Mapping Cultural Schemas: From Theory to Method

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Abstract

A growing body of research in sociology uses the concept of cultural schemas to explain how culture influences beliefs and actions. However, this work often relies on belief or attitude measures gleaned from survey data as indicators of schemas, failing to measure the cognitive associations that constitute schemas. In this article, we propose a concept-association-based approach for collecting data about individuals’ schematic associations, and a corresponding method for modeling concept network representations of shared cultural schemas. We use this method to examine differences between liberal and conservative schemas of poverty in the United States, uncovering patterns of associations expected based on previous research. Examining the structure of schematic associations provides novel insights to long-standing empirical questions regarding partisan attitudes toward poverty. Our method yields a clearer picture of what poverty means for liberals and conservatives, revealing how different concepts related to poverty indeed mean fundamentally different things for these two groups. Finally, we show that differences in schema structure are predictive of individuals’ policy preferences.

Keywords
schemas, culture, methods, semantic network analysis, relational meaning, stratification beliefs, political attitudes

Sociologists have long debated whether and how we ought to go about measuring culture (Fine 1979; Ghaziani 2009; Jepperson and Swidler 1994; Mohr and Ghaziani 2014; Schudson 1989). In his influential review article “Culture and Cognition,” DiMaggio (1997) points to barriers these measurement issues pose to the study of culture as a cumulative theoretical enterprise. As a corrective, he proposed that measurement and theorization of culture in sociology stood to benefit from incorporating insights about cultural processes from the cognitive sciences.

Arguably the most influential export from cognitive scientific work has been the schema concept, which now holds a central place in sociological theory and research. Schemas—sets of cognitive associations, developed over repeated experience, that represent information and facilitate interpretation and action (DiMaggio 1997; Strauss and Quinn 1997; Vaisey 2009)—are increasingly adopted as a theoretical explanation for how culture influences individual action and belief, not only in...
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Cultural sociology (Cerulo 2014; Goldberg 2011; Lizardo 2004; Lizardo et al. 2016; Lizardo and Strand 2010; McDonnell, Bail, and Tavory 2017), but also in social psychology and demography, as well as the sociologies of religion, gender, race, morality, and work and occupations (e.g., Bachrach 2014; Cech and Blair-Loy 2014; Ecklund and Lee 2011; Ecklund et al. 2017; Edgell 2012; Farrell 2011; Gerstel and Clawson 2014; Gorman 2005; Hunzaker 2014; Miles 2014; Ray 2019; Turco 2010). However, this increased prevalence of schema-related work has not been indicative of a coherent or cumulative line of research and theory development regarding culture in sociology (Patterson 2014).

Although the schema concept has provided a useful explanatory tool, in practice theoretical progress has been stymied by a significant disconnect between how sociologists understand and theoretically describe schemas and how they measure them. Researchers often use belief or attitude measures gleaned from survey data as indirect indicators of schemas (e.g., belief items as indicators of moral schemas in Vaisey [2009] or between-individual shared response patterns on belief or preference items in Goldberg [2011] and Boutyline [2017]), with little research devoted to explicitly collecting data on the cognitive associations that constitute schemas (Vaisey and Valentino 2018; although see Ignatow [2009] for a text-analysis based approach for indirectly estimating schemas from existing text corpora).

Belief-based indicators of schemas have several important limitations, which in turn hinder researchers’ understanding of how culture works. First, theoretical expectations lead many researchers to assume that differences in attitudes and preferences are rooted in differences in schema structure and content (D’Andrade 1995; Strauss and Quinn 1997). Yet because researchers generally do not collect data on schema structure, we do not know the scope conditions under which the schema-attitude link does—and does not—hold. Second, measuring schemas using beliefs tends to overlook two core characteristics of schemas that are recognized in schema theory and cognitive science: the concepts that make up a schema are, by definition, interrelated; and some concepts are more central or influential than others. When relying on belief-based measures of schemas, we cannot know whether subscribing to a particular belief means fundamentally different things to two different people. Finally, the ability to measure schemas separately from beliefs, attitudes, and preferences would ultimately enable sociologists to develop improved models of how differences in these cultural elements are developed and transmitted, and how they persist over time.

The primary goal of this study is to develop and test a new concept-association-based method for collecting schema data from individuals. As we will show, this method allows researchers to capture a corresponding concept network measure of cultural schemas that is more consonant with the connectionist models upon which sociological schema theory is based—albeit with some limitations (Clark and Millican 1996; Strauss and Quinn 1997). We also show how data collected using this method can be used to test hypotheses about the relationship between these estimated schemas and other cultural elements—in this case, identities and attitudes.

The method we propose is content agnostic—and so could be used to study schemas in any domain of interest to researchers—but as an initial validation test case, we examine U.S. liberal and conservative schemas of poverty. We chose this case because extensive sociological research on this topic (Baldassarri and Gelman 2008; DiMaggio, Evans, and Bryson 1996; Gilens 2000; Homan, Valentino, and Weed 2017; Manza and Brooks 1999; Merolla, Hunt, and Serpe 2011) provides a useful baseline to gauge the method’s ability to capture expected patterns of associations.

We also show how examining the structure of these associations provides novel insights about long-standing empirical questions regarding beliefs about and attitudes toward poverty. For instance, the stratification beliefs literature has ongoing debates about the meanings of two core components of poverty schemas—“individualist” attributions (i.e.,
understanding poverty to be the result of a person’s own actions, choices, or attributes) and “structuralist” attributions (i.e., understanding poverty to be the result of a person’s circumstances or broader societal forces around them)—as well as debates about whether the meanings of these attributions diverge between social groups (Godfrey and Wolf 2016; Hunt and Bullock 2016; Strauss 2012). The study of beliefs about poverty is therefore a particularly fruitful case for testing whether a more direct way of measuring schemas sheds new light on these old questions.

To lay the groundwork for what would be required of an improved schema measure, we begin with an overview of the schema concept and schema theory in the cognitive sciences, as well as recent work on measuring schemas and cognitive associations in sociology. We then introduce a new concept-association task developed to collect data on individuals’ perceived schematic associations and the method used to estimate shared cultural schemas from individual participants’ schema association data. Following this, we present the study analyses and results in three steps. In the first step, we use cultural consensus analysis (Aßfalg and Erdfelder 2012; Oravecz, Vandekerckhove, and Batchelder 2014; Romney, Weller, and Batchelder 1986) to estimate the shared, cultural schemas for the liberal and conservative groups from the individual-level concept-association data collected using the proposed method.

In the second step, we examine between-group differences in the cultural schemas estimated in the first set of analyses. This allows us to determine whether the proposed method captures expected differences based on prior research regarding partisan beliefs about poverty. Results from this portion of the study indicate that the method indeed captures expected patterns of associations in terms of individualist versus structuralist factors associated with poverty by each group. We also show how the elicited concept network schema representations can be used to operationalize two cultural concepts of interest to sociologists: cultural anchors (Ghaziani and Baldassarri 2011), measured as network centrality, and relational meaning (Mohr 1998), measured in terms of structural equivalence. By examining cultural anchoring and relational meaning within the liberal and conservative schemas of poverty, we will uncover a clearer understanding of what poverty means for liberals and conservatives, and we will see how different concepts related to poverty indeed mean fundamentally different things for these two groups.

Finally, to show how data collected using this method can be used to test schema-related hypotheses, in the third set of analyses we test whether partisan differences in the estimated schema structure found in the previous set of analyses are predictive of differences in policy preferences at the individual level. We also examine the extent to which partisan differences in these cognitive, conceptual structures account for previously well-established effects of partisan identification on policy preferences (Campbell et al. 1960; Green, Palmquist, and Schickler 2004). An ongoing debate in political psychology seeks to establish whether political partisanship operates as a relatively content-free heuristic, eliciting policy stances via identity cues (Achen and Bartels 2016; Campbell et al. 1960; Converse 1964; Kinder and Kalmoe 2017; Lenz 2013; Zaller 2012), or whether political partisanship leads people to actively engage in fundamentally different reasoning that structures their political preferences (Goren 2013; Goren, Federico, and Kittilson 2009; Leeper and Slothuus 2014). Operationally, we will discern whether schemas mediate the relationship between partisanship and policy attitudes, as predicted by the latter perspective, or whether schemas are merely epiphenomenal to party identification, as predicted by the former.

**SCHEMA THEORY AND COGNITIVE SCIENCE**

Perhaps the most prominent touchstone in schema-related research in sociology is Strauss and Quinn’s *A Cognitive Theory of*
Cultural Meaning (1997). Like the DiMaggio review published in the same year, Strauss and Quinn argue that understanding schema-based cognition is key for explaining cultural processes, especially with regard to culture as shared knowledge or meaning. They define schemas as cognitive information processing mechanisms that are composed of “learned or innate mental structures that organize related pieces of knowledge” (Strauss and Quinn 1997:49).

More specifically, drawing on connectionist models of cognition (Churchland 1995; Clark and Millican 1996; Rumelhart and McClelland 1986), Strauss and Quinn argue that cultural knowledge and meaning are the byproduct of internalized networks of cognitive associations. In this model, a concept’s meaning is encoded in networks of associations among many neurons (or more accurately, among many neural networks, because any single concept is composed of a pattern of activation across a configuration of many neurons). Weighted associations between these neural units are developed and adjusted as a result of repeated experience over time. Simultaneous activation of neural units associated with two concepts is caused by seeing or experiencing them at the same time. Repeated co-activations over time strengthen the association between pairs of concepts. This, in turn, increases the likelihood that one concept will be activated, perceived, or expected, given that the other is—regardless of whether it is actually present in the situation at hand. In this way, internalized cognitive schemas influence our memories of the past, interpretations of the present, and expectations about future situations.

Meaning in the connectionist framework is understood to be fundamentally relational—bound up in the associations among the other concepts and conceptual networks to which a given concept is closely associated (Carley and Palmquist 1992; Emirbayer 1997; Mohr 1998). In this connectionist model, meaning is latent in these many schema-based associations, ready to be constructed (and reconstructed) with each activation.

BEYOND BELIEFS: EXISTING ALTERNATIVES FOR MEASURING SCHEMAS AND COGNITIVE ASSOCIATIONS

As noted in a prominent debate (Pugh 2013; Swidler 2008; Vaisey 2008, 2014), this work on schema-based cognition has implications for the study of other cognitive elements of culture that are more traditionally within the purview of sociologists, such as knowledge, attitudes, and beliefs. Like meaning, these elements are theorized as predicated upon schematic associations (D’Andrade 1995; Strauss and Quinn 1997). This insight regarding the link between schemas and beliefs, attitudes, and preferences has provided motivation for numerous studies using attitude or belief measures as indicators for cultural schemas (Badassarri and Goldberg 2014; Bonikowski and DiMaggio 2016; Boutyline 2017; Boutyline and Vaisey 2017; Farrell 2011; Goldberg 2011; Homan et al. 2017; Vaisey 2009).

Yet even individuals reporting similarly strong endorsement of a given belief or value in a survey may hold fundamentally different associative understandings of what that belief or value means, and why it matters. For instance, Martin and Desmond (2010) find that liberals and conservatives believe self-reliance to be equally important for socioeconomic success, but they differ in their beliefs about why the poor are poor: they see different barriers to obtaining that self-reliance (lack of educational opportunities versus lack of work ethic). These differing understandings underlie attitudes toward government spending programs. Belief-based schema measures are thus limited in their ability to locate interpretive schemas that contain both evaluative and ontological components.

Recent work on relational class methods of measuring shared cultural understanding aims to advance beyond this crucial limitation of belief-based measures by capturing the relational nature of schema-based cognition (Badassarri and Goldberg 2014; Boutyline 2017; Goldberg 2011). Rather than examining discrete beliefs or attitudes in isolation as
indicators of schemas, these techniques examine patterns of relations—or relationality—among respondents’ belief and preference item responses. Goldberg (2011:1399) defines relationality in this sense as “the extent to which two individuals exhibit a similar pattern of association on measures of opinion on issues that constitute a particular social domain... it is interpreted as a shared understanding of the structure of that domain.” In this body of work, however, shared understanding need not be associated with shared belief—two people with opposing belief patterns are said to share a “schema” so long as they are in agreement regarding “the relative significance (of the issues) or dimensions along which this significance is scaled” (Goldberg 2011:1398). This limits the type of schema these relational methods can capture to a single, evaluative schema (e.g., like versus dislike, or support versus oppose). Yet schemas are understood to motivate a far broader range of beliefs, attitudes, and ultimately, behaviors.

As an alternative to relational class methods, some sociologists of culture and cognition have proposed adopting indirect measures of attitudes and beliefs developed in cognitive and social psychology, such as the Implicit Association Test (IAT; Greenwald, McGhee, and Schwartz1998) or the Affect Misattribution Procedure (AMP; Payne and Lundberg 2014) as a way to measure implicit schema-based cognition (Miles, Charron-Chénier, and Schleifer 2019; Shepard 2011; Srivastava and Banaji 2011). In a typical IAT, participants are asked to rapidly associate stimulus words or images representing two categories of interest (e.g., black/white, male/female, gay/straight) with either positive or negative evaluative target terms. How easily respondents associate the stimulus concepts with positive versus negative target terms—as indicated by relative response times for each—is used to determine whether respondents hold positive or negative implicit associations with each category. In addition to original evaluation-related association tests, IATs have also been used to test associations between pairs of conceptual categories (e.g., white/black and weapons/harmless objects, male/female and career/family, see Nosek et al. 2007). The AMP is similar to the IAT, but rather than measuring response time, the AMP asks participants for an affective response (typically, whether they find a stimulus pleasant or unpleasant). Participants are first presented with a rapid series of neutral and focal concepts, and then asked to rate their affect toward the neutral concepts. The AMP therefore allows researchers to unobtrusively gauge positive/negative affect toward a set of concepts.

Thus, unlike relational class techniques, indirect measures such as IAT and AMP can, in theory, be used to measure all possible between-concept associations that are expected to form the structure of cognitive schemas. However, the design of the task currently limits the breadth and detail of schematic associations that can be examined in a single study to, at most, four stimulus-target category pairings (e.g., black/white, good/bad). As Lamont and colleagues (2017:870) note, this means IATs (and AMPs) allow researchers to determine whether individuals hold differing evaluative associations for concepts of two different categories (or differing associations between two pairs of concept-categories), but without further context the method cannot “specify the meaning of [these] differential associations.”

The method we propose builds on Relational Class Analysis (RCA), Correlational Class Analysis (CCA), IAT, and AMP approaches for measuring schemas to address some of their limitations. Like RCA and CCA, we will strive to capture relational meaning, but in our case we will use a method that allows us to directly collect data about perceived relations, thus enabling an examination of schemas with more complex and multifaceted structures than have typically been studied using relational class approaches. We borrow IAT’s general rapid concept association approach, but we use an alternative task design that focuses on concept pair (rather than category pair) associations to
facilitate collection of a much broader context of conceptual associations around the target term of interest.

ESTIMATING THE CULTURAL FROM THE INDIVIDUAL: A CULTURE AS CONSENSUS APPROACH

With the exception of relational class methods, most prior work seeking to measure schemas has focused primarily on measuring individuals’ cognitive schemas and associations. However, it is important to note that not all aspects of individuals’ cognitive schemas are inherently cultural (Strauss and Quinn 1997).1 Because cognitive schemas are (1) internal to individuals and (2) built over the course of repeated experience, they may contain elements or associations that are idiosyncratic to individuals (due to unique individual experiences). However, schematic associations are often largely shared by groups or cultures due to common past experiences in shared social structures (see Bourdieu 1990). Because not all schemas are shared, it is important that methods for measuring cultural schemas isolate the cultural component from the idiosyncratic content of individuals’ cognitive schemas. To identify this shared, cultural content we take a “culture as consensus” approach, given the intuition that schemas (and cultural objects generally) are cultural to the extent they are broadly shared among a defined group (Patterson 2010; Strauss and Quinn 1997; Zerubavel 1999). Sharedness—a byproduct of within-group, in-common social experiences and cultural transmission—is key. In this culture as consensus approach, cultures may exist on varying levels, from family cultures, to club or organizational cultures, to professional cultures, to national cultures, where “a culture” is composed of all cultural objects (e.g., beliefs, values, attitudes, meanings, knowledge, schemas, artifacts, practices) largely shared by members of a group.

Operationally, rather than taking representative samples of whole populations and looking for variation in response patterns, as in traditional survey-based cultural research aimed at population inference, a culture as consensus approach entails looking for agreement among respondents drawn from a targeted group regarding the cultural objects (e.g., beliefs, knowledge, attitudes) under study (Heise 2010; Oravecz et al. 2014; Romney et al. 1986). Agreement indicates that group’s shared cultural understanding: the responses with the highest levels of agreement are the shared, cultural responses for a group. Operationalizing culture as consensus in this way helps overcome the “amorphous mist” (Fine 1979; Ghaziani 2009) conundrum that notoriously plagues studies of culture, allowing for increased formalization.

THE TEST CASE: LIBERAL AND CONSERVATIVE SCHEMAS OF POVERTY

As a test case, we examine whether the method we propose can capture expected differences (and overlaps) in liberal and conservative schemas of welfare and poverty in the United States. Social scientists have found little evidence for strong “Culture War”-esque (Hunter 1992) general mass political polarization hypotheses (DiMaggio et al. 1996; Fiorina and Abrams 2008), but differences in economic policy attitudes (particularly regarding government assistance) between self-identified political partisans are well documented (Baldassarri and Gelman 2008; Evans 2003; Manza and Brooks 1999).

Research on partisan beliefs about poverty highlights that differences in support for government assistance are rooted in differences in views about who is poor and why, particularly as this pertains to evaluations of “deservingness” of potential recipients (Goren 2003; Homan et al. 2017; Martin and Desmond 2010). This work finds that liberals are more likely to associate structural-level factors with poverty (e.g., poor education systems, racism), whereas conservatives are more likely to associate individual-level factors
with being poor (e.g., laziness, teen pregnancy) (Robinson 2009; Weiner, Osborne, and Rudolph 2011).

Nevertheless, researchers have pointed out that differences in types of association tend to be a matter of degree, rather than a strict either-or distinction. In a survey of research on Americans’ views of the causes of poverty, Merolla and colleagues (2011:208) note that “this mixing of beliefs stems from individualism’s place as a stable and pervasive cultural belief that shapes the views of Americans at all social locations, alongside structuralist beliefs that are more variable and—depending on persons’ personal and group-based experiences—are ‘layered onto’ an existing individualistic base.” Indeed, the prevalence of this “dual consciousness” about seemingly-incompatible individualist and structuralist beliefs about the causes of poverty has long perplexed researchers who study stratification beliefs (Hunt and Bullock 2016:101). Based on prior research regarding partisan differences in poverty beliefs, as well as the persistent finding that most Americans endorse both individualist and structuralist explanations of poverty, we expect to find overlap between the two groups’ schemas of poverty in terms of associations to individual-level factors, but liberals’ schema will be distinguished by a greater number of associations to structural-level factors (Hypothesis 1).

Additionally, if internalized schemas underpin individuals’ beliefs, preferences, and attitudes, as predicted by schema theory and asserted by previous research, then these partisan differences in schemas should be predictive of partisan differences in policy attitudes. Therefore, we expect to find that individuals whose own poverty schemas are more similar to the conservative cultural schema will be more likely to have typical conservative preferences on government aid spending, preferring spending decreases (Hypothesis 2a).

Finally, to show how data collected using our approach can be used to test hypotheses about the schema-attitude link, we will use the schema measure proposed here to adjudicate between two explanations in political psychology regarding the pathway via which partisan group identity affects policy preferences: (1) via cue-based heuristic processes in which individuals adopt their “team’s” preferences as a shortcut for evaluating complicated policies; or (2) by providing individuals with differing cognitive frameworks for interpreting policy positions (e.g., via shared experience and media/information sources, as would be predicted by schema theory). We expect, in accordance with the second position, that partisan differences in schemas will partially explain (mediate) the effect of partisan identification on policy preferences (Hypothesis 2b).

STUDY DESIGN AND PROCEDURE

Concept Association Task Design

To collect data about individuals’ schematic associations, we use a concept association task. We designed the task to combine elements of concept mapping methods used in cognitive psychology and education research to measure the impact of knowledge acquisition on cognitive structures (Clariana 2010) and rapid association, as well as implicit association tests, designed to encourage participants’ automatic, schema-based responses (Shepherd 2011; Srivastava and Banaji 2011).

In the task, participants are shown a series of concept pairs and asked to respond rapidly, according to their initial instinct, as to whether each pair is related or not related. To facilitate this judgment (by casting a broad net of what is meant by “related”), participants were prompted at the start of the task that “concepts may be related (1) because one causes the others or (2) because they commonly go together in this context [of poverty in the US] for some other reason” (i.e., the relationship between the concepts need not be causal). See Figure S1 in the online supplement for an example screenshot from this task.

To develop the list of concepts used in the association task for this study, we consulted prior studies of Americans’ views of poverty and welfare (e.g., Gilens 2000; Homan et al.
2017; Martin and Desmond 2010; Strauss 2012), with the goal of including the concepts this work has found to be most commonly associated with cultural understandings of poverty and government assistance in the United States. Because prior research indicates that concept level (i.e., individual versus structural causes and correlates of poverty) is likely the important distinction between liberal and conservative groups of interest, when developing the list we selected an equal number of concepts for each level. In addition to eight individual-level concepts (e.g., “being lazy,” “dropping out of school”) and eight structural-level concepts (e.g., “job outsourcing,” “sexism”), we also include eight “interactional”-level concepts that capture factors outside of individuals themselves but that are present in an individual’s immediate environment (e.g., “attending bad schools,” “lacking role models”) (see Homan et al. 2017). We also include eight concepts related to demographic characteristics, to capture associations regarding whom participants perceive as poor, resulting in a total of 32 concepts. See Table S1 in the online supplement for the full list of concepts by level.

In the concept association task, participants were asked about all possible pairwise combinations of these concepts, excluding a handful of pairs of demographic concepts due to the non-logical nature of such pairings (e.g., “Is being white related to being female?”). This resulted in a total of 490 concept pairs. Concept pairs were presented in random order, and concept order within pairs was randomized across participants to prevent ordering effects.

The task requires participants to respond to a large number of prompts as quickly as possible, and unlike traditional survey questions, its IAT-like design makes it difficult for participants to respond in a socially desirable way. Yet because we rely on participants’ judgments about whether a concept pair is related—rather than directly observing the relation itself—the task design does not rule out the possibility that we may be tapping a mixture of automatic and deliberate cognition, both of which play a role when respondents answer forced-choice survey questions (Miles et al. 2019). Schematic cognition is generally understood to be a type of automatic processing, so this is an important limitation we will return to in our concluding discussion.

Study Sample and Recruitment

We fielded this study online using Qualtrics Panels, an online respondent sampling service that recruits targeted samples for researchers interested in studying specific subgroups. Given this study’s culture as consensus approach, sample recruitment for the study was targeted to core members of the partisan groups of interest—liberal Democrats and conservative Republicans. Participants’ political partisanship was assessed at the time of entry into the Qualtrics sample pool (which may have been months or years ago), so prior to beginning the study, we asked participants to respond to two screener questions in which they placed themselves on a standard seven-point liberal-conservative partisan identification scale and selected their political party affiliation. Only individuals who self-identified as being a Republican and either extremely conservative or conservative and participants who self-identified as being a Democrat and either liberal or extremely liberal were allowed to participate in the study. In this way, we recruited an initial sample of 504 participants, with roughly half the sample self-identifying as liberal Democrats (n = 250) and the other half as conservative Republicans (n = 254).

To ensure data quality, the analyses that follow exclude data from 41 participants who showed evidence of attempting to rush through the concept associations task too quickly (selecting the same response choice for nearly all items, completing the task in times well below expected thresholds based on pretests) or not completing the task in one sitting (completing the task in times well above expected thresholds). Additionally, in the sets of analyses devoted to estimating and comparing the shared cultural
schemas for the liberal and conservative groups (Parts I and II of the analyses), we exclude participants who later reported, in response to an additional seven-point liberal-conservative scale measure, that their policy preferences regarding welfare and government assistance were inconsistent with their political group membership9 (e.g., individuals who generally identify as conservative Republicans, but self-identified as having liberal views regarding welfare and government assistance). We excluded 39 conservative participants and 43 liberal participants using this criterion. In keeping with this study’s culture as consensus approach, this strategy intentionally excludes marginal members of liberal and conservative subcultures who are likely to deviate from the groups’ core schemas for the portion of analyses devoted to estimating the shared cultural schemas (see Table 1 for demographic descriptive statistics for this subsample).

We reintroduce data from these participants with non-typical partisan welfare views in the final set of analyses, which focuses on individual-level variation in schemas and its relationship to individuals’ partisan identities and beliefs. Using a separate sample of individuals from across the political spectrum (including non-partisans) would have provided an ideal test of this relationship, but this was not feasible due to resource constraints on data collection. However, reintroducing data from these weaker partisans for this stage of analysis helps provide some assurances that any findings regarding the relationship between schemas and beliefs is not limited to strong partisan ideologues (see Table S2 in the online supplement for full sample descriptive statistics).

**Study Procedure**

After choosing to participate in the study and completing the informed consent form, participants responded to a short open-ended prompt regarding their views about (1) why people become or remain poor in the United States and (2) how individuals who are poor differ from those who are not. These initial questions were included as a prime to activate

<table>
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<th>General Political Ideology</th>
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<th>Republicans</th>
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<tr>
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<tr>
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<tr>
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<tr>
<td>Strongly Conservative</td>
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participants’ relevant cognitive associations with poverty. Participants then completed the main concept association task described above. Following the association task, respondents completed a questionnaire regarding their support for poverty-related government programs and spending, as well as a standard demographic questionnaire.

In the policy spending questionnaire, participants were asked whether they believed the government should spend more, less, or keep spending about the same amount (1) generally on efforts to alleviate poverty and (2) with regard to 14 additional types of aid or government programs—welfare, food stamps, unemployment insurance, social security, social security disability, Temporary Assistance for Needy Families, Medicare, subsidized childcare, crime prevention, Affordable Care Act/Obamacare, public schools, college aid, subsidized housing, and assistance to blacks. These programs were chosen to include a mixture of universal aid as well as aid that specifically targets the poor, and they have been included in recent studies of political polarization (Baldassarri and Goldberg 2014; Gilens 2000). Question wording is patterned after government spending questions used in the American National Election Study (ANES), although not all of these aid types are included in the ANES measures. We use these policy preference measures in the final set of analyses to test study hypotheses regarding the relationship between individuals’ schemas, partisan identities, and attitudes (here, policy preferences).

ANALYSES AND RESULTS
PART I: ESTIMATING CULTURAL SCHEMAS USING CONSENSUS ANALYSIS

Analytic Strategy

We use cultural consensus analysis to estimate each group’s shared, cultural schema from the individual-level concept association data (Oravecz et al. 2014; Romney et al. 1986; Stone-Jovicich et al. 2011). This method was developed by cognitive anthropologists (Romney et al. 1986) to estimate cultural consensus answers from individual responses in ethnographic research. In line with the consensus approach, the model’s basic assumption is that if researchers ask members of some group a series of questions regarding a particular domain, the amount of agreement in their responses can be seen as the product of group members’ shared cultural understanding. Given this intuition, the model works backward from patterns of agreement among respondents on question items to estimate each respondent’s degree of enculturation (i.e., their level of cultural knowledge, based on their frequency of agreement with other respondents on the items), and to recover the “culturally correct” (or consensus) responses to the items under study.

In this study, we use Ásfalg and Erdfelder’s (2012) maximum-likelihood estimation of consensus analysis (CAML). In this method, for binary yes/no question items, respondents’ probability of responding “yes” to a given question is modeled as a function of their probability of correctly knowing/stating whether the answer is yes (this probability is represented by the respondent’s enculturation score), as well as their general probability of guessing an answer is yes when they do not know (represented by a guessing bias score, included in this consensus analysis estimation method to account for the fact that some people may be more likely to guess yes as opposed to no when they do not know the answer to an item). CAML’s measurement model, like that of consensus analysis models generally, expects that when answering items respondents either (1) know the culturally correct answer and give it (with probability = enculturation score), or (2) if they do not know the answer for an item, then they guess (where probability that they guess “yes” is equal to their guessing bias score). Estimation of enculturation and guessing bias scores in CAML is based on signal detection theory measures of hit (P [responds “yes” | answer is “yes”]) and false alarm (P [responds “yes” | answer is “no”]) rates.
Respondents’ hit and false alarm rate estimates are used along with their item responses to estimate the “culturally correct” consensus answers to each response item by estimating the probability that the consensus answer is “yes” versus “no.” When estimating the final cultural consensus “answer key” for the response items for a group, a value of “yes” (or, in our case, “related”) for the consensus answer is assigned to items where $P(\text{consensus answer} = \text{"yes"}) > P(\text{consensus answer} = \text{"no"})$ (see Åsfalg and Erdfelder [2012:190–3] for detailed descriptions of parameter estimation, and comparison to the original Romney and colleagues [1986] factor-analysis-based version of consensus analysis).

In this study, the individual response items used in the consensus analysis are participants’ “related” (1, “yes”) or “not related” (0, “no”) judgments for each of the 490 concept pairs from the association task (analyzed in the consensus analysis as item response vectors, where each respondent is represented by one row in their group’s matrix). We conduct two separate consensus analyses—one for liberals and one for conservatives—to estimate each group’s cultural consensus answer key for the concept association items. Each consensus analysis results in an estimated consensus answer key for the response items (a single row response vector of the 490 binary association items, where $1 =$ “related” and $0 =$ “not related”), as well as model summary data regarding enculturation scores, estimated average guessing bias, and measures of model fit.

To create the concept association network representations of schemas used in the following analysis, we transform each group’s single row vector consensus answer key into a 32 concept x 32 concept adjacency matrix, where each cell represents the relationship between a concept pair. Concept pairs with an estimated consensus answer of “related” (1) are connected by a tie (association) in the concept network. In adjacency matrices used in the analysis, we weight concept associations by their cultural salience (Romney et al. 1986), defined by consensus analysis as the level of cultural agreement on a response item (measured here as the proportion of respondents in the group who reported the association).

### Results

Table 2 summarizes the results from the consensus analysis (we discuss the estimated answer keys in the Results Part II section). To measure how well the estimated consensus analysis model fits the data, CAML estimates a likelihood-ratio test statistic ($G^2$), along with a bootstrapped significance test for this parameter (Åsfalg and Erdfelder 2012). The non-significant $G^2$ test for each model indicates that observed response patterns do not differ significantly from what we would expect to observe based on estimated model parameters if the estimated model (CAML’s response model + estimated answer key, enculturation scores, etc.) were indeed the data-generating mechanism; this indicates satisfactory model fit for the consensus analyses.

Comparing distributions of enculturation scores for each group shows that the liberal subsample has slightly higher enculturation scores compared to conservatives (i.e., higher probabilities of knowing espousing their group’s “culturally correct” responses). This

<table>
<thead>
<tr>
<th>Model</th>
<th>$G^2$ Fit Statistic</th>
<th>Mean Enculturation</th>
<th>Median Enculturation</th>
<th>Std. Dev. for Enculturation</th>
<th>Min. Enculturation</th>
<th>Max. Enculturation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conservative</td>
<td>83600.48</td>
<td>.378</td>
<td>.410</td>
<td>.164</td>
<td>-.060</td>
<td>.670</td>
</tr>
<tr>
<td>p = .32</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Liberal</td>
<td>81963.19</td>
<td>.442</td>
<td>.480</td>
<td>.197</td>
<td>-.550</td>
<td>.740</td>
</tr>
<tr>
<td>p = .26</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
indicates there is greater overall cultural consensus in this domain for liberals compared to conservatives. Recent research suggests that contemporary conservatism in the United States is an amalgam of distinct, yet interrelated, sets of beliefs, rather than a single monolithic ideology (Perrin, Roos, and Gauchat 2014). The lower consensus we observe among conservatives relative to liberals indicates this may be a distinctive feature of contemporary American conservatism in particular. Given satisfactory estimations of model fit to the data, we next focus on the overlapping (consensus) portion of conservatives’ (and liberals’) schemas of poverty and welfare.

ANALYSES AND RESULTS
PART II: LOCATING KEY DIFFERENCES IN CULTURAL SCHEMAS

Analytic Strategy

We now examine the content and form of these two schemas. To do so, we will show how network analysis can be used to locate key differences between the groups’ cultural schemas. We consider three types of differences: differences in content, cultural anchors, and relational meaning.

Content-based differences are the most straightforward of the three: they may occur when some concepts are present in either the liberal or conservative schema but absent in the other. Such concepts may be thought of as the most distinctive between groups (Carley 1986). For a concept to be considered present in a group’s schematic network, it should have ties (associations) to one or more concepts in the poverty schema network.

Still, concepts that are present in both groups’ schemas may not be equally influential for each group’s understanding of poverty. Instead, highly central, well-connected concepts—in terms of schema-based cognition, the ones most likely to lead to more activations and to be activated more often—are likely to be more important for individuals’ understandings of poverty than are barely connected, peripheral concepts. For instance, although prior research indicates that both liberals and conservatives are likely to schematically associate individual-level causes with poverty to some extent, prior research finds that liberals also endorse structural factors as a cause of poverty. We therefore expect individual-level concepts may hold more central positions in conservative schemas and thus exert more influence as cultural anchors for that group than for liberals.

Ghaziani and Baldassarri (2011:180) define cultural anchors as a core of central concepts that “organize differences by providing a ‘conceptual handle or peg,’” and can be used to “connect ideas and respond to external circumstances.” Following previous research, we examine concepts’ network centrality to identify such anchor concepts (Carley 1986; Rackin 2013). We focus specifically on eigenvector centrality (Bonacich 2007)—a measure of centrality in which well-connected concepts associated with other well-connected concepts score the highest—as a measure of each concept’s role as connector among core, central concepts (Ghaziani and Baldassarri 2011).

Finally, a key expectation from cultural sociology, as well as schema theory, is that meanings are not necessarily given but are relational—defined by their associations (see de Saussure [1959] 2011; Mohr 1998). Therefore, it is possible that a concept may be present and connected in both groups’ schemas but colored by a different relational meaning for members of each group, and may thus be understood in very different ways. For instance, we would expect members of a group for which “being a welfare recipient” is associated with “becoming a teen parent” and “committing crime” to have a very different understanding of what “being a welfare recipient” means compared to members of a group for which the concept is associated with “racism” and “lacking job opportunities.” We can therefore use a concept’s structural position in the network as a proxy for its relational meaning.

Following Mohr (1994, 1998), we operationalize concepts’ relational meaning using structural equivalence measures (Lorrain and White 1971). Two concepts are structurally
equivalent to the extent that they have identical associations to all other concepts in the network. In terms of schema-based relational meaning, we might think of the most structurally-equivalent concepts for any given concept—that is, those that have the most similar associations to other concepts in the network as that concept—as those most similar to that concept in relational meaning, because they are the concepts that would most likely call up the same sets of cognitive, conceptual associations when activated. In these analyses, we measure structural equivalence between a pair of concepts in terms of the average absolute difference between the pair of column vectors representing those concepts’ associations to all other concepts in the adjacency-matrix representation of a group’s schema. It is thus a within-group concept-by-concept pairwise similarity measure.

**Results: Content-Based Differences, Comparison of Schema Network Content and Overall Structure**

Figure 1 shows network representations of concept associations found only in the liberal schema (top panel) versus those found only in the conservative schema (bottom panel). (These networks are plotted on the same layout to facilitate between-group comparison.) A tie between two concepts indicates an answer of “related” for that concept pair in the indicated group’s cultural answer key from the consensus analysis. Concept nodes are colored and shaped by level-type (i.e., individual, interactional, structural, and demographic characteristic).

Overall, we find large overlaps in the content of the two schema networks. Only one concept is included in the liberal but not the conservative schema: “lacking government safety nets,” a structural-level concept. No concepts were unique to the conservative schema. There are two concepts that neither group included in their schema: “being male” and “being white.” There is also substantial overlap at the tie level: the liberal schema shares 78 percent of its associations in common with the conservative schema network, and the conservative network shares 87 percent of its associations in common with the liberal one.

We now move from looking at concepts themselves to looking at the associations
between concepts. Of the unique ties in the conservative schema network, 90 percent are linked to an individual-level concept (versus 2 percent for liberals), whereas 92 percent of the unique ties in the liberal schema network are linked to a structural-level concept (versus 3 percent for conservatives), (see Figure S2 in the online supplement for full network figures). These findings align with prior work on stratification beliefs: both liberal and conservative Americans include individual-level concepts in their understandings of poverty, but individual-level concepts are particularly salient for conservatives. By contrast, liberals’ understanding of poverty is characterized by greater salience of structural-level concepts.

However, our method allows us to go beyond these established patterns regarding the importance of individualism and structuralism, which tend to fall along political lines, for understanding poverty. Taking a closer look at the associations unique to each group in Figure 1, we note that conservatives in particular tend to see individual-level concepts as interrelated (shown by more connections between individual-level concepts in the conservative panel), resembling a view of poverty characterized by a “tangle of pathology” (Moynihan 1965). Furthermore, conservatives are more likely to link these individual-level concepts to certain ascribed characteristics (especially “being an immigrant” and “being a racial minority”), suggesting they perceive this pathology as characteristic of particular demographic groups. This method also allows us to see that liberals, unlike conservatives, view structural-level concepts as interrelated (shown by the greater number of associations between structural-level concepts in the liberal panel). We also see that, for liberals, these structural-level concepts are associated with certain characteristics (especially “being female,” “being disabled,” and “being a racial minority”).

Furthermore, we observe partisan differences in ties to interaction-level concepts (i.e., those related to factors falling between individual-level and structural-level concepts, and that occur in an individual’s immediate environment, like “lacking role models” or “attending bad schools”). Conservatives are more likely to link these interaction-level concepts to individual-level concepts, whereas liberals are more likely to link them to structural ones. We suspect these differences may be indicative of divergent understandings of causal order. Because liberals associate interaction-level concepts with structural-level factors, they may perceive interactional concepts (like “lacking social connections”) as ultimately rooted in structural factors (like “discrimination”), whereas conservatives perceive interactional concepts (like “lacking social connections”) as ultimately rooted in individual factors (like “dropping out of school”). Future work is needed to examine this possibility in greater detail.

Previous studies of stratification beliefs have examined the relationship of these individualist, interactional, and structuralist concepts to poverty (represented here as concepts related to the node “being poor”), but our method illuminates how these different types of concepts are related to one another, revealing strikingly different patterns of association between concepts of each level for liberals and conservatives. This helps us begin to unpack the divergent meanings different subgroups attach to these attributions.

We conducted a robustness check to determine whether the differences in patterns of association we observe between the consensus-estimated conservative and liberal schemas of poverty are representative of systematic differences between conservative and liberal respondents’ own specific poverty schemas (reported in the concept association task). We tested for differences in conservatives’ and liberals’ individually-held schemas in terms of the proportion of total ties in their schemas containing associations between each of the four types of concepts. Results from these analyses of respondents’ individual schemas, shown in Figure 2, mirror the consensus schema findings: ties between individual-level concepts make up a larger share of associations in conservatives’ schemas compared to liberals’ schemas ($t = 9.351, p < .001$), and ties between individual and demographic characteristic concepts make up a greater part
of conservatives’ schemas ($t = 6.278, p < .001$). Ties between structural-level concepts comprise a larger share of liberals’ schemas relative to conservatives ($t = -9.553, p < .001$), and ties between structural and demographic concepts take a greater share of liberals’ schemas ($t = -10.470, p < .001$) compared to conservatives. Finally, conservatives’ schemas contain a higher proportion of ties between interaction- and individual-level concepts ($t = 10.056, p < .001$) than do liberals’ schemas, and liberals have a higher proportion of ties between interaction- and structural-level concepts ($t = -8.303, p < .001$). Thus, individually-held schemas differ systematically along the same lines as the consensus-estimated schemas, indicating the differences we observed in estimated cultural schemas are in fact representative of systematic differences between the liberal and conservative respondents in our sample.

Thus far, we have examined the content of liberal and conservative schemas of poverty by comparing the presence and absence of individual concepts and ties of different types. It is important to also consider how the differences in associations shown here may affect the structure of each network. Nearly all concepts tested are present and connected (to some degree) in both schema networks (“lacking government safety nets” being the sole distinguishing factor in this respect), but not all concepts will be equally influential for the understanding of poverty for members from both groups.

Results: Cultural Anchors and Centrality

To identify which concepts are most influential to each group’s schema (i.e., those that act as cultural anchors), we compare concepts’
relative eigenvector centrality in the liberal versus conservative schema. To this end, Figure 3 plots concepts' relative centrality (standardized) for liberals versus conservatives.

The diagonal black reference line in the figure represents a position of equal centrality scores across groups. Concepts higher on the diagonal of the reference line (those positioned nearest to the line, in the upper-right corner) represent the anchors between the two groups with the highest level of consensus (i.e., concepts that are equally highly central, and thus strongly anchoring, for both groups’ cultural schemas of poverty). These shared anchors include “being poor,” “living in a bad neighborhood,” “lacking job opportunities,” “working for low wages,” and “being chronically unemployed.”

Central concepts that are farther off the diagonal of the reference line can be interpreted as those that most strongly distinguish the two subcultures’ understandings of poverty (in this case, the most partisan concepts). A few important concepts fulfill this role: “being lazy” is the primary distinguishing anchor for conservatives in this respect, and “lacking government safety nets,” “discrimination,” “racism,” and “exploitation by employers” perform this role for liberals.

Overall, we find that individual-level concepts hold more central positions in the conservative poverty schema, all falling above the reference line (with the exception of “chronically unemployed”). Structural-level concepts, conversely, are more central in the liberal schema of poverty, falling below the line. Robustness checks looking at liberal/conservative differences in individually-held schemas mirror these findings, showing that individual-level concepts have a significantly higher mean centrality for conservative versus liberal individuals in our sample, whereas structural concepts have a significantly higher mean centrality among liberal individuals, compared to conservatives.12

Our method goes beyond the belief-based findings from stratification research in shedding light on the divergent role of interaction-level concepts in liberals’ and conservatives’ understandings of poverty. Interaction-level concepts tend to be relatively influential for both groups (all fall in the upper-right quadrant). However, interactional (i.e., local environmental) factors related to family environment (e.g., “having parents on welfare,” “lacking role models,” “having a bad upbringing”) tend to be relatively stronger anchors for conservatives, and factors beyond the family (e.g.,
“attending bad schools” and “lacking social connections”) are stronger anchors for liberals. Prior work is mixed on whether liberals or conservatives are more likely to embrace interactional explanations of poverty (see Cozzarelli, Wilkinson, and Tagler 2001; Homan et al. 2017). Our findings shed light on this debate, indicating that interaction-level concepts play a very different role in explaining poverty for these two groups.

Results: Relational Meaning and Structural Equivalence

Comparison of concepts’ relative centralities, however, does not provide a full account of between-group differences. Concepts can hold similarly influential (central) positions for both groups (e.g., those in the top-right quadrant of Figure 3) yet be connected to very different sets of terms for each group. It is thus important to consider between-group differences in relational meaning.

We examine relational meaning in terms of structural equivalence. We measure structural equivalence between a pair of concepts for a group as the average absolute difference between the column vectors representing that pair of concepts’ associations to all other concepts in the concept association adjacency matrix, subtracted from 1 to convert this dissimilarity metric into a similarity score. Potential similarity score values range from 0 (exactly opposing associations) to 1 (exactly identical associations). To show the potential for measures of structural equivalence to indicate between-group differences in relational meaning, Table 3 contrasts the most structurally equivalent concepts (i.e., those that are the most similar in relational meaning) for liberals versus conservatives, for the eight concepts that were highly central (centrality > .75) in both groups’ schemas.

Results shown in Table 3 indicate some important between-group differences in understanding would be missed by focusing exclusively on relative centrality without also examining measures of contextual or relational meaning. These differences tend to be relatively larger for concepts often involved in contentious political discourse (e.g., “chronically unemployed,” “starting from an unlevel playing field”). For other concepts (e.g., “poor,” “lacking job opportunities”) the groups’ meanings more closely overlapped. To conserve space, we focus on concepts whose meanings most strongly differed between groups.

Starting with “being chronically unemployed” (which stood out in the previous set of analyses as the only individual-level concept that was more central for liberals than for conservatives), the table shows that although this concept plays a similar role for both groups’ schemas as an anchoring factor related to poverty, it carries very different connotations for members of each group. For liberals, “being chronically unemployed” is most relationally similar to concepts about inequalities in one’s local community (e.g., “living in a bad neighborhood,” “lacking job opportunities,” “working for low wages”), whereas for conservatives this concept’s meaning is closely linked to welfare use (e.g. “having parents on welfare,” “being a welfare recipient”) and “dropping out of school.” Similarly, conservative versus liberal understandings of “starting from an unlevel playing field” (the most central structural-level concept in the conservative schema) seem to present two different views of a “cycle of poverty,” with distinguishing connotations of welfare use and lack of social ties for conservatives (“welfare recipient,” “parents on welfare,” “lacking social connections”), and distinguishing structural barrier-related connotations for liberals (“declining wages,” “discrimination”).

We find supporting evidence for this interpretation (starting from an unlevel playing field as a result of a “culture of poverty” versus structural barriers) in participants’ responses to the open-ended prompt at the start of the survey, regarding why some people become or remain poor in the United States. When discussing disadvantaged starts, liberal respondents tended to focus on lack of resources, such as financial resources needed to attend school, cultural capital know-how in
applying for higher education and succeeding once there, or parents’ lack of time resources to invest in children’s education. For example, one respondent stated,

Many people who do work have to work multiple jobs to make ends meet. It is a tough system to break above the poverty level. If you work constantly to feed your children, when are you going to school? People who are well above the poverty line often had more opportunities and parental support.

Many liberal respondents also noted barriers related to race- or class-based prejudices, in addition to lack of resources.

By contrast, when discussing disadvantaged starts, many conservative respondents described a negative upbringing or lack of cultural capital that children obtained in the home, including learned bad habits of

<table>
<thead>
<tr>
<th>Focal Concept</th>
<th>Most Similar Concepts for Conservatives</th>
<th>Most Similar Concepts for Liberals</th>
</tr>
</thead>
<tbody>
<tr>
<td>Being a welfare recipient</td>
<td>poor (.91); parents on welfare (.90); chronically unemployed, work for low wages, start from unlevel playing field (.86)</td>
<td>poor, chronically unemployed (.84); attend bad schools, declining wages, lack government safety nets (.83)*</td>
</tr>
<tr>
<td>Being chronically unemployed</td>
<td>parents on welfare (.88); lack job opportunities (.87); poor, welfare recipient, drop out, live in bad neighborhood (.86)</td>
<td>poor (.91); live in bad neighborhood (.88); lack job opportunities (.87); work for low wages (.86)</td>
</tr>
<tr>
<td>Being poor</td>
<td>welfare recipient (.91); work for low wages (.89); lack job opportunities (.87); chronically unemployed (.86)</td>
<td>chronically unemployed (.91); lack job opportunities (.90); start from unlevel playing field; work for low wages (.89)</td>
</tr>
<tr>
<td>Dropping out of school</td>
<td>abuse drugs/alcohol, live in bad neighborhood (.87); chronically unemployed, parents on welfare (.86)</td>
<td>attend bad schools (.91); live in bad neighborhood (.89)</td>
</tr>
<tr>
<td>Lacking job opportunities</td>
<td>work for low wages (.92); chronically unemployed, poor (.87); live in bad neighborhood, start from unlevel playing field</td>
<td>work for low wages (.95); start from unlevel playing field (.93); poor (.90); chronically unemployed (.87); declining wages (.86)</td>
</tr>
<tr>
<td>Living in a bad neighborhood</td>
<td>drop out, parents on welfare (.87); chronically unemployed, lack job opportunities (.86)</td>
<td>attend bad schools (.91); drop out (.89); chronically unemployed, poor, lack social connections (.88); start from unlevel playing field (.87)</td>
</tr>
<tr>
<td>Starting from an unlevel playing field</td>
<td>work for low wages (.88); attend bad schools, lack social connections (.87); welfare recipient, parents on welfare, lack job opportunities (.86)</td>
<td>lack job opportunities, work for low wages (.93); poor (.89); live in bad neighborhood (.87); declining wages, discrimination (.86)</td>
</tr>
<tr>
<td>Working for low wages</td>
<td>lack job opportunities (.92); poor (.89); start from unlevel playing field (.88); welfare recipient, declining wages (.86)</td>
<td>lack job opportunities (.95); start from unlevel playing field (.93); poor (.89); declining wages (.87); discrimination, chronically unemployed (.86)</td>
</tr>
</tbody>
</table>

Note: Focal concepts compared in the table are those that were highly central for both groups (centrality > .75). Focal terms are listed in alphabetical order. Table compares concepts that have average tie similarity over .85 with focal concept for conservatives versus liberals. Similarity values follow the set of terms that have that value for the indicated group.

*No concepts with similarity >.85.
disregard for education or hard work. For example, one respondent stated,

Many people who are poor have never been exposed to what is needed to be done to work your way up the income ladder. They were handicapped as children, by parents that didn’t impress upon them the necessity for education, self-discipline, and a strong work ethic.

Other conservative respondents discussed a learned sense of helplessness or worthlessness, often tied to government assistance use:

[O]ften, poverty is a generational issue that is encouraged by the government. People and government welfare programs sometimes create a sense of learned helplessness that is seldom reversed through multiple generations.

Results of these relational meaning analyses indicate that some between-group differences in conceptual understanding would be missed without consideration of schema structure and contextual meaning. For instance, we see reinforcing evidence that interaction-level concepts carry starkly different meanings for conservatives and liberals: for the interactional concepts listed (“lacking job opportunities,” “living in a bad neighborhood,” and “working for low wages”), twice as many similar concepts are structural-level for liberals than for conservatives (six versus three). Interactional attributions therefore connote a very different set of concepts for liberals and conservatives.

In the context of a fixed-choice survey question regarding issue salience—the way stratification beliefs research has generally been conducted—our findings suggest that participants may be effectively responding to different prompts, given the differences in meaning and interpretation we observe (see also Martin and Desmond 2010). More generally, these results highlight the importance of considering measures of structural equivalence and relational meaning (and the perils of over-focusing on centrality measures) in future semantic network studies.

ANALYSES AND RESULTS
PART III: TESTING THE SCHEMA–ATTITUDE LINK
Analytic Strategy and Key Variables

In the first two sets of analyses, we focused on estimating and comparing liberal and conservative cultural schemas of poverty. People carry around many cognitive associations in their minds, so how do we know that the estimated schema we measured here is relevant to people’s behaviors or attitudes? To test this study’s second set of hypotheses, the final set of analyses examines the implications of these partisan differences in schemas (when internalized at the individual level) for partisan differences in policy attitudes. Specifically, we test whether partisan differences in poverty schemas found at the group level in the first sets of analyses are predictive of individual differences in government spending policy preferences (as predicted by Hypothesis 2a). We also examine the extent to which partisan differences in schemas as measured here account for the effects of partisan identification on policy preferences (as predicted by Hypothesis 2b).

Independent Variables

Partisan schema similarity. We measure respondents’ schemas’ similarity to the liberal and conservative cultural schemas in terms of similarity between adjacency matrix representations of individuals’ responses to the concept association task and the salience-weighted adjacency matrices representing the liberal and conservative cultural schemas used in the preceding analyses. For example, to estimate a respondent’s similarity to the liberal schema, we first generate a difference matrix by subtracting the liberal schema matrix from the respondent’s concept association matrix. Using this difference matrix, we calculate a difference from liberal schema score as the sum of absolute values across all cells in the difference matrix, divided by the possible number of differences. We then subtract this difference score from 1 to create a similarity score. We repeat this process with
the conservative schema matrix to estimate an analogous measure of a respondent’s similarity to the conservative schema.\textsuperscript{14}

However, given the large degree of overlap between the liberal and conservative cultural schemas (as described in Part II of the analyses and results), to construct the final schema similarity variable that we use in the analyses, we subtract each participant’s similarity score for the conservative schema from their similarity score for the liberal schema. This results in a single measure that captures the participant’s similarity to the uniquely liberal versus uniquely conservative aspects of the schemas (it is this difference, rather than the set of overlap between the two, that would be expected to influence partisan differences in spending preferences). Participants with lower values on this measure have schemas more similar to the conservative cultural schema; participants with higher values have schemas more similar to the liberal cultural schema. A participant with a score of 0 on this measure would have an individual schema equally similar to the liberal and conservative cultural schemas. We standardized this similarity measure to have a mean of 0 and a standard deviation of 1 in the formal models to ease interpretation.

**Liberal-conservative partisan identification.** We measure respondents’ partisan identity using a standard seven-point liberal-conservative self-identification scale, described in the study procedure. In this scale, higher values represent more liberal partisan identification.

**Dependent Variables**

We measure the main dependent variables, policy preferences, using participants’ responses to the government spending questions described in the study procedure, with responses dichotomized to represent preference to decrease (versus keep the same or increase) spending for the program in question.\textsuperscript{15} In these analyses, we focus on participants’ preferences regarding the five most polarized spending types (those where liberal respondents tended to prefer increased spending and conservatives preferred decreased spending); these include spending on welfare, SNAP/food stamps, subsidized housing, assistance to blacks, and Obamacare/the Affordable Care Act.\textsuperscript{16} We also estimate models controlling for standard demographic characteristics.\textsuperscript{17}

**Modeling Strategy**

We conduct a mediation analysis to test (1) whether partisan schema differences are predictive of participants’ likelihood of preferring decreases in each of the five most polarized government-spending types (Hypothesis 2a), as well as (2) to what extent schemas serve as a linking mechanism between partisan identification and policy preferences (Hypothesis 2b). To do this, we model each spending preference as a function of the direct effect of partisan identification, as well as the indirect effect of partisan identification via partisan schema similarity. Structural equation modeling (SEM) allows us to identify the proportion of partisan identification’s effect on policy preferences that flows via the schema construct.\textsuperscript{18}

In these models, we reintroduce data from the 39 conservative and 43 liberal participants who were excluded in the first two sets of analyses because they self-reported views about welfare and poverty that were inconsistent with their general political ideological stance (e.g., liberal democrats who reported having moderate or conservative views on welfare and poverty in response to a seven-point scale item). We include these weaker partisans in this set of analyses to provide some assurance that the findings regarding the association between schemas and attitudes are not restricted to core cultural group members. Models including and excluding these individuals yield substantively the same results in terms of relative effect size, significance, and direction.\textsuperscript{19}

**Results: Descriptive Statistics**

Figure 4 plots participants’ unstandardized partisan schema similarity scores by party. Republican participants’ similarity scores
range from −.109 to .103 (M = −.024, SD = .044), and Democrats’ scores range from −.101 to .124 (M = .029, SD = .049). The figure shows that even within each party, there is variability in participants’ relative similarity to the conservative versus liberal schema.

Figure 5 plots the distributions of participants’ responses to each of the five policy preference outcome variables. Bar color denotes the proportion of Republicans (gray fill) versus Democrats (black fill) represented in each response category. The first four spending categories—welfare, food stamps, subsidized housing, and assistance to blacks—all follow similar response patterns, with Republican preferences split between “decrease” and “keep same” and Democratic preferences split between “keep same” and “increase.” Obamacare spending preferences are more strongly divided by party, which is unsurprising in light of public opinion research highlighting the “deeply entrenched” partisan division over this policy (Smith 2015).

Model Results

Table 4 displays SEM results predicting preference to decrease spending for each of the five programs, including estimates of direct effects for each independent variable (partisan identification and partisan schema similarity), as well as indirect effects and total effects for partisan identification.

**Direct effects of partisan schema similarity (Hypothesis 2a).** Model results for the direct effects of the schema measure on spending preference outcomes provide support for Hypothesis 2a: for four of the five outcomes, the models show that individuals with poverty schemas more similar to the liberal cultural schema (those with higher values on the similarity measure) are statistically less likely to prefer decreases in spending.

To provide a clearer picture of the practical significance and size of these effects, Figure 6 plots predicted probabilities for each outcome based on the SEM results. Each panel in the figure shows participants’ predicted probability of preferring decreased government spending for the program labeled at the top of the panel, at varying degrees of similarity to the liberal versus conservative cultural schema, holding partisan identification constant. Even after taking political party into account, individuals with the highest level of resemblance to the conservative cultural schema have an over 50 percentage-point higher predicted probability of preferring cuts to four of the five spending types, compared to individuals with the highest level of resemblance to the liberal cultural schema.

**Partisan schema similarity as a mediator of partisan identification (Hypothesis 2b).** The preceding results show that partisan differences in schemas are
associated with substantial differences in individuals’ likelihood of preferring decreased spending on poverty-related government programs, net of the effect of an individual’s political party on these preferences. In this next set of analyses, we examine the relationship between the proposed schema measure and a well-established predictor of policy

![Figure 5. Distribution of Participant Responses for Policy Preference Variables by Party](image)

*Note:* Bar color denotes proportion of Republican (gray fill) versus Democrat (black fill) participants represented in each response category. For each type of spending, 1 = decrease spending, 2 = keep spending about the same, and 3 = increase spending.

**Table 4.** Results from Structural Equation Models Predicting Government Program Spending Preferences by Schema Similarity Measure (Direct) and Partisan Identification (Direct and Indirect)

<table>
<thead>
<tr>
<th>Outcome Variable</th>
<th>Decrease Welfare</th>
<th>Decrease SNAP</th>
<th>Decrease Subs. Housing</th>
<th>Decrease Aid to Blacks</th>
<th>Decrease Obamacare</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Direct Effects</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lib/Con Self Ident --&gt; Outcome</td>
<td>-0.498***</td>
<td>-0.416***</td>
<td>-0.418***</td>
<td>-0.315***</td>
<td>-0.853***</td>
</tr>
<tr>
<td></td>
<td>(0.063)</td>
<td>(0.071)</td>
<td>(0.069)</td>
<td>(0.060)</td>
<td>(0.076)</td>
</tr>
<tr>
<td>Schema --&gt; Outcome</td>
<td>-0.783***</td>
<td>-0.917***</td>
<td>-0.775***</td>
<td>-0.735***</td>
<td>-0.289</td>
</tr>
<tr>
<td></td>
<td>(0.152)</td>
<td>(0.167)</td>
<td>(0.159)</td>
<td>(0.147)</td>
<td>(0.168)</td>
</tr>
<tr>
<td><strong>Indirect Effects</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lib/Con Self Ident --&gt; Schema --&gt; Outcome</td>
<td>-0.173***</td>
<td>-0.203***</td>
<td>-0.171***</td>
<td>-0.162***</td>
<td>-0.064</td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td>(0.040)</td>
<td>(0.038)</td>
<td>(0.035)</td>
<td>(0.037)</td>
</tr>
<tr>
<td><strong>Total Effects</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lib/Con Self Ident</td>
<td>-0.671***</td>
<td>-0.589***</td>
<td>-0.591***</td>
<td>-0.488***</td>
<td>-1.026***</td>
</tr>
<tr>
<td></td>
<td>(0.066)</td>
<td>(0.080)</td>
<td>(0.078)</td>
<td>(0.070)</td>
<td>(0.084)</td>
</tr>
<tr>
<td>Percent of Identity Effect Mediated by Schema</td>
<td>25.8%</td>
<td>34.5%</td>
<td>28.9%</td>
<td>33.2%</td>
<td>5.1%</td>
</tr>
</tbody>
</table>

*Note:* Standard errors are in parentheses; unstandardized coefficients.

*p < .05; **p < .01; ***p < .001 (two-tailed tests).
preferences: partisan identification. SEM results find a positive association between partisan identification and partisan schema similarity \( (b = .221, SE = .017, p < .001) \), indicating that individuals who identify as more liberal tend to have schemas that more closely resemble the liberal cultural schema, as expected. As shown in Table 4, partisan identification also has significant direct effects on all five spending outcomes. The effect of this measure is strongest for Obamacare spending preferences—the single outcome that was not significantly predicted by the schema measure.

To gauge the extent to which schemas act as a mediating mechanism between partisan identification and policy preference outcomes, the final row of Table 4 compares the percentage of the total effect of partisan identification for each outcome that is mediated by the indirect pathway via the partisan schema similarity measure. These results show that partisan schema differences account for one-quarter to one-third of the estimated effect of partisan identification on spending preferences for four of the five outcomes that were significantly associated with the schema measure. These results provide support for Hypothesis 2b and indicate that partisan differences in schemas are one mechanism by which partisan identities lead to partisan differences in policy preferences. This finding runs counter to the predictions of more purely partisan identity-based cue theories (e.g., Achen and Bartels 2016; Campbell et al. 1960; Converse 1964; Kinder and Kalmoe 2017; Lenz 2013; Zaller 2012).

Obamacare preferences: when identity trumps schemas. Obamacare spending preferences provide an interesting exception to the above-described trend. Of the five policy preferences examined, only Obamacare preferences were influenced primarily by partisan identification and largely disconnected from partisan schema differences. Obamacare stands out among the policies considered as both (1) the most strongly-partisan issue and (2) the most salient in recent partisan political discourse.

We suspect policy attitude preferences related to healthcare generally (and Obamacare in particular) are still nascent, as this is a relatively new issue that voters are only recently ranking as a “top priority” (Bialik 2019). Partisans might rely first on party cues when adopting a policy preference, and only later internalize the relevant cognitive associations that justify the party’s stance—once they have been sufficiently exposed to the partisan discourse and media representations about the policy that reinforce these associations. Indeed, political elites are just beginning to articulate the way healthcare relates to poverty—as both a potential cause and potential effect of poverty (Barrilleaux and Rainey 2014). Alternatively, Obamacare preferences may be more closely tied to some other schema not measured here (e.g., to partisan differences in associations with President

![Figure 6](image-url).

**Figure 6.** Predicted Probabilities from Spending Preference Structural Equation Models.
Obama or to health/healthcare). More research is needed to determine which is the case, particularly longitudinal research documenting schema formation.

**DISCUSSION**

**Summary of Findings**

Cultural schemas have become an increasingly important conceptual tool in sociology since the publication of “Culture and Cognition” (DiMaggio 1997). From cognitive science, by way of cognitive anthropology (D’Andrade 1995; Strauss and Quinn 1997), sociologists borrow the theoretical assumption that schemas are sets of cognitive associations that facilitate perception, motivate action, and shape attitudes and preferences, using this as justification for selecting one method or theoretical explanation over another. However, little previous sociological work has collected data about the cognitive, conceptual associations that should comprise cognitive schemas—or tested assumptions about the relationship between schematic associations and the things we argue they should undergird, like perceptions, actions, and beliefs (Pugh 2013).

Our primary goal in conducting this research was to take an initial step in this direction, toward testing (and eventually extending) our current models of schema-based cognition and how it affects cultural phenomena. The results of this study show the promise of the proposed method. By examining relationships between concepts in people’s poverty schemas, we shed light on two long-standing questions in the area of stratification beliefs.

First, we observed that the “dual consciousness” in which people endorse both individual-level and structural-level explanations of poverty can be explained by the fact that individuals in the United States vary in the degree to which these types of factors are central to their poverty schema. Like poverty itself, mental models of poverty are complex and multicausal; prior belief-based methods in this area of research have been limited in their ability to elicit the structure and complexity of these mental models. By measuring cultural anchors, operationalized here as a concept’s centrality in the semantic network, we have shown a way to overcome this problem by concretizing central and peripheral causes of poverty.

Second, we found that the “interactional” or meso-level concepts evoke divergent meanings—captured via relational meaning/structural equivalence—for conservatives and liberals. This helps explain why interactional attributions of poverty are sometimes more prevalent among conservatives and sometimes among liberals. Simply asking respondents about the perceived importance of interaction-level causes of poverty using agree/disagree Likert scales obscures the fact that these concepts carry very different connotations for members of different cultural groups. These differences likely portend different moral stances (i.e., Is poverty within or outside a person’s control?) and policy preferences tied to deservingness.

**Implications for Work on Cultural Schemas**

Overall, the method introduced here helps provide a quantitative way to capture what respondents *mean* when they answer a survey question in a particular way, allowing the researcher to pinpoint different meanings that occur between known subgroups. In addition, our findings indicate the method may provide a useful means for identifying when the schema-attitude link is or is not operative: schematic associations about poverty account for a substantial part of the effect of partisan identification on policy preferences for four out of five issues. We cannot adjudicate precisely why Obamacare is divorced from these schemas of poverty, but we hypothesized that early-forming political preferences may rely first on partisan cues before the complex conceptual networks set in (as we observed for the four other policy issues). This technique can thus be used to determine which political attitudes are more partisan identity-driven
versus which are more rooted in partisan differences in schemas and understandings, and—when used in the context of longitudinal design—how this process unfolds over time.

We also show how similarly-influential concepts may have starkly different meanings. This has implications for the use of belief-based measures of schemas, as it indicates people may have fundamentally different understandings of a given concept, even when they report it is similarly influential or important. Indeed, using survey-based measures of attributions of poverty may work well when predicting certain policy attitudes (particularly those with the strongest link to concepts with similar cultural anchoring and relational meaning for conservatives and liberals). But for concepts with highly divergent influence and connotations (e.g., “starting from an unlevel playing field,” “dropping out of school”), inclusion of these items in a factor analysis—as is typically done in stratification beliefs research—would obscure the starkly different meanings these concepts carry for conservatives and liberals. The commonly-held belief among both groups that “being chronically unemployed” is strongly related to U.S. poverty likely entails different solutions in the eyes of conservatives versus liberals. For conservatives, who see this concept as most similar to “having parents on welfare,” reducing government spending on cash transfers to the poor will likely seem the most reasonable solution for alleviating poverty by way of promoting employment; for liberals, who see this concept as most similar to “living in a bad neighborhood,” government infusion of money into infrastructure improvements and small business grants in local communities to increase employment will probably seem a better solution for resolving poverty.

Limitations and Suggestions for Future Research

Despite the promises of the proposed method for shedding light on differences in meanings, as the first test, this study is inherently limited in scope. To overcome these limitations, future research could build on and extend our findings in a number of ways. First, this study is an investigation of personal, declarative culture (Lizardo 2017; Patterson 2014). The present method relies on respondents to recognize whether a given pair of concepts is related or not (likely requiring System II processing), yet schemas are generally understood to be nondeclarative cognitive models driven by System I processing (Wood et al. 2018). In practice, this means we have likely captured the perceived network of associations between concepts related to poverty for conservatives and liberals (whereas connectionist models of cognition pertain to the implicit cognitive network of associations and their underlying neural structures).

The present study requires us to assume that respondents are relatively adept at recognizing whether a given pair of concepts is, in fact, related in their minds. This assumption can be relaxed by incorporating indirect techniques for capturing schematic associations—like those from the Implicit Association Test or the Affect Misattribution Procedure—that do not require associations between concepts to be discursively elicited. IATs and AMPs use implicit measures of associations (e.g., relative response latency and accuracy under time constraint for different category pairings in the case of the IAT, and affect resulting from rapid exposure to a prime in the case of the AMP), so one potential improvement on the present method could be the incorporation of short time limits for each concept association item. More generally, future work should strive to measure schematic associations in ways that do not rely on respondents to report these relationships and are thus more likely to tap into System I processing and automatic cognition.

Second, we intentionally set out to examine one set of cultural schemas (liberal and conservative schemas of poverty) where extensive research provided strong expectations about what the resulting patterns of schematic associations should look like, so we could determine whether the proposed method recovers those expected patterns. Results of
the second set of analyses show the method captures and extends what we know about differences in partisan schemas of poverty in terms of connections to—and the relative centrality of—individual- and structural-level associations with poverty. In light of this successful test, future work should use the method as a tool to explore new schemas in domains about which less is known. For example, future research using this method could (1) provide insights about the underpinnings of emerging partisan differences in attitudes about newer policy issues (e.g., net neutrality, vaccine skepticism) where views may still be taking shape, as well as (2) test hypotheses about the relative importance of partisan identification versus differences in schemas at different stages of policy development, different levels of media coverage, and for different sorts of issues.

Third, we relied on respondents’ self-identification as liberal/very liberal Democrats and conservative/very conservative Republicans to identify members of the cultural groups of interest. However, respondents in different social contexts may differ in their thresholds of what they consider to be very liberal versus liberal versus slightly liberal, for example, which may have resulted in more heterogeneous subcultural groups than desired. Model fit statistics from the consensus analyses presented in the Part I results, as well as the robustness checks looking at liberal/conservative differences in individually-held schemas (as shown in Figure 2 and note 12), indicate there was indeed sufficient inter respondent consensus for the model’s purposes. Nevertheless, it is possible that estimating consensus schemas using a sample of stronger or more orthodox partisans may have located more between-group differences in schema content. Future studies of extreme partisans or studies using a larger battery of issue-based partisan identification questions could determine if this is the case.

Consensus schemas should ideally be estimated using samples of individuals who identify strongly with the cultural group of interest, but more diverse samples that include weaker group affiliates and unaffiliated individuals are useful when estimating the effects of schemas on attitudes, behaviors, or other outcomes. Including these individuals would better enable researchers to observe the effects of schematic structures and associations in the absence of group identification. With this consideration in mind, we reintroduced data from 82 weaker partisans who were excluded from consensus schema analyses into our analyses of the association between schemas and attitudes. This provided a provisional test to ascertain whether we could expect the schema-attitude relationship we found to hold for individuals who are not core group members. However, due to resource constraints, we could not representatively sample across the political spectrum and include true moderates, so we cannot be certain whether the schema-attitude link we find for partisans generalizes to the truly unaffiliated or politically moderate. Future research testing the effect of partisan schema similarity on policy preference in a more diverse (or, ideally, representative) sample is needed.

Additionally, the proposed cultural schema estimation method implemented in this study requires the researcher to begin with known cultural groups, in contrast to relational class methods that focus on inductive discovery of cultural classes. To overcome this, researchers might consider combining the concept association task method of collecting data about individuals’ schematic associations proposed here, with inductive cultural class estimation methods such as Latent Class Analysis and Latent Class Regression Analysis.

Finally, future research should move beyond the limitations of this initial study to continue testing current models of the relationship between culture and schema-based cognition. Our results provide support for one such hypothesis—regarding the relationship between schemas and attitudes—but because these data are cross-sectional, we cannot determine whether the association found represents a causal influence of schemas on attitudes (as the theory would predict). Future longitudinal research focusing on schema change is needed to more definitively establish the direction of this relationship. Moreover, future research can
assess the predictive validity of measures from this method (e.g., the schema similarity measure) relative to other measures (e.g., belief-based measures and relational-based measures obtained via RCA or CCA).

Concluding Remarks

Research about culture in sociology has long been plagued by an imbalance between theory and measurement (Mohr and Ghaziani 2014). In turn, these difficulties with operationalization have prevented the cumulative theory-building needed to demystify the notorious “amorphous mist” of culture (Fine 1979; Ghaziani 2009). With this study, we set out to propose a new method for measuring schemas, a recently influential concept in sociological explanations of how culture influences individuals’ beliefs, preferences, and actions (DiMaggio 1997; Lizardo 2017; Patterson 2014). By proposing this measure as a way of improving schemas’ construct validity, we hope to lay the groundwork for future research aimed at testing (and eventually extending) our current models of schema-based cognition and its relationship to cultural phenomena. Such work promises to help sociologists better understand how differences in cultural schemas and their associated beliefs, attitudes, and practices arise and persist over time.

Acknowledgments

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Notes

1. Some associations between concepts may be shared, but they occur due to inherent or natural affinities (e.g., associating “fire” with “hot”). Researchers must carefully examine the specific concepts they are studying to ascertain whether there are any deterministic, natural, or inherent relationships between them.

2. The task was implemented online using Qualtrics survey software. Code to implement the customized question item used in this method is available via the first author’s GitHub account (https://github.com/mbfhunzaker/SchemaMap).

3. When this instruction was not included in earlier rounds of pretesting, many participants assumed the researcher was only interested in causal associations. In the survey debriefing, participants reported struggling to determine whether the first concept in the pair caused the second.

4. Several of these studies rely on inductive, open-ended, interview-based approaches to elicit concepts related to poverty (e.g., Homan et al. 2017; Strauss 2012). This list-construction strategy would not be feasible for studies of less-well-studied or newly emerging issues for which such research does not yet exist. In these cases, the researcher would need to add an additional data collection step to generate the lists, for instance by conducting an initial free-association or concept-elicitation task (e.g., Moore 2017), or conducting open-ended interviews or focus groups to inductively identify the most commonly salient concepts related to the issue of interest for inclusion in the final concept association task.

5. We also included concepts with more positive connotations (e.g., “wants to solve own problems”) in earlier pretests; however, participants consistently reported that they were not related to any concepts and seemed out of place.

6. The survey instrument used to implement the concept association task also provides the researcher with ordering and response time data (in milliseconds) for each concept pair. However, we do not analyze these data in this article.

7. Exact question wording: “Politically, I consider myself to be: Extremely Conservative, Conservative, Slightly Conservative, Moderate, Slightly Liberal, Liberal, Extremely Liberal.”

8. These thresholds were under 12-minute or over 90-minute completion times for the association task, as well as reporting that fewer than 10 or more than 440 concept pairs were related. Participants were also required to pass three active participation checks to be allowed to complete the survey.

9. This multiple-choice question asked participants to respond to the prompt, “On issues of poverty and welfare, my views tend to be,” and used the same seven-point scale as the item regarding overall
10. This relaxes the assumption in Romney and colleagues’ (1986) original, factor-analysis-based consensus analysis model that all respondents were equally likely to guess yes versus no on an item when they did not know the answer.

11. Eigenvector centrality is one way to measure the importance of a given node within a network. Other methods include Bonacich centrality (see Bearman and Stovel 2000), betweenness centrality (see Boutyline and Vaisey 2017), and total constraint (see Converse 1964; Martin 1999). Future work can adjudicate which operationalization of influence has the most validity in the context of schema networks.

12. Individual-level concepts have a mean centrality of .642 among conservatives versus .535 among liberals and are thus significantly more central for conservatives ($t = 6.194, p < .001$); 6 out of 8 individual-level concepts were significantly more central for conservatives than for liberals, and 1 out of 8 was significantly more central for liberals than for conservatives (“chronically unemployed”). Structural-level concepts have a mean centrality of .442 among conservatives versus .649 among liberals and are thus significantly more central for liberals ($t = -9.629, p < .001$); 8 out of 8 structural-level concepts were significantly more central for liberals than for conservatives.

13. That is, $2 \times 490$; the number of pairs in the concept association task, multiplied by 2, because the associations are undirected and the adjacency matrices are symmetrical. This denominator excludes cells representing concept associations about which participants were not asked, to avoid overestimating similarity (as these values would necessarily be “0” in all matrices).

14. Comparing individuals’ schemas to the salience-weighted cultural schemas allows for disagreement between individual and cultural schemas over lower-salience associations (those reported by relatively fewer members of a group) to detract less from the similarity score, while differences on higher-salience associations result in greater reductions to the similarity score.

15. In additional analyses (not shown to conserve space, available upon request), we estimated models using preference to increase spending as the outcome variables, using the original three-category ordinal variables as the outcome variables (using generalized ordered-logistic regression), using a summary scale of the five items as the outcome, and including a fixed effect for party. These models have substantively the same results in terms of relative effect size, effect direction, and significance as those presented here. Additionally, although we focus on the five most polarized spending types to conserve space, models for other aid programs targeted to the poor (programs to alleviate poverty, unemployment) yielded similar relationships between schema measures and spending preferences in terms of effect significance, size, and direction compared to the five spending types analyzed here.

16. Participants were asked separately about spending preferences for welfare and for Temporary Assistance for Needy Families (or TANF, the federal program that makes up the bulk of what is commonly referred to as “welfare”). Preferences for TANF spending were not polarized. Instead, conservative respondents, on average, preferred to keep spending the same when the program was described using the TANF program name. Other programs that were less polarized tended to be less targeted in nature—for example, public school spending, Social Security, and Medicare.

17. These include gender (using a dichotomous indicator for female), race (using a dichotomous indicator for white), age (in years), household income (measured in bins of $10,000 from $0 to 100,000+, treated as continuous for modeling), and education (measured as a dichotomous indicator for having attained a bachelor’s degree or higher in education). In these models, we also include a control measure to account for participants’ previous experience with poverty, measured as a dichotomous indicator of whether participants reported that they or a close family member or friend had experience with poverty or government assistance.

18. SEM improves on simple model comparison techniques—in which the proposed mediator is introduced in a second model and coefficients from different models are compared—because it allows one to determine the mediator’s relative size and significance (VanderWeele 2015).

19. We also fit a model including demographic controls as exogenous predictors of partisan identification. However, including versus excluding these controls does not affect the effect size or significance of the main independent variables of interest. A comparison of BIC scores across models indicates that models without controls are more parsimonious in all cases. Therefore, we focus on the more parsimonious models without controls (see Table S3 in the online supplement for results of models including demographic controls).

References


**M.B. Fallin Hunzaker** is currently a researcher at Facebook. The research presented in this article was designed, conducted, and initially written during her time as a PhD student at Duke University and as an Assistant Professor at NYU. Her research focuses on understanding how cognitive and cultural biases shape the information people share in communication, and developing new methods to study these processes.

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