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Does Color Convey Political Information?

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ABSTRACT We are used to seeing red and blue everywhere in campaign seasons, but do these colors actually convey political information? While decisions of political branding are assumed to be significant for electoral outcomes, we have few theories about the cognitive processes underlying the processing of such information and whether these decisions influence realized political behavior. Building upon interdisciplinary perspectives, in this chapter I first introduce the snap-judgment model of visual political information processing. The theory argues that color allows individuals to form pre-cognitive attitudes of a political object, and that these pre-cognitive attitudes shape latter and more cognitively laborious information processing and behavior – that is, that individuals can activate partisan attachments automatically through information as simple as color. I then present two studies in dialogue with this theory, both of which are inspired by conversations with political marketing professionals. Study one focuses on what we might expect neighborhoods and communities to look like, consistent with my theory; I use a pixel-by-pixel classification of images from over 1000 yard signs for elections in the U.S. House of Representatives. My findings suggest that in districts where Democrats have an electoral advantage, that there is more blue on the yard signs in the district. Study two takes aim at cognitive processes via a controlled experimental setting. I use a novel design, tracking cursor movements and limiting participants' abilities to view a treatment image to only 5000ms. I find that participants make color associations when features of a yard sign are held constant, and that Republicans prefer candidates with red yard signs, and Democrats prefer candidates with blue yard signs.

KEYWORDS visual information; information processing; partisanship

Introduction

(a) Republicans pre-2000

(b) Democrats pre-2000

(c) Republicans 2023

(d) Democrats 2023

Figure 1: Party logos

Do colors actually shape political attitudes among the mass public? There are two goals that I am hoping to achieve in this chapter. The first is to convince the reader that the colors red and blue convey consistent, affiliative information. The second is that these connections between colors and political groups can indeed affect political outcomes.

Many understand – in a general sense – that "colors matter" when it comes to attitudes and behaviors. Color theorists and scholars of marketing understand color as having important implications for reactions to a product and resulting consumer behavior. For example, Kuo and Zhang (2023) demonstrate that hotel rooms that use more "cool colors" (blues, greens, etc.) evoke positive affect for potential customers and that these positive affective responses are predictive of their eventual choice to book the room. Colors mean a varying number of things, however.

The role of visuals in politics is receiving more attention among interdisciplinary scholars in fields like communication, political science, and the psychological sciences. While many of these studies examine fascinating but complicated forms of visual information such as symbology (Williams, Horsting, and Ramirez 2022) and visual framing (Grabe and Bucy 2009), we have yet to integrate these interdisciplinary perspectives with existing models of political information processing – this will enable us to better understand how these visual forms of information act as cues (see Lilleker 2019), and what their potential consequences might be for political behavior among the mass public.

In this chapter, I build upon descriptive evidence suggesting that Democratic campaigns use the color blue more than Republican campaigns (Williams, Horsting, and Ramirez 2022) and that Republican voters express a preference for red during election season (Schloss and Palmer 2014). I present a snap-judgment model of politically-relevant visual information processing that outlines a) the cognitive processes that drive these associations and b) notes how those associations drive important political outcomes. I draw upon theories of associative memory and spreading activation (see Collins and Loftus 1975) to conceptualize the association of the colors red and blue with Republicans and Democrats, thinking of them as as two interconnected nodes. I conceptualize these connections as carrying affective information – an idea informed by perspectives on biological survival reaching back to Darwin (Ralph and Anderson 2018). When these nodes are activated by exposure to these colors in political contexts, other related nodes become active and contain affective information. As partisanship evokes strong affective reactions for many members of the public (Iyengar, Sood, and Lelkes 2012), this activation elicits an affective reaction. Considering that most visual information – including these processes of association – occur pre-cognitively (Ames, Fiske, and Todorov 2012; Fazio 2007; Sander 2013), I argue that the elicited affective response to such information can be "transferred" (see Morris et al. 2003; Taber and Lodge 2016) to later post-cognitive processing of more traditional forms of political information such as stated policy positions. The implication of this is that these associations can *pre-cognitively* inform reactions to political information and political behavior

To preview, in this chapter I propose two studies to evaluate the claims I make about yard signs. Yard signs are a simple yet effective source of campaign branding for political candidates, as they convey information that is often useful for voters' partisanship (Campbell et al. 1969). As yard signs are a simple and static form of campaign advertising, they cannot rely heavily on more complicated forms of information. However, one form of information they rely on and vary in is their color. With these characteristics, yard signs are an ideal candidate both from a design and substantive standpoint. From a design standpoint, as a static form of party branding they have fewer moving parts, which helps isolate the effect that color has on shaping attitudes. From a substantive standpoint, while we understand that yard signs matter to campaigns, we have yet to systematically explore more simple design choices such as color.

In Study 1, I find descriptive evidence suggesting that campaigns use the colors red and blue on their yard signs – in districts – at different rates depending on the success of Republicans and Democrats in previous elections. This paints a picture of the outside world that is consistent with my theory. However, this study does not make clear whether these patterns are based on elite perceptions of how to communicate partisanship to voters, or whether campaigns have successfully identified a cognitive process linking the colors red and blue with Republicans and Democrats. Accordingly, in Study 2, I conduct an online experiment that examines whether individuals notice color, and whether their attitudes are shaped by the presence of "Republican red" and "Democratic blue" on the yard signs of a political candidate. I find that these associations do exist among respondents. Specifically, individuals consistently and strongly associate Republicans with the color red and the Democrats with the color blue. I present experimental evidence that partisan individuals' willingness to vote for a candidate may be different depending on whether the color used in a yard sign aligns with their partisan identification.

While these two studies highlight endogenous processes between campaigns and voters, to be clear, I wish to be clear that I am not arguing that either of these patterns works in one direction. Rather, in all likelihood there is a necessary feedback loop between the parties and their bases of support. Voters support candidates who signal strong allegiance to the party to increase their chances for electoral success (Utych 2020), and the parties are motivated to distinguish themselves (Lee 2016; Clifford 2020) as a result of their high levels of ideological and affective polarization (Dietrich 2021; Enders 2021).

Still, together, the findings bring much needed evidence in support of the conventional wisdom that the colors red and blue convey political information. The implication of the theory and these findings are that partisan attachments are automatically activated through things as seemingly simple and ubiquitous as color. These activated partisan attachments then have causal effects for attitude expression and political behavior. Given the existing literature demonstrating low-levels of political engagement among the mass public (see Hibbing and Theiss-Morse 2002), as well as the hyper-polarized nature of contemporary politics (see Iyengar, Sood, and Lelkes 2012), this chapter's argument and findings reinforce the idea that voters need not consume any substantive political information before expressing a willingness to cast a vote for a candidate.

The role of visual information in politics

A central theme of an edited issue of *The International Journal of Press/Politics* is that visual politics is important, yet understudied (Lilleker, Veneti, and Jackson 2019). Those who are engaged in these questions attribute these challenges to methodological sophistication and the difficult task of interdisciplinary theorizing (Gerodimos 2019).

The rise of television consumption changed the focus on particular mediums for political communication scholars (Hall Jamieson 2014). In a similar way, the rise of image-based social media has set new agendas. For several methodological and disciplinary reasons, the visual aspects of television were of little focus in the literature (Bucy and Joo 2021). However, today news organizations and politicians are responding to the ubiquitous use of image-dominant social media platforms like TikTok and Instagram by joining and posting on such platforms. Scholars need to make this transition as well, integrating the role of simple visual information into theories of political information (abbreviated as *pip*) and attitude formation.

How does politically-relevant visual information matter to politics? From an evolutionary-biological perspective, visual information has been a common source of information for millions of years – information that a variety of single-and-multi-cell organisms have relied upon to evaluate their environment (Grabe and Bucy 2009, see Chapter 1 for a useful discussion). As an ancient biological invention, the human brain is organized around visual information processing. Reflecting on this, many scholars of neuroscience argue that visual information is the fastest form of information processing for humans. For example, even complex visual information, such as the warmth expressed in someone's facial features, is automatically and pre-cognitively processed in only about 33 milliseconds (abbreviated as ms) (Ames, Fiske, and Todorov 2012).

Approached from a different perspective, as humans are cognitive misers, visual information in the realm of politics provides efficient information to voters about politically-relevant actors and events (Lilleker 2019). Evidence suggests that even simple party branding on yard signs can have an emotional appeal, potentially encouraging a shift in attitudes toward the person who owns the yard sign (Makse, Minkoff, and Sokhey 2019). That is, even branding as simple as yard signs appears to influence the attitudes of people who view them. However, as with all types of party branding, questions remain about individual visual components' contributions.

More simple forms of visual information are likely even more efficient forms of information. In the context of the United States, the "Republican red" and "Democratic blue" is a relatively recent invention, but one that likely has significant import in an era where the parties make efforts to distinguish themselves from each other (Clifford 2020), and where voters toe the party line (Utych 2020). Since the 2000 presidential election, the media have consistently used red on their electoral maps in "horserace" journalism to represent Republicans and blue to represent Democrats (Elving 2014). The supposed consequence is that Democrats now report a preference for the color blue over the color red, and Republicans report a preference for the color red over the color blue (Schloss and Palmer 2014). Others have demonstrated the strategic choices that candidates make on branding choices – including color – based on the types of information they want to convey to voters, and to distinguish themselves from their rivals (Williams, Horsting, and Ramirez 2022).

In western Europe, voters are likely better at connecting the ideological positioning of a party with the color they use in their branding (Casiraghi, Curini, and Csumano 2022). The ability to do so is strengthened when the party is longer-surviving and more prominent (Casiraghi, Curini, and Csumano 2022). The use of politically-relevant colors activates biases toward pre-existing ideological and partisan preferences among voters in a Spanish sample (Losada Maestre and Sánchez Medero 2022). In the United States, male and female candidates use different colors – among other things such as fonts – in their campaign branding to convey distinguishing information about themselves (Williams, Horsting, and Ramirez 2022).

What remains unclear is whether these patterns in the United States are meaningful. While political psychologists are increasingly interdisciplinary and rely on insights from fields like neuroscience, we have little systematic evidence about whether and how color can convey complex information about politics. Further, it remains to be seen whether such a simple type of information has enough potency to shape political outcomes such as vote intention. This chapter is a first cut at addressing these open and important questions.

Integrating color into a model of political information processing

Existing models of political information processing (abbreviated here as *pip*) primarily focus on complex forms of political information, such as policy positions, communicated verbally or through text. As individuals process visual information pre-cognitively, we might expect that they may form a snap-judgment about it – this is in contrast to complex forms of information that often require (orders of magnitude) moree cognitive effort.

Colors and other simple pieces of visual information are processed much more quickly; these actually occur more frequently than text-based information that may be communicated, for example, via a news article (Mehta and Zhu 2009). And, it is because color and other visual information are processed differently that their roles in communicating political information need to be considered. As visual information is affectively encoded (Cimbalo, Beck, and Sendziak 1978), it can affect the affective state and the latter processing of more complex information that scholars typically consider (e.g., text). That is, the visual information provides a snap-judgment – an impression of the object through faster processing – and activates particular neurological processes that influence subsequent information appraisals (Ames, Fiske, and Todorov 2012). In other words, this means that snap-judgments from visual political information may have downstream effects that shape the way in which we engage with traditionally considered forms of political information.

Before expanding upon the role of colors in shaping political attitudes, let's first define attitudes. An attitude represents an accessible, valanced evaluation of associated prior information and experiences. This conceptualization fits with that of the Object-Evaluations Association Model (Fazio 2007). As opposed to viewing attitudes as a latent collection of memories, this model views attitudes as measurable evaluations of memories. As memories are at the core of an attitude, the association of memories with its evaluative component (see Kensinger and Fields 2022) contributes to the perspective that attitudes are affective. This implies that we should be able to measure attitudes, but that such an operationalization requires careful consideration of the context's role in any given measure of an attitude (as they result from memories) (Fazio 2007). In this chapter, I consider color's effect when it comes to shaping attitudes about a political object – a yard sign. As I hold certain features constant in my studies, concerns about potential variation in what people are thinking about when seeing the color red and blue are less important for present purposes (though later chapters grapple with this consideration).

I use a popular conceptualization of attitudes as emerging from accessed associated memories (see Lodge and Taber 2013; see also Collins and Loftus 1975). The implication of such a conceptualization is that attitudes may be unstable (though not in the sense that they are random). That is, as attitudes are associative, they manifest slightly differently depending on the associative paths activated (Fazio 2007). The retrieval of relevant memories to the attitude depends on many factors, such as the recency of the event, the similarity of the context, and the importance or salience of the memory (Kahana, Diamond, and Aka 2022). This means that the memories retrieved to contribute to an attitude may be quite variable. However, to understand where that variability comes from, we must understand the deeper processes influencing how information is encoded and later retrieved. This illustrates my need to build upon the reigning models of *pip*. Colors may act as a contextual feature that may lead to variability in how a set of political information may shape attitudes. How might colors do this?

Colors are associative and are affectively encoded (Cimbalo, Beck, and Sendziak 1978). When individuals access a memory, they do not just recall an object, but they may recall visual information, such as the color of an object (Mehta and Zhu 2009). Due to these features, colors are processed pre-cognitively (Mehta and Zhu 2009). As they are affectively encoded, their associations with particular memories contribute to the evaluative component of the memory. For example, individuals associate colors like red with anger and arousal

(Valdez and Mehrabian 1994), whereas they associate blue with things like happiness and pleasure (D'Andrade and Egan 1974).

The implication of such a process is that colors are compelling as contextual information that shapes the subsequent processing and integration of "traditional" forms of political information used to construct attitudes. As theories of affect transfer suggest, the affective reactions to our pre-cognitive processing of information persist when we transition to cognitive and post-cognitive states (Morris et al. 2003; see Taber and Lodge 2016). As the preference for a particular color correlates with political attitudes (Schloss and Palmer 2014), I expect that colors may have a causal influence on post-cognitive expressions of political attitudes.

According to the literature in affective neuroscience, visual information is processed in more than one region of the brain, such as the visual cortex (Goldstein and Brockmole 2017). That is, these types of processes do not occur in discrete regions of the brain, as some like to think. As attitudes are associative, components of the brain work as a complex highway connecting different types of information. As a result, the processing of visual information will activate other areas of the brain and will make associated paths "hot." One such area is the amygdala. Neuroscientists believe that as visual information is quickly and pre-cognitively processed, the amygdala takes and appraises it based on the paths it activated; this generates a simple affective response to such information (Winkielman, Berridge, and Shlomi 2011).

These fast affective classifications are valanced rather than the more laborious categorization of specific emotions (e.g., anger, anxiety, fear, happiness). What this means is that rather than conceptualizing the affective component of this process in line with the popular conceptualizations in political science, such as affective intelligence theory (Marcus 2000), I conceptualize affect as a more extensive system – one that considers emotion a cognitive classification process that occurs after the initial valanced appraisals of an object (Sander 2013; Ralph and Anderson 2018). That is, emotion – the complex classification of appraisals – is a cognitive component of affect. *By contrast, the pre-cognitive process of affect occurs first with the simple and automatic valanced classification of an object (Winkielman, Berridge, and Shlomi 2011; Dror 2017).*

The pre-cognitive appraisals of the visual information one encounters encourages particular behavioral and attitudinal motivations (Valentino et al. 2011; Ralph and Anderson 2018). This has evolutionary roots for survival (Ralph and Anderson 2018; Parker 2003). While affective appraisals can lead to complex motivations, such as anxiety leading to motivations for information seeking (Marcus 2000), affective appraisals are valanced and more automatic (Winkielman, Berridge, and Shlomi 2011). These affective appraisals lead to a desire to either retract or engage more with an object (Valentino et al. 2011). The snap-judgment resulting from the automatic processing of politically relevant visual information should likely lead to an affective response that motivates either a desire to engage or disengage further with an object.

While the visual information may encourage a particular immediate reaction to engage or disengage from the other information, subsequent information processing and more cognitive processing adjusts this initial appraisal generated by the snap-judgment (Kensinger and Fields 2022). While subsequent information may amend one's snap-judgment, the snap-judgment nevertheless influences the processing of subsequent information by activating particular paths – this is later encoded as associated with the object as it converts to a memory (Lodge and Taber 2013; Kensinger and Fields 2022).

Beyond a motivated backlash effect, the popular application of motivated reasoning to political science finds evidence suggesting that individuals take more time processing information that runs against their pre-existing preferences (Taber and Lodge 2006). The explanation for this is that people are finding ways to come up with counterarguments to such information. Therefore, we may expect that those interacting with visual information from a political party with which they disagree to possibly spend more time looking at those objects.

Figure 2 presents an illustration of the snap-judgment model.

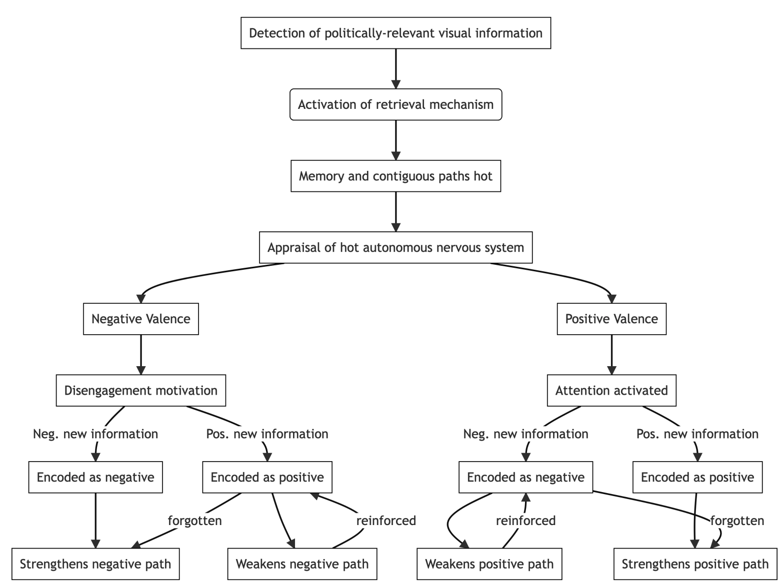


Figure 2: Snap-judgment model of politically-relevant visual information

Let me illustrate the snap-judgment model with a common experience for residents of the United States. Say you are driving down a highway. At 65 miles per hour, you are traveling at about 95 feet per second. You split your attention. You focus your eyes on the conditions of the road in front of you, the cars in front of you, and the rear-view mirror where your kids are either dropping food in the crevice between the seats or trying to grab your attention. Out of the corner of your eye, you see a sign. It is not a road sign because it is not the familiar white or yellow background with black lettering. It is election season. You correctly infer that it is a political yard sign. In this split second, you notice the sign's color and may see a name: Mitch McConnell. You now are racking your brain to think about who that is. If you are politically engaged, you might come to that recognition of the name quickly, or it may take you significantly longer if you are less politically engaged because it is information you do not have to access often (see Kensinger and Fields 2022). You figure out that this is a Republican politician. You may come to this with the help of the fact that every year you have seen yard signs on this stretch of the highway. You know that when you see those red-blue maps pop up on news apps on your phone that the electoral forecasts always represent Republican support with red, and blue for Democrats. Once you have figured out who this person is with the help of this other information, you react: "ugh, that guy is too loyal to Trump," or "yeah! He's loyal to Trump." You've expressed a political attitude.

What the snap-judgment model predicts is happening in your head would be the following: as soon as the light bounces off the sign (to produce a particular wavelength) and reaches your eyes, your brain is already trying to make sense of this information. This is a valuable tool for survival that biology has optimized for millions of years (Parker 2003). Rather than slowly processing the visual information and finding yourself in the jaws of a predator, or processing it quickly but forming the wrong impression and running away from a friend, the brain processes the information quickly and pre-cognitively (Newell 1990). To make sense of such information, it accesses familiar information similar to what it is currently attempting to process, and it does this for the purposes of efficiency (Kahana, Diamond, and Aka 2022). This means accessing memories that contain valanced information (Kensinger and Fields 2022): should I avoid this, or is it pleasant? Once the brain has finished such processing, it can pass its prediction to your cognitive memory. Once you form a reflex of avoid or approach, this opens up space for your brain to process the more complex information: to take the patterns of the light as shapes that construct symbols and letters. This comes later because this information not only requires access to information about what it *is*, but also about what it *means*. Once you understand what it means, you have the information necessary to evaluate it.

The snap-judgment model predicts that you first process the colors of the yard sign. You access associative memory to figure out what those particular wavelengths represent: red, white, blue? As these colors are associated with different emotional states (see Cimbalo, Beck, and Sendziak 1978) and the resulting behavioral consequences, your brain starts sending signals to the rest of your body to prepare for reaction (see Sander 2013; Dror 2017). You now need to figure out what the rest of that information was. What were the patterns of that light? It appears that there were some white letters on the sign. There was an "E," an "L," and "E," a "C," and a "T." That creates the word "ELECT." Meaning to vote for. There were some more letters on the sign. A name. The full name is "Mitch McConnell." Since it is about politics, it must be a politician named Mitch McConnell. Now imagine the information was the same, but the color was blue. You may take more time to figure out who that Mitch McConnell person is and come to your reaction to seeing the yard sign. This is because without the color red, you are first thinking about Democrats who are named Mitch McConnell. Only when you come up empty on your mental Rolodex do you figure out that it is the Republican Mitch McConnell.

How do you react to the color and then to the name? Social groupings are not simply abstract concepts invented by social psychologists; our neurobiology reflects them. For example, researchers find activation of the anterior insula when we observe an instance of an in-group member outperformed by a member of an out-group (see Zink and Barter 2012). The anterior insula activity is associated with physical and emotional pain, and not just for ourselves but also for others (Adolphs and Vanessa 2011). Others have also observed that when perceiving someone as part of a high-status social group, there is an increase in activity in the sensorimotor cortex and supplementary motor area, indicating more activity in the areas of the brain that encourage movement (Zink et al. 2008). Visual information about someone in your social group speeds up processing, is more salient, and demands more attention than visual information about an object outside your social group (Zink and Barter 2012).

There is significant evidence supporting the theory that our partisan identification reflects more than just our attitudes about politics, but a social identity (Campbell et al. 1969; Mason 2018) that guides our attitudes (see Achen and Bartels 2016; White, Laird, and Allen 2014; also Bullock 2011). As our political attitudes reflect shared views among co-partisans (Pickup, Kimbrough, and Rooij 2020), the congruence between political information and our partisan identification influences our reactions to such political information. This means that the visual information we glean from politics will likely motivate the neurological features of social groups, and explain the resulting behavioral manifestations in response to such information. That information is also likely to be processed at different rates. That is, while visual information carries general affective associations, we should also expect associations between politically-relevant colors with partisan identification.

Table 1: Summary of hypotheses

Hypotheses	Expectation
H_1	People notice color
H_2	Colors shape perceptions of candidate based on partisan associations
H_3	Candidates using Red are more supported by Republicans; candidates using Blue are more supported by Democrats
H_4	Republicans spend less time evaluating candidates using Red; Democrats spend less time evaluating candidates using Blue
H_5	Campaigns recognize the importance of color to voters' evaluations of candidates and respond strategically

From this discussion, I expect the following: that the average potential voter pays attention to the colors used in campaign branding (H_1); that colors observed shape perceptions about the person and ideological symbol represented in the branding – this means that individuals express different levels of preference for receiving more information that is consistent with their preferences (H_2); that the consistency of information explains more positive perceptions (i.e., simple visual information paired with more complex "traditional" information) (H_3); positive and consistent information is processed more quickly than negative and inconsistent, negative and consistent, and positive and inconsistent information (H_4); and finally that campaigns make strategic choices about their branding to attract voters (H_5) – this is in line with their primary objective of reelection (Fenno 1973; Mayhew 1974). A summary of these hypotheses is presented in Table 1.

Study 1

In Study 1 I start with testing H_5. Though my focus is on the cognitive mechanisms for individuals, I first want to examine whether practitioners of political marketing also perceive that these associations exist and are influential. In some informal conversations that I had with political campaign professionals, it became clear that the descriptive evidence connecting the colors red and blue with Republicans and Democrats is still very much based on instinct rather than empirical evidence.

> There obviously is a strong association with blue and the Democratic Party and red and the Republican Party. We've seen in some of our testing that specifically MAGA red tends to elicit a slightly stronger association with Republicans/conservatives/Trump than other shades. The rest of color spectrum doesn't seem to have as strong an association, though greens and purples tend to read a little more left, the combination of red, white and blue tends to read a little more right, black and white tends to read a little left, black and red tend to read a little more right, etc.

Comments from practitioners like this suggest that campaigns recognize that these are not simply patterns that journalists (see Elving 2014) and researchers (see Williams, Horsting, and Ramirez 2022) have picked up on; they are associations held by voters, and campaigns respond accordingly:

> Beyond that, I generally suggest that considering associations with party is generally a good place to start. For example, if you're running in a Democratic primary and that's the race that's going to most likely decide who ultimately gets elected, then blues are a good place to start.

In the comments like these, we see some qualification that there are other colors which betray ideological positions. Still, a potential implication is that the value of colors associated with a particular place can be a way for candidates to communicate attachment to a district and its constituents. That said, there is a preference for campaigns to use as few colors as possible to save on costs – simpler is better. A comment that particularly stood out was:

> You want voters to be able to look at whatever collateral you have, including lawn signs, and be able to identify that it's your material without ever having to read it. If you do one thing long enough, voters tend to start to associate specific color schemes with specific candidates.

So, unsurprisingly, a conversation with a practitioner reveals that campaigns care about how they market themselves. And it seems as though campaigns want to tap into quick and efficient information processing for voters and potential voters. However, as also noted during the conversation:

> A lot of decisions are still made on purely gut feelings as opposed to taking a more multi-disciplinary evidence-based approach.

Comments like this suggest the following: although it appears that at least once consulting firm of campaign marketing professionals recognize the potential value of using the colors red and blue to cue to the partisanship of a candidate, there is still significant uncertainty about how widespread these patterns are with political campaigns in the United States, and whether voters actually do make these associations. Do districts in campaign seasons take on a look that is consistent with my theory? The first piece of empirical evidence in this chapter examines whether we observe systematic patterns between campaigns in the use of the colors red and blue on their yard signs. Study 2 then takes my predictions from the snap-judgment model to examine whether these associations exist among voters, and investigates possible consequences.

To gather evidence generalizing the belief that campaigns strategically use the colors red and blue to tap into possible associations of these colors with partisanship, I began by collecting data from the MIT Election Lab – specifically, I gathered data on the electoral results of the House of Representative elections from the years 1970-2020. The data report the number of votes for each candidate in any given race. With these data, I calculate the rolling 5-year average of the Democratic party's vote share for each district to account for particularly unique electoral events.

Next, I use a combination of HTML and XML tags to identify and then download around 1,000 yard signs from House elections from the years 2016 to 2022; these were taken from the website of the Center for American Politics and Design. I used the `OpenCV` library in `Python` to examine the proportion of the colors near the "Republican red"[1] and "Democratic blue"[2] in each of these yard signs.

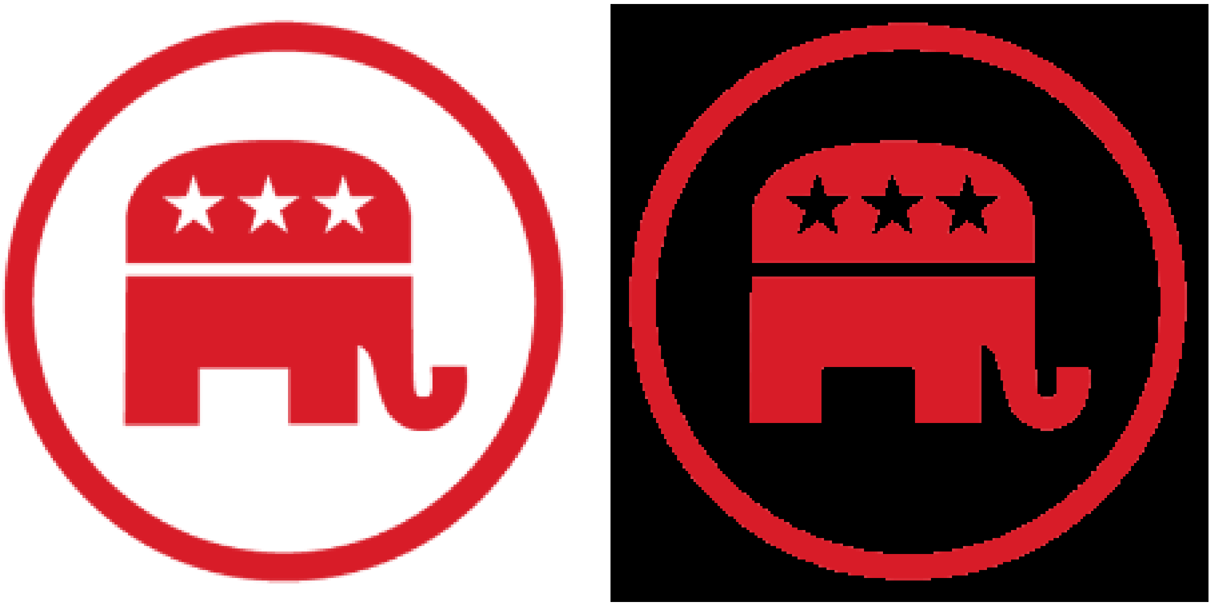
This approach to measuring the proportion of the Republican red and Democratic blue colors takes a lot of the guess work out of manually coding this. For example, I downloaded the GOP logo used on the GOP's official Twitter account during the 2022 midterm election cycle. `OpenCV` loads the image and converts it to a three-dimensional `numpy` array that contains the BGR (reverse of RGB) values for the pixels in the image. I standardize the image to be 224 $\times$ 224 pixels. The computer is trained to detect the "Republican red" and "Democratic blue" colors. Once trained, the computer detects the pixels that do not contain values within the pre-specified range and converts those pixels to be black. To validate this classification and transformation of the pixels, I include the original image next to the transformed image in Figure 3.

I then extract the non-black pixels from my array and calculate the percentage of pixels in the image that are not black.[3] Summary statistics of these calculated proportions for red and blue are included in the Appendix.

For the example in Figure 3, about 30.35 of the image is red.

With the data on the proportion of each of the yard signs using the red and blue colors, I then merge these data with the MIT Election Lab Data. This leaves me with data from the House elections between 2018 and 2020. While the data are limited in the number of elections they reflect, they allow me to hold the district composition constant, as redistricting occurs

[1]lower RGB values: 93, 9, 12; upper RGB values: 236, 69, 75
[2]lower RGB values: 0, 18, 26; upper RGB values [102, 212, 255]
[3]$\text{Color}\% = \frac{\text{Non-black}}{\text{Transformed}} \times \frac{\text{Original}_{\text{Height}}+\text{Original}_{\text{Width}}}{2\text{Transformed}_{\text{Height}}+2\text{Transformed}_{\text{Width}}}$



(a) Resized original image **(b)** Masked

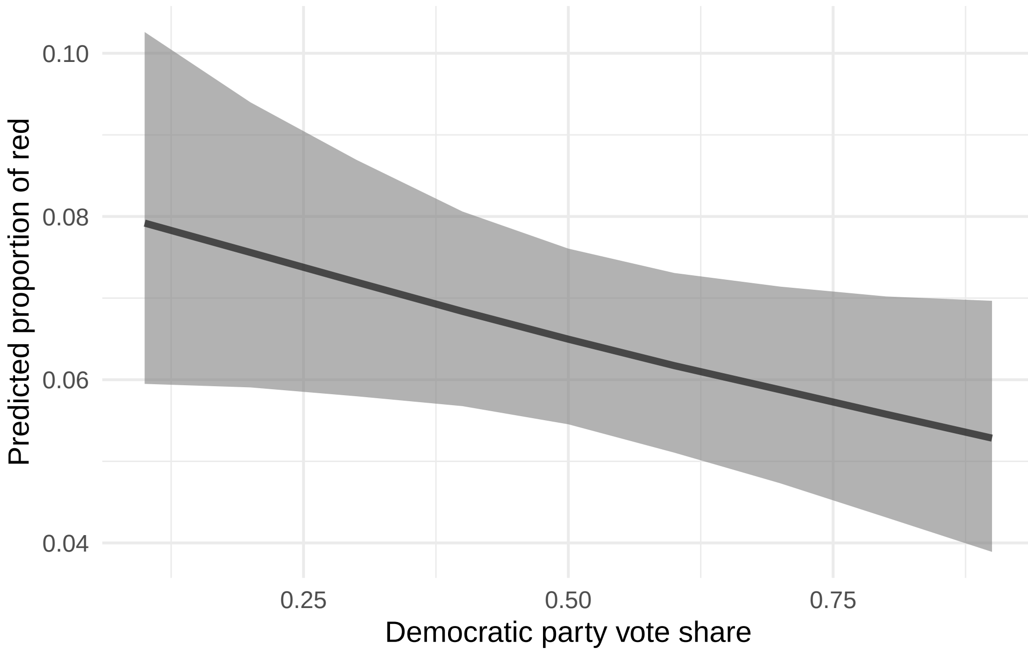
Figure 3: Detecting colors in the GOP logo

after the Census every 10 years. However, each district and state is different in their laws surrounding elections, and are different in terms of political context. I wanted to examine whether there are meaningful differences between districts that are partisan "strongholds" (Democrats or Republicans tend to get elected in a district) relative to districts that are much less so. To do this, I specify a model that includes an intercept for each state-district unit. Though my outcome of interest (proportion of the yard sign that is red or blue) is continuous (it can take any real number), the outcome is bounded between 0 and 1. While the traditional approach may be to use ordinary least squares, such a technique often can result in poor model fit, introduce systematic error, and lead to results that are quite unstable. To account for these concerns, I use an ordered beta regression which specifies a link function constraining the conditional distribution of the outcome to be between 0 and 1; I also induce cut-points akin to the fractional logistic regression which allows for the outcome to also appear as strictly equal to 0 or 1 (Kubinec 2022). Interested readers can find a discussion of how the ordered beta regression compares to other estimators in the beta regression family in the Appendix.

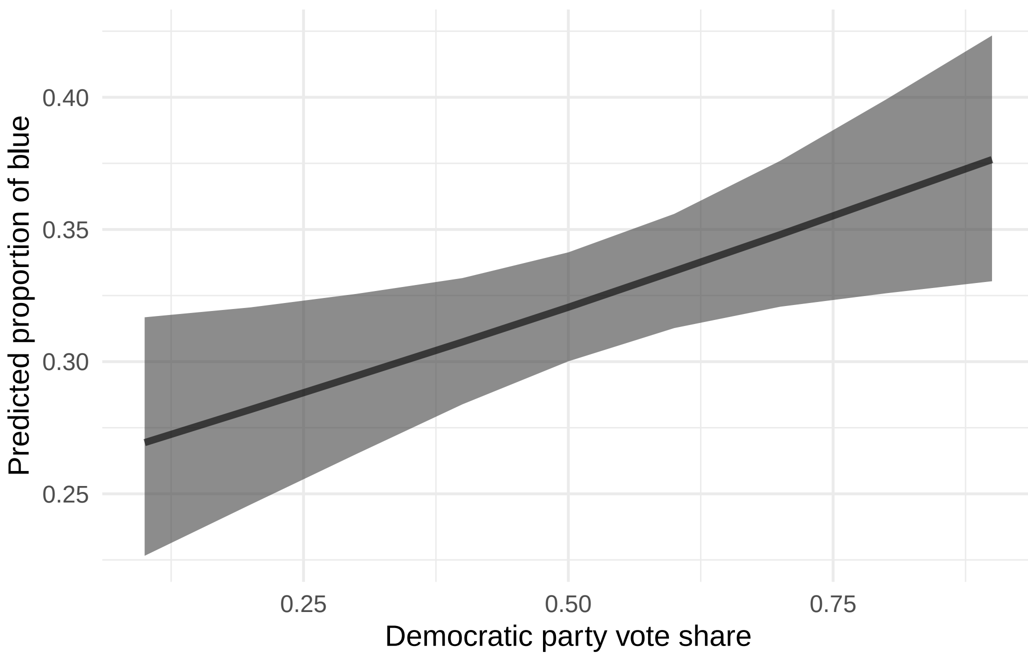
Once I fit these models, I used the `marginaleffects` (Arel-Bundock 2022) package to calculate the grand mean of the predicted proportion of the use of the color red or blue for these yard signs, as it correlates with the 5-year rolling average Democratic candidates' vote share. These results are included in Figure 4.

The results suggest a correlation between districts where Democrats are historically more electorally successful and a lower proportion of red on their yard signs. Inversely, those same districts tend to have yard signs with a higher proportion of blue on them. It is important to note that these results are strictly correlational. From these results I do not claim that campaigns are doing this either because voters are encouraging them to take this strategy, or that they are doing it as a way to proactively get voters to make these associations. Though I do control for unobserved confounds through removing district and year level pooling, there are a number of contextual features that may be unique to a particular district in a particular election year that I do not account for and that threaten claims of causal direction. Though the data available to me limit my ability make a causal claim, these data nonetheless provide evidence consistent with the story I have relayed and the one provided to me in my informal conversations with practitioners.

It appears that Congressional districts take on a look that is consistent with my theory. However, determining how political operatives formulate branding strategies for candidates is not the main focus of my story. While it helps me understand ow the colors red and blue factor into decisions made on the ground by professional political marketers, this imagery coding does not answer my more central questions about 1) whether voters make these associ-



(a) Proportion of red



(b) Proportion of blue

Figure 4: More blue on the yard signs in Democratic strongholds

ations, 2) about what kinds of cognitive mechanisms potentially undergird such associations, and 3) whether there is evidence to support causal claims about the electoral ramifications of such processes.

Study 2

The purpose of Study 2 is to examine whether the color choices on an almost ubiquitous form of campaign branding – yard signs – influence people's perceptions of political candidates. Evidence suggests that yard signs *do* matter in shaping political attitudes (Makse, Minkoff, and Sokhey 2019), vote intentions (Makse, Minkoff, and Sokhey 2019), and even electoral outcomes (Green et al. 2016). As they are simple, cheap, intrusive, and common forms of campaign branding, they provide a conservative test of the effects of color in campaign branding.

Using yard signs in this study, I test the first four hypotheses I derived from the snap-judgment model. First, I test the claim that individuals do indeed notice the color of electoral yard signs. Next, I test the claim that these colors that individuals detect influence their evaluations of the yard sign and the candidate represented on it. I then test the claim that the effects on perception are moderated by how consistent the color is with the more complex information displayed on the yard sign. Finally, Study 2 closes with an examination of whether positive information that contains consistency is processed more quickly than negative or inconsistent information. That is, do partisans quickly detect and encode information from a clearly co-partisan political candidate?

Research design

I recruited participants from Prolific.[4] After providing informed consent to participate in the study, Prolific redirects subjects to Pavlovia,[5] where I provided participants with a demographics and political attitudes questionnaire. Due to concerns about priming effects introduced by these questions as well as concerns of bias introduced by post-treatment control (Montgomery, Nyhan, and Torres 2018), I randomly selected half of the participants to receive the questionnaire post-treatment and the other half receive it pre-treatment. This questionnaire includes common questions about the participant's ascriptive characteristics, and about the participant's political ideology, partisan identification, interest in politics, and political knowledge.

I included those questions due to expectations that they may act as confounds for my hypotheses. I included some questions collecting information on participants' ascriptive and descriptive characteristics such as age, education, gender identity, and racial identity, as a number of these correlate with partisan identification (see Campbell et al. 1969; Mason 2018). Though political knowledge does predict the strength of an individual's partisan identification (Lodge and Taber 2013), attention paid to politics is likely a more important confounding variable for my application. The purpose of color in politics is to act as a heuristic for people (a cognitive shortcut). On the one hand, if individuals are aware of the tendency for Republicans to use and be associated with the color red, and the degree to which they know factual information about politics is not entirely relevant. On the other

[4]I pay subjects a rate of $12.00 per hour. On top of the price per participant, Prolific charges a 30% servicing fee.

[5]Pavolovia allows for researchers to host and run open source experiments for about $0.20 per participant (to cover their server costs). I use it primarily to integrate the JavaScript components from the jsPsych package (Leeuw 2015) for my experimental design.

hand, those that pay no attention to politics whatsoever may be less likely to be aware of such associations. Additionally, those who express less interest in politics are also likely to identify as more moderate when asked about their ideology and partisan identity (Klar and Krupnikov 2016).

Additionally, I included a question about the respondent's sex assigned at birth, and importantly, about whether they have received a diagnosis of *any color blindness*. As some individuals may possess undiagnosed colorblindness, asking about their sex assists in covariate balance. I additionally included an open-ended question asking participants to describe their "first memory of a political event." The use of open-ended questions helps provide an attention check and identify duplicated responses for those spoofing IP addresses with a VPN (Kennedy et al. 2021).

I then presented participants with an instruction screen informing them of the task for the experiment. In the first trial of the experiment, I randomly presented participants with one of three possible yard signs. These yard signs are simple, with the text "Riley Ready to Lead" and a solid background color of either "Republican red," "Democratic blue," or white.[6] There is an added component to this, as well as in the other two trials.

Rather than use eye-tracking devices and software, I instead used Mouseview.js (see Anwyl-Irvine, Armstrong, and Dalmaijer 2022), which either blocks out or blurs a large portion of the participant's screen and encourages them to move their mouse to view different parts of the screen in isolation. As the participants move their cursor around the screen, it tracks the coordinates of the cursor along with the "dwell" time of the cursor in that particular

[6] See Appendix to view all of the stimuli used in Study 1.

coordinate. One primary benefit of Mouseview.js is that it allows researchers to field their experiments outside of a lab-based setting, while providing results that robustly correlate with the results from a design employing eye-tracking hardware (Anwyl-Irvine, Armstrong, and Dalmaijer 2022). This allows researchers to rely less on student convenience samples, which are common with eye-tracking studies. For my design, I am particularly concerned about reliance on a student convenience sample due to variation in participants' ability to detect and process color in the U.S. population. As a result, Mouseview.js enables me to take advantage of a survey experiment format (and a better sample) while capturing information about how participants explored the yard signs.

To ensure that participants have a standardized initial placement of their cursor for each trial, I displayed a blank page before viewing the yard sign that requires participants to click a "Next" button. Immediately after clicking "Next," participants were shown the yard sign. The goal is to ensure that variation in where participants explore the image is not dependent on a non-standard starting point for their cursor.

When viewing each yard sign in each of the three trials, there is a blur over a substantial portion of the screen. At any given point in time, participants can view only 8% of the image without an obstruction, which simulates the observation that we typically foveate on about 8% of our available visual field at any given time (Wedel and Pieters 2008).[7] For the obstruction, I utilized a gaussian blur for the overlay of the image, rather than a solid overlay obstructing the participant's view entirely. The gaussian blur allowed participants to see a blurred visual field beyond the cursor. This allowed participants to see enough to

[7] A screenshot providing an example of what the participants were able to see with the blur included in the Appendix.

take purposeful action to explore blurred parts of the image that attract them (Anwyl-Irvine, Armstrong, and Dalmaijer 2022). The use of the gaussian blur required that participants use a web browser other than Safari because of a known issue (Anwyl-Irvine, Armstrong, and Dalmaijer 2022). This required participants to either switch browsers or to not participate in the study if they were using Safari at the time they are recruited by Prolific to participate in the study. As this requirement is enforced *before* joining the study, this should not have an effect on the number of excluded participants from my original sample.

Participants move their cursor to explore the yard sign. I alloted 5000 ms to perform the exploration before the image disappears; I did this to encourage a consistent and short duration to explore the image and to formulate an impression of the candidate.[8]

After exploring the image in each trial, I asked participants whether they felt that the candidate supposedly owning the yard sign was a Democrat, a Republican, or Neither. After completing the three trials, I asked subjects to indicate their preference among the three signs (one from each trial).

What is different between the two latter trials and the first is that I varied the amount of color that is on the yard sign in the second and third trials. Examples of all of these yard signs are included in the Appendix. For readers interested in the more technical details, the Appendix accompanying this chapter also includes a table of the data collected in the

[8] In marketing research, some studies give participants about 6000 ms in eye-tracking studies to examine a brand and formulate an intention to purchase a product or not (Wedel and Pieters 2008). With Mouseview.js, a study examining the tool's correlation with optical responses to viewing disgust-and-pleasure evoking images uses 1000 ms; but is intended to be an extended amount of time (Anwyl-Irvine, Armstrong, and Dalmaijer 2022).

Table 2: Descriptive statistics of Prolific sample

	Unique (#)	Missing (%)	Mean	SD	Min	Median	Max
Age	59	1	36.6	12.2	18.0	34.0	77.0
Color blind	3	1	0.0	0.1	0.0	0.0	1.0
Female	3	1	0.4	0.5	0.0	0.0	1.0
White	3	1	0.7	0.5	0.0	1.0	1.0
Hispanic	3	1	0.1	0.3	0.0	0.0	1.0
Black	3	1	0.1	0.3	0.0	0.0	1.0
Party ID	8	1	−1.1	1.9	−3.0	−2.0	3.0

Data source: Prolific.

Sample characteristics.

experiment – Table 6; this table reports full results, posterior predictive checks, and more detailed discussions for all of the models used in the remainder of this section.[9]

Table 2 presents some characteristics of the sample on the whole. The sample is relatively young (mean age of 36.6 years old), and with few reporting having been diagnosed with colorblindness. About 40% of the sample identifies as female, and about 70% of the sample identifies as White (while only 10% report being Hispanic and Black). The average respondent in the sample reports leaning Democratic.

Do individuals notice color in political branding?

To address this first question, I use a couple of proxy measures for people's attention paid to the yard signs. I collected the first measure through recording the movement of the

[9] Unless noted otherwise, the reflection of uncertainty in the models are credible intervals at the 90% level. This should not be equated with the frequentist practice of reporting confidence intervals at the 95% level, as credible intervals at this level are often extremely unstable and, more importantly, are interpreted differently. For example, a credible interval at the 90% level can be interpreted as: the probability that the true effect is within that interval, given the data. This interval reflects the degree of uncertainty I have about my point estimate as opposed to being primarily used to interpret levels of statistical significance in a strict null hypothesis test. This contrasts with a confidence interval used in the frequentist framework which is interpreted as: upon repeated samples, 90% of the confidence intervals contain the true effect. To bridge methodological approaches, for those interpreting my credible intervals, I am using two-sided credible intervals here – at the 90% level, the probability that 0 would be the true value given the data would be less than 5% as it would be on one side of my posterior distribution.

Table 3: Average time between cursor movements (Trial 1)

	Blue (N=331)		Red (N=323)		White (N=337)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Δ_t (milliseconds)	36.2	40.9	36.8	52.6	37.5	65.0
Δ_x (pixels)	10.0	9.4	9.8	10.3	9.6	10.1
Δ_y (pixels)	6.6	7.0	6.4	6.7	6.4	6.5

Data source: Prolific sample.

Table 4: Average time between cursor movements (Trial 2)

	Blue (N=347)		Red (N=315)		White (N=324)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Δ_t (milliseconds)	35.0	38.2	39.6	58.5	39.1	62.5
Δ_x (pixels)	7.8	8.7	7.4	7.4	7.4	8.0
Δ_y (pixels)	5.9	5.2	6.0	5.8	5.9	5.5

Data source: Prolific sample.

subjects' cursors along the x-and-y-axes. The second measure accounts for the amount of time participants' cursors linger over a particular coordinate on their screen. Presumably, the more participants explore the yard sign, the more they are finding visual information that they can use to evaluate the candidate. While these two measures are simple proxies and are not direct measures of "noticing the yard sign," they allow for one to get a sense of the patterns by which people explore the yard signs across treatment conditions. This also bolsters my confidence in the degree to which variation between the treatments among different groups of participants is due to actual differences in how people processed these treatments, and not due to random chance.

Table 3, Table 4, and Table 5 report the average difference in milliseconds and pixels along the x-and-y-axis of the subjects' screens. These tables demonstrate a few things. First, the average participant in each treatment condition appears to be spending more time exploring

Table 5: Average time between cursor movements (Trial 3)

	Blue (N=331)		Red (N=333)		White (N=320)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Δ_t(milliseconds)	37.3	45.3	40.4	55.5	36.2	54.0
Δ_x (pixels)	7.0	6.6	7.2	6.7	6.8	7.1
Δ_y (pixels)	6.2	7.4	6.4	6.4	5.6	5.0

Data source: Prolific sample.

the yard signs when there are more "conflicting" colors (trials 2 and 3). Second, we see that, for the most part, the average participant in the red and blue yard sign conditions spends more time exploring those yard signs than the participants viewing the white yard sign.

Overall, it appears that people viewed the yard signs differently depending on which yard sign they were looking at. Now, I turn to exploring how features about the subjects themselves may shape the way that individuals interact and respond to this visual information on the yard signs. The data on the timing and cursor location is much more noisy than I originally anticipated. However, as the tests of the next few questions demonstrate, the evidence supports the general conclusion of systematic differences between individuals that saw either a red, white, or blue yard sign (despite holding everything else but the color constant).

Do colors shape perceptions of political objects?

To address the question of whether colors affect perceptions of the candidate and the yard sign, I asked participants to report whether they perceived the candidate to be a partisan – either a Republican, Democrat, or as non-partisan – immediately after viewing each image. Everything on the yard sign remains constant except for the color. As representations of ideology are associated with more than just political views, but also things like space (Mills et al. 2016) and color (Losada Maestre and Sánchez Medero 2022), differences between respondents on the perceived political affiliations of the candidate should be more than "by chance" differences.

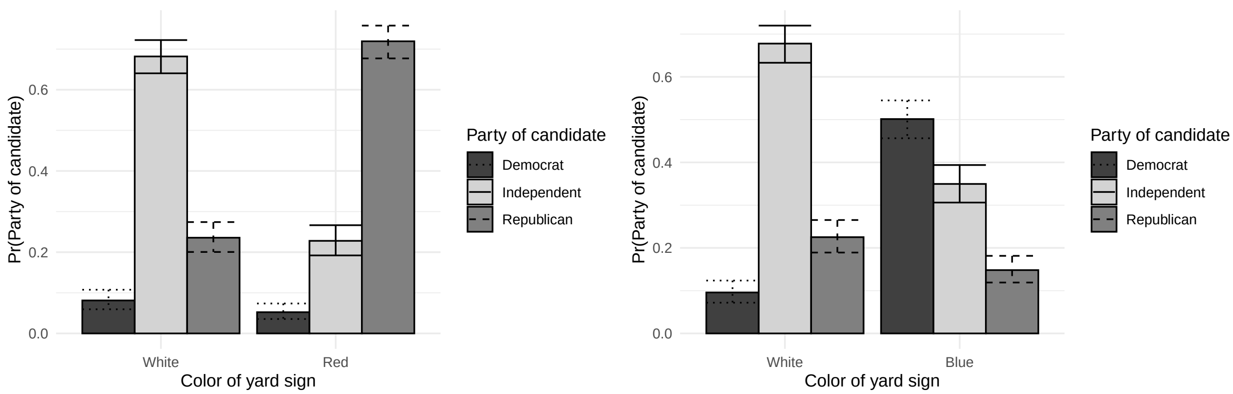
I examine differences in respondents' reported perceptions of the candidate's partisan affiliation. Evidence supporting H_2 would appear as differences between those who saw the white yard signs and the "partisan color" yard signs in reported perceptions of the partisanship of the candidates. I estimate two multinomial logistic regressions where the main independent variables of interest are two indicator variables for whether respondents received the red yard sign or the blue yard sign in Trial 1.[10] The baseline category for both of these indicator variables is if they instead saw the white yard sign.

Figure 5 presents the predicted probabilities of an average subject reporting the candidate as either a Democrat, Independent, or Republican when viewing the different yard signs. The error bars reflect the high density credible interval for 90% of my posterior draws. Each bar reflects the predicted probability of an outcome – listing the candidate as either a Democrat, Independent, or Republican. When interpreting the error bars, you will want to look at the difference in the error bars *between* yard sign treatments rather than *within* treatment.

We see that the models indicate substantive and statistically meaningful differences between the yard sign treatments for each outcome. That is, the red and blue yard signs did shift people's perceptions of the partisanship of the candidate relative to the white yard sign. Specifically, the evidence suggests that the predicted probability of a subject perceiving the candidate with a red yard sign as a Republican is 70%, whereas it is only about 30% when

[10] In Table 8 located in the Appendix I report the results of these regressions as fitted ordered logistic regressions, rather than multinomial. I come to the same substantive conclusions regardless of whether I fit a multinomial or ordinal logistic regression.

viewing a white yard sign. The predicted probability that a participant perceived the candidate with the red yard sign as a Democrat is less than 5%. However, when viewing a blue yard sign, the predicted probability that a participant reports the candidate to be a Democrat is at about 50% whereas it is only about 10% if the yard sign is white. As we saw with the association between a Democratic candidate and a red yard sign, we see that the predicted probability that a participant perceived a candidate with a blue yard sign as a Republican is less than 20%; it is about 45% as an Independent. The full table of results for these models are reported in the Appendix in Table 7.



(a) Red treatment   **(b)** Blue treatment

Figure 5: The perceived partisanship of candidates change depending on the color of the yard sign

As the consistency by which the parties have used either the color red or blue has increased since the 2000's, I suspected that the age of my subjects may moderate this relationship. That is, the tendency for subjects to label red yard signs as a Republican candidate versus a different color may be stronger for those who are younger, given the consistency in branding is the political environment. I expected this particular relationship may be weaker for older subjects as they may place current branding strategies in a larger political context where this was not always the case.

I fit similar regressions as before where the independent variables are indicator variables reporting whether the participant received the red (the first model) or they received the blue treatment (the second model). Those included in the baseline category for both models are those who received the white yard sign treatment. Since I believed that age may moderate this effect, I include an interaction term for both of these models that multiplies these treatment indicator variables with age.

Though my pre-registered expectations were that age would moderate this effect, these models suggest that there are not substantive or statistically meaningful differences in how older and younger participants responded to these treatments. The results of these models included in the Appendix in Table 8.

I also explore whether these effects may be weaker for those with colorblindness. The results of this model are reported in Table 11, which is located in the Appendix. The results do not suggest any effects by colorblindness. However, given that I had a very small number of respondents reporting colorblindness in my sample, the lack of substantive or statistical effects may be due to the fact that I did recruit enough participants with colorblindness in each group to compare.

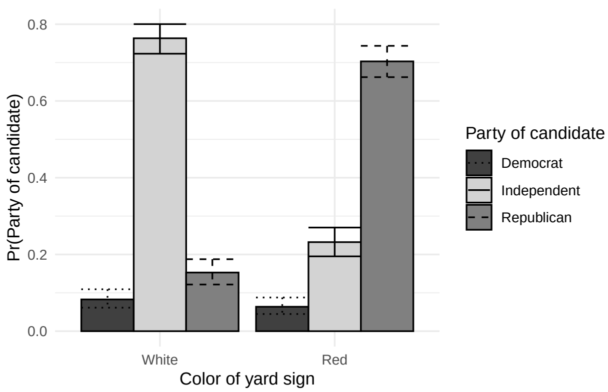
I also test whether my effects here are sensitive to my choice to run two separate regression models – one for each treatment. I fit a single regression with two indicator variables for the treatment coded as: 0 did not receive the red/blue treatment, 1 did receive treatment. The full results of this alternative model specification are included in Table 10. This means that the intercept term for the regression would be the predicted probability of the average respondent labeling the owner of the yard sign as either Democrat, Independent, or Republican. The conclusions I draw from this regression model do not change the ones I make here with Figure 5.

In summary, I find that subjects perceive candidates with red yard signs as Republican, candidates with blue yard signs as Democratic, and candidates with white yard signs as being neither – an Independent. However, these yard signs are *very* red and blue. In the next section, I examine how these effects may be weaker when we use less red or blue/include more blue or red. That is, I consider if using both colors on the yard signs has the capacity to increase uncertainty about the perception of partisan affiliation.

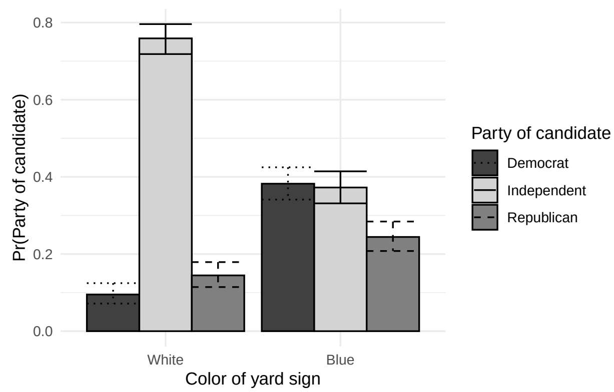
Do these perceptions require consistency between information types?

The design of the latter two trials in the study presents yard signs with mixtures of non-partisan and out-partisan colors. For example, I presented participants with primarily red (and presumably Republican) yard signs, but with some blue or white in them. I pre-registered that the trials that use less "consistent" visual information would demonstrate more uncertainty among respondents in their reported perceptions of the candidate's positions. Specifically, I expected that participants would perceive the yard signs that have both red and blue on them as more moderate, and that the higher proportion of the color red or blue among the two colors would lead respondents, on average, to be more likely to believe that the candidate leans more Republican or Democratic, respectively. This is not to say that I expected the results to change significantly, but rather, that the certainty by which I can predict individuals' guesses of the candidate's partisan affiliation would weaken.

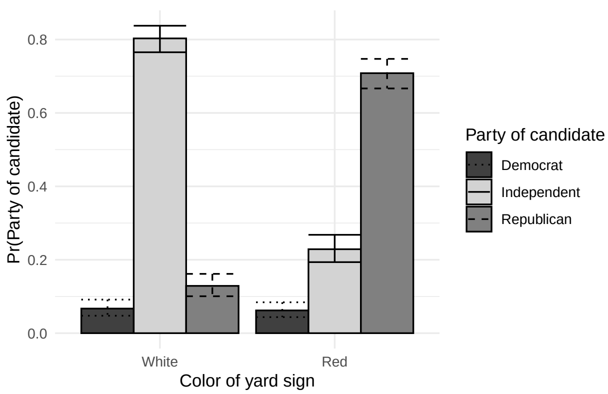
I fit four multinomial logistic regression models, two for each trial.[11] Each model for the trial calculates whether an average subject in the study reported that the yard sign they saw in the trial was for a Democrat, Independent, or a Republican. The predicted probabilities for each outcome occurring under different treatments and for different trials are presented in Figure 6. Table 12 and Table 13 located in the Appendix reports the full results of these models, while Figure 16 located in the Appendix reports the posterior predictive checks of these models.



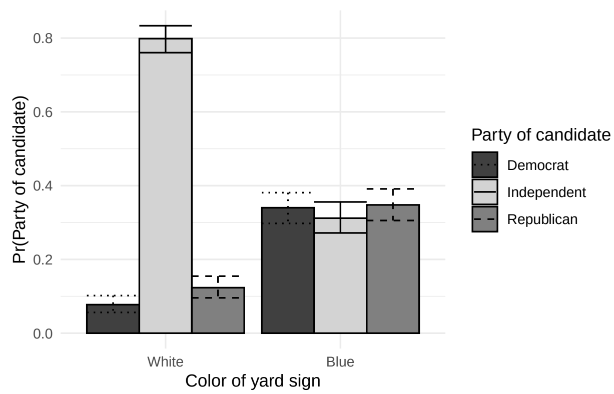
(a) Trial 2 Red treatment



(b) Trial 2 Blue treatment



(c) Trial 3 Red treatment



(d) Trial 3 Blue treatment

Figure 6: Mixing red and blue in a yard sign increases uncertainty about partisanship

[11] I also report the results of these four models as ordered logistic regressions in Table 14 and Table 15 which are located in the Appendix.

The results from these models offer partial support for my pre-registered expectations. First I see that yard signs using less blue are not as distinguishably Democratic as the white yard sign. In other words, voters are not meaningfully more likely to report that the yard sign with less blue on it belongs to a Democratic candidate versus a white and black yard sign. So, the strength of using a blue yard sign to communicate alignment with the Democratic party weakens if you use less blue relative to white, or if you include red on it. With red yard signs, however, we see that voters still see them as belonging to Republican candidates, even when we reduce the amount of red on the yard sign and even when we include blue.

One potential reason for this may be the association of the American flag when using all three colors, given the Republican party's tendency to condemn those who do not adhere to social norms about showing respect to the American flag. This, however, is untestable based on the design of the study. However, what we do see is that there are bounds by which at least the color blue on a yard sign indicates to voters that the candidate is a Democrat. What remains unclear is whether these perceptions of ownership by a partisan candidate influence people's willingness to support that candidate or express favoritism toward them (H_3).

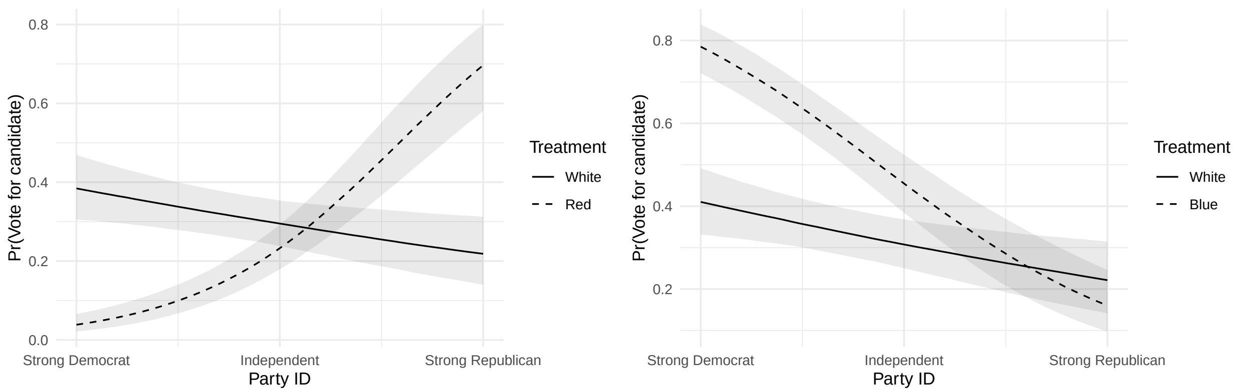
Does the color of a yard sign explain support for a candidate

An important implication of the snap-judgment model is that if individuals perceive candidates using the color red as Republican and candidates using the color blue as Democratic, then partisans may be more attracted to yard signs displaying the color that fits with these associations. That is, if the color red conveys group membership to the Republican party, we should expect that Republican individuals should like the red yard signs more and be more willing to vote for candidates using those colors in their campaign materials. We should expect a similar thing with Democrats but with blue yard signs. Another expectation is that if color does indeed matter as a form of political communication, we should expect these relationships to be relatively strong, despite little substantive information (e.g., policy positions and name recognition) about the candidate.

After the three trials, I asked participants which of the candidates for the three yard signs they would vote for. I create an indicator variable from this question that documents whether participants would vote for the candidate that owns the first yard sign (1) or not(0).

I fit two logistic regression models with the vote variable as the outcome I am trying to explain. In the first of the two logistic regression models, I examine whether the effect of receiving a red versus a white stimuli is moderated by the participants' partisanship. As partisanship and its moderating effect on the treatment is of interest here (and partisanship is not being randomly assigned), I control for a number of confounding variables such as attention paid to politics, age, gender identification, and racial identification. The second logistic regression model is much like the first. The difference is that instead of examining the moderated effect of the red treatment, I examine the moderated effect of the blue treatment. As I am still interested in examining how partisan identification modifies the relationship between support for the candidate when comparing a blue versus a white yard sign, I include the same controls as I did with the first logistic regression model. I include the full table of results for both of these models in Table 16 (Appendix).

Figure 7 presents the average predicted probability of supporting a candidate. The results fit with my pre-registered expectations. First, I see that the predicted probability that a strong Democrat would vote for a candidate with a red yard sign is less than 10% (while for



(a) Red treatment

(b) Blue treatment

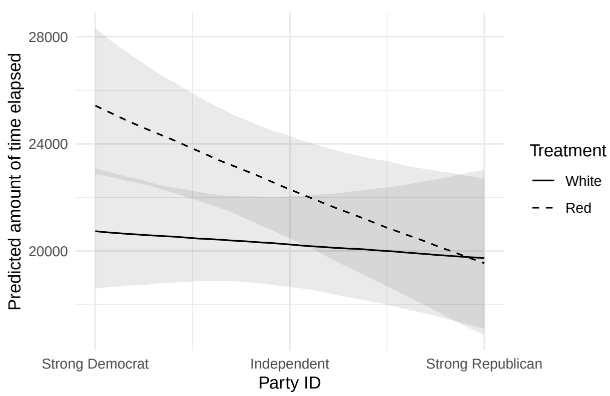
Figure 7: Probability of voting for candidate with yard sign

strong republicans it is at about 70%). Likewise, we see that strong Democrats much prefer a candidate with a blue yard sign than a candidate with a white yard sign, 80% relative to 40%, respectively. Strong Republicans are unlikely to vote for a candidate with a blue yard sign and a white yard sign, with their predicted probability of voting for either of those candidates below 30%.

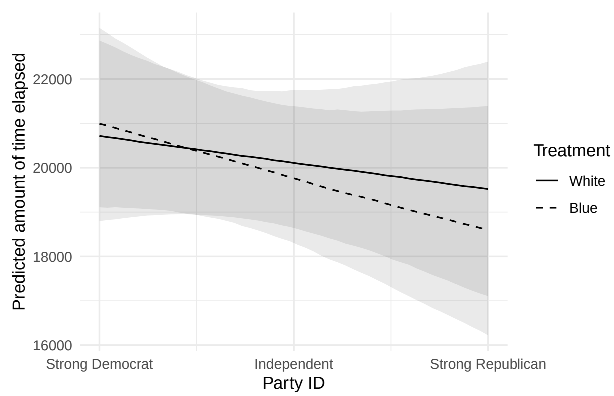
Do partisans process co-partisan branding faster?

Do people process in-group information faster than out-group information? There is, of course, evidence of these tendencies in political circumstances (Lodge and Taber 2013).

To examine my pre-registered expectation that motivated reasoning is also present in the processing of politically-relevant color, I examine the following: the difference in the amount of time between the start of viewing a stimulus and clicking "Next" to stop viewing the stimulus, among those who were viewing a presumed co-partisan yard sign relative to those viewing a presumed out-partisan yard sign. As the outcome is a count of the amount of time participants spent looking at a yard sign, I turn to a class of regression models that work well for explaining outcomes measured as count data.[12] I therefore fit two poisson-gamma models (also referred to as negative binomial regressions). I am interested in explaining whether time elapsed can come not only from the color of the yard sign that the subject is viewing, but also whether this effect is moderated by an individual's partisanship. I therefore include an interaction term between stimuli and the partisan identification of the respondent. Like before, as partisan identification is not randomly assigned, I control for confounds such as attention paid to politics, age, gender identity, and racial identity. Table 18 (Appendix) presents the full table of results for these two poisson-gamma regression models. Figure 20 also indicates that the model does a quite good job at predicting the distribution of the time elapsed outcome variable.



(a) Red treatment



(b) Blue treatment

Figure 8: The effect of party congruency on time spent looking at yard sign

Figure 8 presents the average predicted elapsed time for participants in different contexts. Overall, these results communicate inconclusive support for my pre-registered expectations

[12]By the nature of my measure, I do not believe that participants can record a value of 0 as time elapsed is measured in milliseconds. Additionally, I suspect over-dispersion, as I expect to observe a large bulk of participants recording a very small time elapsed, while for others I expect to record a quite large amount of elapsed time. In the appendix, Table 17 summarizes the time elapsed outcome variable; this demonstrates over-dispersion. Given this, rather than using a count model assuming a poisson-distributed outcome, I instead assume an outcome distributed as poisson-gamma.

on H_4 in either regression model. Strong Democrats do not appear to spend more time looking at red yard signs than white ones, but once I account for the variation in the data, I cannot be sure that these differences are not due to random chance. I also observe that there are not really any differences (substantive or statistical) between partisans looking at blue versus white yard signs.

Conclusions

In this chapter I argue that the colors red and blue provide useful information to voters about politics. Specifically, the colors red and blue provide information about candidates' partisanship. Second, I argue that the information gleaned from these colors can shape how people engage with politics. While I had a number of other expectations this chapter, these were the two primary questions I wanted to address.

I began by looking at whether congressional districts seem to display features that are consistent with my snap-judgment model. I found evidence that campaigns appear to systematically use the colors red and blue at different rates depending on whether the district is more "up for grabs" or whether it is a partisan stronghold. Specifically, my first study suggests that campaigns use more blue on their yard signs in districts that have a higher vote share for Democrats in the five previous years, and use red much less often in these same circumstances. This fits with the strategies communicated to me by a campaign marketing firm. Of course, another question coming from that conversation and the existing literature was, most critically, whether there is individual-level evidence that voters actually make these associations.

Evidence from my experiment suggests that the use of the colors red and blue convey partisan information, while a third color like white provides very little useful political information. The experiment provides systematic evidence that individuals see candidates that use red on a yard sign as more Republican and candidates that use blue as more Democratic. Evidence from the experiment also suggests that using less of those partisan colors and using both colors makes it a bit harder for individuals to make partisan associations. Further, the experiment demonstrates that these associations that we make with color and partisanship are powerful enough that they can shape whether people express a willingness to vote for a candidate. That is, individuals that identify with the Republican party are much more likely to vote for a candidate with a red yard sign than a white yard sign, and Democrats are much more likely to vote for a candidate with a blue yard sign than yard signs with other colors.

Having established some baseline findings, in the next chapter I examine whether the snap-judgment model holds up in more complex settings, and with respect to other behavioral outcomes. Specifically, I next move to consider whether color can shape how we have conversations about politics with others, and whether color can be something that inhibits political persuasion.

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Chapter 2 Appendix

A note about discrepancies between the main text and the pre-registered report

I posted a pre-registration of my hypotheses on OSF. The pre-registration allows me to offer transparency about what I expect to find before I analyze any data. This reduces the amount of post-hoc rationalization of any findings pulled from the data. The pre-registered hypotheses are the same as those that are tested here. Despite the similarities between my pre-registered hypotheses and research design, there are a few subtle differences between what I pre-registered and what I ended up doing. In the spirit of complete transparency, I wanted to make a note of these differences.

Again, the hypotheses that I pre-registered remain the same as what is presented in the main text. The research design also remained the same. During the IRB process, I had to make some decisions about space considerations as I was concerned about participants taking longer than the advertised time (6 minutes). Due to these concerns, I removed some questions. Namely, I no longer asked participants about the color of the yard sign after viewing it nor did I include a battery for political knowledge. These were changes that I made during the IRB process, but did not change in my pre-registered report. In full transparency, mostly because I forgot to make the update as well as having some issues with Dropbox at the time. Removing these questions also had principled reasons. First, I did not want to inflate the treatment effect by asking participants to reflect and tell me the color they saw and then report the partisanship of the candidate. I wanted to get as close to a snap-judgment as I could get and I wanted to immediately ask participants about the partisanship of the candidate after viewing the yard sign to accomplish this goal. For the political knowledge battery, I discuss why I elected to use attention over knowledge in the main text of the chapter. But further, the prevailing questions on political knowledge are suspect as they provide factual information that can be googled participants during the study. Given the length of time it would take for participants to respond to these additional questions and concerns about what value they provide, I did not include them. Those who would like to confirm, I have the IRB materials posted on my github which you can see the history of these files.

Another set of discrepancies is some of my modeling strategies. As I note in the main text, some of the data from the mouseview exercise are not exactly what I had expected initially. I do not have much information about the size of the screen participants had nor do I have precise data for when participants were able to view the yard sign during those 5 seconds that it was up. The data for each trial began recording on an instruction screen that I used to standardize cursor starting position and when they finished the trial. As there is a lot of variation between when participants stopped viewing the instructions, I can't be sure which cursor movements were during the display of the yard sign. Because of the noisiness of the mouseview data, I simplified some of my analyses for H_1 and H_4.

For H_5, I had mentioned that I would include an analysis with a synthetic control. However, the district-level data available at the time of writing is not yet available. Because of this, I cannot leverage redistricting patterns for better causal identification of the question of whether campaigns respond to district characteristics or if they anticipate them. Therefore, I stick with the more descriptive task. Relatedly, I had indicated I would use a multilevel model by using intercepts that partially pool at the district level and intercepts that are not pooled at the state level. Upon further reflection on this strategy, this seemed inappropriate for the question at hand as I did not have clear expectations about variation within states but rather more generally was asking a question about districts at large. Further, I did not specify that I would be using a beta regression for these models so many may read my pre-registration as me implying that I would use ordinary least squares. This is totally reasonable. However, out of concern with reporting results that are extremely unstable because of poor choice in estimator as I discuss in the main text and later in the appendix, the ordered beta regression provides more stable results that I am comfortable making inferences with.

Measures

Table 6: Study 1 Measures

Measure	Question	Coded as
Age	Confirm your age	Text entry
Gender	What is your gender identity?	Non-binary, Female, Male, Prefer not to choose, Other
Sex	What is your sex assigned at birth?	Female, Male, Other
Race	Which ethnic or racial category best describes you?	White, non-Hispanic; Black, non-Hispanic; Hispanic; Asian or Native Hawaiian/other Pacific Islander; Native American/Alaska Native or other race; Multiple races

Measure	Question	Coded as
Color blind	Have you been diagnosed with any of the following visual impairments that are not treated with corrective lenses?	Color blindness (any form); Blurred vision (not treatable by corrective lenses); Macular degeneration; Glaucoma; Cataract; Diabetic retinopathy; None of the above
Attention	How often do you pay attention to what is going on in government and politics?	Always; Most of the time; About half the time; Some of the time; Never
Party ID	Generally speaking, do you usually think of yourself as a Democrat, a Republican, an Independent, or what?; Would you say that you are a strong [Republican/Democrat] or not a very strong [Republican/Democrat]?; Do you think of yourself as closer to the Republican party or to the Democratic party?	Republican, Democrat, Independent, Other; Strong, Not very strong; Closer to the Republican party, Neither, Closer to Democratic
Attn. Check	In a few words describe what is your first memory of a political event.	Text entry

Measure	Question	Coded as
Trial stimuli	Yard sign assigned	0 = White, 1 = Red/Blue
Trial stimuli alt	Yard sign assigned	0 = Not red/blue, 1 = Red/Blue
Time elapsed	NA	Difference between time at start of trial and stop
Δ_t (millisecונds)	NA	Time elapsed between cursor movements
Δ_x (pixels)	NA	Number of pixels moved along x-axis
Δ_y (pixels)	NA	Number of pixels moved along y-axis
Candidate party	Is this candidate a Republican, a Democrat, or Neither?	Republican, Democrat, Neither

Measure	Question	Coded as
Candidate vote	Of the three candidates who would you most likely vote for?	The first yard sign, The second yard sign, The third yard sign
Candidate vote indicator	NA	0 = Would not vote for first yard sign, 1 = Would vote for first yard sign

Treatments

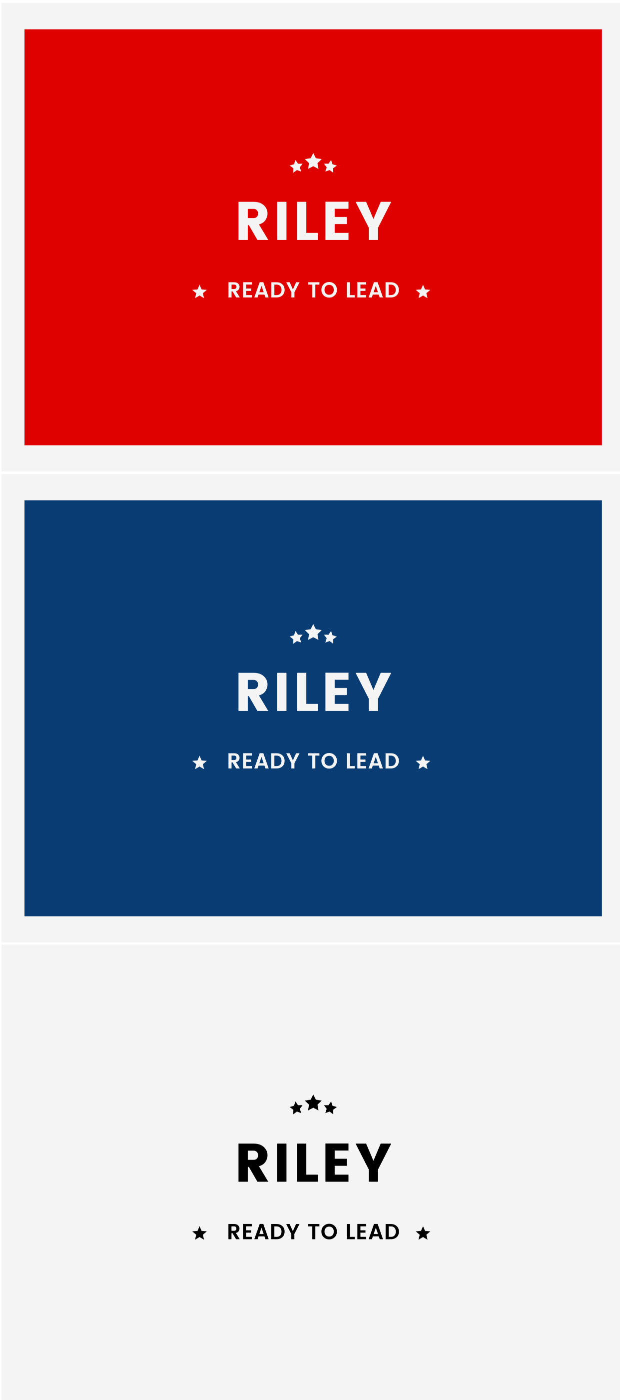


Figure 9: Trial 1 Treatments

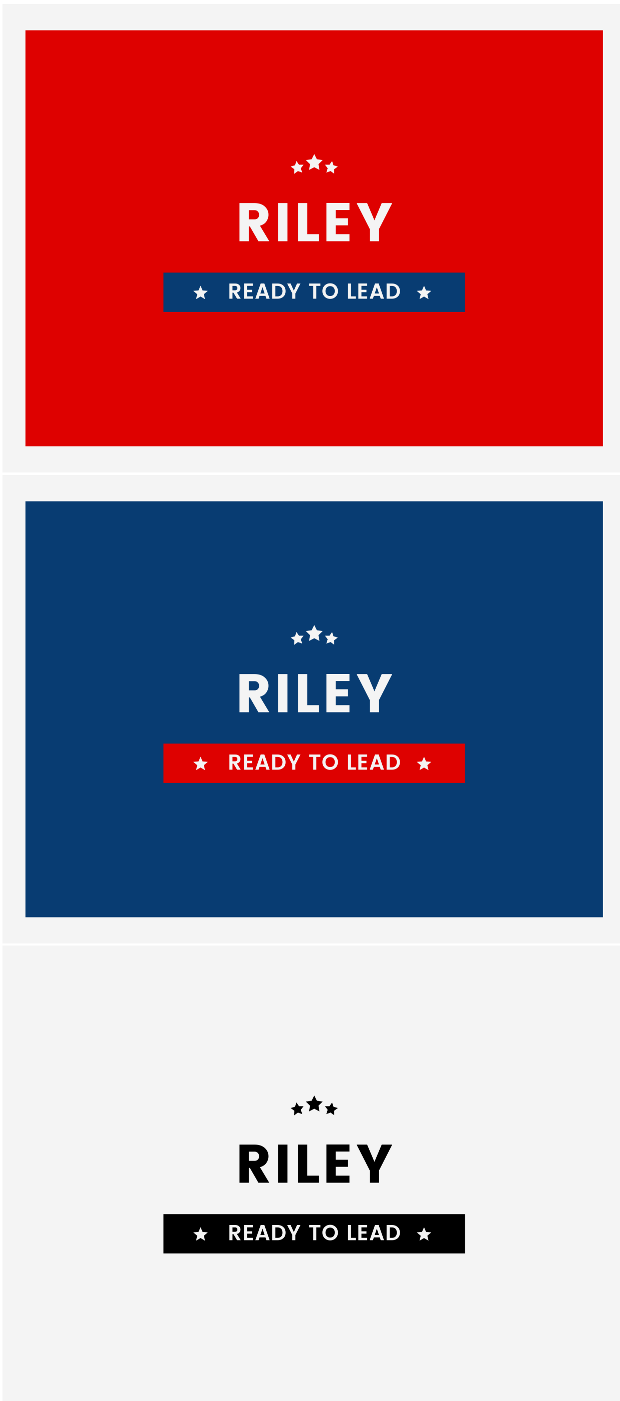


Figure 10: Trial 2 Treatments

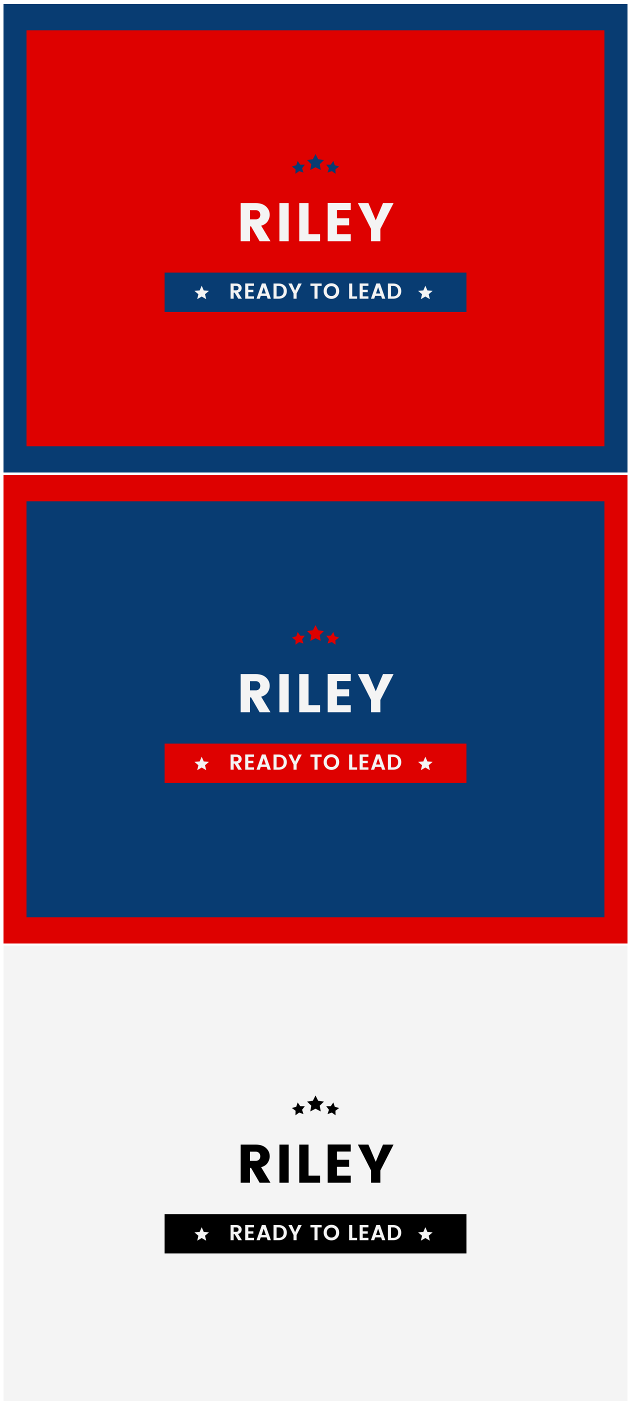


Figure 11: Trial 3 Treatments

Figure 12: Treatment example

H_2

To test whether people associate the color red on a political yard sign with Republicans and the color blue on a political yard sign with Democrats.

Models These first two models are multinomial logistic regressions. The outcome of interest is a 3-item response of whether they perceived the owner of the yard sign to be a Republican, a Democrat, or neither. This variable was recoded to be 1 = Democrat, 2 = Independent, and 3 = Republican. In the first multinomial logistic regression, I predict this outcome with a indicator variable of whether the participant saw a white yard sign (value of 0) or saw a red yard sign (value of 1).

My defined priors for the beta coefficient are $Normal(0, 1)$. This means that I think that 68% of the non-transformed beta coefficients I think will be between -1 and 1, with the remaining 32% being larger than that. I fit the models on 4 chains with 2000 chains each (1000 warmup, and 1000 sampled).

Table 7 reports the logged-odds of a subject reporting that a subject was either a Democrat, Independent, or Republican. Positive logged-odds indicate that the logged-odds of a subject reporting a candidate is a Republican increase, whereas a negative value indicate that the logged-odds of reporting the candidate is a Democrat.

There is also a case to be made about using ordered logistic regressions instead of multinomial logistic regressions if you think of partisanship identification fitting across a continuum and my measure crudely adding break points. Table 8 demonstrates that my substantive conclusions do not change when interpreting a fitted ordered logistic regression instead of a fitted multinomial logistic regression like in Table 7.

Table 7: Full results for reported models in H_2

	Red treatment	Blue treatment
Red yard sign (Independent)	-0.651	
	$[-1.170, -0.146]$	
Red yard sign (Republican)	1.559	
	[1.037, 2.071]	
Blue yard sign (Independent)		-2.323
		$[-2.689, -1.968]$
Blue yard sign (Republican)		-2.078
		$[-2.507, -1.679]$
Intercept - Independent	2.130	1.958
	[1.819, 2.467]	[1.658, 2.273]
Intercept - Republican	1.066	0.852
	[0.718, 1.438]	[0.526, 1.203]
Num.Obs.	658.0	666.0
WAIC	1012.42	1200.99

Data source: Pavlovia
Positive coefficients reflect the logged-odds
of claiming candidate is not a Democrat.
Numbers inside brackets reflect the 5th and 95th percentile
of the draws from the posterior distribution.

Table 8: Full results for reported ordered logistic regression models for H_2

	Red treatment	Blue treatment
Red yard sign	1.926	
	[1.654, 2.212]	
Blue yard sign		−1.617
		[−1.882, −1.356]
Intercept 1	−2.085	−1.732
	[−2.364, −1.828]	[−1.955, −1.525]
Intercept 2	1.041	0.927
	[0.846, 1.245]	[0.745, 1.110]
Num.Obs.	658.0	666.0
R^2	0.19	0.15
WAIC	1031.42	1249.96

Data source: Pavlovia
Positive coefficients reflect the logged-odds of claiming candidate is Republican.
Numbers inside brackets reflect the 5th and 95th percentile of the draws from the posterior distribution.

I also suspected that these effects could be moderated or sensitive to other things. First Table 9 reports how these effects in Table 7 may be moderated by age.

Additionally, I seek to test whether these effects reported in Table 7 are sensitive to the way I chose to test these effects. Specifically, I code the predictor variables as 0 = not red/blue, 1 = red/blue. This gives me two variables that I include in a single ordered logistic regression. This means that the intercept term is the logged-odds of defining the participants as either Democrat, Independent, or Republican if the subject received a white yard sign. The two beta coefficients, in that model reflect the difference in the logged-odds of reporting that the candidate was either a Democrat, Independent, or Republican when they received the red or blue yard sign relative to the white yard sign. The results remain robust to this alternative specification.

Table 9: H_2 models moderated by age

	Red treatment - Age moderating	Blue treatment - Age moderating
Red yard sign	1.770	
	[0.998, 2.490]	
Blue yard sign		−1.454
		[−2.205, −0.725]
Age	0.000	0.008
	[−0.014, 0.014]	[−0.005, 0.022]
Red yard sign × Age	0.004	
	[−0.015, 0.025]	
Blue yard sign × Age		−0.005
		[−0.023, 0.015]
Intercept 1	−2.089	−1.427
	[−2.675, −1.515]	[−1.958, −0.901]
Intercept 2	1.040	1.234
	[0.507, 1.595]	[0.703, 1.766]
Num.Obs.	655.0	664.0
R^2	0.19	0.15
WAIC	1032.97	1250.56

Data source: Pavlovia
Positive coefficients reflect the logged-odds of claiming candidate is Republican.
Numbers inside brackets reflect the 5th and 95th percentile of the draws from the posterior distribution.

Table 10: H_2 models with alternative specification

	Single model
Red yard sign	1.772
	[1.506, 2.047]
Blue yard sign	−1.564
	[−1.840, −1.314]
Intercept 1	−1.672
	[−1.874, −1.463]
Intercept 2	0.866
	[0.688, 1.046]
Num.Obs.	988.0
R^2	0.34
WAIC	1720.81

Data source: Pavlovia
Positive coefficients reflect the logged-odds of claiming candidate is Republican.
Numbers inside brackets reflect the 5th and 95th percentile of the draws from the posterior distribution.

Finally, I check to see if the results reported in Table 7 are moderated by subjects that are colorblind. Though, I have reasons to believe they are, the sample does not really lend itself to a robust test of this. The sample does not have a large number of respondents who indicated that they were diagnosed with some type of colorblindness. Therefore, I likely do not have enough data points for colorblind respondents in these different groups.

Posterior Predictive Checks To check whether my model specification (the variables that I included and the priors I define) are robust, I plot the posterior predictive checks for the model. These posterior predictive checks take the predicted values given my posterior distribution for each of these models, and plots the distribution of these predicted values relative to the distribution of actual values tha I have in my dataset. A well-specified model would show that there are not large nor systematic differences between the distributions of

Table 11: H_2 moderated by colorblindness

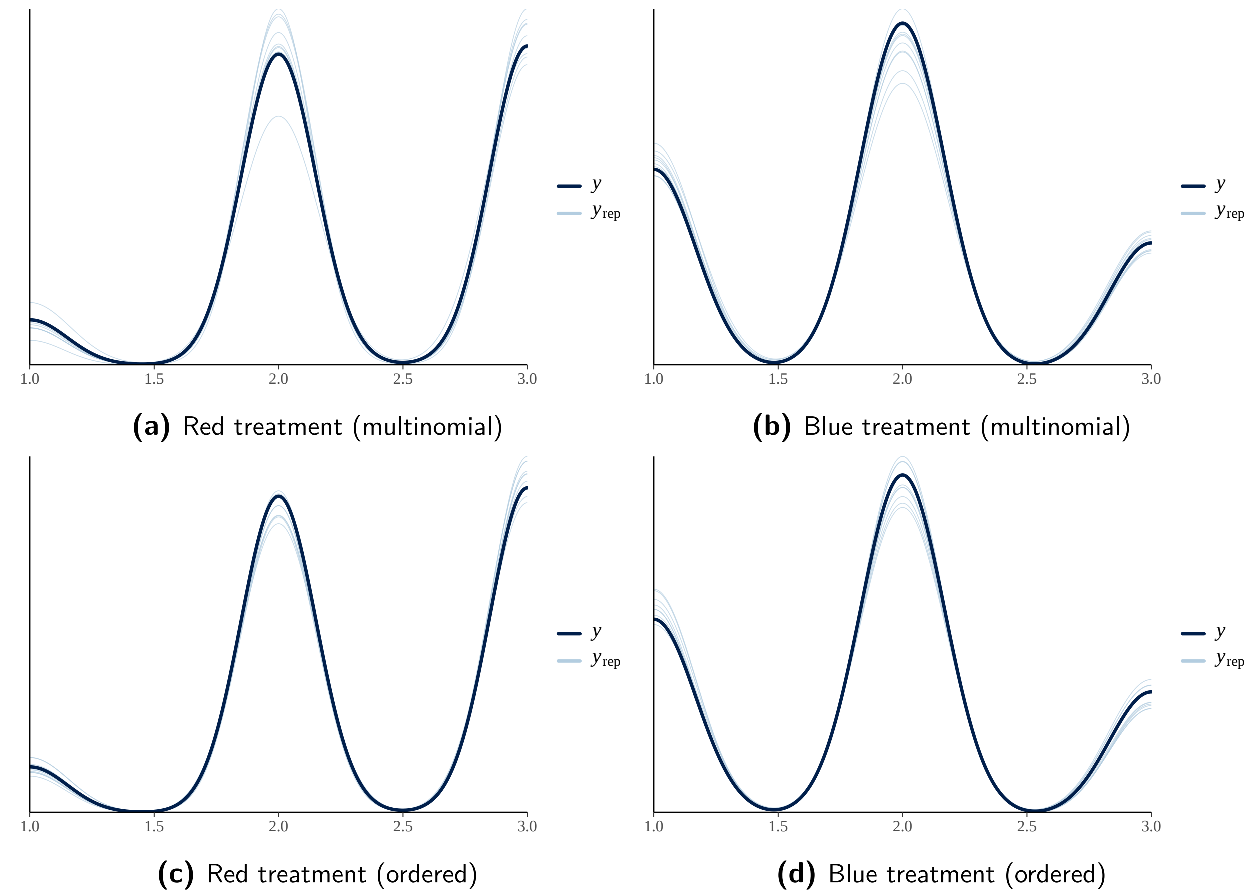
	Red - Color blindness moderating	Blue - Color blindness moderating
Red yard sign	1.912	
	[1.643, 2.190]	
Blue yard sign		−1.613
		[−1.884, −1.348]
Red yard sign × Color blind	0.781	
	[−0.543, 2.161]	
Blue yard sign × Color blind		0.199
		[−1.088, 1.504]
Intercept 1	−2.080	−1.728
	[−2.353, −1.826]	[−1.944, −1.518]
Intercept 2	1.042	0.924
	[0.845, 1.239]	[0.746, 1.098]
Num.Obs.	655.0	664.0
R^2	0.19	0.15
WAIC	1028.60	1248.55

Data source: Pavlovia

Positive coefficients reflect the logged-odds of claiming candidate is Republican.

Numbers inside brackets reflect the 5th and 95th percentile of the draws from the posterior distribution.

the predicted and actual values. Here, it appears that all of the models do a pretty good job.



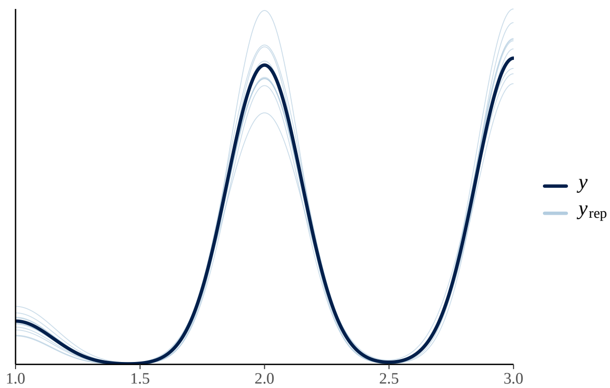
(a) Red treatment (multinomial)

(b) Blue treatment (multinomial)

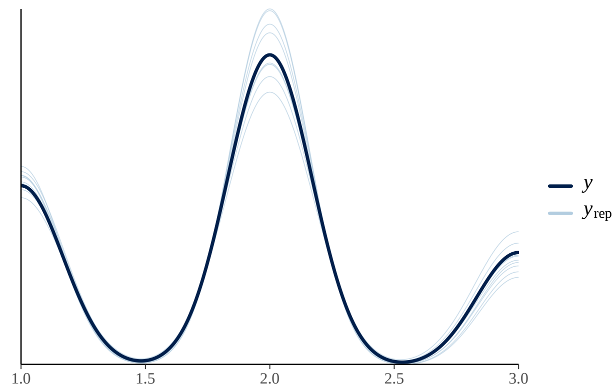
(c) Red treatment (ordered)

(d) Blue treatment (ordered)

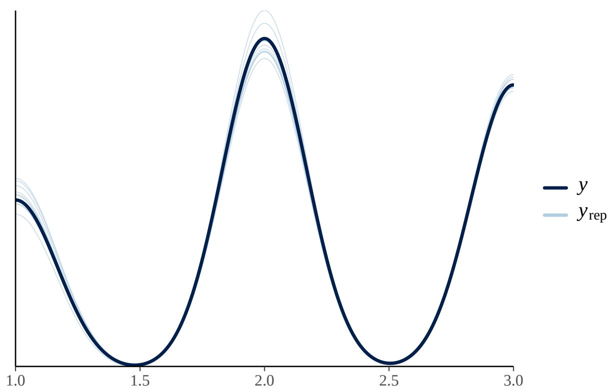
Figure 13: Posterior predictive checks of models in H_2



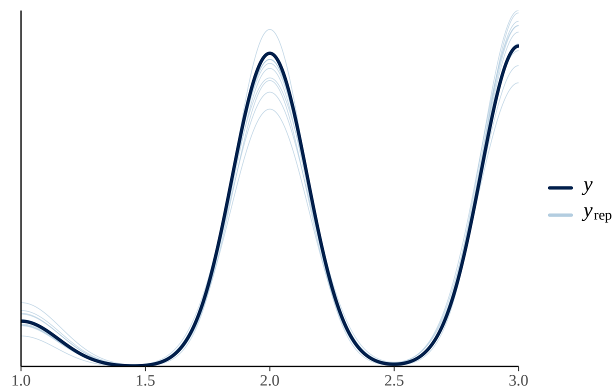
(a) Red treatment (Moderated by age)



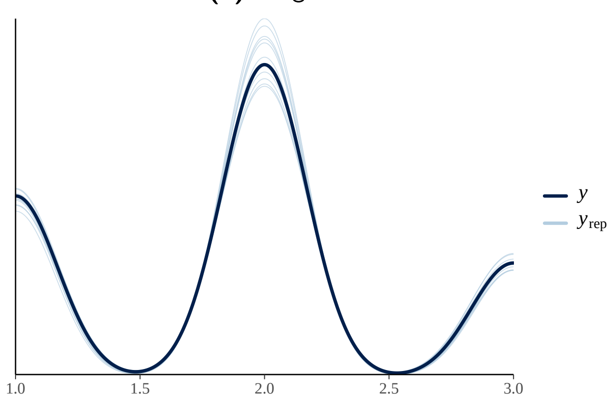
(b) Blue treatment (Moderated by age)



(c) Single model

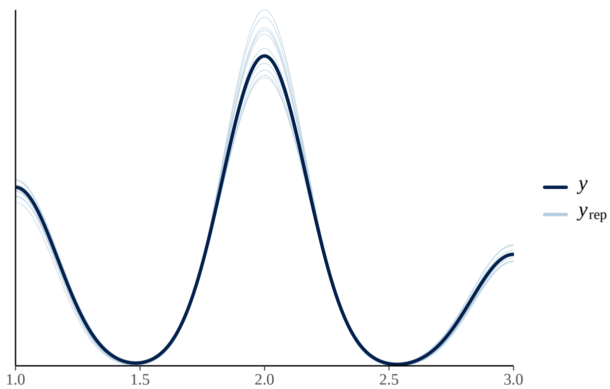


(d) Red treatment (Moderated by colorblindness)



(e) Blue treatment (Moderated by colorblindness)

Figure 14: Posterior predictive checks of models in H_2 (cont.)



(a) Blue treatment (Moderated by colorblindness)

Figure 15: Posterior predictive checks of models in H_2 (cont.)

H_{2a}

An additional analysis I include is to examine the bounds by which these effects hold if we vary the amount of partisan colors are on a yard sign. The second and third trials introduce variations of the yard signs in the first trial that include more white and even more color for the opposing political party (if red or blue condition). The goal here is to see whether these results that are reported in Table 7 are weaker for these other two trials.

I specify the exact same models as I did for Table 7. The only difference is that these variables record responses and treatment assignment for trials two and three. The results that are reported in Table 12 and Table 13 suggest that my initial suspicions have *some* validity to them. That is, we see that the effects reported in Table 7 are much weaker for blue yard signs – participants are not as decisive in reporting that the candidate with the blue yard signs are Democrats. The effects reported in Table 7 seem to hold for the red yard signs, however. Like before, I examine whether these results are robust to an alternative model specification (a single model with two treatment indicator variables). Like with tests of H_2, it appears that they are.

Models

Table 12: Full results for models testing bounds of H_2

	Trial 2 - Red treatment	Trial 2 - Blue treatment	Trial 2 - Single model
Red yard sign (Independent)	−0.925		
	[−1.398, −0.448]		
Red yard sign (Republican)	1.796		
	[1.310, 2.305]		
Blue yard sign (Independent)		−2.104	
		[−2.471, −1.743]	
Blue yard sign (Republican)		−0.866	
		[−1.308, −0.443]	
Red yard sign			1.894
			[1.632, 2.158]
Blue yard sign			−0.647
			[−0.885, −0.392]
Intercept - Independent	2.221	2.078	
	[1.915, 2.555]	[1.773, 2.386]	
Intercept - Republican	0.614	0.421	
	[0.222, 0.988]	[0.036, 0.781]	
Intercept 1			−1.402
			[−1.596, −1.223]
Intercept 2			1.064
			[0.886, 1.253]
Num.Obs.	637.0	671.0	984.0
R^2			0.23
WAIC	931.37	1209.54	1794.79

Data source: Pavlovia

Positive coefficients reflect the logged-odds of claiming candidate is not a Democrat (Columns 1 and 2) or is a Republican (Column 3).

Numbers inside brackets reflect the 5th and 95th percentile of the draws from the posterior distribution.

Table 13: Full results for models testing bounds of H_2 (cont.)

	Trial 3 - Red treatment	Trial 3 - Blue treatment	Trial 3 - Single model
Red yard sign (Independent)	-1.177		
	$[-1.672, -0.673]$		
Red yard sign (Republican)	1.777		
	$[1.260, 2.301]$		
Blue yard sign (Independent)		-2.422	
		$[-2.822, -2.037]$	
Blue yard sign (Republican)		-0.444	
		$[-0.900, -0.008]$	
Red yard sign			1.897
			$[1.628, 2.154]$
Blue yard sign			-0.153
			$[-0.389, 0.096]$
Intercept - Independent	2.483	2.334	
	$[2.143, 2.846]$	$[2.026, 2.676]$	
Intercept - Republican	0.651	0.468	
	$[0.243, 1.077]$	$[0.077, 0.878]$	
Intercept 1			-1.339
			$[-1.525, -1.152]$
Intercept 2			1.036
			$[0.863, 1.220]$
Num.Obs.	652.0	651.0	983.0
R^2			0.18
WAIC	898.12	1129.49	1808.12

Data source: Pavlovia

Positive coefficients reflect the logged-odds of claiming candidate is Republican.

Numbers inside brackets reflect the 5th and 95th percentile of the draws from the posterior distribution.

Table 14: Full results for ordered logistic regressions testing bounds of H_2

	Trial 2 - Red treatment	Trial 2 - Blue treatment
Red yard sign	2.236	
	[1.944, 2.534]	
Blue yard sign		-0.650
		[-0.902, -0.397]
Intercept 1	-1.944	-1.449
	[-2.227, -1.689]	[-1.652, -1.258]
Intercept 2	1.445	1.145
	[1.231, 1.677]	[0.959, 1.327]
Num.Obs.	637.0	671.0
R^2	0.24	0.03
WAIC	970.33	1314.53

Data source: Pavlovia
Positive coefficients reflect the logged-odds
of claiming candidate is Republican.
Numbers inside brackets reflect the 5th and 95th percentile
of the draws from the posterior distribution.

Table 15: Full results for models testing bounds of H_2 (cont.)

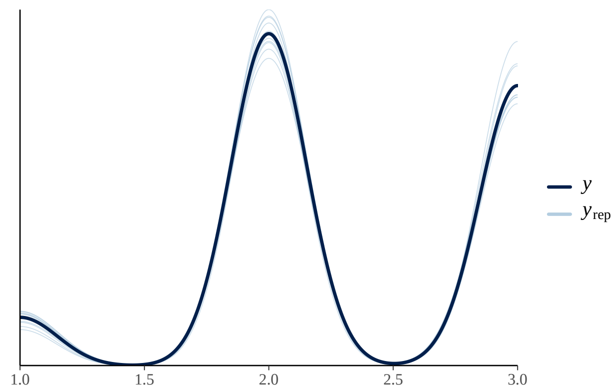
	Trial 3 - Red treatment	Trial 3 - Blue treatment
Red yard sign	2.365	
	[2.060, 2.672]	
Blue yard sign		−0.143
		[−0.386, 0.106]
Intercept 1	−2.053	−1.386
	[−2.328, −1.787]	[−1.577, −1.195]
Intercept 2	1.555	1.108
	[1.330, 1.797]	[0.924, 1.288]
Num.Obs.	652.0	651.0
R^2	0.26	0.00
WAIC	951.19	1304.58

Data source: Pavlovia

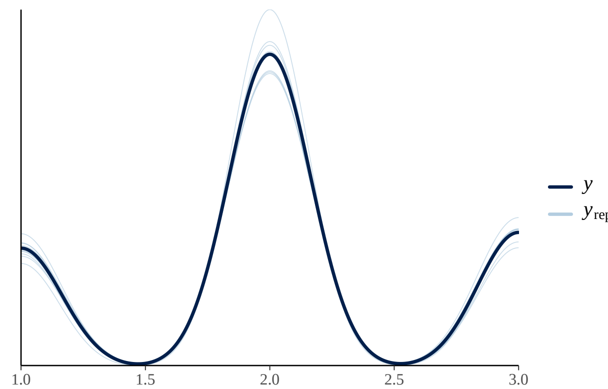
Positive coefficients reflect the logged-odds of claiming candidate is Republican.

Numbers inside brackets reflect the 5th and 95th percentile of the draws from the posterior distribution.

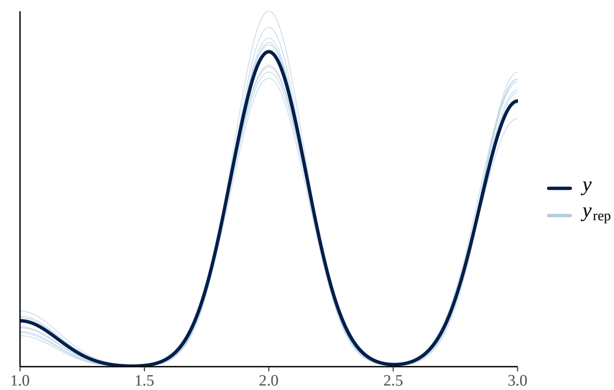
Posterior Predictive Checks To confirm that my models return predicted values from the posterior distribution that reflect my actual data, I plot the posterior predictive checks for each model. All six models appear to do a pretty good job.



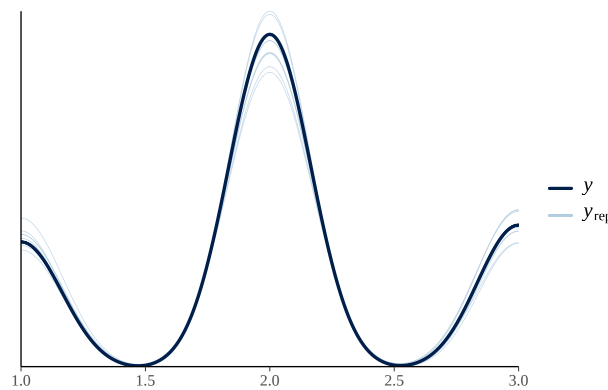
(a) Red treatment (Trial 2 - Multinomial)



(b) Blue treatment (Trial 2 - Multinomial)

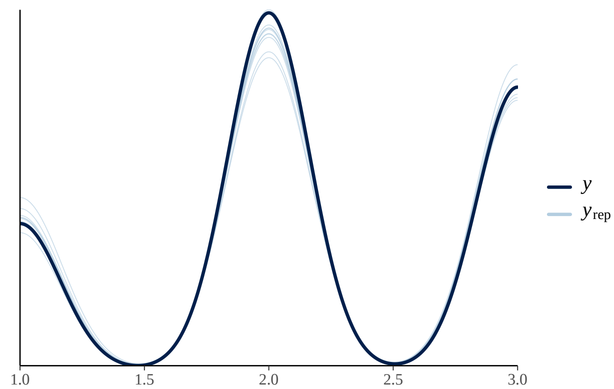


(c) Red treatment (Trial 2 - Ordered)

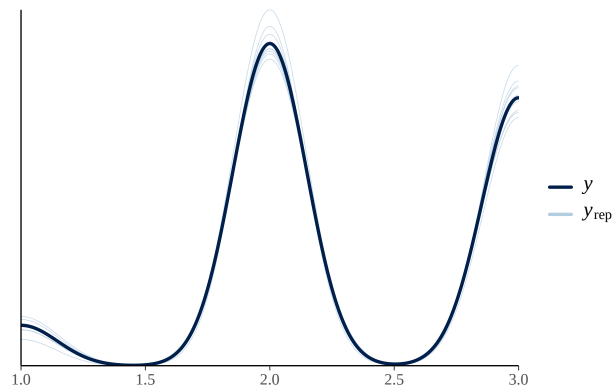


(d) Blue treatment (Trial 2 - Ordered)

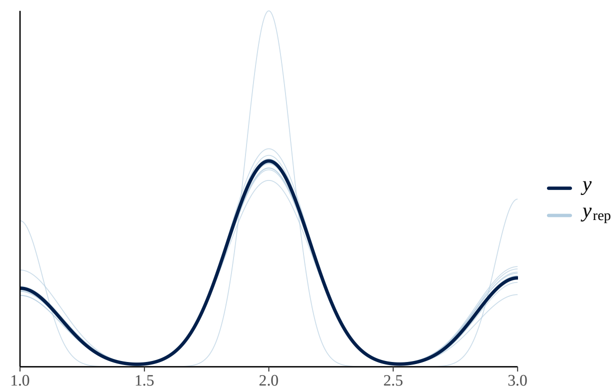
Figure 16: Posterior predictive checks of models in H_2



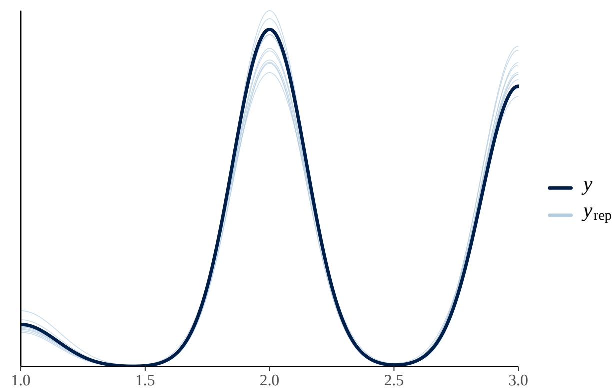
(a) Combined model (Trial 2)



(b) Red treatment (Trial 3 - Multinomial)

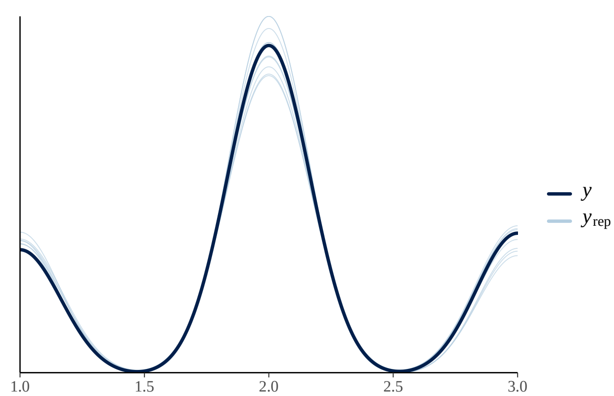


(c) Blue treatment (Trial 3 - Multinomial)

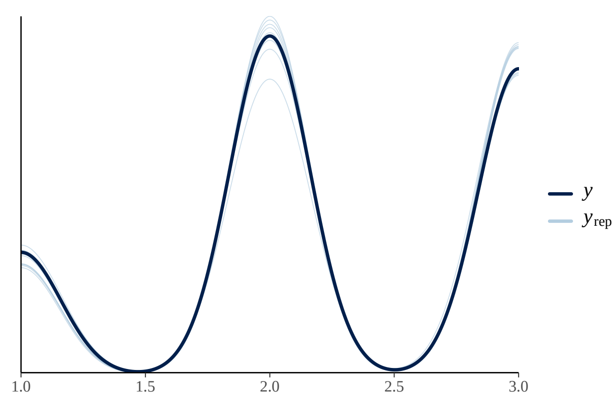


(d) Red treatment (Trial 3 - Ordered)

Figure 17: Posterior predictive checks of models in H_2 (cont.)



(a) Blue treatment (Trial 3 - Ordered)



(b) Combined model (Trial 3)

Figure 18: Posterior predictive checks of models in H_2 (cont.)

H_3

Models Here, I am testing whether candidates with red yard signs are supported more by Republican subjects and whether candidates with blue yard signs are supported more by Democratic subjects. In my original study, I ask participants after all three trials to report which of the three yard signs they would vote for. Here, I recode this response to be a binary outcome – would they vote for the first yard sign they saw (value of 1) or not. Like I have done in previous tests, I run two models – each where the predictor is a indicator of whether they received the red/blue treatment (value of 1) or the white treatment. Since the outcome is dichotomous, instead of an ordered logistic regression, I instead run a logistic regression. Since partisan identification is a primary part of the inferential task here and since it cannot be experimentally treated, I need to control for some confounds such as attention to politics, age, gender identification, and racial identity.

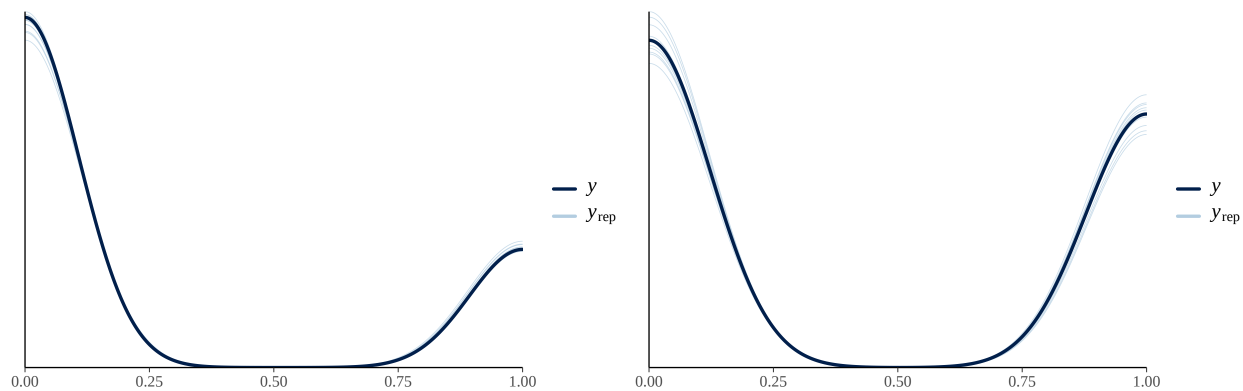
Table 16 reports the results of these models. The results suggest that Republicans are indeed more supportive of candidates using the color red, not supportive of candidates using the color blue, and are not supportive of candidates using the color white. The results also suggest that Democrats are more supportive of candidates of using the color blue, and are much less supportive of candidates using the colors red or white.

Table 16: Support of candidate based on partisanship

	Red stimuli	Blue stimuli
Red yard sign	−0.313	
	[−0.694, 0.036]	
Blue yard sign		0.630
		[0.289, 0.970]
Party ID	−0.133	−0.149
	[−0.251, −0.025]	[−0.264, −0.041]
Red yard sign × Party ID	0.813	
	[0.628, 1.004]	
Blue yard sign × Party ID		−0.343
		[−0.503, −0.182]
Attention	0.059	−0.067
	[−0.104, 0.226]	[−0.219, 0.086]
Age	0.002	−0.001
	[−0.013, 0.016]	[−0.014, 0.011]
Gender - Male	0.040	0.170
	[−0.276, 0.367]	[−0.108, 0.447]
Gender - Non-binary	0.026	0.143
	[−0.998, 0.987]	[−0.817, 1.094]
Gender - Prefer not to choose	0.655	0.382
	[−0.507, 1.780]	[−0.761, 1.445]
Black	0.281	−0.116
	[−0.480, 1.010]	[−0.724, 0.497]
Multiple races	0.020	−0.052
	[−0.808, 0.846]	[−0.747, 0.623]
White	0.506	0.422
	[−0.031, 1.068]	[−0.010, 0.841]
Num.Obs.	650.0	662.0
R^2	0.15	0.15
WAIC	658.81	830.94

Data source: Pavlovia
Positive coefficients reflect the logged-odds
of claiming candidate is Republican.
Numbers inside brackets reflect the 5th and 95th percentile
of the draws from the posterior distribution.

Posterior predictive Checks To confirm that these models return logical predictions, I again plot the posterior predictions. Figure 19 seems to suggest that both models do a pretty good job at returning a distribution fo predicted outcomes in terms of differences between those values and outcomes measured in my sample.



(a) Red treatment **(b)** Blue treatment

Figure 19: Posterior Predictive checks for H_3 models

Table 17: Checking for over-dispersion of data

	Unique (#)	Missing (%)	Mean	SD	Min	Median	Max
data	979	1	22 392.0	27 817.3	2768.0	16 501.0	539 393.0

Data source: Prolific sample.

H_4

H_4 seeks to test whether partisan subjects spend more time looking at the yard sign of political opponents than those they share a partisan identity with. Specifically, it seeks to see whether the elapsed time for the trials are longer for participants assigned to a red or blue yard sign condition if the subject is a Democrat or Republican (respectively) relative to Republicans or Democrats (respectively).

The outcome variable is a count of how many milliseconds a respondent was in a given trial. As this is count data, I have high suspicion of over-dispersion (meaning that the mean value and the median value are unequal). To make sure that I am correct in this, I generate a table reporting the summary statistics of the time elapsed in Table 17.

It appears that there is some over-dispersion here. Therefore, my choices for which type of count model to use leans away from the poisson regression and onto something like a poisson-gamma model.

Models As mentioned above, the outcome here is the time elapsed for a trial (in milliseconds). Since this is a count outcome, I should be using a type of model that uses a link function in the poisson family as opposed to the exponential family. As Table 17 demonstrated, the data are over-dispersed. Therefore, I use a poisson-gamma model as my link function which is often referred to as a negative binomial regression. I still have priors suggesting that my beta coefficients are $Normal(0, 1)$.

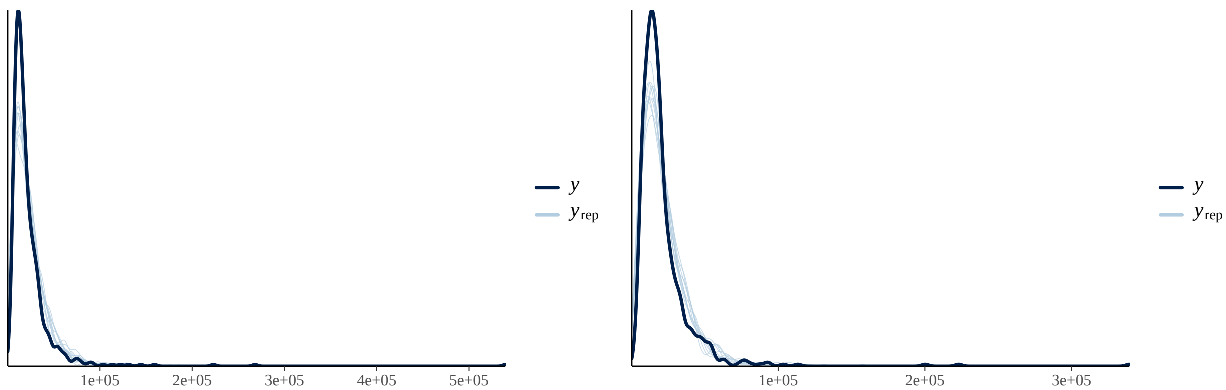
Like I have done before, I run two models. One for each partisan stimuli with the baseline category as the White yard sign condition. As the hypothesis goes beyond saying that I think subjects in the red/blue treatment will spend more time looking at the yard sign than in the white, but instead say that I think this will be moderated by partisanship, I include a interaction term in each of these models. Additionally, as partisan identification is a key explanatory variable here and is not experimentally treated, I control for a number of potential confounds such as attention to politics, age, gender identity, and racial identity. The results of these models are recorded in Table 18.

Table 18: The effect of partisan congruency on time spent looking at a yard sign

	Red stimuli	Blue stimuli
Red yard sign	0.098	
	[−0.006, 0.195]	
Blue yard sign		−0.017
		[−0.109, 0.073]
Party ID	−0.008	−0.010
	[−0.041, 0.026]	[−0.039, 0.021]
Red yard sign × Party ID	−0.036	
	[−0.083, 0.010]	
Blue yard sign × Party ID		−0.011
		[−0.053, 0.032]
Attention	−0.142	−0.120
	[−0.183, −0.099]	[−0.158, −0.081]
Age	0.020	0.020
	[0.016, 0.023]	[0.016, 0.023]
Gender - Male	−0.037	−0.011
	[−0.130, 0.053]	[−0.094, 0.072]
Gender - Non-binary	−0.069	0.173
	[−0.401, 0.278]	[−0.122, 0.493]
Gender - Prefer not to choose	0.281	0.023
	[−0.178, 0.818]	[−0.327, 0.417]
Black	0.293	−0.017
	[0.073, 0.512]	[−0.214, 0.176]
Multiple races	0.130	0.017
	[−0.126, 0.384]	[−0.194, 0.232]
White	0.155	−0.051
	[−0.011, 0.316]	[−0.189, 0.085]
Num.Obs.	653.0	663.0
R^2	0.06	0.07
WAIC	14 202.58	14 240.47

Data source: Pavlovia
Positive coefficients reflect the logged-odds of claiming candidate is Republican.
Numbers inside brackets reflect the 5th and 95th percentile of the draws from the posterior distribution.

Posterior Predictive Checks As I made a modeling choice based on the over-dispersion of the outcome variable, I want to confirm that these models did an adequate job at returning predicted values based on my posterior distribution relative to the actual data in the sample. The posterior predictive checks suggest that it did indeed do a pretty good job. It looks like I may be slightly underestimating some lower values for the elapsed time, but the distribution on the whole looks pretty good – including on the tails.



(a) Red **(b)** Blue

Figure 20: Posterior predictive checks of H_4 models

H_5

For H_5, I am interested in examining whether or not districts that lean towards one party more than the other have candidates use more of the color in line with the party that has a historical advantage and less of the color for the party that tends to suffer electorally speaking.

Summary Statistics of yard sign color measure

Models As I mention in the main text of the book, I note that I regress the 5-year rolling average of the democratic vote share in a state upon the proportion of the color red and blue

Table 19: Summary statistics of proportion of colors present on yard signs

	Unique (#)	Missing (%)	Mean	SD	Min	Median	Max
% Red	351	0	6.1	14.7	0.0	0.7	94.2
% Blue	547	0	31.7	28.2	0.0	21.7	95.3
% White	453	0	17.2	18.0	0.0	12.2	78.2

Data source: CAPD Yard Signs.

on the yard signs downloaded from the Center for American Political Design. The outcome is a continuous and bounded variable between the value of 0 and 1. I note in the main text that I use a ordered beta regression, but here I provide more specifics. As the outcome is continuous but bounded between 0 and 1, treating the outcome variable as a continuous variable with no finite bounding as I would with a OLS would be inappropriate. To ensure that I am using the most appropriate estimator to explain the outcome of interest, I elect to use an ordered beta regression. Beta regression models are a type of distributional model that essentially tries to model the distribution of the outcome variable. The standard beta regression model can fit models where the outcome is (0, 1). However, my outcome is [0, 1). I could elect to use a zero-inflated beta regression which would allow me to appropriately model this outcome. However, Kubinec (2022) demonstrates that the ordered beta regression is a much more efficient and accurate (in terms of a number of various metrics) approach to dealing with outcomes that can equal either 0 or 1.

The default priors for β_i is $N(0, 5)$ in the *ordbetareg* (Kubinec 2022) package that I use to fit the model. However, I receive warnings indicating that there are divergent transitions. For Hamiltonian Monte Carlo, divergent transitions indicate that the sampler is having problems with the curvature of your posterior distribution. As I note in the main text of the book, I am using a multilevel model that includes a partially pooled parameter for the districts and

Table 20: The effect of democratic vote share on color choices for yard sign

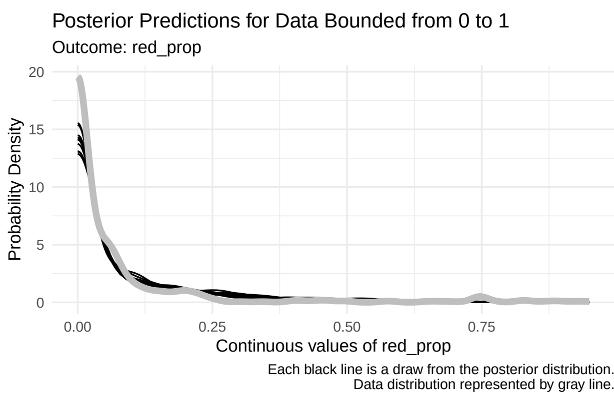
	Prop. yard sign Red	Prop. yard sign Blue
Democratic vote share (percent)	-0.408	0.597
	$[-0.868, 0.063]$	$[0.128, 1.060]$
Intercept	-2.028	-0.996
	$[-2.325, -1.754]$	$[-1.257, -0.734]$
Num.Obs.	725	725
RMSE	0.13	0.22

Data source: Center for Political Design and MIT Election Lab
Positive coefficients reflect the logged-odds
of claiming candidate is Republican.
Numbers inside brackets reflect the 5th and 95th percentile
of the draws from the posterior distribution.

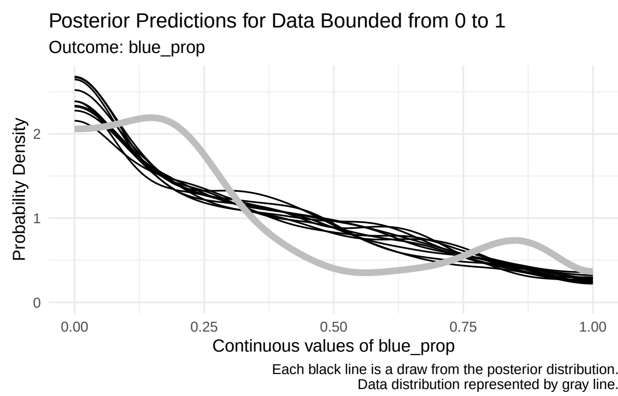
use two non-pooled parameters for the state and the election year. This is a pretty complex problem. Especially given the estimator that I am using here. More troubling still is that my $\hat{R}$ values are not equal to 1 for either model. These two things together suggest that there is a pretty serious problem and that my posterior distributions are quite unstable.

To try to fix this issue, I adjust the prior for β_1 to $N(0, 2)$. While I still receive a warning about divergences in both models, the number of them drops down to about 30 out of 4000. Additionally the $\hat{R}$ values are at 1. Together, these tell me that these priors likely helped the models quite a bit and feel more confident in the stability of my model. Table 20 presents the results of this second specification of the model.

Posterior predictive checks



(a) Proportion of yard signs red



(b) Proportion of yard signs blue

Figure 21: Posterior Predictive checks for H_5