Ideological Segregation:
Partisanship, Heterogeneity, and Polarization
in the United States
by
David B. Sparks
Department of Political Science
Duke University

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John H. Aldrich, Supervisor

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David W. Rohde

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Michael D. Ward

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James A. Stimson

Dissertation submitted in partial fulfillment of the requirements for the degree of
Doctor of Philosophy in the Department of Political Science
in the Graduate School of Duke University
2012
ABSTRACT

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Abstract

I develop and justify a measure of polarization based on pairwise differences between and within groups, which improves on previous approaches in its ability to account for multiple dimensions and an arbitrary number of partitions. I apply this measure to a roll-call based ideological mapping of U.S. legislators to show that while the contemporary Congress is polarized relative to mid-century levels, the current state is not historically unprecedented.

I then estimate the ideology of public opinion using survey respondent thermometer evaluations of political elites and population subgroups. I find that party affiliation is polarizing in this space, but that alternate partitions of the electorate, along racial, educational, and other socio-demographic lines, are de-polarized.

Finally, I estimate a two-dimensional latent space based on social identity trait co-occurrence. I show that positions in this space are predictive of survey respondent ideology, partisanship, and voting behavior. Further, I show that when conceived in this way, we do observe a polarization of the social space over the last half-century of American politics.
To Summar.
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List of Abbreviations and Symbols

Abbreviations

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<th>Description</th>
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<tr>
<td>ANES</td>
<td>American National Election Studies</td>
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<tr>
<td>LOR</td>
<td>Logged odds ratio matrix</td>
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<td>MCA</td>
<td>Multiple correspondence Analysis</td>
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<td>Principal component analysis</td>
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<td>PID</td>
<td>Party identification</td>
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<td>SSIP</td>
<td>Spatial Segregation Index of Polarization</td>
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I am very much the product of my intellectual environment, and this dissertation reflects that. Fortunately, during my time at Duke I have had the opportunity to learn from some of the best political scientists in the country. I owe many thanks, in particular, to the members of my dissertation committee: John Aldrich, Scott de Marchi, Dave Rohde, Mike Ward, and Jim Stimson, each of whom challenged me, and lead me down the path toward discovering the political science which most interested me. I would also like to thank the late George Rabinowitz, who kindly served on my committee until his unfortunate and too-soon passing. His work was an obvious inspiration for much of what I do here.

John Aldrich is deserving of particularly great thanks, not only for supervising this dissertation, but for mentoring me throughout my time at Duke, leading me directly to most of the interesting ideas I’ve ever worked on, and for his kind encouragement.

Part of my gratitude due to Dr. Rohde is for his Political Institutions and Public Choice program, in which I was fortunate enough to be a participant. In PIPC, I worked alongside more senior students, including Mike Brady, Brendan Nyhan, and Jacob Montgomery, who set a high standard of excellent work, even as they patiently offered useful advice and answers to my myriad questions.

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Finally, my greatest debt is to my wife Summar, who has sustained me throughout this process, as she does in all of our adventures.
1 Ideological Segregation

1.1 The importance of polarization

The latter part of the twentieth century witnessed a significant and consistent shift among U.S. political elites toward consolidation into two distinct and opposed camps. Nowhere is this change more evident than in the Congress, where party unity scores ubiquitously approach their maximum, and Mayhew’s (1974) original list of three basic congressional activities has been amended to include “partisan taunting” (Grimmer and King, 2011).

Rohde (1991) notes that this polarization is not a new phenomenon, but a return to a historical norm, dampened temporarily in the middle of the previous century by virtue of a consistent, yet fractious Democratic majority. Rules reforms in the 1970s, along with a shift in the electoral base of both parties, have lead elected representatives to behave in ways that are increasingly similar within their own party, just as they become more distinct from those with opposing affiliations.

Under conditions such as these, with high levels of intraparty homogeneity and interparty heterogeneity, Rohde suggests that we observe Conditional Party Govern-
ment (CPG), under which members of the majority are sufficiently unified to cede power to party leaders, in order to further a mutually-approved agenda. Policy produced in such settings will tend to reflect more the median of the majority party, rather than that of the chamber as a whole, and observed or measured behavior will tend to appear increasingly bi-modal/-polar and partisan.

Aldrich and Rohde (1998, pg. 5) offer a specific understanding of the particular conditions of CPG: “It is increasingly well satisfied the more homogeneous the preferences of Members are within each party (especially the majority party), and the more different the preferences are between the two parties’ Members. The more one party agrees that it wants outcomes that are different from those desired by the opposition, the more the condition is satisfied.” If these conditions are met, several consequences are entailed for the organization of party leadership and the nature of policy being produced.

Given the potential consequences of polarization, both in terms of its implications for legislative behavior and as a divisive force in politics more generally, I am interested in measuring the degree to which the conditions of polarization are satisfied – that is, how polarized the parties are. Esteban and Ray (1994) use a definition of polarization which is identical to that used by Aldrich and Rohde in describing the conditions for CPG, and it is this definition on which I base the measure below.

In short, polarization is an important concept, both as a cause and effect of institutions and political behavior. In this paper, I discuss methods of measuring polarization, focusing on these phenomena as they occur in legislative institutions. I first review two distinct approaches to the problem – one which assesses several different metrics based on reduced-dimensionality representations of the ideological space, and another which applies the social network concept of modularity to partitions of roll-call similarity networks. I then offer an extension to the modularity-based measure, allowing for the estimation of confidence intervals. Upon reviewing the
existing measures, I suggest a novel approach, adapted from the literature on residential segregation, which is flexible enough to apply to multiple dimensions and multiple parties. I apply this measure to the history of U.S. Congressional ideology, as well as the third legislative session of the French Fourth Republic. Finally, I briefly describe a series of Monte Carlo simulations that test the construct validity of this new approach.

1.1.1 Measuring Polarization

Given the importance of polarization, it is no surprise that several approaches have been suggested to measure the concept. The most straightforward approach is to, for a given unidimensional measure of spatial location $\mathbf{v}$ and a partition or grouping of observations $\mathbf{c}$, estimate a measure of central tendency for each group, and report the difference between groups. This is the approach typically taken by Keith Poole, Howard Rosenthal, and others who work with NOMINATE scores (see, e.g. McCarty, Poole and Rosenthal (2006)), but it works only in the two party case, and fails to account for intra-party variance.\(^1\)

Aldrich and Rohde (1998) and Aldrich, Berger and Rohde (2002) handle the problem of operationalization through a multi-measure approach. Since polarization is itself a multifaceted concept, they propose a suite of four measures, each of which encapsulates to a greater or lesser extent inter-party heterogeneity, intra-party cohesion, and the degree to which party labels predict ideological placement. They combine these highly-correlated aspects into a single factor score measure of polarization, and find a distinct post-Depression-era drop in polarization that lasts until

\(^1\) It should be noted that in this article, I take all input measurements as given. That is, to the extent that NOMINATE is a flawed measure of ideology, or the nature of roll-call voting has changed over time, any measure of polarization based on such data may be similarly flawed. However, the single-index method introduced later in this discussion to measure polarization is sufficiently general to apply to any means of measuring ideology, and can be based on any type of data – the sole requirement is that the data must be amenable to the calculation of a distance matrix.
the 1980s.

Aldrich, Rohde and Tofias (2004) extend this multi-measure framework to more than one dimension, expanding each of the four metrics to use medians in the two reported NOMINATE\textsuperscript{2} dimensions, defining measures of heterogeneity, homogeneity, overlap/separation, and party label fitness in multiple dimensions. Their findings suggest that to disregard the second ideological dimension returned by NOMINATE scaling under-emphasizes the sharpness and degree of the drop in polarization, and the inclusion of the second dimension locates the nadir of polarization later in the time series, placing it in the very late 1970s. Figure 1.1 reproduces the multidimensional four-factor measures of polarization for all of congressional history.

Among other interesting phenomena, we can note the relative consistency of high values across all four measures in the postbellum two-party era, although we can note a dip in the mid-twentieth century. The “Era of Good Feelings” is marked, unsurprisingly, by an absence of polarization, just as the turn of the twentieth and twenty-first centuries are characterized by high levels. While an improvement, these measures still apply only to a two-party system, meaning that for eras and contexts in which we might observe more than two groupings of observations, another approach is required.

Rehm and Reilly (2010) suggest a modification to the distance metric typically used to measure polarization, which incorporates internal homogeneity by discounting the distance between parties with a function of the range covered by members of each party. They incorporate their modified distance measure into the unidimensional estimation framework proposed by Esteban and Ray (1994), and find that the two major parties in the U.S. have polarized over the last thirty years, in contrast with the major parties of several other OECD countries, which do not evince such

\textsuperscript{2} See McCarty, Poole and Rosenthal (2006) for an explanation of the NOMINATE estimation procedure.
a trend. While this modified distance measure does well to explicitly accommodate homogeneity, it is only applied to the two-party, unidimensional case.

1.2 Modularity

An alternative approach to the measurement of polarization, network modularity, is suggested by Waugh et al. (2009), and applied to cosponsorship data by Zhang et al. (2008).

This technique begins with an $n \times m$ roll-call matrix, and transforms it to a $n \times n$ “agreement matrix” between each pair of legislators, the elements of which are defined as:
\[ A_{ij} = \frac{1}{b_{ij}} \sum_k \alpha_{ijk} \] (1.1)

Where \( \alpha_{ijk} \) equals 1 if legislators \( i \) and \( j \) voted similarly on bill \( k \) (otherwise, 0), and \( b_{ij} \) is the total number of bills on which both legislators cast a vote. Thus, each element of the matrix represent the proportion of votes on which each pair of legislators agree.

Given this agreement matrix, and a partition \( \mathbf{c} \) of legislators into groups, we can calculate the modularity of the network as follows (per Newman and Girvan (2004)):

\[ Q = \frac{1}{2m} \sum_{ij} \left[ A_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j) \] (1.2)

Here, \( m = \frac{1}{2} \sum_k k_i \) is the sum of the value of all ties in the network, \( k_i = \sum_j A_{ij} \) is the strength of the \( i^{th} \) node, \( c_i \) is the group to which \( i \) belongs, and \( \delta(c_i, c_j) \) is the Kronecker delta function (see Equation 1.6). Modularity ranges from \(-1\) to \(1\), and positive values indicate that the network has stronger intra-group ties than we would expect to observe by chance. In the present case, positive values indicate that co-partisans tend to agree with each other more than randomly drawn pairs of legislators.

Waugh et al. (2009) then apply this measure to roll-call agreement matrices across U.S. legislative history, using both party-based communities and (nearly) optimal modularity-maximizing partitions. The modularity approach has the advantage of permitting arbitrary numbers of parties/groups/communities/partitions. However, there are at least two disadvantages to the use of this technique. First, their work lacks any provision for the estimation of standard errors for the statistic. Second, this approach treats all roll-call votes as equal, when in actuality much of the information encoded in each distinct vote is redundant, and the relationship between legislators
can more efficiently and accurately be represented in a latent space.

In the following sections, I offer solutions to each of these problems.

1.2.1 Inferences about modularity

The first problem is that if we accept modularity as a valid measure of polarization, we are still left with only a point estimate, meaning that we cannot make statistically valid comparisons of modularity levels across multiple networks or partitions thereof.

The simplest means by which we can estimate standard errors is through resampling. The estimator for modularity is based on a static and fixed adjacency matrix and partitioning of the nodes. If we wish to find the variance of the estimator for a given partition, we need to know the uncertainty characterizing the initial adjacency matrix.

The agreement matrix employed by Waugh et al. (2009) consists of elements as defined by Equation 1.1, meaning that they are empirically-derived and asserted as true point estimates, leaving us with no sense of uncertainty about the strength of each tie.

However, the elements of the agreement matrix are, by definition, probabilities. Thus, for a given agreement matrix, we can sample a Bernoulli trial for each element, and generate a “Bernoulli matrix” consisting of only 1s and 0s.

For two legislators $i$ and $j$ with an agreement score $A_{ij} > 1/2$, we will expect our Bernoulli trials to result in “successes” more often than not. If this sampling process is done repeatedly, the mean value of a given element across all sampled matrices will approach the initial agreement probability from which we are sampling.

The reason to create such a succession of random binary matrices is to generate variance from the initial configuration, and estimate the network modularity of each of the Bernoulli matrices. In the limit, the mean modularity value of these matrices will approach that of the initial agreement matrix, but the distribution of
modularity values generated from the matrix resampling process allows us to construct standard errors for and confidence intervals around the point estimate of our modularity statistic.

Figure 1.2: Time series of modularity of the co-voting network. Points depict median estimate from 1000 resampled networks derived from probabilistic co-voting ties, vertical range lines depict upper- and lower- 95% confidence intervals.

From agreement matrices generated for each term of the House and Senate, I resample 1000 adjacency networks and estimate their modularity as partitioned by party label. The median of each sample modularity, as well as the upper- and lower-95% intervals of the estimates, are shown in Figure 1.2.

As can be seen in the figure, confidence intervals are consistently very narrow in

---

3 Waugh et al. (2009) focus primarily on modularity-maximizing partitions, which may or may not align with party divisions, but for the present purposes, I am more interested in the polarization between parties, rather than arbitrary subsets of legislators.
the House and in recent terms of the Senate. However, they allow us to make conclusions that point estimates alone do not support. For example, with the exception of the 107th term, polarization in the Senate has been relatively constant since the 103rd term. Also, in only one case, the 17th Senate, which served 1821-22, do we fail to reject the null hypothesis that $Q = 0$ with 95% confidence.

1.3 Indices of segregation

The literature on ethnic residential segregation, completely distinct from that on network modularity, also focuses on measuring differences in the partitioning of groups. Early work focused on so-called indices of dissimilarity, which essentially measure the proportion of the minority (or majority) population (of a city or other geographic entity) which would have to be redistributed so that each parcel (or subdivision of the city or geographic entity of interest) would have exactly the same composition as the city as a whole.

Early work (Duncan and Duncan, 1955) noted that many of the attempts to measure this concept were really specific cases of a more general segregation curve (analogous to the Lorenz Curve), which is based on the proportion of nonwhites in all geographic subunits for an area. Subsequent advances have been made in identifying a more appropriate baseline level of segregation (Winship, 1977), and extending the measure to account for space and distance, using the centroid of the smallest geographic unit for which demographic information is available (White, 1983).

Massey, White and Phua (1996) and Reardon and O’Sullivan (2004) survey the menagerie of segregation and spatial segregation measures, identifying five dimensions of segregation (evenness, exposure, concentration, centralization, and clustering) and listing eight criteria on which such measures should be evaluated. Other research (including Wong (2005) and Brown and Chung (2006)) emphasizes the importance of different patterns in spatial location, but even these are typically con-
strained to application to the two-group (white/non-white) case.

If the large set of segregation measures based on composition of discrete geographic subunits can be analogized to the modularity-based measure of polarization described above, what follows is the introduction of a measurement of ideological polarization that explicitly accounts for spatial location. Where explicit spatial location data is available, the extra information it affords should be incorporated into our estimates of segregation/dissimilarity/polarization.

1.3.1 Ideological segregation

Polarization is fundamentally a concept that contrasts intra-party homogeneity with inter-party heterogeneity. For the purposes of operationalization, this means measuring and comparing two distinct variables simultaneously, as the multi-factor approach of Aldrich et al. suggests. However, it is desirable to employ a single-index metric that encodes information about both within-party and cross-party variance. Extending measures suggested by the spatial segregation literature, I now propose just such an index, to which I will refer as the Spatial Segregation Index of Polarization (SSIP).

Given some set of entities located in an arbitrary space, as well as a partitioning of these entities into groups, this polarization index expresses the difference between the mean distance between pairs of individuals in the same group and the mean distance between pairs of individuals in different groups.

Thus, ceteris paribus, as intra-party homogeneity increases, distance between pairs of individuals from the same group decreases, and the SSIP index increases. Also, as inter-party heterogeneity increases, distances between pairs of individuals from different groups increases, and the SSIP index increases. This index can be formally computed as follows:
Within

$$
\| \text{within} \| = \frac{\sum_{i,j,i \neq j} \left[ \text{dist}(i,j) \right] \delta(c_i, c_j)}{\sum_{i,j,i \neq j} \delta(c_i, c_j)}
$$

(1.3)

\[ \text{between} \]

$$
\| \text{between} \| = \frac{\sum_{i,j,i \neq j} \left[ \text{dist}(i,j) \right] (1 - \delta(c_i, c_j))}{\sum_{i,j,i \neq j} (1 - \delta(c_i, c_j))}
$$

(1.4)

\[ \text{SSIP}(\text{dist}, c) = \frac{\| \text{between} \|}{\| \text{within} \|} \]

(1.5)

Where \( \text{dist} \) is an \( n \times n \) distance matrix representing the dissimilarity or distance between all pairs of objects in the set, \( c \) is a vector indicating the categories to which each object belongs, and \( \delta(c_i, c_j) \) is the Kronecker delta symbol:

$$
\delta_{ij} = \begin{cases} 
1 & \text{when } i = j, \\
0 & \text{when } i \neq j.
\end{cases}
$$

(1.6)

The standard error of this measure can be approximated (per Fieller, 1954) by calculating the standard errors of between- and within-category distances, and then combining them as follows:

$$
SE_{\text{SSIP}} = \frac{\| \text{between} \|}{\| \text{within} \|} \times \sqrt{\left( \frac{\| \text{between} \|}{SE_b} \right)^2 + \left( \frac{\| \text{within} \|}{SE_w} \right)^2} 
$$

(1.7)

For ease of interpretation, it is useful to take the log of this index, and refer to the \( \log_{10}\text{SSIP} \), which I will do throughout the remainder of this discussion, wherever I refer to the SSIP. Since the index is calculated as a ratio, to ensure scale comparability across applications, it can range from 0 to \( \infty \). Such a range is not easily
understood or compared, so expressing the SSIP in its logged form permits a more
direct interpretation: any value greater than 0 implies polarization, while any value
less than 0 implies that the mean distance between cross-group pairs is less than the
mean within-group distance. A one-unit change in the logged SSIP implies a tenfold
change in the original ratio, but for most applications, including all those discussed
in this study, the (logged) SSIP will fall within the interval \((-1,1)\).

The advantages of this SSIP index are several. First, it is applicable to any
number of dimensions, as it reduces any space to vectors of within- and between-
group distances. Second, it differentiates among configurations with varying levels
of intra-party homogeneity, as illustrated in Figure 1.3. The figure depicts four
possible spaces, each with two parties (filled versus unfilled circles) of two members
in two dimensions. The typical measurement approach offered by McCarty, Poole
and Rosenthal (2006), as well as three of the four factors defined by Aldrich, Rohde
and Tofias (2004) would not differentiate between all four arrays.\(^4\) The SSIP index
correctly ranks the four scenarios in order of polarization, taking into account the
relative magnitude of within- and between-party variance. That is, from left to right
in Figure 1.3, points grouped as co-partisans become increasingly proximate relative
to the distance between the parties, and this change is captured by the index.

A third advantage of the SSIP index is that it applies to multi-party contexts.
Unlike the McCarty, Poole and Rosenthal (2006) and Aldrich et al. approaches,
which are applied only to the U.S. two-party case, the metric proposed here can
be used for any number of parties greater than one. It is desirable that a measure
of polarization be able to account for the existence of multiple major parties, as
certainly the concept of polarization can apply to more than two groups in relation
to one another.

\(^4\) The fourth factor, which they call “Intra-party Homogeneity,” applies only to the majority party,
and thus would still fail to distinguish between several of the spaces shown.
Figure 1.3: As intra-party homogeneity increases relative to inter-party heterogeneity (from left to right), the conditions for polarization are increasingly satisfied. The spatial segregation index improves on previous measures by accounting for within-party variance.

Figure 1.4 illustrates the application of this metric to various permutations of party groupings of six evenly-spaced entities. As the graphic shows, polarization is highest when party members are proximate to one another, and relatively distant from members of other parties, and lowest when members of different parties are thoroughly mixed.

An additional benefit of the SSIP approach to measuring polarization over the modularity-based scheme proposed by Waugh et al. (2009) is that it permits the proper weighting of redundant data through data-reduction techniques. In contrast to the co-voting network approach, which weighs all votes equally, the SSIP index can use any representation of the space, including the original roll-call matrix, or any reduced representation thereof.

In the 110th Senate, for example, we observe consecutive votes on the Dodd Amendment to H.R. 1424 (establishing the Troubled Asset Relief Fund) and on Final Passage of the bill. In both cases, the count was 74 to 25 in favor, with Senator Kennedy not voting, and all Senators maintaining the same position across
### Estimates of Spatial Segregation for Some Simple Spaces

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<table>
<thead>
<tr>
<th>-0.073</th>
<th>-0.091</th>
<th>-0.111</th>
<th>-0.114</th>
<th>-0.166</th>
</tr>
</thead>
<tbody>
<tr>
<td>A C</td>
<td>A C</td>
<td>A C</td>
<td>A B</td>
<td>A C</td>
</tr>
<tr>
<td>B B</td>
<td>B A</td>
<td>B B</td>
<td>B B</td>
<td>B A</td>
</tr>
<tr>
<td>A A</td>
<td>A B</td>
<td>A B</td>
<td>A B</td>
<td>C A</td>
</tr>
</tbody>
</table>

**Figure 1.4:** Examples of spatial segregation estimates of SSIP, with locations held constant, but varying group labels. The most polarized partitions (upper left) exhibit tight clusters of co-partisans, while the least polarized arrays (bottom right) are characterized by complete spatial integration.

For the purposes of calculating an agreement matrix, these two votes each carry full weight, despite the fact that the votes are redundant: given the information encoded in the first roll-call, adding the second gives us no additional information about the legislators’ preferences or spatial position, except that the issue merited a second vote.\(^5\)

Using a dimensionality-reduction technique such as principal component analysis or NOMINATE, only non-redundant information is retained. The latent spaces

\(^5\) see [http://www.senate.gov/legislative/LIS/roll_call_lists/vote_menu_110_2.htm](http://www.senate.gov/legislative/LIS/roll_call_lists/vote_menu_110_2.htm)

\(^6\) There may be value in the knowledge that the same preferences were elicited twice, or that the legislative agenda was occupied by two votes with identical status quo and proposal positions, but no new cutline is offered by the addition of the second vote.
identified by these techniques can be used in calculating SSIP, without bias from superfluous, highly correlated, dimensions.

1.4 Empirical application

Thus far, I have attempted to define and describe the advantages of a multidimensional, multigroup measure of polarization based on pairwise distances. To illustrate the use and interpretation of the SSIP, I now explore two very different legislative contexts for which roll-call voting data are available: the U.S. House and Senate, and the National Assembly of the French Fourth Republic.

1.4.1 United States Congress

Poole and Rosenthal (1997, 2007) describe the NOMINATE dimensionality-reduction technique for Congressional roll-call voting, and find that it typically requires “one-and-a-half” dimensions to explain the variance in historical roll-call patterns.

NOMINATE, like other such methods, generates a set of orthogonal vectors, or components, which correspond to latent dimensions estimated to account for as much of the variance in the original data as possible. In the case of the U.S. Congress (and, as it turns out, many other cases), the first dimension alone is sufficient to correctly predict around 80% of voting decisions, while a second dimension occasionally becomes important to discriminate among positions that have not yet been folded into the main axis of partisan conflict.

Aldrich et al. base their estimates of polarization on these NOMINATE estimates, as I do here, focusing only on the first two dimensions, as suggested by Poole and Rosenthal. Figure 1.5 plots these first two dimensions, as estimated for the 111th Senate. The two spatially distinct partisan clusters are easily identifiable, and separable by a linear cutline, indicating that the conditions for polarization are present in the data.
Figure 1.5: First two dimensions of the Poole-Rosenthal DW-NOMINATE space for the 111th Senate. Blue dots indicate members of the Democratic party, red triangles are Republicans, and the lone yellow square represents Independent Bernie Sanders of Vermont. The y-axis is compressed to reflect Poole’s suggested downweighting of the second dimension.

From this set of 105 individual legislator estimates, we can identify 2733 co-partisan and 2727 cross-partisan pairs, and find the distance between each pair. Figure 1.6 depicts the distributions of these distances, by pair type. Both distributions are approximately normal, although the within-party distances are obviously truncated at approximately zero. In this case, the mean distance between cross-partisan pairs is 0.783, and the average co-partisan distance is 0.250. The ratio of these two means is 3.13, which, logged, results in a spatial segregation estimate of 0.496.

Any single value of ssip is difficult to interpret without a basis for comparison, so Figure 1.7 shows the time series of ideological segregation in both chambers for
FIGURE 1.6: Empirical distribution of normalized distances between all pairs of Senators in dw-nominate space, separated into co-partisan and cross-partisan pairs. The mean co-partisan distance is 0.250 (with a standard deviation of 0.144) and the mean cross-partisan distance is 0.783 (0.188), resulting in a SSIP value of 0.496.

In general, we observe similar patterns to those uncovered by the Aldrich et al. and Waugh et al. (2009) approaches: high levels of polarization in the years around the turn of the twentieth century, followed by a trough and subsequent return to high levels in the modern era. In fact, they correlate fairly well, but not perfectly, as shown in Table 1.1 – suggesting that they are measuring related but not identical concepts.

Table 1.1: Correlations between time series of polarization in the U.S. Congress, as measured with three different approaches. Values in the upper triangle are for the Senate, lower triangle for the House.

<table>
<thead>
<tr>
<th></th>
<th>Factor</th>
<th>Modularity</th>
<th>Segregation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Factor (Aldrich)</td>
<td>1.00</td>
<td>0.51</td>
<td>0.84</td>
</tr>
<tr>
<td>Modularity (Waugh)</td>
<td>0.41</td>
<td>1.00</td>
<td>0.61</td>
</tr>
<tr>
<td>Segregation (Sparks)</td>
<td>0.81</td>
<td>0.51</td>
<td>1.00</td>
</tr>
</tbody>
</table>

There are some important differences in the view afforded here, as compared.

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7 I also illustrate the single-term case of the 34th House in Appendix A, as an example of a U.S. legislature with a large third-party presence.
Figure 1.7: Time series of partisan spatial segregation, with indicators of the 95% confidence intervals for the estimate.

to the modularity-based approach. First, the modularity measure shown in Figure 1.2 identifies several polarization low-points – around the early 1800s, before and after the Civil War, and the mid-late 1900s – all of which are evaluated at approximately 0.05. In contrast, the spatial segregation approach distinguishes from the local minimum of the mid-1900s, and the much less polarized Era of Good Feelings. Subjectively, the differentiation in the latter measure better fits our conception of levels of partisanship in the two time periods.

Additionally, the SSIP measure exhibits much higher levels of autocorrelation, as compared to the modularity measure, which varies widely between consecutive sessions. This suggests that the method of spatial segregation, based on a latent space, rather than directly on roll-calls themselves, is less sensitive to idiosyncrasies
of the congressional agenda, and is a more valid measure of the underlying concept of polarization.

1.4.2 French National Assembly

To illustrate the use of this measure of polarization in a multi-party context, I use roll-call voting data from the French Fourth Republic (1956-1958), collected and made available by Rosenthal and Voeten (2004). In this case, rather than estimate two W-NOMINATE dimensions, I use principal component analysis (PCA) to identify the latent space derived from the roll-call matrix.\(^8\)

Given that this matrix consists of 1196 legislators’ votes on 163 roll-calls, PCA will calculate 163 components, giving us a space of more than two dimensions on which to apply our measure of spatial segregation. Here, though, the first two dimensions account for 68.6% of the variance in the data, meaning that additional dimensions weigh relatively little in the calculation of distances between legislators. Nevertheless, this example shows the utility of the spatial segregation approach to reduce ostensibly complex spaces to a simple comparison of pairwise distances.

The first two dimensions estimated from the PCA are shown in Figure 1.8. As the plot shows, there is a high degree of discipline within several of the major parties, most notably among Christian Democrats, Communists, and Socialists. Even the other four major parties can be said to exhibit a relatively high degree of cohesion. Further, there is clear separation among the parties on the second dimension along the pro- and anti-regime continuum, and an even more stark differentiation that isolates Communists on the Left. As a result of these observably high levels of internal homogeneity and external heterogeneity, the spatial segregation statistic for

---

\(^8\) It is certainly possible to estimate NOMINATE scores for this data, as in fact Rosenthal and Voeten (2004) do. I use PCA here to illustrate the fact that SSIP can be assessed on any given space, in any number of dimensions. PCA is simply one of many methods which make it straightforward to estimate a high-dimensional space.
Principal Component Analysis of the 3rd Legislature of the French Fourth Republic

First Component

Second Component

Figure 1.8: First two principal components representing the latent space of roll-call voting in the Third Legislature of the French Fourth Republic, 1956-1958. The first component corresponds to a Left-Right dimension, while the second component is related to pro- or anti-regime stance.

this space is 0.380 (se = 0.004), which would fall in the middle of the distribution of the levels observed in the historical U.S. Congress.

1.5 Monte Carlo testing

As an additional test of the comparative usefulness of the measures described above to accurately capture the concept of polarization, I employ a series of Monte Carlo simulation tests.

Using simulation code developed by Aldrich, Montgomery and Sparks (2011), I generate policy ideal points for 100 “Senators” in two-dimensional space with a random multivariate normal distribution. These legislators then cast 800 votes, comparing randomly drawn proposal and status quo points, to generate roll-call matrices.
For each simulated legislature, I measure partisan polarization using each of the six measures described above: the four factors proposed by Aldrich, et al., modularity, and the spatial segregation approach outlined here.

To assess the construct validity of these measures, I run a parameter sweep in which I vary the distance between party-based modes, as well as the variance, of the multivariate normal distribution from which legislator ideal points are drawn. I generate ten legislatures at each combination of party separation and intraparty variance, where parameter values vary by increments of $\frac{1}{2}$ between zero and ten, for a total of 4,410 simulations.

As Figure 1.9 shows, the spatial segregation approach best reflects the concept of polarization. The measures of Heterogeneity and Homogeneity are one-dimensional, and thus do not reflect the dual facets of polarization. The measures of party overlap/separation and party label fit offer an improvement, but do not discriminate well in the higher ranges of polarization, where variance is low relative to the distance between party means. Modularity, estimated from roll-call votes which are themselves an imperfect reflection of legislator ideal points, measures polarization with a high degree of error. Only the spatial segregation approach consistently and accurately reflects the joint effect of interparty heterogeneity and intraparty homogeneity.

Table 1.2 summarizes the fit of each measure to the two dimensions of polarization. Using known input levels of party separation and variance, as well as the interaction of the two, I predict polarization as measured in each of six ways. The graphical results of Figure 1.9 are supported by this evidence, which suggests that the spatial segregation measure is the approach best explained by the simulation parameters.
Monte Carlo Results for Measures of Polarization

Interparty Heterogeneity
Intraparty Homogeneity

Figure 1.9: At each combination of “true” input values of interparty heterogeneity and intraparty homogeneity, I take the average measured polarization from ten unique simulations, using each of the six metrics described above. Normalized values of these mean measures are plotted, and magnitude is indicated by color. In general, the concept of polarization should be measured as increasing from top-to-bottom and left-to-right. Here, the spatial segregation approach is shown to most closely hew to our understanding of the concept of polarization.

1.6 Summary and conclusion

As the foregoing discussion has illustrated, polarization is an important, yet difficult, concept to measure. Along with the related concept of polarization, several approaches have been proposed in the literature to assign a numeric estimate to the degree of polarization evident in observed patterns of behavior.

Previous attempts evince several shortcomings, but a measure grounded in the concept of spatial segregation, here called the SSIP index, simultaneously captures both intra-party homogeneity and inter-party heterogeneity. I have offered several
Table 1.2: Mean, standard error, and upper- and lower- 95% confidence intervals of $R^2$ values from 1,000 bootstrapped regressions predicting each of six measures of polarization with known simulation parameters. These results indicate that nearly 90% of the variance in the spatial segregation measure is explained by the distinction between ideal points across parties and the cohesion of ideal points within parties.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Mean</th>
<th>SE</th>
<th>Lower</th>
<th>Upper</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heterogeneity</td>
<td>0.857</td>
<td>0.002</td>
<td>0.853</td>
<td>0.861</td>
</tr>
<tr>
<td>Homogeneity</td>
<td>0.858</td>
<td>0.002</td>
<td>0.854</td>
<td>0.862</td>
</tr>
<tr>
<td>Separation</td>
<td>0.775</td>
<td>0.002</td>
<td>0.771</td>
<td>0.780</td>
</tr>
<tr>
<td>Fit</td>
<td>0.850</td>
<td>0.002</td>
<td>0.846</td>
<td>0.853</td>
</tr>
<tr>
<td>Modularity</td>
<td>0.079</td>
<td>0.004</td>
<td>0.071</td>
<td>0.087</td>
</tr>
<tr>
<td>Segregation</td>
<td>0.892</td>
<td>0.002</td>
<td>0.888</td>
<td>0.896</td>
</tr>
</tbody>
</table>

abstract examples of the flexibility and validity of this approach, application to two very different historical cases, and Monte Carlo evidence in support of construct validity. Some of the differences between the measure presented here and previous attempts to assess the concept of polarization can be seen by direct comparison of the time series of polarization in the U.S. House and Senate, as shown in Figure 1.10.

Each of the six panels presents a comparison of the three primary approaches discussed here – the Aldrich, et al. four-factor measure, the Waugh, et al. modularity measure, and the segregation index measure defined above. The most notable differences in the substantive understanding afforded by each approach can be seen when the time series are superimposed. The four-factor approach suggests that aside from the brief period around 1820, the level of polarization has been high and remarkably stable, aside from a dip in the 1930s, which is almost imperceptible in the House. This is likely due to the relative consistency of the party label fitness measure, which composes the largest single component of the factor measure. Modularity of the voting network is much more variable, and suggests that the lowest levels of twentieth century polarization nearly match those observed during the Era of Good Feelings. Here both the variability and lack of differentiation are due to the basis of the roll-call voting network itself, rather than a latent spatial representation of
FIGURE 1.10: Three measures of polarization for each U.S. legislative chamber over time. Each panel depicts all three time series, but only one approach is highlighted, allowing for comparison of the normalized values.

preferences, making this measure more reflective of random variation in the agenda and individual decisions than is perhaps desirable.

The spatial approach, wherein polarization is understood as something like ideological segregation, depicts a smooth u-shaped decline and rise from Reconstruction-era highs, to the local minima of the Civil Rights era, and back to the partisan divide of twenty-first-century politics. Further, even the lowest levels of polarization in recent memory, 1966 in the House and 1946 in the Senate, are substantially higher than the global low occurring in 1822-24.

Along with a different substantive understanding of polarization through history, the spatial segregation approach offers the greatest amount of flexibility, as it is ap-
pplicable to any numeric data (even binary roll-call votes themselves), in any number of dimensions, for any number of parties. The flexibility demonstrated on roll-call data is only a limited example of the utility of this metric. In any situation in which data amenable to the calculation of pairwise distances and a partition of observations are available, levels of polarization can be found.
2.1 The polarization of public opinion

It has been demonstrated, and is widely accepted, that the second half of the twentieth century witnessed substantial and significant polarization among political elites, especially visible among Members of Congress. In contrast, there is much debate about the extent and magnitude of polarization in public opinion (see Fiorina and Abrams, 2008, for a review of this debate). Some research, such as Abramowitz and Saunders (1998) and Abramowitz (2010), find strong evidence of polarization or “party sorting” in the electorate, while others, using different data, find a less comprehensive shift (Fiorina, Bradburn et al., 2005; Fiorina, Abrams and Pope, 2008; Levendusky, 2009).

In general, this debate is characterized by its reliance on various competing and imprecise approaches to the measurement of polarization. For example, the plot on the left of Figure 2.1, from Abramowitz (2010, pg. 71), shows a pooled time-series of the proportion self-identified as Democratic among Liberal, Moderate, and Conservative Northern White Catholics.
Figure 2.1: An exercise in graphical rhetoric: At left, Abramowitz (2010) delves into the depths of the data to find diverging time trends, while, at right, Fiorina, Abrams and Pope (2008) take full advantage of a 100-point y-axis to emphasize a lack of the same divergence.

Here, survey respondents have been subsetted into very narrowly-defined categories, sliced into groups based on region, race, religion, ideology, and party identification. This extremely narrow focus likely necessitated the decision to pool respondents across multiple survey years, to give increased confidence in the mean proportion of Democratic identifiers. Further, this approach offers only group means, and no sense of within-group variance, which could technically (although not necessarily) be large enough to make the cross-group differences appear small. This type of evidence is being marshaled in support of the contention that polarization is happening across identity subgroups – but though it is possible to find trends that suggest polarization, at its extreme, this approach amounts to “categorical curve-fitting,” missing the forest by highlighting the trees.

In contrast, Fiorina, Abrams and Pope (2008), whose work features on the right side of Figure 2.1, take the mean difference between Democrats and Republicans across a pool of 40 political and social issue questions, and find that there is almost no increase in polarization over the last 20 years. Though presumably these two studies are sampling from the same pool of all Americans, it appears possible to derive any
conclusion one desires from the available data: polarization is either clearly occurring or barely happening, depending on the researcher’s chosen approach and frame.

In the previous chapter, I defined and explored a summary metric which seeks to eschew such choices, by taking into account the two aspects of polarization: relatively great intragroup homogeneity and intergroup heterogeneity. In the case of party ideology, polarization is high when Democrats (Republicans) all share very similar ideological positions, while Democrats and Republicans are very ideologically distinct from each other.

More generally, for any spatial configuration of individuals and any partitioning of those individuals into groups, a measure of polarization can be calculated by dividing the mean pairwise distance between individuals from different groups (between) by the mean pairwise distance between individuals from the same group (within). This permits the assessment of polarization for individuals in any number of dimensions classified into any number of groups – avoiding the compromises made with respect to measurement in much of the polarization literature.

The outline of this paper is as follows: in the next section, I describe and estimate an ideological space based on thermometer rating evaluations of political entities and population subgroups from the American National Election Study from 1965-2008. I then identify the location of individual respondents in this space, and use a multidimensional, multi-group measure to illustrate the trend of increasing partisan ideological polarization in public opinion. To better understand the causes of this increase in polarization, I investigate several hypotheses. First, I note the variance in the slope of the time trend of polarization across the states – in general, the sharpest increases have been observed in southern states, a finding in accord with the notion of an ideological realignment based in the South. Second, I assess the degree of ideological polarization across ascriptive identity traits. Historically, polarization levels are greatest across racial identity groups, but there are no social-group partitions
of survey respondents that evince an increase in ideological polarization, suggest-
ing somewhat of a paradox: party polarization in the electorate is at a modern-era high, but Americans are less ideologically divided today than they have been in a half-century.

2.2 The ideological space of public opinion

In order to assess ideological polarization, it is first necessary to develop reasonable estimates of ideology. Though the standard seven-point ideological self-identification scale could be used, I am interested in creating a more nuanced, continuous, and potentially multidimensional measure. For this reason, I use a large collection of thermometer ratings from the anes Cumulative Data File (The American National Election Studies, 2008). These thermometer ratings\(^1\) are designed to solicit respondents affective evaluations of various individuals and groups in society. Unsurprisingly, respondent’s ratings of political figures and, to a lesser extent, population subgroups, correlate with partisan affiliation and self-reported ideology. The use of many such evaluations, aggregated and scaled, permits the identification of a latent evaluation space. There have been a wide variety of stimuli for which thermometer ratings have been solicited, Figure 2.2 illustrates both the breadth and incidence of the thermometer ratings employed in this analysis.

To derive a latent space from these thermometer ratings, I employ a technique similar to that used by Rusk and Weisberg (1972) and Rabinowitz (1978). From the full set of thermometer ratings accumulated across anes studies over time, an \(n \times p\) individual \(\times\) stimuli matrix, I construct a \(p \times p\) matrix of the pairwise corre-

\(^1\) Sample question wording: “We’d also like to get your feelings about some groups in American society. When I read the name of a group, we’d like you to rate it with what we call a feeling thermometer. Ratings between 50 degrees-100 degrees mean that you feel favorably and warm toward the group; ratings between 0 and 50 degrees mean that you don’t feel favorably towards the group and that you don’t care too much for that group. If you don’t feel particularly warm or cold toward a group you would rate them at 50 degrees. If we come to a group you don’t know much about, just tell me and we’ll move on to the next one.”
**Figure 2.2:** This graphic indicates both the surveys in which each thermometer stimulus was included and the mean rating for that stimulus.
lations between each thermometer stimulus. The substantive interpretation of these correlations is that stimuli with highly-correlated thermometer ratings are perceived as being similar in some sense. For example, the most highly-correlated pair of thermometer stimuli is George W. Bush and Dick Cheney; the next most highly-correlated pair is Hillary and Bill Clinton. The strongest negative correlations are between John Kerry and George W. Bush and between Kerry and the Republican Party. As these examples show, entities which are closely associated with each other are consistently evaluated at similar levels by respondents, while entities standing in strong contrast with one another typically receive divergent ratings. A respondent who thinks highly of John Kerry will tend to evaluate George W. Bush negatively, and vice-versa. Thus, the correlation matrix represents the perceived similarity between all pairs of thermometer stimuli.

To estimate the dimensions of evaluation that underlie these similarities, I calculate a pairwise distance matrix from the correlation matrix – converting a measure of similarity to one of dissimilarity, wherein entities whose correlations with other thermometers are similar are more proximate to each other. This dissimilarity matrix can then be used in a multidimensional scaling (MDS) algorithm, to find the latent space which best fits the dissimilarities between entities.

The resulting space, shown in Figure 2.3, is very nearly unidimensional: principal component analysis suggests that the first dimension accounts for 87.9% of the variance, and the second component accounts for 8.2%, suggesting that any additional dimensions are essentially capturing noise.

The estimation of this evaluation space is only the first step. My primary interest is in developing thermometer evaluation-based estimates of ideology for respondents, which I calculate as a weighted average of stimulus locations, as seen in Equation 2.1, where \( \Omega \) is the \( n \times p \) individual \( \times \) stimuli matrix and \( \theta \) is the vector of stimulus locations in the dimension of interest. The implicit assumption made here is
Figure 2.3: The first two dimensions of latent evaluation space, derived from MDS of pooled ANES thermometer ratings. Darker names are those stimuli asked more frequently. The first dimension discriminates along ideological lines, separating Democratic and Republican identifiers and elites, while the second dimension differentiated between political elites and population subgroups. In general, proximity in this space reflects a high correlation between respondents’ thermometer ratings of these stimuli.

that respondents are more closely aligned ideologically with those entities that they evaluate favorably.

\[ \text{Evaluative Ideology}_i = \frac{\sum_1^p \Omega_{ij} \times \theta_j}{\sum_1^p \Omega_{ij}} \]  

(2.1)

2.2.1 Exploring the space

As can be seen in Figure 2.3, the first dimension of the evaluation-based space is clearly ideological, featuring the Liberals, the Democratic Party and Democratic politicians, including Jesse Jackson, Barack Obama, and both Clintons on the left,
while Conservatives, the Republican Party, and figures such as George W. Bush, Ronald Reagan, and Sarah Palin are on the right. The second component, on the vertical axis, serves to distinguish between entities that are an explicit part of the governing process and those that represent electoral subgroups. Among these subgroups, however, we observe structure informed by the principal latent ideological dimension: “Women’s Libbers,” Gays and Lesbians, Environmentalists, and Civil Rights Leaders are on the left, while Christian Fundamentalists, Big Business, Military, and Southerners are to the right of the spectrum.\(^2\)

While the estimated locations of thermometer stimuli appear to be strongly informed by ideology, it remains to be seen whether these estimates can be used to make inferences about the ideology of respondents in the manner described above. Indeed, as Figure 2.4 shows, there is a clear linear relationship between this measure of evaluative ideology and both party identification and self-reported ideology.

As an additional check on the validity of this thermometer-based measure as a proxy for ideology, I construct an issue scale from 13 issue-related questions, ranging from the role of government, women’s equality, and defense spending, to family values and tolerance (specific question wordings are listed in Appendix C). Factor analysis of these issue questions generates a first factor (explaining 30% of the variance) which corresponds to a general social values / moral issues scale, on which questions about tolerance of moral views and traditional values versus newer lifestyles load strongly. The scores returned by this factor analysis indicate where individuals in the electorate fit within this space, based on their responses to the scaled issue questions. I use the vector of first factor scores as an additional, confirmatory measure of ideology, against which to compare the more comprehensive measure derived from the large set of thermometer rating questions.

\(^2\) I also use a methodology similar to that employed by Jacoby and Armstrong, II (2011) to estimate bootstrap confidence regions around these estimates, as depicted in Appendix B.
Figure 2.4: Each facet of these two graphs plots respondents’ thermometer-evaluation based ideology estimates against their (jittered) self-reported partisanship or ideology. This relationship is consistently strong, although it is increasingly so in recent years.

Figure 2.5 shows how well self-reported ideology, seven-point party identification, and the issue-based index of preferences correlate with the thermometer-based evaluative ideology measure over time. In general, the correlations are high, suggesting that the first dimension of evaluation space reflects considerations similar to those informing the three other approaches to assessing individuals’ political positions. In
particular, the last quarter-century has seen these measures essentially converge, due to an increasing alignment between partisan and ideological preferences. It is increasingly rare to find a self-reported "liberal Republican" or "conservative Democrat," and this rarity is reflected in the degree to which these measures covary. One useful interpretation of these trends is that, knowing a respondent’s position on one scale is increasingly informative about his or her position on the other scales.

2.3 Assessing partisan ideological polarization

If we accept this thermometer-based measure of evaluative ideology as a useful measure of respondent’s ideological preferences, it is of interest to see how ideology is distributed within the electorate. As Figure 2.6 indicates, the distribution is much as we would expect, with the majority of respondents massed in the center of the distribution and relatively few individuals populating the liberal and conservative extremes. Individuals who voted for Democratic presidential candidates come pri-
marily from the left side of the distribution, while Republican supporters populate the right side. Non-voters and those who support minor party candidates come from the entire spectrum of ideological positions, but there is a distinct mode in the center, perhaps reflecting apathy or indifference between the major party candidates.

![Ideological Distribution by Presidential Vote](image)

**Figure 2.6:** Empirical density of evaluative ideology by reported presidential vote. Those who report voting for the Democratic candidate are generally found to the left of the distribution, those who voted Republican are massed to the right, and supporters of other candidates and non-voters are spread throughout the spectrum, though concentrated in the center.

Though it is not immediately apparent from this illustration that the electorate is increasingly polarized, there is substantial evidence to suggest that such is the case. One place this can be seen is in the change in imputed locations for party-related thermometer stimuli.

Recall that the initial estimation of the latent space was based on correlations...
between thermometer ratings pooled across the entire ANES space. This was done to avoid generating a correlation matrix dominated by missing values, due to complete pairwise-missingness between thermometer evaluations from different surveys (no individual who evaluated Al Gore in 2000 also evaluated him in 2002, therefore correlations cannot be found across survey years even for the same thermometer stimulus).

From this pooled evaluation space, I inferred respondent locations as a weighted average of evaluations, and these respondent evaluations can now be used to assess how the latent-space location of stimuli have changed over time. By taking an evaluation-weighted average of respondent locations, I infer back to single-survey locations of entities of interest. In this case, it is of interest to observe how the perceived ideological positions of party-related stimuli have changed. Figure 2.7 illustrates this change.

![Ideological Location of Party Thermometers Over Time](image_url)

**Figure 2.7:** Based on respondents' ideology and thermometer ratings of the Democratic and Republican Parties, these lines track the mean (and standard error of the mean estimate) perceived location of the two major parties over time.

Early in the time series, thermometer question wording referred to the parties as “Democrats” and “Republicans.” In 1978, “Democratic Party” and “Republican
“Party” were added to the list of thermometer questions, and both phrasings were used though 1982, after which “Democrats” and “Republicans” were dropped. As Figure 2.7 shows, for the 1980 and 1982 surveys, the implied ideology of these two phrasings moved in tandem toward the extremes, and the “Party” thermometers have been gradually trending apart since that time.

This gradual shift is also reflected in the trend of mean ideology by party identification. I divide all respondents according to party identification; I class as a Republican any respondent whose seven-point party identification marks them as a Republican-leaning independent, or as a weak or strong Republican; likewise for Democrats. Only those who identify as independent and do not lean toward either major party are treated as Independents in this analysis. Of the 48,130 responses to the standard party identification scale from 1952-2008, 52.7% of respondents identify as Democrats, 35.6% as Republicans, while the remaining 11.7% are Independents. Figure 2.8 depicts the mean evaluative ideology of each party’s identifiers over time.

Figure 2.8: Mean (and standard errors of the mean) evaluative ideology of ANES respondents, by three-category party identification. The major deviations in 1978 and 1982 are due to the absence of many of the population subgroup stimuli from those surveys (see Figure 2.2), which have a moderating influence on the estimates.
While the mean Independent is consistently near the mean of the overall distribution, the mean Republican identifier is increasingly ideologically conservative (to the right of the spectrum) over time, while the mean Democrat is increasingly liberal. In 1964, the median Democrat fell into the 32\textsuperscript{nd} percentile of ideology, while the median Republican was in the 57\textsuperscript{th} percentile. By 2008, those medians had moved to 24\textsuperscript{th} and 70\textsuperscript{th}, respectively.

Though these trends suggest that parties in the electorate are increasingly polarized, they suggest only that the mean identifiers for each party are increasingly distinct, reflecting increased interparty heterogeneity. As discussed in Chapter 1, polarization is a function of this increased distinction between groups, but also of increased intraparty homogeneity.

Again looking at ideology percentiles, we can get an idea of internal homogeneity by looking at the interquartile range of ideology by party over time. In 2008, the difference in ideology percentile between the most and least conservative quartiles of Democrats was 28. For Republicans, that difference was 17. In the 1960s, the figures are similar, but throughout the 1970s both Democrats and Independents were extremely diverse: the interquartile range for Democrats in 1972 was 42 percentile points. Though Republicans maintained remarkably stable and high levels of homogeneity, Democrats (and Independents) have come to match those levels from their peaks in the 1970s, contributing to an overall polarizing trend.

In Chapter 1, I outlined an approach to the measurement of polarization that simultaneously accounts for variance across and among party co-identifiers. In that chapter, I used this Spatial Segregation Index of Polarization (SSIP) with NOMINATE estimates of legislator ideology, contrasted across congressional party lines.

In this chapter, I have developed a thermometer evaluation-based estimate of survey respondent ideology, across which are arrayed self-identified Republicans, Democrats, and Independents. By comparing the mean ideological distance between
co-partisans and the mean distance between respondents from different parties, we can replicate the approach taken in Chapter 1 for public opinion, rather than congressional behavior.

Figure 2.9: Spatial Segregation Index of Polarization (SSIP) estimates for the electorate in one-dimensional evaluative ideology space, partitioning on three-category party identification and presidential vote choice. The electorate appears to be polarizing across party lines.

Figure 2.9 traces the SSIP over time, for ANES respondents partitioned by three-category party identification and by presidential vote. Both approaches show that the ideology of parties-in-the-electorate is polarizing over time. Positive values of the SSIP indicate that the average pair of co-partisans is more similar than the average pair of non-co-partisans – that is, parties are internally homogeneous and externally heterogeneous. The higher the SSIP, the more precisely information about an individuals’ group classification (e.g. by identification or vote) informs us about his or her location in ideological space. Inversely, given information about a respondent’s ideology, high SSIP values suggest that we can more reliably predict their partisanship.³

³ Note that although the trend in electoral polarization is increasing, the time series maximum
2.4 State-level ideological polarization

One oft-cited source of polarization, acting on the electorate, and in turn on the Congress, is the realignment of parties-in-the-electorate in the South. The argument is that the mid-Twentieth-Century trichotomy of Republicans, Southern Democrats, and Northern Democrats underwent a shift through the course of the 1960s, 70s and 80s, wherein conservative Southern Democrats increasingly came to identify as Republicans, while liberal Northern Republicans increasingly came to identify as Democrats.

This had the effect of making the parties, both in government and in the electorate, more internally homogeneous. Democrats no longer required a clarifying ideological or regional adjective, since the “Southern” and “conservative” branch of the party became both less numerous and less influential.

Simultaneously, as liberals more consistently identified themselves as Democrats and voted for Democratic candidates, while conservatives increasingly aligned themselves with the Republican party, the typical ideological positions of party members became increasingly distinct.

Thus, it is argued that electoral realignment contributed to concurrent increasing trends in interparty heterogeneity and intraparty homogeneity. One implication of this argument is that polarization is driven primarily by partisan sorting in the South. This claim can therefore be tested by assessing the polarization of public opinion at the state level.

Figure 2.10 shows the relationship between state-level aggregate ideology and polarization early in the first and second halves of the ANES time series. Taking the mean ideology of respondents by state from 1964-1986 and again from 1988-2008, a SSIP value of 0.23 is less than the Twentieth-Century minimum observed in Congress (see Figure 1.7). Unsurprisingly, the ideological differentiation among professional partisans under a coherent leadership is substantially greater than that among the mass electorate.
it is clear that though public ideology has shifted in many states (in a conservative direction in South Dakota, Kentucky, and Indiana; leftward in Oklahoma, South Carolina, and North Carolina), ideology in the early portion of the period is a reasonably good predictor of ideology in the latter period.

In fact, the states with the largest number of survey respondents, in which estimates we can be most confident (New York, California, Texas, Florida, Michigan, Ohio, and Pennsylvania), all fall more or less exactly on the 45° line. Ideological change, per this measure, does not appear to be a regional phenomenon, as states that lie substantially above and below the line come from all parts of the nation.

Contrast this relatively stable picture of state-aggregate ideology with that of state-level polarization, on the right-hand panel of Figure 2.10. In that plot, the variable on the x-axis is an average of state-level partisan ideological polarization, calculated for each survey-year as in Figure 2.9, weighted by the number of respondents by state, 1964-1986. The y-axis represents the same average estimate, calculated for the latter half of the time series.
As this scatterplot makes clear, there has been a nearly-universal secular increase in polarization, across all but four states. While nearly every state has become more polarized, the list of most-polarized states has changed: early in the period, Arizona, Nebraska, and Utah were the most extreme; more recently, Mississippi, Iowa, Illinois and Indiana are the most polarized.

**Figure 2.11:** States in this map are colored according to the degree to which their electorate polarized over the period 1964-2008, darker states saw relatively little polarization, lighter states more. Uncolored states are those from which there were too few respondents to draw useful conclusions. Note the concentration of lighter-hued states in the southeast/Deep South/Gulf Region.

Unlike the plot contrasting ideology over time, there does appear to be a regional bias to the set of states which have polarized the most. The left side of the space is populated with states with low early-period polarization, all of which have polarized over the last half-century to fall in line with the rest of the country. The plot suggests
that most of the states with the largest increase in polarization are of the once-Solid South, an inference supported by the map presented in Figure 2.11.

This thematic map shades each state according to the degree to which it has polarized over the period 1964-2008, and shows the geographic variance in the slope of this shift. Lighter hues, indicating greater shifts in state-level SIP, are to be found predominantly in the Deep South, and the former states of the Confederacy more generally. Contrast this regional pattern with that of the Mountain West, where we find four of the least-polarizing states.

As a final check of the evidence for the polarizing South hypothesis, I examine the time trend in ideological polarization for all respondents aggregated and partitioned into two subgroups of Southerners4 and non-Southerners. Figure 2.12 illustrates this trend.

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**Figure 2.12:** Polarization calculated for the full sample and for Southern and non-Southern subsets of ANES respondents. The South as a region has typically been less polarized than the non-South, but has “caught up,” to the rest of the country, helping to drive the nationwide increase in polarization.

---

4 Respondents from the “Solid South”: Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, Missouri, North Carolina, South Carolina, Tennessee, Texas, Virginia, and Maryland.
Even in the aggregate, when split into two subnational groups, the trend in SSIP in the electorate supports the patterns suggested by the previous analyses. Two stories are revealed in this figure. The first is as noted before: a nationwide, secular increase in polarization as measured by SSIP. The second is that the non-Southern states have been consistently more polarized than the South – in fact, at its 1972 low, polarization in the South was nearly zero, suggesting that the average pair of co-partisan respondents were only slightly more similar ideologically than the average pair of respondents from different parties. Since that time, however, the South has polarized more rapidly than has the rest of the country, to the point at which there is no significant regional difference in SSIP, as seen by the lack of variance in the vertical dimension of the right panel of Figure 2.10.

Given the evidence, it is reasonable to conclude that electoral realignment – the more consistent sorting of ideologues into parties, rather than increased ideological extremity – has contributed to the nationwide increase in polarization over the last half-century. The once-one-party South now features general elections in which both major parties are competitive, and the factional differences which once characterized the Democratic party have been folded into the primary dimension distinguishing the parties from each other.

2.5 Ideological polarization by ascriptive identity

The partisan sorting that has resulted from ideological realignment appears to be contributing to the rise in electoral polarization, but what about a Pat Buchananesque “culture war?” In this section, I introduce a paradox: though it is clear that party identifiers are polarizing, and doing so across essentially all states, public opinion is not polarizing across any number of other identifiers.

That is, if we divide the electorate not by partisanship, but into subgroups based on demographic traits such as gender, age and race, socioeconomic categories like
income and education, or cultural markers such as marital status and religion, ideological polarization is not occurring.

In order to see this, I look again to the ANES time series. In looking for interesting and useful categorical variables, I sought to maximize duration and consistency, seeking questions that have been asked in all or nearly all survey-years and for which a fairly consistent set of responses have been offered. I also tried to cover the gamut of socioeconomic/demographic dimensions most often invoked in our explanations of political behavior.

Thus, although several more recent ANES surveys offer a seven- or eight-category religious classification, these categories are inconsistent across the duration of the time series, so I opt to use the more consistent four-category “major groups” scheme. At the same time, the same seven-category employment classification scheme is available for almost the entirety of the dataset – though the same scheme is not used in 2008, I choose to include the variable anyway, due to its potential importance as an explanatory variable.

Figure 2.14 (included at the end of the chapter) serves to introduce the identity dimensions I choose to analyze, and lists the categories into which each variable is divided. Further, for each category, I denote the mean and standard error of the mean estimate of evaluative ideology for each of four selected survey years.

In general, these mean estimates fall in line with our expectations of the ideological positions of these identity groups. The average male is slightly more conservative than the average female; conservatism tends to increase with age and income. Married respondents are the most conservative; Protestants are the most conservative religious subgroup, while Jews are the most liberal. The average white respondent is more conservative than the average respondent who identifies as black.

Earlier in this chapter, I illustrated how partisanship and presidential preference were polarizing in ideological space. By dividing the electorate into ascriptive identity
groups, like those listed in Figure 2.14, it is possible to assess whether polarization is occurring across socioeconomic/demographic lines as well.

Figure 2.13: Each facet depicts the trend in polarization levels for respondents partitioned into ascriptive identity subgroups, rather than by partisanship. Panels are sorted from upper left to bottom right according to mean polarization, and each trend is superimposed over the trend in polarization by party identification (in gray). Historically, only racial polarization has been as high as party polarization, and many of these variables are essentially unpolarized.

As Figure 2.13 indicates, the answer is that polarization is almost certainly not occurring across non-partisan partitionings of the electorate; if anything, we actually observe depolarization. The panels in Figure 2.13 are ordered by mean SSIP across all years. Race has historically been the most polarized dimension, by a significant margin. The highest SSIP value for any other characteristic is around 0.05; racial ideological polarization has only come down to those levels in the last 15 years. Also notable is that only racial polarization in the 1970s and 80s is in the same range as
typical levels of partisan polarization — in general, party identification is much more polarizing than any identity subgrouping.

In some cases, identity SSIP is actually negative, indicating that the ratio of mean between-group distance over mean within-group distance is less than one, implying that ascriptive identity subgroups aren’t differentiated in ideology space. Men and women, for example, are never substantially different from each other, and the same is true for religious affiliations for the last three decades. In the DiMaggio, Evans and Bryson (1996) sense of polarization manifesting as a state or as a process, these traits are in a depolarized state.

Most importantly, the linear trend of polarization over time is decreasing for seven of these nine dimensions, and where the trend is technically increasing (i.e. across income quintiles and gender), it is not significantly so. This finding is in contrast to the arguments advanced by Stonecash (2005); Gelman, Park and Shor (2009); Ansolabehere, Rodden and Snyder (2006); Bartels (2006); McCarty, Poole and Rosenthal (2006), who relate the increase in income inequality to ideological polarization across income groups. Though the time series of these two variables is indeed correlated, it does not appear to be the case that survey respondents from differing income quintiles are becoming ideologically more distinct.

Thus, it appears that previous findings of polarization across social groups derive their results, at least in part, from their measurement approach and the specific groups which are compared.

2.6 Summary and conclusion

We have covered a lot of ground in this chapter. Making liberal use of the SSIP measure defined in Chapter 1, I have shown that party identifiers in the electorate are becoming ideologically polarized, though not to the extent observed among members of Congress. Some of this increase in polarization may be driven by the ideological
realignment which began in the South – in the beginning of the time series, respondents living in southern states were less polarized than non-Southerners, but levels have equilibrated in recent years. While polarization has increased across all states, it has increased more rapidly in the South.

Despite this clear positive trend, the data reveal that ascriptive social identity groups are not concurrently becoming more ideologically distinct. Indeed, though they are technically polarized in every case (that is, internal differences are less than external ones), the trend across racial, educational, marital, age, geographic, income, employment, religious, and gender groups is of either constant or decreasing polarization.

This is in contrast to the common understanding of U.S. politics as increasingly marked by “culture war,” between Evangelical Christians and non-believers, suburbanites and city-dwellers, the middle class and the working class. If one slices the data enough, and compares point estimates of group means for variables like “proportion Democratic,” it is possible to find trends that suggest polarization. However, taking the comprehensive approach used here, such findings are not in evidence.

Still open is the question of how identities are converging while partisanship is diverging in the ideological space. The answer lies in the structure and dimensionality of the social space, and it is to this subject we turn in the next chapter.
**Figure 2.14:** Mean evaluative ideology by characteristic for four selected survey years. Error bars indicate standard errors of the mean. This plot is intended to illustrate how the ideology of population subgroups has shifted over time, in some cases polarizing, in other cases moderating.
3

Parties in a Social Space

3.1 An increasingly diverse electorate

Alongside the trend in partisan ideological polarization, we observe an increase in the socioeconomic diversity of the U.S. electorate. Electoral complexity, to which socioeconomic diversity may be thought to contribute, has been variously found to boost party competition (Sullivan, 1973; Fenno, 1978), or to increase incumbent advantage (Ensley, Tofias and De Marchi, 2009) – but certainly it serves as a foundation for a shifting political landscape.

Of the social identity dimensions discussed in Chapter 2, five have experienced an increase in group heterogeneity over the duration of the ANES time series: race, religion, marital status, education, and age. The other four categories, residential density, income level, gender, and type of employment, have remained essentially stable in their level of diversity. I formalize a measure of group heterogeneity or diversity with an inverse Herfindahl-Hirsch Index (Hirschman, 1945; Herfindahl, 1950), which simply divides the square of the sum of the count for each category by the sum of the squares of the count for each category:
\[
EN_{groups} = \left( \sum_{i=1}^{K} \frac{n_i}{K} \right)^2 \bigg/ \left( \sum_{i=1}^{K} n_i^2 \right)
\]  

(3.1)

I refer to this index as the effective number of groups \(EN_{groups}\), because integer values of the index reflect the values that would be assessed if that number of groups were represented equally\(^1\). Figure 3.1 plots the time trend of the \(EN_{groups}\) values for nine socio-demographic dimensions of interest, divided into the categories shown in Figure 2.14.

As the figure makes clear, ANES respondents have become sharply more racially diverse, as immigration and Latino population growth have drastically changed the ethnic distribution of the population. Similarly, religious and marital status heterogeneity has increased, as once-rare affiliations and domestic arrangements become more common. Educational attainment has become more diverse because though individuals with grade-school-only levels of formalized learning have become less common, the increase in college and post-graduate degree attainment has more than made up for the decrease. The slight increase in age diversity is a function of Americans’ increasing longevity.

We do not observe similar increases in the variety of residential settings or income levels – the latter due to the fact that income categories are defined by quantile – nor gender, which continues to stay at a fairly constant 1:1 ratio. Employment diversity, if anything, has decreased over time, due to an increased concentration of the labor force in Clerical, Professional, and Skilled employment, at the expense of the Farmer, Laborer, and Homemaker categorizations.

\(^1\) In other words, a population divided equally into three subgroups would return an \(EN_{groups}\) value of 3. There is also substantial precedent for this nomenclature. See for example Laakso and Taagepera (1979) and many subsequent uses of an “effective number of parties.”
Figure 3.1: Trends in group heterogeneity over time, from ANES data. Each panel depicts heterogeneity as measured by an effective number of groups index, wherein higher values reflect greater levels of diversity. Racial, religious, marital status, educational, and age diversity are increasing over time.

3.1.1 Party heterogeneity and the “Big Tent”

In 1976, in the wake of his loss to Jimmy Carter, Gerald Ford claimed that “The Republican tent is big enough to encompass,” himself, John Connally, Ronald Reagan and Nelson Rockefeller (Safire, 2008). Some dozen years later, RNC Chairman Lee Atwater advocated a “big-tent approach” to Republican politics, in an effort to avoid a major rift between pro-Choice and pro-Life factions of the party, as well as to attract African-American voters (Donovan, 1992). A decade later, in the wake of another losing GOP presidential campaign, Republicans were calling for a return to the “big tent” philosophy of accepting disagreements within the party (Nather,
While Republicans sought a bigger tent, Democrats pursued a “50-state strategy.” As early as 1980, Democratic primary candidate John Connally employed such a scheme, though due to the sequential nature of the primary campaign, which rewards momentum and early success, such a diffused effort was not successful (Peterson and Curtis, 1980). 25 years later, Howard Dean employed a 50-state strategy, both in his unsuccessful 2004 primary campaign and on behalf of the Democratic Party in 2008 as chair of the Democratic National Committee, arguably contributing to unexpectedly close races and surprising victories at all levels (Weisman, 2008).

Just as the diversity of the electorate is increasing, so too is the diversity of each major party’s electoral coalition. In this chapter, I touch on the idea that parties are competing over voters in a social space, seeking to construct winning coalitions by attracting various population subgroups through policy, ideology, or other appeals. Conceived of in this way, candidates must make many trade-offs between, among other things, ideological purity and breadth of appeal, number of groups in a coalition versus the size of each group, etc. Full exploration of this model is left for another venue, but Figure 3.2 illustrates the pattern over time in how the parties have built their coalitions.

Dividing ANES respondents into very narrow subgroups based on all facets of their socioeconomic/demographic identity\(^2\), I estimate the \(\text{EN}_{\text{groups}}\) of each party’s coalition of supporters. As the overall population has gradually become more diverse, so have the subsets of the population identifying with both of the major parties. Democratic identifiers are consistently more heterogeneous than are Republicans – the average Democratic-identified subgroup is smaller than the average Republican

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\(^2\) As an example, the most populous subgroup in the pooled ANES sample are White Married Protestant Young Adult Female Homemakers with a High School education, living in a Rural area and earning a mid-level Income. Of the 362,880 possible combinations of identity traits available given the categories I use here, only 10,017 are present in the data.
Figure 3.2: Time series of the effective number of distinct social identity types identifying with the two major parties or as an Independent, with the total $EN_{Groups}$ for comparison. The overall trend is of increasing diversity, and this is reflected in the membership of each party-in-the-electorate. Respondents identifying with the Democratic Party are consistently more heterogeneous than those identifying as Republican.

... subgroup, and the number of distinct subgroups in the Democratic coalition is larger.

I have shown in the previous chapter that despite these increases in group and partisan heterogeneity, groups are not polarizing in ideological space. But what if we consider the inverse proposition – are parties polarizing in social space?

3.2 Social space

First, what is a social space, and why is it interesting? By “social space,” I mean a reduced-dimensionality model of the demographic and socioeconomic characteristics of the population. The foregoing discussion treats these traits, such as race, age, income, and gender, as orthogonal, fully separated dimensions, which is the manner in which they are typically used.

However, each of these dimensions interact and covary with one another in meaningful ways. For example, consider the interaction between income and education, as depicted with 2008 ANES data in Table 3.1.
Table 3.1: Cross-tabulation of the income and education levels of 2008 ANES respondents, suggesting that higher income levels are associated with higher educational attainment.

<table>
<thead>
<tr>
<th>Inc. / Ed.</th>
<th>Grade School</th>
<th>High School</th>
<th>Some College</th>
<th>Advanced Degree</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Income 1</td>
<td>44</td>
<td>248</td>
<td>99</td>
<td>29</td>
<td>420</td>
</tr>
<tr>
<td>Income 2</td>
<td>19</td>
<td>240</td>
<td>117</td>
<td>38</td>
<td>414</td>
</tr>
<tr>
<td>Income 3</td>
<td>15</td>
<td>318</td>
<td>302</td>
<td>183</td>
<td>818</td>
</tr>
<tr>
<td>Income 4</td>
<td>2</td>
<td>97</td>
<td>124</td>
<td>161</td>
<td>384</td>
</tr>
<tr>
<td>Income 5</td>
<td>1</td>
<td>17</td>
<td>26</td>
<td>52</td>
<td>96</td>
</tr>
<tr>
<td>Total</td>
<td>81</td>
<td>920</td>
<td>668</td>
<td>463</td>
<td>2132</td>
</tr>
</tbody>
</table>

As this simple cross-tabulation makes clear, income and education level are not independent. In general, the more education an individual has received, the higher his or her income, and vice-versa. This table doesn’t permit inference about the causal relationship between these two variables, but it does support the contention that they are related, regardless of causal direction or whether they are both influenced by a third, unmeasured variable – which could be thought of as a latent dimension. In a similar manner, marital status is related to age, race to religion, occupation to gender – in fact, each of these characteristics, in the aggregate, has some relation to each other – none are perfectly orthogonal dimensions. From the correlations between these traits, a social space emerges.

This is not a new concept, particularly in sociology. The sociology literature typically conceives of social space as a function of “social distance,” measured in terms of social association—through interaction, mobility, or marriage, for example—between groups, based on the assumption that “social associations are more prevalent among persons in proximate than those in distant social positions.” (Blau, 1977a,b; Blau and Schwartz, 1997)

The principle of homophily—that social ties are more likely between similar individuals—is widely used as a basis for the sociological study of what Miller McPherson calls

\[ \chi^2 \text{ statistic for this table is } 372.5 \text{ on } 12 \text{ degrees of freedom, leading me to reject the null hypothesis of independence.} \]

Pierre Bourdieu’s (1984) work adapts the idea of a social space to an understanding of cultural tastes and preferences – suggesting that these consumption patterns are a function of socio-economic structure. From survey data, Bourdieu re-constructs a spatial representation of the “dominant” and “petit-bourgeois” tastes (an example of which is shown in Figure 3.3). Common to all of these varied approaches is the recovery of a principal component aligned with variables associated with common understandings of socioeconomic status.

Figure 3.3: Reproduction of a graphic from Bourdieu (1984, 340). Bourdieu employs multiple correspondence analysis on demographic and preference data to construct a spatial representation of cultural tastes. The first principal component in this configuration is associated with socioeconomic status, which Bourdieu suggests varies inversely with cultural capital.
3.2.1 Estimating a social space

The estimation approach I employ here differs from that adopted by the bulk of sociological work in two primary ways. The first is more concerned with data than method, and the second is more purely methodological.

As noted above, the typical conception of a social space is based on “social distance” between groups, which is assumed to drive frequency of social interaction. That is to say, the space is based on relations between individuals, rather than on traits of individuals themselves. The data I use is centered entirely around the individual survey respondents. Rather than looking at the frequency of interactions between individuals with different traits, I assess the frequency of trait co-occurrence within individuals. In doing so, I am able to use multiple dimensions of sociodemographic identity to inform my understanding of how categories within dimensions are related.4

The technique most commonly used for dimensional analysis of nominal variables is multiple correspondance analysis (MCA, see Hill, 1974, for an early overview of the developoment of this technique). MCA is performed by finding the singular value decomposition of an indicator matrix, $X$, derived from the matrix of categorical data. An alternative and equivalent, but computationally less-intensive approach replaces the indicator matrix with a Burt Table – the interior product of the indicator matrix: $X'X$ (Burt, 1909). The Burt Table for the simple crosstab in Table Table 3.1 is shown in Table 3.2.

The diagonal elements are the category marginal counts, and the off-diagonal elements reproduce the cross-tabulation. Obviously, a respondent reporting a Grade

---

4 For example, a sociologist studying the latent structure of occupational types may use frequency of relations between types, because there is no co-occurrence between mutually-exclusive employment types at the individual level. By contrast, the ANES data which I use here does not consistently include information about respondents’ social associations. However, by using information from other aspects of identity, I can make inferences about the structure of occupational types, despite the lack of co-occurrence within those types.
Table 3.2: Burt Table for the interaction between income and education. Each element counts the number of observations at the intersection of each categorical level of the two variables. Such tables are typically used as the basis for multiple correspondence analysis.

<table>
<thead>
<tr>
<th></th>
<th>Inc1</th>
<th>Inc2</th>
<th>Inc3</th>
<th>Inc4</th>
<th>Inc5</th>
<th>Grade</th>
<th>High</th>
<th>College</th>
<th>Adv.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Income 1</td>
<td>420</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>44</td>
<td>248</td>
<td>99</td>
<td>29</td>
</tr>
<tr>
<td>Income 2</td>
<td>0</td>
<td>414</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>19</td>
<td>240</td>
<td>117</td>
<td>38</td>
</tr>
<tr>
<td>Income 3</td>
<td>0</td>
<td>0</td>
<td>818</td>
<td>0</td>
<td>0</td>
<td>15</td>
<td>318</td>
<td>302</td>
<td>183</td>
</tr>
<tr>
<td>Income 4</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>384</td>
<td>0</td>
<td>2</td>
<td>97</td>
<td>124</td>
<td>161</td>
</tr>
<tr>
<td>Income 5</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>96</td>
<td>1</td>
<td>17</td>
<td>26</td>
<td>52</td>
</tr>
<tr>
<td>Grade School</td>
<td>44</td>
<td>19</td>
<td>15</td>
<td>2</td>
<td>1</td>
<td>81</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>High School</td>
<td>248</td>
<td>240</td>
<td>318</td>
<td>97</td>
<td>17</td>
<td>0</td>
<td>920</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Some College</td>
<td>99</td>
<td>117</td>
<td>302</td>
<td>124</td>
<td>26</td>
<td>0</td>
<td>0</td>
<td>668</td>
<td>0</td>
</tr>
<tr>
<td>Adv. Degree</td>
<td>29</td>
<td>38</td>
<td>183</td>
<td>161</td>
<td>52</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>463</td>
</tr>
</tbody>
</table>

School-level education cannot also report an Advanced Degree, so all within-variable off-diagonal elements are zero.

In the analysis that follows, I replace the Burt Table with a table of the logged odds ratio of each pair of columns of the indicator matrix $X$. This serves two purposes: it accounts for the relative frequency of each trait in the population and it produces approximately normally-distributed variables, amenable to principal component analysis. The formulation of the odds ratio matrix from the trait indicator matrix $X$ is:

$$
\frac{X^T X}{X^T (1 - X)} / \frac{X^T (1 - X)}{(1 - X)^T (1 - X)}
$$

When logged, the odds ratio table for the income-education data is as shown in Table 3.3. Represented in this manner, the relationships suggested by Table 3.1 are made clear. The strongest positive relationship is that between High School education and the lowest income level, the second strongest positive relationship is between holding an Advanced Degree and the highest income level. This log odds ratio (LOR) matrix can be straightforwardly employed as a similarity matrix, for use as an input for any scaling technique.
Table 3.3: Table of the logged odds ratios for trait co-occurrence for income level and educational attainment. Positive values reflect a relatively high degree of association between two characteristics, negative values reflect uncommon co-occurrence. For example, respondents with a Grade School level of education are disproportionately likely to fall into the lowest income category.

<table>
<thead>
<tr>
<th></th>
<th>Inc1</th>
<th>Inc2</th>
<th>Inc3</th>
<th>Inc4</th>
<th>Inc5</th>
<th>Grade</th>
<th>High</th>
<th>College</th>
<th>Adv.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Income 1</td>
<td>1.67</td>
<td>0.80</td>
<td>-0.48</td>
<td>-1.52</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income 2</td>
<td>0.25</td>
<td>0.74</td>
<td>-0.18</td>
<td>-1.18</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income 3</td>
<td>-1.04</td>
<td>-0.28</td>
<td>0.42</td>
<td>0.06</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income 4</td>
<td>-2.20</td>
<td>-0.97</td>
<td>0.05</td>
<td>1.24</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income 5</td>
<td>-1.36</td>
<td>-1.31</td>
<td>-0.22</td>
<td>1.54</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Grade School</td>
<td>1.67</td>
<td>0.25</td>
<td>-1.04</td>
<td>-2.20</td>
<td>-1.36</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High School</td>
<td>0.80</td>
<td>0.74</td>
<td>-0.28</td>
<td>-0.97</td>
<td>-1.31</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Some College</td>
<td>-0.48</td>
<td>-0.18</td>
<td>0.42</td>
<td>0.05</td>
<td>-0.22</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adv. Degree</td>
<td>-1.52</td>
<td>-1.18</td>
<td>0.06</td>
<td>1.24</td>
<td>1.54</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The social space is potentially very highly-dimensional, and a LOR can be produced for an arbitrary number of categorical variables. Figure 3.4 illustrates the relationships between all of the traits I have discussed thus far in this study. This heatmap is a graphical version of a multivariate table of logged odds ratios just like Table 3.3 – bright red cells indicate strong positive relationships, while black cells indicate strong negative relationships. The figure captures the overrepresentation of highly-educated respondents among the higher income levels, the prevalence of Farmers in Rural settings, and the relative dearth of Male respondents employed as Homemakers.

This matrix is one representation of the social space, but I am particularly interested in identifying the principal latent dimensions underlying these relationships, which I do by use of PCA on the LOR matrix.\(^5\) The first two components of the reduced-dimensionality social space, as produced by this PCA, are plotted in Figure 3.5.

The first two components account for nearly equal portions of 92.5% of the vari-

\(^5\) I also employ a bootstrap technique to estimate confidence intervals around these PCA point estimates, as discussed in Appendix D.
Figure 3.4: Graphical representation of the logged odds ratios between each social identity trait of interest. Bright red cells suggest a high degree of association between two traits, while black cells indicate a negative association. Because the levels of each variable are mutually exclusive, they cannot co-occur, and thus their intersections are given a neutral color in this matrix.

The second dimension is somewhat more difficult to characterize, but as Figure
3.5 shows, the variable with the most variance on this second dimension is age. At the high end of this axis, we find Seniors, as well as traits more commonly found among those born less recently, such as Homemaking as an occupation, Widow status, and Grade School education. At the low end of the spectrum are variables associated with being a Young Adult, such as living in a domestic Partnership, Never being Married, or being in the military, which falls under Other Occupation.

In among the traits which help define the components are other traits whose positions align with our expectations. Life expectancies are higher among Whites and Women, Males tend to have higher incomes, and Other Religions are more prevalent among the young.
3.2.2 The internal structure of the social space

The space presented in Figure 3.5 is based on odds ratios constructed from the set of nearly 50,000 ANES respondents pooled over time – thus it represents the general structure of society over the last half-century or so. It is of interest, however, to see how this structure has changed over time – is society becoming increasingly one-dimensional? Are certain aspects of individuals’ identity realigning from one dimension to another?

To understand this, I replicate the scaling process described above, using only respondents from a single survey-year each time. Each application of this procedure produces a unique scaling, but in every case, the overall structure of the space is consistent: socioeconomic status on the x-axis, age-related variables on the y-axis. Since scaling results are only unique up to an affine transformation, it is necessary to rotate and transform the resultant spaces toward a common target space in order to compare them year-to-year.

I do this by finding the Procrustes superimposition (Oksanen et al., 2012) that optimally fits each year’s social space to the temporally-pooled social space shown in Figure 3.5. I then estimate the within-variable standard deviation by year and component, weighing each category’s location by the number of respondents in that category. Figure 3.6 plots the smoothed time trends of this variance.

Income and educational level, and to a lesser extent, employment, religion and residential population density, all load more strongly on the first component of the space, which I earlier described as socioeconomic status. The only variable which consistently exhibits greater variance on the second dimension than on the first is age, which supports my previous description of the second principal component as “age-related.” Gender is consistently uncorrelated with either of these two social dimensions.
Interestingly, employment type has become increasingly aligned with the primary socioeconomic status dimension, and less with age, whereas the opposite is the case for marital status, the varieties of which are increasingly correlated with respondent age.

Also evident is a general increase in variance over time in both dimensions, implying that social identity categories are increasingly uncorrelated/decreasingly predictable/increasingly different. This trend is a manifestation of the increase in group heterogeneity discussed in Section 3.1 above. The remainder of this chapter investigates whether this changing social landscape interacts with shifts in electoral partisanship to produce partisanship.

3.3 Parties in social space

Having now thoroughly defined and explored the latent structure of an American social space, we can think of parties and candidates for office as competing over this
space. Perhaps a spatial proximity model applies, in which candidates attempt to
signal positions in this social space to maximize the number of individuals closer to
them than to their opponents. This could take the familiar form laid out by Hotelling
(1929), Downs (1957) and Black (1958), or could be modeled as a dynamic agent-
based process (Laver and Hunt, 1992; Laver, 2005; Laver and Sergenti, 2010), or as
a problem of competitive facility location (ReVelle and Eiselt, 2005; Eiselt, Laporte
and Thisse, 1993). Regardless, McKelvey’s instability results (1976), suggest that in
the two-dimensional social space recovered from the PCA, there is no equilibrium
set of party locations.

This lack of equilibrium does not mean that the question of party locations in this
space is an uninteresting one. Indeed, vast swaths of the political science literature,
from Campbell, et. al’s The American Voter (1960) to Gelman et al. (2008), has
concerned itself with the manner in which social identity subgroups divide across
parties. In a similar vein, much of the popular media coverage of elections and
campaigns concerns how well candidates do among groups and how campaigns build
coalitions of voters. News articles on the campaign are peppered with quotes from
election observers like Bush campaign advisor Terry Nelson, saying things like, “The
country is changing. In every election cycle, every year, every day, this country
becomes more ethnically diverse. And that has an impact on the kind of coalition
that you need to put together to win,” (Calmes and Landler, 2009). Indeed, as
suggested by Figure 3.2, parties’ electoral coalitions are in flux.

Given the locations of traits estimated in the PCA and shown in Figure 3.5,
the multidimensional matrix of which I will call $\theta$, it is possible to place individual
respondents in the social space by taking a weighted average of his or her specific
trait locations with the binary indicator matrix $X$:
Respondents are distributed throughout the social space, although not evenly so. The center and upper-right quadrant are somewhat more densely populated. Using a two-dimensional logistic general additive model (Hastie and Tibshirani, 1990; Hastie, 2011), I estimate the probability of a respondent identifying as a Republican rather than as a Democrat (Independents are omitted here) as it varies across social space. Figure 3.7 offers a graphical representation of these probabilities for a selected subset of ANES survey years.

Figure 3.7: Probability of Republican party identification, as a function of location in two-dimensional social space, based on a logistic general additive model. White lines indicate points at which the predicted probability of identifying as a Republican is the same as the probability of identifying as a Democrat.
In general, Republicans “own” the upper-right of the space – the high end of both the socioeconomic and age-related latent dimensions. While this pattern changes somewhat over time, the general finding is in line with our expectations. Note however, that the dimensionality reduction, averaging, and spatial smoothing lead to some questionable inferences, if the graphic alone is our basis for understanding politics and demographics. The points overlaid on top of the smoothed probability estimate map correspond to locations of traits from the latent space shown in Figure 3.5, and the point in the upper-right corner, in an area of the space where partisanship is predicted to be very likely Republican, represents the location of the Jewish trait. Of course, respondents who identify as adherents to Judaism also identify as Democrats, as opposed to as Republicans, 83.4% of the time in the aggregate ANES time series data. It is a function of the trait’s co-location in space with other, more commonly-reported variables that strongly predict Republicanism which generates this misleading finding.

To formalize the intuition of this visualization, I model evaluative ideology, party identification, and presidential vote preference as a function of the two principal components of social space. These models are depicted in Table 3.4.

Each of these three models is fitted as a multilevel mixed-effects model (Bates, Maechler and Bolker, 2011), using survey year and respondent state as random effect parameters, with location in social space – along the primary “socioeconomic status” dimension, the secondary age-related dimension, and the interaction of the two – as the sole independent variables.

In predicting the measure of evaluative ideology developed in the previous chapter, respondents are increasingly conservative as their location on either of the first two social identity dimensions shifts in a positive direction. The negative coefficient
Table 3.4: Results for three logistic mixed-effects models, predicting political variables of interest as a function of respondent location in social space. Both dimensions of that space are significant predictors of ideology, partisanship, and presidential party preference. Values in parentheses represent the standard errors of their associated estimates.

<table>
<thead>
<tr>
<th></th>
<th>Evalutive Ideology</th>
<th>Party ID</th>
<th>Republican Vote</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>-0.306</td>
<td>3.491</td>
<td>-0.190</td>
</tr>
<tr>
<td></td>
<td>(0.231)</td>
<td>(0.067)</td>
<td>(0.114)</td>
</tr>
<tr>
<td>Socioeconomic Dimension</td>
<td>0.753</td>
<td>0.247</td>
<td>0.262</td>
</tr>
<tr>
<td></td>
<td>(0.040)</td>
<td>(0.010)</td>
<td>(0.018)</td>
</tr>
<tr>
<td>Age-related Dimension</td>
<td>1.515</td>
<td>0.240</td>
<td>0.375</td>
</tr>
<tr>
<td></td>
<td>(0.052)</td>
<td>(0.014)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>SES × Age Interaction</td>
<td>-0.285</td>
<td>-0.011</td>
<td>-0.017</td>
</tr>
<tr>
<td></td>
<td>(0.051)</td>
<td>(0.013)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>Random Effect - State</td>
<td>2.152</td>
<td>0.126</td>
<td>0.079</td>
</tr>
<tr>
<td></td>
<td>(1.467)</td>
<td>(0.356)</td>
<td>(0.281)</td>
</tr>
<tr>
<td>Random Effect - Year</td>
<td>0.079</td>
<td>0.039</td>
<td>0.159</td>
</tr>
<tr>
<td></td>
<td>(0.282)</td>
<td>(0.199)</td>
<td>(0.398)</td>
</tr>
<tr>
<td>Random Effect - Residual</td>
<td>4.786</td>
<td>4.064</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6.913)</td>
<td>(2.016)</td>
<td></td>
</tr>
<tr>
<td>Log-likelihood</td>
<td>-134371.609</td>
<td>-99840.916</td>
<td>-11632.835</td>
</tr>
<tr>
<td>Deviance</td>
<td>268743.219</td>
<td>199681.833</td>
<td>23265.670</td>
</tr>
<tr>
<td>AIC</td>
<td>268757.219</td>
<td>199695.833</td>
<td>23277.670</td>
</tr>
<tr>
<td>BIC</td>
<td>268817.405</td>
<td>199757.144</td>
<td>23324.336</td>
</tr>
<tr>
<td>N</td>
<td>40055</td>
<td>47038</td>
<td>17637</td>
</tr>
</tbody>
</table>

for the interaction suggests that this effect is accelerated in the lower left quadrant and attenuated in the upper right. The same results are found when predicting party identification, measured on the standard seven-point scale, treated as a continuous variable.

The third column reports results for a logistic mixed-effects model, with an identical specification, except the dependent variable is a binary indicating whether the respondent voted for the Republican presidential candidate and not the Democratic presidential candidate; all other candidates’ supporters and nonvoters are omitted. The estimated coefficients evince the same pattern as in the other models.

To get a better idea of the substantive magnitude of these effects, Figure 3.8 plots
simulated predicted values from each of these models under four different scenarios: one in which a respondent falls at the first quartile value on both social dimensions ("low-low"), another in which a respondent falls at the first quartile on the socioeconomic dimension and the third quartile on the age-related dimension ("low-high"), and so on.\(^6\)

**Figure 3.8:** Distribution of predicted values for four hypothetical survey respondents, based on estimated coefficients and variance-covariance matrices from the models reported in Table 3.4. “Low” values are drawn from the first quartile of the distribution of social identity locations, “High” values are from the third quartile, on the first and second components, respectively.

In each case, an individual in the lower-left quadrant of the social space ("low-low") is predicted to have the most liberal ideology/strongest Democratic lean/lowest probability of voting for the Republican presidential candidate, while the “high-high” scenario produces the highest values on each dependent variable. Interestingly though, the 50 percentile shift in the age-related component produces a greater shift in evaluative ideology than does an analogous shift in socioeconomic status, while the opposite is true for predictions of party identification. These interquartile shifts

\(^6\) Note that these predicted values are based on the systematic error in each model. The stochastic error is large enough to obscure the apparent differences between scenarios.
have a nearly identical effect in determining the probability of voting Republican.

Now that it has been established that these latent social identity dimensions are related to politically-relevant variables in a consistent manner, it is of interest to gain a sense of where party identifiers are found in this space. Figure 3.9 represents one approach to assessing the density and centers of mass of respondents by partisanship.

![Party Identifier Locations in Social Space](image.png)

**Figure 3.9**: Regions indicating smallest contiguous area in which 50% of each parties' identifiers fall, intended to give a sense of the distribution of parties in a fairly diffuse social space. Over time, there is a decrease in the degree to which these regions overlap, reflecting increased polarization.

There is a great deal of overlap across party identifiers in social space. That is, Democrats, Independents, and Republicans can all be found across the spectrum of possible social identity coordinates. Thus, a simple scatterplot of all respondents, distinguished by party ID, is too cluttered to offer much useful information. Rather, it is more instructive to examine the densities of party identifiers in ideology space.
Figure 3.9, for a selected subset of ANES survey years, indicates the smallest-area contiguous regions in which 50% of Democratic, Independent, and Republican party identifiers fall.

In 1968, there was substantial overlap in social space across the three categories, but over time, we observe increasing separation in these highest-density regions, as Democrats shift down and left and Republicans shift up and to the right. To the extent these probability masses drift apart, the parties-in-the-electorate are polarizing in social space. Of course, we can get a more precise measure of this trend by using the SSIP approach, where instead of parties dividing an ideological space as before, they instead divide the social space. The time trend of polarization is shown in the left panel of Figure 3.10.

Figure 3.10: Two ways of representing party polarization in the social space. At left, the SSIP indicating an increasing trend since around 1970. At right, the same trend decomposed into its two constituent parts–mean distance between pairs of respondents between versus within the same party–suggesting that the main driver of polarization has been increasing distinction between the parties.

Whereas Chapter 1 concluded with the observation that subgroup partitionings of the ideological space were not polarizing, here we see evidence that partisan partitionings of the social space are indeed polarizing. As discussed in Chapter 1, po-
larization is a function of two separate components, intraparty homogeneity and interparty heterogeneity. The SSIP approach, used throughout this study, accounts for both of these factors by measuring the distance between pairs of individuals who share a party identification or group classification ("within") as well as the distance between pairs of individuals from different groups ("between"). The right panel of Figure 3.10 decomposes the SSIP trend into the two mean distance values that factor into its calculation. The plot highlights the stability of within-party variance over time as compared to a consistent increase in between-party differences since the beginning of the 1970s. When there is relative ideological consensus within each party and a great deal of disagreement between parties, as in 2008, we observe high levels of polarization.

It is worth noting that despite the clear positive trend over time, none of these SSIP values is far from zero. This is a function of the diffuse spread of partisans throughout the social space. Using an alternate specification, in which respondents are partitioned by their seven-point party identification (rather than three-point, as used throughout this study), SSIP is consistently greater, but still shows an increasing trend.

Additionally, by randomly permuting the vector of party identification, and re-assessing SSIP values, it is possible to generate a null distribution of random values against which to compare the true observed level of polarization. Taking this approach to significance testing, measured SSIP values are above the 85th percentile of the random distribution in every election year since 1980.

3.4 Summary and conclusion

The social landscape of the U.S. electorate has become more heterogeneous over the past half-century. The population has diversified – “types” of individuals who were once uncommon are now more commonly found in survey data. For example, there
has been an increase in the number of young white married Protestant women with advanced degrees earning high incomes working as professionals, while fewer of these women have a high school education and identify themselves as a homemaker. To the extent that parties and candidates for political office can be thought of as competing over social and demographic subgroups in the electorate, this shift suggests that the politicians’ optimization problem has become more complex. There are more important (i.e. large) subgroups with potentially widely varying policy and issue preferences.

This increasing social complexity does not imply political consequences unless there is a consistent link between social identity and ideology or partisanship. In Chapter 2, I showed that it is indeed not the case that having information about an individual’s social categorization allows us to reliably predict his or her ideology. In other words, the difference in ideology between two Protestants or between two Catholics is likely to be as large as the difference between a randomly selected Protestant-Catholic pair. Even for the one variable, race, which was once polarized, I find a decreasing trend in polarization, as within-group homogeneity has decreased relative to cross-group heterogeneity of ideological positions. Only affinative (as opposed to ascriptive) traits, such as party identification and presidential vote are becoming more polarized.

However, this approach, in which we examine social identity one-variable-at-a-time, is at once overly simple and too complicated. Overly simple because social identity is an inherently multidimensional construct, for which we should expect the interactions between dimensions to matter. Too complicated because there is substantial redundancy in the information contained even in nine ostensibly orthogonal nominal sociodemographic variables. In this chapter, I have proposed and explained a “Goldilocks” approach, in which I understand individuals in the electorate as occupying positions within a two-dimensional latent social space.
The idea of a social space has a long history in sociology, where it is used as a basis for discussions of homophily, discrimination, and cultural tastes. Here, I have explored the way political parties interact with and occupy this space, and the degree to which social position is predictive of partisanship (and vice-versa).

I find that respondent location on both of the first two principal components of the reduced social space is significantly predictive of ideology, partisanship, and presidential vote. Further, I find that when partitioned by party identification, individuals in the social space are becoming increasingly polarized: whereas the early part of the available ANES time series is essentially unpolarized, we now consistently observe significant levels of polarization, and have since the first Reagan administration.

The implications of these findings are several. First, as the results of this and the previous chapter suggest, there is some truth to both sides of the academic debate on polarization in public opinion. To a great extent, both in the present discourse and in the work of others, answers are very much a product of the way questions are asked and approached. I have attempted to be thorough and consider the problem from several angles, and have as a result found a nuanced answer to the question: political parties in the electorate are polarizing ideologically, but simple social categories are not. However, a comprehensive picture of society suggests that parties do operate in a social space, and are dividing it with increasing precision.

Second, an implication for microtargeting as a part of campaign strategy: demographic data on individuals in the electorate can be useful, even absent any additional information about issue positions or policy preferences. However, treating individuals simply as instances of the marginal categories into which they can be classified may result in the communication of unappealing or conflicting messages. Rather, it may be more useful to take advantage of any available information to make informed guesses about individuals’ positions within the social space, and adapt campaign
appeals to match.

Finally, the relatively greater heterogeneity of the Democratic coalition, and the relative concentration of Republican identifiers in the upper-right of the social space, may have implications for the adoption of asymmetric party strategies. To the extent that Republicans are more socially homogeneous, it may be cost-effective to focus on sending a single, clear message, and emphasize from the party’s center of gravity. To the extent that Democrats are more socially diffuse, but potentially more numerous, leadership may be required to broaden its appeal and encourage turnout around the edges of the party distribution in social space, not just from the center. The idea of different strategies being adopted by different types of parties is not a new one (see Laver, 2005), but merits further exploration.
Appendix A

A multi-party U.S. Congress

In contrast to the arrangement observed in the 111th Senate (Figure 1.5), party membership in the 34th House (Figure A.1) is a less certain determinant of ideology, as measured by DW-NOMINATE. Indeed, many members of each of the major parties are less proximate to the mass of their fellow partisans than that of their opponents. Further, the ideological variance within each faction is large relative to that observed in the 111th Senate, or even the Third Session of the French National Assembly (Figure 1.8). The 34th House served in 1855-57, and the party composition reflects the political upheaval of the time, in which the plurality of representatives were affiliated with an anti-slavery Opposition Party composed primarily of former Whigs, and the Republican Party had not yet been formally organized in the legislature.

Figure A.2 depicts the distributions of pairwise distances between co- and cross-partisan pairs. In contrast to the distributions found in the 111th Senate, we see much greater overlap between the two densities, jointly caused by greater spread in the distance between members of the same party and a relatively greater incidence of members of different parties holding similar positions in the ideological space. In
**Figure A.1:** First two dimensions of the Poole-Rosenthal DW-NOMINATE space for the 34th House. Party affiliation is indicated by initial: Democratic, American, Republican, and Opposition. The y-axis is compressed to reflect Poole’s suggested downweighting of the second dimension.

In this case, the mean distance between cross-partisan pairs is 0.656, and the average co-partisan distance is 0.335, resulting in an SSIP index value of 0.293.
Figure A.2: Empirical distribution of normalized distances between all pairs of Senators in DW-NOMINATE space, separated into co-partisan and cross-partisan pairs. The mean co-partisan distance is 0.335 (with a standard deviation of 0.208) and the mean cross-partisan distance is 0.656 (0.294), resulting in a spatial segregation estimate of 0.293
Appendix B

Bootstrapped estimates of electoral ideology

Figure 2.3 shows the identity space on which the rest of that chapter is based. That figure and subsequent analyses are based on point estimates of trait position in a latent space derived from principal component analysis of respondent thermometer evaluations.

PCA is based on an orthogonal singular value decomposition of the input matrix, and as such, is not associated with any estimation error. However, the input matrix of thermometer ratings is based on survey data, meaning that it is subject to sampling error. It is therefore of interest to make an effort to understand the influence this error has on the precision with which we can locate stimulus and respondent positions in latent space.

To do so, I adopt an approach similar to that recommended by Jacoby and Armstrong, II (2011). From the full matrix of respondent thermometer evaluations, I draw 1,000 bootstrap samples, on each of which I re-estimate a principal component analysis, and rotate the resultant configurations to ensure that the Republican Party is located in the upper-right quadrant, for consistency.
These bootstrap estimates produce a distribution around the initial point estimates of trait locations. Figure B.1 depicts stimulus locations in the first dimension of evaluative ideological space with the addition of 95% confidence regions around each point estimate. Table B.1 lists the bootstapped mean estimates and confidence bounds around those estimates in numerical form.
Table B.1: Means and confidence intervals around the mean estimates of thermometer stimulus locations in ideological space. Based on 1,000 bootstrap samples.

<table>
<thead>
<tr>
<th>Thermometer</th>
<th>Mean</th>
<th>Lower</th>
<th>Upper</th>
<th>Thermometer</th>
<th>Mean</th>
<th>Lower</th>
<th>Upper</th>
</tr>
</thead>
<tbody>
<tr>
<td>Democratic Party</td>
<td>-0.874</td>
<td>-0.893</td>
<td>-0.856</td>
<td>Perot</td>
<td>0.045</td>
<td>0.012</td>
<td>0.082</td>
</tr>
<tr>
<td>Clinton</td>
<td>-0.851</td>
<td>-0.870</td>
<td>-0.831</td>
<td>Young People</td>
<td>0.057</td>
<td>0.009</td>
<td>0.100</td>
</tr>
<tr>
<td>Hillary Clinton</td>
<td>-0.809</td>
<td>-0.827</td>
<td>-0.790</td>
<td>Congress</td>
<td>0.069</td>
<td>0.032</td>
<td>0.112</td>
</tr>
<tr>
<td>Kerry</td>
<td>-0.785</td>
<td>-0.843</td>
<td>-0.723</td>
<td>Elderly</td>
<td>0.101</td>
<td>0.066</td>
<td>0.136</td>
</tr>
<tr>
<td>Liberals</td>
<td>-0.745</td>
<td>-0.759</td>
<td>-0.726</td>
<td>Jews</td>
<td>0.106</td>
<td>0.069</td>
<td>0.145</td>
</tr>
<tr>
<td>Edwards</td>
<td>-0.742</td>
<td>-0.802</td>
<td>-0.691</td>
<td>Catholics</td>
<td>0.121</td>
<td>0.087</td>
<td>0.155</td>
</tr>
<tr>
<td>Gore</td>
<td>-0.699</td>
<td>-0.725</td>
<td>-0.673</td>
<td>Supreme Court</td>
<td>0.129</td>
<td>0.087</td>
<td>0.172</td>
</tr>
<tr>
<td>Obama</td>
<td>-0.689</td>
<td>-0.729</td>
<td>-0.647</td>
<td>Polit Independents</td>
<td>0.130</td>
<td>0.091</td>
<td>0.179</td>
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Figure B.1: Means and confidence intervals around the mean estimates of thermometer stimulus locations in ideological space. Based on 1,000 bootstrap samples.
Appendix C

Issue item scale question wording

• Some people are afraid the government in Washington is getting too powerful for the good of the country and the individual person. Others feel that the government in Washington is not getting too strong.

• Some people feel that the government in Washington should make every effort to improve the social and economic position of blacks. Others feel that the government should not make any special effort to help blacks because they should help themselves.

• Some people are primarily concerned with doing everything possible to protect the legal rights of those accused of committing crimes. Others feel that it is more important to stop criminal activity even at the risk of reducing the rights of the accused. Where would you place yourself on this scale, or haven’t you thought much about this?

• Recently there has been a lot of talk about women’s rights. Some people feel that women should have an equal role with men in running business, industry
and government. Others feel that a women’s place is in the home. And of course, some people have opinions somewhere in between.

- There has been some discussion about abortion during recent years. Which one of the opinions on this page best agrees with your view? You can just tell me the number of the opinion you choose.

- Some people think the government should provide fewer services, even in areas such as health and education, in order to reduce spending. Other people feel that it is important for the government to provide any more services even if it means an increase in spending. And of course, some other people have opinions somewhere in between.

- Some people think we need much tougher government regulations on business in order to protect the environment. Other think that current regulations to protect the environment are already too much of a burden on business. And, of course, some other people have opinions somewhere in between.

- Some people believe that we should spend much less money for defense. Others feel that defense spending should be greatly increased. And, of course, some other people have opinions somewhere in between.

- In the future, how willing should the United States be to use military force to solve international problems – extremely willing, very willing, somewhat willing, not very willing, or never willing?

- Now, I am going to read several statements. After each I would like you to tell me whether you agree strongly, agree somewhat, neither agree nor disagree, disagree somewhat or disagree strongly with this statement. You can just give me the number of your choice from the booklet. The first statement is....
– The newer lifestyles are contributing to the breakdown of our society.

– The world is always changing and we should adjust our view of moral behavior to those changes.

– This country would have many fewer problems if there were more emphasis on traditional family ties.

– We should be more tolerant of people who choose to live according to their own moral standards, even if they are very different from our own.
Appendix D

Confidence regions for the social space

Figure 3.5 shows the social space on which the rest of that chapter is based. That figure and subsequent analyses are based on point estimates of trait position in a latent space derived from principal component analysis of a logged odds ratio matrix of trait co-occurrence.

PCA is based on an orthogonal singular value decomposition of the input matrix, and as such, is not associated with any estimation error. However, the input LOR matrix is based on survey data on the similarities between social identity subgroups, some of which are uncommon in the ANES sample, and all of which are subject to sampling error. It is therefore of interest to make an effort to understand the influence this error has on the precision with which we can locate trait positions in latent space.

To do so, I adopt an approach similar to that recommended by Jacoby and Armstrong, II (2011). From the full matrix $X$ of respondent identity trait indicators, I draw 1,000 bootstrap samples, from each of which I construct an LOR matrix. From each of these matrices, I re-estimate a principal component analysis, and rotate the
resulant configurations to ensure that the highest income level is located in the upper-right quadrant. These bootstrap estimates produce a distribution around the initial point estimates of trait locations. Figure D.1 reproduces the social space with the addition of 95% confidence regions around each point estimate.

**Figure D.1:** Confidence regions for trait locations in a latent social space. Based on 1,000 bootstrap samples.

In general, there is little overlap between categories within each variable. The exceptions are in the location of Skilled workers and Laborers, those who have Never Married and those living in a domestic Partnership, and Native Americans and self-identified Other Race respondents. In each case, it is not certain that a different sample of respondents would produce the same ordinal ranking of the two categories in either dimension.
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Biography

David Bruce Sparks was born July 1, 1983 in Terre Haute, Indiana. He received his B.A. in Political Science and Economics from Vanderbilt University in 2006 and his Ph.D. in Political Science in 2012 from Duke University, where he was a James B. Duke Fellow and a Fellow in the Program for Advanced Research in the Social Sciences. David is married to Summar C. Sparks.