.79$, $p = .074$, $\eta_p^2 = .012$; orthogonal quadratic contrast code, $b = -0.839$, $SE = 0.249$, $t(300) = -3.37$, $p < .001$, $\eta_p^2 = .037$.

Model 2: The interaction between color scale and gradient on perceived polarization.

The second set of linear regressions tested hypotheses 2 and 3 by comparing the dichotomous and continuous colormaps. Hypothesis 2 explored the effect of dichotomous vs continuous colormaps and hypothesized that Polarization in voting estimates would be greater for dichotomous colormaps than continuous colormaps for both color scales (red/blue and orange/green). Our third hypothesis tested for an interaction between party association and dichotomization for polarization. The effect of color scales (red/blue versus orange/green) on polarization in voting estimates were predicted to be greater for dichotomized compared to continuous color scales. In other words, depicting political parties with non-traditional color scales (orange/green), in addition to using alternate (continuous) gradient steps may interact to further reduce predicted polarization.

We regressed polarization—and, secondarily, SSW and SSB—on Color Scale (orange/green = -.5, red/blue = .5), Gradient Step (continuous = -.5, dichotomous = .5), and their interaction. The Gradient Step contrast tested hypothesis 2, that polarization would be greater for dichotomous than continuous colormaps. The interaction term tests hypothesis 3, that the effect of Color Scale would be dampened when the gradient was continuous rather than

dichotomous.

Polarization. The effect of Color Scale was again significant when the continuous colormaps were included, with more polarized judgments for red-blue maps than the orange-green maps, $b = 0.241$, $SE = 0.059$, $t(398) = 4.06$, $p < .001$, $\eta_p^2 = .040$. The main effect of Gradient Steps was not significant, $p = .340$, so hypothesis 2 was not supported. The interaction between Color Scale and Gradient Steps was significant, however, supporting hypothesis 3, $b = 0.298$, $SE = 0.119$, $t(398) = 2.51$, $p = .013$, $\eta_p^2 = .016$. The interaction is apparent in **Figure 6**.

To interpret the interaction between Color Scale and Gradient Steps, we re-centered the Gradient Steps variable and reran the model to estimate the simple effects of Color Scale when the maps were dichotomous and when they were continuous (note: we did not preregister this test of the simple effects). The continuous gradient red-blue maps (untransformed F-values, $M = 4.45$, $SD = 15.84$) were significantly less polarizing than dichotomous red-blue maps ($M = 17.80$, $SD = 69.19$; $b = 0.199$, $SE = 0.085$, $t(398) = 2.36$, $p = .019$, $\eta_p^2 = .014$). However, there was not a significant difference between continuous orange-green maps ($M = 1.99$, $SD = 4.54$) and dichotomous orange-green maps ($M = 1.55$, $SD = 3.24$; $p = .237$). These results suggest that dichotomization only polarizes voting predictions when the color scales have prior associations with the groups they represent.

Cluster and Spread. Neither Color Scale, Gradient Steps, nor their interaction significantly affected how clustered participants' judgments were within-color (SSW), $|t's| < 1.5$, $p's > .14$. The pattern for spread (SSB), or the difference in participants' judgments between color types, again mirrored the pattern for polarization (F values). The main effect of color was significant, with greater between-color variance for red-blue maps compared to orange-green maps, $b = 0.593$, $SE = 0.207$, $t(399) = 2.97$, $p = .004$, $\eta_p^2 = .020$. The main effect of Gradient

Steps was not significant, $p = .566$, but the interaction between Color Scale and Gradient Steps was significant, $b = 1.014$, $SE = 0.414$, $t(399) = 2.45$, $p = .015$, $\eta_p^2 = .015$.

Exploratory analyses of the effect of color scales on polarization. The following analyses explore possible moderators of the effects of the Polarization Task experimental manipulations.

Does being a Trump vs. Biden supporter moderate responses? We reran Model 2 with an additional variable coding whether the participant supported Biden (-0.5) or Trump (0.5), which interacted with the original Color Scale X Gradient Steps interaction. The model thus included a three-way interaction, all two-way interactions, and the three main effects. The interaction from the preregistered analysis still held, $p = .038$, as did the effect of Color Scale, $p < .001$. A notable, but marginally significant effect is found in the interaction between support for Biden vs. Trump and the Gradient Steps variable. This effect is slightly above the $p < .05$ threshold for significance, $b = 0.262$, $SE = 0.125$, $t(348) = 1.89$, $p = .0599$, $\eta_p^2 = .010$. Unpacking this marginally significant interaction term reveals Trump supporters' predictions were more polarized by the continuous gradient (untransformed F-values: $M = 2.04$, $SD = 3.84$) versus dichotomous scale ($M = 15.64$, $SD = 69.82$) manipulation than were Biden supporters' ($M = 4.49$, $SD = 16.55$ and $M = 4.70$, $SD = 25.19$, respectively).

Does concern about polarization predict the polarization of participants' judgments? We repeated Model 2 and added the four self-report questions about polarization concerns as covariates ("Do you think the United States is more politically divided now than in the past?"; "Do you think political polarization is a problem in our country?"; "Do you think half of the country is being ignored by politicians?"; and "Do you think Red state Americans and Blue state

Americans ultimately share the same values?”). None of these measures of self-reported concern about polarization predicted participants’ actual judgment polarization, p ’s $\geq .305$.

Polarization Task summary of findings. Hypothesis 1 stated that red/blue judgments would be more polarized than orange/green judgments, followed by grey judgments. While the central prediction—that red/blue maps would result in the most polarized judgments—was supported, the judgments for grey maps were unexpectedly more polarized than the judgments for orange/green maps. Hypothesis 2 stated that the dichotomous gradients (for both red/blue and orange/green maps) would lead to more polarized judgments than the hue and saturation continuous gradients. This hypothesis was supported for red/blue maps, but, unexpectedly, was not supported for orange/green maps. Hypothesis 3, which predicted an interaction between Gradient Steps and Color Scale, was supported.

Base Rate Task preregistered analyses

Effect of color and base rate on generic voter’s likelihood of being Republican. The Base Rate Task tested the prediction that, compared to neutral and orange or green color-coded maps, red or blue color-coded maps cause participants to ignore base rate statistics to a greater degree.

The six possible maps (red R majority, blue D majority, orange R majority, green D majority, grey R majority, grey D majority) can be described as the interaction between two variables: Majority Condition (Democrat majority = -.5 and Republican majority = .5) and Color Condition (a dummy-coded variable with levels for red/blue, orange/green, and uniformly grey, with uniformly grey as the reference level). Because the uniformly grey condition is the reference level for the Color Condition, the main effect of Majority serves as an attention/manipulation check on whether people paid attention to the reported base rates for the

hypothetical county. We assumed that participants exposed to a uniformly grey county with a Republican majority would rate the voter as likelier to vote Republican than participants exposed to a grey county with a Democratic majority. The interaction between Majority Condition and the uniformly grey versus red/blue dummy variable tested hypothesis 4, that participants would overestimate the voting margin (ignoring the provided base rate percentage for the county) when the map was colored as red or blue, compared to when it was uniformly grey.

The base rate manipulation failed: for the grey maps, participants' judgments of Chris's political leaning were not significantly influenced by whether they were told Chris's county was 51% Democrat or 51% Republican, $b = 1.480$, $SE = 4.588$, $t(494) = 0.32$, $p = .747$. Thus, although the interaction between Color Condition and Majority was not significant, $b = 0.096$, $SE = 5.647$, $t(494) = 0.017$, $p = .987$, we cannot draw any conclusions about Hypothesis 4. The dummy variable comparing grey and red/blue maps was significant, $b = -6.114$, $SE = 2.823$, $t(494) = -2.17$, $p = .031$, $\eta_p^2 = .011$. Controlling for whether Republicans or Democrats were represented as the numeric majority, Chris was judged as likelier to be Republican when the map was grey ($M = 60.84\%$, $SD = 21.44\%$) compared to red or blue ($M = 54.74\%$, $SD = 23.81$).

Effect of color and base rate on the influence the generic voter could have on an election outcome. Finally, we ran an identical model as before with participants' estimates of how influential Chris's vote would be as the outcome variable. None of the main effects or interaction terms were significant, p 's $\geq .404$.

Discussion

Two decades ago, the media arbitrarily chose red to represent Republicans and blue to represent Democrats, perhaps without realizing that these colors would become the embodiment of tribal bipartisan polarization. Just nine years later, Rutchick et al (2009) found that using

dichotomous red-blue maps increased predicted polarization compared to using continuous purple maps¹⁴. The goal of the present study was to understand whether increased predicted polarization in votes is due to the conditioned associations people have created between blue and red to represent the Democratic and Republican parties, or whether it is due to the categorical dimensions inherent to dichotomous color scales (as opposed to continuous color scales). Instead of using continuous purple maps as in prior work¹⁴, we used a gradient going from dark red to dark blue going through white, which is more informative given the U.S. state-by-state winner-takes-all election system.

As hypothesized, participants' predictions were more polarized when maps used party color (red/blue) compared to arbitrary colors (orange/green). Polarization was less for uniform grey maps and orange/green maps compared with dichotomous red/blue maps. This suggests that the effect of polarized predictions is mostly driven by prior color association rather than the categorical process depicting the results uniformly or dichotomously. We further found that when people have salient associations between groups and colors (red-Republican and blue-Democrat), continuous maps decrease predicted voting polarization, but when there are no prior conditioned associations (green-Democratic, orange Republican) the dichotomization of colors has no significant effect on perceived polarization.

The polarizing effects we observed were driven by the spread, or predicted difference between two states of different colors, rather than the clustering, or predicted similarity between two states of the same color. Thus, changing the color and gradient scales of a political map appear to have greater impact on the predicted between-group difference than on the predicted within-group consistency. We did not find moderating effects of conditions based on political ideology (measured by intended voting choice for the 2020 presidential election) or general

concerns about polarization. While people may be concerned with polarization, such a concern is not reflected in their predictions about voting patterns.

The second task was intended to test whether party associated red-blue maps would cause participants to ignore base rate statistics more than orange-green or grey maps. The results are inconclusive because we did not successfully manipulate base rates in the control (i.e., neutral map) condition. We note that the hypothetical voter was on average perceived as being more Republican across conditions. Future studies could improve on the experimental design by sampling many opinions and pre-testing them to be sure that they are non-partisan.

In addition to our current findings, the polarizing consequences of using dichotomous red/blue maps are particularly well instantiated by a tweet from former president Donald Trump³⁸. Shortly preceding his first impeachment, Trump shared a U.S. electoral map depicting dichotomous (blue/red) voting outcomes from the 2016 US presidential election by county. The map was visibly a sea of highly saturated red with few blue counties mostly clustered on the coasts. Inscribed on this map was the caption: “try to impeach this!” Such a tweet exemplifies the potentially misleading effects of dichotomous red/blue color maps.

In a time where U.S. politics appear to be deeply divided, we conducted the present study to draw attention to the ways the usage of color in political maps might play a role in exacerbating polarization. We also aimed to identify the mechanisms which give rise to these effects and found that the effects are driven by the particular conditioned associations between red/blue and Republican/Democrat political parties. These colors have come to embody and even, perhaps, exacerbate the present political divide. Future studies should explore the conditioning of colors with various meanings and further test the ways prior and novel association might interact with categorical versus continuous representations. The present results

suggest one way to avoid the polarizing effect of dichotomous color maps is with alternative color scales that do not carry the partisan semantic associations attached to red and blue.

However, novel color mappings might, over time, become partisan shorthand, thus perpetuating polarizing voting predictions when visualizing electoral maps.

Data availability statement

All anonymized data is available on OSF at the following link: <https://osf.io/gq8f2/>

Code availability statement

All code is available on GitHub at the following link: <https://github.com/adriennewood/red-state-blue-state/blob/master/README.md>

Author contributions: P.N. and A.W. conceived the research idea and K.S. and G. L. provided feedback. R.F. and A.W. developed the stimuli, designed the experiment, planned the analyses, and wrote the first draft. R.F. collected the data and A.W. conducted the final analyses. All authors contributed to the final draft.

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