Supplementary material of: The role of majority status in close election studies

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A Related literature

Our paper fits in the large literature that applies RD design to close-elections, first initiated by Lee (2008), Pettersson-Lidbom (2008) and Lee et al. (2004) in order to estimate different types of *partisan effects*.

Pettersson-Lidbom (2008) studies whether left-wing municipal governments implement different policies than right-wing ones in Sweden. The importance of the left-right dimension in determining policies has been investigated by many others in different settings (e.g. Ferreira and Gyourko, 2009; Solé-Ollé and Viladecans-Marsal, 2013). In a similar vein, Meyersson (2014) investigates the effect of Islamic party rule on female education attainments in Turkey, while Brollo and Nannicini (2012) focus on the effect of party alignment between local and national governments on transfers in Brazil.

A relevant stream of literature was originated by Lee (2008), who aimed at estimating the *incumbent party advantage*, that is at answering the question: "From the partys perspective, what is the electoral gain to being the incumbent party in a district, relative to not being the incumbent party?" (Lee, 2008, page 692).[1] In his specification, the running variable is the reference party vote share in t, and the outcome is the reference party vote share in $t+1$, or an indicator for the victory of the reference party in $t+1$. Many papers have applied this design to other settings, in particular in single-member districts elections. The estimated *incumbent party advantage* is large and positive in the U.S. House (Lee et al., 2004; Lee, 2008), Senate (Cattaneo et al., 2015), and state legislatures (Uppal, 2010). Moreover Fouirnaies and Hall (2014) provide evidence that party incumbency in the U.S. has a positive effect on campaign contributions to the party from lobbies. Kendall and Rekkas (2012) estimate positive incumbency advantage in the Canadian House, and Uppal (2009) negative ones in India state legislatures. Eggers and Spirling (2017) provide evidence from the UK House, where more than two parties field candidates, and show that the party incumbency effect after a Conservative-Liberals race is much larger than the one after a Conservative-Labor race.

The validity of applying the RD design to close elections has been scrutinized extensively. Some argue that the identification assumptions are violated (Snyder, 2005; Caughey and Sekhon, 2011; Grimmer et al., 2011; Marshall, ming), while others support their validity, and propose ways to reconcile apparently contradictory findings (Eggers et al., 2015; Snyder et al., 2015; Erikson and Rader, 2017; Hyytinen et al., 2018).[2] The point we make in this paper is different from what discussed in this literature. We do not argue for covariate imbalances or for manipulation of the running variable. Instead, we argue that the RD design in single-member legislative districts assigns two different treatments when crossing the threshold.

Finally our work is related to previous studies on the effect of majority status (Albouy, 2013; Cox and Magar, 1999); however neither paper discusses explicitly the importance of controlling for majority status to estimate *partisan effects*, like we do.

[1] This estimate is different from the incumbency advantage previously studied in political science, which focused on the effect of running with an incumbent *candidate* (Gelman and King, 1990).

[2] See de la Cuesta and Imai (2015) for a review.

B Sample covariance between D_{it} and M_{it}

Denote by $m(\cdot)$, $s(\cdot)$, and $c(\cdot,\cdot)$ the sample mean, sample variance, sample covariance respectively. Notice that we have variables varying both within years ($t = 1, ..., T$) and districts ($i = 1, ..., n$). Let $\mathbf{D} = (\mathbf{D}_1, \mathbf{D}_2, ..., \mathbf{D}_T)$, where $\mathbf{D}_t = (D_{1t}, D_{2t}, ..., D_{nt})$ (define $\mathbf{M}$ and $\mathbf{M}_t$ similarly). The sample covariance between $\mathbf{D}_t$ and $\mathbf{M}_t$ is

$$\begin{aligned} c(\mathbf{M}_t, \mathbf{D}_t) =& \frac{1}{n-1} \sum_{i=1}^{n} [M_{it} - m(\mathbf{M}_t)][D_{it} - m(\mathbf{D}_t)] = \\ =& \frac{n}{n-1} \left[m(\mathbf{M}_t\mathbf{D}_t) - m(\mathbf{M}_t)m(\mathbf{D}_t) \right], \end{aligned} \tag{A1}$$

where $m(\mathbf{M}_t\mathbf{D}_t) = \frac{1}{n}\sum_{i=1}^{n} M_{it}D_{it} := \frac{1}{n}\mathbf{M}_t \cdot \mathbf{D}_t$, the operator "$\cdot$" being the inner product.

Notice that, from the definition of majority status it follows that

$$c(\mathbf{M}_t, \mathbf{D}_t) = \begin{cases} s(\mathbf{D}_t), & \text{if } m(\mathbf{D}_t) > 0.5 \\ -s(\mathbf{D}_t), & \text{if } m(\mathbf{D}_t) < 0.5. \end{cases} \tag{A2}$$

The average of the covariances across electoral years can be written as:

$$\frac{1}{T}\sum_{t=1}^{T} c(\mathbf{M}_t, \mathbf{D}_t) = \frac{n}{n-1} \left[\frac{1}{T}\sum_{t=1}^{T} m(\mathbf{M}_t\mathbf{D}_t) - \frac{1}{T}\sum_{t=1}^{T} m(\mathbf{M}_t)m(\mathbf{D}_t) \right]. \tag{A3}$$

Using (A1) and (A3), we can write the overall sample covariance as:

$$\begin{aligned} c(\mathbf{M}, \mathbf{D}) =& \frac{nT}{nT-1} \left[m(\mathbf{MD}) - m(\mathbf{M})m(\mathbf{D}) \right] = \\ =& \frac{nT}{nT-1} \left[\frac{1}{T}\sum_{t=1}^{T} m(\mathbf{M}_t\mathbf{D}_t) - \frac{m(\mathbf{M})}{T}\sum_{t=1}^{T} m(\mathbf{D}_t) \right] = \\ =& \frac{n}{nT-1} \left[\frac{n-1}{n}\sum_{t=1}^{T} c(\mathbf{M}_t, \mathbf{D}_t) + \sum_{t=1}^{T} m(\mathbf{M}_t)m(\mathbf{D}_t) - m(\mathbf{M})\sum_{t=1}^{T} m(\mathbf{D}_t) \right] = \\ =& \frac{n}{nT-1} \left[\underbrace{\frac{n-1}{n}\sum_{t=1}^{T} c(\mathbf{M}_t, \mathbf{D}_t)}_{A} + \underbrace{\sum_{t=1}^{T} m(\mathbf{D}_t)\left[m(\mathbf{M}_t) - m(\mathbf{M}) \right]}_{B} \right]. \end{aligned} \tag{A4}$$

Now, the first element in the square parenthesis in (A4) (labeled as A) is not equal to zero in general. Using (A2) we can write, with a slight abuse of notation:

$$\sum_{t=1}^{T} c(\mathbf{M}_t, \mathbf{D}_t) = \sum_{t \in DemYears} s(\mathbf{D}_t) - \sum_{t \in RepYears} s(\mathbf{D}_t). \tag{A5}$$

The summation in equation (A5) is equal to zero if the sample features the same number of democratic-controlled years and republican-controlled years, and the variance of the treatment dummy is constant across years. It is important to notice that: a) the absolute value of the term A decreases as the dataset is more balanced in terms of democratic-controlled years and republican-controlled years; b) the term A increases as the fraction of democratic-controlled years increases; c) the term A decreases as the fraction of republican years increases.

The second element in the square parenthesis in (A4) (labeled as B) is never exactly equal to zero. In fact, we can write:

$$m(\mathbf{M}_t) - m(\mathbf{M}) = \frac{1}{n} \sum_{i=1}^{n} \left[M_{it} - m(\mathbf{M}_t) \right], \tag{A6}$$

which, in practice, is never equal to zero because $M_{it} \neq m(\mathbf{M}_t)$, unless all the districts are conquered by one party.[3] Nevertheless, the term B is likely to be often negligible, as it involves differences between two numbers both between 0.5 and 1, than multiplied times a number between 0 and 1. As such, $A + B$ is in general different from zero.

C Saturated models and heterogeneous effects

The data generating process (DGP)

$$Y_{it} = \gamma_0 + \gamma_1 D_{it} + \gamma_2 M_{it} + \varepsilon_{it}. \tag{A7}$$

restricts the functional form of the conditional expectation function. In other words, it has only three parameters compared to the four groups of districts in the data: demo-

[3]Majority status is a dummy, so its mean can not be equal to any value taken by the variable unless they are all zero (impossible), or all ones (one party wins all the seats).

cratic districts that belong to majority, democratic districts that belong to opposition, republican districts that belong to majority, and republican districts that belong to opposition.[4] Let us assume instead the more general DGP that not only includes D_{it} and M_{it}, but also their interaction:

$$Y_{it} = \gamma_0 + \gamma_1 D_{it} + \gamma_2 M_{it} + \gamma_3 D_{it} \cdot M_{it} + \varepsilon_{it}. \tag{A8}$$

The model in (A8) is fully saturated, because it has one different parameter for each of the values taken by the conditional expectation function.[5] However, this model, even if saturated, does not allow to identify heterogeneous effects of D_{it} conditional on different value of M_{it}. To see why, consider that the quantity

$$\mathbb{E}[Y_{it}|D_{it} = 1, M_{it} = 1] - \mathbb{E}[Y_{it}|D_{it} = 0, M_{it} = 1] = \gamma_1 + \gamma_3$$

actually compares democratic districts in years when democrats have control of the house, to republican districts when republicans have control of the house. This opens the possibility that the estimate is biased by a *partisan effect* at the house level, or more generally by year-level confounders. Augmenting the specification in (A8) with an indicator variable for democratic control of the house, that is $\mathbb{1}(\overline{D}_t > 0.5)$, $\overline{D}_t = \sum_{i=1}^{n} D_{it}/n$, does not help. It actually results in perfect collinearity because districts represented by the democratic party, that belong to the majority, in years when the republicans hold control of the house do not exist by construction.[6] This fact is reflected in the possibility to rewrite (A8), as:

$$Y_{it} = \beta_0 + \beta_1 D_{it} + \beta_2 \mathbb{1}(\overline{D}_t > 0.5) + \beta_3 D_{it} \cdot \mathbb{1}(\overline{D}_t > 0.5) + \varepsilon_{it}, \tag{A9}$$

[4]These groups can be described as: democratic districts in years when democrats hold control of the house, democratic districts when republicans hold control, republican districts when republicans hold control, republican districts when democrats hold control.

[5]The four values are: $\mathbb{E}[Y_{it}|D_{it} = 0, M_{it} = 0] = \gamma_0$; $\mathbb{E}[Y_{it}|D_{it} = 1, M_{it} = 0] = \gamma_0 + \gamma_1$; $\mathbb{E}[Y_{it}|D_{it} = 0, M_{it} = 1] = \gamma_0 + \gamma_2$; $\mathbb{E}[Y_{it}|D_{it} = 1, M_{it} = 1] = \gamma_0 + \gamma_1 + \gamma_2 + \gamma_3$.

[6]In other words, there would be five parameters for the same four values of the conditional expectation function.

by using the definition

$$M_{it} = D_{it} \cdot \mathbb{1}(\overline{D}_t > 0.5) + (1 - D_{it}) \cdot [1 - \mathbb{1}(\overline{D}_t > 0.5)]. \tag{A10}$$

The coefficients in (A9) are such that $\gamma_0 = \beta_0 + \beta_2$, $\gamma_1 = \beta_1 - \beta_2$, $\gamma_2 = -\beta_2$, and $\gamma_3 = \beta_3 + 2\beta_2$. Yet a different way to write the exact same model is the following:

$$Y_{it} = \alpha_0 + \alpha_1 D_{it} + \alpha_2 M_{it} + \alpha_3 \mathbb{1}(\overline{D}_t > 0.5) + \varepsilon_{it}, \tag{A11}$$

where $\beta_0 = \alpha_0 + \alpha_2$, $\beta_1 = \alpha_1 - \alpha_2$, $\beta_2 = \alpha_3 - \alpha_2$ and $\beta_3 = 2\alpha_2$. Use the definition of M_{it} in (A10) into (A11) to obtain (A9). This model is analogous to the reduced-form model in Albouy (2013), that includes D_{it} and M_{it}, and year fixed effects.

To sum up the models in (A8), (A9) and (A11) are equivalent and even if they do not restrict the functional form of the DGP, they do not allow to identify heterogeneous effects of D_{it} with respect to M_{it}. However, it is possible to identify the arithmetic average between the effect of D_{it} when democrats have majority status and the effect of D_{it} when democrats have opposition status. We define this as the average *partisan effect* (PE)[7]. The PE can be estimated by either one of equations (A8), (A9) and (A11):

$$\text{PE} = \alpha_1 = \beta_1 + \beta_3/2 = \gamma_1 + \gamma_3/2. \tag{A12}$$

C.1 The average *partisan effect*

Assume that each district has four potential outcomes: $Y_{it}^{D,M}, Y_{it}^{D,O}, Y_{it}^{R,M}, Y_{it}^{R,O}$, where the first apex refers to the party (democrat or republican) and the second to the majority status (majority or opposition). Let δ_t be a dummy for D having the majority at t:

[7] Of course in a RD setting the PE will be local in the sense that it applies only to observations in the neighborhood of the threshold.

$\delta_t = \mathbb{1}(\overline{D}_t > 0.5)$. The observed outcome is thus:

$$\begin{aligned} Y_{it} =& D_{it} \cdot \delta_t \cdot Y_{it}^{D,M} + \\ & D_{it} \cdot (1-\delta_t) \cdot Y_{it}^{D,O} + \\ & (1-D_{it}) \cdot \delta_t \cdot Y_{it}^{R,O} + \\ & (1-D_{it}) \cdot (1-\delta_t) \cdot Y_{it}^{R,M}. \end{aligned} \tag{A13}$$

We are interested in identifying the *partisan effect* (PE), defined as:

$$\begin{aligned} \beta = \mathrm{PE} &= 1/2 \cdot \left[Y_{it}^{D,M} + Y_{it}^{D,O} - Y_{it}^{R,M} - Y_{it}^{R,O}\right] \\ &= \underbrace{1/2 \cdot [Y_{it}^{D,M} + Y_{it}^{D,O}]}_{\textit{average potential outcome if democrat}} - \underbrace{1/2 \cdot [Y_{it}^{R,M} + Y_{it}^{R,O}]}_{\textit{average potential outcome if republican}} \\ &= 1/2 \cdot [\underbrace{Y_{it}^{D,M} - Y_{it}^{R,M}}_{\textit{PE on the majority members}} + \underbrace{Y_{it}^{D,O} - Y_{it}^{R,O}}_{\textit{PE on the opposition members}}]. \end{aligned} \tag{A14}$$

The PE has an intuitive interpretation: it can be written as the difference between the average potential outcome when the district is democrat and the average potential outcome when the district is republican (second line of (A14)) or, equivalently, as the average between the PE on the majority members and the PE on the opposition members (third line of (A14)).

D Main simulation

Here we provide additional details on the simulation used in the paper. We take the number of districts n equal to 601, and the number of election-years T equal to 100.[8] For each election-year t we proceed as follows: first, we draw the identity of the party who holds control of the assembly, with probability 0.5 each. The vote share for the democratic party in each district i is then drawn from a beta distribution:

$$X_{it} \sim Beta(\vartheta_t, 10 - \vartheta_t), \tag{A15}$$

[8]The number of districts is of the same order of magnitude of real-world lower houses.

where ϑ_t depends on which party holds control of the assembly. In particular, ϑ_t is drawn from a uniform $\mathcal{U}[5.1, 5.5]$ if the democrats hold control of the assembly, and from $\mathcal{U}[4.5, 4.9]$ if republicans hold control, to make sure that $E[X_{it}] > 0.5$ in case of democratic control, and $E[X_{it}] < 0.5$ in case of republican control.[9] The variables D_{it} and M_{it} follow from X_{it}.

We assume the following DGP for the outcome:

$$\begin{aligned} Y_{it} = {} & 0.5 + 0.3D_{it} + 0.3M_{it} + 0.5\mathbb{1}(\overline{D}_t > 0.5) + \\ & + 20X_{it}^3 - 20X_{it}^2 + 2X_{it} + 0.5 + \\ & + \theta_t \sim \mathcal{N}(0, 0.05) + \varepsilon_{it} \sim \mathcal{N}(0, 0.03). \end{aligned} \tag{A16}$$

The PE is thus equal to 0.3.

Table B1: Summary statistics - simulated data.

	Republican majority		Democratic majority	
	mean	sd	mean	sd
Democrats' vote share, X_{it}	0.471	0.151	0.532	0.151
Democratic seat (0/1), D_{it}	0.425	0.494	0.583	0.493
Majority status (0/1), M_{it}	0.575	0.494	0.583	0.493
Interaction term (0/1), $D_{it} \times M_{it}$	0.000	0.000	0.583	0.493
Democratic majority (0/1), $\mathbb{1}(\overline{D}_t > 0.5)$	0.000	0.000	1.000	0.000
Outcome variable, Y_{it}	0.108	0.442	0.550	0.327
$n \times T$	33055		27045	

$\mathbb{C}\text{or}(.,.)$	X_{it}	D_{it}	M_{it}	$M_{it} \times D_{it}$	$\mathbb{1}(\overline{D}_t > 0.5)$
Democratic seat, D_{it}	0.82	1			
Majority status, M_{it}	-0.08	-0.1	1		
Interaction, $M_{it} \times D_{it}$	0.53	0.6	0.51	1	
Democratic majority, $\mathbb{1}(\overline{D}_t > 0.5)$	0.20	0.16	0.01	0.66	1
Outcome variable, Y_{it}	-0.27	-0.21	0.43	0.4	0.49

% dem. maj. years	10	20	30	40	50	60	70	80	90
$\mathbb{C}\text{or}(D_{it}, M_{it})$	-0.8	-0.6	-0.4	-0.2	0	0.2	0.4	0.6	0.8
$\mathbb{C}\text{ov}(D_{it}, M_{it})$	-0.2	-0.15	-0.1	-0.05	0	0.05	0.1	0.15	0.2

Table B1 reports: the summary statistics of key variables, separately for years with democratic majority and republican majority (upper panel); the correlation coefficients

[9] Note that $E[X_{it}] = \vartheta_t/10$, so in years of democratic control the mean of the distribution is between 0.51 and 0.55, and in years of republican control is between 0.45 and 0.49.

between some of the key variables (central panel); the correlation coefficients and covariances between D_{it} and M_{it} in sub-samples with different ratios of democratic to republican years (lower panel). Note that when the balance between democratic-controlled years and republican-controlled years is perfect, the covariance between M_{it} and D_{it} is zero. Instead, when we consider different sub-samples, the covariance increases as the fraction of democratic years increases, while it decreases as the fraction decreases.

E Alternative simulation

In this alternative simulation, we attempt to produce a distribution of vote share across districts that is more similar to the actual distribution in the U.S. House. We take again the number of districts n equal to 601; here we assume that 51 districts are highly competitive, 275 are democratic-leaning and 275 republican-leaning. We take the the number of election-years T equal to 100. For each election-year t we proceed as follows: first, we draw the identity of the party who holds control of the assembly, with probability 50% each. The vote share for the democratic party in each of the 51 competitive districts is then drawn from a beta distribution:

$$X_{it} \sim Beta(100\vartheta_t, 100(1-\vartheta_t)), \tag{A17}$$

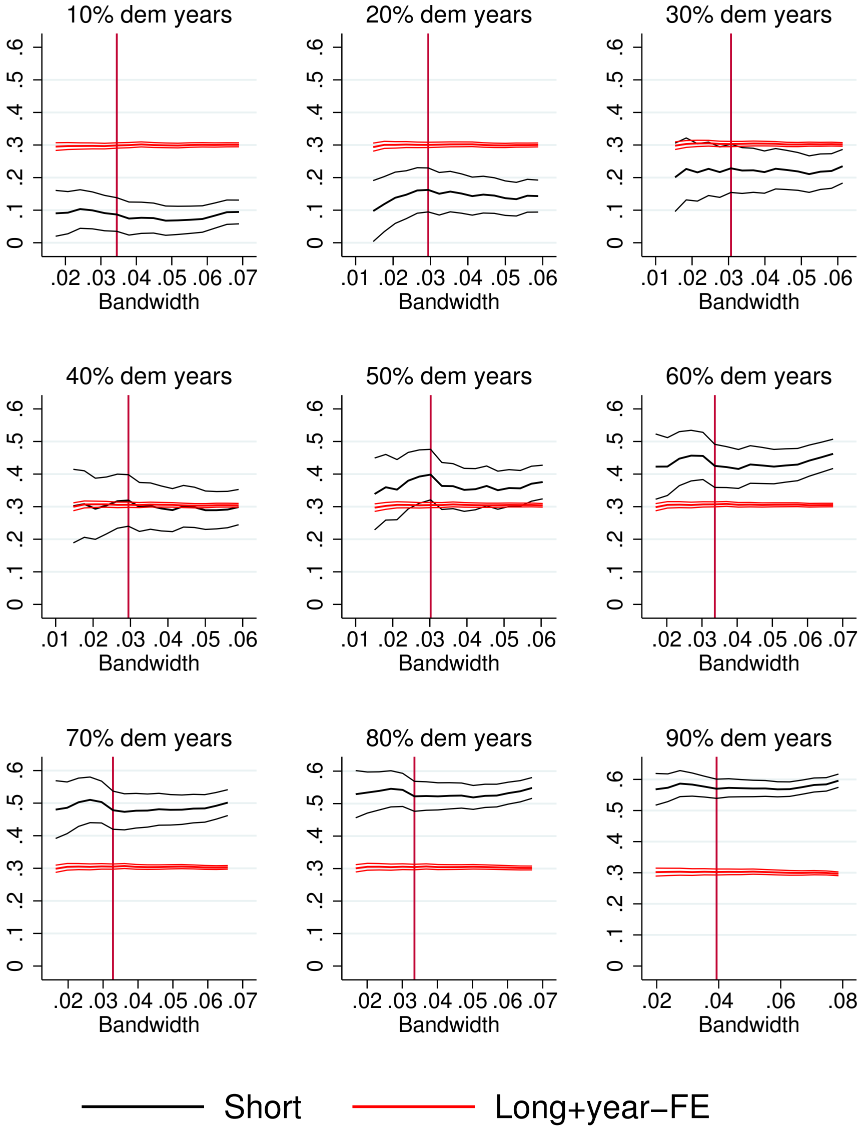
where ϑ_t depends on which party holds control of the assembly. In particular, ϑ_t is drawn from a uniform $\mathcal{U}[0.51, 0.55]$ if the democrats hold control of the assembly, and from $\mathcal{U}[0.45, 0.49]$ if republicans hold control.[10] The vote share for the other districts is drawn from a beta distributions with parameters 250 and 150 in case of democratic-leaning districts, and 150 and 250 in case of republican-leaning districts[11]; the seat in these districts can be only occasionally won by the underdog party. The final distribution of X_{it} is thus trimodal, and in the RD design the estimating sample will be made mainly by highly competitive districts, as happens in real applications. The rest of the exercise is the same as in the baseline simulation. The results are in line with those obtained using

[10] In this way, in years of democratic control the expected value of the distribution in the competitive districts is between 0.51 and 0.55, and in years of republican control is between 0.45 and 0.49.

[11] This corresponds, to an expected value of 5/8 for democratic-leaning districts and of 3/8 for republican-leaning districts.

the baseline simulation. The model that controls for majority status and time fixed effects performs well in all subsamples; the standard model is more biased the more unbalanced is the sample.

Figure B1: Estimates of *partisan effect* in simulated data. True effect=0.3.



Note: each panel reports estimates of the *partisan effect* α_1 from a different sub-sample of 50 election-years, with different ratios of democratic years reported below. Estimates and 95% confidence interval are plotted against the bandwidth used. Vertical red lines indicate the optimal bandwidth by Calonico et al. (2014). Estimation by OLS, and standard errors adjusted for heteroskedasticity. The "short" model include as regressors: D_{it}, the margin of victory, and its interaction with an indicator for observations to the right of the threshold. The "long+year-FE" model control for both majority status and year fixed effects. The true *partisan effect* is equal to 0.3 .

F Data

F.1 Replication of Lee et al. (2004)

The dataset[12] in Lee et al. (2004) includes electoral results for the U.S. House in the period 1946-1994, and voting scores of House representatives on a right-left scale 0-100 based on high-profile roll-call votes.[13] The unit of analysis is the district-year. The timing notation is as follows: t denotes electoral terms, so $t = 1984$ denotes the election in November 1984, and congressional voting in years 1985 and 1986 (U.S. House representatives are elected every two years.). The authors drop the years that ends with two because they correspond to the time when the boundaries of the district change. They also drop observations for which either D_{it} or D_{it-1} are missing. The final sample is thus composed by electoral terms t =1948, 1950, 1954, 1956, 1968, 1960, 1964, 1966, 1968, 1970, 1974, 1976, 1978, 1980, 1984, 1986, 1988, 1990. However, in all these terms the House was under democratic control. Therefore, we introduce back in the sample $t = 1946$ to break the perfect correlation between D_{it} and M_{it}. Summary statistics of the key variables are reported in this Online appendix.

F.2 Roll-call voting in U.S. House 1947-2008

We download data on U.S. House elections held between 1946 and 2006 from the Constituency-level election archive (Kollman et al., 2016) maintained by the University of Michigan.[14] We follow Lee et al. (2004) in measuring roll-call voting on the liberal-conservative scale using the ADA scores adjusted according to the methodology by Groseclose et al. (1999). In particular, we download the dataset by Anderson and Habel (2009), who make available this measure until 2008.[15] We match the two datasets by name, surname, state and election year, collapse the data at the electoral term-district level, and use as outcome the adjusted ADA score averaged across the term.

[12] Available at https://eml.berkeley.edu/~moretti/data3.html

[13] The measure used is the voting score constructed by Americans for Democratic Action (ADA). It is based on about twenty high-profile roll-call votes per Congress, and ranges from 0 to 100, where lower score represents more conservative voting record. The measure is adjusted to ensure comparability over time following Groseclose et al. (1999).

[14] http://www.electiondataarchive.org/

[15] dataverse.harvard.edu/dataset.xhtml?persistentId=hdl:1902.1/12339

F.3 Electoral financing in U.S. House 1979-2006

We download the replication data of the paper by Fouirnaies and Hall (2014). They estimate the incumbency advantage in campaign financing in the U.S. House. They find that the incumbent party raises more funds than the other party. Data available at: stanforddpl.org/papers/fouirnaies_hall_financial_incumbency_2014. The dataset includes information on campaign financing for U.S. House elections held between 1980 and 2006, and electoral results for U.S. House elections held between 1978 and 2004. The original source of the data on campaign financing is the U.S. Federal Election Commission. The time coverage includes both democratic-controlled years and republican-controlled years. We take as outcome variable the campaign funds raised for the election at $t+1$ in district i by the party that won the election at t in i. We exclude from the outcome variable funds from "investor" donors. Investor donors include the categories of donors that finance candidates in exchange for policy favors, and not on ideological grounds (Snyder, 1990; Fouirnaies and Hall, 2014). These include Political Action Committees (PACs) connected with corporations, cooperatives, and Trade, Health and Membership PACs. The categories included in our outcome variables are mainly "consumer" donors (individuals and non-connected PACs), and party contributions.[16] The outcome variable is measured in thousands of 1990 U.S. dollars. The running variable is the margin of victory which is calculated, slightly differently from what used elsewhere in this paper, using the democratic partys share of the total votes received by Democrats and Republicans in i at t.[17]

G Additional empirical results

G.1 Replication of Lee et al. (2004)

The reader may wonder if the changes in the coefficients are due to a general violation of the assumption of quasi-random assignments, rather than due to the relationship between D_{it} and M_{it}. To test this, we augment the specification with a vector of representative's

[16] We exclude "investor" donors because the estimates obtained using those categories as outcome variable are small and not significant, and so not very useful to illustrate the confounding role of majority status. These estimates are available upon request.

[17] We use the same running variable as in Fouirnaies and Hall (2014).

	Republican majority		Democratic majority	
	mean	s.d.	mean	s.d.
Democrats' margin of victory	0.047	0.246	0.082	0.230
Democratic seat (0/1), D_{it}	0.420	0.494	0.596	0.491
Majority status (0/1), M_{it}	0.580	0.494	0.596	0.491
Interaction term (0/1), $D_{it} \times M_{it}$	0.000	0.000	0.596	0.491
Democratic majority (0/1), $\mathbb{1}(\overline{D}_t > 0.5)$	0.000	0.000	1.000	0.000
ADA score, RC_{it}	22.326	29.411	41.914	32.633
Observations	791		13577	

Table B2: Summary statistics of key variables in Lee et al. (2004)

characteristics available in the replication data: age, gender, education, occupation, military service and an indicator for having a relative in politics.[18] If the assumption of quasi-random assignments is violated, the introduction of controls that have predictive power on the outcome would potentially affect the coefficient on D_{it}. This is not the case as shown in Table B3: for all three outcomes the coefficient on D_{it} barely changes when we add controls, even if a joint test of significance of these variables rejects the null at conventional significance levels (columns 4 to 6).

Finally, we test the robustness of our results to the choices of bandwidth and estimator. We focus on two models: the model with only D_{it}, and our preferred specification which controls for majority status and time fixed effects. Here control for a linear function in the margin of victory on each side of the threshold and we report estimates obtained using bandwidths between 3.25 and 12 percentage points.[19] The estimates, reported in Figure B2 along with 95% confidence intervals, draw a similar picture as those in Table B3. Our preferred specification (in red) delivers an higher estimate than the model with only D_{it} (in black) for RC_{it}, and a lower one for RC_{it+1} and D_{it+1}.

G.2 Roll-call voting in U.S. House 1947-2008

[18] We pick these control variables because they are readily available in the replication dataset. There is evidence that some of these politicians' characteristics affect policy in other contexts (Clots-Figueras, 2011; Lahoti and Sahoo, 2020; Alesina et al., 2019).

[19] The optimal bandwidth by Calonico et al. (2014) is 6 percentage points when the outcome is D_{it+1} or RC_{it+1}, and 7.5 percentage points when the outcome is RC_{it}.

Table B3: Replication of Lee et al. (2004): additional controls

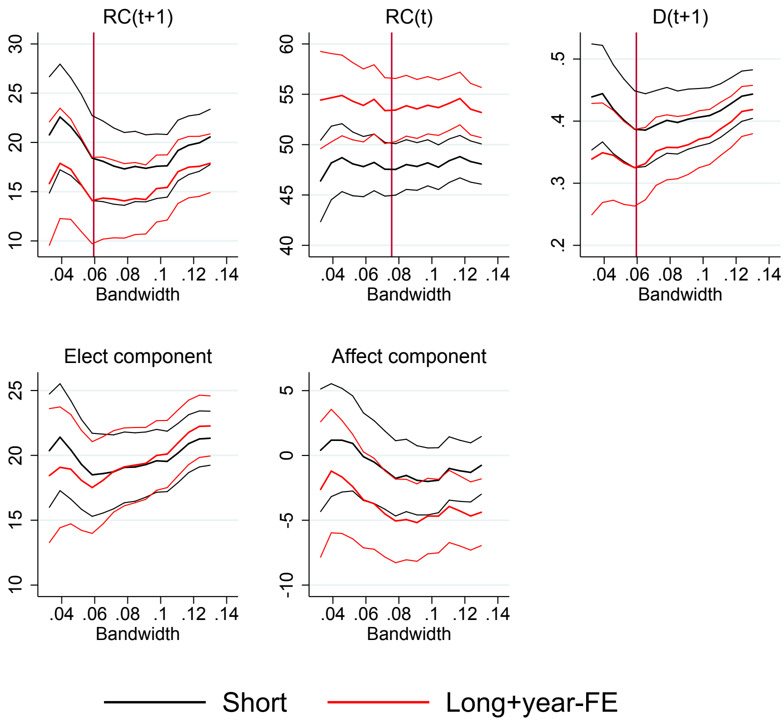
	Outcome variable: RC_{it+1}					
	(1)	(2)	(3)	(4)	(5)	(6)
D_{it}	20.75	13.15	17.63	18.84	12.20	16.41
	(1.98)	(2.84)	(2.94)	(2.06)	(2.97)	(3.06)
M_{it}		10.31	7.17		9.10	5.62
		(2.84)	(2.94)		(2.94)	(3.07)
Time-FE	No	No	Yes	No	No	Yes
Controls	No	No	No	Yes	Yes	Yes
P-value controls				0.09	0.16	0.00
Observations	887	887	887	887	887	887

	Outcome variable: RC_{it}					
	(1)	(2)	(3)	(4)	(5)	(6)
D_{it}	48.28	60.99	57.91	45.83	59.57	58.33
	(1.30)	(1.87)	(1.93)	(1.36)	(1.88)	(2.08)
M_{it}		-14.18	-11.36		-15.25	-14.45
		(1.82)	(1.93)		(1.78)	(2.11)
Time-FE	No	No	Yes	No	No	Yes
Controls	No	No	No	Yes	Yes	Yes
P-value controls				0.00	0.00	0.00
Observations	955	955	955	955	955	955

	Outcome variable: D_{it+1}					
	(1)	(2)	(3)	(4)	(5)	(6)
D_{it}	0.530	0.337	0.389	0.540	0.350	0.388
	(0.058)	(0.069)	(0.064)	(0.059)	(0.069)	(0.064)
M_{it}		0.262	0.182		0.267	0.186
		(0.050)	(0.048)		(0.049)	(0.048)
Time-FE	No	No	Yes	No	No	Yes
Controls	No	No	No	Yes	Yes	Yes
P-value controls				0.04	0.03	0.00
Observations	887	887	887	887	887	887

Note: OLS regressions without controlling for the margin of victory. Robust standard errors in parenthesis. Observations included only if the margin of victory is between ± 2 percentage points. Controls include dummies for age, gender, relative who served, secondary education, college, last occupation and military service.

Figure B2: Replication of Lee et al. (2004): bandwidth robustness

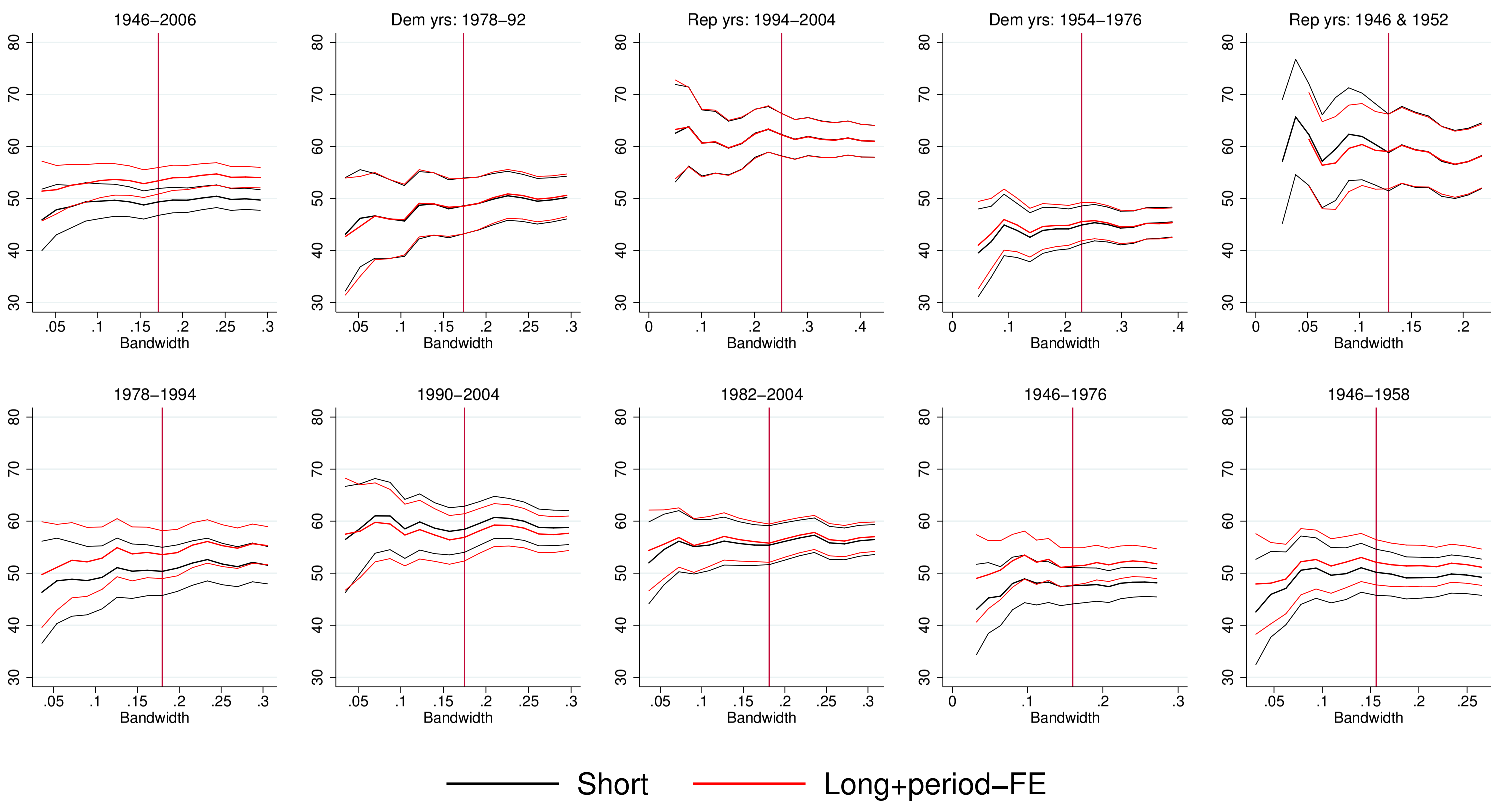


Note: The three upper panel report RD estimates of the *partisan effect* and 95% confidence interval plotted against the bandwidth used. Vertical red lines indicate the optimal bandwidth by Calonico et al. (2014). Estimation by OLS, and standard errors adjusted for heteroskedasticity. The "short" model includes: D_{it}, the margin of victory, and its interaction with an indicator for observations to the right of the threshold. The "long+year-FE" model also controls for majority status and year fixed effects. The elect component is the product of the estimates in the central and right upper panels. The *affect* component is the difference between the estimate in the upper left panel and the *elect* component.

	Republican majority		Democratic majority	
	mean	s.d.	mean	s.d.
Democrats' margin of victory	0.050	0.380	0.117	0.377
Democratic seat (0/1), D_{it}	0.496	0.500	0.580	0.494
Majority status (0/1), M_{it}	0.504	0.500	0.580	0.494
Interaction term (0/1), $D_{it} \times M_{it}$	0.000	0.000	0.580	0.494
Democratic majority (0/1), $\mathbb{1}(\overline{D}_t > 0.5)$	0.000	0.000	1.000	0.000
ADA score, RC_{it}	41.552	36.340	43.730	32.436
Observations	2785		8468	

Table B4: Summary statistics, U.S. House electoral terms 1947-2008

Figure B3: *Partisan effect* and *majority status effect* on conservativeness in roll-call voting.



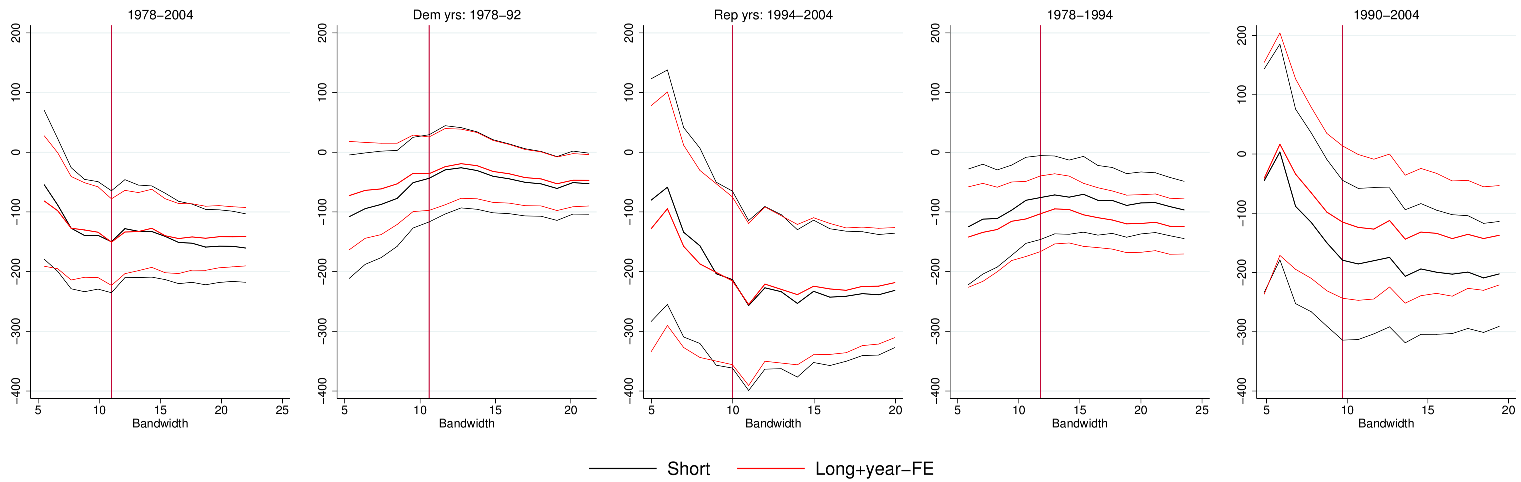
Note: RD estimates of the *partisan effect* and 95% confidence intervals plotted against the bandwidth used. Outcome variable: adjusted ADA score (Groseclose et al., 1999; Anderson and Habel, 2009). Lower values of the ADA score represents more conservative roll-call voting; higher values, more liberal roll-call voting. Vertical red lines indicate the optimal bandwidth by Calonico et al. (2014). Estimation by OLS, and standard errors clustered at the district level. The "short" model includes: D_{it}, the margin of victory, and its interaction with D_{it}. The "long+year-FE" model also controls for majority status and electoral term fixed effects.

G.3 Electoral financing in U.S. House 1979-2006

	Republican majority		Democratic majority	
	mean	s.d.	mean	s.d.
Margin of victory	-0.034	22.325	4.946	24.596
Democratic seat (0/1), D_{it}	0.479	0.500	0.588	0.492
Majority status (0/1), M_{it}	0.521	0.500	0.588	0.492
Interaction term (0/1), $D_{it} \times M_{it}$	0.000	0.000	0.588	0.492
Democratic majority (0/1), $\mathbb{1}(\overline{D}_t > 0.5)$	0.000	0.000	1.000	0.000
Funds at $t+1$ for incumbent party	423.950	385.118	191.163	230.149
Observations	1945		2383	

Table B5: Summary statistics, U.S. House electoral terms 1979-2006 from Fouirnaies and Hall (2014)

Figure B4: *partisan effect* and majority status con campaign financing



Note: Outcome variable are campaign funds from non "investor" donors in thousands of 1990 U.S. dollars (Fouirnaies and Hall, 2014). RD estimates of the *partisan effect* and 95% confidence intervals plotted against the bandwidth used. Vertical red lines indicate the optimal bandwidth by Calonico et al. (2014). Estimation by OLS, and standard errors clustered at the district level. The "short" model includes: D_{it}, the margin of victory, and its interaction with D_{it}. The "long+year-FE" model also controls for majority status and electoral term fixed effects.

H Additional details on the replication of Lee et al. (2004)

The research question in Lee et al. (2004) is the following: do voters affect or merely elect policies? To answer, the authors rely on U.S. House district-level election data. They use a RD design to estimate the causal effect of having the democratic party in office (the treatment is D_{it}) on three outcome variables: a measure of policy stance on a right-left scale, RC_{it}, the same measure in the subsequent term, RC_{it+1}, and the treatment variable itself in the next election D_{it+1}. Their test is inspired by the model in Alesina (1988), and its logic can be explained as follows. The effect of D_{it} on RC_{it+1} can be decomposed into two components: on the one hand, D_{it} affects the equilibrium probability that democrats will be in office next term as well, and therefore will implement their preferred policy: the *elect* component; on the other hand, D_{it} affects the underlying popularity of the democratic party, and therefore the extent to which the democrats must compromise on their policy stance to please the electorate: the *affect* component. The *elect* component can be estimated separately as the product between the effect of D_{it} on D_{it+1}, and the effect of D_{it} on RC_{it}. Finally, the *affect* component is obtained by subtracting the *elect* component from the joint effect. The strategy is formalized in the following equations:

$$RC_{it+1} = \quad constant + \pi_1 D_{it} + \varepsilon_{it} \tag{A18}$$

$$RC_{it} = \quad constant + \pi_2 D_{it} + \varepsilon_{it} \tag{A19}$$

$$D_{it+1} = \quad constant + \pi_3 D_{it} + \varepsilon_{it} \tag{A20}$$

$$\pi_1 = \quad elect\ component + affect\ component \tag{A21}$$

$$\pi_2 \cdot \pi_3 = \quad elect\ component \tag{A22}$$

Despite the differences in some of the RD estimates, the main qualitative conclusion in Lee et al. (2004) is robust to our replication exercise. The estimates of the *elect* component are large and positive with or without controlling for majority status and time fixed effects. To see why, recall that the *elect* component is the product between π_2, whose estimate is higher using our specification, and π_3, whose estimate is lower using our specification. Our preferred specification delivers a lower estimate of the *affect* component, but still not significantly different from zero for many bandwidth choices. The overall conclusion is that the *elect* component largely dominates the *affect* component in elections to the U.S. House, as in the original paper.[20]

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[20] Albouy (2011) extends the analysis in Lee et al. (2004) to incorporate the effect of seniority on roll-call voting, and finds that the *affect* component is positive.

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