

Pluralistic Collapse: The “Oil Spill” Model of Mass Opinion Polarization

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Abstract

Despite widespread feeling that public opinion in the United States has become dramatically polarized along political lines, empirical support for such a pattern is surprisingly elusive. Reporting little evidence of mass polarization, previous studies assume polarization is evidenced via the amplification of existing political alignments. This article considers a different pathway: polarization occurring via social, cultural, and political alignments coming to encompass an increasingly diverse array of opinions and attitudes. The study uses 44 years of data from the General Social Survey representing opinions and attitudes across a wide array of domains as elements in an evolving belief network. Analyses of this network produce evidence that mass polarization has increased via a process of belief consolidation, entailing the collapse of previously cross-cutting alignments, thus creating increasingly broad and encompassing clusters organized around cohesive packages of beliefs. Further, the increasing salience of political ideology and partisanship only partly explains this trend. The structure of U.S. opinion has shifted in ways suggesting troubling implications for proponents of political and social pluralism.

Keywords

political polarization, public opinion, belief networks, political pluralism

Social and political theorists have long argued that differentiated societies are best able to integrate diverse interests when relying on a foundation of cross-cutting social and political cleavages (Blau and Schwartz 1984; Dahl 1961; Durkheim 1933; Lipset 1963; Simmel 1955; Truman 1951). Unlike stultifying monocultures built on public consensus (Arendt 1968), cross-cutting lines of conflict and disagreement found in pluralistic societies embed individuals in overlapping groups (Baldassarri and Diani 2007; Centola 2015; Mutz 2002). Even if people fight over differing views on taxation, they may still agree on issues of foreign policy or overlap in religious views; these areas of agreement are thought to

prevent disagreement in one arena from escalating into all-out (metaphorical or literal) warfare. As long as opinion cleavages remain cross-cutting rather than all-encompassing, pluralistic disagreement should channel social conflict toward mutual tolerance (Stouffer 1955), political forbearance (Levitsky and Ziblatt 2018), and other liberal ends.

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Against this backdrop, recent decades have brought mounting concern among social scientists, journalists, policymakers, and the general public that the pluralistic structure of U.S. politics has turned to all-encompassing conflict between increasingly polarized camps. In their provocatively titled book *How Democracies Die*, Levitsky and Ziblatt (2018) frame polarization as a fundamental problem for U.S. democracy—not merely a nuisance but a potentially existential threat. Such alarmism is not uncommon in mainstream discourse. Yet despite the common belief that the United States has become dramatically more politically polarized, social-scientific support for such a pattern has been surprisingly elusive.

In the rarefied air of the U.S. Congress, there is clear evidence that the Democratic and Republican parties have moved far apart in recent decades (Andris et al. 2015; Lee 2009; Moody and Mucha 2013; Poole and Rosenthal 1984). In the broader public, adherents of the two major political parties have become increasingly distinct, as Democrats have become more consistently liberal and Republicans more reliably conservative (Baldassarri and Gelman 2008). However, although people have become better sorted by party and political ideology, public attitudes on most political issues seem to have remained unpolarized to a remarkable degree (DiMaggio, Evans, and Bryson 1996; Evans 2003; Fiorina 2004; Hill and Tausanovitch 2015).

Although knowing someone's political party or self-described ideology allows us to predict their attitudes with increased accuracy, these attitudes themselves have *not* become much more strongly aligned with *other* attitudes, as we would expect in a world of mass polarization (Baldassarri and Gelman 2008; Fiorina and Abrams 2008; Fischer and Mattson 2009; Park 2018).¹ Unlike the political elite, the broader public is composed of large numbers of "ideological innocents" (Converse 1964; Kinder and Kalmoe 2017) who espouse cross-cutting and often inconsistent beliefs across political issues. This raises the question: If opinions have not become markedly more polarized, why is it so widely believed—and so easy to intuit—that

they have? Why, in other words, does polarization appear as such a salient social fact despite its apparent absence in the U.S. population?

Previous studies suggest the gap between popular and scholarly consensus could be due to the tendency for media reports to pay selective attention to polarized "hot-button" issues like abortion (Baldassarri and Bearman 2007; DiMaggio et al. 1996; Evans 2003); outsized focus on political elites who have become increasingly partisan and polarized themselves (Hetherington 2001); social sorting leading to a sense of political homogeneity in our personal networks (Baldassarri and Bearman 2007; Cowan and Baldassarri 2018; DellaPosta, Shi, and Macy 2015); or increasing geographic polarization in which regions and locales increasingly feature one-party dominance even when elections split evenly at the national level (Bishop 2008; but see Abrams and Fiorina 2012).

Measuring Polarization

Nevertheless, although many scholars have critiqued the lack of a clear index of polarization in previous work (e.g., Fiorina and Abrams 2008), less attention has been paid to the ubiquity of a particular (and implicit) model of *how* polarization would appear in population-level survey data. The common empirical strategy in prior research is to select and analyze a limited set of survey questions on political issues, focusing on questions the researcher identifies as most politically relevant (e.g., opinions on abortion, climate change, taxation, or foreign policy). By selecting on an issue's already-established political relevance, however, the researcher implicitly assumes that polarization occurs via *heightened* alignment along existing lines of political debate, akin to a fence the researcher can observe getting taller over time.

But what if polarization is less like a fence getting taller over time and more like an oil spill that spreads from its source to gradually taint more and more previously "apolitical" attitudes, opinions, and preferences? DellaPosta and colleagues (2015) show that even many

initially apolitical lifestyle characteristics, from musical taste to belief in astrology, can become politicized as signals for deeper beliefs and preferences—a tendency most saliently captured in the popular image of the “latte liberal” (see also Hetherington and Weiler 2018; Mutz and Rao 2018; Shi et al. 2017).

This suggests a different answer to the puzzle posed at the outset: rather than heightened alignment across already-politicized opinion dimensions, the crux of contemporary polarization might lie in the increased *breadth* of opinions and preferences that have come to be associated with political identities and beliefs. This broadening of opinion alignment to encompass areas typically thought of as nonpolitical would not be picked up in studies that only consider polarization along existing lines of political debate. However, the widespread impression that polarization has dramatically increased may reflect real politicization of an increasingly diverse span of beliefs and preferences that once cut across (or lay apart from) ideological divides.

Belief Network Analysis

Rather than focusing on a selected subset of political opinion items, I broaden the scope of analysis to include *any* opinion question ever presented in the General Social Survey (GSS) between 1972 and 2016. Building on Boutyline and Vaisey (2017), I represent correlations between opinions in a representative sample of the U.S. population as relational ties in a network of interconnected beliefs. Rather than a traditional social network analysis where *nodes* are human or organizational actors and the ties or *edges* between nodes represent social connections (Wasserman and Faust 1994), the belief network conceives of each attitude, opinion, or belief as a node; the strength of the edges or ties between beliefs reflects the extent to which two beliefs are correlated in survey data. The analysis of belief networks represents one strand in the growing field of cultural network analysis, where “networks of co-occurrence relations among such cultural elements as words, tropes, attitudes, symbols, or tastes” are used

to analyze how these cultural elements cohere into a broader structure of meaning (DiMaggio 2011:287; see also Lizardo 2014; Mohr and White 2008; Pachucki and Breiger 2010; Vilhena et al. 2014).

This conceptual approach dovetails with classic work on beliefs and opinions (e.g., Converse 1964) in which the meaning and importance of a particular belief derives from its relationships to *other* beliefs (for some recent examples, see Baldassarri and Goldberg 2014; Boutyline and Vaisey 2017; Friedkin et al. 2016). Whereas recent work typically conceives of polarization as increasing *extremism* on issues (e.g., DiMaggio et al. 1996) or heightened *alignment* across pairs of issues (e.g., Baldassarri and Gelman 2008), the belief network approach recasts polarization as a particular *structure* of opinion.

Scholars of public opinion have long recognized the importance of belief structure, meaning an ordered arrangement of beliefs such that holding one belief implies holding other beliefs (Kinder and Kalmoe 2017:13; see also Converse 1964). However, recent research on polarization conceptualizes structure in terms of pairwise relationships among beliefs, ignoring the larger webs of association and mutual implication in which these dyadic relationships are embedded (Baldassarri and Goldberg 2014).

To understand what polarization looks like in a structure of associated beliefs, we can compare it to its opposite: cross-cutting opinion pluralism. In a pluralistic belief network, attitudes may be correlated with one another, but these correlations are cross-cutting. For example, perhaps attitudes toward gun control are correlated with attitudes toward abortion. But attitudes toward gun control may also be correlated with attitudes toward racial justice, which may themselves not be correlated with abortion attitudes; abortion attitudes, in turn, may be correlated with attitudes toward LGBT rights, despite the latter remaining uncorrelated with gun control attitudes. As a whole, this hypothetical belief network consists of relationships that cut across and offset each other without cohering into large cohesive clusters of densely connected attitudes.

Substantively, this lack of coherence means two people who disagree on one or even most things will still likely be able to find some issue on which they agree, creating an opportunity to bridge the ideological distance between them.

In this conceptualization, opinion pluralism collapses into polarization via the *consolidation* of previously cross-cutting alignments into increasingly broad and encompassing ones. Drawing on theories of belief formation, I argue that beliefs will tend to cohere into modular “packages” that can be distinguished based on clustered items in the belief network. Beliefs falling within the same package tend to be more strongly connected to one another, and items in different modules tend to be more weakly connected. Simply put, a belief network becomes more consolidated as the distinct modules of beliefs become *larger* in size but *fewer* in number. I find that—in line with claims for increased polarization—the structure of U.S. opinion has shifted in recent decades away from one made up of narrower but cross-cutting modules of beliefs and toward fewer modules, indicating broadly-encompassing alignments.

Representing mass beliefs as networks, as in the present study, does not directly tell us about the underlying mechanisms giving rise to belief polarization. Correlations between beliefs in the population aggregate need not imply cognitive associations between these beliefs at the individual level (Martin 2000), although aggregate belief structures can shape individual belief formation by determining which attitudes and behaviors are most likely (or unlikely) to co-occur in the population, which in turn affects how individuals will perceive the associations among different attitudes and behaviors (Goldberg and Stein 2018). Individuals, social groups, and the contentions and conflicts among them will effectively “fall out” of the analysis presented here, leaving a descriptive picture—albeit a rich one—of larger-scale trends in population belief structure. Experimental and other approaches (e.g., Bail et al. 2018; Hunzaker and Valentino 2019) remain necessary for discovering the underlying root causes driving

belief formation and change. Yet, by demonstrating *in what way* mass beliefs have become more polarized, and by using network analytic tools to describe the structure of this polarization, this article provides three linked contributions.

First, the article fleshes out a novel conceptualization of polarization—the earlier referenced “oil spill” model—rooted in the *breadth* of opinion alignment, and places this conceptualization in dialogue with previous ones. Second, I use the formal tools of network analysis to develop previous research on opinion alignment in a way that more fully accounts for the structure of associations among beliefs. Finally, the article builds on and extends Boutyline and Vaisey’s (2017) cross-sectional analysis of belief networks to show how this approach can be used to track changes over time in mass beliefs.

THE ILLUSION OF POLARIZATION?

Previous work describes the process of mass opinion polarization in one of two ways: (1) as increasing extremism (i.e., bimodality) of attitudes on political issues or (2) as increasing alignment (i.e., correlation) of attitudes across political issues. In the first tradition, DiMaggio and colleagues (1996) used data from the General Social Survey (GSS) and the American National Election Studies (ANES) to show that U.S. attitudes and opinions had largely *not* become more extreme over time, with the notable exceptions of attitudes toward abortion and opinion differences between partisan identifiers (see also Evans 2003; Fiorina 2004; Fiorina and Abrams 2008). The *alignment* tradition, which provides the starting point for the present study, can be traced to the work of Converse (1964), who proposed that belief structures should be described in terms of their degree of *constraint* (see also Baldassarri and Gelman 2008; Friedkin et al. 2016; Martin 2002).

A highly constrained belief structure is one in which holding some beliefs strongly implies holding other beliefs, producing correlations

across a wide range of issues. If knowing someone's attitude on issue *X* allows us to predict attitudes on issues *Y* and *Z*, then *X*, *Y*, and *Z* make up a constrained set of beliefs. Applying this logic to the polarization debate, researchers examine correlations or alignments *between* issues rather than distributions of attitudes *within* issues. When strong correlations across multiple dimensions of opinion indicate high levels of constraint—for example, when knowing someone's attitude on abortion helps predict their attitude on gun control—the population can be said to be more polarized. In contrast, if there are null or weak alignments across pairs of issues, the belief structure as a whole would be made up of intersecting, cross-cutting dimensions of opinion that resist polarization.

Tracking alignment across a broad set of political opinions, Baldassarri and Gelman (2008) report that, on one hand, attitudes on particular issues have become increasingly aligned in recent decades with both self-reported political ideology and party identification. This finding fits with other studies reporting that the Democratic and Republican parties (and liberal and conservative identifiers) have become increasingly ideologically coherent (e.g., Abramowitz and Saunders 1998, 2008; Fiorina and Abrams 2008; Layman and Carsey 2002; Levendusky 2009; McCarty, Poole, and Rosenthal 2006; but see Kinder and Kalmoe 2017). On the other hand, what Baldassarri and Gelman (2008) call “issue alignment”—or the actual extent of correlation across different attitude dimensions—has remained relatively stable. Self-identification as a liberal now increasingly predicts one's attitudes on specific issues, yet attitudes on issue *X* evidently do not predict one's attitudes on issue *Y* with significantly greater accuracy than in past decades thought to be less polarized. With these patterns at loggerheads—partisan alignment evidently on the rise yet little evidence of issue alignment—Baldassarri and Gelman (2008) conclude that the U.S. population has followed the lead of party elites in becoming increasingly consistent partisans but that polarization at the level of actual attitudes has not increased. As Baldassarri and

Gelman (2008:441) summarize, any apparent polarization in the population should be seen as an “illusory” artifact of the reshuffling of partisan labels.

Despite key differences in how scholars conceptualize attitude polarization and the mechanisms producing it, previous studies have one thing in common: they approach polarization by focusing on a selective set of political issues curated by the researcher. Whether conceiving of polarization as extremism on single issues or as alignment across pairs of issues, studies of mass polarization seem to invariably begin with the researcher selecting a set of political opinion questions from a national survey. In their exemplary study, Baldassarri and Gelman (2008) analyze pairwise alignments across 47 issues sorted into four topical domains (economic, civil rights, moral, and security and foreign policy). This approach is eminently sensible because it focuses attention on the issues we would presume to be most relevant to understanding polarization and reduces the complexity that would emerge from taking a more inclusive approach absent such presumptions. However, this strategy also imposes an implicit constraint on *how* polarization can appear in the data. Namely, the only residue of polarization that can be uncovered using this approach would be heightened alignment across issues that the researcher has defined a priori as being most relevant to the study of polarization, typically issues that can be widely categorized as “political” in nature.

More recently, DellaPosta and colleagues (2015) replicated Baldassarri and Gelman's (2008) approach using an eclectic set of items from the General Social Survey (GSS), including a mix of political “hot-button” issues and seemingly less political lifestyle questions, such as musical taste, attitudes toward art, parenting beliefs, and even belief in astrology. Their cross-sectional focus was not designed to identify over-time shifts in alignment across these dimensions, yet their analysis is notable for the surprisingly large number of such seemingly nonpolitical items that nevertheless displayed strong and statistically significant correlations with both

self-described political ideology and more explicitly political attitudes.

This motivates the questions addressed in the present study: Is mass polarization an illusion caused by the reshuffling of party labels, as much previous work suggests, or have we not taken a broad enough view of the beliefs that might be involved in producing polarization? Put differently, is the evident lack of belief polarization found in previous work a true signal of stably cross-cutting opinions in the U.S. population, or a result of underspecifying the full scope of beliefs relevant to understanding the structure of polarization?

To address these questions, this study replicates key features of the correlational or alignment-based approach offered by Baldassarri and Gelman (2008) while going beyond this previous work in two respects. First, I reassess the claim that partisan alignment has increased but mass polarization has not, and I do this for a broader cross-section of issues drawn from the totality of opinion questions ever presented in the General Social Survey (GSS) in place of a more narrowly selected subset of explicitly political items. Second, I use the pairwise alignments between issues as a baseline for further analysis rather than as an end point. Specifically, the correlations between pairs of beliefs are used to induce a holistic network depicting the structure of U.S. mass opinion. The structural properties of this belief network provide a novel grammar for measuring mass polarization.

BELIEFS AS NETWORKS

Sociologists, political scientists, psychologists, and cognitive scientists alike have long proposed that beliefs are not held in isolation; rather, they are held in relation to *other* beliefs. For example, Converse (1964:207) defines a *belief system* as a “configuration of ideas and attitudes in which the elements are bound together by some form of constraint or functional interdependence” (see also Baldassarri and Goldberg 2014; Bonikowski and DiMaggio 2016; Friedkin et al. 2016; Kinder and Kalmoe 2017; Martin 2002). Jost, Federico,

and Napier (2009) define *ideology* as a network of interconnected beliefs that, taken together, form a coherent whole or “world view.”

In a study of the emergence of cultural variation, Goldberg and Stein (2018:899) define *culture* in terms of “social conventions that associate practices with meanings,” that is, cognitive frames via which people come to understand distinct beliefs and ideas as being functionally dependent on one another (see also DiMaggio 1997; Ghaziani and Baldassarri 2011; Lizardo 2017; Mohr 1998; Patterson 2014). What these different perspectives have in common is the shift from studying distributions of particular beliefs or even correlations among pairs of beliefs to representing the overall *structure* of beliefs in relation to one another. Rather than describing particular beliefs, the key question concerns how various beliefs cohere into a larger network and the structural properties of that network.

Previous work often uses network metaphors to describe structures of interconnected beliefs, yet most empirical studies of belief structure and polarization nonetheless limit themselves to methods that do not fully account for patterns of relations among beliefs. Summarizing this critique, Baldassarri and Goldberg (2014:54) write, “Most scholars, following Converse, measure ‘constraint’ using bivariate relationships (e.g., correlation coefficients) or, alternatively, summary indices (e.g., factor scores). Such approaches, however, either presuppose or overlook the overall pattern of political attitudes that characterize a belief structure.” As previously noted, for example, Baldassarri and Gelman (2008) track patterns of belief constraint in the U.S. population by estimating weighted averages of bivariate correlations among beliefs. Earlier work often conceived of beliefs as being collapsible into one or several underlying linear dimensions. For example, Fleishman (1988) applies factor-analytic methods to survey data to show that attitudes are generally organized along two broad dimensions: one concerning attitudes toward individual liberty and the other pertaining to economic welfare policy.²

More recently, scholars have begun to use network-analytic techniques to examine the formal properties of belief structures (Baldassarri and Goldberg 2014; Boutyline and Vaisey 2017; Friedkin et al. 2016; for an earlier forerunner, see Martin 2002). The several formal approaches that have emerged are based on the duality between persons and the beliefs they hold, practices they exhibit, or objects with which they associate (e.g., Lee and Martin 2018; Lizardo 2014; Pachucki and Breiger 2010; Puetz 2017). Goldberg's (2011) relational class analysis (RCA) approach exploits the duality of persons and beliefs to inductively uncover groups of individuals in survey data who organize their attitudes in similar ways (see also Baldassarri and Goldberg 2014; DiMaggio and Goldberg 2018; DiMaggio et al. 2018). For example, two people who share the same opinions across a range of questions organize their beliefs similarly, but so do two people who hold directly opposed positions on those same questions. RCA provides the counterintuitive insight that two people who disagree with regard to every issue still share the same fundamental cognitive model of the way those issues are connected to one another.³

Rather than seeking to uncover groups of individuals who "construe" the world in similar ways (DiMaggio and Goldberg 2018), the *belief-networks* approach proposed by Boutyline and Vaisey (2017) exploits the duality of persons and beliefs to study the patterns of connections among those beliefs at the population level. In their approach, responses to attitudinal survey questions generate networks of interconnected beliefs linked by the magnitude of their bivariate associations with one another. In the belief network, each opinion or attitude is a *node* and its correlation with another opinion or attitude produces a network tie or *edge* weighted according to the strength of the correlation. The goal of this approach is to represent the central elements organizing beliefs in the population aggregate. To this end, Boutyline and Vaisey (2017) represent aggregate correlations among political beliefs as a network configuration to show the central role

that liberal-conservative ideology plays in organizing the political beliefs of the U.S. public. They contrast their findings with Lakoff's (1996) famous claim—which finds little support in the aggregate data—that Americans derive their beliefs on political issues from metaphorical models of the family (liberals favoring a "nurturant parent" model versus conservatives favoring a "strict father" model).

Previous studies in both of these molds have been cross-sectional in focus, rather than studying change over time in mass opinion. RCA and related approaches seek to identify heterogeneous cognitive mappings of issues within a population. Any such over-time analysis would likely require a constant set of survey items appearing in every cross-section of the data. In comparison, aggregate belief-centric approaches, such as Boutyline and Vaisey's (2017), provide a less granular focus on population heterogeneity *within* cross-sections while providing the potential for greater comparison *across* cross-sections. This is because the aggregate belief network for a representative sample of the population allows individuals to "drop out" of the analysis.⁴ As with previous studies of pairwise opinion alignment (Baldassarri and Gelman 2008; DellaPosta et al. 2015), the researcher can then statistically model population time trends in the correlations between beliefs, using estimates from these models to interpolate missing observations for years in which a particular survey item did not appear. This interpolation makes focusing directly on relationships among beliefs themselves especially useful for tracking changes over long periods of time in the structure of mass beliefs.

Individuals within a population may vary in their conformity to an aggregate belief structure (Baldassarri and Goldberg 2014; Martin 2002), and such heterogeneity would not be captured by studying the population-level belief network.⁵ Yet, as recently illustrated in a theoretical model by Goldberg and Stein (2018), aggregate belief structures can shape individual belief formation by providing ready instances of association between beliefs and practices that are likelier than not

to co-occur in the population. For example, if every time I go to a football game, I see parking lots full of cars with Trump bumperstickers, I will tend to see football fandom as being associated with Trump support. If I already like football but do not yet support Trump, I might conclude from this that I *should* naturally support Trump due to my other preferences. In other words, to the extent that individuals (a) associate commonly co-occurring beliefs and practices and (b) update their own beliefs and practices to maintain consistency with these mental maps and avoid cognitive strain, aggregate belief structures can be expected—at least to a modest extent—to shape individual beliefs (Festinger 1957; Goldberg and Stein 2018; Heider 1946; Hunzaker 2016; Kunda 1990).

The present study builds on the methodological framework introduced by Boutyline and Vaisey (2017). Whereas Boutyline and Vaisey analyzed a selected cross-section of beliefs from the 2000 edition of the American National Election Studies, the present study applies the belief-network approach to map the structure of a large number of attitudes and opinions over more than 40 years of the General Social Survey. By comparing the same belief network over long periods of time among representative aggregates of the population, the present study brings the belief-network approach to bear on the question of whether and how mass opinion has shifted in the United States. Previous public opinion research in the tradition of Converse (1964) frequently invokes the importance of structure, but the belief-network approach allows for a more fully network-based view of mass polarization.

THE NETWORK STRUCTURE OF BELIEF POLARIZATION

Fence and Oil Spill Models of Polarization

To return to an earlier metaphor, measuring the average alignment across pairs of quintessentially political issue dimensions (e.g.,

Baldassarri and Gelman 2008) is akin to observing the height of a fence. The researcher takes observations at multiple points in time to see whether the alignment between these issues has increased—in other words, whether the fence has gotten higher. This *fence model* of polarization is illustrated in Panel A of Figure 1, where beliefs are represented as nodes in a network and the lines connecting these beliefs represent the absolute correlation between those beliefs in a hypothetical population. At Time 1, beliefs about abortion, climate policy, and taxation are all weakly aligned with one another; by Time 2, each of these pairwise alignments has become stronger. Two people who disagreed about abortion at Time 1 may still have agreed on climate policy or taxation, given that these beliefs were only weakly correlated. By Time 2, however, the same two people would be likelier to either agree or disagree on all issues, as the three beliefs have all become more strongly correlated with one another. This is the model of polarization as the heightening of existing opinion alignments across pairs of issues.

Cross-cutting opinion pluralism can collapse not just through *heightening* alignment across pairs of issues but also through *broadening* alignment across a wider range of issues than were previously aligned. Broadening alignment is less like a fence and more like an *oil spill*. In Panel B of Figure 1, initial alignments on abortion, climate policy, and taxation at Time 1 expand to implicate LGBT rights and religious beliefs at Time 2. It is not that the particular alignments between the original set of issues have become stronger, necessarily, but rather that the introduction of new issue dimensions has expanded the range of these previous alignments.⁶ At Time 1, people may tend to either agree or disagree on a set of core political issues; at Time 2, as new (political, lifestyle, and other) issues are introduced into existing alignments, the range of agreement and disagreement broadens. Tracing the expanding boundaries of the “oil spill” as it taints an increasingly broad set of issues represents a distinct challenge for

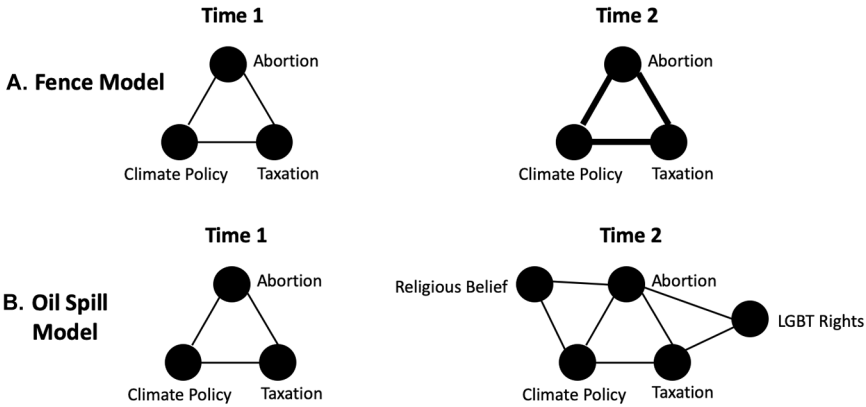


Figure 1. Two Models of Polarization

Note: Each node represents an opinion or attitude and each solid line indicates an absolute correlation or alignment observed between those opinions or attitudes in the population. Thicker lines indicate higher-magnitude correlations than thinner lines.

empirical research on polarization. Unless the researcher knows ahead of time which issues will (and will not) be drawn into range of the spill, they cannot define the relevant set of issues a priori but instead must allow the broadest possible range of data to speak to this question.

Belief Modules and Consolidation

Network structures commonly feature groups or clusters of nodes that associate more strongly with one another than with others. The *modularity* or “clusteredness” of a network refers to the extent to which the network is divided into neatly compartmentalized modules with more edges occurring within—as opposed to across—modules (Newman 2006). In a modular belief network, beliefs group into cohesive “packages” featuring strong associations among the beliefs contained in a given package (i.e., believing something about one issue in the package strongly implies believing something about another issue in the same package).

Increasing mass polarization in an aggregate belief network should bear a distinct empirical signature, which I call *consolidation*. Simply put, belief networks with high consolidation are composed of cohesive and

clearly defined belief modules that are relatively large in size and few in number. In contrast, an unconsolidated belief network could simply lack any clear modular structure, such that the belief network cannot be divided into distinct “packages” of correlated beliefs. Or, in another scenario, a relatively unconsolidated belief network might feature a larger number of modules where no single module or handful of modules dominates by containing all or most beliefs. By analogy, we could compare a highly consolidated belief network to a monopolistic or oligopolistic market or industry dominated by one or a few firms holding giant market shares. In contrast, a less consolidated belief network would more resemble a competitive marketplace with many smaller firms competing for market share.

Figure 2 illustrates the difference between modular belief networks with differing levels of consolidation using simple “toy” networks. As in Figure 1, each node in the network represents a belief on an issue or topic as measured by a survey question. A line or edge between two issues indicates that opinions on those issues tend to be strongly correlated in the population. These correlations can be positive or negative—it is the magnitude, not the direction, that matters. For example, if support

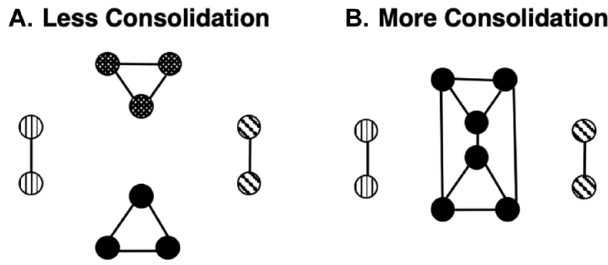


Figure 2. Illustrative Examples of Belief Networks

Note: Each node represents an opinion or attitude and each solid line indicates a strong absolute correlation. Patterned fills indicate different belief modules.

for legal abortion is strongly negatively correlated with support for teaching creationism in public schools, beliefs on these two issues should be likelier *ceteris paribus* to be placed into the same belief module. Finally, the patterned fills on the nodes indicate distinct modules, each containing an internally cohesive (correlated or aligned) “package” of beliefs (setting aside for now the question of how one would formally identify these modules beyond mere visual inspection).

Panel A in Figure 2 displays a belief network with modular groupings but little consolidation. The network is modular because the only strong correlations occur within clearly differentiated packages of attitudes or opinions; despite the strong clustering evident in the network, however, modules are similar in size and none dominate the network. This unconsolidated arrangement suggests cross-cutting packages of opinions that do not cohere into a larger whole. In the more consolidated belief network in Panel B, by contrast, most beliefs adhere to a single central module. In other words, the belief network in Panel B is dominated by a central cluster of beliefs that correlate together closely. In this consolidated arrangement, one might hypothesize the existence of a central organizing principle from which all the beliefs in this central module originate—for example, liberal or conservative political identity (Boutyline and Vaisey 2017; Jost et al. 2009), underlying moral frames (Haidt 2012), deep-rooted cognitive associations (Lakoff 1996), shared

lifestyle and culture (Hunter 1991), or underlying sociodemographic and material causes (Brooks and Manza 1997; Lipset and Rokkan 1967; Marx and Engels 1978). As I will discuss, however, such formations could also plausibly emerge even in the absence of any coherent organizing principle (DellaPosta et al. 2015).⁷

As discussed earlier, previous work on cross-issue alignment in the tradition of Converse (1964) generally focuses on the average correlation strength across pairs of beliefs (e.g., Baldassarri and Gelman 2008; DellaPosta et al. 2015). Yet, even two networks that are identical with regard to the average strength of the correlations between beliefs could evince different structural arrangements depending on how those individual beliefs fit to produce the larger *gestalt* of the belief network.⁸ To be clear, it is not my argument that the overall strength of correlation between pairs of beliefs is irrelevant to polarization. Rather, my argument is that structural differences that can be observed independently from the aggregate strength of alignments between issues are *also* empirically and theoretically significant but have been comparatively neglected in previous work. Thus, analysis of structure provides a key avenue through which we can apply a new lens to the question of polarization.

Importantly, even a highly modular belief network could be seen as supporting pluralistic, cross-cutting alignments rather than polarization. Panel A of Figure 2 illustrates

such a dynamic, where opinions cluster in several clearly differentiated modules lacking a broader alignment with one another. Theories of political pluralism suggest that such cross-cutting alignments, far from representing a social ill, are in fact central to organic solidarity in modern, complex societies composed of many heterogeneous subpopulations (Baldassarri and Diani 2007; Baldassarri and Gelman 2008; Mutz 2002). The real concern for polarization occurs as these networks cease to consist of such cross-cutting alignments. This happens when previously distinct belief modules are subsumed into increasingly encompassing alignments—as reflected in the high-consolidation example of Panel B. As a belief network becomes more consolidated, the *breadth* of polarization increases—two people who disagree on one issue, for example, become increasingly likely to disagree on an expanded range of other issues.⁹

To summarize the argument: the structural properties of belief networks can shed light on whether the U.S. public has become more polarized, or whether cross-cutting pluralistic alignments remain. Drawing on theories of belief formation, networks of interconnected beliefs can be approached by identifying the different modules or “packages” of correlated beliefs that comprise the broader network. Then, drawing on theories of political pluralism, polarization should manifest in increasing *consolidation* as previously cross-cutting clusters of beliefs collapse to form increasingly broad and encompassing groupings, thus shrinking the space available for agreement across the divides created by opinion cleavages.

DATA AND METHODS

Survey Data

The General Social Survey (GSS) is a nationally representative survey of U.S. attitudes, behaviors, and demographics fielded by the National Opinion Research Center (NORC) at the University of Chicago since 1972. The GSS allows for consideration of a broad

range of opinions and attitudes encompassing not just straightforwardly political issues but also social, moral, and cultural values. To examine structural alignments across the widest available array of attitudes over the entire span of years covered by the GSS, I sought to include as many of these items as possible. Following Boutyline and Vaisey (2017), I adopt Alwin’s (2007) distinction between “factual” questions—for which the answers can be objectively verified—and “non-factual” questions—namely attitudes, opinions, beliefs, and values—that reflect respondents’ subjective viewpoints. I sought to include every item ever asked in the GSS that fell into the latter category of presenting respondents’ subjective viewpoints. This agnostic approach to item inclusion broadens the scope of previous analyses by considering all available opinions and attitudes rather than a smaller curated subset of charged political questions, but we are still constrained by what the purveyors of the GSS chose—or did not choose—to ask about in the first place.¹⁰ Because the focus of the analysis is on the correlation *between* items, I only included items with binary, interval-scaled, or continuous responses, or items that could be recoded to reflect such a scale. In other cases, multiple versions of the same question had to be reconciled by recoding and then consolidated.

This initial selection process produced a list of 1,357 GSS items. Adapting a procedure developed by Baldassarri and Gelman (2008), I next obtained the zero-order Pearson correlation between *each unique pair* of items for *every year* in which those two items appeared together in the GSS.¹¹ Because we are interested in the magnitude of the correlation—or the strength of the alignment between any two items—rather than the direction, I use the absolute value of the correlation coefficients throughout the analysis (Boutyline and Vaisey 2017; DellaPosta et al. 2015). Over the 31 editions of the GSS issued between 1972 and 2016, this procedure produced 474,199 unique year-specific correlations between pairs of opinions, attitudes, and beliefs. However, these year-specific *instances* of correlations

between items only reflect a total of 216,704 *unique pairs* of items—in other words, the average pair of items appeared together in the same edition of the GSS just between two and three times. Moreover, the modal pair would have appeared together just once. This reflects the structure of the GSS, in which a relatively small number of items appears reliably across successive editions of the survey, and other questions are asked just once or a handful of times, typically as part of a larger set of items rotated into the survey to address an area of timely interest to researchers.

The sparsity of data for most unique pairs of GSS items presents a double-edged problem. First, it makes the process of inferring an over-time trend of increasing, decreasing, or stable alignment between any such pair of items arguably tenuous, due to the lack of data points with which to observe such a trend. One possible solution would be to restrict analysis to only the observed correlations without any reliance on statistical modeling of over-time trends. However, this solution would only induce a much deeper selection problem: the list of items analyzed in any given year would differ radically from other years. Because the goal of the analysis is to identify changes over time in the belief network owing to corresponding changes in the alignment of different attitudes, it is essential that the population of GSS items represented in the belief network remain constant. Otherwise, observed changes in the structure of the belief network could easily be explained by the somewhat arbitrary mix of questions that happened to be asked from one edition to the next.

In seeking a solution that balances both edges of this data sparsity problem, I restricted analysis to the 14,910 pairs of items that appeared together in at least five years of the GSS. Although this subset of reliably observed correlations includes only approximately 7 percent of all possible pairs of items, it still retains roughly 43 percent of all year-specific correlations observed in the original set (a total of 202,928 such correlations).¹² The retained questions cover a wide array of topics, ranging from the traits people would

desire to see in their children to attitudes toward abortion, foreign policy, and taxation and economic regulation.

Constructing the Belief Network

In the belief network, each GSS item becomes a *node* and the correlations between items become *edges* linking these nodes into a broader structure of connection (Boutyline and Vaisey 2017). Edges are *weighted* by the magnitude of the correlation between the two connected nodes. The goal is to create a graphical representation of this belief network for each of the 31 years in which the GSS was conducted from its 1972 inception to the 2016 edition. To make apples-to-apples comparisons across the belief networks for different years, I hold constant the set of *items* captured in the network and focus only on changes in the *relationships* among these items.

Building on previous work (Baldassarri and Gelman 2008; DellaPosta et al. 2015), I use a multilevel mixed-effects model (Gelman and Hill 2007) to estimate the linear trend of increasing or decreasing magnitude of correlation over time for each pair of GSS items (see the Appendix for more detail). For years in which two items co-appeared in the GSS, the weight of the edge between those two items is the absolute value of their observed correlation for that year. Then, for years in which those two items did *not* co-appear, I retain them in the network and estimate the weight of the edge between them using predicted values from the mixed-effects model, incorporating intercepts and time trends that vary for each pair of items.

In effect, missing observations stemming from the absence of some items in certain years of the GSS are filled in based on the statistical trends observed for those items in the years for which they *did* appear. This approach requires a heavy reliance on statistical estimates to fill gaps in the record of empirical observation, but avoids the more vexing dilemma of accounting for the countless idiosyncratic changes in the number and composition of items appearing in the GSS for any given year. Yet, there are consequent

limitations in how the results of the analyses should be interpreted. Namely, because the network tie between any given pair of items in any given year will often be based on a statistical estimate, we should be cautious in interpreting short-run year-by-year changes as substantively meaningful. Rather, our focus should remain on the longer-term trends the mixed-effects model is designed to capture.¹³

The belief network for each year contains 219 nodes, each representing a GSS item. To inductively uncover the distinct *belief modules*—internally cohesive clusters of highly correlated opinions—present in the network for a given year, I rely on widely-used community detection algorithms designed for use in complex networks. In particular, I implement the “walktrap” method, which discovers communities in a network based on the logic that a random walk through the network will tend to become trapped within the dense clusters of nodes belonging to the same community (Pons and Latapy 2006). In a simulation study, Gates and colleagues (2016) found that the walktrap method outperformed other community detection algorithms in recovering community structures for dense weighted networks; the belief network, derived from correlation matrices among pairs of survey items, is just such a structure (for other applications of the walktrap approach in correlation networks, see Dalege et al. 2017; Golino and Epskamp 2017).

Accounting for Partisan and Ideological Sorting

Although self-reported political ideology (on a scale from “Extremely Liberal” to “Extremely Conservative”) and party identification (on a scale from “Strong Democrat” to “Strong Republican”) could be seen as sociodemographic traits rather than beliefs, I include both in the belief network to account for the role of partisan and ideological sorting. I call this the *baseline network* because it simply contains the full set of zero-order correlations among all belief items (including ideology and party identification).

To further distinguish time trends owing to partisan sorting from those reflecting broader shifts in the belief structure, I replicate the analysis while removing from the belief network all correlations featuring either political ideology or party identification as one of the two focal variables. I call this second condition the *ideology-removed network*; comparing the baseline and ideology-removed networks will help answer the question of whether any observed changes over time persist beyond the direct influence of partisan sorting (in which particular opinions become more strongly correlated with partisan and ideological identity without the relationships among the opinions themselves necessarily shifting).

I then go a step further by also adjusting for self-reported ideology and party identification in all the remaining correlations between belief-pairs. This third condition, which I call the *ideology-controlled network*, includes the partial correlations between belief items after controlling for ideology and party and removing all correlations that directly involve either of these variables from the network. Clearly, this third condition presents the most stringent test of whether any observed shifts in the belief network persist apart from sorting, because it adjusts for both direct (i.e., partisan identity’s correlation with particular beliefs) and indirect (i.e., the extent to which partisan identity moderates the correlation between other beliefs) pathways through which partisan and ideological identity may influence the belief network structure. Figure 3 summarizes the key steps in the analytic procedures used to generate the belief networks.¹⁴

ANALYSIS

Describing the Belief Network

Figure 4 presents a visual depiction of the belief network for 1972, the first year in the observation period.¹⁵ Belief modules are distinguished by color (see the online version of this article for color figures); note, however, that the belief modules are induced separately

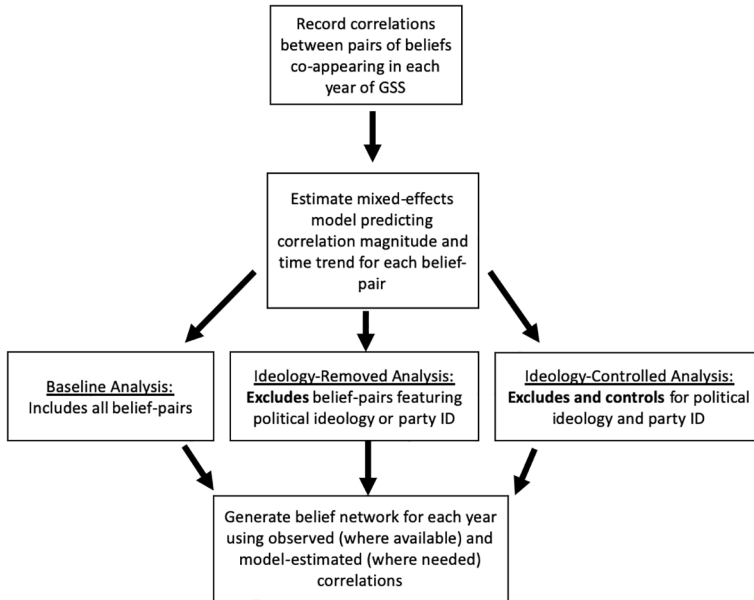


Figure 3. Analytic Procedures Used to Generate Belief Networks

for each year, so the colors are not necessarily consistent across years. The largest module in the 1972 network contains 30 percent of beliefs (purple-colored in the right region of the graph). This module is organized around beliefs about race, gender, and civil liberties—it features questions (labeled in the graph by their GSS mnemonic) such as whether African Americans have “worse jobs, income, and housing than white people” due to having “less in-born ability to learn” (*racdif2*), whether it is “much better for everyone involved if the man is the achiever outside the home and the woman takes care of the home and family” (*fefam*), and whether books written by communists should be permitted in libraries (*libcom*). The second largest module (green), containing 24 percent of beliefs, includes (among other things) questions gauging confidence in core social and political institutions like big business (*conbus*), the military (*conarmy*), and the clergy (*conclerg*). A third central module (orange), which cuts across the first two and contains 10 percent of beliefs, includes law-and-order-tinged beliefs about capital punishment (*cappun*), crime (*natcrime*), and guns (*gunlaw*). In addition to these

three visible central modules, the network contains a number of peripheral modules that are less clearly connected to the central core.

When looking at the network snapshot for any single year, the relative placement of nodes is partly arbitrary, because an edge is only present between two beliefs if those items co-appeared in enough editions of the GSS for the correlation between them to be included in the analysis (as discussed earlier, I use five co-appearances as the threshold for inclusion). However, these snapshots become meaningful when compared to earlier or later snapshots. The set of nodes (beliefs) and edges (correlations) is the same in every snapshot of the network, so any change over time in the structure of the belief network stems from changes in the relative *weights* of the edges that are present. As the alignments between pairs of beliefs change over time, the structure of the belief network shifts accordingly.

Figure 5 shows the 2016 belief network. Each of the two largest belief modules have now increased in size relative to the others. The largest module (purple) now contains 37 percent of all items, and the second largest (green) now contains another 32 percent. This

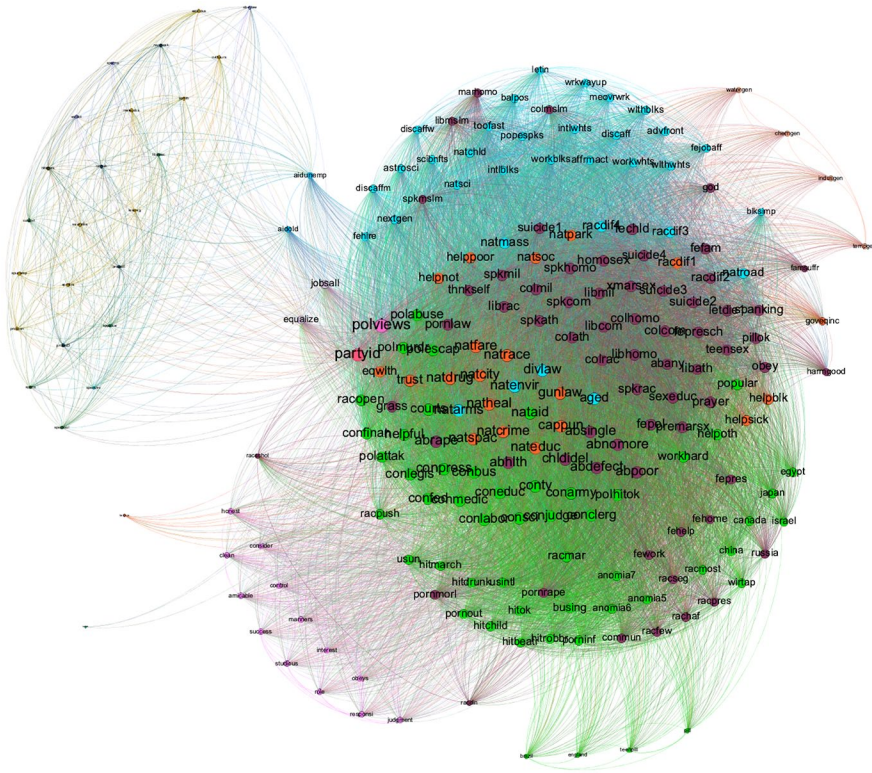


Figure 4. Belief Network for 1972

trend suggests that previously peripheral beliefs belonging to their own smaller modules have been pulled closer over time to the dense core of political identity reflected at the center of the network. The set of beliefs that moved from smaller modules into the two largest ones over the observation period reflect a wide-ranging set of concerns, including race-based affirmative action (*affirmact*), the appropriateness of older people sharing a home with their children (*aged*), whether most people can be trusted (*trust*), the scientific credibility of astrology (*astrosci*), and the moral infallibility of the Pope (*popespk*).

Trends in Belief Network Structure

Visual inspection of these belief networks provides initial evidence that beliefs have become increasingly consolidated, meaning previously cross-cutting (or relatively uncorrelated) modules of opinion have collapsed

into fewer and more encompassing modules. To provide a more rigorous test of these claims, Figure 6 shows changes over time in formal properties of the belief network. Each panel displays local polynomial regression fits of over-time network properties in the baseline condition containing all zero-order correlations (solid lines), the ideology-removed condition where self-reported ideology and party identification are excluded from the network (dashed lines), and the ideology-controlled condition featuring partial correlations between beliefs after adjusting for political ideology and party identification (dotted lines). To assess the significance of the observed trends relative to those that could plausibly emerge through sampling variability, I generated 5,000 bootstrapped replications of the belief network for each year of the GSS. Adapting the procedure used by Boutyline and Vaisey (2017), each nonparametric bootstrap replication involved

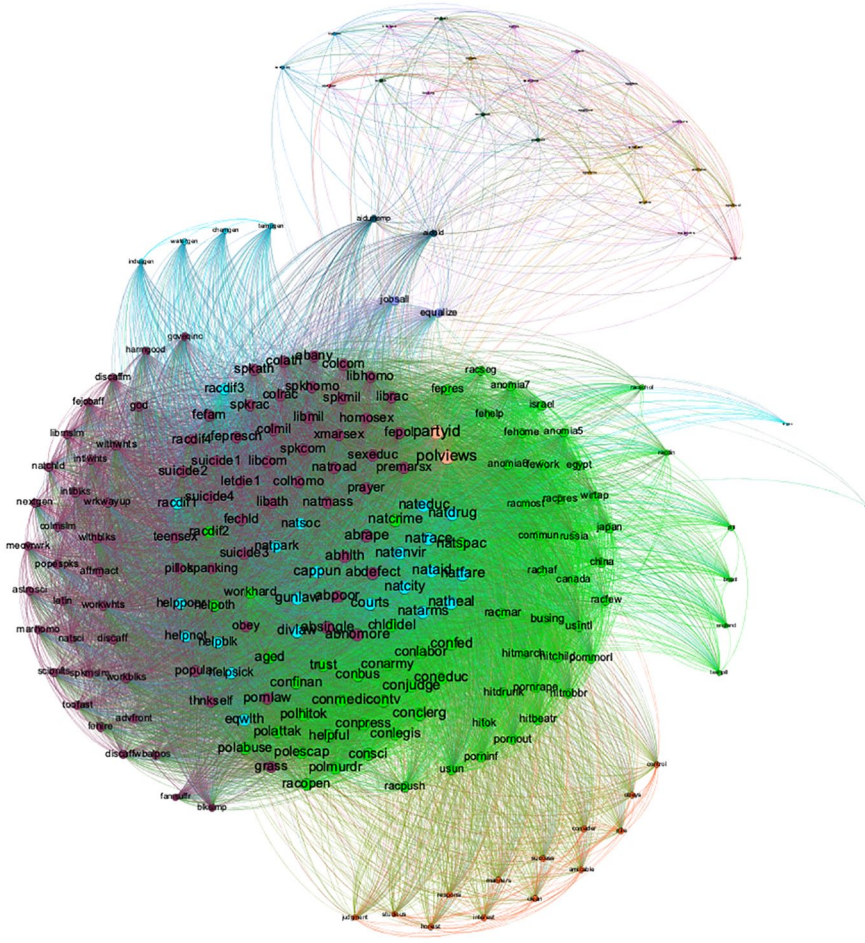


Figure 5. Belief Network for 2016

resampling the GSS respondents for each year with replacement, re-computing the observed correlations in each bootstrapped sample, re-generating the statistical models of these observed correlations, and using the results of the model to produce yearly belief networks (thus repeating the procedures described in Figure 3 for each bootstrap replication). The trends depicted in Figure 6 are based on the yearly means across all 5,000 bootstrap replications.

Panel A of Figure 6 finds that the overall network *density* (i.e., the average weight of the edges across all pairs of beliefs) increased modestly across the 1972 to 2016 observation period in the baseline belief network. I begin

with density because this metric provides an analogue to measures of average alignment across pairs of issues in previous studies of opinion alignment. The overall trend for the ideology-removed network is similar to that of the baseline network. However, it is notable that the ideology-controlled network featuring partial correlations (adjusting for political ideology and party identification) between beliefs saw a slight *decrease* in density over the same span. These trends support previous work (e.g., Baldassarri and Gelman 2008) by showing that the increase in average alignment or correlation between pairs of beliefs owes much to the mediating effect of partisan and ideological labels. Yet, the fact

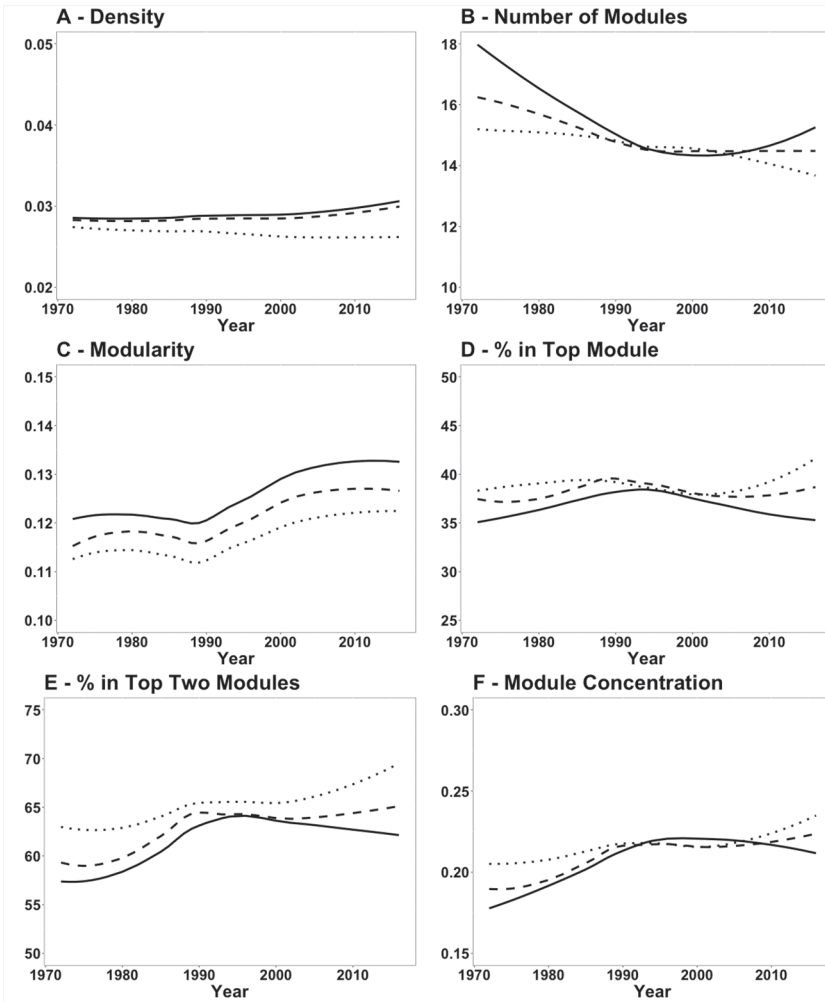


Figure 6. Time Trends in the Belief Network

Note: Displayed lines are based on local polynomial regression fits from 5,000 bootstrap replications across all years in the observation window. Solid lines reflect the baseline condition featuring unadjusted zero-order correlations; dashed lines reflect the ideology-removed condition with correlations directly involving political ideology and party identification removed from the network; and dotted lines reflect the ideology-controlled condition featuring partial correlations adjusting for the influence of political ideology and party identification.

that this pattern is confirmed here puts even greater importance on where the belief network analysis diverges from previous studies, which is in examining the broader structure of aggregate beliefs rather than the average pairwise alignment.

As described earlier, belief consolidation will be most evident when belief modules are few in number, modular (i.e., cohesive and

distinct) in construction, and large in size. Corresponding to these three structural signatures, the main analyses presented here rely on simple network metrics capturing the ways beliefs are arranged across different belief modules in the network. Panel B in Figure 6 shows the *number of belief modules* uncovered by the walktrap community detection algorithm across the observation period.

Consistent with increasing consolidation, the number of modules decreased over time in all three network conditions.

Panel C tracks the *modularity* of the belief network. As mentioned earlier, modularity captures the “clusteredness” of the network, conceived as the amount of information a given clustering solution gives us about the actual structure of relationships in the network (Newman 2006). More formally, modularity represents the proportion of edges (or weight attached to those edges, as in the present case) occurring *within* clusters or modules compared to the proportion one would expect by chance in a network with the same degree distribution as the observed one. Importantly, this means modularity captures the extent of clustering within dense communities while adjusting for effects of the overall density of ties in the network, such that time trends in the modularity of a given network can be interpreted independent of changes in the network’s underlying degree distribution. As shown in Panel C, modularity increased similarly over time across all three network conditions.

Panel D of Figure 6 shows the percentage of beliefs placed into the *largest module* by the community detection algorithm; in other words, the size of the largest single grouping of cohesively tied beliefs in the network. In the visual inspections, we saw that growth in the second largest module also seemed to indicate consolidation, so Panel E tracks the percentage of nodes in the *two largest modules* combined. The percentage of nodes placed in the single largest module remained relatively consistent over time. However, the combined size of the top two modules saw a more visible increase, a pattern consistent with increasing consolidation. Panel F shows an overall summary measure of the concentration of beliefs within modules using the Rosenbluth market concentration index (Hall and Tideman 1967).¹⁶ As with the previous measures, this summary metric increased over the observation period.

To test the significance of these over-time differences, I estimated a linear regression fit of the time trends for each of the 5,000 bootstrap replications. Figure 7 plots the

percentage linear change between 1972 and 2016 based on these regression fits, both in terms of the mean change and the variability across bootstrap replications. Clearly, each bootstrap replication can produce substantially variable results due to the several analytic steps involved in each such replication and the path-dependence among these steps (as summarized in Figure 3). This high degree of variability is reflected in the wide confidence intervals (90 and 95 percent intervals are shown) around the mean estimates in Figure 7. Still, some notable trends emerged reliably across a high percentage of bootstrap replications.

First, Panel A in Figure 7 shows there are statistically significant changes in density over the observation period: we see positively increasing density in the baseline and ideology-removed conditions and decreasing density in the ideology-controlled condition. With regard to the number of belief modules, Panel B shows that the observed decrease is most reliably observed in the baseline network and less consistently seen in the other two network conditions. In these latter two conditions, the trend still appears to be in the same direction as in the baseline network, but the trend is clearly weaker and less distinguishable from a null pattern. As Panel C shows, the 12.3 percent average increase for modularity in the baseline network and the 11 percent increase in the ideology-removed network are both observed consistently enough across bootstrap replications that the 95 percent confidence intervals do not include zero. Strikingly, even the ideology-controlled network—in which political ideology and party identification are not just removed from the network but further adjusted for in computing the partial correlations between all other pairs of beliefs—sees a marginally significant 10 percent average increase in modularity ($p < .10$).

Panel D confirms the suspicion that the size of the single largest belief module did not noticeably change over the observation period. Panel E shows that although an average increase in the combined size of the two largest modules is observed across all network conditions, the point estimates vary

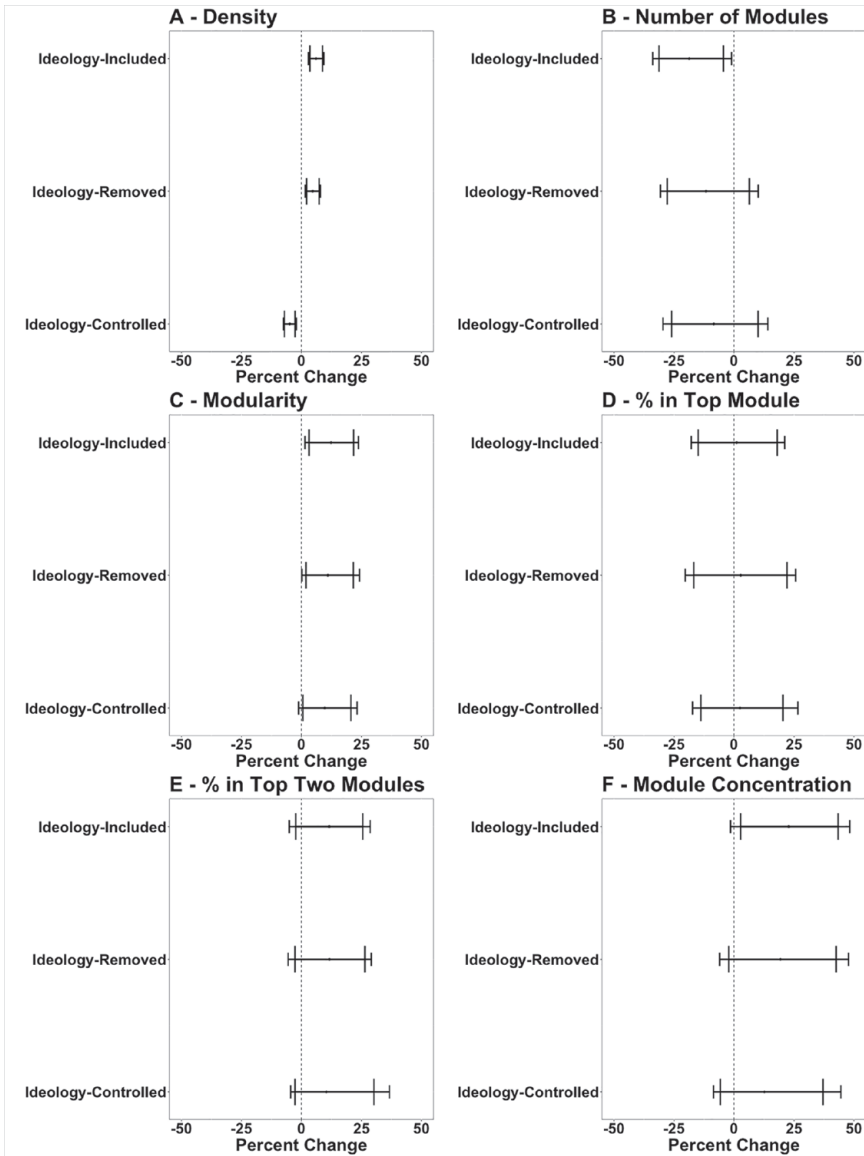


Figure 7. Bootstrapped Confidence Intervals for Network Trends

Note: Results are based on linear regression fits of the time trends across 5,000 sets of bootstrapped belief networks. For each network condition, panels show the mean percent linear change across all bootstrapped replications and the 90 and 95 percent confidence intervals.

widely enough that the confidence intervals still intersect zero (although barely) in all three cases. A similar pattern appears in Panel F for the summary measure of module concentration, which sees a marginally significant ($p < .10$) increase in the baseline condition and slightly less consistent increases in the other two conditions.

In short, analyses of the aggregate belief networks suggest that, on the whole, the structure of beliefs has moved in meaningful ways toward increasing consolidation—beliefs increasingly concentrated within fewer and more encompassing modules rather than a greater number of more cross-cutting modules. As in most such studies that attempt to

encompass a wide and agnostically-selected range of opinions, the overall time trends are substantively modest; yet, they are sufficiently consistent with one another that the overall shift in the structure of the belief network is unlikely to be a product of chance statistical variation. Even still, the observed trends encompass substantial uncertainty and merit cautious interpretation.

Like previous work, I find clearer evidence of a shift with regard to opinion alignments that include salient markers of partisan and ideological identity. However, even after removing these partisan identity markers from the belief network, I still observe a statistically significant increase in network density (i.e., average correlation strength) and modularity (i.e., the tendency for beliefs to cluster into coherent and internally cohesive packages). The trends observed for even the most stringent condition—where partisan and ideological identification are both removed from the network and controlled while computing the correlations between other beliefs—are less precise but still suggestive. In particular, the fact that this network featured a significant *decrease* in the average correlation while still likely moving toward consolidation in other ways (e.g., increasing modularity) that appear similar to the baseline network suggests the network approach captures shifts in the structure of beliefs that would not be obvious using traditional techniques—in particular, approaches that measure belief structure by averaging the dyadic alignments among pairs of beliefs without placing these relationships in broader relational context.

DISCUSSION AND CONCLUSIONS

Limitations and Suggestions for Future Research

The analysis presented here remains limited in several important ways. The aim of the present study was to conceptualize and measure aggregate trends reflecting mass belief

polarization; however, important questions concerning underlying causal mechanisms remain for future work. Because survey data based on probability sampling isolate individuals from the networks and social contexts in which they are embedded (McPherson 2004), these data do not allow us to rigorously disentangle the various within-individual (e.g., effects of sociodemographic background) and between-individual (e.g., effects of social influence) mechanisms that may give rise to belief structures (DellaPosta et al. 2015). Moreover, because the repeated cross-sectional data do not follow the same individuals over time, little can be gleaned about individual-level processes of belief formation and change (but see Kiley and Vaisey 2020). By focusing on aggregate belief structure in a representative sample of the U.S. population, the analysis also leaves open the question of group-level opinion cleavages and how belief heterogeneity *within* the population has evolved over time.

Correlated sets of beliefs may give rise to social identities organized around those beliefs (e.g., people who oppose legal abortion and gay rights organizing as the “Religious Right”). Just as importantly, however, the existence of certain social identities provides signals for how individuals should form new beliefs in connection with others, reversing the causal sequence (Achen and Bartels 2016; Converse 1964; Lazarsfeld, Berelson, and Gaudet 1944). Political ideology and party identification are commonly proposed as the connective tissues linking otherwise unconnected beliefs; for a signal of how one should form beliefs on a given issue, partisans look to what their co-partisans—including public figures—are saying about the issue. Through such influence processes, the original or orienting belief (e.g., belief in liberalism) acts as a constraint on the formation of subsequent subsidiary beliefs (e.g., support for abortion rights).

In still other cases, cohesive belief modules may be epiphenomenal to other underlying social forces only loosely related (or perhaps unrelated) to social identity. For example, a

variety of attitudes toward civil liberties, non-conformity, and the value of societal tolerance might cluster because they all stem from a greater “open-mindedness” rooted in sociodemographic variables like education, urbanism, and occupation (Stouffer 1955). Or, beliefs may become clustered in sociodemographic space due to “bottom-up” processes of homophily and social influence whereby people with similar lifestyles or cultural values have greater chances to interact and thereby further influence one another’s opinions (DellaPosta et al. 2015; McPherson 2004; McPherson, Smith-Lovin, and Cook 2001; Vaisey and Lizardo 2010). Via a gradual process of social influence channeled through these homophilous ties, DellaPosta and colleagues (2015) show that initially small alignments between substantively unconnected issues can tip the population into highly polarized alignments (see also Baldassarri and Bearman 2007; DellaPosta and Macy 2015; Flache and Macy 2011; Macy et al. 2003).

The present study mostly abstracts away from the historically specific processes through which mass opinion in the United States became increasingly consolidated, but the belief-network approach can also be used to home in on such questions. Structurally, two previously distinct belief modules would become likelier to collapse into a single module after the emergence of new “bridging” associations linking beliefs located in the previously separate modules. These bridges play a role analogous to the “weak ties” described by Granovetter (1973), bridging ties spanning structural holes (Burt 1992; for a related discussion of cultural holes, see Pachucki and Breiger 2010), and “rewired” ties that link otherwise disconnected segments of small-world networks (Watts and Strogatz 1998). In other words, these are associations or alignments between beliefs that one would not otherwise expect to be associated, given their different locations in the overall network. The addition of such distance-spanning bridges collapses the network into fewer modules by reducing the distance between otherwise-disconnected sets of beliefs. For example,

Perlstein’s (2001) narrative history of the U.S. conservative movement describes how conservative intellectuals and activists fused the previously unaligned (or weakly-aligned) identities of anti-communist Cold Warriors, socially conservative Christians, and economic libertarians to craft a combined political identity powerful enough to take over the Republican Party.

These ideological bridges can also emerge from a process that Goldberg and Stein (2018) call *associative diffusion*. In their model, people are influenced by observing what behaviors tend to co-occur among their peers (who need not be closely tied to the actors, and in fact might be strangers). Observing the co-occurrence of two behaviors creates a cognitive association between those behaviors, leading to people seeing them as naturally related to each other. Like beliefs, practices, and behaviors themselves, Goldberg and Stein (2018) convincingly argue, cultural associations among such objects can also diffuse through repeated observations of the social world. If two otherwise unrelated beliefs or opinions (i.e., liberalism and latte-drinking or football fandom and Trump support) come to be seen as associated through enough instances of co-occurrence, the resulting associative bridge might gradually collapse the distance between them. Once I come around to drinking lattes through this practice’s association with liberalism, I might also proceed to adopt a series of other beliefs and practices associated with latte-drinking—such as driving a hybrid electric car or listening to indie rock.

Yet, there is nothing inherently irreversible about these dynamics. It would also be possible via the reverse process for a previously cohesive module of beliefs to split into two through the emergence of a new fault line—that is, when one or more associations holding together beliefs in the same module weaken, causing the module to disintegrate. Particular beliefs can move over time from one module to another when the package of other beliefs with which they are associated become “rewired.” For example, it is

reasonable to suspect that in the wake of the Republican Party's tacit acceptance of Russian interference in the 2016 presidential election, the set of beliefs associated with Americans' liking for Russia (a question featured in the General Social Survey) may become quite different than during the height of Cold War hawkishness.

Implications for the Pluralism Debate

Conceived as a structure of interrelated attitudes, opinions, and beliefs, the U.S. belief network as captured in General Social Survey (GSS) data experienced increasing consolidation over time. Yet, even knowing these trends, it is difficult to know what baseline to compare them against. Is the United States today polarized or pluralistic? One's answer likely depends on how one perceives the present sociopolitical moment. For those inclined to feel U.S. society and the political system is currently paralyzed by partisan conflict between polarized groups, the evidence presented here supports the hypothesis that attitudes have indeed shifted in a way likely to intensify such conflict. For others inclined to respond that Americans retain many cross-cutting and pluralistic attitudes, the evidence presented here may suggest that, although this pluralism is apparently on the decline, a number of cross-cutting dimensions remain.

History may not furnish us with enough examples to validate the harshest warnings one could offer based on these findings. Yet, neither would this history make us particularly optimistic. The starting point of analysis here follows the widespread conflict and violence of the late 1960s and early 1970s, often cited as the closest comparison to the current moment. The toll in human carnage of this previous era of polarization—assassinations, pitched street battles between police and protesters, and corruption driven by partisan malice—is well-documented (e.g., Perlstein 2008), and the fact that polarization proceeded apace from this starting point is suggestive of a potential for further deepening conflict. As recent scholarship highlights, the deep fissures

between polarized political and social identities can be seen as contributing factors to a politics steeped in racial resentment (Bonikowski 2017; McVeigh and Estep 2019; Sides, Tesler, and Vavreck 2017), cultural backlash (Hochschild 2016; Skocpol and Williamson 2012), and demagoguery encouraged by a lack of binding legitimate institutions (Hahl, Kim, and Zuckerman Sivan 2018).

Bail and colleagues (2018) even cast doubt on political pluralists' favored argument that more cross-cutting interactions would lead to greater mutual understanding and less polarization. The researchers randomly assigned a sample of Twitter users to follow a "bot" account that would share content from the opposing side of the political divide. Rather than decreasing polarization, they found that exposure to opposing viewpoints pushed people even further toward their own side. One might ask, however, whether this polarizing effect of outgroup exposure would materialize if the political and social identities associated with the two sides had not already become increasingly totalizing over recent decades, as Mason (2018) argues.

Perhaps interactions with members of the political outgroup would work as pluralists expect if the population featured enough cross-cutting cleavages, but these effects dissipate once those cross-cutting cleavages have collapsed to form more encompassing partisan identities with little common ground between them. Whereas overlapping identities generate common ground and the possibility of mutual understanding, the existence of polarized "super-identities" feeds affective polarization by leading people to simplify the outgroup (e.g., as an evil force unworthy of civil engagement) and attach negative stereotypes (Brewer and Pierce 2005). Theories from social psychology (e.g., Roccas and Brewer 2002) suggest such a collapse of previously cross-cutting identities will likely reduce outgroup tolerance and might thereby account for the increasingly harsh tenor of political disagreement perceived by scholars of affective polarization (Iyengar, Sood, and Lelkes 2012; Mason 2018).

At the same time, the present study qualifies previous work on identity-based polarization by suggesting that polarization has *also* occurred at the level of beliefs and issue positions, once we conceive more fully of the structure of polarization among beliefs. This is most clearly evident in the fact that some markers of belief consolidation persist in the over-time trends even after adjusting for partisan and ideological identity. This observation should complement ample existing evidence for polarization in social and political identity, which can be a *cause* of issue polarization (i.e., when people form opinions based on signals from their co-partisans) but also a *consequence* of issue polarization (i.e., when consistent identities are easier to form and maintain due to their being rooted in coherent sets of issue positions).

According to the political pluralism narrative, a high-dimensional public space in which agreement on some dimensions balances against disagreement on others is self-reinforcing as long as divisions remain cross-cutting and overlapping rather than absolute and all-encompassing. From this perspective, the analysis presented here carries troubling implications because it suggests the number and plurality of cross-cutting alignments in U.S. public opinion has declined. Such collapses in pluralistic structure lead to disagreements becoming increasingly all-encompassing because there are fewer mitigating domains in which two opponents may find agreement. Conceived in terms of structures of attitudes, the trend toward an increasingly polarized and consolidated opinion space—and thus one that amplifies rather than tamping down conflict—may be clearer and less elusive than previous studies would suggest.

APPENDIX: STATISTICAL MODEL

In the multilevel framework, year-specific bivariate correlations between any given pair of items x and y are treated as observations nested within item-pairs indexed by j . For

instance, the pairing of *premarsex*, a question eliciting respondents' views on the morality of premarital sex, and *gunlaw*, which asks whether respondents would favor a law requiring a police permit before buying a gun, would constitute a pair indexed by j . Then, the 23 (in this case) measured correlations between responses to these two items between 1972 and 2016 would represent observations nested within the pairing. The resulting mixed-effects model across all such pairs j takes the form

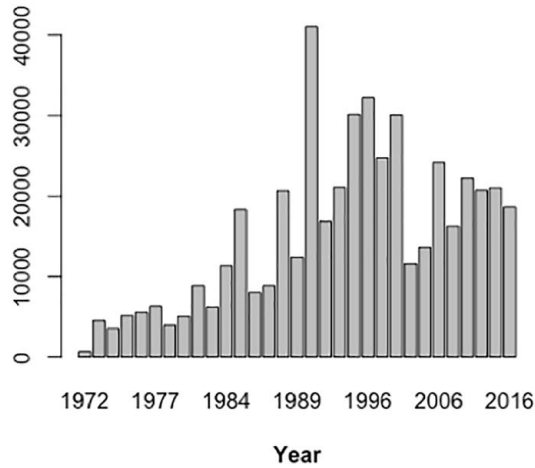
$$|r|_{j,t} = \alpha_j + \beta_j t + s_{j,t} \quad (1)$$

where $|r|_{j,t}$ is the magnitude of the observed correlation between items in pairing j in year t ; α_j is an intercept that varies by pair j ; β_j is a time trend that also varies by pair j ; and $s_{j,t}$ captures residual variation across different years within the same pair of items.

The purpose of this model is to produce year-specific estimates of the correlations between items while adjusting for the fact that pairs of items appear in different years and with varying frequency (Baldassarri and Gelman 2008; DellaPosta et al. 2015). The main strength of the mixed-effects strategy is that it allows for estimation of separate intercepts and time trends for each pair of items, avoiding the assumption of homogeneity in the tendency for any two items in a pair to become more or less aligned over time. The assumption of linearity in the trend toward increasing or decreasing alignment for any given pair of items remains somewhat restrictive. However, estimation of the linear trend is still sufficient for the purpose of assessing long-term trends in the structure of the correlations.

Table A1 gives the results of the mixed-effects model when all zero-order correlations between beliefs are included as well as when the model uses partial correlations to adjust for the influence of political ideology and party identification on each bivariate association. In both cases, the typical pair of beliefs would have seen only very modest changes over time. In the baseline condition,

A. Initial Distribution of Correlations



B. Final Distribution of Correlations

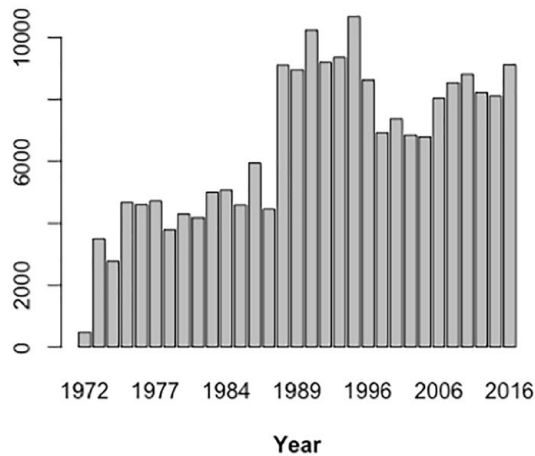


Figure A1. Yearly Numbers of Observed Correlations Before and After Sample Restriction
Note: Each bar chart shows the number of correlations observed for each year of the GSS. Panel A shows all observed correlations; Panel B shows correlations retained for analysis after dropping those for items that co-appeared fewer than five times.

the typical correlation increased in magnitude by less than .01 with each decade, meaning a typical pair of items would become slightly more strongly correlated between 1972 and 2016. For the ideology-controlled condition, the sign of the time coefficient is

reversed but the coefficient remains substantively small in magnitude. In both cases, the variance across pairs of items for this time trend far outweighs the magnitude of the average or typical time trend across all such pairs.

Table A1. Multilevel Mixed-Effects Model Predicting Magnitude of Correlations between Beliefs

	Zero-Order Correlations		Partial Correlations	
	<i>b</i>	s.e.	<i>b</i>	s.e.
Fixed-Effects				
Intercept	.09	<.01***	.08	<.01***
Time (decades)	<.01	<.01***	>-.01	<.01***
Residual SD				
Intercepts	.08		.08	
Time trends	.01		.01	
Within-pairs	.03		.03	

Note: $N = 202,928$ unique correlations nested within 14,910 unique pairs of items for the model using all zero-order bivariate correlations; $N = 191,890$ unique correlations nested within 14,476 unique pairs for the partial-correlation model that excludes and controls for political ideology and party identification. Estimated coefficients and standard errors are shown for fixed effects, and residual standard deviations are shown for random effects. Time is grand-mean centered.

*** $p < .001$ (two-tailed tests).

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Notes

1. This is true, at least, of the population in aggregate. However, there is evidence that polarization of attitudes *has* increased among some groups, such as strong partisans and socioeconomic elites (Baldassarri and Gelman 2008; Evans 2003).
2. Dimensional methods have also been influential in studies of congressional polarization, most notably with the widespread use of the DW-Nominate scores of political ideology used by Poole and Rosenthal (1984).
3. Boutyline (2017) argues for a similar approach (called correlational class analysis [CCA]) to the same problem of inductively uncovering groups organizing their beliefs in similar ways (see also Daenekindt, de Koster, and van der Waal 2017), finding that this approach out-performs RCA across a wide range of starting assumptions. Neither RCA nor CCA is used in the present study, however.
4. More specifically, the main difference is that belief networks represent correlations between beliefs in a population aggregate, rather than directly clustering individual survey respondents as RCA and related methods do. To maintain a constant set of beliefs in the network, person-clustering approaches like RCA would seem to require modeling and imputing missing “cells” in the respondent-belief matrix separately for each individual survey respondent every time a particular survey item did not appear for a given cross-section of the survey. Because the assumptions required for such an exercise would be difficult to justify, one would likely have to restrict analysis to the small and selective set of belief items that appear in every cross-section of the survey.
5. Notably, however, it is not clear that the U.S. population features much of this heterogeneity. Boutyline and Vaisey (2017) examined 44 subpopulations and found remarkable consistency in belief-network structure across these groups; some groups exhibited greater or less amounts of overall organization and cohesion in their belief networks, but the beliefs that held relatively central or peripheral positions in the networks were virtually the same.
6. The “oil spill” model is in some ways anticipated by Converse’s (1964) original formulation of constraint, although it departs from the measurement of constraint offered by him and subsequent scholars. Converse (1964:208) points out that “belief systems

- may . . . be compared in a rough way with respect to the *range* of objects that are referents for the ideas and attitudes in the system.” An increase in the range of beliefs that come to be incorporated in a structure of opinion alignment might be usefully thought of as the breadth of constraint or alignment.
7. The two examples in Figure 2 do not exhaust the possibilities for how belief networks may be arranged. As mentioned previously, a belief network could lack a modular structure, meaning attempts to partition the network into modules would produce results that do not much describe the actual arrangement of cross-issue alignments. Such a “non-modular” structure may be cross-cutting at the level of individual issues, rather than the example in Panel A of Figure 2 where links between beliefs cut across modules. Furthermore, a belief network could be organized around a single *belief* rather than a *module* containing multiple beliefs. For example, Boutyline and Vaisey (2017) found political ideology played a key centralizing role among the smaller set of issues they analyzed. Yet, the centralizing role of any single belief in the network is notably distinct from what I call consolidation; a more consolidated belief network does not necessarily become more centralized in graph-theoretic terms (see Freeman 1978:227ff), because the more beliefs getting pulled into large central modules can offset the ability of any one or a few central beliefs to dominate connectivity in the network.
 8. In fact, the simplest way to illustrate such a tendency empirically would be to generate a consolidated network such as the one in Panel B and then randomly “rewire” all or most edges in that network (Maslov and Sneppen 2002). The result is a structure with the same average strength of correlation but in which the network does not divide into modular groupings. As the patterning of ties comes closer to a pattern of “random association,” the belief network will increasingly lack any coherent structure linking the beliefs as a whole. Formally speaking, modularity is measured by comparing the extent of within-module ties in an observed network to the extent of within-module ties that would be expected in a randomly permuted version of the same network, one that features the same nodes and degree distribution but in which the arrangement of ties or edges is random (Newman 2006).
 9. In a limiting case, consolidation could also increase due to the emergence of a consensual “monoculture” in which everyone agrees with everyone else (Arendt 1968). In the U.S. context, this may seem to be a relatively remote possibility. In robustness checks, I found that relatively few beliefs in the GSS became more consensual over time, and these beliefs did not account for the time trends reported here. These analyses are available upon request from the author.
 10. I am not aware of existing survey data sources that could overcome this limitation. Recently, however, Salganik and Levy (2015) proposed a new set of survey techniques, which they term “Wiki Surveys,” that would allow for a greater balance between researcher-generated and respondent-generated content in survey construction. If such an approach were scaled to the level of repeated and nationally representative surveys of attitudes, this might allow us to more fully overcome the limitations imposed by researcher selectivity in survey construction.
 11. I only included correlations based on more than 100 responses, however, to ensure sufficient precision in the observations used for subsequent analysis.
 12. Appendix Figure A1 shows the number of observed correlations from each edition of the GSS before and after this sample restriction process. One consequence of dropping pairs of items that seldom appear together is that the resulting analytic sample retains a relatively more even number of correlations from year to year than it would otherwise.
 13. Similarly, because the focus will be on changes over a long time in the structure of relationships among a fixed set of GSS items, I did not engage in any procedure to combine substantively linked items into common scales or dimensions. Even if, for example, two different questions about abortion were so strongly correlated as to suggest they belong to one underlying scale, we might *still* be interested in whether the correlation between the two items grew stronger or weaker over time. As with the decision to include any GSS item that could be considered an opinion, belief, or attitude, the goal is to analyze the data in a way that loses as little information as possible, allowing patterns in the data to emerge naturally with few externally-imposed constraints from the researcher.
 14. Replication data and code for all analyses are available on the author’s “dataverse” at <https://dataverse.harvard.edu/dataverse/dellaposta>.
 15. Figure 4 and all other network visualizations in this article were generated using the Fruchterman-Reingold spring-embedding algorithm (Fruchterman and Reingold 1991).
 16. Formally, the index is computed as $C = 1/(2\sum iP_i) - 1$ where i indicates the size rank of a given belief module, and P_i is the proportion of nodes belonging to the module with rank i .

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