# Revisiting the Measurement of Group Schemas in Political Science

Kirill Zhirkov[1] and Nicholas A. Valentino[2]

[1] Department of Politics, University of Virginia

[2] Department of Political Science, University of Michigan

[Forthcoming in *The Cambridge Handbook of Implicit Bias and Racism*]

**Abstract**

While schema theory motivated the original measures of automatic cognitive associations between constructs in memory, researchers soon modified these to explore a different domain: implicit attitudes about social groups that elude standard self-reports. As the so-called implicit attitude revolution gained steam, the original measurement goal got much less attention, especially in political science. We believe the schema concept—automatic cognitive associations between features of an attitude object—continues to hold great value for political psychology. We offer a retrofit of the popular implicit association test (IAT), one more efficient than many lexical tasks, to tap these associations in surveys. The new technique captures the degree to which citizens link ideas about ostensibly group-neutral policies to specific social categories. We use this measurement strategy to explore the psychological mechanisms underlying group centrism in politics, an effort that has been largely abandoned due to measurement difficulties. Results from four studies offer practical suggestions about the application of implicit measures for capturing the automatic ways people link groups to important political objects. We conclude by discussing the broader promise of implicit measurement of group schemas, not just implicit affect, for political psychology.

*Keywords:* group schema, partisanship, affective polarization, welfare, public opinion, implicit cognition, gender, race

# Revisiting the Measurement of Group Schemas in Political Science

In his groundbreaking work, *The Nature of Belief Systems in Mass Publics*, Converse (1964) raised a number of foundational puzzles for political psychologists. The central finding, defying the conventional wisdom at the time, was that very few people think of politics in ideologically coherent ways. This result has held up nicely over the last fifty years (Kinder & Kalmoe, 2017): Instead of left–right ideology, most citizens seem to rely on social identities as shortcuts for constructing political judgments. In other words, policy opinions are group-centric, i.e. driven strongly by attitudes toward groups who might help or harm the individual or his co-ethnics (Nelson & Kinder, 1996). Group centrism implies that policies benefiting "deserving" groups—the ones a respondent identifies with or likes—receive greater support. Converse's work, followed by many others, suggests that effortful thought about how policies and parties map onto the interests of the individual citizen was not an empirically valid model for explaining mass politics. Instead, political thinking seems to be quick, group-centric, affective, and highly symbolic (Sears, 1993).

So, we begin with these assumptions that group identities and affect are central to political cognition, and that people do not usually think very hard about politics. The limitations of human information processing have been recognized for over a half-century (Simon, 1957). These constraints are often conceptualized in the form of social stereotypes—strong and persistent connections linking groups to other categories, attributes, and/or behaviors (Schneider, 2004). Stereotypes may help simplify complex social interactions and facilitate political coalition building, but they also can exacerbate discrimination and undermine citizens' ability to make choices that maximize benefits and minimize costs (Page, 2007). Furthermore, stereotyping has a decidedly affective dimension: People feel strongly about specific groups, and those attitudes contribute to the severity of problems stereotypes create. All these insights have led to large advances in understanding mass political dynamics. Unfortunately, they may also have led scholars away from consequential variation in non-affective political cognition—the simple but important linkages people make about what goes with what in the political world.

In order to more fully understand the origins and dynamics of group centrism in politics, we revisit some basic insights about social cognition that emerged in social psychology almost four decades ago in the form of the schema theory (Fiske & Linville, 1980; Taylor & Crocker, 1981). Soon after, political scientists suspected that the theory could explain the persistence and real-life impact of automatic cognitive associations between social groups and political objects. The schematic model was thus introduced to political science in the 1980s (Conover & Feldman, 1984). Unfortunately, it was never exhaustively tested—primarily, we think, due measurement challenges. Public opinion surveys carry serious obstacles for directly measuring automatic mental connections. Instead, the existence of schemas was often inferred by associations between group attitudes and political objects.

In this chapter, we propose a novel measurement strategy that addresses a core weakness of existing approaches, namely their inability to assess the strength of associations between social groups and political attitude objects at the individual level. Our method is based on objective time response technique and uses the architecture of the implicit association test (IAT; Greenwald et al., 1998). We thus revisit the original goal of implicit tasks: measuring associations between concepts in memory independent of their emotional or affective content. Using this strategy, we run four studies testing the schematic approach.

The chapter is organized as follows. We first recapitulate the basic tenets of the schematic approach to social cognition and, specifically, its application to the realm of politics.

Then, we briefly outline the history of implicit measurement, emphasizing its original focus on non-affective associations in memory, and introduce our original instrument. We next present results from four studies, in which we apply the new measure across political attitude domains and national contexts. Following these results, we formulate some practical suggestions for researchers interested in using this approach in their own work.

## The Schematic Model of Human Cognition

Schema theory posits that the human brain builds associative networks over time, linking related concepts in memory (Anderson, 1983). Each specific concept in memory is conceived of as a node, with linkages between nodes varying in strength depending on how frequently or recently concepts have been paired in previous experience. A schema is thus a network of nodes (concepts) in memory connected with edges (cognitive associations).

Consider the following example. Humans tend to associate birds with singing, so that hearing birdsong causes a person to automatically imagine a bird, even if one is not seen. The association is likely automatic, i.e. an image appears in the mind without conscious effort. Greater experience with birds leads to more developed associations. For instance, experienced birders easily recognize many species by their songs, and can call up in their minds the coloration, size, and behavior of the bird producing a given melody. In general, a target category (bird) becomes associated with attributes (singing, coloration, size) in memory.

In just the same way, social schemas help individuals to organize existing knowledge and collect new information about the world. Specifically, they help people make sense of abstract social categories by associating them with familiar people and/or situations, reducing the cognitive effort needed to process novel information and make decisions about how to act (Moskowitz, 2005). Associations between social attributes within schemas allow people to correctly interpret relevant information about the object and use it to make guesses about other characteristics that are unavailable at the time. As noted by Bruner and Goodman (1947):

> Perceptual categorization of an object or event permits one to go beyond the properties of the object or event perceived to a prediction of other properties of the object not yet tested. The more adequate the category systems constructed for coding environmental events in this way, the greater the predictive veridicality that results. (p. 14)

In other words, schemas significantly enhance the efficiency of social cognition.

At the same time, schema-based reasoning carries several potential costs. First, schemas lead individuals to discount or dismiss information that does not fit the mental model (Hunzaker, 2016), even when the new information is valid. In other words, schemas are relatively stable and resilient to change. Second, schemas do not necessarily spring from lived experiences, but can also be derived from biased sources such as friends, media, or trusted authorities. Third, schemas are usually assumed to be activated automatically in response to stimuli, without regard for their usefulness in each particular case (Bargh et al., 1996). All these features suggest the use of schemas can sometimes lead to suboptimal outcomes. Think, for example, about rejecting a prospective job candidate as a result of negative stereotypes about their ethnic group even when the individual is trustworthy, hardworking, and would ultimately do the best job.

Another point of debate is whether the impact of schemas springs entirely from the massive unconscious underside of the iceberg of human cognition or, instead, from the conscious tip visible above the waves. Social and cognitive psychologists have yet to arrive at a consensus about how much of our cognition is automatic and outside conscious awareness (Bargh & Chartrand, 1999; Dijksterhuis & Bargh, 2001). However, they do agree that schemas need not be consciously acknowledged in order to impact opinions and behavior.

## The Schematic Model for Politics

All the features of schemas discussed above make their application particularly relevant for the study of political cognition since politics often forces people to make judgments about objects that are distant and unfamiliar. For example, the decision whether to support a single-payer system of health care provision vs. one based on the private insurance market requires a great deal of information almost no one posseses. This makes the application of schemas useful. If one's schema for "government" includes the features like "wasteful" and "inefficient," it is much easier to make this decision. Of course, the nature of the political process amplifies the perils of schemas as cognitive tools: They can make political loyalties more rigid, give political actors incentives to misrepresent information, and lead to decisions that undermine the interests of voters.

An important contemporary example of this logic lies in the domain of immigration. If the theory we advance is correct, policy schemas that become entwined with social groups may lead to profound biases in the application of the law. For instance, one of the strictest and most sweeping immigration laws in the U.S., SB 1070, was passed in 2010 in Arizona requiring law enforcement officers to inquire about the citizenship status of individuals they were arresting if they suspected that person was in the U.S. illegally. Critics of the law argued that citizens belonging to social groups stereotypically marked as immigrants—most importantly, Latinos—would be actively and disproportionately profiled. Indeed, Americans do seem to think of Latinos when they think about immigrants (Valentino et al., 2013). These well-worn mental links might lead to an unfair burden on innocent Latino citizens.

The schematic model was originally imported into political science from social psychology in order to explain the origins and evolution of mass belief systems (Conover &

Feldman, 1984). The initial formulation of the model was therefore quite broad: It was thought to encompass the way the brain stored information about a wide array of political attitude objects including values, issue positions, party attachments, and candidate preferences. However, the approach was later narrowed to specify the way attitudes about social groups in particular mapped onto mass political preferences (Conover, 1988).

The model rests on a series of assumptions that are now widely accepted in behavioral political science. It begins with the premise that human cognitive resources are limited, so that the average person prefers not to deliberate very extensively about politics. In order to make judgments about political objects more efficient, individuals rely on schemas.[1] A large share of these schemas represent links between political objects—policies, parties, and candidates—and social groups, with which people have a lot of experience. Importantly, as a group and a political object become schematically linked, emotions about the group are transferred onto political preferences.

The model offers a nice framework for understanding the role of groups in public opinion formation. First, it is grounded in a large literature in social and cognitive psychology. Second, it is based on intuitive and uncontroversial assumptions. Third, it illuminates a psychological mechanism that may underlie the long observed statistical association between opinions about social groups and political preferences. Finally, this model is general: It can help explain public opinion formation in a variety of cultural contexts and across national borders.

To date, however, applications of the schematic model in empirical research on public opinion have been surprisingly limited. We suspect the measurement of schemas has been a key

[1] Our use of the term "schema" is different from the one suggested by Conover (1988). She distinguishes between the four types: self-schemas, ingroup schemas, outgroup schemas, and causal schemas. We believe the first three types are largely equivalent to group identities and/or group attitudes. Therefore, we reserve the term "schema" for the fourth category: a cognitive linkage between a social group and a political attitude object.

obstacle. Consider the elements of the model as presented in Figure 1. Figure 1a represents the model as it has been tested to date in a variety of studies, including the original paper by Conover (1988). Researchers estimate a regression model predicting a political preference, such as issue opinion or evaluation of a political party/candidate, with a relevant group attitude and interpret a significant coefficient as evidence for the respective schema.

INSERT FIGURE 1 HERE.

This approach is problematic because the key variable—the nature and strength of a cognitive association between a group and a political object—is never measured. By omitting schema from the estimated model, researchers essentially assume it to be constant at a relatively high level across the population. A strong test of the model would include an individual-level measure of schema direction and strength (as in Figure 1b). Conceptually speaking, schemas moderate the effect of group attitudes on political preferences.

## Measuring Cognitive Associations

Scholars have explored a wide variety of techniques for tapping cognitive associations between constructs in memory. Early attempts were based on observable implications of the underlying model: Activating one node in a schematic network would bring closely linked nodes to mind, a phenomenon known as “spreading activation” (Collins & Loftus, 1975). For example, making gender salient by having a person focus on what it is like to be a man or woman leads them to identify gendered nouns (such as “mother” vs. “father”) more quickly than gender neutral ones in a lexical task. The original motivation for measures like this one was to examine whether automatic accessibility could be altered by a prime (Fazio, 1990). So, for example, one would prime the concept “rude” via a sentence construction task where random word strings were placed in an order that would convey norm violating behavior and then an observation of the individual's subsequent behavior would be taken (Bargh et al., 1996). Simple lexical response tasks like this were also used in priming research, where the speed of recognition of words relevant to a schema were contrasted with unrelated letter strings after exposure to a stimulus.

Several consistent empirical patterns have emerged from this body of work, largely confirming the basic tents of schema theory. First, people cannot recall or process every possible category relevant to a given decision (Taylor & Fiske, 1978), so they utilize the most accessible categories to classify stimuli while making decisions. For instance, impressions of a person are significantly colored by priming a positive or a negative trait in an unrelated task (Higgins et al., 1977): An individual described as enjoying risky outdoors activities is assessed as "adventurous" vs. "reckless" depending on whether affectively charged personality traits (persistant vs. stubborn) have been primed. This result is in line with the accessibility hypothesis as salient categories are used more readily than others during impression formation about the self and others (Tversky & Kahneman, 1974; Srull & Wyer, 1979).

Another important aspect of the category activation process is the "fit" of the primed category with the incoming stimulus (Bruner, 1957): The priming effect is strongest when the active trait categories are applicable to the description of the stimulus person. In the example above (Higgins et al., 1977), the primed traits were only applied to behaviors that were relevant. This phenomenon has important implications for priming effects related to social identities, such as gender. For example, priming gender-specific traits leads subjects to more quickly identify female pronouns compared to nonsense letter strings—even when they are told that the gender primes are irrelevant to the task, suggesting gender stereotypes are activated automatically (Banaji & Hardin, 1996). Similarly, subjects primed to think of women as sexual objects respond faster to sexist words in a lexical task and are subsequently more likely to evaluate female job applicants in stereotype-consistent ways (Rudman & Borgida, 1995). Thus, when a social group is made salient, it is invoked automatically in subsequent decision-making involving the relevant identity.

Altogether, these early attempts to capture schematic associations attempted to change the cognitive associations of interest—and, therefore, were based on the assumptions that relatively strong and uniform schemas existed within the population. It is interesting that the two most widespread types of survey experiments in political psychology, aimed at identifying framing and priming effects (Chong & Druckman, 2007; Hutchings & Jardina, 2009), make assumptions identical to the schematic model. Priming experiments attempt to activate or suppress a specific schema, such as in the case of race and redistribution (Valentino et al., 2002), whereas framing studies aim to switch between different schemas, such as free speech vs. public safety in the context of a Klan rally (Nelson et al., 1997). These experiments, however, return only a single result indicating either the presence or absence of the hypothesized association, not its strength in the mind of any individual in the sample. Our goal in this chapter is to come up with an individual-level measure of schema strength that would allow the reseacher to (a) uncover the previously underexplored variance of schematic associations and (b) estimate the effects of these schemas on political outcomes of interest.

## The Implicit Association Test Architecture

To measure the direction and strength of group schemas in political cognition, we adopt a modified version of the implicit association test (IAT; Greenwald et al., 1998). The IAT has been validated repeatedly in psychological research (Greenwald et al., 2009), and its creators maintain a comprehensive online infrastructure that eases its application in practice.

The standard IAT measures the strength of associations between concepts (e.g., flowers vs. insects) and affective attributes (e.g., pleasant vs. unpleasant). The task requires respondents to quickly sort stimuli (pictures, symbols, or words) into categories that are on the left- and right-hand side of the computer screen by pressing the left-hand key if the word belongs to the category on the left and the right-hand key if the word belongs to the category on the right. The main idea behind the IAT architecture is that classification is easier, and therefore faster, when closely related items share the same response key. If an attitude object is positively affectively valenced ("flower"), an individual will more quickly pair the object with an affectively positive word ("pleasant") compared to an affectively inconsistent one ("unpleasant"). The normalized difference between sorting times in affectively consistent versus inconsistent pairs is known as the D-score.

To date, timed-response tasks have been applied most often to measure implicit affective evaluations of social groups or political objects, which are then used to predict explicit attitudes and behvaiors (for a comprehensive review, see Gawronski et al., 2015). A more recent application is the "implicit identity" task, a variant of the IAT that uses references to the respondent ("self") vs. others and a social group of interest to measure identification strength (Hawkins & Nosek, 2012; Theodoridis, 2017). Within the task, respondents sort stimuli denoting self (e.g., Me or My) and others (e.g., Them or Their) and stimuli denoting the identity category of interest, such as a political party. This particular application is closest to ours because it does not involve affective evaluations of any object—but also distinct because it taps links between the self and an attitude object, not general associations between concepts and/or attributes.

The IAT has drawn some criticism for both theoretical and methodological reasons. Some have suggested that differences in sorting times may simply tap the awareness of a group's social stigma, not the respondent's true attitude, let alone an intention to discriminate (Arkes & Tetlock, 2004). Low test–retest reliability of individual IAT scores has also been a persistant problem (Nosek et al., 2005). In addition, it is unclear how the scores substantively map to the underlying theoretical construct—such as prejudice in the case of the best known "race IAT" (Blanton & Jaccard, 2006). Finally, IAT scores heavily depend on the specific stimuli used as well as on the overall context in which the test is taken (Meissner & Rothermund, 2015; Rothermund & Wentura, 2004).

Here, we do not use the IAT to measure affect, therefore the problems mentioned above are not germane. Our application of the task is not designed to categorize respondents as prejudiced or not—instead, D-scores simply rate respondents in terms of direction and strength of the cognitive association between a social group and a political object. We can then asses whether this mental link interacts with explicit affective evaluations of the former to predict explicit affective evaluations of the latter. Whether the IAT measures "true" cognitive linkages between social groups and political objects or just the "awareness" that many others believe such linkages exist is, after all, an empirical question. If we are simply tapping beliefs about the societal prevalence of such associations, and those are orthogonal to an individual's own cognitive associations, then the interaction between schema strength and group attitudes will be unrelated to political outcomes of interest.

Finally, since the IAT requires precision in capturing response times, its use online—the most cost-effective mode of data collection in the social sciences—has been limited until recently due to wide variations in internet connection speeds. Fortunately, a variety of software solutions exist. One is Inquisit Web, software developed especially for implementation of the timed-response tasks in online studies.[2] Respondents download a browser plugin that implements the task on their local hard drive and then transfers recorded data to a server, so that response latencies are not impacted by the user's network connection speed.

## Outline of Empirical Studies

We validated our measurement instrument and test the schematic approach to public opinion formation in four studies. Studies 1 and 2 addressed the cognitive linkages between political parties and social groups building upon the approach to partisanship as an "umbrella" identity (Green et al., 2002; Lazarsfeld et al., 1948). Studies 3 and 4 revisited a well-known example of group–policy linkage in political psychology: the racialization of social welfare in the United States (Brown-Iannuzzi et al., 2017; Gilens, 1999).

In all four studies, we followed the same procedure. We measured the schemas of interest using the proposed IAT architecture. Then, we looked at descriptive statistics on schema distributions within the studied samples. Mean scores significantly different from zero signified the presence of a non-trivial association between the two categories of interest, e.g. a social group and a party or policy. Then, we used these scores to predict relevant political outcomes. See Table 1 for the list of studies.

INSERT TABLE 1 HERE.

## Study 1: Gender and Parties in the U.S.

We first explored the value of our new measure by examining the political consequences of variation in the cognitive association between gender and the two major parties in the United States. We refer to these associations as the "gender–party schemas." Americans have been found to hold gendered images of the parties—i.e., they commonly associate femininity with

[2] https://www.millisecond.com/products/inquisit5/weboverview.aspx

Democrats and masculinity with Republicans—according to both explicit and implicit measures (Winter, 2010). In addition, gender attitudes have been found to significantly impact political behavior in the United States (Valentino et al., 2018). Here, we used a measure of group–party linkages based on the IAT architecture to replicate and extend these previous findings. Our goals have been to validate the proposed measurement strategy and test whether gendered images of parties are consequential for partisan attitudes.

**Data and Measures**

We recruited respondents using Amazon Mechanical Turk (MTurk), oversampling moderates and conservatives to balance the sample on political ideology.[3] Analyzed dataset included only those who completed both survey and IAT parts, responded from the United States, had unique IP addresses, and showed acceptable error rates in the IAT task (less than 25%).[4] The total number of valid cases was 619 out of 703 otherwise completed surveys.[5] In the analyzed sample, 84.8% respondents self-identified as White. The sample was balanced in terms of gender (54.9% female), but overrepresented the highly educated, with nearly half having Bachelor’s degrees or higher (47.4%). The modal household income was between $30,000 and $39,999. The modal age was between 25 and 34 years. In terms of partisanship, 37.0% of respondents identified as Democrats, 35.9% as Republicans, and 27.1% as independents.

In constructing the gender–party IAT, we used masculine and feminine English nouns—e.g., Boy vs. Girl—similar to the “gender–career IAT” (Nosek et al., 2002). For the symbols of the Democratic Party and the Republican Party, we used a collection of publicly available

[3] Despite being substantially more diverse than most other convenience samples, such as college students, MTurk is know to significantly overrepresent liberals compared to the general population (Berinsky et al., 2012).

[4] For each unique IP address, we kept only the first (earliest) response. This procedure was applied in all four studies described in this chapter.

[5] Throughout all four studies, we also lost participants when merging survey and IAT responses across Qualtrics and Inquisit software platforms. We elaborate on this technical problem and potential ways to deal with it in General Discussion.

images representing official as well as unofficial logos and mascots (elephants vs. donkeys), campaign buttons, and posters. IAT D-scores were calculated from the observed response latencies according to the updated guidelines (Greenwald et al., 2003). Note that, in theory, D-scores can assume values in the interval from −2 to 2.

Gender attitudes were assessed using a shortened 4-item version of the hostile sexism scale (Glick & Fiske, 1996). Cronbach's $\alpha$ statistic was .88 suggesting good reliability. In our regression analyses, we normalized respondents' sexism scores from 0 (least sexist) to 1 (most sexist).

Attitudes towards political parties were measured using an 11-point scale with greater values indicating more positive feelings. Using these scores, we calculated the difference in attitudes towards Democratic Party and the Republican Party that could take values from −10 (maximum attitudinal preference for Democrats) to 10 (maximum attitudinal preference for Republicans).

**Results**

Figure 2 presents the empirical density of D-scores in the sample. The distribution was bi-modal and a Shapiro–Wilk test rejected normality ($z = 3.30$, $p < .001$). One mode coincided with the neutral point, where respondents were no faster in identifying the schema-consistent pairings (Democrat/female, Republican/male), compared to the schema-inconsistent pairings (Democrat/male, Republican/female). Another mode indicated a group of respondents with rather strong stereotype-consistent gender–party linkages. The overall mean D-score was therefore positive ($b = 0.16$, $p < .001$), indicating that the average respondent in our sample implicitly associated the Democratic Party with women and the Republican Party with men.

INSERT FIGURE 2 HERE.

Next, we turned to a test of a substantive hypothesis regarding the impact of gender–party schemas on partisan attitudes. We first estimated regression models independently for males and females. If the schematic model is correct, the more strongly one associates own gender with a given party, the greater should be one's attitudinal preference for that party. Results of the regression analysis presented in Table 2 showed strong support for this conjecture. In both cases, schema strength had a statistically significant effect on partisan attitudes in the predicted direction. Specifically, males who thought of the Republican Party as male and the Democratic Party as female expressed much more positive evaluations of the Republican party. For females, the effect was the complement: Having a masculine image of the Republicans and feminine image of the Democrats led women to feel much warmer towards the Democratic Party. The magnitude of the schema effect on party preference was somewhat larger for women than for men but the difference was not significant ($p$ = .073). The explained variance in partisan preference was almost three times as large for women than for men but variables other than the gender–party schema such as age, education, and race contributed to this difference.

INSERT TABLE 2 HERE.

To test whether schema strength multiplies the impact of group attitudes on partisan preferences, we estimated the interactive effect of gender–party schema strength and hostile sexism on attitudinal preference for the Republican Party. Results are presented in Table 3. The interaction was significant and in the predicted direction: Schema strength amplified the relationship between sexism and the preference for Republicans over Democrats.

INSERT TABLE 3 HERE.

In order to interpret the coefficients in Table 2, we present the interaction in graphical form (Brambor et al., 2006). Figure 3 plots the estimated effects of sexism on the affective distance between Republican and Democratic parties, moderated by the strength of gender–party schemas. Overall, everyone in the sample exhibited the expected effect as those high in sexism felt more warmly toward the Republican Party relative to the Democratic Party. However, the magnitude of this effect increased substantially as the strength of gender–party schemas increased. Specifically, the effect of sexism on affective preference for Republicans over Democrats was almost three times greater for respondents who thought of Republicans as masculine and Democrats as feminine, compared to those holding the opposite schema. The estimated difference in partisan preference between the least and most sexist respondents was 5 points (out of maximum 20) among those with counter-stereotypical gender–party schemas, but more than 15 points among those with pro-stereotypical schemas.

INSERT FIGURE 3 HERE.

**Discussion**

The results of Study 1 supported the schematic model with regard to gender and partisan attitudes. First, we found that respondents had relatively strong cognitive linkages between gender and political parties: Individuals, on average, were quicker to pair Democratic/feminine cues and Republican/masculine ones compared to when counter-stereotypical pairings are given. Second, the strength of this linkage was a significant predictor of partisan affective polarization. Respondents felt warmer towards the party they implicitly linked to their gender. Finally, the gender–party schemas interacted significantly with attitudes towards women. Specifically, endorsement of pro-stereotypical gender–party schemas powerfully amplified the effect of sexism on attitudinal preference for the Republican Party.

## Study 2: Religion and Parties in the UK

We next extended the investigation of implicit group–party schemas to a different context. In Study 2 we explored whether respondents in West European countries had developed schemas linking center-left parties with minority groups. Center-left parties, compared to their right-wing counterparts, are more willing to embrace growing ethnic and religious diversity in Europe—for instance, by nominating politicians with minority backgrounds for political offices (Dancygier, 2017). This shift might have altered popular schemas about partisan coalitions and contributed to the observed decline of the mainstream social democratic parties (Berman, 2016). As a testing ground, we used the UK and religious (Christian vs. Muslim) schemas about its main center-left political force, the Labour Party.

### Data and Measures

To collect the data, we used the UK-based crowdsourcing platform Prolific. A recent study has suggested that its participants are naiver, come from more diverse backgrounds, and provide data comparable in quality to MTurk (Peer et al., 2017). Since Prolific allows pre-screening, we recruited only British citizens who reported that their first language was English. Altogether, we obtained 442 complete questionnaires.[6] As in Study 1, we excluded duplicated IP addresses, those who responded to survey from outside of the UK, and cases with too many errors in the IAT. Due to the nature of the research question, Muslim respondents were not included in the analyses.[7] As a result, the analyzed sample consisted of 361 respondents. Modal age was between 25 and 34 years; 51.7% of respondents were female; 59.6% had a Bachelor's degree or higher; 92.8% self-identified as White. When asked about partisan prefernces, 34.9%

---

[6] It is necessary to note that many respondents were unable to complete the IAT part due to technical difficulties. We elaborate on the nature of these difficulties and potential remedies in General Discussion.

[7] Only six participants self-identified as Muslims.

of respondents identified with the the Labour Party, 24.1% with the Conservative Party, and 41.0% with some other party or no party.

To measure religion–party schemas, we built a single-category implicit association test (SC-IAT; Karpinski & Steinman, 2006). The SC-IAT is a modification of the original IAT format that measures strength of implicit associations between two attributes and a single object category. Our choice was motivated by the multiparty character of the British political system: It was difficult to choose a single comparison party category to pair with Labour.[8] Within the test, the Labour Party was represented using official logos and badges—similar to ones used for the two major U.S. parties in Study 1. The IAT stimuli for the two religious groups were commonly recognizable Muslim and Christian names, both male and female (e.g., Mohammad and Fatima vs. Harry and Emily). The names were pre-tested on Prolific in a separate sample of 100 individuals, and all names used in the study were consistently classified as either Muslim or Christian.

Anti-Muslim prejudice was assessed by asking respondents about four statements concerning Muslims in Britain. A sample statement: "For Muslims who live in Britain, how likely is it that their first loyalty is to Britain rather than to their home country?" Resulting scale reliability was .85 according to Cronbach's $\alpha$ statistic. In our regression analyses, we normalized respondents' anti-Muslim prejudice scores from 0 (least prejudiced) to 1 (most prejudiced).

Attitudes toward the Labour Party were measured using the 11-point party feeling question, identical in format to Study 1.

[8] It was unclear, for instance, whether the center-right Conservative Party or the radical right UK Independence Party should have been chosen as comparisons.

**Results**

Figure 4 presents the density of D-scores in the UK sample. The distribution was unimodal and not significantly different from normal according to a Shapiro–Wilk test ($z$ = −1.24, $p$ = .892). The mode of the distribution was situated almost exactly at the neutral point and the mean was not significantly different from zero ($b$ = −0.03, $p$ = .076). In other words, the average respondent in our sample did not implicitly associate the Labour Party with Muslims rather than Christians.

INSERT FIGURE 4 HERE.

Moreover, variation in this schema was also not consequential for respondents' feelings toward the Labour Party according to our inferential analysis. Results of both additive and interactive regression models are presented in Table 4 (Model 1 and Model 2 respectively). The cognitive link between Muslims and the Labour Party, as measured here at least, did not significantly influence feelings toward the Labour Party. Opinions on taxes vs. spending issue and anti-Muslim prejudice, on the other hand, strongly predicted partisan attitudes in the expected way. The interaction effect of anti-Muslim prejudice and religion–party schema on attitudes toward the Labour Party was was not statistically significant.

INSERT TABLE 4 HERE.

**Discussion**

Study 2 explored the religion–party schemas in the UK, and returned null results. First, respondents, on average, did not implicitly associate the Labour Party with Muslims more strongly than with Christians. Second, variation in the strength of this linkage was not politically consequential: Respondents with higher D-scores did not report more negative feelings about the

Labour Party overall. Third, religion–party schemas did not moderate the effect of prejudice toward Muslims on attitudes to the Labour Party, contrary to our prediction.

It is possible to interpret the null result substantively: Most respondents in the sample did not possess strong cognitive links between Muslims and the Labour Party, and for those who did, the linkage was not consequential. However, anti-Muslim prejudice significantly impacted feelings toward the Labour Party in our analysis. Therefore, we suspect that our respondents might have still held relative religious stereotypes about the Labour Party (as opposed, for instance, to the Conservative Party), but the measure based on SC-IAT simply did not capture them. We elaborate further on potential advantages of the traditional symmetric IAT format to measure relative rather than absolute group schemas in General Discussion.

## Study 3: Race and Welfare Programs in the U.S.

In Study 3, we applied the schematic model to a widely debated topic in U.S. politics: the origin of welfare policy opinion. The work by Gilens (1999) have demonstrated that, when coverage of welfare programs disproportionately depicts African Americans as poor, Whites' opposition to redistribution grows. He also found that explicit perceptions about the race of welfare beneficiaries influenced Whites' support for the respective programs. Here, we revisit this same policy domain to validate our measurement. In our analysis, we used the proposed measurement strategy based on the IAT architecture to test the power of race–welfare linkages in predicting opposition to welfare spending at the individual level.

### Data and Measures

We returned to the MTurk platform for respondents in this study. Initially, we obtained 500 completed questionnaires but, as in previous studies, we deleted duplicate IP addresses, respondents from outside the U.S., and those with high error rates in the IAT. The final sample consisted of 429 cases. The modal age was between 25 and 34 and modal yearly income was between \$30,000 and \$39,999. Also, 52.5% of respondents were female, 82.8% were White, and 54.5% had a Bachelor's degree or higher. We oversampled moderates and conservatives, so the sample was relatively balanced in terms of partisanship: 38.9% Democrats, 30.3% Republicans, and 30.8% independents.

We took the stimuli for the racial groups from the standard "race IAT" intended to measure automatic preference for White vs. Black faces (Nosek et al., 2007): morphed young Black and White faces cropped at forehead and chin. Welfare was represented with the names of specific government policies aimed at reducing poverty and/or providing urgent assistance such as food stamps and Medicaid. As a non-racialized comparison to welfare, we chose environmental programs.[9]

Anti-Black prejudice was measured using the standard American National Election Study stereotype battery. We asked respondents to what extent they considered Blacks and Whites hardworking vs. lazy and law-abiding vs. violent. To calculate the overall prejudice scores, we subtracted respondent's ratings of Whites from those of Blacks on the two traits and then took the average of the differences. In our regression analyses, we normalized respondents' anti-Black prejudice scores from 0 (least prejudiced) to 1 (most prejudiced).

To measure support for redistributive policies, we asked respondents about government programs such as public schooling, assistance to the poor, public healthcare, and assistance to the homeless. Answers were on a 7-point scale with higher values representing preference for

[9] The opposite category is required by the standard IAT design (two categories, two attributes). Given results of Study 2, we decided against using a SC-IAT with welfare as the single target category. We also wanted to have a spending counter-category that would not be likely opposed by liberals/Democrats such as policing or defense—as that would potentially bias the IAT results in our favor.

increased spending. These items responses were combined into an index of support for welfare programs (Cronbach's $\alpha$ reliability statistic was .84).

**Results**

We began by examining the distribution of race–welfare schemas, presented in Figure 5. The mode was at zero but the distribution was slightly skewed—more mass was situated on the right, corresponding to those with faster associations between Blacks and welfare. However, a Shapiro–Wilk test showed no significant deviations from normality ($z = -0.27$, $p = .605$). At the same time, the mean was greater than zero ($b = 0.12$, $p < .001$), suggesting the expected association of welfare policy with African Americans in the sample.

INSERT FIGURE 5 HERE.

However, according to our inferential analysis, these associations were not consequential for respondents' opinions about redistributive policies. Results of both additive and interactive regression models are presented in Table 5 (Model 1 and Model 2 respectively). The strength of the race–welfare schema did not impact support for welfare spending. However, income and anti-Black prejudice were significantly associated with opposition to redistributive programs, as many other studies have shown. The null result for schema strength held for both the direct effect and the interaction with anti-Black prejudice.

INSERT TABLE 5 HERE.

**Discussion**

The results of Study 3 were ambiguous. On the one hand, we found that our respondents were faster in associating Blacks rather than Whites with welfare programs—consistent with the race–welfare linkages in the direction hypothesized by Gilens (1999). At the same time, that linkage was not consequential for policy attitudes in this sample.

Do these findings mean that racialized schemas do not play a role in respondents' positions on welfare? Not necessarily. Remember that anti-Black prejudice did lead to opposition to welfare spending—thus suggesting that some connection between race and welfare existed in respondents' minds. Therefore, the null finding might again have been the product of measurement issues, as in Study 2. By requiring respondents to recognize the names of fairly arcane policy measures, we might have introduced a cognitive burden that interfered with the IAT method. We address this possibility in Study 4.

## Study 4: Race and Poverty in the U.S.

The null result in Study 3 is consistent with at least three possibilities. First, racialized schemas about welfare recipients are not consequential for policy preferences. Second, implicit associations are unrelated to explicit opinions about policies. Third, the IAT task we used containd too much noise to reliably capture schema strength. Specifically, recognizing the names of welfare policies in the IAT might have been difficult for those respondents who do not follow politics closely. In Study 4, we addressed this concern. In doing so, we retained the previous IAT format but altered the target categories and the stimuli. We measured race–poverty schemas (rather than race–welfare schemas), and used visual rather than textual stimuli in order to improve the reliability of the measure.

### Data and Measures

Respondents again recruited were using MTurk. They answered a web-based survey on the Qualtrics platform with the IAT administered using Inquisit. We removed duplicate IP addresses, cases with too many errors in the IAT, and those who completed the survey from outside of the United States. The total of 498 questionnaires were completed and the final sample contained 441 observations. The sample was disproportionately female (61.4%) and college educated (50.6%). The modal household income was between $30,000 and $39,999. The sample was also relatively young, with a mean age between 25 and 34 years. Again, non-liberals were oversampled, so partisanship was balanced with 35.1% of respondents were Democrats, 32.7% were Republicans, and 32.2% were independents. Finally, 82.8% of the sample self-identified as White.

In the new IAT-type task designed to capture associations between race and poverty, we kept the same stimuli for race that we used in Study 3. Following Newheiser and Olson (2012), we used pictures to depict poverty vs. wealth in the task. This choice minimized confounding with vocabulary since the latter might be correlated with both schemas of interest and support for welfare. Specifically, 12 pictures were used to represent objects that people of different income levels might possess: expensive vs. cheap houses, cars, clothing, and so on.

To measure support for various government programs, we asked respondents 11 questions regarding spending on welfare, public safety, military/intelligence, and infrastructure. We have included different categories as a placebo test: If the "racialized welfare" hypothesis is valid, implicit associations between race and poverty should suppress support for welfare spending—but not for other forms of spending. Answers were given on a 7-point scale with higher values representing preference for increased spending.

**Results**

Figure 6 presents the densities of the race–poverty schemas. The distribution was effectively normal according to a Shapiro–Wilk test ($z = 0.39$, $p = .348$). As before, the mean was positive, indicating that the average respondent was faster associating poverty with Blacks and wealth with Whites ($b = 0.21$, $p < .001$).

INSERT FIGURE 6 HERE.

Since the dependent variables were measured using multi-item batteries, to make inferences about the association between race–poverty schemas and welfare spending we used structural equation modeling (Kline, 2010). We estimated the effects of the race–poverty schema on various spending preferences controlling for age, gender, education, income, and race/ethnicity. The results are presented in Figure 7. They strongly confirm that the race–poverty schema significantly predicts welfare spending preferences but is unrelated to spending in other domains. Those with racialized images of poverty strongly preferred less support for spending on welfare: The difference in welfare spending support between individuals with very weak and very strong race–poverty schemas was nearly one point on the 7-point scale.

INSERT FIGURE 7 HERE.

**Discussion**

In Study 4, we again applied the schematic model to understand whether group attitudes impact preferences on welfare redistribution. Results provided strong support for the schematic approach to formation of political preferences: Individuals with pro-stereotypical schemas (i.e., those who associated African Americans with poverty) tended to oppose spending on welfare—but not other spending domains. This result supports our interpretation of the null finding in Study 3: The previous measure of race–welfare schemas has been too noisy. It means that, in designing IATs for tapping linkages between social groups and political objects, researchers should pay close attention to the cognitive load inherent in recognizing the symbols used in the task. We turn to this and other methodological aspects of our measurement strategy in General Discussion.

## General Discussion

In this chapter, we have proposed and validated a novel application of implicit measurement technique, and of the IAT architecture in particular: measuring non-affective associations between social groups and political objects. Since this application of the IAT is new, we can offer some advice for researchers.

First, the standard IAT task is symmetric: It has two target categories matched to either end of an affective dimension, and can be modified to measure binary group schemas such as Black/White, male/female, rich/poor, and so on. However, researchers are often interested in associations between a single political object or a single target group among many. A modification of the IAT has been offered to solve this problem that uses only a single target category (SC-IAT). In Study 2 we attempted to capture the schematic association of British Labour Party with Muslims vis-a-vis Christians but found no demonstrable effect of variation on this score with political preferences. The reasons for this null result are unclear. Of course, they can reflect the absence of the association of interest in the sample—but strong links between anti-Muslim prejudice and support for the Labour Party contradict this interpretation. The null result may instead hint at a different theoretical interpretation of the underlying schema architecture: A two-category task effectively measures the *relative* association between contrasting political objects (parties) and social groups in their coalitions, whereas a single category task captures the *absolute* association of groups with only one party. Expecting such a strong and asymmetric stereotype may be unrealistic even among politically sophisticated or ideologically extreme respondents. Therefore, we recommend that researchers use symmetric (two-category) IAT rather than its single-category variant when relative strength of a politically relevant schema is of interest.

Another important challenge for using the IAT-based tasks is technical. Behavioral political scientists often seek samples that are diverse, if not representative of large populations. Among survey modes that allow reaching such populations, only internet surveys facilitate objective timed-response tasks like the IAT. At the same time, the IAT D-scores rely on high-precision timed response data, and many online survey platforms do not currenty maintain this functionality. The of special IAT-capable software, in turn, creates a number of practical costs, including programming time, data loss due to platform compatibility issues, and the requirement that respondents download and install the software on their home computer. Altogether, these challenges create a higher risk of non-response and drop-outs which can lead undermine statistical power and, more seriously, biased parameter estimates. We encountered relatively high drop-out rates in all four studies—but most prominently in Study 2 due to an apparent conflict between the recruitment platform and the IAT software. One solution for this problem is to use packages that allow timed-response tasks to be integrated directly into survey platforms, such as the one recently introduced by Qualtrics (Carpenter et al., 2019). We encourage researchers to explore attrition in similar studies in order to determine how highly correlated it is with key covariates of interest in order to offer design-based or estimation-based solutions.

The final problem in applying the IAT architecture to the measurement of political schemas involves the role of political sophistication. Standard timed-response tasks deal with target concepts and attributes that are simple and familiar to participants whereas many political objects are abstract, with few common symbols or words that can be used to cue them in memory. In such cases, it is challenging to come up with appropriate stimuli for an IAT: Stimuli used to represent political categories can differ enough in complexity to cause difficulties in recognition, even after the “practice” session in the IAT. In this case, response latencies are contaminated by the differential effort required to recognize the stimuli. We think the above bias may explain the results in Study 3, where we attempted to tap the strength of the race–welfare linkage in the United States. Respondents needed a lot of time to recognize many of the policies we used as cues for government redistribution. Our conjecture is that the policy-related stimuli in Study 3 were simply too complex even for relatively knowledgeable MTurk respondents—suggesting that this might be an even bigger problem for a more diverse national sample. Therefore, we advise researchers to minimize the complexity of the stimuli they use to represent political objects in timed-response tasks.

## Conclusion

Over the last half century, from Converse (1964) to Kinder and Kalmoe (2017), political psychologists have argued that most voters lack coherent ideological worldviews as a base for coming to opinions about specific issues. Instead, political preferences are consistently and powerfully influenced by group identities and attitudes. In this chapter, we re-introduce the notion that group attitudes get translated into political opinions via group schemas: Cognitive linkages between social groups and political objects like parties and/or policies moderate the transfer of affect about the former onto the latter. Here we offer a new approach to the measurement of group schemas in politics that builds on classic contributions in the discipline as well as on recent developments in the measurement of implicit social cognition. Specifically, in order to assess the degree of cognitive overlap between a social group and a political object for each respondent, we rely on a timed-response sorting task based on the IAT architecture.

Altogether, our findings provide evidence in favor of the schematic model of political belief formation and validate the proposed measurement strategy based on the IAT technique. The method has several limitations related to the cognitive effort required to recognize specific stimuli within the sorting task and technical challenges for implementation in modern-day online surveys. However, proper design and selection of the stimuli can significantly mitigate these problems. Also, technical developments in both survey platforms and time response software should allow for more seamless integration in the near future. In addition, the proposed method is universal and can be applied to almost any theorized cognitive linkage between social groups and political objects—as long as the categories of interest can be represented by visual and/or textual stimuli. Therefore, the method is not confined to American public opinion and, as the discipline becomes internationalized, its applicability in comparative political behavior may well deliver substantial returns to knowledge.

**References**

Anderson, J. R. (1983). A spreading activation theory of memory. *Journal of Verbal Learning and Verbal Behavior, 22*(3), 261–295. https://doi.org/10.1016/S0022-5371(83)90201-3

Arkes, H. R., & Tetlock, P. E. (2004). Attributions of implicit prejudice, or “Would Jesse Jackson ‘fail’ the implicit association test?” *Psychological Inquiry, 15*(4), 257–278. https://doi.org/10.1207/s15327965pli1504_01

Banaji, M. R., & Hardin, C. D. (1996). Automatic stereotyping. *Psychological Science, 7*(3), 136–141. https://doi.org/10.1111/j.1467-9280.1996.tb00346.x

Bargh, J. A., & Chartrand, T. L. (1999). The unbearable automaticity of being. *American Psychologist, 54*(7), 462–479. https://doi.org/10.1037/0003-066X.54.7.462

Bargh, J. A., Chen, M., & Burrows, L. (1996). Automaticity of social behavior: Direct effects of trait construct and stereotype activation on action. *Journal of Personality and Social Psychology, 71*(2), 230–244. https://doi.org/10.1037/0022-3514.71.2.230

Berinsky, A. J., Huber, G. A., & Lenz, G. S. (2012). Evaluating online labor markets for experimental research: Amazon.com’s Mechanical Turk. *Political Analysis, 20*(3), 351–368. https://doi.org/10.1093/pan/mpr057

Berman, S. (2016). The lost left. *Journal of Democracy, 27*(4), 69–76. http://doi.org/10.1353/jod.2016.0063

Blanton, H., & Jaccard, J. (2006). Arbitrary metrics in psychology. *American Psychologist, 61*(1), 27–41. https://doi.org/10.1037/0003-066X.61.1.27

Brambor, T., Clark, W. R., & Golder, M. (2006). Understanding interaction models: Improving empirical analyses. *Political Analysis, 14*(1), 63–82. https://doi.org/10.1093/pan/mpi014

Brown-Iannuzzi, J. L., Dotsch, R., Cooley, E., & Payne, B. K. (2017). The relationship between mental representations of welfare recipients and attitudes toward welfare. *Psychological Science, 28*(1), 92–103. https://doi.org/10.1177/0956797616674999

Bruner, J. S. (1957). On perceptual readiness. *Psychological Review, 64*(2), 123–152. https://doi.org/10.1037/h0043805

Bruner, J. S., & Goodman, C. C. (1947). Value and need as organizing factors in perception. *Journal of Abnormal Psychology, 42*(1), 33–44. https://doi.org/10.1037/h0058484

Carpenter, T. P., Pogacar, R., Pullig, C., Kouril, M., Aguilar, S., LaBouff, J., … Chakroff, A. (2019). Survey-based implicit association tests: A methodological and empirical analysis. *Behavior Research Methods, 51*(5), 2194–2208. https://doi.org/10.3758/s13428-019-01293-3

Chong, D., & Druckman, J. N. (2007). Framing theory. *Annual Review of Political Science, 10*, 103–126. https://doi.org/10.1146/annurev.polisci.10.072805.103054

Collins, A. M., & Loftus, E. F. (1975). A spreading-activation theory of semantic processing. *Psychological Review, 82*(6), 407–428. https://doi.org/10.1037/0033-295X.82.6.407

Conover, P. J. (1988). The role of social groups in political thinking. *British Journal of Political Science, 18*(1), 51–76. https://doi.org/10.1017/S0007123400004956

Conover, P. J., & Feldman, S. (1984). How people organize the political world: A schematic model. *American Journal of Political Science, 28*(1), 95–126. http://doi.org/10.2307/2110789

Converse, P. E. (1964). The nature of belief systems in mass publics. In D. E. Apter (Ed.), *Ideology and discontent* (pp. 206–261). Free Press.

Dancygier, R. M. (2017). *Dilemmas of inclusion: Muslims in European politics*. Princeton University Press.

Dijksterhuis, A., & Bargh, J. A. (2001). The perception–behavior expressway: Automatic effects of social perception on social behavior. In M. P. Zanna (Ed.), *Advances in experimental social psychology* (Vol. 33, pp. 1–40). Academic Press. https://doi.org/10.1016/S0065-2601(01)80003-4

Fazio, R. H. (1990). A practical guide to the use of response latency in social psychological research. In C. Hendrick and M. S. Clark (Eds.), *Review of Personality and Social Psychology, Vol. 11. Research methods in Personality and Social Psychology* (pp. 74–97). Sage Publications.

Fiske, S. T., & Linville, P. W. (1980). What does the schema concept buy us? *Personality and Social Psychology Bulletin, 6*(4), 543–557. https://doi.org/10.1177/014616728064006

Gawronski, B., Galdi, S., & Arcuri, L. (2015). What can political psychology learn from implicit measures? Empirical evidence and new directions. *Political Psychology, 36*(1): 1–17. https://doi.org/10.1111/pops.12094

Gilens, M. (1999). *Why Americans hate welfare: Race, media, and the politics of antipoverty policy*. University of Chicago Press.

Glick, P., & Fiske, S. T. (1996). The ambivalent sexism inventory: Differentiating hostile and benevolent sexism. *Journal of Personality and Social Psychology, 70*(3), 491–512. https://doi.org/10.1037/0022-3514.70.3.491

Green, D., Palmquist, B., & Schickler, E. (2002). *Partisan hearts and minds: Political parties and the social identities of voters*. Yale University Press.

Greenwald, A. G., McGhee, D. E., & Schwartz, J. L. K. (1998). Measuring individual differences in implicit cognition: The implicit association test. *Journal of Personality and Social Psychology, 74*(6), 1464–1480. https://doi.org/10.1037/0022-3514.74.6.1464

Greenwald, A. G., Nosek, B. A., & Banaji, M. R. (2003). Understanding and using the implicit association test: I. An improved scoring algorithm. *Journal of Personality and Social Psychology*, 85(2), 197–216. https://doi.org/10.1037/0022-3514.85.2.197

Greenwald, A. G., Poehlman, T. A., Uhlmann, E. L., & Banaji, M. R. (2009). Understanding and using the implicit association test: III. Meta-analysis of predictive validity. *Journal of Personality and Social Psychology, 97*(1), 17–41. https://doi.org/10.1037/a0015575

Hawkins, C. B., & Nosek, B. A. (2012). Motivated independence? Implicit party identity predicts political judgments among self-proclaimed independents. *Personality and Social Psychology Bulletin, 38*(11), 1437–1452. https://doi.org/10.1177/0146167212452313

Higgins, E. T., Rholes, W. S., & Jones, C. R. (1977). Category accessibility and impression formation. *Journal of Experimental Social Psychology, 13*(2), 141–154. https://doi.org/10.1016/S0022-1031(77)80007-3

Hunzaker, M. B. F. (2016). Cultural sentiments and schema-consistency bias in information transmission. *American Sociological Review, 81*(6), 1223–1250. https://doi.org/10.1177/0003122416671742

Hutchings, V. L., & Jardina, A. E. (2009). Experiments on racial priming in political campaigns. *Annual Review of Political Science, 12*, 397–402. https://doi.org/10.1146/annurev.polisci.12.060107.154208

Karpinski, A., & Steinman, R. B. (2006). The single category implicit association test as a measure of implicit social cognition. *Journal of Personality and Social Psychology, 91*(1), 16–32. https://doi.org/10.1037/0022-3514.91.1.16

Kinder, D. R., & Kalmoe, N. P. (2017). *Neither liberal nor conservative: Ideological innocence in the American public*. University of Chicago Press.

Kline, R. B. (2010). *Principles and practice of structural equation modeling* (3rd ed.). Guilford Press.

Lazarsfeld, P. F., Berelson, B., & Gaudet, H. (1948). *The people's choice: How the voter makes up his mind in a presidential campaign* (2nd ed.). Columbia University Press.

Meissner, F., & Rothermund, K. (2015). A thousand words are worth more than a picture? The effects of stimulus modality on the implicit association test. *Social Psychological and Personality Science, 6*(7), 740–748. https://doi.org/10.1177/1948550615580381

Moskowitz, G. B. (2005). *Social cognition: Understanding self and others*. Guilford Press.

Nelson, T. E., Clawson, R. A, & Oxley, Z. M. (1997). Media framing of a civil liberties conflict and its effect on tolerance. *American Political Science Review, 91*(3), 567–583. https://doi.org/10.2307/2952075

Nelson, T. E., & Kinder, D. R. (1996). Issue frames and group-centrism in American public opinion. *Journal of Politics, 58*(4), 1055–1078. https://doi.org/10.2307/2960149

Newheiser, A.-K., & Olson, K. R. (2012). White and Black American children's implicit intergroup bias. *Journal of Experimental Social Psychology, 48*(1), 264–270. https://doi.org/10.1016/j.jesp.2011.08.011

Nosek, B. A., Banaji, M. R., & Greenwald, A. G. (2002). Harvesting implicit group attitudes and beliefs from a demonstration web site. *Group Dynamics*, *6*(1), 101–115. https://doi.org/10.1037/1089-2699.6.1.101

Nosek, B. A., Greenwald, A. G., & Banaji, M. R. (2005). Understanding and using the implicit association test: II. Method variables and construct validity. *Personality and Social Psychology Bulletin*, *31*(2), 166–180. https://doi.org/10.1177/0146167204271418

Nosek, B. A., Smyth, F. L., Hansen, J. J., Devos, T., Lindner, N. M., Ranganath, K. A., … Banaji, M. R. (2007). Pervasiveness and correlates of implicit attitudes and stereotypes. *European Review of Social Psychology*, *18*(1), 36–88. https://doi.org/10.1080/10463280701489053

Rudman, L. A., & Borgida, E. (1995). The afterglow of construct accessibility: The behavioral consequences of priming men to view women as sexual objects. *Journal of Experimental Social Psychology, 31*(6), 493–517. https://doi.org/10.1006/jesp.1995.1022

Page, S. E. (2007). *The difference: How the power of diversity creates better groups, firms, schools, and societies*. Princeton University Press.

Peer, E., Brandimarte, L., Samat, S., & Acquisti, A. (2017). Beyond the Turk: Alternative platforms for crowdsourcing behavioral research. *Journal of Experimental Social Psychology*, *70*, 153–63. https://doi.org/10.1016/j.jesp.2017.01.006

Rothermund, K., & Wentura, D. (2004). Underlying processes in the implicit association test: Dissociating salience from associations. *Journal of Experimental Psychology: General, 133*(2), 139–165. https://doi.org/10.1037/0096-3445.133.2.139

Schneider, D. J. (2004). *The psychology of stereotyping*. Guilford Press.

Sears, D. O. (1993). Symbolic politics: A socio-psychological theory. In S. Iyengar & W. J. McGuire (Eds.), *Explorations in political psychology* (pp. 113–149). Duke University Press.

Simon, H. A. 1957. *Models of man: Social and rational*. Wiley.

Srull, T. K., & Wyer, R. S. (1979). The role of category accessibility in the interpretation of information about persons: Some determinants and implications. *Journal of Personality and Social Psychology*, *37*(10), 1660–1672. https://doi.org/10.1037/0022-3514.37.10.1660

Taylor, S. E., & Crocker, J. (1981). Schematic bases of social information processing. In E. T. Higgins, C. P. Herman, & M. P. Zanna (Eds.), *Social cognition: The Ontario symposium* (pp. 89–134). Lawrence Erlbaum.

Taylor, S. E., & Fiske, S. T. (1978). Salience, attention, and attribution: Top of the head phenomena. In L. Berkowitz (Ed.), *Advances in experimental social psychology* (Vol. 11, pp. 249–288). Academic Press. https://doi.org/10.1016/S0065-2601(08)60009-X

Theodoridis, A. G. (2017). Me, myself, and (I), (D), or (R)? Partisanship and political cognition through the lens of implicit identity. *Journal of Politics*, 79 (4): 1253–1267. https://doi.org/10.1086/692738

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science, 185*(4157), 1124–1131. https://doi.org/10.1126/science.185.4157.1124

Valentino, N. A., Brader, T., & Jardina, A. E. (2013). Immigration opposition among U.S. Whites: General ethnocentrism or media priming of attitudes about Latinos? *Political Psychology*, *34*(2), 149–166. https://doi.org/10.1111/j.1467-9221.2012.00928.x

Valentino, N. A., Hutchings, V. L., & White, I. K. (2002). Cues that matter: How political ads prime racial attitudes during campaigns. *American Political Science Review*, *96*(1), 75–90. https://doi.org/10.1017/S0003055402004240

Valentino, N. A., Wayne, C., & Oceno, M. (2018). Mobilizing sexism: The interaction of emotion and gender attitudes in the 2016 US presidential election. *Public Opinion Quarterly, 82*(S1), 799–821. https://doi.org/10.1093/poq/nfy003

Winter, N. J. G. (2010). Masculine Republicans and feminine Democrats: Gender and Americans’ explicit and implicit images of the political parties. *Political Behavior*, *32*(4), 587–618. https://doi.org/10.1007/s11109-010-9131-z

**Table 1**

*Outline of Empirical Studies*

| | | |
|---|---|---|
| Study 1 | Country | United States |
| | Schema | Gender–party |
| | | (male vs. female, Democrats vs. Republicans) |
| | Outcome | Partisan attitudes |
| | | (Republican Party vs. Democratic Party) |
| Study 2 | Country | United Kingdom |
| | Schema | Religion–party |
| | | (Christian vs. Muslim, Labour) |
| | Outcome | Partisan attitudes |
| | | (Labour Party) |
| Study 3 | Country | United States |
| | Schema | Race–welfare |
| | | (Black vs. White, welfare vs. environment) |
| | Outcome | Support for welfare spending |
| Study 4 | Country | United States |
| | Schema | Race–poverty |
| | | (Black vs. White, rich vs. poor) |
| | Outcome | Support for welfare spending |
| | | (vs. other programs as a placebo test) |

**Table 2**

*Regression Analysis: Effects of Gender–Party Schemas on Attitudinal Preference for the Republican Party among Men and Women*

| | Men | Women |
|---|---|---|
| Gender–party schema | $3.73^{***}$ | $-5.05^{***}$ |
| | (0.70) | (0.51) |
| Age | 0.00 | $0.82^{**}$ |
| | (0.29) | (0.24) |
| Education | −0.42 | $-0.70^{**}$ |
| | (0.26) | (0.22) |
| Income | 0.05 | 0.17 |
| | (0.12) | (0.10) |
| Black | −1.84 | $-3.58^{***}$ |
| | (1.25) | (1.02) |
| $N$ | 279 | 336 |
| $R^2$ | 0.113 | 0.304 |

*Note.* Standard errors in parentheses. Greater gender–party schema = stronger association of the Democratic Party with women and the Republican Party with men

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

**Table 3**

*Regression Analysis: Interactive Effect of Gender–Party Schemas and Sexism on Attitudinal Preference for the Republican Party*

| | Estimate |
|---|---|
| Gender–party schema | $-2.46^{***}$ |
| | (0.68) |
| Hostile sexism | $10.88^{***}$ |
| | (0.74) |
| Schema × Sexism | $3.26^{*}$ |
| | (1.31) |
| Age | $0.60^{***}$ |
| | (0.16) |
| Female | 0.23 |
| | (0.40) |
| Education | −0.24 |
| | (0.15) |
| Income | 0.12 |
| | (0.07) |
| Black | $-2.73^{***}$ |
| | (0.71) |
| *N* | 615 |
| $R^2$ | 0.377 |

*Note.* Standard errors in parentheses. Greater gender–party schema = stronger association of the Democratic Party with women and the Republican Party with men

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

**Table 4**

*Regression Analysis: Additive and Interactive Effects of Religion–Party Schemas and Anti-Muslim Prejudice on Attitudes to the Labour Party*

| | Model 1 | Model 2 |
|---|---|---|
| Religion–party schema | −0.68 | −0.99 |
| | (0.42) | (0.80) |
| Anti-Muslim prejudice | $-2.91^{***}$ | $-2.88^{***}$ |
| | (0.52) | (0.52) |
| Schema × Prejudice | | 0.78 |
| | | (1.70) |
| Issue: government spending (pro) | $-0.25^{***}$ | $-0.25^{***}$ |
| | (0.06) | (0.06) |
| Issue: environment (pro) | −0.05 | -0.05 |
| | (0.06) | (0.06) |
| Age | $-0.22^{*}$ | $-0.22^{*}$ |
| | (0.09) | (0.09) |
| Female | 0.31 | 0.32 |
| | (0.23) | (0.23) |
| Education | 0.02 | 0.02 |
| | (0.10) | (0.10) |
| Working class | $0.48^{*}$ | 0.47 |
| | (0.24) | (0.24) |
| Non-White | −0.27 | −0.25 |
| | (0.44) | (0.44) |
| *N* | 358 | 358 |
| $R^2$ | 0.224 | 0.225 |

*Note.* Standard errors in parentheses. Greater religion–party schema = stronger association of the Labour Party with Muslims (rather than Christians)

$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

**Table 5**

*Regression Analysis: Additive and Interactive Effects of Race–Welfare Schemas and Anti-Black Prejudice on Support for Welfare Spending*

| | Model 1 | Model 2 |
|---|---|---|
| Race–welfare schema | −0.22 | −0.23 |
| | (0.19) | (0.80) |
| Anti-Black prejudice | $-2.58^{***}$ | $-2.42^{***}$ |
| | (0.57) | (0.63) |
| Schema × Prejudice | | −0.84 |
| | | (1.46) |
| Age | −0.07 | −0.07 |
| | (0.05) | (0.05) |
| Female | 0.00 | 0.01 |
| | (0.13) | (0.05) |
| Education | −0.09 | −0.09 |
| | (0.05) | (0.05) |
| Income | $-0.08^{***}$ | $-0.08^{***}$ |
| | (0.02) | (0.02) |
| Black | $0.62^{*}$ | $0.61^{*}$ |
| | (0.29) | (0.29) |
| *N* | 426 | 426 |
| $R^2$ | 0.139 | 0.140 |

*Note.* Standard errors in parentheses. Greater race–welfare schema = stronger association of welfare programs with Blacks and non-welfare programs with Whites

$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

**Figure 1**

*The Two Variants of the Schematic Model*

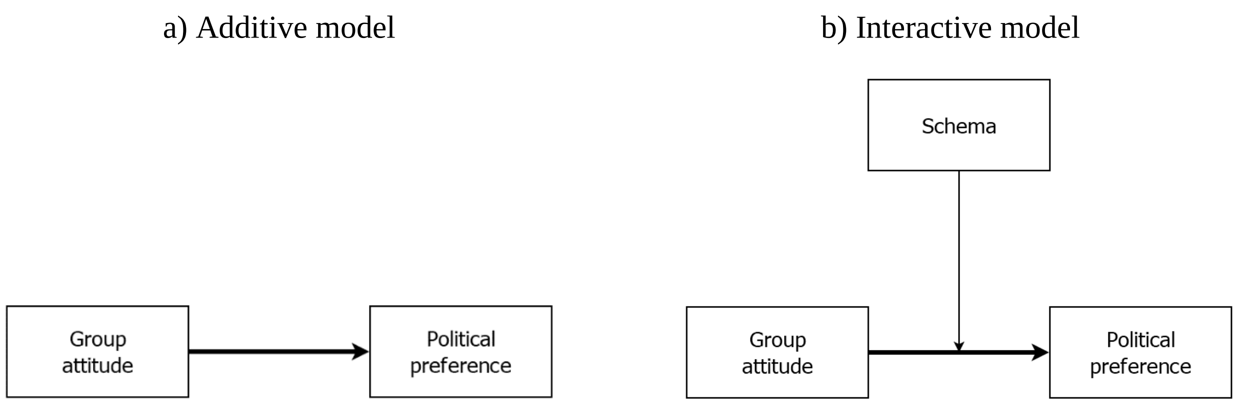


**Figure 2**

*Observed Distribution of the Gender–Party Schemas*

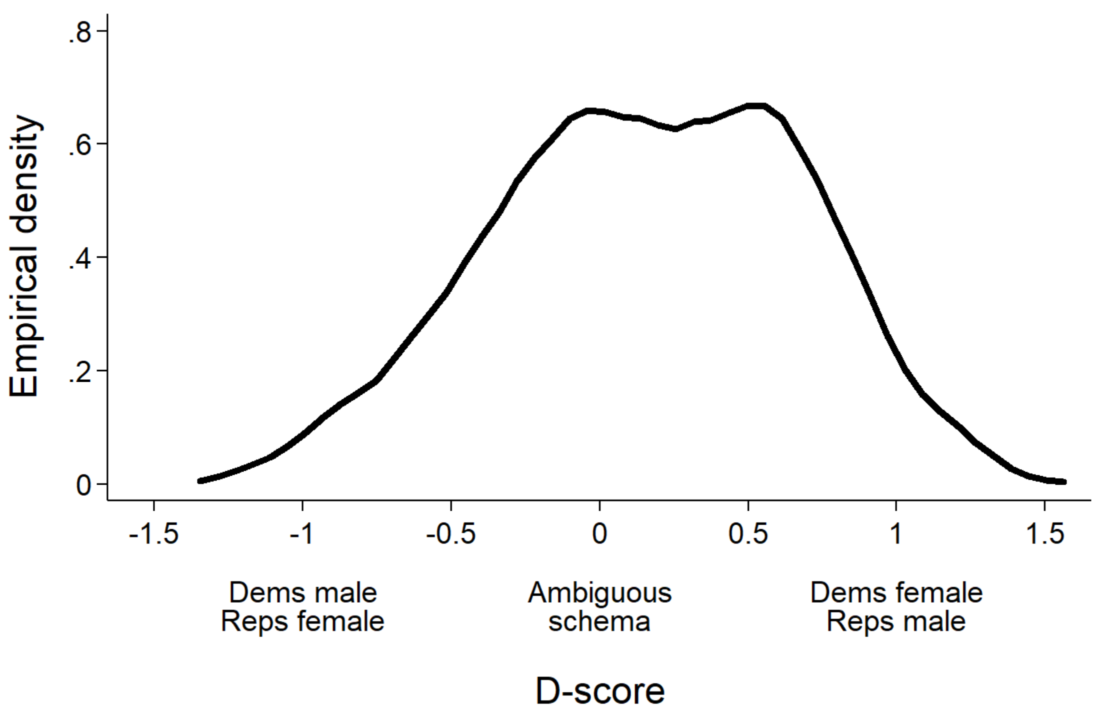


**Figure 3**

*Estimated Effects of Sexism on Attitudinal Preference for the Republican Party by Gender–Party Schema*

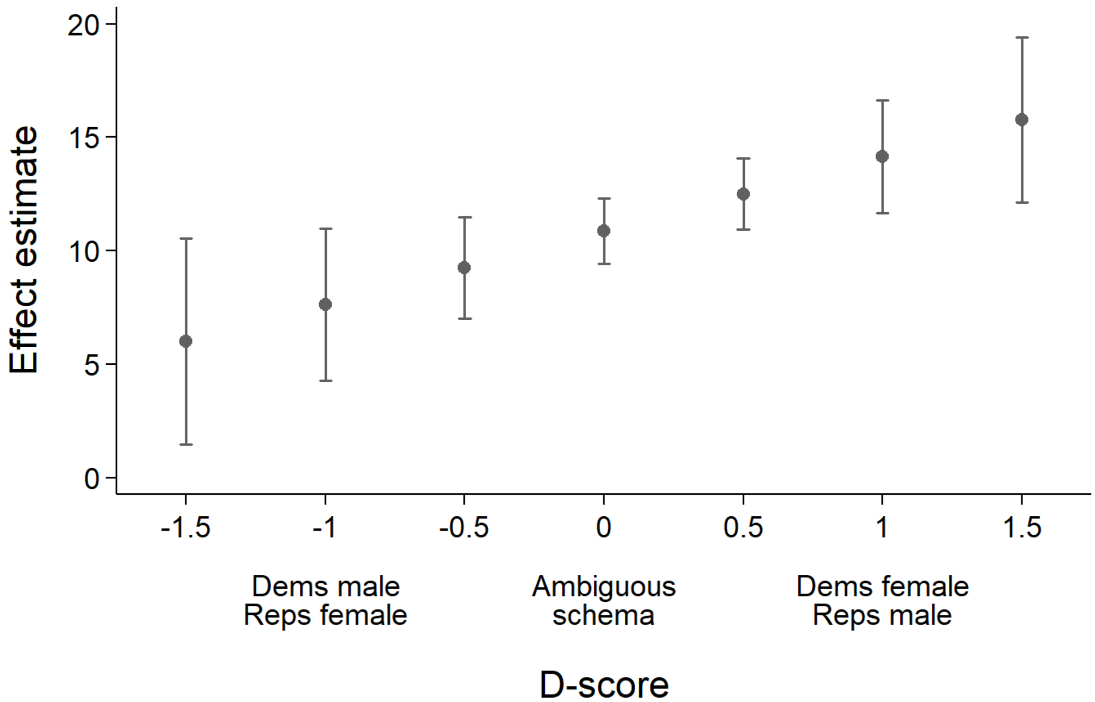


**Figure 4**

*Observed Distribution of the Religion–Party Schemas*

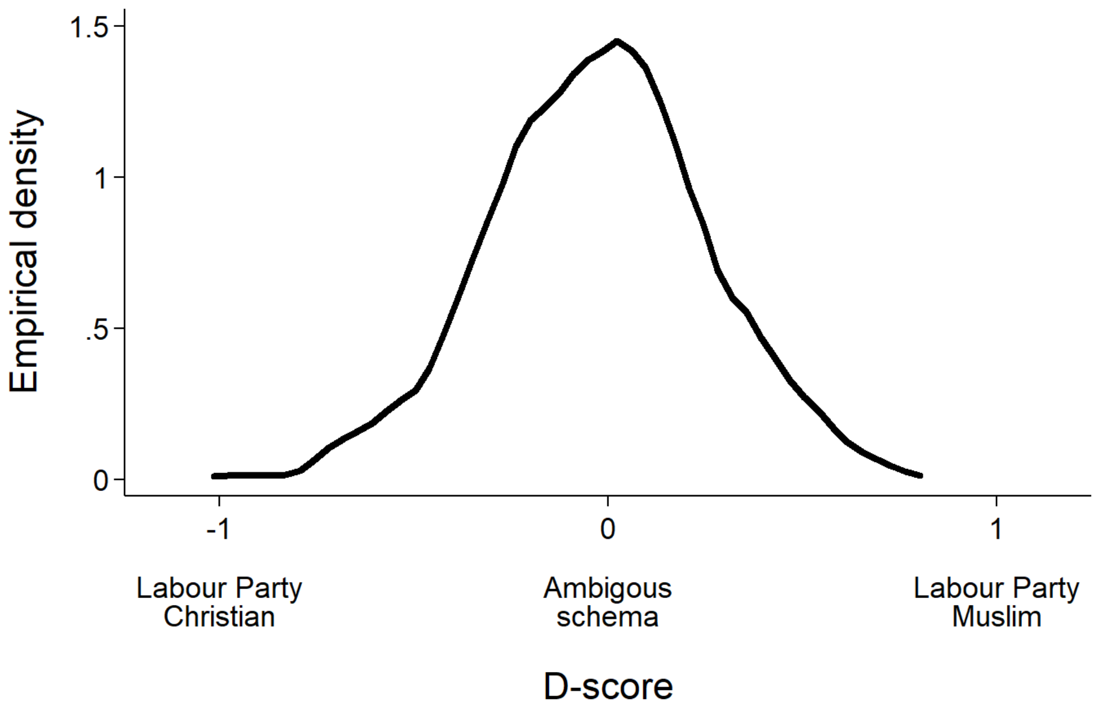


**Figure 5**

*Observed Distribution of the Race–Welfare Schemas*

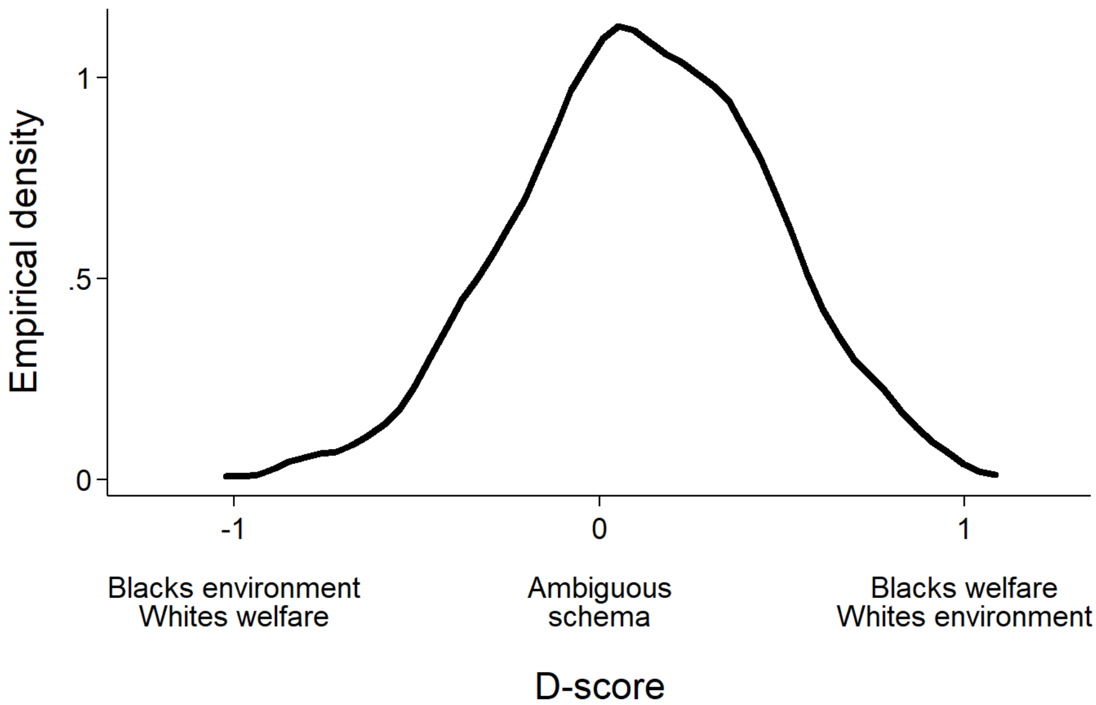


**Figure 6**

*Observed Distribution of the Race–Poverty Schemas*

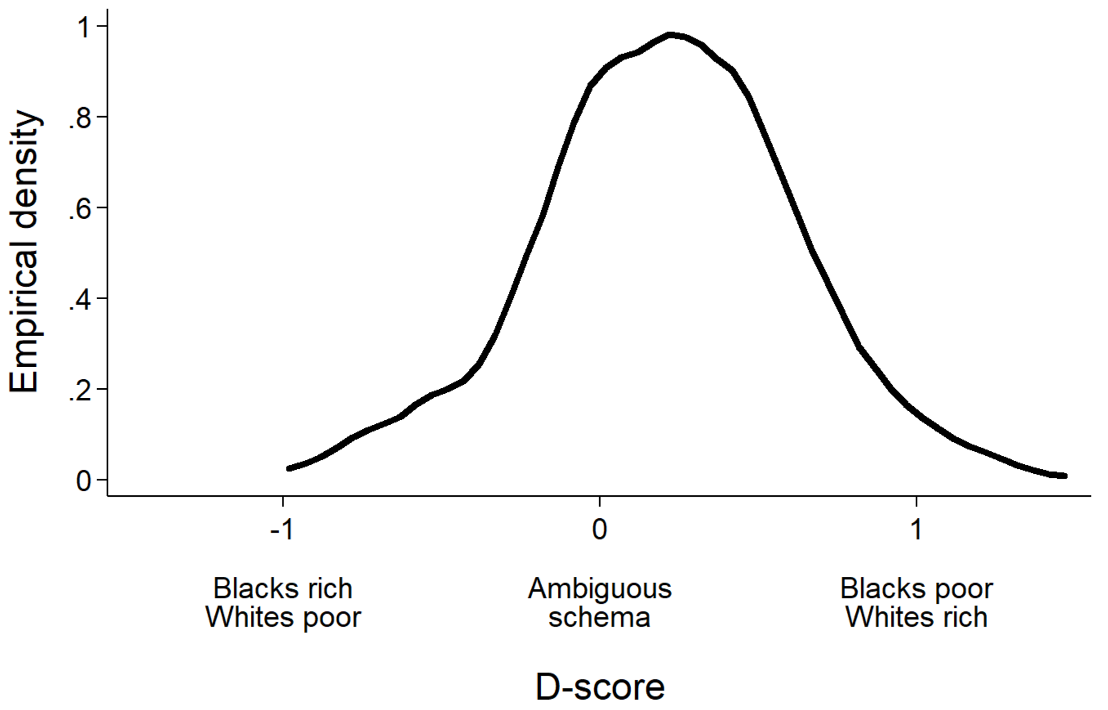
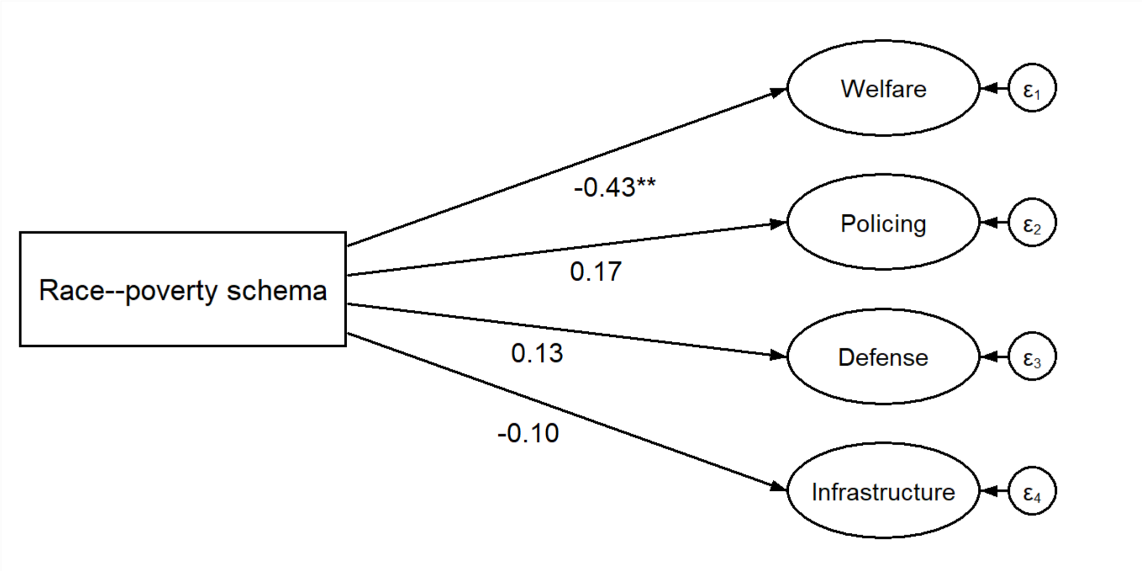


**Figure 7**

*Effects of Race–Poverty Schemas on Support for Spending Programs*




*Note. N* = 440. Fit indices: RMSEA = .074, CFI = .912, SRMR = .063. Measurement parts and controls omitted for space considerations. Greater race–poverty schema = greater association of poverty with Blacks and affluence with Whites. Control variables: age, gender, education, income, race

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

# Online Appendix

## Study 1: Gender and Parties in the U.S.

**Partisan attitudes**

"We would like to get your feelings towards the two main political parties in the U.S. Please rate each party using a scale that runs from 0 to 10, where 0 means strongly dislike and 10 means strongly like."

- How do you feel about the Democratic Party?
- How do you feel about the Republican Party?

Question order randomized.

**Hostile sexism**

"Now you will see series of statements with which you may either agree or disagree. For each of the following statements, we would like you to indicate the extent to which you agree or disagree."

- Many women are actually seeking special favors, such as hiring policies that favor them over men, under the guise of asking for "equality."
- Feminists are NOT seeking for women to have more power than men. (reversed)
- Most women interpret innocent remarks or acts as being sexist.
- Feminists are making entirely reasonable demands of men. (reversed)

Question order randomized.

Answers coded from 1 = *Strongly disagree* to 7 = *Strongly agree*.

**IAT: gender stimuli**

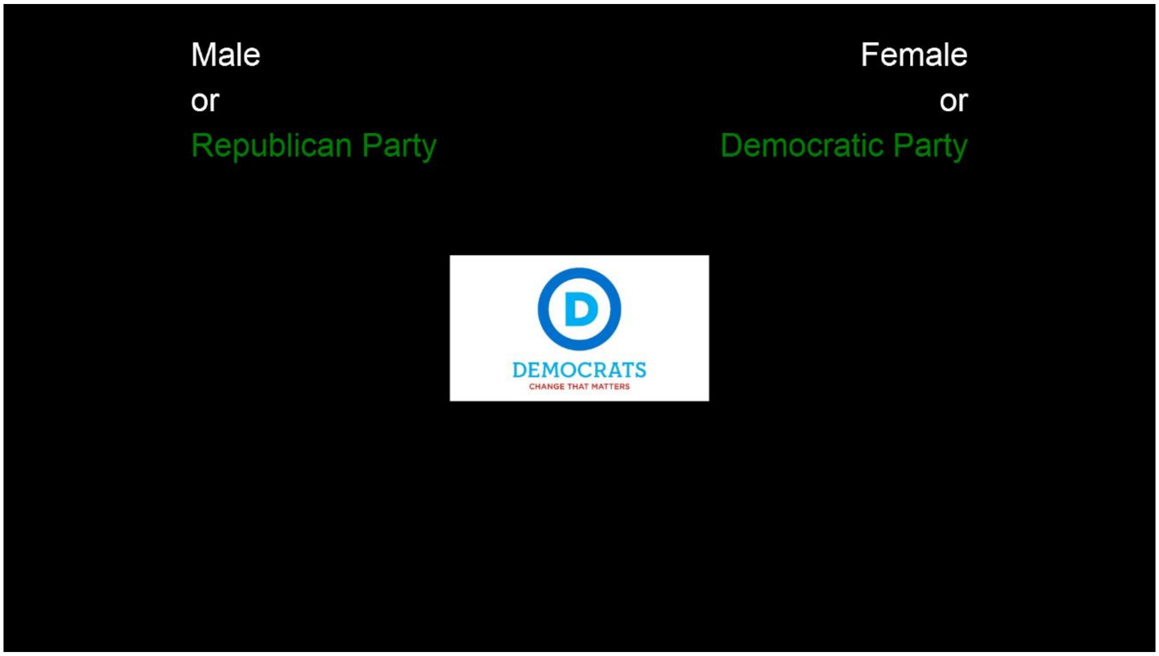
*Female nouns:* Girl, Daughter, Wife, Woman, Mother, Grandma

*Male nouns:* Boy, Son, Husband, Man, Father, Grandpa

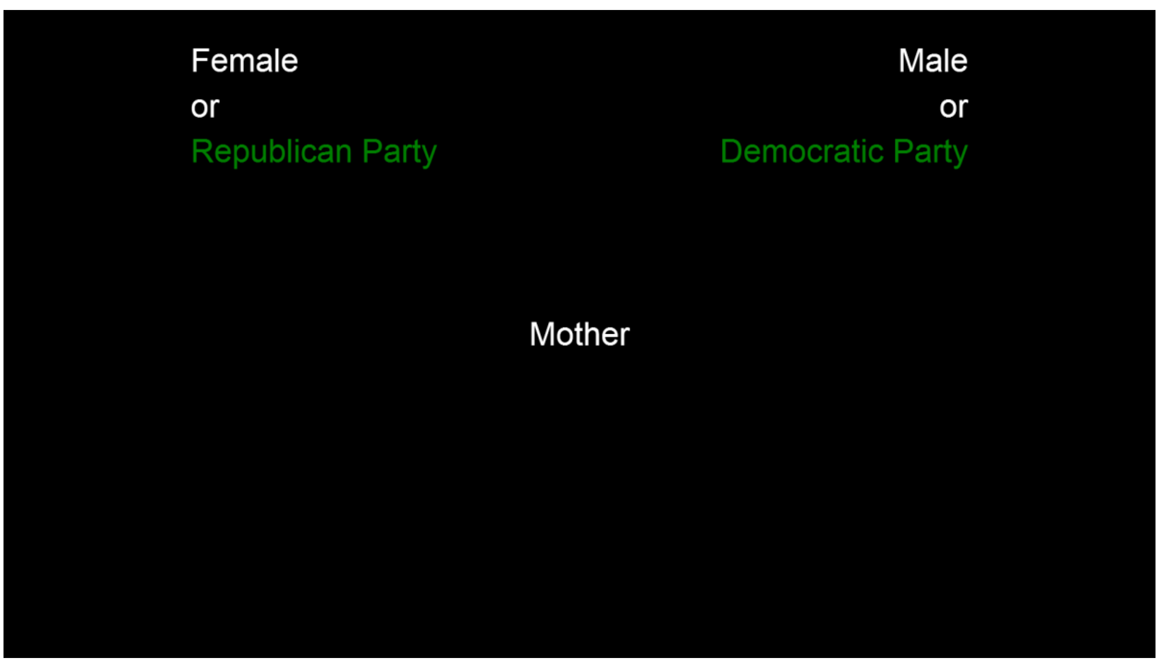
**IAT: party stimuli**

Available upon request

**IAT: sample screen (pro-stereotypic sorting, image stimulus)**




**IAT: sample screen (counter-stereotypic sorting, noun stimulus)**



## Study 2: Religion and Parties in the UK

### Partisan attitudes

“We would like to get your feelings toward some of the British political parties. Please rate each party using a scale that runs from 0 to 10, where 0 means strongly dislike and 10 means strongly like”

- How do you feel about the Labour Party?

### Issue positions

- *Taxes vs. spending:*

  “Consider a 0 to 10 scale, where the end marked 0 means that government should raise taxes a lot and spend much more on health and social services, and the end marked 10 means that government should cut taxes and spend much less on health and social services.

  As a point of reference, the Labour Party is usually placed at 4 on this scale.

  Where would you place yourself?”

- *Environment vs. growth:*

  “Consider a 0 to 10 scale, where the end marked 0 means that protecting the environment should have priority even if that reduces economic growth, and the end marked 10 means that economic growth should have priority even if that hinders protecting the environment.

  As a point of reference, the Labour Party is usually placed at 5 on this scale.

  Where would you place yourself?”

Question order randomized.

**Anti-Muslim prejudice**

"For each of the following statements, we would like you to indicate your opinion."

- For Muslims who live in Britain, how likely is it that their first loyalty is to Britain rather than to their home country?
- How likely is it that increasing numbers of Muslims in Britain will make our country less safe?
- When young Muslim men get together, how likely is it that they are planning some kind of criminal activity?

Answers coded from 1 = *Extremely unlikely* to 7 = *Extremely likely*.

- How comfortable do you feel when Muslims display non-British dress, manners and customs?

Answers coded from 1 = *Extremely comfortable* to 7 = *Extremely uncomfortable*.

Question order randomized.

**IAT: religion stimuli**

*Muslim names:* Mohammad, Ali, Hussain, Omar, Bilal, Usman, Zahid, Shahid, Saqib, Nomaan, Fatima, Fozia, Sadia, Sobia, Salma, Maryam, Farzana, Ayesha, Sakeena, Zainab

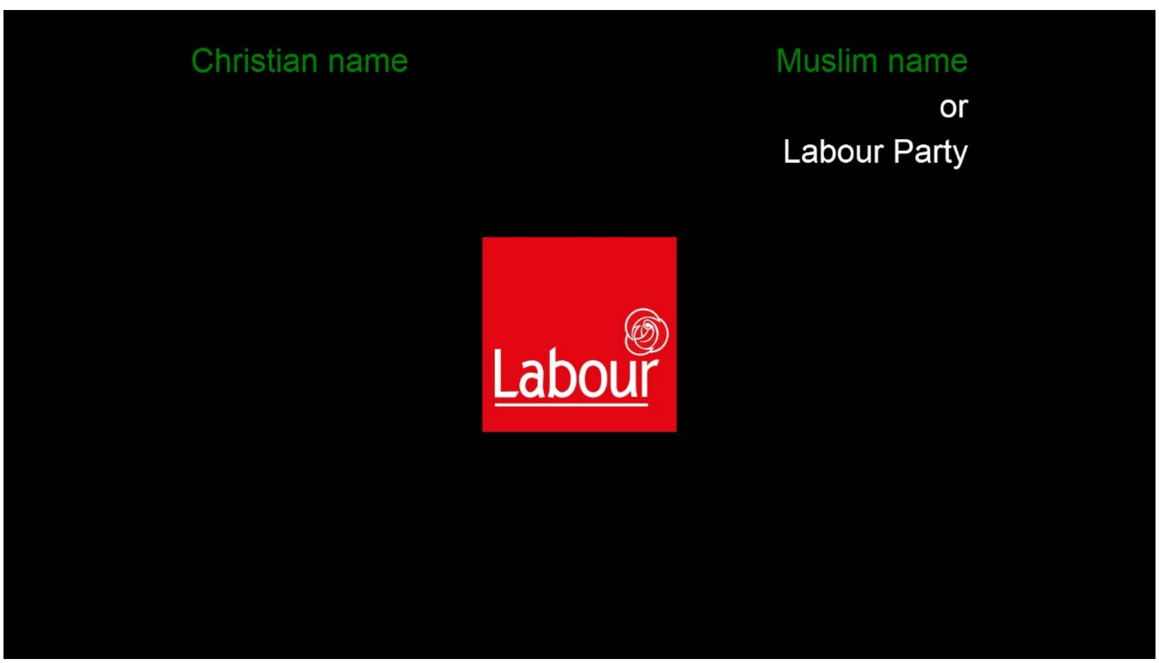
*Christian names:* Oliver, Jack, Harry, George, Charlie, Jacob, Thomas, Noah, William, Oscar, Amelia, Olivia, Emily, Isla, Ava, Jessica, Ella, Isabella, Poppy, Mia

**IAT: party stimuli**

Available upon request

**IAT: sample screen (composition one, name stimulus)**


**IAT: sample screen (composition two, picture stimulus)**



## Study 3: Race and Welfare Programs in the U.S.

### Spending preferences

"We would like to ask you about various ways in which the government spends the public's tax money. There are various government programs that address different problems. In the questions to follow, we would like to get your opinions about some of them. For each, please use the scale provided to indicate whether you think spending should be increased, decreased, or kept about the same."

- What about spending on public schools?
- What about spending on assistance to the poor?
- What about spending on public healthcare?
- What about spending on assistance for the homeless?

Question order randomized.

Answers coded from 1 = *Decreased substantially* to 7 = *Increase substantially*.

### Anti-Black prejudice

"Now please answer some questions about different groups in our society. You will be presented with a 10-point scale on which the characteristics of the people in each group can be rated.

Where would you rate BLACKS in general on this scale?

Where would you rate WHITES in general on this scale?"

- 0 = *Hardworking* to 10 = *Lazy*.
- 0 = *Intelligent* to 10 = *Unintelligent*.
- 0 = *Law-abiding* to 10 = *Violent*.

**IAT: race stimuli**

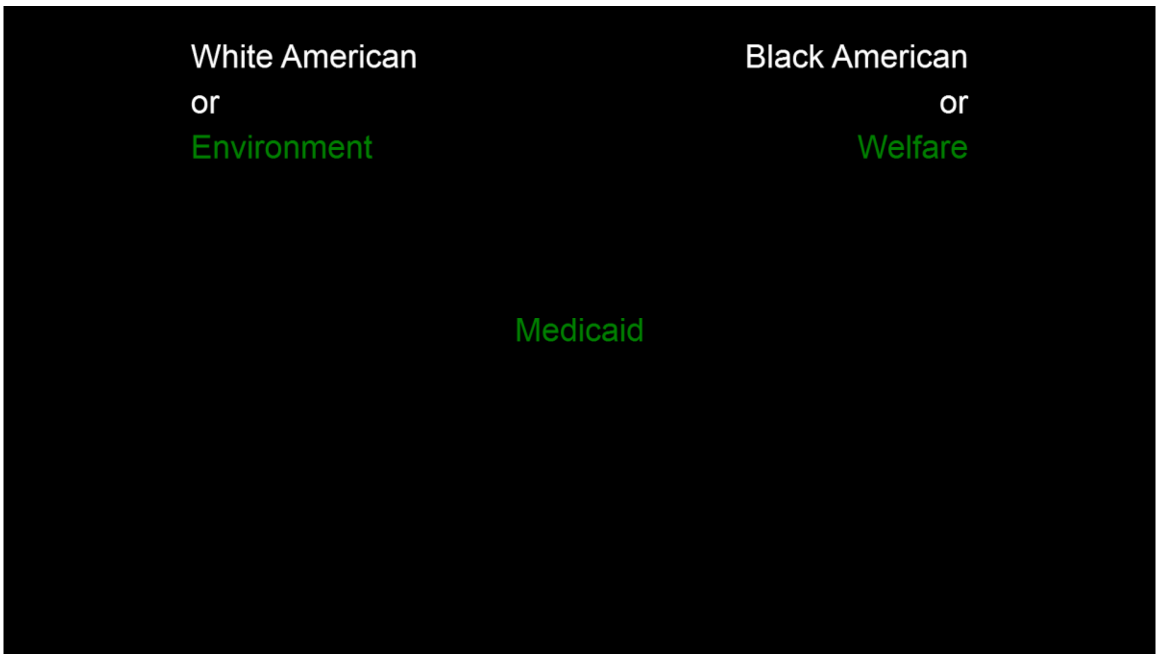
The stimuli are available at: https://www.projectimplicit.net/stimuli.html

**IAT: welfare stimuli**

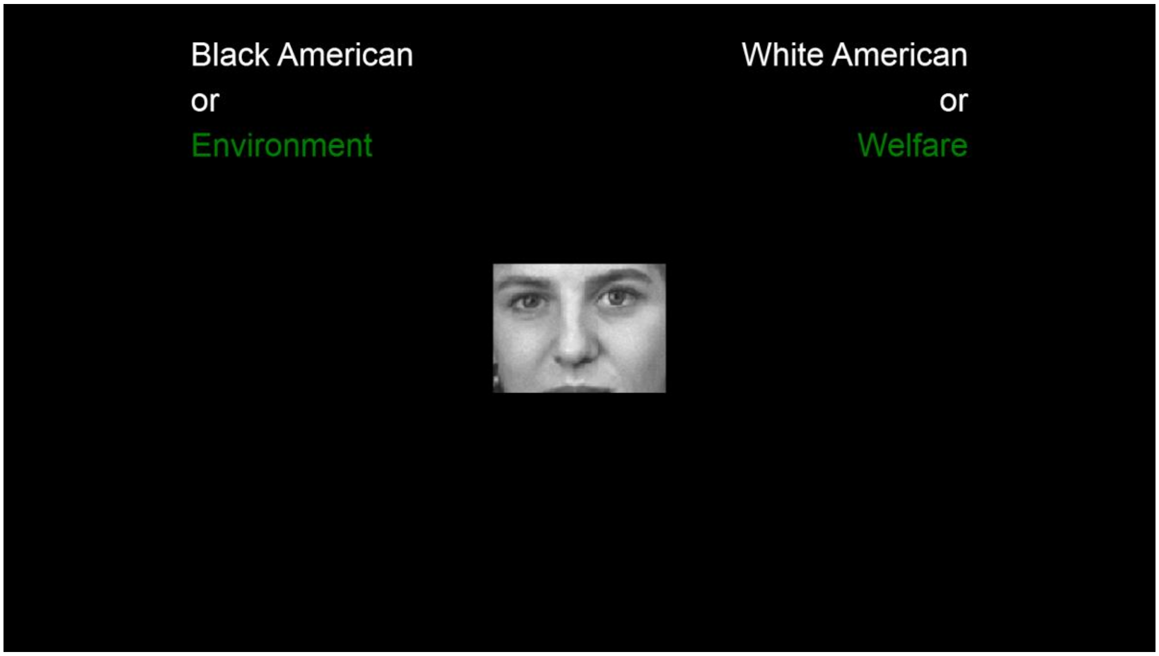
*Welfare:* Food Stamps, Medicaid, Public Housing, Health Clinic, Homeless Shelter, School Lunches

*Environment:* Clean Air, Waste Disposal, Water Quality, Pollution Control, Solar Power, Wind Energy

**IAT: sample screen (pro-stereotypic sorting, word stimulus)**



**IAT: sample screen (counter-stereotypic sorting, picture stimulus)**



## Study 4: Race and Poverty in the U.S.

### Spending preferences

"We would like to ask you about various ways in which the government spends the public's tax money. There are various government programs that address different problems. In the questions to follow, we would like to get your opinions about some of them. For each, please use the scale provided to indicate whether you think spending should be increased, decreased, or kept about the same. Please remember that increasing spending in many categories will either mean taxes will need to be increased or the federal deficit will have to grow. So, prioritize the spending you think is most important."

1. What about spending on Medicaid, the health care program for families and individuals with limited resources?
2. What about spending to assist poor people in acquiring basic food items, also known as "food stamps"?
3. What about spending on rental housing assistance to low-income households?
4. What about spending on education programs for disadvantaged students?
5. What about spending on immigration control and border security?
6. What about spending on public safety and crime prevention?
7. What about spending to modernize the Armed Forces?
8. What about spending on foreign intelligence efforts of the CIA?
9. What about spending to improve the nation's roads and bridges?
10. What about spending to maintain underground infrastructure like sewer and water systems?
11. What about spending on major transportation systems like train lines and airports?

Item numbers correspond to Table A1.

Question order randomized.

Answers coded from 1 = *Decreased substantially* to 7 = *Increase substantially*.

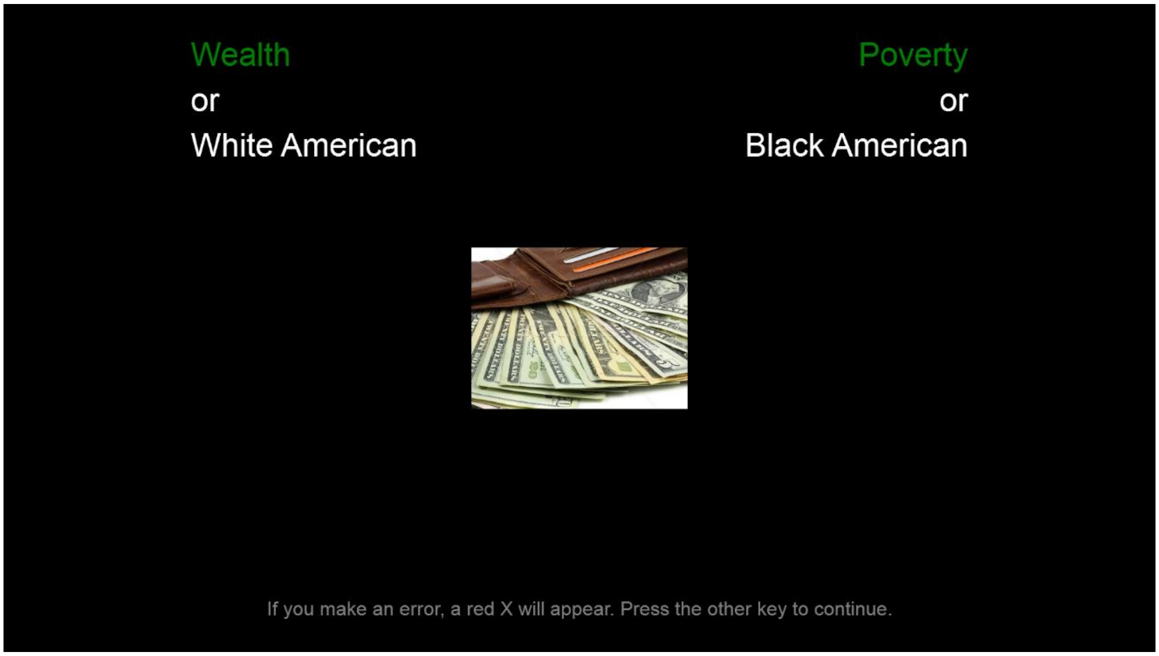
**IAT: race stimuli**

Same as in Study 3

**IAT: income stimuli**

Available upon request

**IAT: sample screen (pro-stereotypic sorting, income stimulus)**



**IAT: sample screen (counter-stereotypic sorting, race stimulus)**

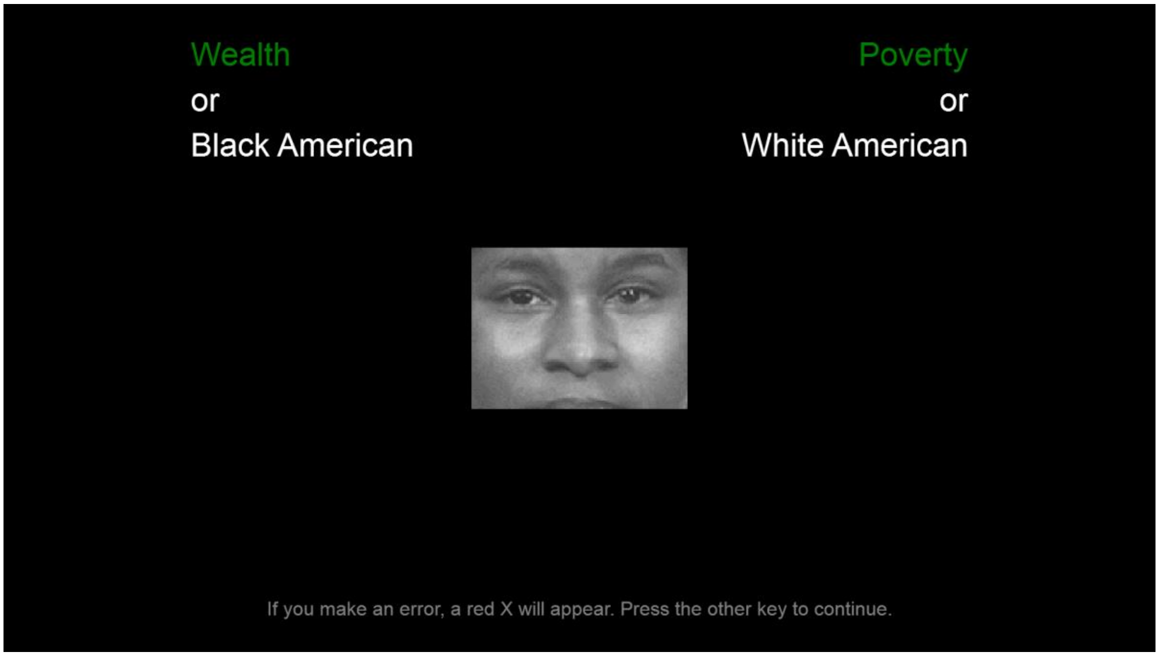


**Table A1**
*Full Results of the Structural Equation Model*

| | Estimate |
|---|---|
| Support for spending on welfare ← | |
| Race--poverty schema | -0.43** |
| | (0.15) |
| Age | -0.06 |
| | (0.05) |
| Female | 0.28* |
| | (0.13) |
| Education | 0.09 |
| | (0.05) |
| Income | -0.10*** |
| | (0.02) |
| Black | 0.50* |
| | (0.25) |
| Support for spending on policing ← | |
| Race–poverty schema | 0.17 |
| | (0.19) |
| Age | 0.11 |
| | (0.06) |
| Female | 0.06 |
| | (0.16) |
| Education | -0.19** |
| | (0.06) |
| Income | 0.07** |
| | (0.02) |
| Black | 0.24 |
| | (0.30) |
| Support for spending on defense ← | |
| Race–poverty schema | 0.13 |
| | (0.20) |
| Age | 0.29*** |
| | (0.07) |
| Female | 0.01 |
| | (0.17) |
| Education | -0.10 |
| | (0.07) |
| Income | 0.05 |
| | (0.03) |
| Black | -0.01 |
| | (0.33) |

(continued on the next page)

**Table A1**
(continued)

| | Estimate |
|---|---|
| Support for spending on infrastructure ← | |
| Race–poverty schema | -0.10 |
| | (0.13) |
| Age | 0.11** |
| | (0.04) |
| Female | -0.31** |
| | (0.11) |
| Education | 0.06 |
| | (0.04) |
| Income | -0.02 |
| | (0.02) |
| Black | 0.08 |
| | (0.21) |
| Support for spending on welfare → | |
| Item 1 | 1.00[a] |
| | (.) |
| Item 2 | 1.18*** |
| | (0.05) |
| Item 3 | 1.17*** |
| | (0.05) |
| Item 4 | 0.81*** |
| | (0.05) |
| Support for spending on policing → | |
| Item 5 | 1.00[a] |
| | (.) |
| Item 6 | 0.50*** |
| | (0.07) |
| Support for spending on defense → | |
| Item 7 | 1.00[a] |
| | (.) |
| Item 8 | 0.34*** |
| | (0.06) |
| Support for spending on infrastructure → | |
| Item 9 | 1.00[a] |
| | (.) |
| Item 10 | 0.84*** |
| | (0.07) |
| Item 11 | 0.82*** |
| | (0.07) |

(continued on the next page)

**Table A1**
(continued)

| | Estimate |
|---|---|
| Intercepts | |
| Item 1 | 4.91*** |
| | (0.29) |
| Item 2 | 4.36*** |
| | (0.36) |
| Item 3 | 4.44*** |
| | (0.34) |
| Item 4 | 4.92*** |
| | (0.24) |
| Item 5 | 4.13*** |
| | (0.35) |
| Item 6 | 4.55*** |
| | (0.18) |
| Item 7 | 3.00*** |
| | (0.39) |
| Item 8 | 3.48*** |
| | (0.16) |
| Item 9 | 4.80*** |
| | (0.25) |
| Item 10 | 4.64*** |
| | (0.21) |
| Item 11 | 4.20*** |
| | (0.21) |
| Error variances[b] | |
| Item 1 | 0.75 |
| | (0.06) |
| Item 2 | 0.58 |
| | (0.06) |
| Item 3 | 0.53 |
| | (0.06) |
| Item 4 | 1.29 |
| | (0.09) |
| Item 5 | 1.28 |
| | (0.21) |
| Item 6 | 1.04 |
| | (0.08) |
| Item 7 | 0.41 |
| | (0.34) |
| Item 8 | 1.39 |
| | (0.10) |

(continued on the next page)

**Table A1**
(continued)

| | |
|---|---|
| Item 9 | 0.43 |
| | (0.07) |
| Item 10 | 0.59 |
| | (0.06) |
| Item 11 | 0.95 |
| | (0.08) |
| Support for spending on welfare | 1.48 |
| | (0.14) |
| Support for spending on policing | 1.42 |
| | (0.24) |
| Support for spending on defense | 2.40 |
| | (0.39) |
| Support for spending on infrastructure | 0.92 |
| | (0.10) |
| Error covariances | |
| Spending on welfare, Spending on policing | -0.64*** |
| | (0.12) |
| Spending on welfare, Spending on defense | -0.86*** |
| | (0.12) |
| Spending on welfare, Spending on infrastructure | 0.49*** |
| | (0.07) |
| Spending on policing, Spending on defense | 1.50*** |
| | (0.15) |
| Spending on policing, Spending on infrastructure | -0.07 |
| | (0.08) |
| Spending on defense, Spending on infrastructure | -0.37*** |
| | (0.09) |

*Note.* Standard errors in parentheses. Item numbers correspond to ones listed in “Spending preferences”
[a] Parameter constrained to achieve identification
[a] Significance tests for variance estimates not available
* $p < .05$, ** $p < .01$, *** $p < .001$