A Group-Based Approach to Measuring Polarization

Isaac D. Mehlhaff[*]

August 27, 2022

Abstract

Despite its growing importance in social scientific topics, the quantitative measurement of polarization has lagged behind its conceptual development. Political and social polarization are group-based phenomena characterized by intergroup heterogeneity and intragroup homogeneity, but existing measures capture only one of these features or make it difficult to compare across cases or over time. To bring the concept and measurement of polarization into closer alignment, I introduce the cluster-polarization coefficient (CPC), a measure of multimodality that allows scholars to incorporate multiple variables and compare across contexts with varying numbers of parties or social groups. Simulation exercises and applications to two datasets of elite ideological ideal points demonstrate that the CPC returns more substantively sensible results than other popular measures. An open-source software package implements the measure.

---

[*]The University of North Carolina at Chapel Hill; `mehlhaff@live.unc.edu`; word count: 9,429.

Polarization has become a key concept in the social sciences, playing a role in important political outcomes ranging from representation (Ahler and Broockman 2018) and party-building (Lupu 2015) to policymaking (Sinclair 2008) and democracy (McCoy and Somer 2019). Yet despite the proliferation of research on polarization, analysts often arrive at different conclusions with respect to its effect on key variables of interest, and they enthusiastically debate whether polarization is occurring at all (Abramowitz and Saunders 2008; DiMaggio, Evans, and Bryson 1996; Fiorina 2011). Conceptually, polarization has two important features: intergroup heterogeneity and intragroup homogeneity. But this theoretical foundation is rarely translated into empirical application, as the most common measures of polarization—difference-in-means and variance—are ill-suited to capture both features.

I offer an alternative. The cluster-polarization coefficient (CPC) explicitly models intergroup heterogeneity and intragroup homogeneity, placing polarization's conceptual foundation front and center. I apply the CPC to two datasets of elite ideological ideal points and evaluate its ability to discern polarization relative to difference-in-means and variance—the two most widely used measures of polarization. This analysis highlights three advantages of the CPC, one theoretical and two empirical: It better captures the theoretical concept, it displays greater flexibility when considering multiple variables, and it facilitates measurement of and comparison across cases that include more than two groups. Given that most party systems have more than two parties and most political conflict occurs along more than one dimension, the CPC provides a very useful tool for scholars studying polarization. I demonstrate these advantages with synthetic data and two datasets of ideology among political elites.

To make the measurement procedure widely accessible to researchers and practitioners, I provide an open-source R package, CPC: Implementation of Cluster-Polarization Coefficient, which is freely available on the Comprehensive R Archive Network (https://cran.r-project.org/package=CPC). In addition to calculating the CPC with researcher-specified group memberships, this package contains support for a variety of clustering methods to assign observations to groups, making the measure easily applicable to a wide variety of data structures.

Features of Polarization

Polarization is a phenomenon that happens both between and within groups, emerging when group members disagree with members of other groups and agree with members of their own. It thus has two conceptual features: distance from opponents (intergroup heterogeneity) and concentration within groups (intragroup homogeneity). The challenge for measuring polarization in real-world data is that these two features can occur separately, simultaneously, or not at all, and each may increase or decrease independent of the other. This challenge is reflected in the diversity of measures used by scholars. A survey of eight political science journals reveals 322 articles published about polarization since 2000,[1] employing at least twenty distinct operationalizations. However, two approaches account for most uses: Measures of difference-in-means and variance were used in 57% and 14% of articles, respectively.[2]

Disagreement—intergroup heterogeneity—is one critical feature of polarization. For instance, as parties' ideal points gradually approach opposite ends of a policy space, that party system becomes more polarized. The most popular measurement approach—difference-in-means—approximates distance by subtracting the ideological or policy positions of one party from another (Abramowitz and Saunders 2008; Hetherington 2001; McCarty, Poole, and Rosenthal 2009). However, this has the effect of data reduction—extremists get rolled into their parties' overall mean, perhaps leading to an estimate of polarization which is biased downward. Moreover, polarization is not merely an increase in distance between the extremes; it also implies some level of concentration around the emerging poles. There can be a wide distance between the two most extreme parties in a given party system but, if voters are evenly dispersed throughout the policy space, that party system may not be polarized. Below, I demonstrate why Levendusky and Pope (2011) urge scholars to "go beyond the mean" when measuring polarization.

Group concentration—intragroup homogeneity—is the second critical feature of polarization. As the ideal points of party members cluster more tightly together, each party becomes more

---

[1] See Supplementary Information section S1 for details and results of this search.
[2] Throughout this paper, "variance" refers to total variance, as opposed to within-group variance.

internally homogeneous, parties share less in common with each other, and the party system becomes more polarized. Crucially, polarization can increase in this manner even in the *absence* of increasing intergroup heterogeneity. Party sorting is one process through which this happens; individuals do not become more extreme but the population nevertheless polarizes due to individuals sorting themselves into parties with positions similar to their own (Levendusky and Pope 2011). As groups become more homogeneous, the amount of overlap between them decreases. Scholars frequently point to this group overlap as an important diagnostic of polarization (e.g. Han and Brady 2007; Levendusky and Pope 2011) and attempt to capture it using variance (Hill and Tausanovitch 2015; Lupu 2016) because it is "the most common measure of dispersion" and "does not depend on whether [data points] are clustered in distinct groups" (Lindqvist and Östling 2010, p. 546). While true, this operationalization seems at odds with the conceptual understanding of polarization, which emphasizes distinct clusters of opinions as one of the phenomenon's defining characteristics. Ideally, a measure of polarization would model those clustering properties directly instead of smoothing over them.[3]

To accurately capture polarization, both features are necessary. Without intergroup heterogeneity, there are no differences in position to analyze. Without intragroup homogeneity, there are no meaningful group positions to compare.[4] In this conceptualization, polarization can increase as the positions of social or political groups grow farther apart from one another, as they become more internally cohesive, or both. Many scholars either explicitly or implicitly adopt this conceptualization of polarization (Baldassarri and Bearman 2007; Fortunato and Stevenson 2021; Hill and Tausanovitch 2015; Maoz and Somer-Topcu 2010; Rehm and Reilly 2010), and the combina-

---

[3]Many public opinion researchers attempt to capture the concentration of survey responses by calculating the correlation between ideology and policy preferences (e.g. Abramowitz and Saunders 2008; Hetherington, Long, and Rudolph 2016). By contrast, I see correlations across issue positions as representations of issue constraint (Converse 1964). This may be a fine approximation of within-group variation, but individuals lack coherent ideologies even in polarized societies (Kinder and Kalmoe 2017) and simply showing high issue constraint does not necessarily imply the distance associated with polarization.

[4]The measure I propose below is designed to capture these two features. It may not be suitable for analysis of party system polarization (e.g. Dalton 2008), which affords fewer data points and places less emphasis on intragroup homogeneity.

tion of interparty conflict and intraparty homogeneity lays at the root of theories that explain how polarization develops (e.g. Aldrich and Rohde 2000).

In addition, only considering one feature has an impact on the substantive inferences one can draw. Abramowitz and Saunders (2008) and Fiorina, Abrams, and Pope (2008) engage in a prominent debate on the very existence of polarization in the American mass public, with both sets of scholars presenting compelling evidence. Abramowitz and Saunders use measures designed to capture intergroup heterogeneity to argue that the American public has polarized in recent years, while Fiorina, Abrams, and Pope incorporate other measures designed to capture intragroup homogeneity and conclude that the public has *not* polarized but has instead sorted itself by party Fiorina (see also 2011) and Levendusky and Pope (2011). Even if the public has not become more extreme, the party sorting process hypothesized by Fiorina, Levendusky, and others has nevertheless had a significant impact on American mass politics, resulting in polarization even in the supposed absence of increasing extremity.

To illustrate why both features are important and why difference-in-means and variance may paint an incomplete picture, consider the stylized distributions in Figure 1. They imitate four possible combinations of intergroup heterogeneity and intragroup homogeneity. The distribution in plot A has neither feature of polarization. Two clusters are faintly apparent, but they are close together and display little cohesion. Plot B has high intragroup homogeneity and low intergroup heterogeneity, and plot C has the reverse. The group means are the same in plot B as in plot A, but the groups are more concentrated. Intragroup homogeneity is the same in plot C as in plot A, but group means are further apart. Finally, plot D has high levels of both characteristics of polarization.

A measure correctly measuring polarization levels should indicate more polarization in plots B, C, and D relative to A and less polarization in plots A, B, and C, relative to D. Plot labels display the estimated level of polarization in each distribution as measured by difference-in-means, variance, and the CPC. In all cases, higher numbers indicate greater polarization.

Difference-in-means successfully distinguishes between plots A and C and between plots B and D, assigning a higher polarization estimate to the latter plot in each pairing, but it cannot distinguish
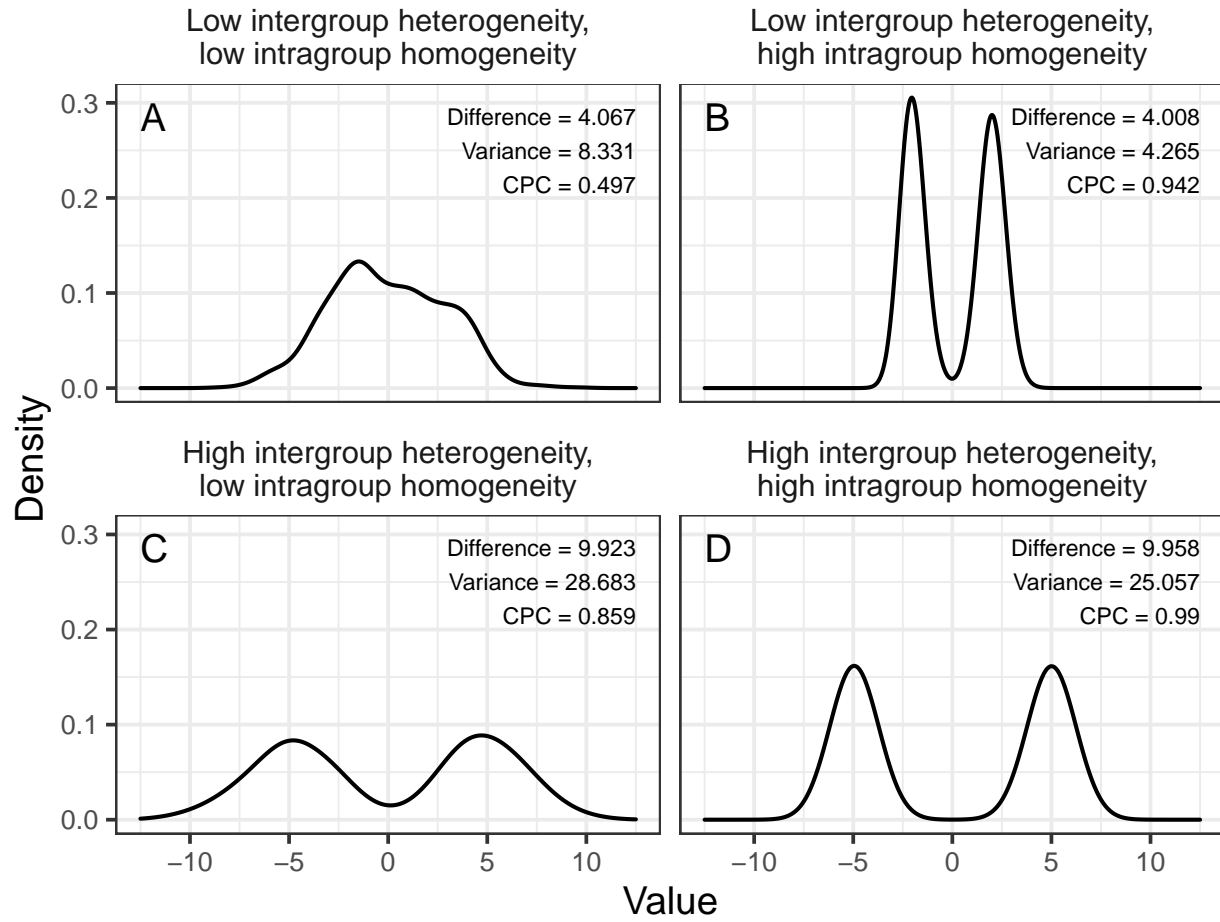
Figure 1: Stylized Distributions of Polarization Features. Simulated bimodal Gaussian mixture distributions all with $\mu_{global} = 0$. Labels show polarization levels according to difference-in-means, variance, and the CPC.

plot A from B nor plot C from D. It assigns identical polarization estimates to each distribution even though plots B and D are qualitatively more polarized than plots A and C, respectively. Variance performs even worse. It, too, distinguishes between plots A and C and between plots B and D, but cannot identify polarization vis-à-vis intragroup homogeneity. In fact, it assigns *lower* polarization estimates to plots B and D relative to plots A and C, a result opposite the conceptual understanding of polarization. This simple exercise suggests that using difference-in-means and variance may, in some cases, allow polarization to go undetected and, in others, identify it where it does not exist. The CPC is the only measure of the three that accurately mirrors the qualitative comparisons between all four distributions and captures both features of polarization.

6

Cluster-Polarization Coefficient

I begin from the premise that social scientific data—just like the distributions in Figure 1—are often comprised of distinct clusters of observations. In political contexts, such clusters are typically represented by parties or social groups. To derive the CPC, I decompose the total variance of this clustered data (*TSS*) in (1) into components corresponding to the two features of polarization: the variance accounted for between the clusters (*BSS*, corresponding to intergroup heterogeneity) and the variance accounted for within all clusters (*WSS*, corresponding to intragroup homogeneity). Dividing by *TSS* and solving for the *BSS* term in (1) gives an expression for the proportion of the total variance accounted for by the between-cluster variance—what I call the cluster-polarization coefficient. As it is a proportion, the value produced by this expression varies on the domain $[0,1]$.

$$TSS = BSS + WSS,$$

$$\rightarrow CPC = 1 - \frac{WSS}{TSS} = \frac{BSS}{TSS}. \tag{1}$$

More formally, the CPC takes the expression in (2), where each individual i in cluster k holds a position on dimension j, and n_i, n_j, and n_k denote the number of observations, dimensions, and clusters, respectively. Similarly, x signifies a data point and μ gives the mean of those data points.[5]

$$CPC = 1 - \frac{\sum_{k=1}^{n_k}\sum_{i=1}^{n_i}\sum_{j=1}^{n_j}(x_{ikj} - \mu_{kj})^2}{\sum_{i=1}^{n_i}\sum_{j=1}^{n_j}(x_{ij} - \mu_j)^2} = \frac{\sum_{k=1}^{n_k}\sum_{j=1}^{n_j}(\mu_{kj} - \mu_j)^2}{\sum_{i=1}^{n_i}\sum_{j=1}^{n_j}(x_{ij} - \mu_j)^2}. \tag{2}$$

Expressed in this way, the CPC appears related to a one-way ANOVA F-statistic and the coefficient of determination (R^2). These are useful similarities for exploring properties of the measure, which I do below. But first, one additional modification is needed to make the CPC appropriate for comparison across contexts with varying numbers of observations, variables, and clusters. This is critical because intra-state political dynamics, the number and nature of sociopolitical cleavages,

---

[5]Full derivations are shown in Supplementary Information section S2.1.

and the size and number of political coalitions typically vary across countries or within countries over time. The expression in (2) will be biased upward in small samples, so I incorporate corrections for lost degrees of freedom and express the adjusted CPC in (3):

$$CPC_{adj} = 1 - \frac{\frac{\sum_{k=1}^{n_k}\sum_{i=1}^{n_i}\sum_{j=1}^{n_j}(x_{ikj}-\mu_{kj})^2}{n_i-n_jn_k}}{\frac{\sum_{i=1}^{n_i}\sum_{j=1}^{n_j}(x_{ij}-\mu_j)^2}{n_i-n_j}} = 1 - (1-CPC)\frac{n_i-n_j}{n_i-n_jn_k}. \tag{3}$$

By explicitly modeling both BSS and WSS, the CPC takes into account both features of polarization. It increases when the distance between groups increases or when groups become more tightly concentrated around their collective ideal point, with the rate of those increases depending on the relative levels of BSS and WSS. All calculations in this paper use the adjusted CPC.

Distribution and Properties

Because the CPC is effectively a ratio of two variances, an F statistic can be calculated:[6]

$$F = \frac{\frac{BSS}{n_jn_k-n_j}}{\frac{WSS}{n_i-n_jn_k}} = \frac{n_i-n_jn_k}{n_jn_k-n_j}\frac{CPC}{1-CPC}, \tag{4}$$

where $BSS \sim \chi^2(n_jn_k - n_j)$ and $WSS \sim \chi^2(n_i - n_jn_k)$ under the null hypothesis that $BSS - WSS = 0$. F is therefore distributed as a central $F(n_jn_k - n_j, n_i - n_jn_k)$ random variable. Solving for the CPC term from (4) produces:

$$F = \frac{n_i-n_jn_k}{n_jn_k-n_j}\frac{CPC}{1-CPC},$$

$$\rightarrow CPC = \frac{(n_jn_k-n_j)F}{(n_i-n_jn_k)+(n_jn_k-n_j)F}, \tag{5}$$

---

[6]This set-up and the proofs which follow are similar to the derivation of a sampling distribution for R^2 (Magee 1990). Full derivations are shown in Supplementary Information section S2.2-S2.4.

implying that $CPC \sim \text{Beta}\left(\frac{n_j n_k - n_j}{2}, \frac{n_i - n_j n_k}{2}\right)$ under the null—a sensible result given that the CPC and the Beta distribution both have continuous support on the $[0, 1]$ interval. From this distribution, it is straightforward to recover the mean:

$$E(CPC) = \frac{\frac{n_j n_k - n_j}{2}}{\frac{n_j n_k - n_j}{2} + \frac{n_i - n_j n_k}{2}} = \frac{n_j n_k - n_j}{n_i - n_j}. \tag{6}$$

The unadjusted CPC is therefore asymptotically unbiased, again under the null hypothesis that $BSS - WSS = 0$, as $\lim_{n_i \to \infty} E(CPC) = 0$. However, it will be biased upward in finite samples, and the degree of that bias will depend on both the number of dimensions and number of clusters, underscoring the need for the degrees-of-freedom corrections shown above. Taking advantage of the expression in (6) reveals that the *adjusted* CPC is, in fact, an unbiased estimator under the null:

$$E(CPC_{adj}) = E\left[1 - (1 - CPC)\frac{n_i - n_j}{n_i - n_j n_k}\right] = 0. \tag{7}$$

The variance of the CPC can also be recovered from its sampling distribution:

$$\text{Var}(CPC) = \frac{\frac{n_j n_k - n_j}{2} \frac{n_i - n_j n_k}{2}}{\left(\frac{n_j n_k - n_j}{2} + \frac{n_i - n_j n_k}{2}\right)^2 \left(\frac{n_j n_k - n_j}{2} + \frac{n_i - n_j n_k}{2} + 1\right)} = \frac{2(n_j n_k - n_j)(n_i - n_j n_k)}{(n_i - n_j)^2 (n_i - n_j + 1)}. \tag{8}$$

Using (8), the variance of the adjusted CPC is therefore:

$$\text{Var}(CPC_{adj}) = \text{Var}\left[1 - (1 - CPC)\frac{n_i - n_j}{n_i - n_j n_k}\right] = \frac{2(n_j n_k - n_j)}{(n_i - n_j n_k)(n_i - n_j + 1)}, \tag{9}$$

implying that the adjusted CPC is consistent, as $\lim_{n_i \to \infty} \text{Var}(CPC_{adj}) = 0$. Supplementary Information section S2.5 presents additional properties of the measure.

Simulation Evidence

Set-Up

In this section, I present evidence for the efficacy of the CPC by simulating both univariate and bivariate data using Gaussian mixture distributions. The purpose of this simulation exercise is to evaluate—in a controlled environment—the extent to which the CPC captures the two features of polarization, and whether it does so better than existing measures. Gaussian mixtures are uniquely suited for this purpose because they provide a straightforward method for mimicking distributional polarization. Each component of a Gaussian mixture is parameterized by a location parameter μ and scale parameter σ, which neatly correspond to the two features of polarization: intergroup heterogeneity and intragroup homogeneity, respectively.

Figure 2 presents a visualization of this intuition. This figure displays kernel density plots for simulated univariate data with two components. The plots are arranged such that the least polarized distributions fall at the top left and the most polarized distributions fall at the bottom right, and component parameters are provided by the plot labels along the top and right axes. Consider what happens to these component parameters as we move from a less polarized to a more polarized distribution. Moving from left to right across the rows of the facet plot, for example, the distributions become more polarized as the difference between component means increases and the components grow farther apart. Likewise, moving from top to bottom along the columns of the facet plot, the distributions become more polarized as component standard deviations decrease and the components grow more compact.

By manipulating these component parameters, therefore, I can generate mixture distributions with varying levels of polarization and estimate those levels using the CPC and other existing measures. I focus here on comparing the CPC to the two most popular strategies for measuring polarization in the political science literature: difference-in-means. To identify the accuracy of each polarization measure, I examine the intergroup heterogeneity and intragroup homogeneity
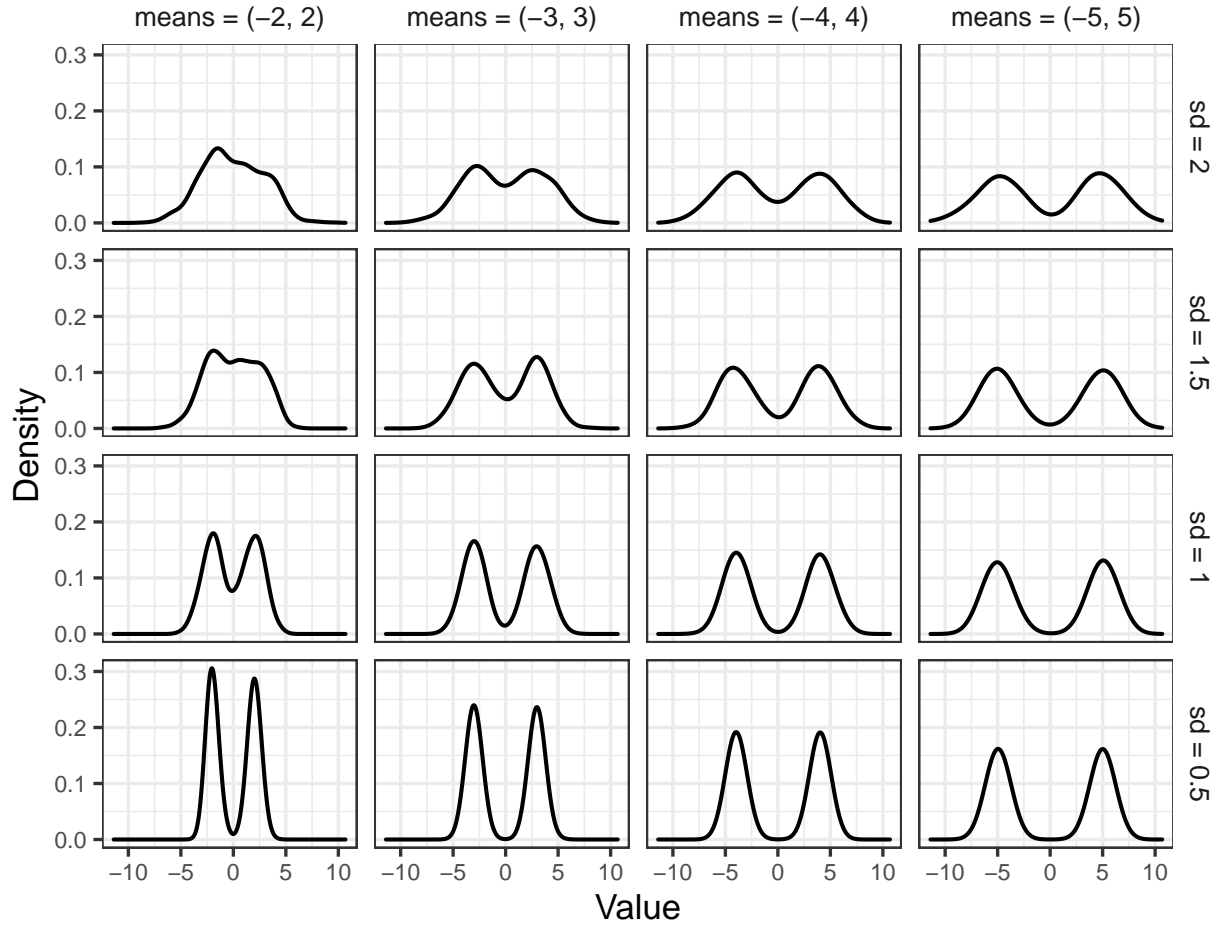
Figure 2: Visualization of Simulation Set-Up. Simulated Gaussian mixture distributions with $\mu_{global} = 0$; rows represent diverging means with standard deviations held constant and columns represent decreasing standard deviations with means held constant; thus, the least polarized distributions appear at top left and the most polarized distributions appear at bottom right.

features separately. To simulate polarization as a result of increasing intergroup heterogeneity, I

execute a four-step simulation exercise:

1. Fix component standard deviations at a range of values $\sigma \in \{0.5, 1, 1.5, 2\}$.[7] For identifica-

    tion, I use the same σ for each component and maintain a global mean of zero.

2. For each component standard deviation σ, select 1,000 values of μ as independent draws

    from $U(2, 5)$.

---

[7]As seen in Figure 2, even this relatively short range of values is sufficient to generate distributions ranging from
unimodal to distinctly bimodal.

3. Take 1,000 independent draws from a Gaussian mixture parameterized by $N(-\mu, \sigma; \mu, \sigma)$.

4. Apply each polarization measure to the resulting distribution.

The result of this procedure is 1,000 distributions, each with $N = 1000$, with which to evaluate the performance of each polarization measure. To simulate polarization as a result of increasing intragroup homogeneity, I execute a similar four-step simulation exercise:

1. Fix component means at a range of values $\mu \in \{2, 3, 4, 5\}$.[8] For identification, I use the same absolute value of μ for each component and maintain a global mean of zero.

2. For each component mean μ, select 1,000 values of σ as independent draws from $U(0.5, 2)$.

3. Take 1,000 independent draws from a Gaussian mixture parameterized by $N(-\mu, \sigma; \mu, \sigma)$.

4. Apply each polarization measure to the resulting distribution.

The result of this procedure is 1,000 distributions, each with $N = 1000$, with which to evaluate the performance of each polarization measure. For identification, I use equal component weights across all simulated distributions.[9]

Using these simulation frameworks, I evaluate the performance of the adjusted CPC relative to difference and variance in both univariate and bivariate contexts.[10] Pursuant to the two definitional characteristics of polarization, an appropriate measure should indicate higher polarization when the distance between component means increases or when the standard deviation of each component decreases. Because polarization can occur around more than two poles, especially in multiparty systems, I conduct these procedures for distributions with two, three, and four components.[11] For all simulations, I calculate the adjusted CPC using true group memberships, which are known from

---

[8]Again, as seen in Figure 2, even this relatively short range of values is sufficient to generate distributions ranging from unimodal to distinctly bimodal.

[9]Additional simulations in Supplementary Information section S3.3 investigate how the CPC changes in response to varying component weights.

[10]For bivariate data, I calculate difference by taking the average Euclidean distance between all component means, and I calculate variance using the sum of squared Euclidean distances.

[11]For three and four components, I calculate the difference score by taking the average distance between all component means.

the data randomization procedure. By using true group memberships instead of estimating them using a clustering algorithm, we can be sure that any advantages or disadvantages uncovered in the simulation results are attributable to the CPC itself and not to a clustering method being well- or ill-suited to this particular data structure.

Results

I evaluate each simulated distribution using all three measures and present the results in two ways. First, Figures 3 and 4 present the raw polarization estimates as a function of the randomized parameters for two-component simulations with univariate and bivariate data, respectively.[12] All measures are scaled to $[0,1]$ to enable comparison and plotted using locally estimated scatterplot smoothing (LOESS). A measure performing in line with theoretical expectations would register a positive slope in plot (a) and a negative slope in plot (b). However, the magnitude of those slopes and the absolute level of estimated polarization should differ depending on the fixed parameter. For example, the sets of distributions with fixed $\sigma = 0.5$ or fixed $\mu = (-5, 5)$ are more polarized on average than the distributions with a greater fixed σ or fixed μ parameters that are closer to-gether. As a result, polarization estimates should generally be higher for those distributions and less sensitive to the value of the randomized parameter.

The results presented in Figures 3 and 4 generally align with expectations. Looking first at plot (a), slopes for difference, variance, and the adjusted CPC carry the expected sign. The magnitude of the difference and variance slopes, however, is relatively constant regardless of the fixed param-eter, and the absolute level of estimated polarization appears similar. For example, with random component means of $(-5, 5)$ at the far right hand side of each facet, difference and variance output almost identical polarization estimates regardless of whether component standard deviations are 0.5, 2, or anywhere in between. The CPC, on the other hand, appears more sensitive to those fixed

---

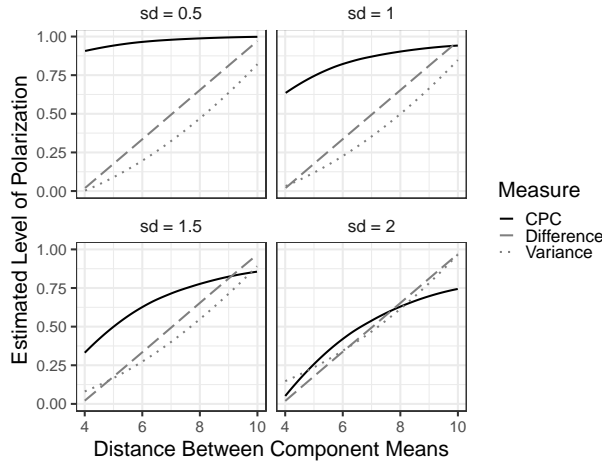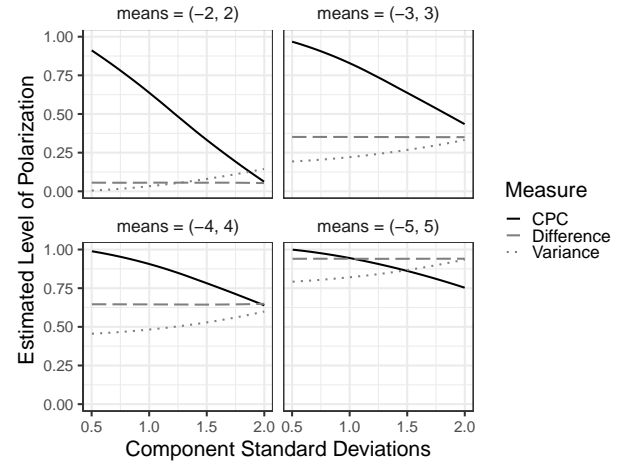[12]Supplementary Information section S3.1 contains results of three- and four-component simulations.

(a) Random μ (intergroup heterogeneity)   (b) Random σ (intragroup homogeneity)

Figure 3: Univariate Polarization Estimates with Two Components. Results from univariate simulations of polarization measures with two components, showing estimated level of polarization for a randomly varying distribution parameter, holding the other parameter constant. All measures scaled to $[0, 1]$ to enable comparison and plotted using LOESS.

(a) Random μ (intergroup heterogeneity)   (b) Random σ (intragroup homogeneity)

Figure 4: Bivariate Polarization Estimates with Two Components. Results from bivariate simulations of polarization measures with two components, showing estimated level of polarization for a randomly varying distribution parameter, holding the other parameter constant. All measures scaled to $[0, 1]$ to enable comparison and plotted using LOESS.
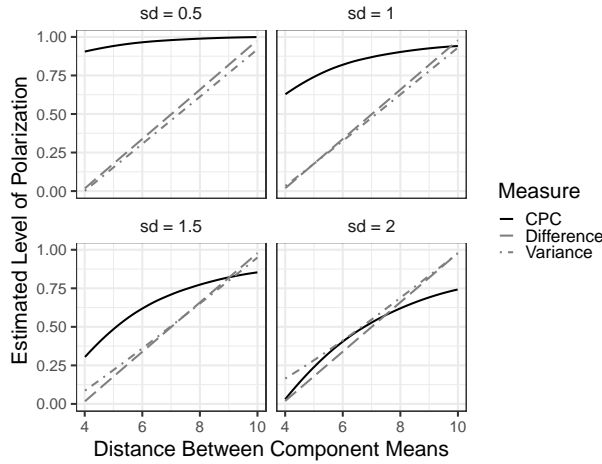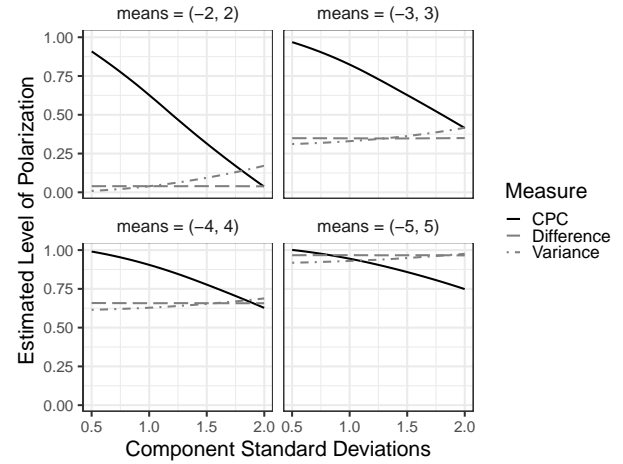
parameters and displays intercepts and slope magnitudes more in line with expectations.[13] The insensitivity of difference and variance to component standard deviations can be seen more clearly in plot (b). While the adjusted CPC again performs as expected, difference and variance appear as nearly flat lines, although they do output higher polarization estimates when the difference between fixed component means grows larger.

Understanding how raw polarization estimates track with distributional characteristics is valuable, but it complicates a formal evaluation of a measure's effectiveness because the estimated level of polarization (the output of each measure) and the parameters controlling the simulated level of polarization (standard deviation or distance between means) are different quantities and are on different scales. Moreover, we do not have information about the "true" level of distributional polarization—estimating such quantities is the very goal of this measurement approach.[14]

By holding all other distributional characteristics constant and randomly varying only component means and standard deviations, however, we do have information about each distribution's level of polarization *relative* to every other distribution. For example, the simulation to assess the intergroup heterogeneity feature holds standard deviations constant and randomly varies component means. Randomly generated means that are further apart will generate a distribution that is, in theory, more polarized. The result of the simulation, then, is 1,000 distributions that randomly vary in their level of polarization, and those relative levels of polarization can be identified by the relative value of the random component means. I therefore follow the approach taken by Lupu, Selios, and Warner (2017) and use the estimated polarization from each measure to rank order the distributions and compare those rankings to the true rank order recovered from the randomized parameters, with a higher rank indicating a greater level of polarization.[15]

---

[13]At extremely high levels of polarization (e.g. $\sigma = 0.5$), however, the CPC is likewise relatively insensitive to increasing the distance between component means. This may not be a desirable property if the intended use is to measure polarization when groups are extremely concentrated around their ideal point.

[14]Supplementary Information section S4 pursues another strategy for procuring "ground-truth" polarization estimates: using human coders to evaluate relative polarization levels.

[15]One downside to this rank order approach is that it coerces all polarization measurements to an evenly spaced scale, thereby requiring an assumption of cardinality. However, when considered in conjunction with Figures 3 and 4, I believe the benefit from evaluating the magnitude of error introduced by each measure is greater than the cost imposed by this assumption.

		Univariate			Bivariate		
		Difference	Variance	CPC	Difference	Variance	CPC
			$k = 2$				
RMSE	Intergroup Heterogeneity	**14.67**	15.38	30.73	**10.59**	11.05	22
	Intragroup Homogeneity	406.65	572.36	**24.01**	406.15	569.16	**16.79**
	Overall	287.73	404.87	**27.58**	287.29	402.53	**19.57**
MAE	Intergroup Heterogeneity	**10.73**	11.2	23.84	**7.68**	7.9	17.16
	Intragroup Homogeneity	335.05	496.49	**17.54**	334.47	494.54	**12.28**
	Overall	172.89	253.84	**20.69**	171.07	251.22	**14.72**
			$k = 3$				
RMSE	Intergroup Heterogeneity	17.7	**19.03**	32.33	16.39	**12.48**	21.91
	Intragroup Homogeneity	400.4	573.84	**25.41**	409.82	570.81	**18.08**
	Overall	283.4	405.99	**29.07**	290.02	403.72	**20.08**
MAE	Intergroup Heterogeneity	**12.88**	13.64	25.13	11.99	**8.99**	17.12
	Intragroup Homogeneity	329.82	497.46	**18.41**	338.37	495.52	**13.27**
	Overall	171.35	255.55	**21.77**	175.18	252.26	**15.2**
			$k = 4$				
RMSE	Intergroup Heterogeneity	**10.22**	10.39	103.02	15.17	**11.4**	21.81
	Intragroup Homogeneity	403.64	567.64	**21.5**	433.29	569.87	**17.35**
	Overall	285.51	401.45	**25.5**	306.57	403.04	**19.71**
MAE	Intergroup Heterogeneity	**7.44**	7.54	22.38	11	**8.15**	16.91
	Intragroup Homogeneity	332.94	493.01	**15.91**	361.31	494.82	**12.73**
	Overall	170.19	250.27	**19.15**	186.16	251.49	**14.82**

Table 1: Error of Distribution Rankings in Simulation. Root mean squared error and mean absolute error calculated for univariate and bivariate simulations with two, three, and four components; bolded values denote measure with lowest error in each category.

Table 1 reports the root mean squared error and mean absolute error for all three measures across all simulations. Bolded values represent the best-performing measure in each category. Examining these results, a clear pattern emerges. Difference and variance register the lowest error rates on the intergroup heterogeneity feature, regardless of the number of variables or components. This makes intuitive sense; holding the standard deviations of a mixture distribution constant and pulling the component means in opposite directions should, by definition, result in wider differences between means and higher variance for the distribution as a whole. The CPC performs as expected on both features and often improves slightly in higher dimensions and multimodal distributions, which enables comparison across a wider variety of contexts.

Finally, although it is necessary to examine each feature in isolation, real-world data rarely holds one feature constant while manipulating the other. When looking at each measure's respective overall performance, the CPC appears to perform best regardless of the number of variables or components, and often by a drastic margin.[16] As seen in Table 1, this performance gain appears to come from the CPC performing only slightly worse on the intergroup heterogeneity feature but dramatically better on the intragroup homogeneity feature.

The Supplementary Information contains three additional validation exercises using synthetic data. In section S3.2, I use heavy-tailed log-normal distributions to show that the CPC can be sensitive to outliers, but that scaling the data before applying the measure can ameliorate this problem. In section S3.3, I show that the CPC is relatively insensitive to changes in polarization when the difference in component weights is very high. However, it still performs better than difference-in-means and variance. Finally, in section S4, I benchmark each measure's performance against "ground-truth" data gathered from human annotators. The CPC consistently captures both features of polarization better than difference-in-means and variance, and it adheres more closely to intuitive identifications of polarization.

Applications: Ideology of Political Elites

In addition to a close fit with the conceptual understanding of polarization, the CPC proves valuable when studying multiple dimensions of contestation or comparing across cases with more than two groups. I use two datasets of elite ideological ideal points to illustrate these benefits. First, I engage the well-researched connection between congressional polarization and income inequality in the United States, showing that the CPC is the only measure of polarization that recovers this connection in multidimensional data. Next, I turn to a set of six industrially developed, consolidated democracies, taking on the methodological puzzle of how to measure polarization in multi-party systems and compare across systems with different numbers of parties or groups.

---

[16]Overall performance is calculated by simply combining results from the intergroup heterogeneity and intragroup homogeneity simulations and calculating error statistics over the entire body of evidence.

Throughout both applications, I compare the CPC to difference-in-means and variance, the two most popular strategies for measuring polarization in the political science literature.

Polarization in the United States Congress

I calculate congressional polarization using DW-NOMINATE data (Lewis et al. 2021), which uses a scaling procedure to estimate the ideology of individual legislators in a two-dimensional latent space. The first dimension generally captures economic issues and the second captures racial and other social issues. The presence of two dimensions enables me to show how the CPC can extract theoretically sensible polarization estimates from multiple variables at once, an exercise that can undermine the performance of difference-in-means and variance.

To establish the CPC's construct validity, I show that it produces estimates consistent with well-known historical patterns. Historians and political scientists frequently point to three periods of ideological change in Congress. These periods are shaded on Figure 5. First, distinct partisan divides emerged as the Democratic Party made its comeback following the end of Reconstruction (Theriault 2008). During this "Gilded Age" around the turn of the twentieth century, the parties fiercely debated fiscal policy and foreign affairs strategy (Azari and Hetherington 2016; Brady and Han 2006). Second, party convergence and high levels of bipartisanship characterized the "Textbook Congress" in the mid-twentieth century (Fenno 1965; Shepsle 1989). Finally, consistently high levels of polarization are well-documented in the lead-up to the twenty-first century and extending to the present (Hill and Tausanovitch 2015; Theriault 2006), with the partisan chasm in the House of Representatives especially widening upon Newt Gingrich's rise through the leadership ranks in the 1990s (Mason 2018; Rosenfeld 2018).

Each measure should therefore indicate high polarization in the first time period, low polarization in the second period, and high polarization again in the third. Measures should reveal similar trends whether they are examining only the first dimension or incorporating both dimensions. Many polarizing events in these time periods had social issues at their root, such as the racial tensions surrounding Reconstruction or the Southern strategy that pushed the Republican

Party to the right following the civil rights movement. Even economic issues—which are captured by the first dimension—are often racialized in the United States (Gilens 1999), implying that the two dimensions are often linked in practice.
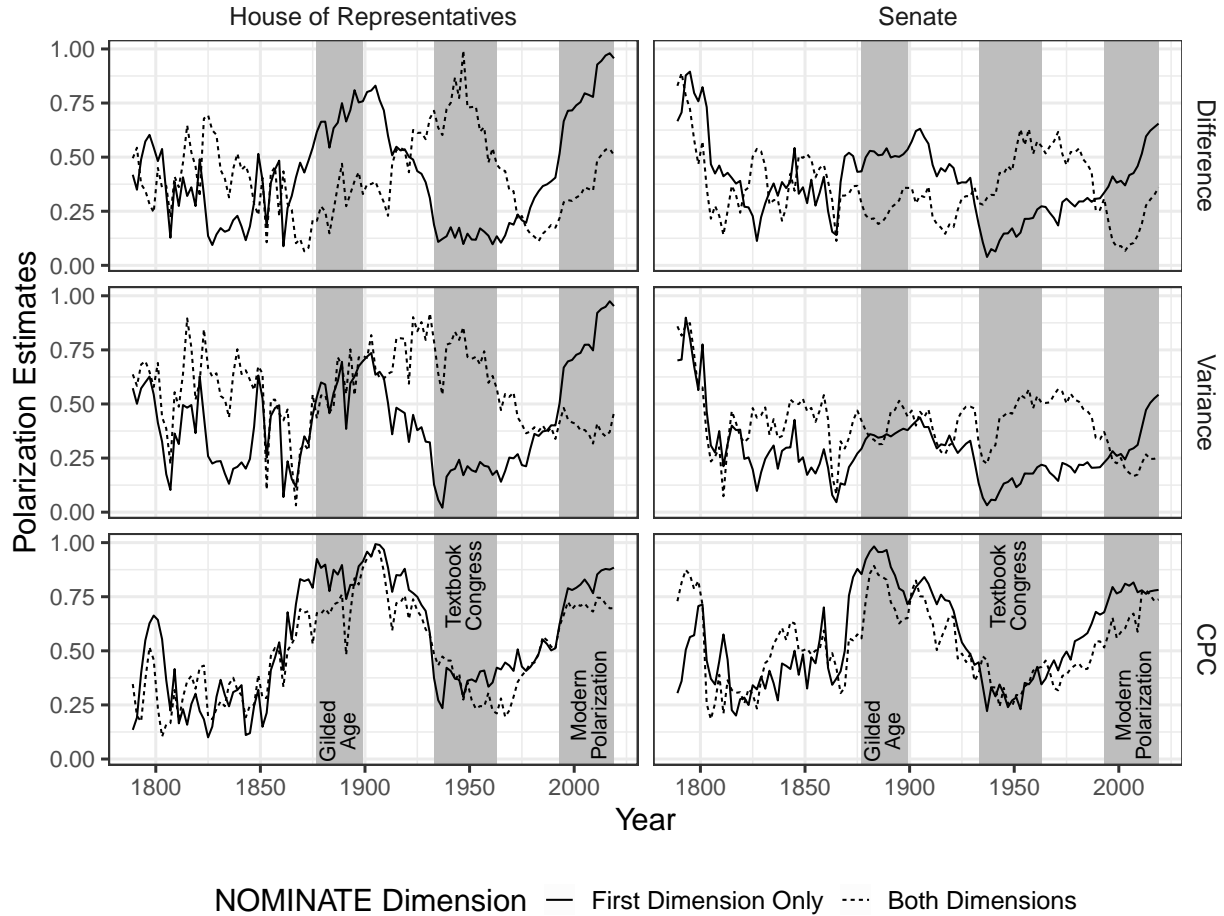

Figure 5: Estimates of Congressional Polarization. Calculated using NOMINATE ideological estimates; each measure scaled to $[0, 1]$ to enable comparison.

For each Congress, I estimate the level of polarization in DW-NOMINATE scores using difference-in-means, variance, and the CPC. These estimates appear in Figure 5. All measures generally capture the expected trends in the first NOMINATE dimension. Adding the second dimension, however, leads difference-in-means and variance to return trends that do not match the historical record.[17] For example, difference-in-means estimates detect increasing polarization in the modern

---

[17]I calculate difference-in-means by taking the average Euclidean distance between group means, and I calculate variance using the sum of squared Euclidean distances from the means.

period, but they also indicate that Congress experienced some of its most polarized years during the Textbook Congress. Variance estimates make similar indications, and they even find flat or declining polarization levels leading up to the present-day. In contrast, the CPC handles the addition of the second dimension well and recovers trends that reflect the historical record in each period.

To examine whether the accuracy of different measures might lead researchers to different substantive conclusions, I turn to the connection between congressional polarization and economic inequality. As inequality and polarization in the United States have coevolved over the last few decades, scholars have contributed to an influential literature positing a link between the two (Barber and McCarty 2015; Bonica et al. 2015; Stewart, McCarty, and Bryson 2020). McCarty, Poole, and Rosenthal (2016) argue that rising inequality since the 1970s has tracked closely with polarization at both the elite and mass levels, and other scholars suggest this relationship may extend to other contexts. Gelman (2009) and Rehm (2011) provide evidence at the level of individual party identification and voting behavior, Garand (2010) contends that similar dynamics work at the state level, and several comparative studies argue that inequality is strongly associated with polarization cross-nationally (Grechyna 2016; Gunderson 2022; Pontusson and Rueda 2008). Assuming these previous works have accurately identified an association between economic inequality and polarization, measures of congressional polarization should correlate strongly with measures of inequality.

The CPC performs well on this test, while the other measures lag behind. Figure 6 plots each measure's estimates of congressional polarization against the Gini coefficient of household income during the corresponding Congress (Atkinson et al. 2017). The first column of plots uses difference-in-means, the second column variance, and the third the CPC. A steep, positive slope for both the House of Representatives and Senate would indicate that a polarization measure is performing well.

The top row of Figure 6 shows that all measures recover positive correlations when using one dimension. The CPC, in particular, is strongly correlated with inequality. However, the bottom row of Figure 6 clearly indicates that difference-in-means and variance struggle after adding the second
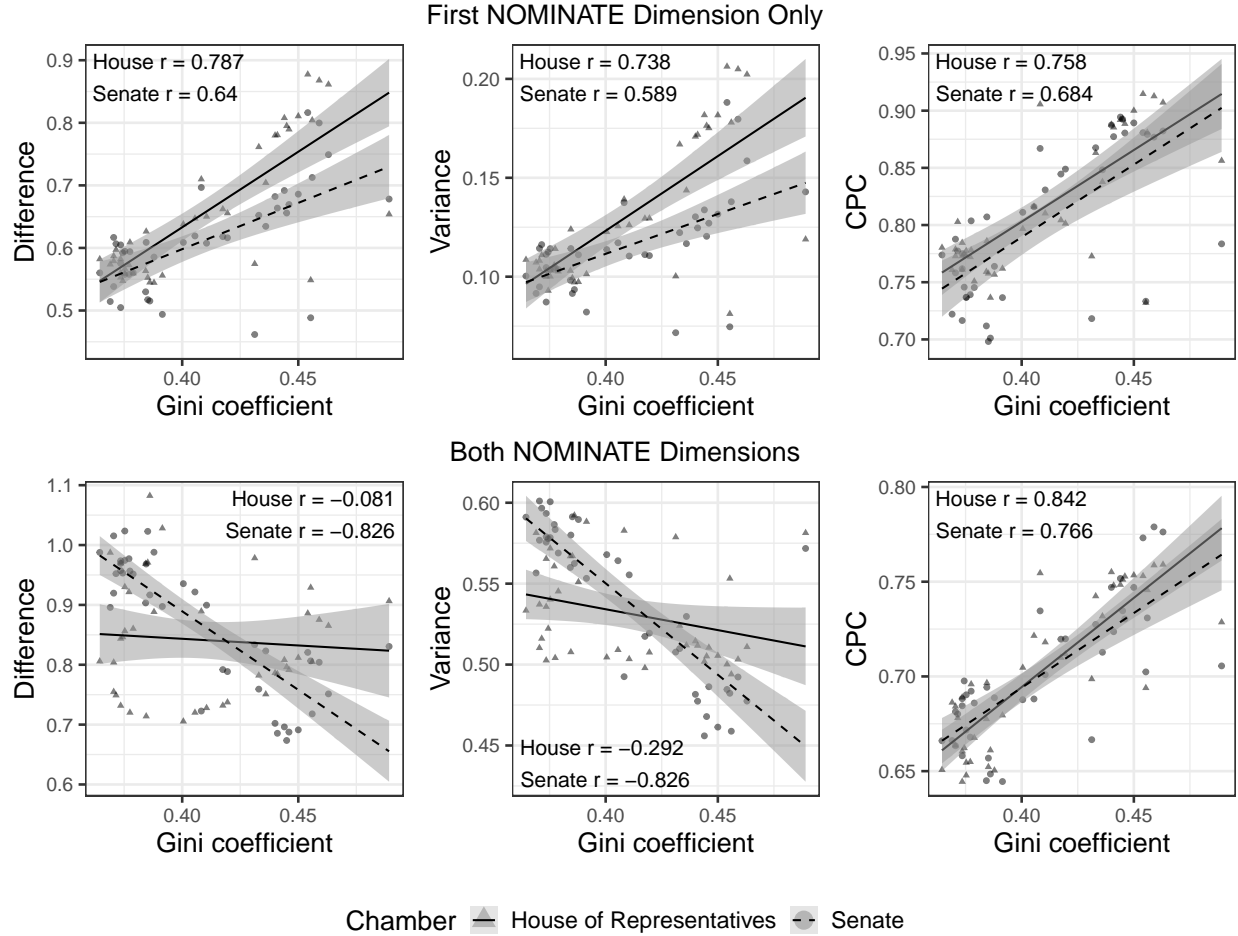
Figure 6: Correlations Between Adjusted CPC and Economic Inequality Within Chambers and Across Congresses 65-114. Polarization calculated using NOMINATE ideological estimates. Shaded areas represent 95% confidence intervals. Results of models generating lines-of-best-fit shown in Supplementary Information section S5.

ideological dimension. All correlations between polarization and inequality are now negative. In the case of difference-in-means and variance, results differ drastically across chambers. The CPC is the only measure of the three that maintains a positive correlation after adding the second dimension of ideology, and the correlations in both chambers even increase in magnitude compared to the one-dimensional case.[18]

---

[18]Including the second dimension should still result in high correlations for two reasons. First, immigration is an important mechanism linking polarization to inequality (McCarty, Poole, and Rosenthal 2016). Second, redistributive issues in the United States are often racialized (Gilens 1999). If the second dimension captures attitudes toward race and immigration, polarization on that dimension should still track closely with inequality.

This underscores an important benefit of the CPC. Aldrich, Montgomery, and Sparks (2014) show that high-dimensional estimates are crucial for accurate ideal point estimation, especially in polarized contexts. Researchers using current measures may need to ignore higher-dimensional information as a pragmatic matter, but the CPC allows it to be preserved, resulting in more accurate polarization estimates.

## Polarization in Multi-Party Systems

One common challenge confronted by scholars is how to measure polarization in multi-party systems (Gidron, Adams, and Horne 2020; Reiljan 2020; Ward and Tavits 2019)—an obstacle that applies to most modern democracies. To demonstrate how the CPC captures polarization across contexts with different numbers of groups, I turn to elite ideological ideal points from six countries in Western Europe and North America (Barberá 2015). These countries differ in the extent to which their latent elite groups are internally homogeneous and externally heterogeneous, and even in how many groups exist within each country. These differences can be seen in Figure 7, plot (a). For instance, some countries—like the United States and Germany—exhibit two parties or ideological coalitions, while Spain and the Netherlands have three. Even comparing across countries with the same number of coalitions reveals substantial variation in the size and strength of each. In the United States, the two parties are of roughly equal size and are tightly concentrated around their midpoints. In contrast, Germany's left-most coalition is small but homogeneous while its right-most coalition is large but more heterogeneous. Taking all this variation into account and enabling comparison across diverse cases is a challenging task for most measures of polarization, but the CPC offers a solution.

Figure 7, plot (b) displays the degree to which each measure suggests the party systems are polarized.[19] The CPC is shown in the leftmost facet, and countries are ordered by their estimated level of polarization. CPC estimates indicate that Spain, the United Kingdom, the Netherlands,

---

[19]The CPC and difference-in-means measures require knowledge of the cluster to which each observation belongs, so I perform k-means clustering with the number of clusters in each country implied by Figure 7, plot (a). For example, Germany has two clusters, Spain has three, and so on.
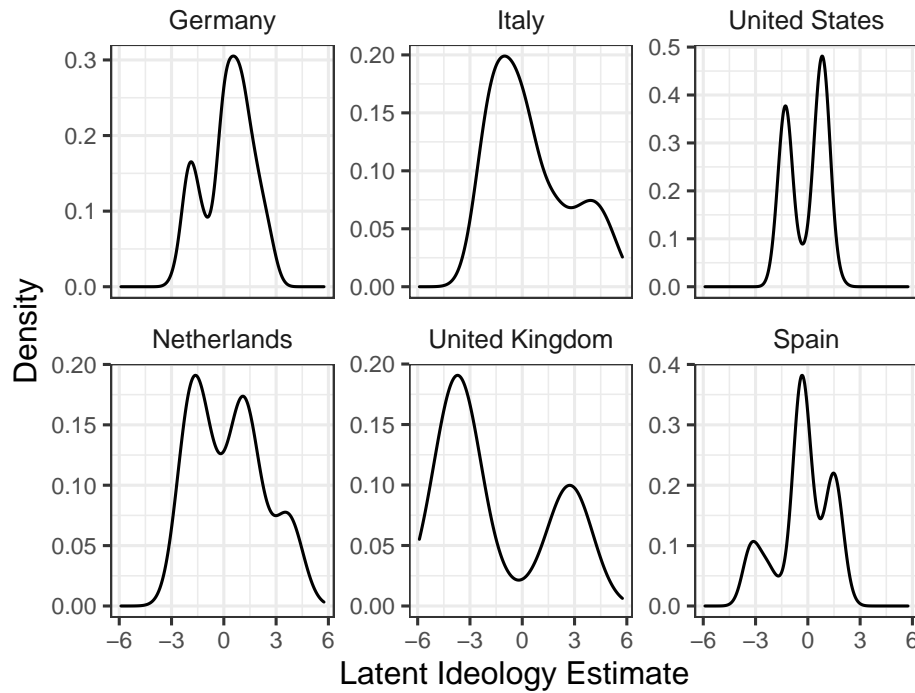
(a) Kernel density plots of ideal points
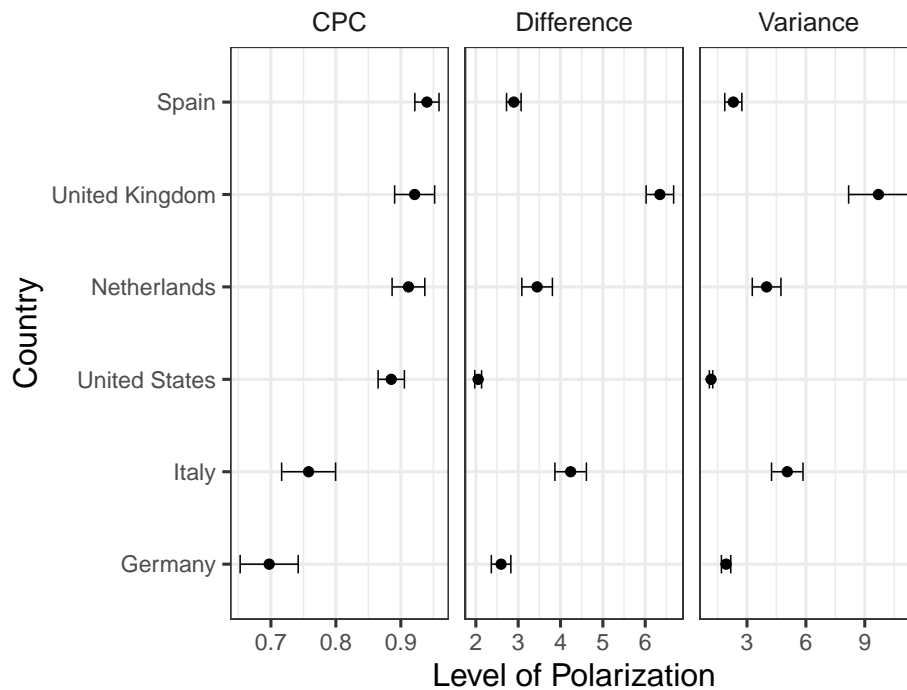
(b) Ideological polarization estimates

Figure 7: Estimates of Polarization in Elite Twitter Data. Plot (a) presents kernel density estimates for each country, with facets ordered by level of polarization. Plot (b) presents polarization estimates with 95% confidence intervals, calculated using a case-resampling bootstrap and again ordered by level of polarization estimated by the CPC. Supplementary Information section S6 presents the polarization estimates and standard errors shown in plot (b).

and the United States have similar, relatively high levels of polarization, while Germany and Italy are significantly less polarized. The distributions in Figure 7, plot (a) seem to support such a conclusion if one considers polarization as a function of both intergroup heterogeneity and intragroup homogeneity. The United Kingdom and the Netherlands have high intergroup heterogeneity, the United States has high intragroup homogeneity, and Spain has a fair amount of both. Italy and Germany both have two identifiable modes, but their intragroup homogeneity is so low and their minor-party coalitions so small in relation to their major-party coalitions that their consequent levels of polarization are not appreciable.

These results also correspond with contemporaneous political events. At the time of data collection, Spain was enduring vigorous debate over austerity measures in the wake of the Euro crisis (Miley 2017), the United Kingdom was beginning down the path toward Brexit (Hobolt, Leeper, and Tilley 2021), and the Netherlands was navigating growing tensions surrounding immigration and ethnic integration (Oosterwaal and Torenvlied 2010). Germany, on the other hand, was enjoying its third grand coalition since the mid-2000s (Voigt 2019), and this legislative cooperation is reflected in its low level of elite polarization as measured by the CPC.

Difference-in-means and variance—shown in the center and right facets in Figure 7, plot (b)— tell very different stories that are often at odds with the visual representation of the data. They suggest that the United States is the least polarized, despite a distribution that displays perhaps the highest intragroup homogeneity of the six countries. Italy is the second-most polarized according to these measures, despite a nearly unimodal distribution of ideal points. In sum, current measures of polarization frequently fail to return sensible estimates because they cannot account for both intergroup heterogeneity and intragroup homogeneity, they struggle in more than one dimension, or they are not comparable across distributions with varying numbers of groups.

Conclusion

Polarization is a critical concept in a wide variety of social scientific phenomena, yet efforts to quantify it fail to capture its two core conceptual elements: intergroup heterogeneity and intragroup homogeneity. The cluster-polarization coefficient takes both features into account, more closely aligning concept and measure and producing more sensible estimates of polarization in important contexts.

Critically, the CPC enables comparison over time and space. Political systems and attitudes—and thus the polarization of those systems and attitudes—are multidimensional (Bermeo 2003), yet scholars often restrict their analysis to a single left-right dimension. However, the CPC can accommodate numerous variables, allowing polarization estimates to accurately reflect the character of contestation in a political system. Equally important is the CPC's ability to compare across systems with different numbers of parties and groups. Multi-party systems are common outside the United States, but scholars often ignore this contextual feature either by calculating the variance of the entire distribution (Ward and Tavits 2019) or by converting party systems into a series of dyads and measuring polarization as if they were two-party systems (Gidron, Adams, and Horne 2020). The CPC, on the other hand, is explicitly designed to measure polarization in such contexts.

Though difference-in-means and variance are the most widely used measures in political science and related fields, the measure perhaps most similar to the CPC is that of Esteban and Ray (1994), which has been used most frequently in economics and ethnic studies. However, Clark (2009) shows that this measure is not much different from variance, with correlations as high as 0.933. Maoz and Somer-Topcu (2010) further argue that it is based on arbitrary assumptions, such as a small number of groups, and is very highly correlated with the number of groups and the size of each group. The CPC is conceptually simpler than Esteban and Ray's measure, and the adjusted CPC, in particular, is explicitly developed to correct for these types of issues.

I focused my demonstrations on elite ideological ideal points, but elites are not the only political actors who display polarization. The CPC can be used to aid measurement in a wide variety of

substantive applications. Existing work that could benefit from employing the CPC includes stud-ies of polarization in mass attitudes (DiMaggio, Evans, and Bryson 1996), affective polarization (Wagner 2021), racial polarization (Jardina and Ollerenshaw 2022), economic polarization (Dwyer 2013), and religious polarization (Ribberink, Achterberg, and Houtman 2018). Because the CPC is ultimately a measure of multimodality, it can also be used to gain information about other quan-tities of interest. One example is conditional party government, which mirrors the two-feature definition of polarization by emphasizing the degree of preference homogeneity *within* parties and the degree of preference conflict *between* parties (Aldrich 2011; Rohde 1991). Studies building on the conditional party government theory have utilized a wide range of measures to capture a holistic picture of its implications, but a summary measure similar to what the CPC provides has remained elusive. By introducing the CPC and providing an open-source software package to simplify its implementation, I aim to advance the critical study of polarization's causes and consequences.

References

Abramowitz, Alan I. and Kyle L. Saunders (Apr. 2008). "Is Polarization a Myth?" In: *The Journal of Politics* 70.2, pp. 542–555.

Ahler, Douglas J. and David E. Broockman (Oct. 2018). "The Delegate Paradox: Why Polarized Politicians Can Represent Citizens Best". In: *The Journal of Politics* 80.4, pp. 1117–1133.

Aldrich, John H. (2011). *Why Parties? The Origin and Transformation of Political Parties in America*. 2nd ed. Chicago: The University of Chicago Press.

Aldrich, John H., Jacob M. Montgomery, and David B. Sparks (Oct. 2014). "Polarization and Ideology: Partisan Sources of Low Dimensionality in Scaled Roll Call Analyses". In: *Political Analysis* 22.4, pp. 435–456.

Aldrich, John H. and David W. Rohde (Feb. 2000). "The Republican Revolution and the House Appropriations Committee". In: *The Journal of Politics* 62.1, pp. 1–33.

Atkinson, Anthony B. et al. (2017). *The Chartbook of Economic Inequality*. URL: `https://www.chartbookofeconomicinequality.com`.

Azari, Julia and Marc J. Hetherington (Sept. 2016). "Back to the Future? What the Politics of the Late Nineteenth Century Can Tell Us about the 2016 Election". In: *The ANNALS of the American Academy of Political and Social Science* 667.1, pp. 92–109.

Baldassarri, Delia and Peter Bearman (Oct. 2007). "Dynamics of Political Polarization". In: *American Sociological Review* 72.5, pp. 784–811.

Barber, Michael J. and Nolan McCarty (2015). "Causes and Consequences of Polarization". In: *Solutions to Political Polarization in America*. Ed. by Nathaniel Persily. New York: Cambridge University Press, pp. 15–58.

Barberá, Pablo (2015). "Birds of the Same Feather Tweet Together: Bayesian Ideal Point Estimation Using Twitter Data". In: *Political Analysis* 23.1, pp. 76–91.

Bermeo, Nancy (2003). *Ordinary People in Extraordinary Times: The Citizenry and the Breakdown of Democracy*. Princeton, NJ: Princeton University Press.

Bonica, Adam et al. (2015). "Congressional Polarization and Its Connection to Income Inequality: An Update". In: *American Gridlock: The Sources, Character, and Impact of Political Polarization*. Ed. by James A. Thurber and Antoine Yoshinaka. New York: Cambridge University Press, pp. 357–377.

Brady, David W. and Hahrie C. Han (2006). "Polarization Then and Now: A Historical Perspective". In: *Red and Blue Nation? Characteristics and Causes of America's Polarized Politics*. Ed. by Pietro S. Nivola and David W. Brady. Vol. 1. Baltimore: Brookings Institution Press, pp. 119–174.

Clark, Tom S. (Mar. 2009). "Measuring Ideological Polarization on the United States Supreme Court". In: *Political Research Quarterly* 62.1, pp. 146–157.

Converse, Philip E. (1964). "The Nature of Belief Systems in Mass Publics". In: *Ideology and Discontent*. Ed. by David E. Apter. New York: The Free Press of Glencoe, pp. 206–261.

Dalton, Russell J. (July 2008). "The Quantity and the Quality of Party Systems: Party System Polarization, Its Measurement, and Its Consequences". In: *Comparative Political Studies* 41.7, pp. 899–920.

DiMaggio, Paul, John Evans, and Bethany Bryson (Nov. 1996). "Have American's Social Attitudes Become More Polarized?" In: *American Journal of Sociology* 102.3, pp. 690–755.

Dwyer, Rachel E. (June 2013). "The Care Economy? Gender, Economic Restructuring, and Job Polarization in the U.S. Labor Market". In: *American Sociological Review* 78.3, pp. 390–416.

Esteban, Joan-María and Debraj Ray (July 1994). "On the Measurement of Polarization". In: *Econometrica* 62.4, pp. 819–851.

Fenno, Richard F. (1965). "The Internal Distribution of Influence: The House". In: *The Congress and America's Future*. Ed. by David B. Truman. Englewood Cliffs, NJ: Prentice-Hall, pp. 52–76.

Fiorina, Morris P. (2011). *Culture War? The Myth of a Polarized America*. In collab. with Samuel J. Abrams and Jeremy C. Pope. 3rd ed. London: Pearson.

Fiorina, Morris P., Samuel A. Abrams, and Jeremy C. Pope (Apr. 2008). "Polarization in the American Public: Misconceptions and Misreadings". In: *The Journal of Politics* 70.2, pp. 556–560.

Fortunato, David and Randolph T. Stevenson (May 2021). "Party Government and Political Information". In: *Legislative Studies Quarterly* 46.2, pp. 251–295.

Garand, James C. (Oct. 2010). "Income Inequality, Party Polarization, and Roll-Call Voting in the U.S. Senate". In: *The Journal of Politics* 72.4, pp. 1109–1128.

Gelman, Andrew (2009). *Red State, Blue State, Rich State, Poor State: Why Americans Vote the Way They Do*. 2nd ed. Princeton, NJ: Princeton University Press.

Gidron, Noam, James Adams, and Will Horne (2020). *American Affective Polarization in Comparative Perspective*. New York: Cambridge University Press.

Gilens, Martin (1999). *Why Americans Hate Welfare: Race, Media, and the Politics of Antipoverty Policy*. Chicago: The University of Chicago Press.

Grechyna, Daryna (July 2016). "On the Determinants of Political Polarization". In: *Economics Letters* 144, pp. 10–14.

Gunderson, Jacob R. (July 2022). "When Does Income Inequality Cause Polarization?" In: *British Journal of Political Science* 52.3, pp. 1315–1332.

Han, Hahrie and David W. Brady (July 2007). "A Delayed Return to Historical Norms: Congressional Party Polarization after the Second World War". In: *British Journal of Political Science* 37.3, pp. 505–531.

Hetherington, Marc J. (Sept. 2001). "Resurgent Mass Partisanship: The Role of Elite Polarization". In: *American Political Science Review* 95.3, pp. 619–631.

Hetherington, Marc J., Meri T. Long, and Thomas J. Rudolph (2016). "Revisiting the Myth: New Evidence of a Polarized Electorate". In: *Public Opinion Quarterly* 80.S1, pp. 321–350.

Hill, Seth J. and Chris Tausanovitch (Oct. 2015). "A Disconnect in Representation? Comparison of Trends in Congressional and Public Polarization". In: *The Journal of Politics* 77.4, pp. 1058–1075.

Hobolt, Sara B., Thomas J. Leeper, and James Tilley (Oct. 2021). "Divided by the Vote: Affective Polarization in the Wake of the Brexit Referendum". In: *British Journal of Political Science* 51.4, pp. 1476–1493.

Jardina, Ashley and Trent Ollerenshaw (Aug. 2022). "The Polarization of White Racial Attitudes and Support for Racial Equality in the US". In: *Public Opinion Quarterly* 86.S1, pp. 576–587.

Kinder, Donald R. and Nathan P. Kalmoe (2017). *Neither Liberal nor Conservative: Ideological Innocence in the American Public*. Chicago: The University of Chicago Press.

Levendusky, Matthew S. and Jeremy C. Pope (Sum. 2011). "Red States vs. Blue States: Going Beyond the Mean". In: *Public Opinion Quarterly* 75.2, pp. 227–248.

Lewis, Jeffrey B. et al. (2021). *Voteview: Congressional Roll-Call Votes*. URL: https://voteview.com/.

Lindqvist, Erik and Robert Östling (Aug. 2010). "Political Polarization and the Size of Government". In: *American Political Science Review* 104.3, pp. 543–565.

Lupu, Noam (June 2015). "Party Polarization and Mass Partisanship: A Comparative Perspective".
In: *Political Behavior* 37.2, pp. 331–356.

— (2016). *Party Brands in Crisis: Partisanship, Brand Dilution, and the Breakdown of Political
Parties in Latin America*. New York: Cambridge University Press.

Lupu, Noam, Lucía Selios, and Zach Warner (Jan. 2017). "A New Measure of Congruence: The
Earth Mover's Distance". In: *Political Analysis* 25.1, pp. 95–113.

Magee, Lonnie (Aug. 1990). "R2 Measures Based on Wald and Likelihood Ratio Joint Significance
Tests". In: *The American Statistician* 44.3, pp. 250–253.

Maoz, Zeev and Zeynep Somer-Topcu (Oct. 2010). "Political Polarization and Cabinet Stability
in Multiparty Systems: A Social Networks Analysis of European Parliaments, 1945–98". In:
British Journal of Political Science 40.4, pp. 805–833.

Mason, Lilliana (2018). *Uncivil Agreement: How Politics Became Our Identity*. Chicago: The Uni-
versity of Chicago Press.

McCarty, Nolan, Keith T. Poole, and Howard Rosenthal (July 2009). "Does Gerrymandering Cause
Polarization?" In: *American Journal of Political Science* 53.3, pp. 666–680.

— (2016). *Polarized America: The Dance of Ideology and Unequal Riches*. 2nd ed. Cambridge,
MA: The MIT Press.

McCoy, Jennifer and Murat Somer (Jan. 2019). "Toward a Theory of Pernicious Polarization and
How It Harms Democracies: Comparative Evidence and Possible Remedies". In: *The ANNALS
of the American Academy of Political and Social Science* 681.1, pp. 234–271.

Miley, Thomas Jeffrey (Apr. 2017). "Austerity Politics and Constitutional Crisis in Spain". In:
European Politics and Society 18.2, pp. 263–283.

Oosterwaal, Annemarije and René Torenvlied (Mar. 2010). "Politics Divided from Society? Three
Explanations for Trends in Societal and Political Polarisation in the Netherlands". In: *West
European Politics* 33.2, pp. 258–279.

Pontusson, Jonas and David Rueda (2008). "Inequality as a Source of Political Polarization: A
Comparative Analysis of Twelve OECD Countries". In: *Democracy, Inequality, and Represen-*

tation in Comparative Perspective. Ed. by Pablo Beramendi and Christopher J. Anderson. New York: Russell Sage Foundation, pp. 312–353.

Rehm, Philipp (Apr. 2011). "Risk Inequality and the Polarized American Electorate". In: *British Journal of Political Science* 41.2, pp. 363–387.

Rehm, Philipp and Timothy Reilly (Mar. 2010). "United We Stand: Constituency Homogeneity and Comparative Party Polarization". In: *Electoral Studies* 29.1, pp. 40–53.

Reiljan, Andres (May 2020). ""Fear and Loathing across Party Lines" (Also) in Europe: Affective Polarisation in European Party Systems". In: *European Journal of Political Research* 59.2, pp. 376–396.

Ribberink, Egbert, Peter Achterberg, and Dick Houtman (May 2018). "Religious Polarization: Contesting Religion in Secularized Western European Countries". In: *Journal of Contemporary Religion* 33.2, pp. 209–227.

Rohde, David W. (1991). *Parties and Leaders in the Postreform House*. Chicago: The University of Chicago Press.

Rosenfeld, Sam (2018). *The Polarizers: Postwar Architects of Our Partisan Era*. Chicago: The University of Chicago Press.

Shepsle, Kenneth A. (1989). "The Changing Textbook Congress". In: *Can the Government Govern?* Ed. by John E. Chubb and Paul E. Peterson. Washington, DC: Brookings Institution Press.

Sinclair, Barbara (2008). "Spoiling the Sausages? How a Polarized Congress Deliberates and Legislates". In: *Red and Blue Nation? Characteristics and Causes of America's Polarized Politics*. Ed. by Pietro S. Nivola and David W. Brady. Vol. 2. Washington, DC: Brookings Institution Press, pp. 55–87.

Stewart, Alexander J., Nolan McCarty, and Joanna J. Bryson (Dec. 2020). "Polarization under Rising Inequality and Economic Decline". In: *Science Advances* 6.

Theriault, Sean M. (July 2006). "Party Polarization in the US Congress: Member Replacement and Member Adaptation". In: *Party Politics* 12.4, pp. 483–503.

— (2008). *Party Polarization in Congress*. New York: Cambridge University Press.

Voigt, Linda (July 2019). "Get the Party Started: The Social Policy of the Grand Coalition 2013–2017". In: *Germany Politics* 28.3, pp. 426–443.

Wagner, Markus (Feb. 2021). "Affective Polarization in Multiparty Systems". In: *Electoral Studies* 69.

Ward, Dalston G. and Margit Tavits (Aug. 2019). "How Partisan Affect Shapes Citizens' Perception of the Political World". In: *Electoral Studies* 60, pp. 1–9.