Online Appendix

Party Competition and Coalitional Stability: Evidence from American Local Government

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A Data and Measurement

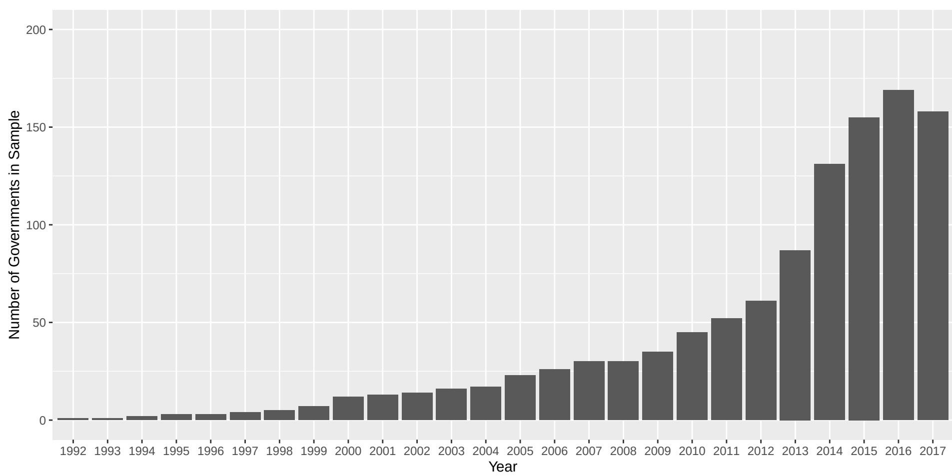
A.1 Descriptive Statistics and Features of the Sample

Table A1: Summary Statistics for Cities and Counties in Sample

Statistic	N	Median	Mean	St. Dev.	Min	Max
Population	151	75,180	336,223.10	895,848.10	4,958	8,175,133
Percent Urban	151	1.00	0.94	0.15	0.15	1.00
Percent Non-Hispanic White	151	0.64	0.60	0.21	0.12	0.96
Percent Black	151	0.08	0.13	0.14	0.005	0.64
Percent Hispanic	151	0.12	0.18	0.16	0.01	0.75
Median Rent	151	885	927.00	249.82	526	2,001
Percent HS Grads	151	0.87	0.87	0.07	0.60	0.99
Median HH Income	151	50,285	55,550.56	19,137.16	26,734	131,723
Percent HH Poverty	151	0.13	0.13	0.06	0.03	0.37
2008 Dem. Vote Share	151	57.81	57.96	15.90	22.91	94.57
Local Ideology	121	−0.10	−0.11	0.34	−1.00	0.61

Figure A1 shows the total number of cities and counties in my sample using Legistar over time. As the trend shows, most of the cities and counties using the platform adopted it in the past few years, and so I restrict the sample to this period (2012 onward) to ensure that I am comparing a similar set of local governments during a time span when most were using the service.

Figure A1: Total Number of Councils in Full Legistar Sample by Year



A.2 Baseline Factors Affecting Measurement

Figure A2 shows the relationship between the log total number of votes included in the scaling model and the resulting APRE for the model. Regardless of the council size, we see a modest negative relationship between these two measures, such that the scaling model does not fit as well in councils with a high number of votes. Similarly, Figure A3 shows the distribution of APRE for councils that are of a similar size. While there is considerable variation within each of these groups, the median APRE decreases with the size of the council. While this may be a function of council size making it easier or harder to come to a consensus, it also is likely reflective of the fact that in small councils, there are simply fewer potential orderings of ideal points possible, which means the model should improve fit. As a result, I account for both of these measurement-related factors throughout the analysis.

In addition, there is also a concern that minority votes may mean different things in different contexts. In particular, there is an issue of scale, such that a single nay vote in a 7 member council, for example, may be very different than a single nay vote in a 50 member council. To account for this imbalance, I use a relatively high 'lop' parameter when conducting the scaling. Specifically, I only include contested votes in which 1 in 10 members voted in the minority. Altering this parameter, however, to be more consistent with studies of large chambers—typically closer to 1 in 40—does not change the results (see Figure A6 in Appendix C.3).

Figure A2: Relationship between the APRE Statistic and Log Total Contested Votes

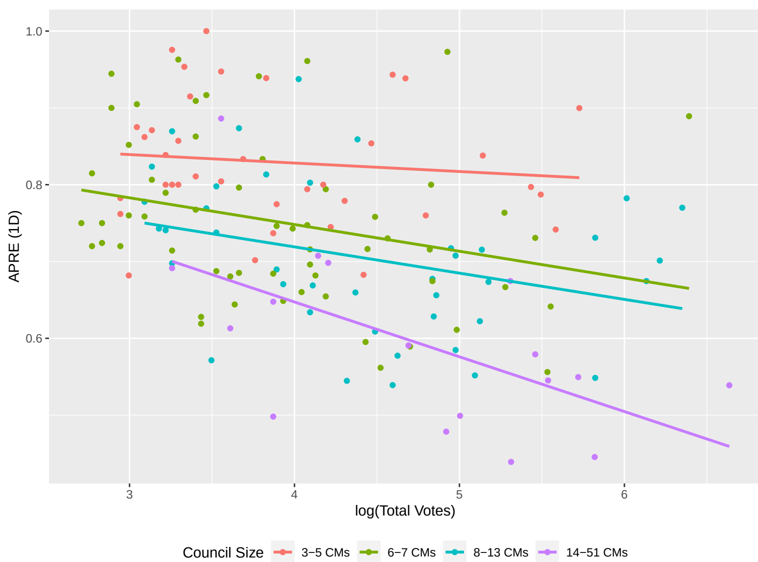
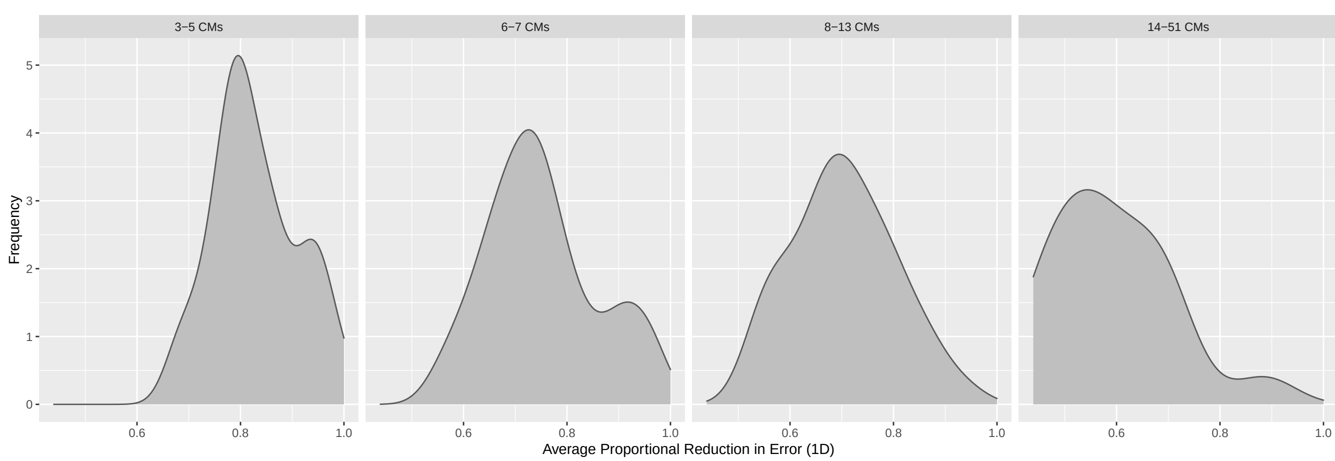


Figure A3: Distribution of the APRE Statistic by Council Size Groups



A.3 Full List of Partisan Cities and Counties

Table A2: Partisan Cities and Counties Ordered by Imbalance in Local Presidential Voting

City/County	State	APRE (1D)	Imbalance in Local Presidential Voting	2008 Obama Vote Share	Population
Gulfport	MS	0.76	0.00	49.99	67,793
Jackson County	MO	0.94	0.01	49.42	674,158
Hattiesburg	MS	0.94	0.11	55.60	45,989
Louisville	KY	0.65	0.12	56.06	741,096
Sedgwick County	KS	0.94	0.13	43.52	498,365
Harrisonburg	VA	0.98	0.16	58.05	48,914
Allegheny County	PA	0.89	0.16	57.81	1,223,348
Albemarle County	VA	0.71	0.18	59.15	98,970
Ashe County	NC	0.91	0.24	38.10	27,281
Gaston County	NC	0.94	0.25	37.41	206,086
Harrison County	MS	0.80	0.26	36.91	187,105
Charlotte	NC	0.54	0.31	65.31	731,424
Laurel	MS	0.66	0.32	65.85	18,540
Rutherford County	NC	0.94	0.32	33.94	67,810
St Charles	LA	0.55	0.32	34.12	52,780
Annapolis	MD	0.63	0.37	68.37	38,394
Allentown	PA	0.72	0.46	72.86	118,032
Walton County	FL	0.68	0.46	26.83	55,043
Pittsburgh	PA	0.72	0.52	76.21	305,704
New York City	NY	0.70	0.60	80.13	8,175,133
Ann Arbor	MI	0.73	0.66	82.86	113,934
Philadelphia	PA	0.69	0.67	83.56	1,526,006
Prince Georges County	MD	0.58	0.79	89.54	863,420
Washington, DC	DC	0.61	0.87	93.40	601,723

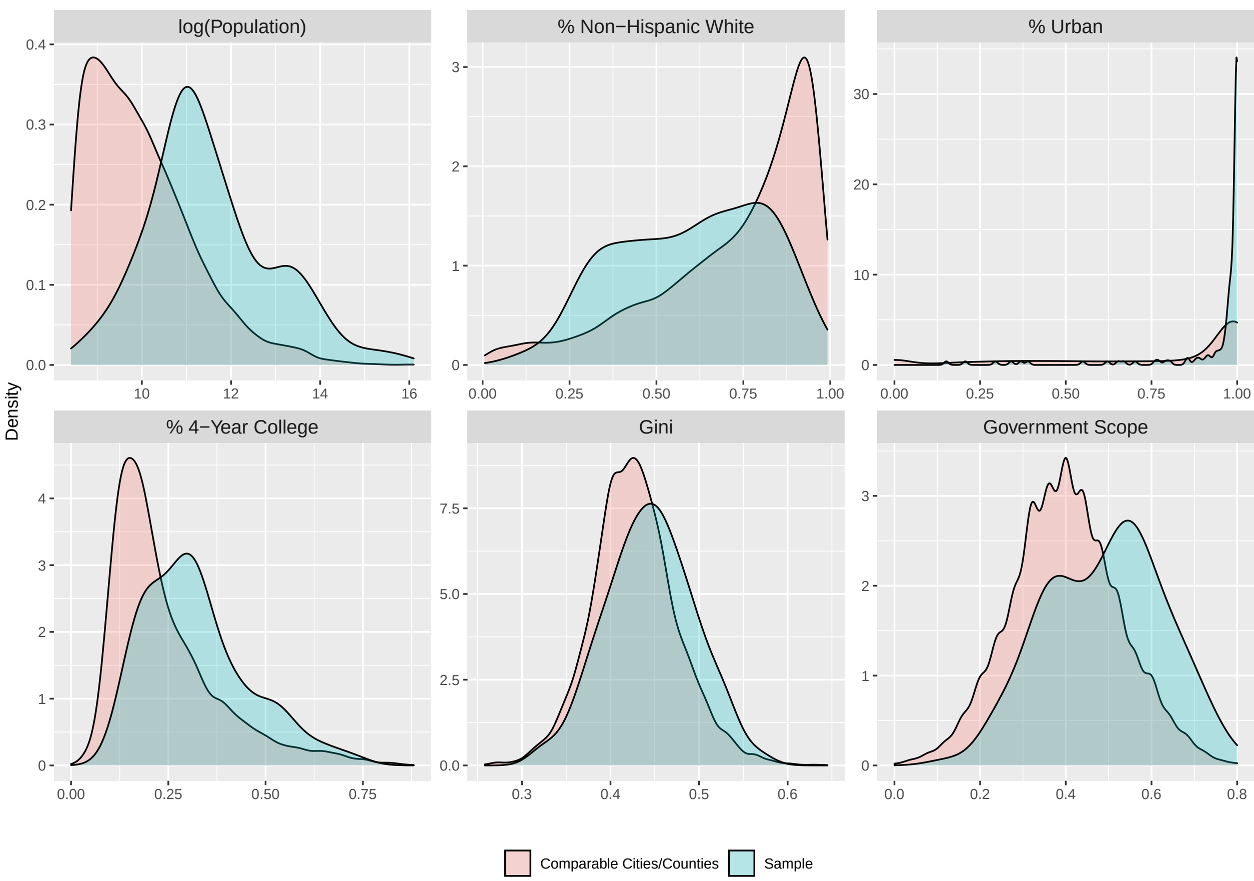
B Sample Comparisons

B.1 How Does the Sample Compare to the Population?

How similar are the cities and counties that use Legistar to manage their council records to those that do not? To answer this question, I first gather data on all cities and counties with a population of 4,500 or higher. I use this population threshold because the smallest municipality in my primary sample of 151 cities and counties (Indian Wells, CA) has a population of 4,958, and there are a significant number of cities across the United States that have smaller populations and thus may not be comparable. Indeed, dropping all cities and counties below this value eliminates over 65 percent of the country's municipalities but only about 3 percent of the population living in incorporated areas.

After subsetting the data to a more comparable population, I next compare the distributions of all municipal governments in the sample and population across 6 background characteristics. These include: total population (logged), percent non-hispanic white, percent urban, percent of residents with a 4-year college degree, the gini coefficient (measuring local income inequality), and my measure of government scope. As Figure A4 shows, there are substantial differences across these two groups, even after omitting the smallest of municipalities in the population. Specifically the cities and counties in my sample are—to varying degrees—larger in size, more racially diverse, more urban, more highly educated, more unequal, and govern in a broader range of policy areas. In many ways, however, this makes sense: content management platforms are not free, and so only cities that are large, with broad authority and relatively more engaged constituents are likely to sign on. Thus, the results in this paper should be interpreted primarily as applying to these types of local governments.

Figure A4: Characteristics of Cities and Counties in Sample and Comparable Population



B.2 Comparing Included and Omitted Legistar Councils

At the time of data collection, approximately 180 cities and counties used Legistar to manage their legislative records. Since these governments adopted the service at different times, with many only doing so recently or on a trial basis, there were a number of cities with only a small number of contested votes. As a result, I only include cities and counties in the main analysis if they have at least 15 contested votes. A cutoff of this kind is necessary to ensure that the scaling results are not simply a function of noise from a small number of votes. To evaluate the consequences of this decision, in Figure A5, I compare the baseline features of the cities and counties that are included and excluded from the analysis. As the plot shows, there are some small differences between the governments that are included and excluded as a result of this criteria, particularly in terms of population and the scope of government authority, but there is little evidence that these contexts are fundamentally different.

Next, to identify whether the specific choice of cutoff affects the results, I estimate a series of regressions that are identical to those presented in Table 1, Column 2, but with increasingly restrictive criteria for the minimum number of contested votes. In Figure A6, I plot the coefficient on partisan elections and the interaction between partisan elections and partisan imbalance from each these regressions, along with 95% confidence intervals. The x-axis on the plot indicates the threshold for inclusion in the sample—so, a value of 30 means all cities and counties with at least 30 contested votes are included—and the y-axis corresponds with the value of the coefficient. Despite increasingly smaller sample sizes, the point estimates are remarkably stable across all thresholds, suggesting that the specific threshold—and the composition of the sample that follows from it—is not driving the results.

Figure A5: Characteristics of the Legistar Councils that are Included and Excluded from the Analysis

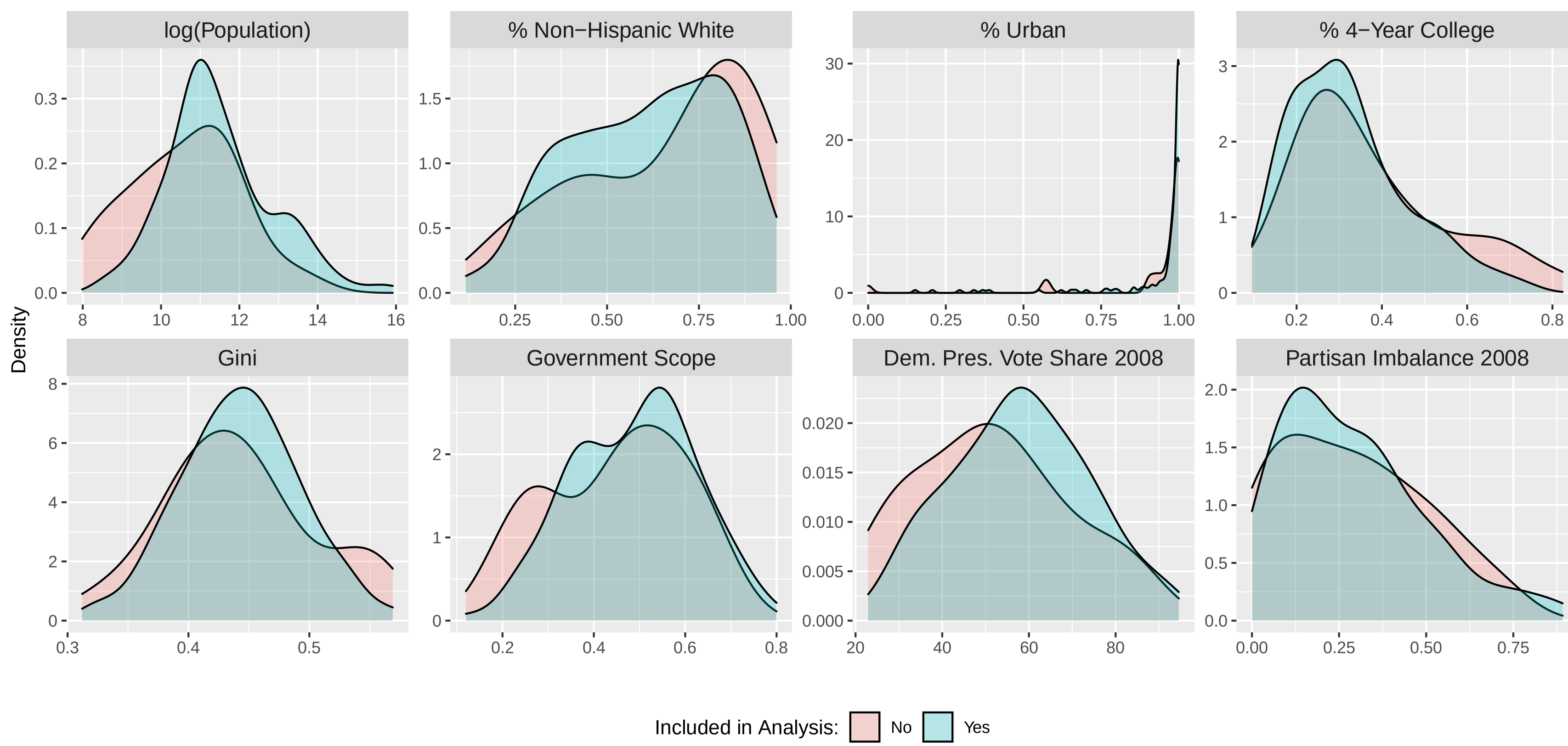
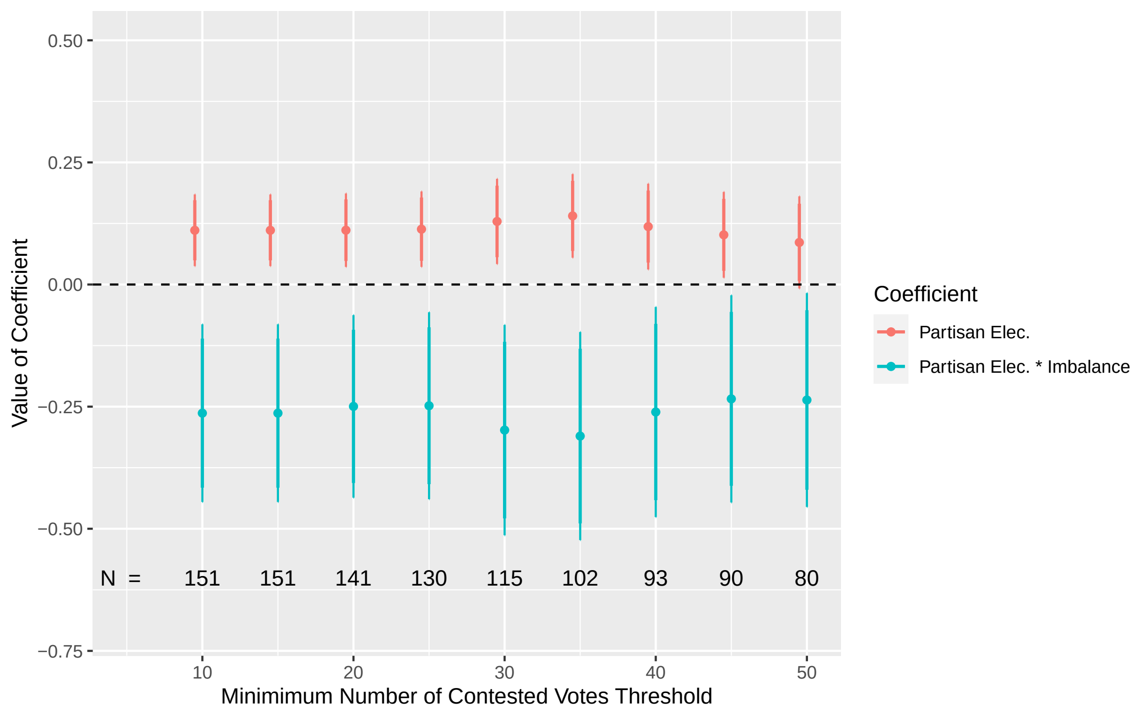


Figure A6: Examining the Stability of the Results across Contested Vote Thresholds



C Robustness of Dimensionality Analysis

C.1 Alternate Measures of Legislative Dimensionality

Tables A3 and A4 present regression results using two alternate measures of legislative dimensionality: the percent of the variance explained by the scaling model's first dimension and the share of nay votes that are correctly classified. As with the aggregate proportional reduction in error (APRE), which is the statistic I use in the main text, higher values of each of the statistics imply better fit and, in turn, a more one-dimensional legislative environment. In both Tables, the relationship between competition, partisan elections, and legislative dimensionality is substantively identical to the results presented in the main text.

Table A3: Alternate DV: Variance Explained by 1st Dimension

	Dependent Variable: Percent of Variance Explained by First Dimension					
	OLS					WLS
	(1)	(2)	(3)	(4)	(5)	(6)
Partisan Elections	0.23**	0.21**	0.25**	0.16	0.26**	0.20**
	(0.06)	(0.06)	(0.07)	(0.10)	(0.08)	(0.06)
Partisan Imbalance	0.06	0.03	0.04	0.01	0.05	0.05
	(0.07)	(0.08)	(0.08)	(0.10)	(0.09)	(0.08)
Partisan Elections * Imbalance	−0.47**	−0.49**	−0.58**	−0.37	−0.66**	−0.46**
	(0.15)	(0.16)	(0.17)	(0.26)	(0.23)	(0.16)
% Non-White		−0.03	−0.04	−0.06	−0.03	−0.01
		(0.08)	(0.08)	(0.11)	(0.08)	(0.08)
Government Scope		−0.03	0.03	0.14	0.09	−0.05
		(0.12)	(0.13)	(0.17)	(0.16)	(0.12)
log(Total Population)		0.001	0.001	−0.02	−0.01	0.01
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
% 4-Year College		−0.05	−0.03	−0.15	−0.05	0.01
		(0.10)	(0.11)	(0.12)	(0.12)	(0.11)
log(Direct Expenditures)		0.02	0.02	0.03	0.03	0.01
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
log(Total Votes Scaled)	−0.08**	−0.09**	−0.09**	−0.07**	−0.09**	−0.08**
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Constant	0.97**	0.75**	0.74**	0.64**	0.74**	0.72**
	(0.06)	(0.14)	(0.15)	(0.21)	(0.18)	(0.14)
Council Group FE	Yes	Yes	No	Yes	Yes	Yes
Exact Council Size FE	No	No	Yes	No	No	No
State FE	No	No	No	Yes	No	No
Omit Large Councils (>= 10)	No	No	No	No	Yes	No
N	151	151	151	151	122	151
R^2	0.46	0.47	0.51	0.59	0.37	0.47

$^{+}$p<0.1; *p<0.05; **p<0.01

Table A4: Alternate DV: Percent 'Nay' Votes Correctly Classified

	Dependent Variable: Percent of Nay Votes Correctly Classified					
	OLS					WLS
	(1)	(2)	(3)	(4)	(5)	(6)
Partisan Elections	0.06*	0.06*	0.07*	0.09*	0.07*	0.06*
	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
Partisan Imbalance	−0.01	−0.01	−0.02	0.003	−0.02	−0.01
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)
Partisan Elections * Imbalance	−0.15*	−0.15*	−0.18*	−0.23*	−0.23*	−0.14*
	(0.07)	(0.07)	(0.07)	(0.11)	(0.09)	(0.07)
% Non-White		−0.01	−0.01	−0.01	−0.01	−0.004
		(0.03)	(0.03)	(0.05)	(0.03)	(0.03)
Government Scope		0.004	0.003	0.08	0.04	−0.01
		(0.05)	(0.05)	(0.07)	(0.06)	(0.05)
log(Total Population)		0.0001	−0.001	0.003	−0.01	0.002
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
% 4-Year College		−0.01	−0.03	−0.03	−0.06	0.01
		(0.04)	(0.04)	(0.05)	(0.05)	(0.04)
log(Direct Expenditures)		0.003	0.005	−0.004	0.01	0.002
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
log(Total Votes Scaled)	−0.01*	−0.01*	−0.01*	−0.01	−0.01*	−0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	0.96**	0.93**	0.94**	0.98**	0.97**	0.90**
	(0.03)	(0.06)	(0.06)	(0.09)	(0.07)	(0.06)
Council Group FE	Yes	Yes	No	Yes	Yes	Yes
Exact Council Size FE	No	No	Yes	No	No	No
State FE	No	No	No	Yes	No	No
Omit Large Councils (>= 10)	No	No	No	No	Yes	No
N	151	151	151	151	122	151
R^2	0.31	0.31	0.41	0.42	0.29	0.31

$^{+}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$

C.2 Alternate Measures of Competition

This section presents results using two alternate measures of competition: imbalance in local ideology and imbalance in local partisan identification. The first two sections discuss the data sources used for each measure, explain how each was constructed, and then present regression results for each akin to those in the main text. The third section checks the robustness of the presidential voting-based measure of competition used in the main text, particularly the decision to impute vote share for a small number of cities. The final section compares each measure of party competition in the electorate to measures of party control.

C.2.1 Imbalance in Local Ideology

While the measure of presidential vote share used in the main text captures imbalance in competition in the electorate using observed behavior in each municipality, we can also gauge the potential for party competition using the preferences of individuals who live in each city and county. To do so, I use data from Tausanovitch and Warshaw (2014), who combine an item response model with multilevel regression with poststratification (MRP) to estimate the liberalism or conservatism of the electorate in all cities with populations greater than 25,000 in the United States. I supplement this city-level data with more recent data on the ideological leanings of each county in the United States, released by Tausanovitch and Warshaw on the website for their project in 2016.[1]

After matching these estimates of local ideology to each corresponding city and county in my data, I take the absolute value of each estimate to construct my measure of ideological imbalance. Thus, a value of 0 indicates that the mean of the ideology distribution in a city is 0, implying that there is a large population of individuals in the electorate who hold both liberal and conservative views. In contrast, the higher the value of ideological imbalance the more the electorate in each municipality increasingly leans towards one ideology, regardless of whether the dominant ideology is liberalism or conservatism.

[1] For additional details, see `http://www.americanideologyproject.com/`

Table A5 displays regression results from using this measure of ideological imbalance as the primary independent variable, mirroring each of the regression models used in Table 1 in the main text. Across all specifications, the coefficient on partisan elections is positive, the coefficient on ideological imbalance (representing the slope in nonpartisan contexts) is small and insignificant, and the interaction between these measures is both negative and substantively large. The only difference between the estimates in the main text and those in Table A5 is that the primary coefficients of interest are less precise in the models with state fixed effects (column 4). Given that the measure of local ideology is estimated via an MRP model with state-specific intercepts, this is not entirely surprising. Indeed, in municipal contexts with few survey responses, the estimate of ideology will pool towards the group-level mean. This, in turn, will attenuate the variation across contexts, which may explain the deviation.

Table A5: Alternate Measure of Competition: Imbalance in Local Ideology

	Dependent Variable: Imbalance in Local Ideology					
			OLS			WLS
	(1)	(2)	(3)	(4)	(5)	(6)
Partisan Elections	0.10*	0.09*	0.12**	0.05	0.13*	0.10*
	(0.04)	(0.04)	(0.04)	(0.07)	(0.05)	(0.04)
Ideological Imbalance	0.02	−0.01	−0.02	−0.004	−0.05	−0.003
	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.05)
Partisan Elections * Ideological Imbalance	−0.19+	−0.17+	−0.26*	−0.06	−0.31*	−0.18+
	(0.10)	(0.10)	(0.11)	(0.16)	(0.15)	(0.10)
% Non-White		0.04	0.02	0.04	0.03	0.06
		(0.05)	(0.06)	(0.08)	(0.06)	(0.05)
Government Scope		−0.06	−0.03	0.14	−0.01	−0.06
		(0.09)	(0.09)	(0.12)	(0.11)	(0.09)
log(Total Population)		0.03	0.03	0.03	0.02	0.03
		(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
% 4-Year College		0.003	−0.01	0.05	−0.04	0.04
		(0.07)	(0.07)	(0.09)	(0.08)	(0.07)
log(Direct Expenditures)		−0.001	−0.003	−0.03	0.004	−0.01
		(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
log(Total Votes Scaled)	−0.03**	−0.03**	−0.03**	−0.03*	−0.03**	−0.03**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	0.95**	0.69**	0.71**	0.81**	0.69**	0.67**
	(0.05)	(0.12)	(0.12)	(0.18)	(0.14)	(0.12)
Council Group FE	Yes	Yes	No	Yes	Yes	Yes
Exact Council Size FE	No	No	Yes	No	No	No
State FE	No	No	No	Yes	No	No
Omit Large Councils (>= 10)	No	No	No	No	Yes	No
N	122	122	122	122	93	122
R^2	0.44	0.49	0.55	0.62	0.37	0.50

+p<0.1; *p<0.05; **p<0.01

C.2.2 Imbalance in Local Partisan Identification

As a second, alternate measure of competition, I estimate the absolute difference in the share of the population identifying as one of the two major parties using four distinct MRP models, one for each party and context (city vs county). Estimating this type of quantity via MRP involves a number of challenges—notably the need to impute city of residence for survey respondents and the absence of individual-level microdata for poststratification—and so I follow the procedures used by Warshaw and Rodden (2012) and Tausanovitch and Warshaw (2014) to prepare and poststratify the data. However, because I cannot leverage multiple responses from each respondent as in Tausanovitch and Warshaw (2014) and need to use four distinct MRP models to estimate partisan affiliation by group and location, this measure is likely to be noisier than both the measure of presidential vote share in the main text and the measure of ideological imbalance.

First, I gather all of the survey responses from the iterations of the Cooperative Congressional Election Study (CCES) administered between 2010 and 2016 (Kuriwaki 2018). Next, because the CCES does not include respondent city, I use data from the Missouri Census Data Center to estimate each respondent's city of residence probabilistically using their county and zipcode.[2] As Tausanovitch and Warshaw (2014) explain, this process should not bias the estimates from the model, but it may introduce noise.

Next, I estimate four separate multilevel regression models, two for each type of government (city or county), each with indicator variables for Democratic and Republican partisan identification as the dependent variables. For party identification, I code any individual as being affiliated with one of the two major parties if they either report identifying with that party (including leaners) or if they are registered with that party, based on validated voter registration records. The multilevel model is specified as follows:

[2] The interface to access the data is available here: `http://mcdc.missouri.edu/applications/geocorr2014.html`. To gather the same data, select all states, select county and zip/zcta as the source geographies, and then select place as the target geography.

$$Pr(y_i = 1) = logit^{-1}\left(\gamma_0 + \alpha^{race\_gender}_{r[i]} + \alpha^{educ}_{e[i]} + \alpha^{state}_{s[i]} + \alpha^{year}_{t[i]}\right) \tag{1}$$

where

$$\alpha^{race\_gender}_{r} \sim N\left(0, \sigma^2_{race\_gender}\right), \text{for } r = 1, ..., 10$$
$$\alpha^{educ}_{e} \sim N\left(0, \sigma^2_{educ}\right), \text{for } e = 1, ..., 4$$
$$\alpha^{year}_{t} \sim N\left(0, \sigma^2_{year}\right), \text{for } t = 1, .., 7$$

and the geographic-level intercepts are specified in the following way, with $\alpha^{local\_gov}_{g}$ being a unique intercept for each city or county, depending on the model:

$$\alpha^{local\_gov}_{g} \sim N\left(\alpha^{state}_{s[g]} + \gamma^{inc} \times inc_g + \gamma^{pop} \times pop_g + \gamma^{unemp} \times unemp_g + \gamma^{age} \times age_g, \sigma^2_{local\_gov}\right), \text{for } t = 1, .., 51$$
$$\alpha^{state}_{s} \sim N\left(\beta_0 + \beta^{urban} \times urban_s + \beta^{obama} \times obama\_2012_s, \sigma^2_{state}\right), \text{for } t = 1, .., 51$$

Thus, for each individual, party identification is modeled as a function of race, gender, education, and year. In addition, the model includes intercepts for each city (or county), which are modeled as a function of attributes of that city (or county) and the state within which it resides. Specifically, the local-level covariates include median income, population, the percent unemployed, and the percent of the population that is over 60, while the state-level covariates include the percent of the state population living in urban areas and the share of the vote received by Barack Obama in that state in 2012. The primary difference between this model and the model used by Warshaw and Rodden (2012) is the addition of an interaction between race and gender (which better captures how how men and women of different racial groups identify with each party) and the inclusion of somewhat different covariates for each of the geographic levels.

After estimating each model, I estimate the share of the population that identifies as a Democrat and the share of the population that identifies as a Republican via poststratification for each city and county. To do so, I use information on the joint distribution of the population in each city and county (by race, gender, and education) from the 2015 American Community Survey (5-Year Estimates).[3] After constructing city and county-level estimates of identification by party, I take the absolute value of the difference of these measures. The resulting measure captures the relative imbalance in local party identification. A value of 0 means that equal shares of the local population identify as Democrats and Republicans, while higher values mean that residents of a municipality increasingly align with one of the major parties. Thus, a value of .20 means that one of the two major parties has a 20 percent advantage in party identification compared to the other.

Figure A7 shows the results of a simple validation exercise using local level registration data from California.[4] On the x-axis, I plot my measure of imbalance in local party identification. On the y-axis, I plot a nearly identically constructed metric calculated using city- and county-level registration figures reported annually by the state of California. While party identification and party registration are different conceptually, they should be correlated, making this a good test of the model's validity. And indeed, as Figure A7 shows, cities and counties that I estimate as having more imbalance in local party identification also tend to have more imbalance in local party registration. This relationship is noisy, of course, but it suggests that—at least to a degree—the MRP estimates are capturing real differences in party identification across municipalities.

With this validation in mind, Table A6 evaluates the relationship between party competition (as measured by local imbalance in party identification) and legislative dimensionality. Across all six specifications, the results in Table A6 are consistent with those in the main text, with cities and counties that are both competitive and partisan having APRE statistics that are .06 to .10 higher, on average. As with the measure of ideological imbalance in the

[3]I cannot use individual-level micro data, which is often used for state-level MRP models, because such data is not available for municipalities. Instead, I follow Tausanovitch and Warshaw (2014) in using ACS data. The primary downside to this is that it prevents me from including age as an individual-level predictor in the hierarchical models.

[4]This data can be found here: `https://elections.cdn.sos.ca.gov/ror/ror-pages/60day-general-12/politicalsub1.pdf`

previous section, we see some attenuation with the inclusion of state fixed effects. Again, this should not be surprising given the construction of the MRP model, particularly the state-level intercepts. Taken together, the evidence in this and the previous section provide compelling evidence that the findings documented in the main text are consistent across a variety of measures of party competition in the electorate.

Figure A7: Imbalance in Local Party Identification (MRP) Versus Imbalance in Local Registration (California Only)

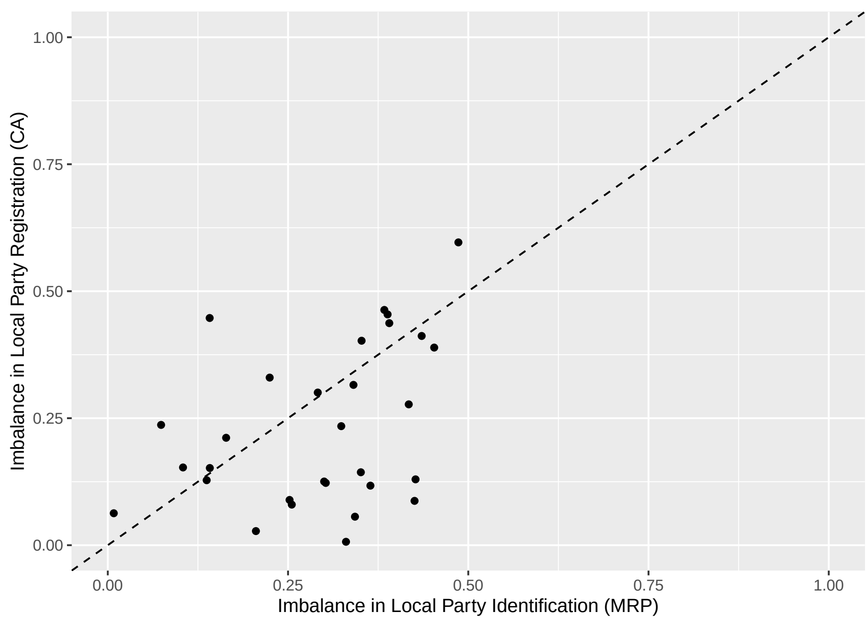


Table A6: Alternate Measure of Competition: Imbalance in Local Partisan Identification

	Dependent Variable: Imbalance in Local Partisan Identification					
	OLS					WLS
	(1)	(2)	(3)	(4)	(5)	(6)
Partisan Elections	0.10^{*}	0.08^{+}	0.09^{*}	0.07	0.06	0.07^{+}
	(0.04)	(0.04)	(0.04)	(0.06)	(0.05)	(0.04)
PID Imbalance	0.13^{+}	0.05	0.09	0.30^{+}	0.09	0.06
	(0.07)	(0.08)	(0.09)	(0.17)	(0.10)	(0.08)
Partisan Elections * PID Imbalance	-0.24^{*}	-0.20^{+}	-0.26^{*}	−0.25	−0.20	−0.19
	(0.12)	(0.12)	(0.13)	(0.21)	(0.16)	(0.12)
% Non-White		−0.001	−0.02	−0.13	−0.02	0.01
		(0.05)	(0.05)	(0.09)	(0.05)	(0.05)
Government Scope		−0.06	−0.04	0.14	0.01	−0.07
		(0.07)	(0.08)	(0.10)	(0.09)	(0.07)
log(Total Population)		0.02	0.02	0.01	0.02	0.02
		(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
% 4-Year College		−0.005	−0.02	−0.03	−0.03	0.03
		(0.06)	(0.06)	(0.07)	(0.07)	(0.06)
log(Direct Expenditures)		0.004	−0.002	−0.01	−0.01	−0.001
		(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
log(Total Votes Scaled)	-0.04^{**}	-0.04^{**}	-0.04^{**}	-0.02^{*}	-0.03^{**}	-0.03^{**}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	0.94^{**}	0.78^{**}	0.81^{**}	0.87^{**}	0.84^{**}	0.75^{**}
	(0.04)	(0.09)	(0.09)	(0.13)	(0.11)	(0.09)
Council Group FE	Yes	Yes	No	Yes	Yes	Yes
Exact Council Size FE	No	No	Yes	No	No	No
State FE	No	No	No	Yes	No	No
Omit Large Councils (>= 10)	No	No	No	No	Yes	No
N	151	151	151	151	122	151
R^2	0.42	0.44	0.50	0.57	0.28	0.46

$^{+}$p<0.1; *p<0.05; **p<0.01

C.2.3 Imbalance in Local Presidential Voting Without Imputation

In this section, I validate the decision to impute local presidential vote share using county-level vote share for the 8 cities in the sample for which I do not have city-level presidential returns. Table A7 shows the results of this comparison. The left two columns reproduce the findings in the main text, using the imputed measure of presidential voting. The right two columns use a non-imputed measure, thereby dropping the 8 cities for which I do not have data. As Table A7 makes clear, the coefficients are functionally identical, meaning that the inclusion of these cities does not bias the results in the main text.

Table A7: Comparing Measures of Imbalance in Local Presidential Voting With and Without Vote Share-Imputed Cities

	Dependent Variable: APRE Statistic			
	With 8 Imputed Cities		Without 8 Imputed Cities	
	(1)	(2)	(3)	(4)
Partisan Elections	0.12^{**}	0.11^{**}	0.12^{**}	0.11^{**}
	(0.04)	(0.04)	(0.04)	(0.04)
Partisan Imbalance	0.02	−0.02	0.02	−0.004
	(0.04)	(0.05)	(0.04)	(0.05)
Partisan Elections * Imbalance	-0.25^{**}	-0.26^{**}	-0.25^{**}	-0.26^{**}
	(0.09)	(0.09)	(0.09)	(0.09)
% Non-White		0.02		0.001
		(0.04)		(0.05)
Government Scope		−0.06		−0.06
		(0.07)		(0.07)
log(Total Population)		0.01		0.01
		(0.02)		(0.02)
% 4-Year College		0.02		−0.003
		(0.06)		(0.06)
log(Direct Expenditures)		0.01		0.01
		(0.02)		(0.02)
log(Total Votes Scaled)	-0.03^{**}	-0.04^{**}	-0.03^{**}	-0.04^{**}
	(0.01)	(0.01)	(0.01)	(0.01)
Constant	0.95^{**}	0.74^{**}	0.95^{**}	0.72^{**}
	(0.04)	(0.08)	(0.04)	(0.09)
Council Group FE	Yes	Yes	Yes	Yes
N	151	151	143	143
R^2	0.43	0.47	0.45	0.48

$^{+}$p<0.1; *p<0.05; **p<0.01

C.2.4 Comparing Party Competition in the Electorate to Partisan Control

How does party competition in the electorate compare to party control of government? While the primary focus of this paper is on electoral competition and the insecurity it creates for politicians, it is worth comparing how the balance in the electorate compares to the balance between the parties in office. Indeed, though state politics scholars typically conceive of these two types of competition as fundamentally different concepts (Shufeldt and Flavin 2012), recent evidence suggests that both forms of competition map onto important legislative outcomes (see, e.g., Hinchliffe and Lee (2016)). In turn, in this section I examine whether balance in the electorate correlates with more balanced control of office. The short answer is yes, but that the mapping is not always perfect, perhaps as a function of the small size of many local legislative bodies.

To make this comparison, I construct a weighted measure of party control using individual-level, hand-coded data on the party affiliation of all members of the partisan governments in my sample.[5] I weight the measure to account for the fact that the cities and counties in my data do not follow a standard electoral calendar and do not all have equal term lengths, and thus some municipalities have more opportunities for turnover in the sample period than others. This is necessary because the alternative, a simple measure of the mean party identification across all years, underweights members who serve the entire sample period if there is any turnover on the council.

After estimating weighted measures of partisan affiliation for each council, I calculate a fourth and final measure of party competition, imbalance in party control, by taking the absolute value of the weighted share of Democrats on the council minus the weighted share of Republicans on the council. That is, I calculate the majority party's year-weighted margin of control.

Figure A8 compares the bivariate relationship between all four measures of party com-

[5]I omit the nonpartisan governments from this analysis as gathering party identification for council members in these contexts is significantly more challenging and would likely require labor-intensive matching to external sources (e.g., a voter file or campaign contribution records).

petition and the three different measures of dimensionality, with the imbalance measures varying across columns and the dimensionality measures varying across rows. Looking at the first three columns first, we see that for each of the measures of party competition in the electorate, there is a clear relationship, such that more evenly balanced contexts are more one-dimensional and more one-party dominant contexts are less one-dimensional. This holds across all three measures of dimensionality (the rows). In contrast, in the fourth column, which uses the measure of imbalance in party control, we see a much weaker relationship. Indeed, though all three plots in this column are certainly consistent with those shown using the measures of party competition in the electorate, in that they depict negative slopes, the relationships are both flatter and less precise.

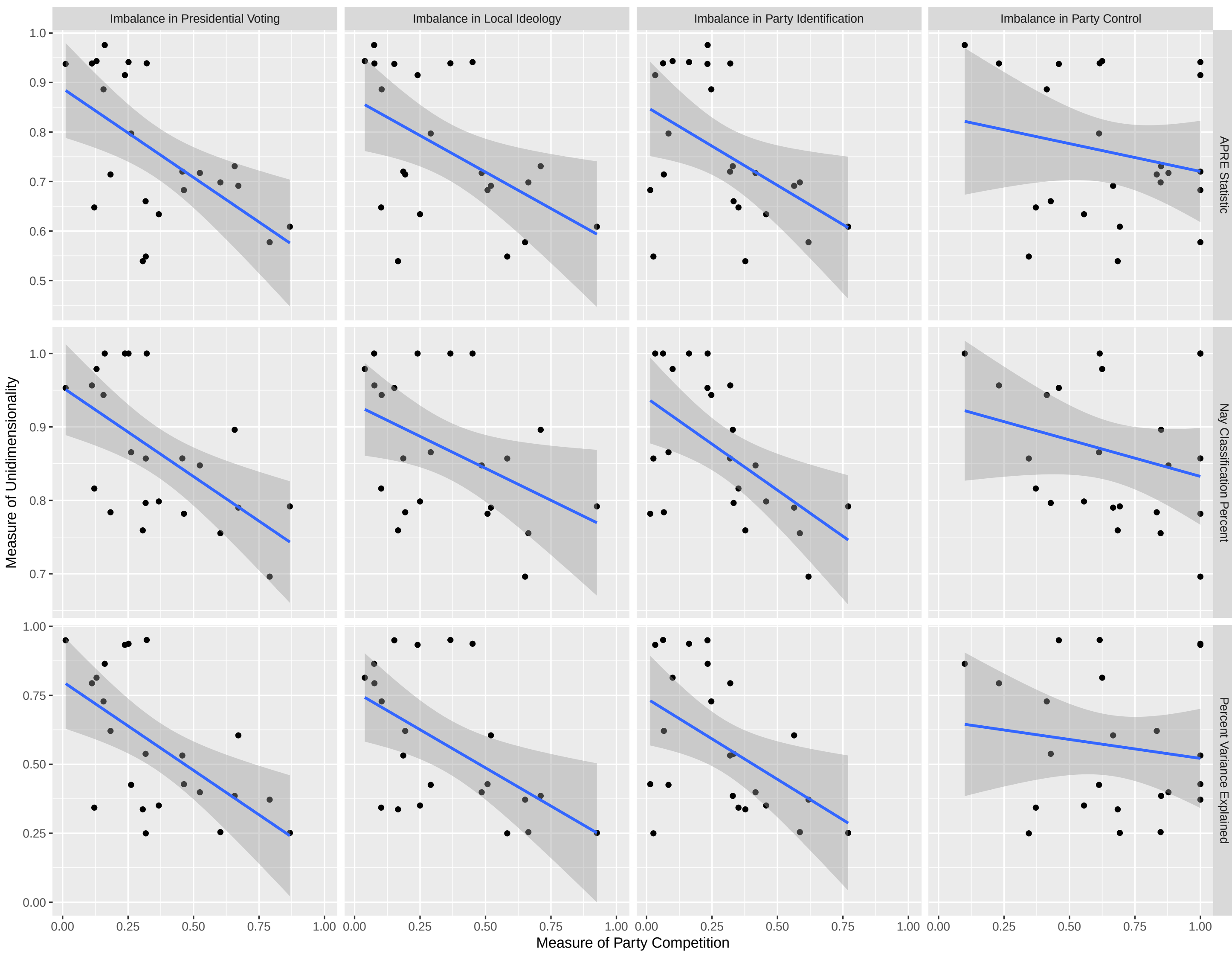
What explains this seeming difference across party in the electorate and party in government? The answer likely lies in the fact that partisan electoral competition and party competition in government are inherently different concepts. One measures the level of electoral insecurity in the pursuit of office while the other is related to the probability a party can implement its policy agenda. While they may be correlated sometimes, they need not be so, particularly if election returns are highly variable from term to term. For example, at the state level, electoral and governmental measures of competition were highly correlated in the 1970s and 1980s, but the correlation has since declined considerably, and in some periods is even negative (Shufeldt and Flavin 2012). At the local level, this problem is likely to be equally present, if not more so, particularly in contexts where the local council is small (meaning only a few seats need to switch parties for large differences in party control), elections are at-large, or districts are drawn in a manner that distorts aggregate competition. Indeed, in these types of contexts, elected officials may still feel electoral pressure but features of the local context may inefficiently translate votes into seats, whether consistently every election or idiosyncratically from time-to-time. Thus, to the extent that electoral insecurity drives intraparty cooperation in competitive contexts, it is unsurprising that we see a somewhat attenuated relationship in the rightmost column of Figure A8 because some of the councils that are heavily controlled by a single party are likely to still have a credible out-party come election time.

As an example, consider Ashe County, North Carolina, which is the most extreme outlier in this regard. It is a 5-member partisan council, with staggered at-large elections, that has been controlled entirely by the Republican Party for about 10 years. The APRE is .91, which is relatively high for a council of that size (the median is .80 and the low is .68). Despite complete Republican control in the council over this time period, however, from 2008 to 2014, the Democratic Party ran the maximum number of candidates (3) and had a realistic chance at winning office, with the highest vote-getting Democrat losing by somewhere between 150 and 500 votes in each election (in 2014, for example, the margin was 224 votes or .84% of the total number of votes). In 2016, the maximum number of Democrats ran again, but the gap started to widen (636 votes) and in 2018, with only 2 Democratic candidates running, it doubled (1367 votes). This pattern is also present in presidential voting in the county over time, with McCain getting about 60% of the vote, Romney 65%, and Trump 70%. Yet, despite this trend, at least locally, Democratic competition was present and generally credible throughout the bulk of the sample period despite the party not actually holding any seats, which may very well explain why we see relatively stable patterns of disagreement (perhaps among moderate/extreme Republicans) in the council as opposed to more idiosyncratic, issue-specific coalitions.[6]

Unfortunately, given the number of partisan governments in the sample, parsing these differences further is difficult. In turn, as additional data becomes available at this level, future work should explore the difference across measures in more depth.

[6]It is worth noting here that the appropriate counterfactual is not that there is no intraparty disagreement in the presence of electoral competition, but that disagreement is both more limited and more predictably stable and ideological than it would be without that competition. Indeed, what I have described in Ashe County is quite similar to what Key (1949) described for North Carolina, Tennessee, and Virginia, the one-party states that had the most credible Republican opposition (p. 299–300).

Figure A8: Comparing Party Competition in the Electorate to Party Control of Government Across All Measures of Dimensionality



C.3 Varying the 'Lop' Threshold for Contested Votes

In the process of scaling roll call votes, scholars need to specify a 'lop' threshold, which defines which contested votes should be included in the analysis. In studies of Congress, for example, this threshold is typically .025, meaning that any vote with greater than 2.5 percent of the chamber voting in the minority is included in the analysis. At the local level, however, where there is significant variation in the size of each council, this decision is more complicated. For example, a 5 person council implicitly has a 'lop' threshold of .20, as any dissenting vote represents 20 percent of the voting body. This presents challenges in comparing large councils with small councils because the meaning of a what a vote against the majority means may vary significantly across contexts.

For the results in the main text, I set the lop threshold at .10, meaning a contested vote is only included in the analysis if at least 1 of every 10 members in the chamber votes in the minority. I use this relatively higher threshold to even the balance between what it means to vote no in a council of 5 and a council of 50. To validate that this decision does not alter the findings, Table A8 presents results using four different lop thresholds, both with and without supplementary covariates. As the results make clear, raising or lowering the threshold from .10 (or, 1 of every 10 members) yields nearly identical findings to those presented in the main text.

Table A8: Relationship Between Partisan Elections, Competition, and Legislative Dimensionality Using Different 'Lop' Cutoffs

	Dependent Variable: APRE Statistic							
	Lop = 1/100		Lop = 1/20		Lop = 1/10		Lop = 1/7	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Partisan Elections	0.12**	0.11**	0.12**	0.11**	0.12**	0.11**	0.11**	0.11**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Partisan Imbalance	0.02	−0.01	0.02	−0.01	0.02	−0.02	0.03	−0.01
	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)
Partisan Elections * Imbalance	−0.27**	−0.28**	−0.27**	−0.28**	−0.25**	−0.26**	−0.23*	−0.24**
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
% Non-White		0.02		0.02		0.02		0.03
		(0.05)		(0.05)		(0.04)		(0.05)
Government Scope		−0.07		−0.07		−0.06		−0.06
		(0.07)		(0.07)		(0.07)		(0.07)
log(Total Population)		0.01		0.01		0.01		0.01
		(0.02)		(0.02)		(0.02)		(0.02)
% 4-Year College		0.01		0.01		0.02		0.03
		(0.06)		(0.06)		(0.06)		(0.06)
log(Direct Expenditures)		0.01		0.01		0.01		0.01
		(0.02)		(0.02)		(0.02)		(0.02)
log(Total Votes Scaled)	−0.03**	−0.03**	−0.03**	−0.03**	−0.03**	−0.04**	−0.03**	−0.03**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	0.94**	0.72**	0.94**	0.72**	0.95**	0.74**	0.94**	0.72**
	(0.04)	(0.09)	(0.04)	(0.09)	(0.04)	(0.08)	(0.04)	(0.09)
Council Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	151	151	151	151	151	151	148	148
R^2	0.45	0.48	0.45	0.48	0.43	0.47	0.41	0.45

$^{+}$p<0.1; *p<0.05; **p<0.01

C.4 Analyzing Democratic and Republican Contexts Separately

One potential concern with the analysis in the main text is that the findings may be driven entirely by democratic-leaning cities. Indeed, the vast majority of large urban environments in the United States are heavily Democratic, and it's possible that some unique feature of these environments, or of Democratic-dominance generally, may underlie the findings. This section evaluates the extent to which this might be true in the data, showing ultimately that the results in the main text hold within subsets of the sample that lean toward each party.

First, Figure A9 plots the distribution of 2008 Democratic presidential vote share for partisan and nonpartisan governments. Two points stand out from this figure: first, there is a relatively large amount of overlap in the distributions across partisan and nonpartisan governments. While it is true that partisan municipalities are a bit more extreme (in that they voted for one candidate at a relatively high rate), on average, there are still nonpartisan cases in the data that are comparable in these cases. Second, consistent with the potential concern motivating this section, the most extreme Democratic-leaning cities and counties are significantly more Democratic than their highly Republican counterparts.

Figure A10 delves further into this imbalance for the partisan councils only, using data from Appendix C.2.4. Specifically, Figure A10 depicts the relationship between Republican vote share in the 2008 presidential election and Republican party control in the cities and counties that use partisan elections. As the plot shows, places that voted for John McCain at a higher rate in 2008 are more likely to see Republicans hold office locally. However, while the sample of partisan governments includes a number of heavily Democratic cities, which both voted for Obama at a rate over 70 percent *and* have few or no Republicans elected officials, the sample mostly lacks Republican-leaning cities that fit this description. Of course, as we saw in Figure A9, there are still a number of heavily Republican municipalities in the sample; places that voted for McCain at a rate 20 to 40 percentage points higher than they voted for Obama. However, what the sample does not have are places that voted for McCain at the most extreme of levels. Thus, this difference lends some credence to the concern that there is a type of one-party, Democratic city for which we don't have comparable Republican contexts.

Does this imbalance influence the findings? Figure A11, suggests that the answer is no. Specifically, Figure A11 plots the bivariate relationship between my primary measure of party competition—partisan imbalance in local presidential voting—and my measure of coalitional stability, the APRE statistic, for cities and counties that are (1) competitive or Democratic-leaning (where Barack Obama received more than 40 percent of the two-party vote) and (2) competitive or Republican-leaning (where John McCain received more than 40 percent of the two-party vote). Two conclusions are immediately clear: first, for nonpartisan municipalities (the left column), there remains little-to-no relationship between the relative skew in local presidential voting and local legislative dimensionality. Second, while there are certainly more heavily-Democratic municipalities in the sample than heavily-Republican municipalities, the trends for partisan governments are quite similar, such that contexts with relatively more balance among the electorate are more one-dimensional, while those with less balance, and thus less competition, are more multi-dimensional.

Finally, in Table A9, I present regression results using the two main specifications from the paper on each of the two samples above. In addition, in column five, I use the full sample but add in a control for 2008 Democratic vote share for president. Across all 5 specifications, the results are consistent with those presented in the main text: partisan cities and counties that have more party competition in the electorate, as measured by the imbalance in local presidential voting, have more one-dimensional local councils. In contrast, partisan cities and counties with more imbalance in local competition are more multidimensional. Taken together, the evidence in this section suggests that—while there are some differences across the most extreme Democratic- and Republican-leaning contexts—these differences do not affect the findings in the main text. Indeed, there is variation in competition in cities and counties that lean toward each party, and–as that competition wanes—we see similar patterns.

Figure A9: Distribution of 2008 Democratic Presidential Vote Share for Partisan and Nonpartisan Governments in the Sample

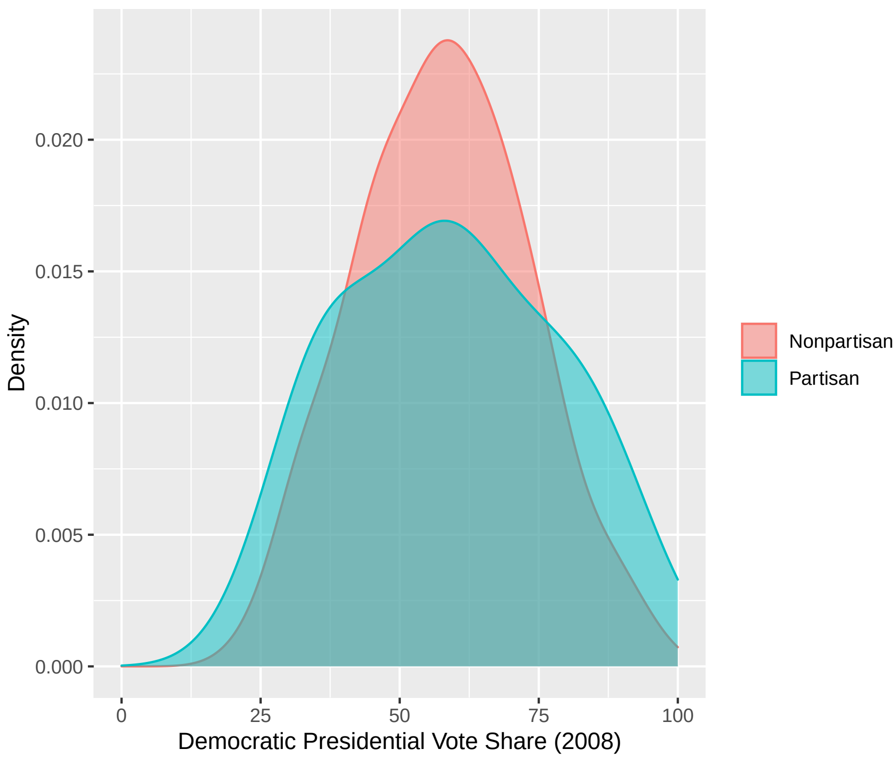


Figure A10: One-Party Dominance in Democratic- and Republican-Leaning Contexts (Partisan Councils Only)

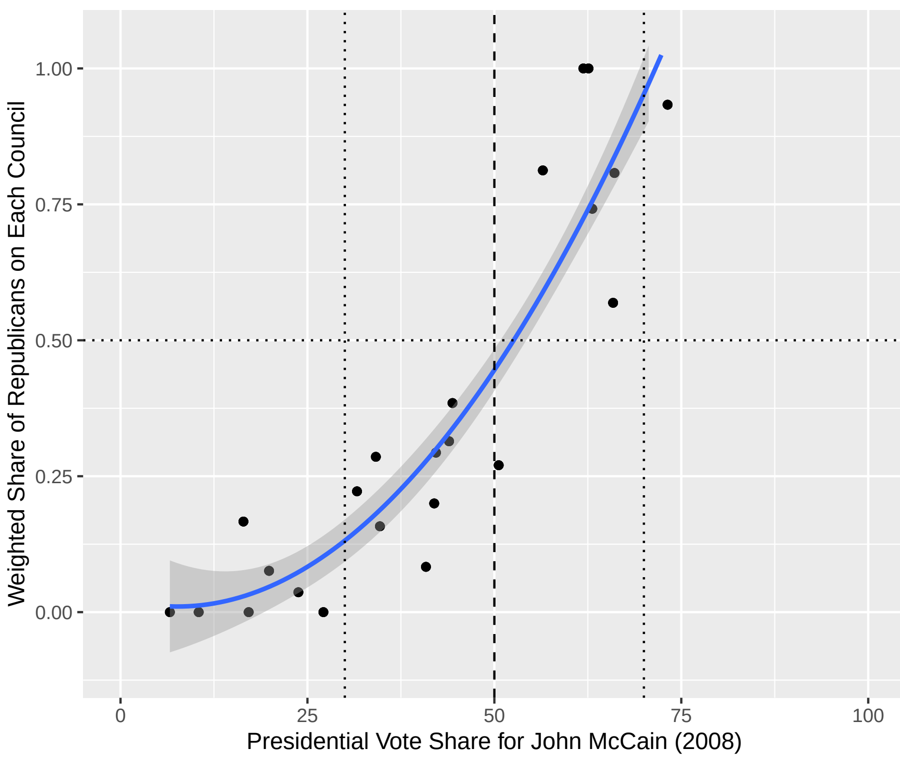


Figure A11: Bivariate Relationship between Party Competition and Legislative Dimensionality for Democratic- and Republican-Leaning Municipalities

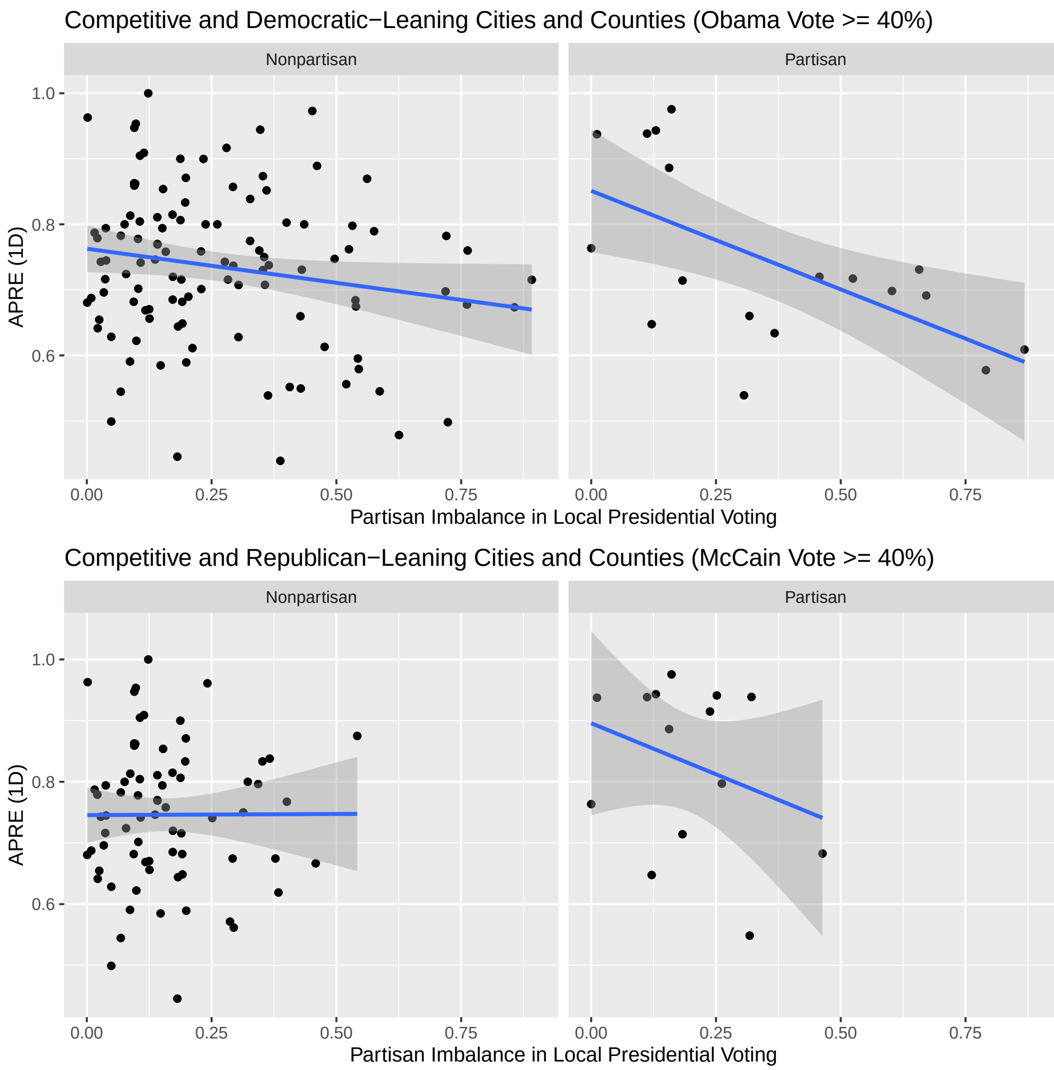


Table A9: Relationship between Party Competition and Legislative Dimensionality, Accounting for Democratic and Republican Lean

	Dependent Variable: APRE Statistic				
	Democratic-Leaning		Republican-Leaning		Full Sample
	(1)	(2)	(3)	(4)	(5)
Partisan Elections	0.12**	0.10*	0.19**	0.16**	0.11**
	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)
Partisan Imbalance	0.03	−0.01	−0.04	−0.01	−0.01
	(0.05)	(0.05)	(0.09)	(0.10)	(0.05)
Partisan Elections * Imbalance	−0.24*	−0.24*	−0.50*	−0.49*	−0.26**
	(0.09)	(0.09)	(0.22)	(0.23)	(0.09)
2008 Democratic Vote Share					−0.0003
					(0.001)
% Non-White		0.004		−0.05	0.03
		(0.05)		(0.07)	(0.05)
Government Scope		−0.04		−0.08	−0.06
		(0.08)		(0.10)	(0.07)
log(Total Population)		0.01		0.01	0.01
		(0.02)		(0.02)	(0.02)
% 4-Year College		0.05		−0.05	0.02
		(0.07)		(0.08)	(0.06)
log(Direct Expenditures)		0.01		0.02	0.01
		(0.02)		(0.02)	(0.02)
log(Total Votes Scaled)	−0.03**	−0.04**	−0.05**	−0.05**	−0.04**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	0.95**	0.72**	1.02**	0.80**	0.74**
	(0.04)	(0.09)	(0.05)	(0.14)	(0.09)
Council Group FE	Yes	Yes	Yes	Yes	Yes
N	123	123	81	81	151
R^2	0.45	0.49	0.51	0.54	0.47

$^{+}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$

C.5 Alternate Specifications

In Table A10, I further probe the robustness of the results presented in the main text with nine alternate specifications. Columns 1 and 2 swap out the council group fixed effects and control for the total number of council members instead, with the first model taking the log of this measure and the second using a quadratic trend. This ensures that the selection of council groups is not driving the findings.

Next, Columns 3 and 4 incorporate additional control variables to account for both a city or county's history of machine politics and the historical presence of traditional party organizations (TPOs). These additions might be important if having a legacy of an organization of this kind has shaped the structure and groups that are active in modern politics. To create the machine variable, I draw on data from (Trounstine 2008, p. 241), coding any city in my data that is identified as having had a historical machine as 1. In addition, given that the Chicago machine was broadly affiliated with Cook County, I code this variable as 1 for Cook County as well. In total, I identify 10 municipalities with a history of machine politics, four of which are partisan, the other six nonpartisan. While the list compiled by Trounstine (2008) is seemingly exhaustive for large cities, there is less information available about machine politics for smaller cities (absent in-depth studies of each), and so it is possible that missingness remains for this variable for smaller municipalities. To create the TPO variable, I code any state that Mayhew (1986) identifies as being organized (TPO score of 4 or 5) as 1 and all others 0.

Similarly, in Column 5, I add control variables to account for racial diversity and economic inequality. For the measure of racial diversity, I use census data for each city and county to construct a Herfindahl index, measured as the sum of squared proportions of each of five racial groups (Asian, African-American, Hispanic, White, and Other). I subtract this index from 1 so that higher values indicate more racial heterogeneity. In addition, as my measure of economic inequality, I use the Gini coefficient, of which higher values on the 0 to 1 scale indicate more economic inequality in the income distribution.

Next, in Columns 6, 7, and 8, I evaluate the relationship in three additional subsamples of the data, created by: (1) dropping cities and counties with populations greater than or equal to 100,000, to ensure that this is not just a feature of big-city governments; (2) dropping the smallest size councils in the data (5 or 6 members), to make sure that the relationship holds beyond these particularly small chambers; and (3) dropping the most extreme one-party dominant cities and counties from the data, identified as those with values of presidential partisan imbalance greater than or equal to .70.

Finally, in Column 9, I dichotomize my measure of local partisan imbalance, splitting it at .20. Thus, cities and counties that are coded 1 are relatively less competitive in that the electorate tends to vote for one party at a rate greater than 20 percent, while those coded as 0 tend to be more competitive.

Across all nine additional specifications, the findings reinforce those documented in the main text, providing greater confidence that particular features of the sample and choices in the measurement strategy are not driving the results.

Table A10: Alternate Specifications: Relationship Between Partisan Elections, Competition, and Legislative Dimensionality

	Dependent Variable: APRE Statistic								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Partisan Elections	0.11^{**}	0.12^{**}	0.11^{**}	0.11^{**}	0.13^{**}	0.13^{+}	0.09^{+}	0.10^{*}	0.11^{**}
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.07)	(0.05)	(0.04)	(0.04)
Partisan Imbalance	−0.01	−0.01	−0.02	−0.01	−0.004	−0.01	−0.05	−0.01	
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.06)	
Partisan Elections * Imbalance	-0.24^{*}	-0.26^{**}	-0.26^{**}	-0.28^{**}	-0.30^{**}	-0.47^{*}	-0.24^{*}	-0.23^{+}	
	(0.09)	(0.09)	(0.09)	(0.09)	(0.10)	(0.23)	(0.11)	(0.12)	
Partisan Imbalance > .20									0.01
									(0.02)
Partisan Elections * Imbalance > .20									-0.13^{**}
									(0.04)
log(Number of Council Members)	-0.16^{**}								
	(0.02)								
Number of Council Members		-0.03^{**}							
		(0.004)							
Number of Council Members^2		0.0004^{**}							
		(0.0001)							
History of Machine Politics			−0.01						
			(0.04)						
TPO State				0.03					
				(0.02)					
Racial Diversity (H-Index)					−0.07				
					(0.11)				
Econ. Inequality (Gini)					−0.24				
					(0.19)				
log(Total Votes Scaled)	-0.04^{**}	-0.04^{**}	-0.04^{**}	-0.03^{**}	-0.04^{**}	-0.04^{**}	-0.04^{**}	-0.04^{**}	-0.03^{**}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Additional Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Council Group FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Drop Large Municipalities ($\geq$ 100,000)	No	No	No	No	No	Yes	No	No	No
Drop Smallest Councils (5 or 6 CMs)	No	No	No	No	No	No	Yes	No	No
Drop Extreme One-Party (*geq* .70)	No	No	No	No	No	No	No	Yes	No
N	151	151	151	151	151	89	108	142	151
R^2	0.45	0.45	0.47	0.47	0.48	0.53	0.43	0.46	0.47

$^{+}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$

C.6 Results Using Matching

One concern might be that the cities and counties that use partisan elections are fundamentally different than the nonpartisan local governments included in the analysis. In this section, I use matching to narrow the analysis to a set of more comparable partisan and nonpartisan governments. To do so, I match each of the partisan cities and counties to a single nonpartisan government using the Matching package in R (Sekhon 2011). I use the default implementation which sets the weight for each covariate equal to the inverse of the variance. To conduct the matching, I use same set of covariates as in the main analysis (e.g., Table 1, Column 2), but substitute a continuous, logged measure of council size instead of matching directly on the council size fixed effects. Figure A12 depicts the level of balance that results from this process across the full set of covariates, along with the initial unadjusted balance from before matching. While there is relatively considerable imbalance along a number of the variables, particularly government expenditures and population size, these imbalances are dramatically reduced after matching.

Table A11 replicates the main findings from Table 1 in the paper but using the matched sample. The first column includes only the primary interaction of interest without any controls. Column two adds in factors related to measurement as control variables and column three includes the full set of covariates. Across all three specifications, the point estimates are quite similar, both to each other and to the estimates presented in the main text. While the estimates in column one are slightly less precise, they remain consistent with our expectations, particularly given the sample size, and the inclusion of additional covariates decreases the variance in subsequent specifications without significantly altering the point estimates.

Figure A12: Covariate Balance Before and After Matching

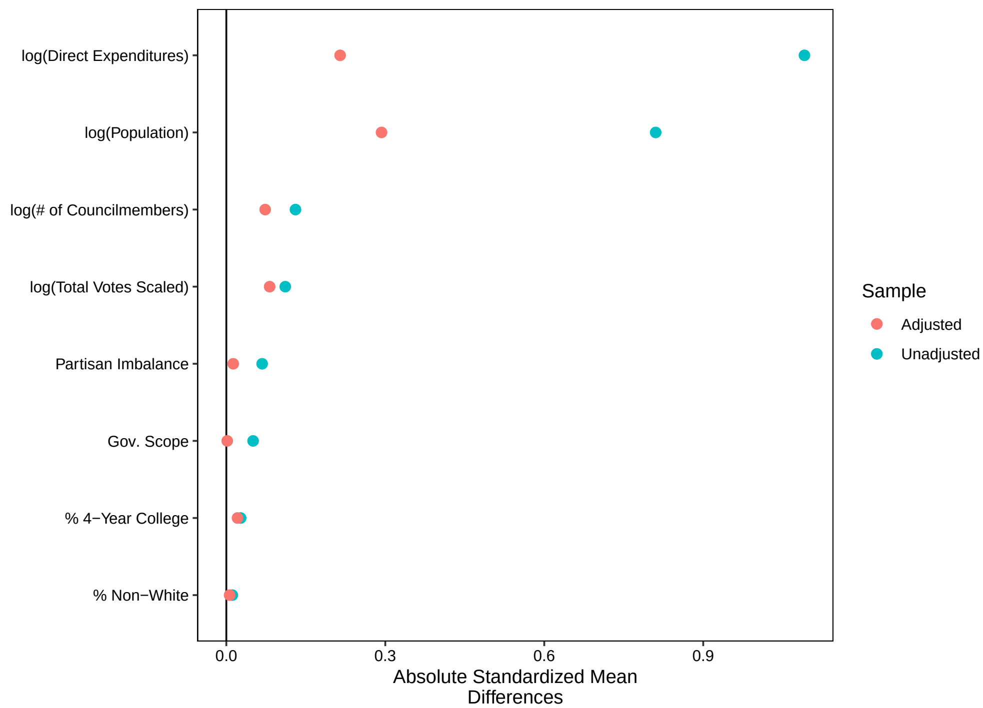


Table A11: Regression Results After Matching

	Dependent Variable: APRE Statistic		
	(1)	(2)	(3)
Partisan Elections	0.12^{+}	0.14^{*}	0.13^{*}
	(0.07)	(0.06)	(0.06)
Partisan Imbalance	-0.10	0.06	0.04
	(0.12)	(0.11)	(0.13)
Partisan Elections * Imbalance	-0.23	-0.27^{+}	-0.27^{+}
	(0.16)	(0.14)	(0.14)
log(Total Votes Scaled)		-0.04^{*}	-0.04^{*}
		(0.02)	(0.02)
log(Number of Council Members)		-0.11^{**}	-0.17^{**}
		(0.03)	(0.04)
% Non-White			-0.14
			(0.10)
Government Scope			0.06
			(0.15)
log(Total Population)			0.03
			(0.03)
% 4-Year College			0.08
			(0.14)
log(Direct Expenditures)			0.01
			(0.03)
Constant	0.75^{**}	1.10^{**}	0.74^{**}
	(0.05)	(0.10)	(0.17)
N	48	48	48
R^2	0.19	0.43	0.53

$^{+}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$

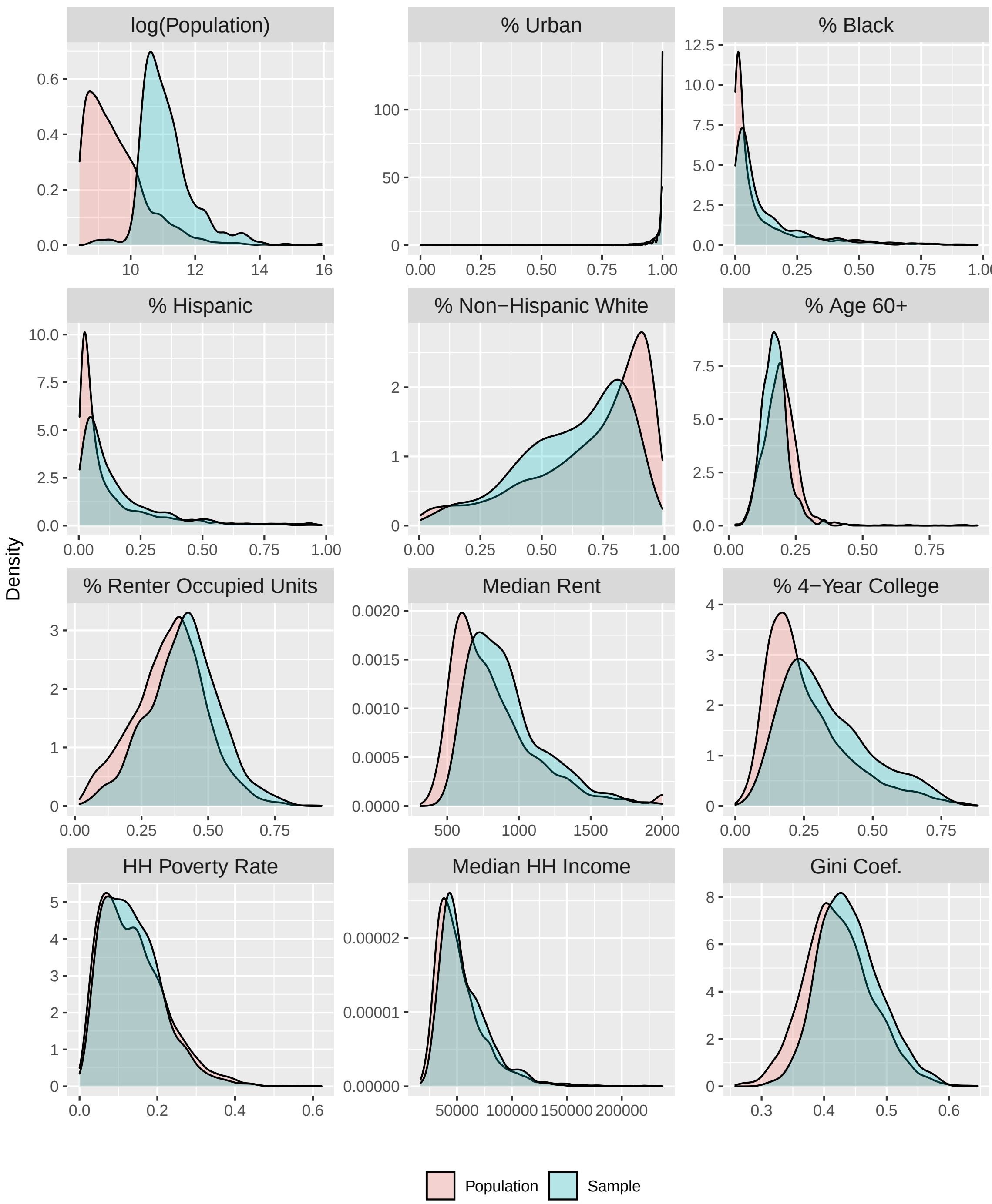
D Survey Data and Analysis

The sample of emails used to contact council members for the survey was drawn from the data maintained by Project Vote Smart. For municipal governments, the organization tracks data for all cities with a population greater than roughly 29,000, though this does not appear to be a hard cutoff as a number of smaller cities are present in their data as well. This appendix details how the cities of the council members who responded compare to the population of cities across the country and provides additional information about the estimation of the ideal points. For more details, however, see Bucchianeri et al. (2017).

D.1 Survey Sample and Population

Figure A13 compares the sample of cities where a council member responded to the survey to the population of cities at-large. To keep the comparisons consistent with those in Appendix B.1, I include all cities with a population of 4,500 or more. As Figure A13 shows, the sample is not representative of cities at overall. It is larger, more racially diverse, more highly educated, and more unequal (along multiple metrics). While this suggests that the generalizability of the findings is narrower than the full population, the imbalances align with those from the observational analysis of legislative behavior, suggesting that the legislators who responded come from a similar type of mid- to large-sized, diverse city.

Figure A13: Sample of Cities with a Responding Council Member Compared to the Population



D.2 Policy Issues and Ideal Points

To estimate measures of local legislator ideology on a common scale across cities, Bucchianeri et al. (2017) use responses to twelve policy tradeoff questions from their survey of municipal officials. These questions cover a broad range of locally relevant policy areas and goals, including: affordable housing, charter schools, climate change, inequality, LGBT rights, the minimum wage, privatization, property values, public safety, school choice, social justice, and public transportation. To construct the ideal points, Bucchianeri et al. (2017) use the 'basic space' method developed by Poole (1998) for estimating latent preferences from issues scales. The results indicate two dimensions underlying elite preferences at this level. The first dimension is consistent with the traditional liberal-conservative scale, with issues such as inequality, climate change, affordable housing, the minimum wage, LGBT rights, and social justice all loading on this dimension. The second dimension, which they interpret as preferences towards market-based policy solutions, includes issues such as privatization, school choice, and charter schools. For additional details about the survey instrument and construction of these measures, see Bucchianeri et al. (2017).

D.3 Equivalence Testing

In this section, I use equivalence testing to bound the magnitude of the differences between partisan and nonpartisan governments documented in the survey analysis in the main text. This is both necessary and worthwhile because traditional hypothesis tests evaluate the sample relative to a null hypothesis of no difference, which makes them inadequate to test for the absence of a difference. To implement the equivalence test, I follow the advice of Rainey (2014) and use 90 percent confidence intervals in a manner that is equivalent to the TOST (two one-sided test) approach with alpha equal to .05. Specifically, if the 90 percent confidence interval for a quantity of interest falls within the bounds -m and m, then we can reject the null hypothesis that the two values are different.

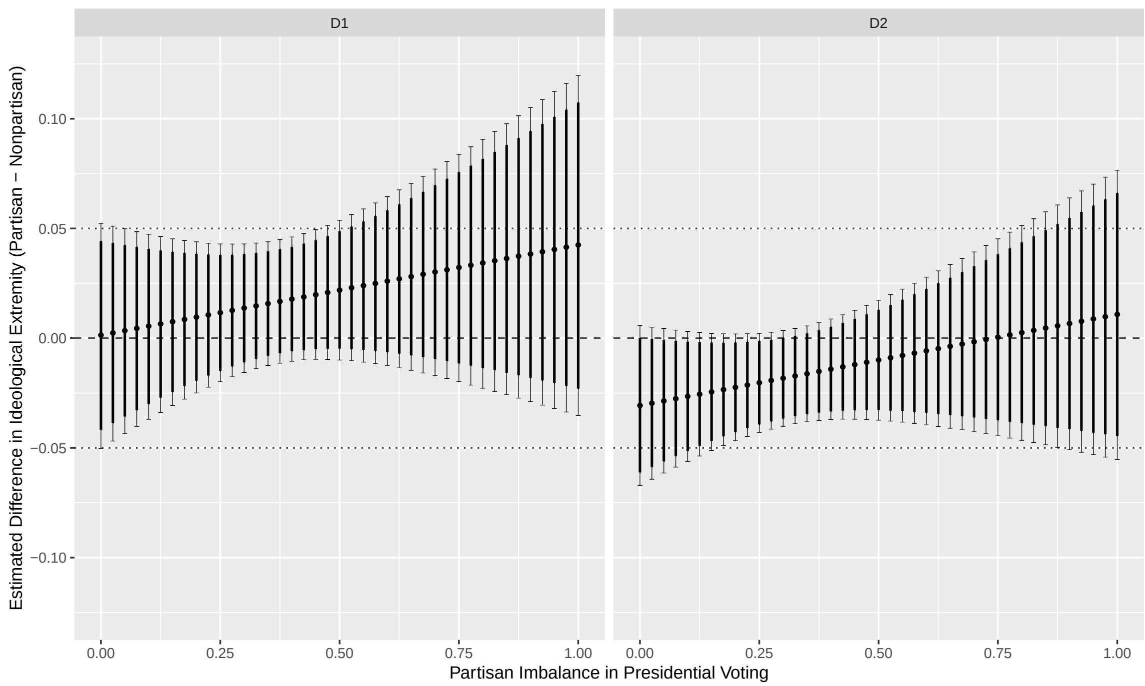
In Figure A14, I plot the predicted difference in ideological extremity between council members in partisan and nonpartisan governments for each ideological dimension across all levels of partisan imbalance. I estimate these differences via simulation using the regression coefficients from the models using clustered standard errors (Columns 2 and 4 in Table 2) and plot both 90 and 95 percent confidence intervals for each (the thick and thin bars, respectively). The horizontal dashed lines depict bounds of $\pm .05$. A magnitude of .05 represents approximately one-third of a standard deviation of first dimension (D1) ideological extremity and two-fifths of a standard deviation of second dimension (D2) ideological extremity. Throughout this section, I focus primarily on the more competitive (or balanced) contexts as these governments are where we observe a difference in dimensionality in the roll call analysis.

Starting with the first dimension ideal points in the leftmost panel, Figure A14 shows that all of the 90 percent confidence intervals for values of partisan imbalance less than .50 fall within the bounds $\pm .05$. This means that for the most competitive contexts, along with many less competitive contexts, we can reject differences in ideological extremity greater than .05 (if not smaller). Given that this represents a relatively small magnitude, particularly in relation to the standard deviation, it seems reasonable to conclude that—even if there are differences between competitive partisan and nonpartisan contexts—they are unlikely to be substantively meaningful.

Turning next to the right panel of Figure A14, we can repeat the same exercise for the second dimension. In this case, for nearly all of values of partisan imbalance greater than .10, the 90 percent confidence intervals fall within the $\pm.05$ bounds, meaning we can reject the null of a difference across contexts at this magnitude. For the most competitive govenrments, however, this is not the case; rather, we can reject the null using slightly larger bounds of $\pm.06$. Given that the standard deviation of ideological extremity for this dimension is .12, this represents a bound of approximately one-half of a standard deviation for the most competitive of contexts.

Taken together the evidence from the equivalence tests in this section imply that—at most—there is a small difference in the ideological polarization of council members in partisan and nonpartisan governments in municipalities where the electorate is evenly balanced. This provides suggestive evidence that differences in the extreme preferences for members across contexts are unlikely to underlie the differences in dimensionality documented in the main text.

Figure A14: Simulated Differences in Ideological Extremity Across Council Members in Partisan and Nonpartisan Governments



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