How Local Factions Pressure Parties:

Activist Groups and Primary Contests in the Tea Party Era

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The contemporary Republican Party has been the site both of asymmetric partisan entrenchment and of factional infighting. We test whether factional pressure from a far-right faction (the Tea Party) exacerbated the party's rightward movement with a granular analysis of Republican factionalism at the congressional district level. We develop a measure of local factionalism using novel datasets of activist presence and primary contests, then conduct a difference-in-differences analysis to assess whether local factionalism in the Tea Party era heightened Republican partisanship and legislative extremism at the district level. We find that districts that experienced factional pressure moved rightward on both measures. These findings help clarify how the Tea Party captured the Republican Party and support a focus on the role of party factions in fomenting partisan conflict.

Keywords: party factions, Tea Party, U.S. party primaries, political parties, political activism, difference-in-differences

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Recent decades have seen a pronounced rightward shift in the Republican Party (Lewis et al. 2020; Hacker and Pierson 2006; Theriault 2013). Republican representatives in Congress have become entrenched in their partisan positions (McCarty, Poole, and Rosenthal 2006; Theriault 2008) as their voters have embraced partisanship as a social identity (Mason 2018). With the rise of the Tea Party as an electoral force in 2010, the Republican Party became the site of intense factional infighting. Between 2010 and 2014, Tea Party-aligned candidates sought to oust 'establishment' Republicans in elections (Blum 2020), and Tea Party caucuses fought with Republican Party leadership in Congress (Bloch Rubin 2017; Clarke 2020; DiSalvo 2012; Gervais and Morris 2018). The party's rightward movement does not appear to be abating. This raises the question, to what extent is today's Republican partisan entrenchment the result of an extreme faction drawing its party rightward?

In this study, we assess the effect of Tea Party factionalism on the Republican Party. Theoretically, we seek to clarify the mechanisms by which the Tea Party gained influence over the Republican Party. Empirically, we perform the first systematic analysis of the impact of factionalism at the local (congressional district) level, hypothesizing that both voters and representatives from districts experiencing local factionalism would move further to the right between 2008 and 2016 than areas that did not experience such pressure. We test this hypothesis using a difference-in-differences (DiD) design, constructing a proxy for local factionalism (treatment) as the combined presence of Tea Party activist groups and Tea Party-supported candidates in Republican congressional primaries. Specifically, we compare congressional districts that experienced local factional pressure from the Tea Party between 2010 and 2014 to those that did not on two outcomes: (1) district-level Republican presidential vote share, and (2) the position of the district's representative in the U.S. House of Representatives.

We find that districts that experienced local factionalism moved rightward under both metrics between the 2008 election/111th Congress, and the 2016 election/115th Congress compared to other districts. These findings are consistent with claims that Tea Party groups exercised disproportionate influence during the candidate selection process (Blum 2020) which contributed to a transformation of the Republican Party (Rouse, Hunt, and Essel 2022). Our findings also underscore the importance of district-level analyses for understanding contemporary U.S. parties.

How Party Factions Matter

The Republican Party's marked rightward movement appears, at least in part, a consequence of efforts from an extreme faction during and since the Obama presidency (Skocpol and Tervo 2020; Tarrow 2021). The Tea Party insurgency was characterized by reactionary conservatism, anti-establishment posture, and scorched-earth tactics which sought to take control of the party by any means necessary (Blum 2020; Parker and Barreto 2014; Skocpol and Williamson 2012). Notably, this faction applied pressure over multiple institutions, including Congress (Gervais and Morris 2018) and state legislatures (Institute for Research & Education on Human Rights 2022; Rouse, Hunt, and Essel

2022). Qualitative and case study evidence suggests that the Tea Party's efforts also relied on strong state and local operations (Blum 2020; Skocpol and Williamson 2012). We know less, however, about the connection between these local efforts and the national Republican Party's rightward movement. Using two original measures of Tea Party factionalism at the congressional district level, we test whether and how local factionalism in the Tea Party era—roughly 2010 to 2014—caused the Republican Party to move rightward.

In what follows, we define factions and their goals. Next, we identify venues where we might observe factional behavior and discuss how local factionalism might matter. We focus on the impact factions might have on different parts of the party, including elected officials, party organizations, and voters.

Operationalizing Factions

In keeping with existing scholarship, we define factions as organized sub-party groups. Several recent studies focus on factions in Congress, where factions organize into voting blocs or caucuses that allow them to effectively pressure their party and its leadership (Bloch Rubin 2017; Clarke 2020; Cowburn and Kerr 2023). In her 2020 book on the Tea Party, Rachel Blum provides a broader framework for factions, defining them as miniature parties within parties, or as shadow parties (Blum 2020, 17). In Blum's account, factions like the Tea Party target their host party across multiple types of political terrain by shadowing the party's structure. In a sub-national context, this might involve creating shadow state and local party organizations, taking over these party organizations, or running an alternative slate of candidates for public office.

Party members might organize as an insurgent, sub-party apparatus to meet the goal of a faction: to overhaul its host party from within. Factions contest their host party's identity, seeking to redefine what it means to be Republican, or even what it means to be conservative. Accordingly, Daniel DiSalvo (2012) describes factions as the engines of ideological change in the U.S. party system. We consider the Tea Party as a shadow party that sought to systematically challenge the Republican Party and empirically test the extent to which its local factional efforts contributed to the rightward trend in the contemporary Republican Party.

We consider the most likely scenario of factional presence in a district. If the Tea Party faction had a foothold in a district, then we should expect to observe, at minimum, the following two things. The first is the presence of multiple organized factional activist groups in the district. As we explain, we operationalize factional organization using a directory of local Tea Party groups. Existing scholarship suggests that these groups played a significant role in organizing members against the established party apparatus (Blum 2020; Skocpol and Williamson 2012) and therefore serve as a proxy for the extent of the faction's shadow-party organization.

Second, we look for a pattern of contested Republican primaries in the district. If a faction seeks to challenge its party, then we should see evidence of this pressure in party nominating contests.

We focus on contested Republican primaries for the U.S. House. House primaries are appealing for a couple of reasons. With the potential to occur in every district every two years, they provide a large enough sample to evaluate systematically (as opposed to Senate primaries). These primaries are also the most localized contests for which we have reliable data on a variety of metrics. Taken together, these two components provide the most likely conditions under which we might observe factional activities moving the party rightward.

Party Factions and Local Party Change

Here, we explain the mechanisms by which local factionalism might push the party rightward. A faction aims to internally reshape its party, requiring it to take over some of the party's functions. At the local level, this could happen in a couple of ways. First, the faction might target the local party organization and persuade officials to embrace the faction's issues and candidates. This is important, as local parties are primarily responsible for recruiting and nominating candidates *who can win* (Broockman et al. 2021; Crowder-Meyer 2013; Hassell 2018; Masket 2009). Persuading the party to support a factional candidate might be difficult, especially if an incumbent is running.

If an incumbent from the party is *not* on the ballot, a faction might attempt to change the party's perception of the faction and its candidates through the efforts of local activists. Activists can "barrage local elites with expressions of support for extreme policies, via direct communication, at town halls, with protests, through partisan media, and more" (Broockman et al. 2021, 5). By amplifying extreme positions and candidates, activists can subtly alter voters' preferences *and* party leaders' perceptions of these preferences (Miler 2009). Activists on the right have been especially successful at convincing Republican officials that nominating extremists will drive turnout among the 'base' (Broockman et al. 2021), thereby persuading local leaders to look favorably on the candidate preferred by the most vocal segment of their supporters.

If a faction is unable to influence internal party decisions by persuasion alone, it might resort to more hostile means, such as taking over the party from within. Activists might target local party positions and fill them with their own members; unfortunately, no comprehensive database of local party leadership contests is available. Factional efforts to reshape the party can take another, more readily observable, form. A faction can formally challenge the party's chosen candidate with a candidate of their own in a primary. The combination of minimal restrictions on candidate eligibility, decentralized selectorates, low voter turnout, and less media attention in down-ballot primaries make parties vulnerable to factional primary challenges (Dominguez 2011; Manento 2019; Masket 2009). Indeed, ideological and factional primary contests have been increasing since at least 2006, especially on the right (Boatright 2013, 2014; Cowburn 2022).

Drawing from a large body of research, we view activists as an essential component of credible local factional primary challenges. Since the primary reforms of the 1970s, a para-party apparatus of issue activists and interest groups has increasingly taken on roles that used to fall to the formal party

(Grossmann and Dominguez 2009; Koger, Masket, and Noel 2009; Schlozman and Rosenfeld 2019; Tarrow 2021), providing resources and volunteers necessary to conduct successful campaigns (Enos and Hersh 2015), and mediating between party elites and the voting public (Carmines and Stimson 1989; Carmines and Woods 2002; Layman et al. 2010; Layman and Carsey 2002). Activists played an invaluable role in supporting Tea Party-style candidates in congressional elections (Bailey, Mummolo, and Noel 2012).

The complex network of local Tea Party organizations staffed by local activists that proliferated between 2010 and 2014 was most prominent in Republican-leaning areas of the country. As an example, Blum discusses Republican incumbent Eric Cantor's 2014 surprise defeat in the Republican primary in Virginia's 7th district at the hands of Tea Party-backed candidate David Brat. Brat lacked support from the Republican Party (local or otherwise) and brought in few outside donations. He defeated Cantor in the primary due to the volunteer campaign efforts of the eleven active Tea Party groups in Virginia's 7th District (Blum 2020, chap. 4). Drawing on such studies, when we talk about local faction members, we are talking about Tea Party activists.

Factions and District Position

Activist-backed primary challenges are a key way that factions might force party change. Here, we describe the mechanisms by which Tea Party challenges might move a district rightward. First, we explain what we mean by moving a district 'rightward,' a term with distinct meanings in reference to political elites and voters.

The elites we focus on are U.S. representatives. Factional pressure from the right could result in a district being represented by a member with more extreme issue positions or a more stridently partisan posture *via* two pathways: adaptation and replacement. A primary challenge from the right could incentivize an incumbent Republican representative to adapt their position toward the faction in an attempt to maintain their seat in Congress (Brady, Han, and Pope 2007). Alternatively, the district could move rightward by replacing a more moderate incumbent Republican with someone more extreme (Theriault 2006). A Tea Party factional challenger might successfully primary an incumbent, as famously happened in several contests. Alternatively, an incumbent might react to changing local conditions, such as a faction gaining control over a local party organization by declining to run for another term, thereby leaving the field open to more extreme candidates, possibly fielded by a more extreme party organization. Our empirical analyses will evaluate both whether and how the district's representative moved rightward.

We operationalize the rightward movement of voters as a higher percentage of voters in a district supporting the Republican candidate in the highest-turnout elections: presidential general elections. This ought to provide the hardest possible test for our theory, given that general election voters are thought to exert a somewhat moderating effect on a district (Hirano et al. 2010) and presidential elections are, clearly, the most nationalized.

We propose two mechanisms by which a district might become more solidly Republican at the presidential level due to activity from a far-right faction, which likely have a cumulative effect. The first involves the efforts of local Tea Party activists to shape the opinions of and mobilize fellow voters in the district. As Skocpol and Tervo suggest when comparing the efforts of factional activists in the Tea Party and the left's Resistance, "organized local citizens made a difference for their respective causes and parties by influencing local public opinion, boosting like-minded voter participation, or both" (Skocpol and Tervo 2021). The second mechanism is elite persuasion (Broockman and Butler 2017). In districts where the Tea Party faction was successful in reorienting elites, voters were represented by and recipients of messaging from officials who endorsed Tea Party-style positions involving no-compromise extremism and hyper-partisanship. Inasmuch as Republican-leaning voters are receptive to such messaging, we expect to see an intensification of mass partisanship in the district.

Expectations of Factional Pressure

We evaluate two hypotheses about the impact of factional pressure—understood as the presence of both activist groups and factional candidates—and party change. As discussed above, we operationalize change in terms of voter and legislator shifts in two mutually reinforcing hypotheses shown below.

> **H1 Voter shifts**: Voters in districts that experienced factionalism will vote for the Republican presidential candidate at higher levels in 2016 than in 2008, compared with those districts that did not experience factionalism.
>
> *H1 Null:* Factionalism will not result in more partisan voting behavior.
>
> **H2 Legislator shifts**: Representatives from districts that experienced factionalism will move further rightward in their roll-call voting between the 111$^{\text{th}}$ and 115$^{\text{th}}$ congresses than representatives from districts that did not experience local factionalism.
>
> *H2 Null:* Factionalism will not result in more extreme legislative voting behavior.

We also consider the possibility that parties may change for reasons bearing little relationship to factions. Increased partisanship at both the mass and elite levels may stem from a secular trend towards greater polarization, especially on the right (Arceneaux, Johnson, and Murphy 2012; Druckman, Peterson, and Slothuus 2013; Prior 2013), institutional factors such as redistricting (Altman and McDonald 2015; Carson, Engstrom, and Roberts 2007), or the novel candidacy of Donald Trump. To address these possibilities, we isolate the impact of factionalism through our identification strategy.

Data and Research Design

Our identification strategy leverages a canonical difference-in-differences (DiD) design with a single treatment period.[1] The treatment variable, *factionalism*, is operationalized as the combined presence of Tea Party activist groups and Tea Party candidate(s) in a congressional district during the *treatment period*; the three election cycles between 2010 and 2014, when the Tea Party was active in national elections (Blum 2020; Gervais and Morris 2018). The final *pre-treatment period* is therefore 2008 (111th Congress for H2), and the first *post-treatment* period is 2016 (115th Congress). We estimate the effects on vote share and legislator position in separate models.

Dataset Construction

Our dataset contains original sources on Tea Party activism and Tea Party candidacy, which we combine with data on district-level characteristics. We summarize the key variables in our analysis, with an overview in Table 1.

Table 1: Full List of Variables

Variable	Values	Measurement periods	Time invariant	Source
	Outcome Variables			
Republican presidential vote share	5.2% to 76.99% (2008); 4.9% to 80.37% (2016)	2000 to 2016	No	FEC Data
Legislator position	–1 (liberal) to +1 (conservative)	2004 to 2016	No	Nokken-Poole
	Treatment Variable			
Factionalism (Activist presence & Candidate presence)	1 (factionalism), 0 (no factionalism)	2010 to 2014	Yes	Blum 2020 and Cowburn 2020 data
	District Variables for Propensity Score Estimation			
Percent White	0.026% to 96.6%	2006 to 2018	No	American Community Survey
Median Income	\$23,773 to \$129,821	2006 to 2018	No	American Community Survey
Median Age	21 to 55.7	2006 to 2018	No	American Community Survey
Rural–Urban	Pure rural (1); Rural-suburban mix (2); Sparse suburban (3); Dense suburban (4); Urban-suburban mix (5); Pure urban (6)	2002–2010; 2012–2020	No	CityLab data
Democratic 2008	1 (district represented by a Democrat in 2008), 0 (Republican in 2008)	2008	Yes	FEC Data

Outcome Variable H1: Republican Presidential Vote Share

The first outcome variable is the Republican presidential candidate's total district-level vote share. Presidential vote share is the most commonly used measure of district partisanship in both the political science literature and popular media coverage when discussing the partisan identity of a

[1] We repeat both analyses using a series of alternative DiD estimators in the supplementary materials. Our results are unchanged.

district. In short, we think this measure is substantively meaningful. The measure also benefits from uniformity across all districts, with the same candidates running across the country, serving as a control for district-level differences in candidate quality or contest dynamics. Finally, the presidency is manifestly the most important single office in the U.S. political system, meaning the outcome of these elections is important because of its implications for who holds power.

Outcome Variable H2: Legislator Position (Nokken-Poole scores)

We operationalize our second outcome variable using first-dimension Nokken-Poole ideal points. Nokken-Poole scores are one-congress-at-a-time snapshots of a legislator's roll-call voting behavior aggregated across a single congress (Nokken and Poole 2004). As with NOMINATE (Poole and Rosenthal 1985), Nokken-Poole ideal points scale legislators from –1 to 1, where negative scores correspond with a more 'liberal' voting record, and positive scores correspond with more 'conservative' voting. We use this dynamic measure of representative position to capture adaptation and replacement effects. We expect that representatives in districts experiencing factionalism will either adapt their voting practices towards the right or be replaced by someone whose preferences align more closely with those of the conservative faction in their district. In our analysis section, we isolate the replacement effect using NOMINATE scores[2] to better understand the underlying mechanism driving our results.

Treatment Variable: Factionalism

We operationalize local factionalism as the interaction of two components: Tea Party activist presence and Tea Party candidate presence. The interaction of these variables produces the treatment variable, an indicator where one corresponds with districts where activists and candidates are *both* present. We explain each component below.

Activist presence: The *activist presence* proxy comes from an enhanced version of Rachel Blum's list of local Tea Party groups (Blum 2020). This list includes all Tea Party activist groups with an online presence (e.g., website, meetup page, ning, Facebook, Twitter) between 2012 and 2014. Initially, these groups were geo-coded using the district boundaries of the 113$^{\text{th}}$ Congress (2013–2015).[3] In 2020, this list was updated to include group ZIP codes using archived versions of Tea Party group pages, enabling precise identification of Tea Party group locations both pre and post-2010 redistricting.

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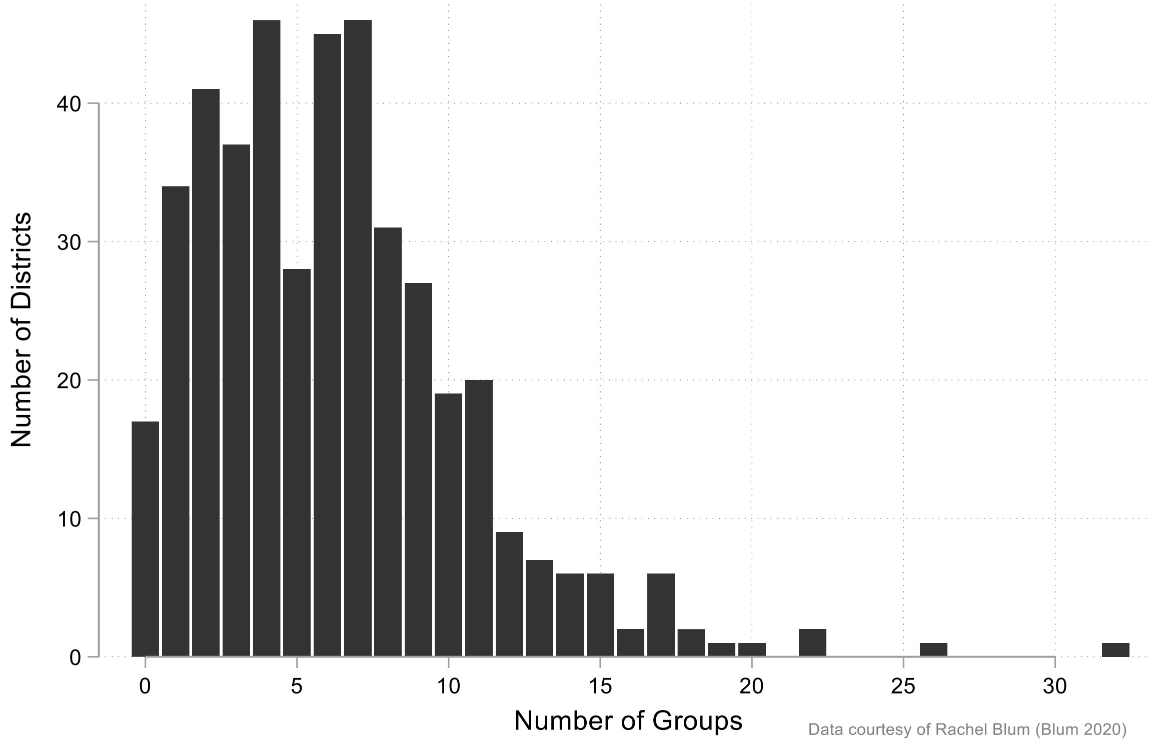
[2] Which use the same scaling method as Nokken-Poole scores aggregated across a representative's career, meaning they do not allow for intra-representative adaptation.

[3] By 2015, most groups had either stopped updating their websites, switched to a different web hosting platform, or transitioned exclusively to a social media platform (typically Facebook) which they primarily used to share memes, making it impossible to use group websites to draw accurate conclusions about changes over time. These data thus provide a maximum count of the number of Tea Party groups that were active in a given district during the faction's heyday. These data overlap substantially with the list of local groups in Skocpol and Williamson (2012).

Figure 1: Distribution of Tea Party Groups by Congressional District



We construct the indicator variable for activism presence by referencing the distribution of Tea Party group-per-district. As Figure 1 shows, all but seventeen congressional districts hosted at least one Tea Party group during the treatment period.[4] The average number of groups per district was 6.25, the median was six, the 25th percentile marker was three, and the 75th percentile marker was nine. To identify districts where the Tea Party was strong enough to pressure the local party, we collapsed this count variable into an indicator variable where one corresponds with districts above the 25th percentile (three or more groups), and zero corresponds with districts containing fewer than three groups. Collapsing this count variable to an indicator also prevents at-large and highly populated districts at the right-hand side of the distribution from skewing our estimates. To ensure our results are not an artifact of the cut-off decision made here, we repeat our main analyses moving this boundary in the robustness checks section of our supplementary materials.[5]

Candidate presence: The Tea Party *candidate presence* was adapted from Mike Cowburn's dataset of primary candidates (Cowburn 2022). Candidate presence was hand-coded as one when a district had at least one contested primary featuring a Tea Party-aligned candidate during our treatment period, and zero if it did not. We define contested primaries as those where two or more candidates are listed on the Republican primary ballot. We include contested nominations from all fifty states. For states with nonpartisan primaries (California, Louisiana, and Washington), a contested primary means two or more Republicans compete in the same district.

[4] The district with the most Tea Party groups was Montana's at-large congressional district (32). Other districts towards the maximum end of the distribution were either at-large or highly populated districts.

[5] Our results for H2 are robust regardless of the number of TP groups used as the cut-off (Table C2, supplementary material), our results for H1 lose significance when we use one or two groups as the treatment cut off (Table C1, supplementary material). The results and implications of our robustness checks are discussed at the end of our analysis section.

Candidates were coded as Tea Party-aligned if they met one or more of the following criteria: (1) Expressed support for or publicly associated with the Tea Party on platforms including active or archived campaign websites, media interviews, and speaking appearances at Tea Party events; (2) Received direct endorsements or funding from Tea Party political action committees (PACs) such as Tea Party Express, FreedomWorks, and Tea Party Patriots; (3) Received direct endorsements from notable figures in the Tea Party (e.g., Michele Bachman, Sarah Palin, Jim Jordan, Ted Cruz, Jim DeMint); (4) If serving in Congress, held membership in a Tea Party-aligned caucus; defined as the Tea Party Caucus, Liberty Caucus, or House Freedom Caucus (Bloch Rubin 2017; Blum 2020). When a candidate's alignment with the Tea Party was unclear based on these criteria, campaign positions were referenced (5), with direct expressions of hostility towards the Republican Party establishment taken as indicative of Tea Party alignment.[6]

Figure 2: Tea Party Candidates in Contested Republican Primaries

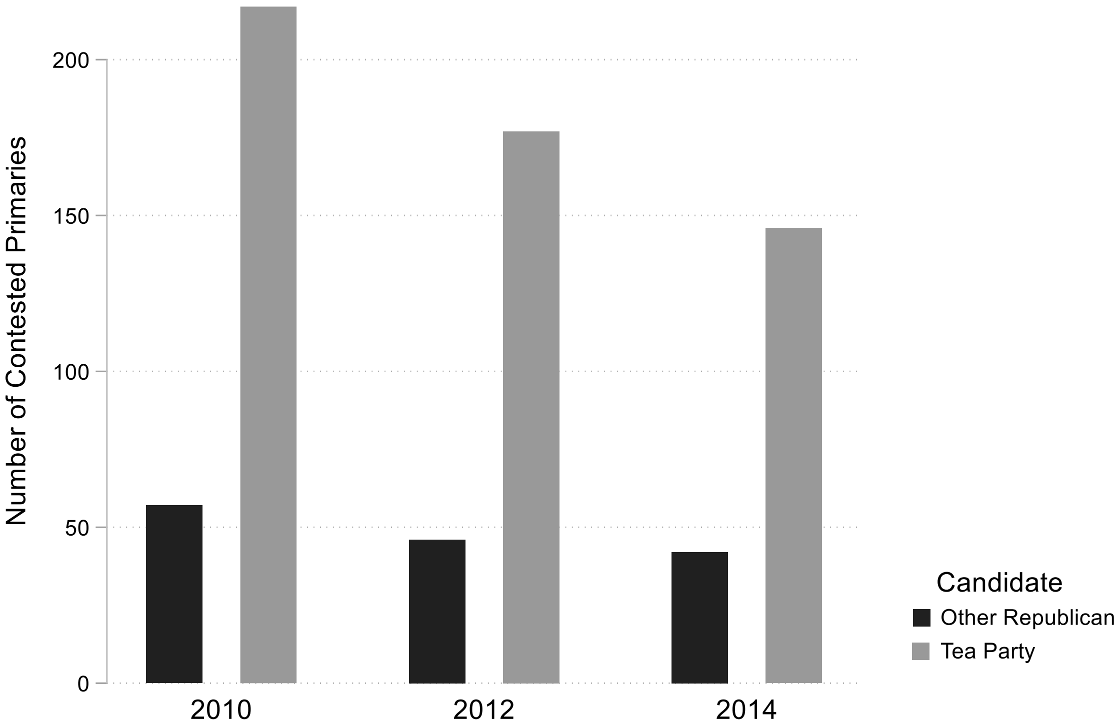


Figure 2 shows the breakdown of contested Republican primaries in the three congressional election cycles during our treatment period (2010, 2012, and 2014). Although the number of contested primaries varied (274 in 2010, 223 in 2012, and 188 in 2014), the proportion of contests featuring at least one Tea Party candidate remained stable. In 2010 and 2012, 79 percent of contested primaries featured at least one Tea Party-supported candidate; in 2014, 78 percent did.

District-Level Controls

We balance our control and treatment groups on factors that might offer alternative explanations for why a district could experience factionalism or move rightward. As summarized in Table 1, these

[6] Similar methods for coding primary candidates' factional affiliation have been undertaken elsewhere, most comprehensively in *The Primaries Project* (Kamarck and Podkul 2018), and most similarly in coding Tea Party affiliation of candidates in the 2010 primary and general election cycle (Jewitt and Treul 2014).

"true confounders" (Austin 2011) are: percentage of White voters, median household income, median age, rural–urban population, and pre-treatment partisan control. These variables are exogenous to but predictive of both our treatment variable of Tea Party presence (Walker 2011; Willer, Feinberg, and Wetts 2016), and our outcome variables of voting behavior (Gelman et al. 2007; Gramlich 2020) and ideological position (Jardina 2019; McCall and Manza 2011). Data on district whiteness, median household income, and median age come from one-year American Community Survey (ACS) estimates.[7] Our measure of district density comes from the CityLab project (Montgomery 2022), and balanced according to CityLab's fuzzy-c means clustered groups, ranging from pure rural to pure urban. Even balancing on these diverse explanations of the Republican Party's rightward movement, underlying partisan differences may contribute to the distance between our control and treatment districts, meaning we also balance on pre-treatment partisanship in the form of partisan control of the district in the final pre-treatment period, 2008.[8]

Redistricting

Our analysis time frame overlaps with the post-2010 census redistricting cycle. Measurements up to and including 2010 are based on the 2000 census district boundaries, and our measurements from 2012 onwards are based on boundaries drawn using the 2010 census. We address incongruences by matching districts based on shared populations, using the method detailed by Crespin (2005) and data from the Geographic Correspondence Engine (Missouri Census Data Center 2014). This approach spatially intersects boundaries of the old and new districts using census tract files of population counts to match new (post-2010) districts with their 'most similar' or 'parent' districts prior to redistricting based on population overlap (see also Cox and Katz 2002). This approach enables us to track continuity even in defunct or newly created districts, and in states where boundaries or district numbers were reconfigured following redistricting (e.g., California, Florida). In districts with minimal change in district boundaries, the shared populations are at or close to 100 percent. In all states, this approach ensures that incumbents are held constant when the geographic territory they represent is reconfigured by redistricting. We control for other district-level differences between our control and treatment groups through our identification strategy.

Identification Strategy

Here, we discuss how our treatment and control groups differ in ways that might affect our outcomes, and how our identification strategy mitigates these differences. We focus on the components necessary to satisfy the stable unit treatment value assumption (SUTVA): comparable units, and parallel trends prior to treatment. We balance districts that do and do not experience local factionalism by

[7] Using the `getcensus` Stata module (Zippel et al. 2022).

[8] Given that we are able to demonstrate 'raw' partisan trends absent the balancing of districts (Figure B1 & B2, supplementary materials), balancing on pre-treatment outcomes does not violate the assumptions for a DiD design. In our robustness checks, we include more granular levels of partisanship, including an originally constructed partisan index and 2008 PVI (Table C17, supplementary materials). As in several of our other checks, our findings for H2 are robust to these more granular controls, though our results for H1 lose some significance.

estimating propensity scores from district-level characteristics not affected by our treatment or outcomes. We then use inverse probability of treatment weighting (IPW) to balance our groups. We demonstrate the validity of this process by presenting the weighted distributions of our propensity scores and balancing statistics. Finally, we demonstrate that both models meet the parallel trends assumption (PTA).

Difference-in-Differences Design

We use a 2x2 DiD identification strategy to isolate the impact of local factionalism on district partisanship. Our analyses of presidential vote share use data beginning in 2000, with the 2008 presidential election as the final pre-treatment period, and the 2016 presidential election as our post-treatment period. Our analyses of legislator change include data beginning in the 109th Congress and consider the congresses immediately after the 2008 and 2016 presidential elections as the final pre- (111th) and post-treatment (115th) periods.

Our DiD estimator $\hat{\delta}_{it}$ is the difference in the sample average outcome for treated districts pre- and post-treatment ($\bar{Y}_1{}^T - \bar{Y}_0{}^T$) minus the difference in the sample average outcome for untreated districts pre- and post-treatment ($\bar{Y}_1{}^C - \bar{Y}_0{}^C$). We model the treatment effect on our outcome variables using pooled ordinary least squares (OLS) regression rather than two-way fixed effects (TWFE) because our panel ID (district) is unbalanced by redistricting, making OLS more precise (Lechner, Rodriguez-Planas, and Fernández Kranz 2016). We report results using robust standard errors clustered at the district level to correct for autocorrelation and heteroskedasticity (Bertrand, Duflo, and Mullainathan 2004). We use the following additive form for both models:

$$Y_{it} = \alpha + \lambda^{2016}{}_t + \gamma^{\text{Factionalism}}{}_i + \delta^{(2016\text{*Factionalism})}{}_{it} + \varepsilon_{it}$$

Where Y is our respective outcome variable in district i at time t. α is the constant, the value of the control group in the pre-treatment period. λ indicates the post-treatment period, labeled as '2016 (Time)' below. A district assigned to the treatment group is denoted by γ and reported as 'Factionalism (Treatment)'. The interaction of the effect of treatment and time, δ, is our main DiD estimator, labeled 'Diff-in-Diff (Time x Treatment)' in the analyses below.

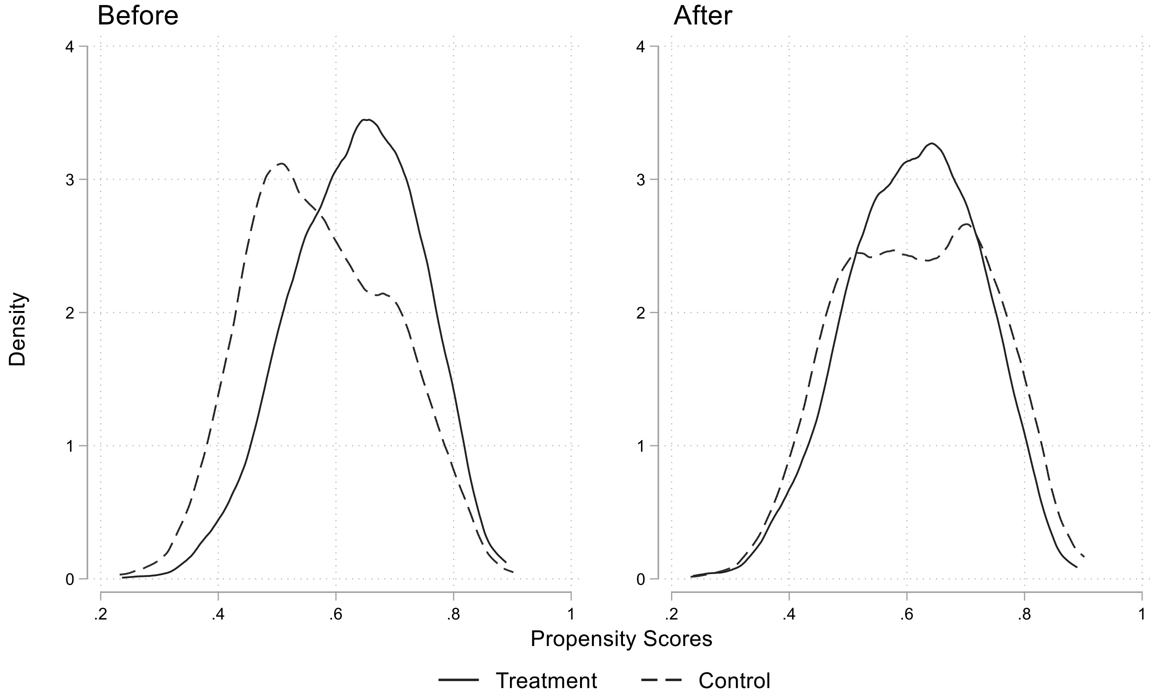
Comparable Units

Identifying comparable units in the pre-treatment period is a key challenge for estimating DiD using observational data. We first estimate propensity scores using the district-level controls discussed above and then use IPW to balance our treatment and control groups (Abadie 2005; Desai and Franklin 2019), thereby satisfying the assumption of conditional independence.[9] The propensity scores are the probability of a district being assigned to the treatment group based on observable

[9] IPW has the additional advantage of allowing us to assign weights that vary over time, as opposed to having a weight fixed to the pre-treatment panel ID of congressional districts.

covariates (Rosenbaum and Rubin 1983). This mitigates bias and endogeneity issues that can result from generating propensity scores from outcome variables (Rosenbaum 2012; Rubin 2007). We estimate propensity scores via a fitted logistic regression, where all observations are on common support, meaning we do not trim our data. We estimate weights separately for districts in the pre- and post-treatment periods—as validated elsewhere (Stuart et al. 2014)—enabling us to include all 435 districts before and after redistricting, including districts that only exist in one time period.[10]

Figure 3: Congressional District Propensity Scores Before & After Weighting



Prior to weighting, districts with high propensity scores were disproportionately assigned to the treatment group (Figure 3, left). These districts tended to be older, whiter, and in rural areas of Republican-leaning states; examples include Indiana's 9th, Kentucky's 4th, Missouri's 7th, Nebraska's 3rd, and West Virginia's 2nd districts. Ninety-eight districts in 2008 had propensity scores above 0.7 in the treatment group, compared to 37 in the control; in 2016 there were 110 and 37 districts in the respective groups. We show the greater similarity of propensity score distribution after weighting in Figure 3 (right).

[10] Using fixed weights or coarsened exact matching removes many redistricted congressional districts and gives potential spurious weights to districts that were radically transformed by the redistricting process.

Table 2: Summary of Balance and Weighting Scheme

Values of Weights (IPW)	Mean	Sd	p50	Max	Min	SMD
Control	2.601	0.982	2.287	10.171	1.302	-
Treatment	1.631	0.318	1.565	4.232	1.12	-
Unweighted Values						
Percent White (Control)	37.911	33.622	33.500	96.6	0.026	-
Percent White (Treatment)	48.000	36.305	62.925	95.8	0.098	0.288
Median Income (Control)	$54,555	$16,778	$51,647	$125,675	$19,311	-
Median Income (Treatment)	$54,992	$15,244	$51,700	$129,821	$25,630	0.027
Median Age (Control)	36.591	3.956	36.7	51.1	22.3	-
Median Age (Treatment)	37.929	3.468	37.8	55.7	21.0	0.360
Rural–Urban (Control)	3.443	1.846	3	6	1	-
Rural–Urban (Treatment)	3.408	1.551	4	6	1	–0.021
Democratic 2008 (Control)	0.682	0.466	1	1	0	-
Democratic 2008 (Treatment)	0.524	0.500	1	1	0	–0.327
Weighted Values						
Percent White (Control)	44.607	35.029	48	96.6	0.026	-
Percent White (Treatment)	44.234	36.398	56.1	95.8	0.098	–0.010
Median Income (Control)	$54,584	$16,216	$51,738	$125,675	$19,311	-
Median Income (Treatment)	$54,751	$15,353	$51,576	$129,821	$25,630	0.010
Median Age (Control)	37.598	4.045	37.7	51.1	22.3	-
Median Age (Treatment)	37.480	3.542	37.4	55.7	21.0	–0.031
Rural–Urban (Control)	3.416	1.81	3	6	1	-
Rural–Urban (Treatment)	3.421	1.585	4	6	1	0.003
Democratic 2008 (Control)	0.570	0.495	1	1	0	-
Democratic 2008 (Treatment)	0.580	0.494	1	1	0	0.021

Table 2 clarifies how IPW alters our data, with weights for both groups and a comparison of means and sample variances of our unweighted and weighted baseline covariates, in line with IPW best practice (Austin and Stuart 2015). Our weighting process reduces the standardized mean differences (SMD) between our control and treatment groups' characteristics to zero, giving confidence that we satisfy the conditional independence requirement.

Parallel Trends Assumption (PTA)

DiD estimation assumes that the treatment and control groups should follow parallel trends in respect to the pre-treatment outcome variables, conditional on confounders (see e.g., Heckman, Ichimura, and Todd 1997). To satisfy SUTVA, we must be reasonably sure that differences between the two groups were constant prior to treatment and would have remained constant over time absent treatment. We evaluate PTA by graphing the differences between treatment and control groups across three pre-treatment observations in Figure 4 (H1) and Figure 5 (H2). Both figures indicate parallel trends with similar differences between groups during the pre-treatment period. These trends deviate during our treatment period, consistent with PTA and indicating the suitability of our control and treatment groups.

Figure 4: Presidential Vote Share Parallel Trends

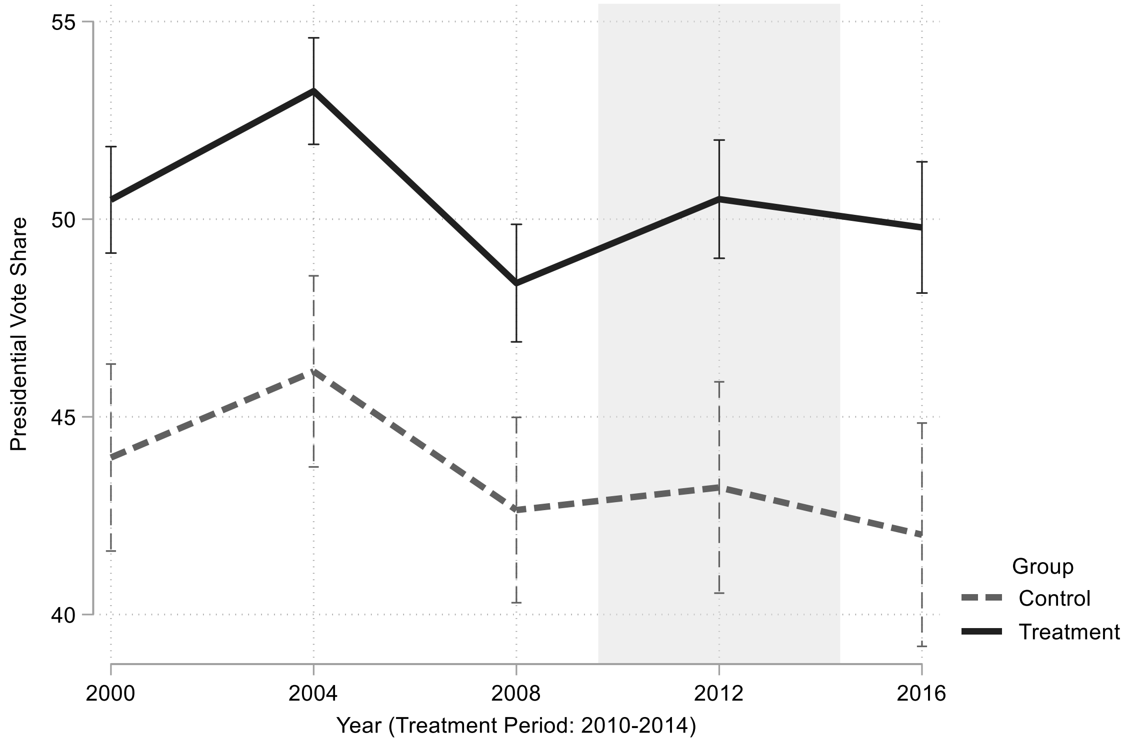
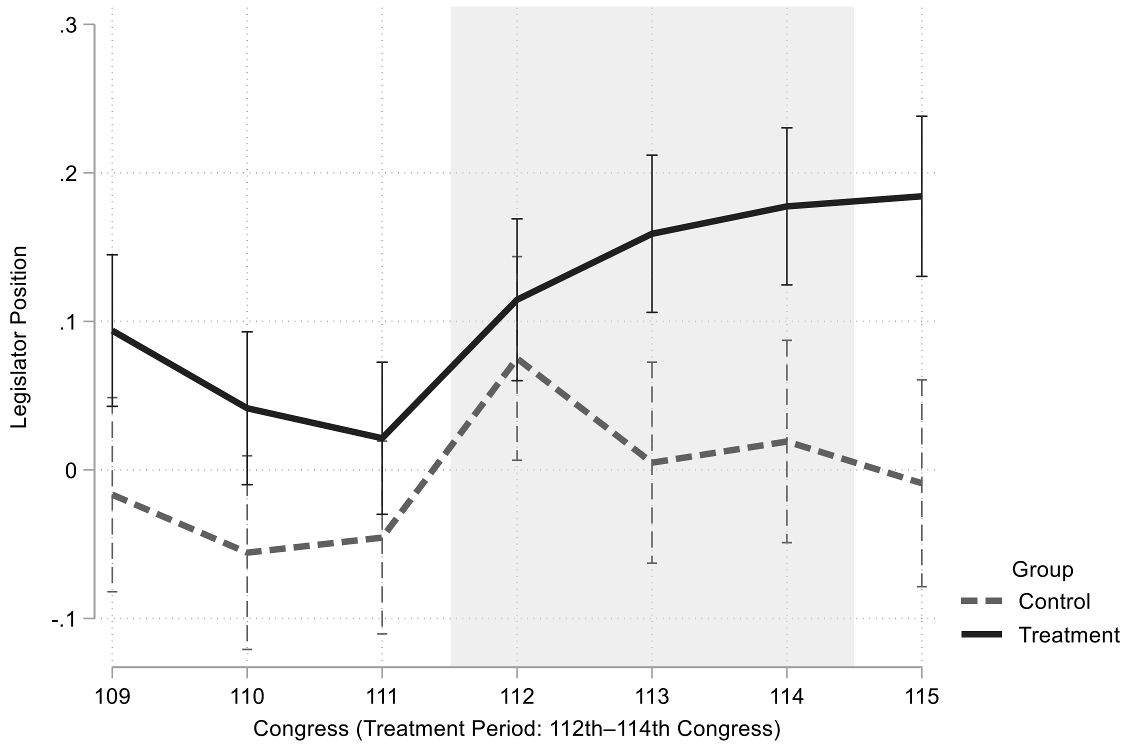


Figure 5: Legislator Position Parallel Trends



Analysis

We present the full results of both main models, including weighted means and coefficients, in Tables 3 and 4. We extend each of the analyses in Figure 6 and Table 5.

Presidential Vote Share

In Table 3 (and Figure 4), we show the weighted means and regression coefficients for Republican vote share in treated and control districts in our pre- and post-treatment periods in order to evaluate the impact of district-level factionalism on district Republican presidential vote share (H1). Voters in treated districts shifted towards the Republican candidate between 2008 and 2016 compared to voters in control districts. In 2008, there was a roughly six-point difference (5.740) in Republican vote share between districts in treatment and control groups, with treated districts voting for the Republican presidential candidate at a slightly higher rate. By 2016, this gap increased to roughly eight percentage points (7.772).

Most of this effect came via improved performance in factional districts, where Donald Trump's vote share (49.79%) was roughly one and a half percentage points more than McCain's (48.38%). In contrast, Trump's vote share in non-factional districts (42.64%) was slightly less than McCain's (42.06%). The primary object of interest in Table 3 is therefore the DiD coefficient, indicating that local factionalism had a weakly significant ($p<0.1$) positive effect on Republican vote share. *Ceteris paribus*, local factional pressure improved Republican presidential performance by roughly two points (2.032) between 2008 and 2016, plus or minus about a point (1.182).

Table 3: Presidential Vote Share Model

	Pres Vote Share
2016 (Time)	–0.623
	(0.806)
Factionalism (Treatment)	5.740***
	(1.460)
Diff-in-diff (Time x Treatment)	2.032*
	(1.182)
Observations	870
R-squared	0.047
Mean Control 2008	42.64
	(1.232)
Mean Treated 2008	48.38
	(0.783)
Diff 2008	5.740
	(1.460)
Mean Control 2016	42.02
	(1.552)
Mean Treated 2016	49.79
	(0.878)
Diff 2016	7.772
	(1.783)

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Raw Number of Republican Votes

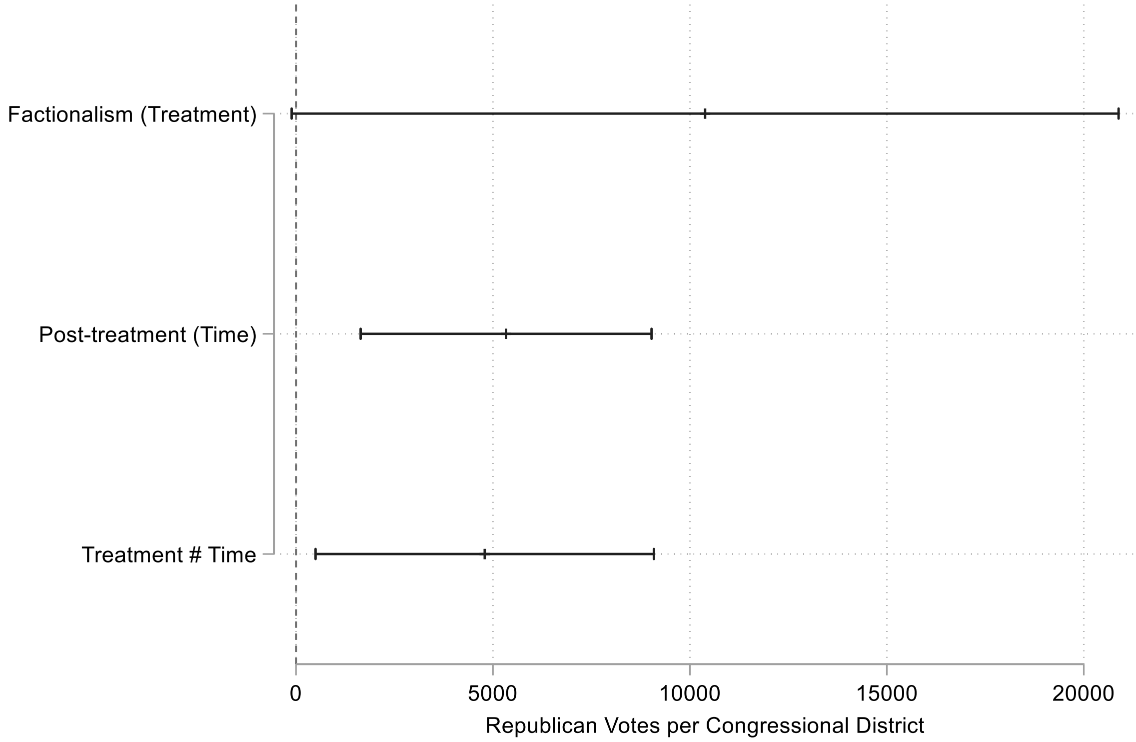
Several mechanisms could drive improved Republican performance in presidential elections. We might be observing a mobilization effect (Holbrook and McClurg 2005) due to the efforts of an engaged faction in the district. To test this mechanism, we isolate the number of Republican votes in a congressional district in 2008 and 2016 and repeat our main analysis with the raw number of votes for the Republican presidential candidate as our dependent variable, using the 2016 district boundaries for both years (Daily Kos 2016).[11] Unfortunately, due to restrictions on data availability,

[11] This approach has the additional benefit of mitigating any potential effects of our redistricting strategy, as both our pre- and post-periods use the same districts.

we cannot go back further in time to demonstrate the necessary assumptions for a causal design, as in our main analysis. We nevertheless demonstrate a substantively significant relationship between the interaction of time and treatment variables and the number of votes for the Republican presidential candidate in each district in a pooled OLS regression model.

The time coefficient in Figure 6 indicates that all districts saw higher numbers of Republican votes in 2016 than in 2008. Nevertheless, being in our treatment group was associated with almost five thousand (4,792) additional Republican votes in 2016, give or take two thousand (2,185) votes. Though the design here means that we cannot attribute causality, this significant relationship suggests that our main finding in H1 is driven by Tea Party factionalism mobilizing Republicans in our treatment districts. That most of the effect in our main analysis was the result of increased vote share in treatment districts rather than reduced performance in control districts further aligns with this claim. The lower significance of the effect in our main analysis may indicate that factional Republican engagement also mobilized Democratic voters (see also Ballard, Hassell, and Heseltine 2020).

Figure 6: Republican Presidential Votes 2008 to 2016



Legislator Position

The partisan shifts brought about by district-level factionalism might also influence the behavior of elected officials. Specifically, we expect a move to the right among representatives from treated districts, compared to other representatives (H2).

Figure 5 showed the weighted means with confidence intervals for our control and treatment groups. In the 111th Congress, the ideal points of representatives from districts assigned to the treatment and control groups were not significantly different (0.067); by the 115th Congress, a clear difference had emerged. As shown in Table 4, representatives in our control group moved only slightly (non-significantly) to the right (0.037). In contrast, representatives from districts that experienced local factionalism were significantly further to the right post-treatment, with a 0.126 DiD effect. This effect is larger than the asymmetry in partisan differences between the mean Republican and Democratic representative in the 115th Congress (0.090). In other words, representatives from districts experiencing local factionalism moved more than three times further rightward (0.126) than those from districts that did not (0.037). In the supplementary material (Table C12), we repeat this analysis using the 116th Congress (2019–2021) as our first post-treatment observation. The effect remains in this analysis, though it decreases slightly in size, indicating an element of 'decay' post-Tea Party.

Table 4: Legislator Position Model

	Legislator Position
2016 (Time)	0.037
	(0.031)
Factionalism (Treatment)	0.067
	(0.044)
Diff-in-diff (Time x Treatment)	0.126***
	(0.043)
Observations	870
R-squared	0.037
Mean Control 2008	–0.046
	(0.036)
Mean Treated 2008	0.021
	(0.026)
Diff 2008	0.067
	(0.044)
Mean Control 2016	–0.009
	(0.038)
Mean Treated 2016	0.184
	(0.029)
Diff 2016	0.193
	(0.047)

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Representative Adaptation or Replacement

We also analyze whether these effects are the result of representatives adapting their positions over time or being replaced by new representatives further to the right. Our dataset includes eighty Republicans present in both the 111th and 115th congresses who may have been subjected to an adaptative effect. An additional 161 Republican representatives are present only in the post-treatment period and might contribute to a replacement effect.[12] Of these 161 representatives, 131 were more conservative than the equivalent representative in the pre-treatment period and 29 were more moderate, with one representative having an identical score. One-congress-at-a-time NOMINATE, our dependent variable in our main model above, allows for variation both within and

[12] Ninety-eight Republican representatives were present in 2008 and not in 2016.

between representatives. We therefore repeat our analysis for H2 using DW-NOMINATE scores as our dependent variable. Because these scores are estimated over a politician's career,[13] this analysis only allows for variation *between* representatives (replacement).

Table 5 shows the results of this additional model. Replacement appears to drive our main results for H2, contributing 0.103 of 0.126, roughly four-fifths of the effect. This finding aligns with other research indicating that the replacement of more moderate members by comparatively extreme alternatives drives congressional polarization (Theriault 2006). In districts that experienced factionalism, newly elected Republican representatives were more consistently conservative in their roll-call voting behavior than the representatives they replaced. Examples of this replacement effect in factional districts include Florida's 1st District, where Jeff Miller (Nokken-Poole score of 0.591 in 2008) was replaced by the more conservative Matt Gaetz (0.931 in 2016); and Michigan's 3rd District, where Vern Ehlers (0.310 in 2008) was replaced by Justin Amash (0.558 in 2016).

Table 5: H2 Replacement Effect Only

	Leg Replacement (DW-NOMINATE)
2016 (Time)	0.028
	(0.031)
Factionalism (Treatment)	0.074*
	(0.043)
Diff-in-diff (Time x Treatment)	0.103**
	(0.042)
Observations	870
R-squared	0.031
Mean Control 2008	–0.026
	(0.035)
Mean Treated 2008	0.048
	(0.026)
Diff 2008	0.074
	(0.043)
Mean Control 2016	0.002
	(0.037)
Mean Treated 2016	0.179
	(0.027)
Diff 2016	0.176
	(0.046)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Representative adaptation contributes less to our main finding, in line with research that indicates that members of Congress "die in their ideological boots" (Hall and Snyder 2015, 28). Anecdotally, many Republican representatives in treated districts who were present in both periods did not become systematically more conservative in their voting behavior, regardless of their ideological position within the party. Relative moderates such as Don Young (0.242 in 2008, 0.277 in

[13] For example, Rep. Don Young scores 0.283 in each congress from the 93rd to the 117th.

2016), those from the middle of the party such as Joe Wilson (0.524, 0.508), and highly conservative members such as Kenny Marchant (0.619, 0.591) remained relatively consistent in their Nokken-Poole scores. A few representatives from factional districts, such as John Duncan (0.694 in 2008, 1 in 2016), did adapt their positioning in a conservative direction during the treatment period.

Summary & Robustness

We find that Republican legislators moved further to the right following the entrance of the Tea Party faction (H2). This movement appears to stem from legislator replacement rather than the adaptation of incumbents. The rightward movement of voters (H1) in districts where the Tea Party was active is substantively and statistically smaller, though improved Republican performance appears connected to partisan mobilization in factional districts.

We subject both models to a series of robustness checks.[14] We summarize these results and present them in full in our supplementary materials. These checks increase our confidence that factional activity moved the party at the elite level in a more conservative direction (H2). Our findings for H2 are robust to all checks, retaining significance in the theorized direction. For both hypotheses, no matter how we measure factionalism, the direction of the results is the same. Whereas representatives appear responsive to *any* factional pressure, voters are more responsive to a more visible factional presence, where pressure in primaries alone does not affect voting behavior in presidential elections. H1 appears sensitive to a 'critical mass' of factionalism, requiring a local factional structure that shadows the party structure—measured as having several groups alongside factional candidates—and is thus powerful enough to elicit a response from voters. Local factionalism may therefore be better conceived as a spectrum than as dichotomous in its effect on voters.

As a further check, we conduct two placebo tests on each model, constructing independent placebos for treatment and time. For the treatment placebo, we show that using alternative measures of district partisanship in 2008 to assign treatment does not produce significant results in equivalent models. In the second set of placebo tests, we keep the treatment assignment from our main analysis but randomize the observation dates. Again, this placebo produces null effects. These results give further confidence that our results do not merely reflect underlying trends during this period, or uncontrolled differences between our treatment and control districts, but are instead caused by local factionalism.

[14] These include: moving the boundary for the number of Tea Party groups, using the separate components of the local factionalism variable—activist presence and candidate presence—as our treatment, restricting to primary challengers who received at least twenty-five percent of the vote, restricting our analyses to 'quality' challengers, restricting to primary challengers who filed campaign receipts with the Federal Election Commission (FEC), using static weights based on 2008 district boundaries, extending our treatment period to include primaries in 2016, repeating our analysis of legislator position using 2018 as the post-treatment period, using lagged versions of our dependent variables, including the alternative dependent variable as a confounding variable, using a variety of alternative DiD estimators, and adding more granular controls for district partisanship.

Discussion and Conclusion

Our results underscore the role factions can play in party change, particularly at the local level. U.S. politics has undergone a process of nationalization, where even local elections are now contested over national issues (Hopkins 2018). Our findings suggest that local factional activists have found a way to retain influence in a nationalized electoral environment by focusing on national issues, potentially exacerbating the nationalization of local politics. Further, our findings suggest that the link between intra-party homogeneity and inter-party polarization may be weaker than previously thought. The presence of a faction within the Republican Party appears to have exacerbated trends toward ideological extremism, underscoring the importance of understanding how intra-party dynamics contribute to inter-party trends.

We uncover evidence that districts experiencing a critical mass of factional pressure from both activists and candidates shifted rightward between 2008 and 2016. These results were most pronounced when it came to elite behavior. Such findings suggest that the intra-party strife over policy, practice, and adherence to democratic norms under Trump can be understood as a continuation of factional divisions that were exacerbated during the Tea Party era. This work also highlights the importance of factions like the Tea Party in shaping parties' policy platforms, election strategies, communication, and organizational structures (Bendix and Mackay 2017; Bloch Rubin 2017; Blum 2020; Clarke 2020; Cohen et al. 2016; Cowburn and Knüpfer 2023; DiSalvo 2012; Kamarck 2014; Masket 2020; Noel 2016; Saldin and Teles 2020; Thomsen 2017).

Our results in terms of voter behavior were less robust. Voters in treated districts, those with three or more Tea Party groups and factional primary candidates, supported the Republican presidential candidate at slightly larger margins. Districts with fewer than three Tea Party groups did not experience this effect, indicating that Republican-leaning voters trended rightwards at the presidential level only when the local factional apparatus was strong enough to achieve its objectives of taking over the operations of the local Republican Party.

Finally, our research provides a potential template for the impact that local factions on the left might have on the Democratic Party if the influence of progressives within the party continues to grow (Schoen 2021; Wehner 2019). The Tea Party on the right and progressive groups on the left differ in organizational structure and electoral strategies (Skocpol and Tervo 2020), reflecting both the Democratic Party's historic aptitude at appeasing competing interests (Manento 2019) and the different geographies of progressive voters (Medvic 2021). Nevertheless, the Tea Party's model of combining activism with primary challenges might offer a path forward for factions on the left.

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Data Availability Statement

All data and replication materials for this paper are available at:

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Supplementary Material

This supplementary material includes three sections: descriptive statistics about the variables in our study, further details about approach to district assignment and balancing assignment, and a series of robustness checks used to further support our main results.

Descriptive Statistics

This section includes basic descriptive information about the key variables in our study, and the relationships between them absent any weighting or conditioning.

Table A1 shows the correlations between our key variables, including our two dependent variables, our treatment variable as well as the components that are used to construct the treatment, and the variables used for propensity score estimation.

Table A1: Correlation between variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Republican Presidential Vote Share *(H1 DV)*	1.000									
(2) Legislator Position *(H2 DV)*	0.730	1.000								
(3) Factionalism *(Treatment)*	0.356	0.270	1.000							
(4) TP Primary Candidate *(Treatment Component)*	0.205	0.131	0.777	1.000						
(5) 3+ TP Groups *(Treatment Component)*	0.474	0.332	0.649	0.226	1.000					
(6) District Median Income *(Propensity Score Estimation)*	-0.120	-0.055	0.014	0.027	-0.002	1.000				
(7) District % White *(Propensity Score Estimation)*	0.306	0.325	0.201	0.079	0.302	0.153	1.000			
(8) District Median Age *(Propensity Score Estimation)*	0.214	0.185	0.193	0.070	0.288	0.187	0.448	1.000		
(9) District Rural–Urban *(Propensity Score Estimation)*	-0.073	-0.039	-0.005	0.021	-0.011	0.155	-0.000	0.075	1.000	
(10) Democratic 2008 *(Propensity Score Estimation)*	-0.491	-0.598	-0.152	-0.084	-0.179	-0.034	-0.159	-0.035	-0.034	1.000

Table A2: Correlation Between Dependent Variables in Treatment and Control Groups by Year

Year	Group	Correlation
2008	Control	0.525
2008	Treatment	0.608
2016	Control	0.810
2016	Treatment	0.788

Table A2 shows the correlations between our dependent variables in our treatment and control groups in our final pre-treatment and initial post-treatment years of our analysis.

Figure A1: Correlation Between Change in Dependent Variables

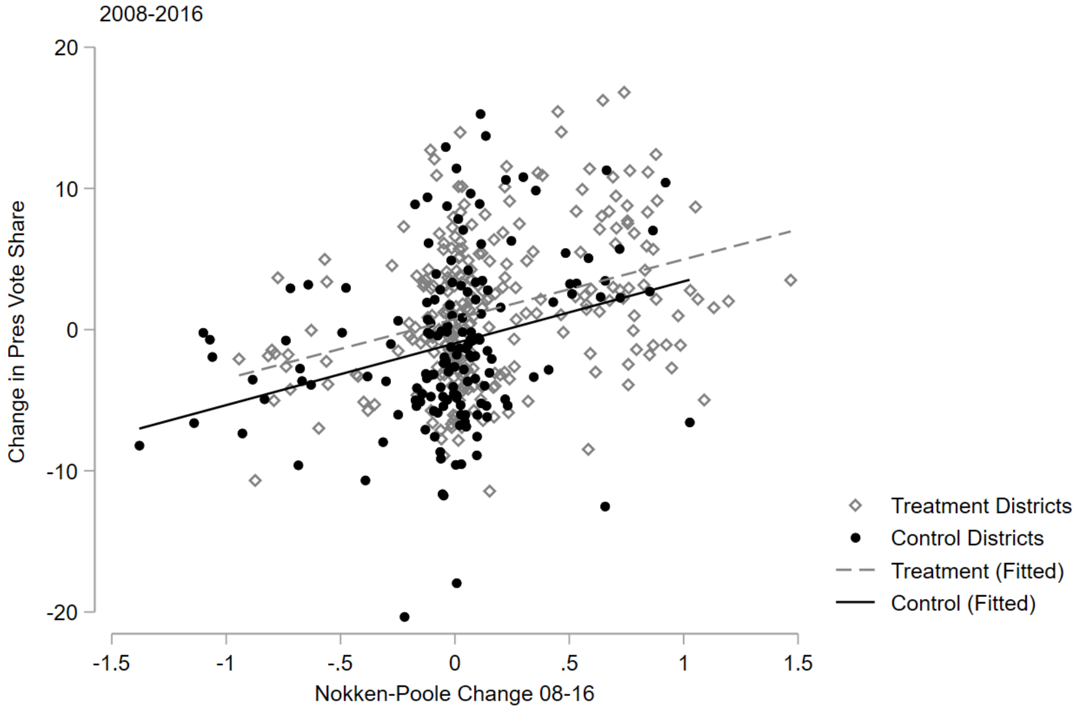


Figure A1 shows the correlation between the change in our dependent variables between 2008 and 2016 for our treatment and control districts. As expected, our dependent variables are correlated in both groups. Our treatment districts experience higher levels of change on both outcomes, as shown in our main findings, but these changes are aligned, as shown by the parallel fitted lines in this figure.

Figure A2: Correlation between Tea Party groups and Republican presidential vote share.

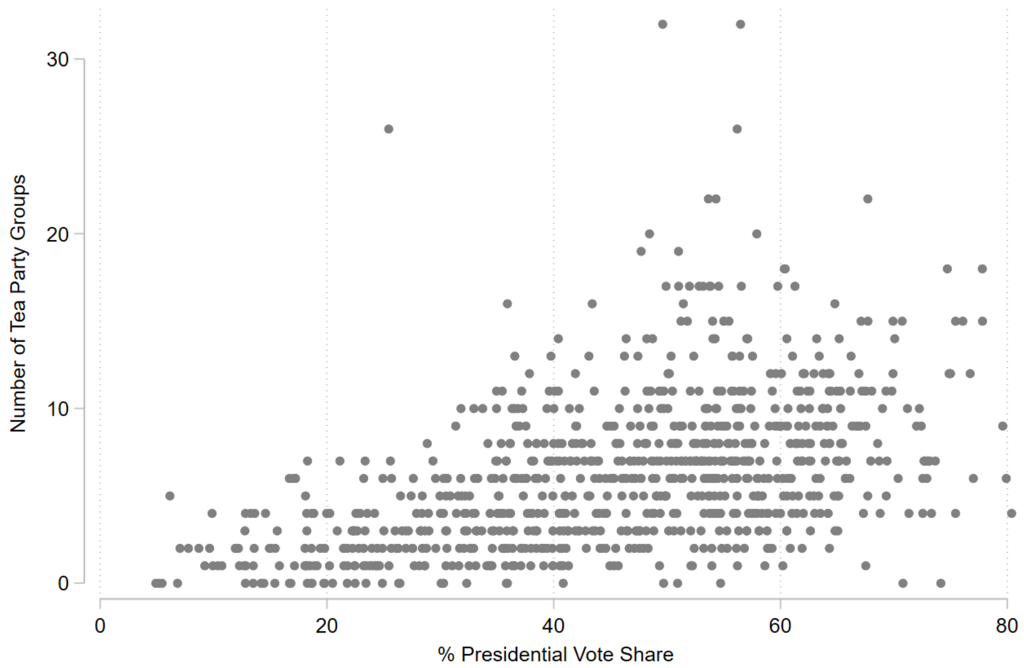


Figure A2 shows the correlation between the number of Tea Party groups in a district (one component of our treatment variable) and the presidential vote share in that district. Though there is a clear alignment in terms of the lower end of the presidential vote share and the number of Tea

Party groups it is also notable that there are many districts with comparatively few groups and high levels of Republican presidential vote share.

Table A3 and Table A4 present the descriptive statistics for our two dependent variables in both the final pre-treatment (2008) and initial post-treatment (2016) years.

Table A3: Presidential Vote Share (H1) Descriptive Statistics

Year	N	Mean	Sd	Min	Max
2008	435	45.423	14.326	5.204	76.994
2016	435	45.972	16.797	4.896	80.372

Table A4: Legislator Position (H2) Descriptive Statistics

Year	N	Mean	Sd	Min	Max
2008	435	-0.173	0.434	-0.726	0.991
2016	435	0.093	-0.470	-0.761	1

Figure A3: Tea Party Candidates in Contested Republican Primaries by Type

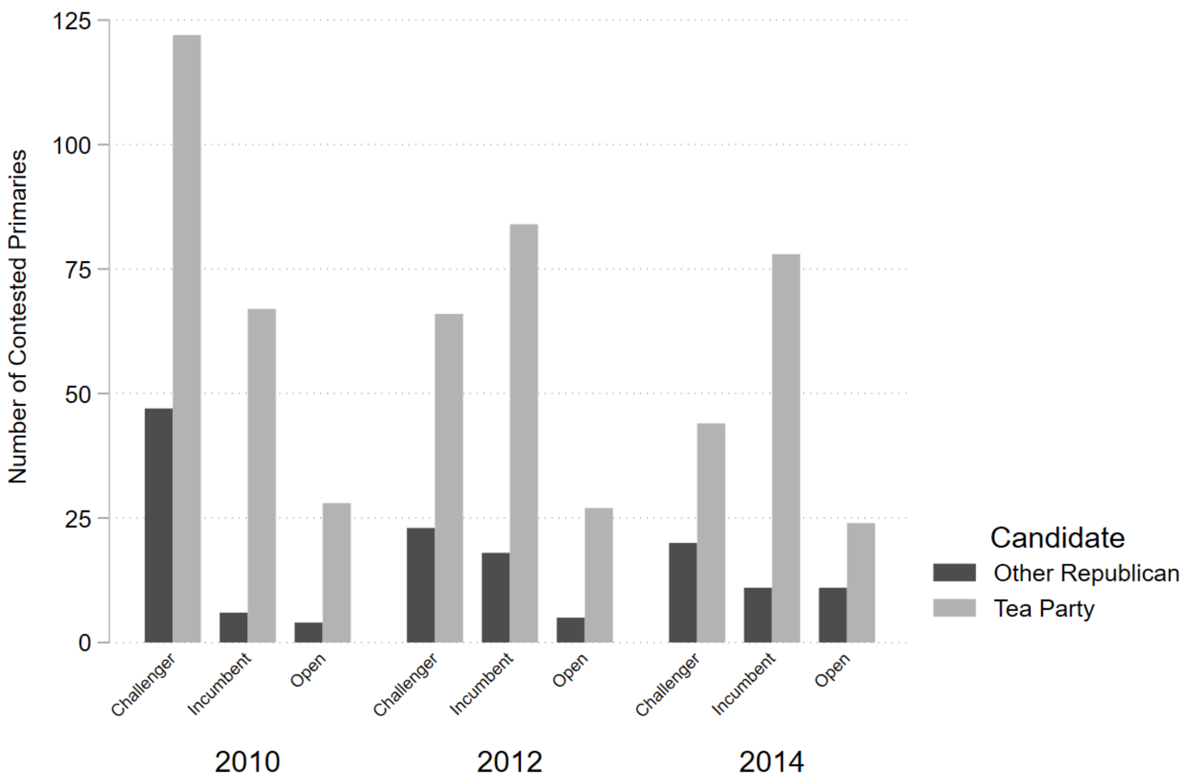


Figure A2 shows the number of Tea Party candidates in challenger (Democratic incumbent running for in the district), incumbent (Republican incumbent running in the district), and open (incumbent not running for either party) in each of the election cycles in our treatment period.

District Assignment

This section provides further information about the identity of and differences between the districts in our control and treatment groups. In Table B1 we present the number of districts that are assigned into control and treatment groups in our main analyses, as well as the number of groups that would be assigned if we used each of the two components of our treatment group as our treatment.

Table B1: Districts in Treatment & Control Groups

	Factionalism (Treatment)		Activist Presence		Candidate Presence	
	Interacted Pre	Interacted Post	TP Groups Pre	TP Groups Post	Primary Pre	Primary Post
Control	171	167	91	92	121	120
Treated	264	268	344	343	314	315
Total	435	435	435	435	435	435

In Figure B1 (H1) and Figure B2 (H2) we present our 'raw' parallel trends between our control and treatment groups. These are the trends of our groups without balancing using our propensity scores. In both cases, we are clearly able to demonstrate parallel trends in the three periods prior to our treatment. Though our treatment group is more Republican (H1) and further to the right (H2) on these measures, the trends only begin to diverge once we enter our treatment period. That we can demonstrate PTA absent our IPW approach gives further confidence in the robustness of our findings, and our inclusion of pre-treatment partisanship in our IPW estimation. We demonstrate the weighted parallel trends in Figure 4 and Figure 5 of the main text.

Figure B1: PTA Using Unweighted Figures – Presidential Vote Share (H1)

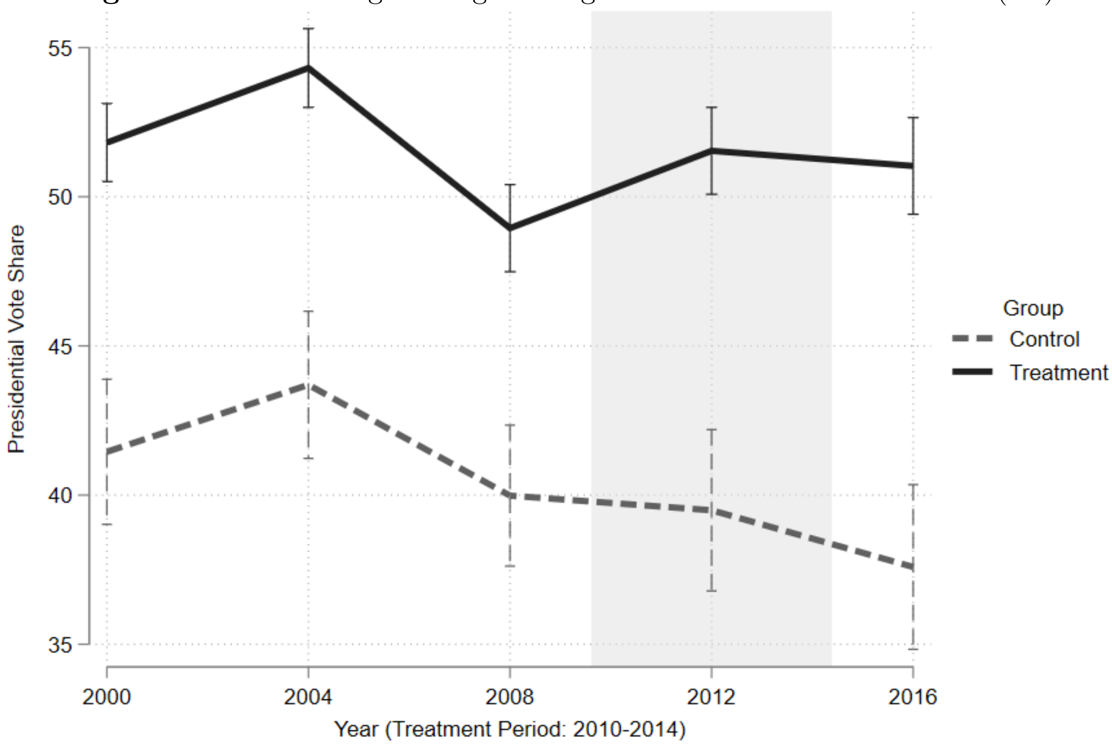
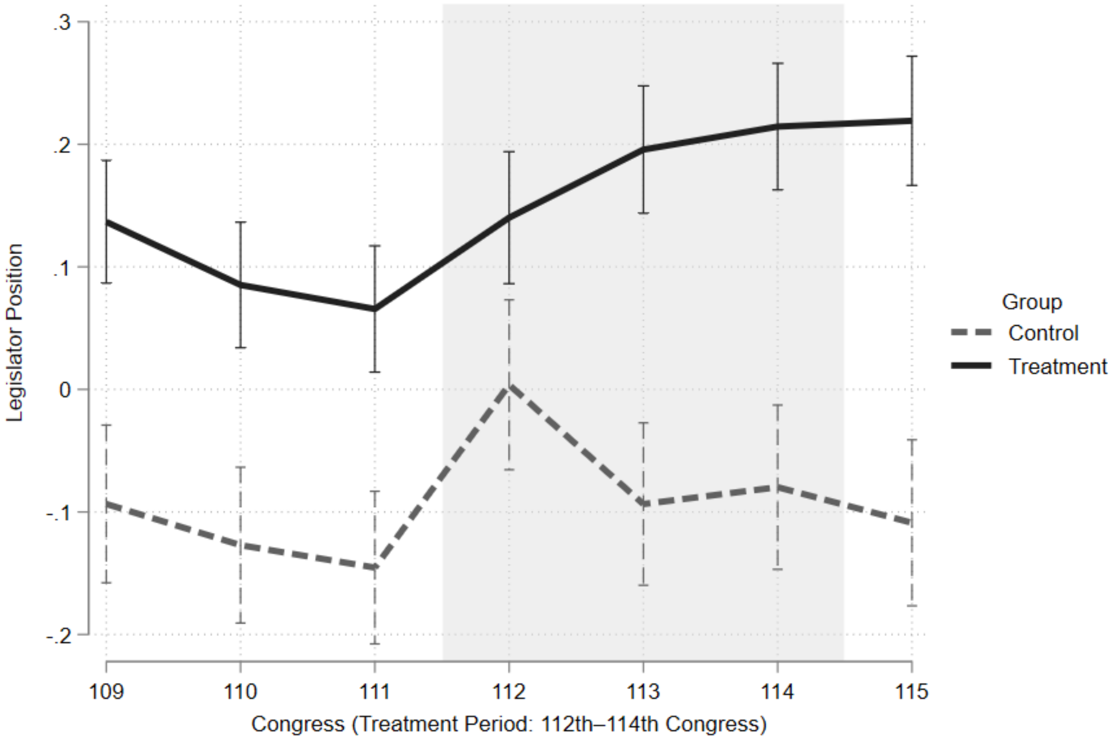


Figure B2: PTA Using Unweighted Figures – Legislator Position (H2)



Balance with Other Numbers of Tea Party Groups

The following tables demonstrate balance using one to six Tea Party groups in the district as the cut-off for treatment with balance on the confounding variables used for propensity score estimation before and after the weighting process. These tables were used to justify the selection of three or more Tea Party groups as the cut-off for treatment assignment in our main analyses. Our models are repeated in the robustness checks which follow this section using different cut-offs for treatment.

Table B2: One TP Group

Values of Weights (IPW)	Mean	Sd	p50	Max	Min	SMD
Control	3.371	0.800	3.225	5.713	2.191	-
Treatment	1.423	0.133	1.408	1.833	1.224	-
Unweighted Values						
Percent White (Control)	51.249	31.576	61.45	96.6	0.026	-
Percent White (Treatment)	58.669	30.021	68.7	95.8	0.098	0.241
Median Income (Control)	$56,583	$16,987	$53,222	$125,675	$23,773	-
Median Income (Treatment)	$57,548	$15,636	$53,732	$129,821	$31,368	0.059
Median Age (Control)	37.248	3.720	37.45	51.1	26	-
Median Age (Treatment)	37.825	3.434	37.6	55.7	28.2	0.161
Rural–Urban (Control)	3.415	1.735	3	6	1	-
Rural–Urban (Treatment)	3.432	1.642	4	6	1	0.010
Democratic 2008 (Control)	0.663	0.474	1	1	0	-
Democratic 2008 (Treatment)	0.551	0.498	1	1	0	–0.232
Weighted Values						
Percent White (Control)	56.921	30.741	67.3	96.6	0.026	-
Percent White (Treatment)	56.570	30.781	67	95.8	0.098	–0.011
Median Income (Control)	$57,212	$16,797	$53,746	$125,675	$23,773	-
Median Income (Treatment)	$57,264	$15,619	$53,505	$129,821	$31,368	0.003
Median Age (Control)	37.700	3.730	38.1	51.1	26	-
Median Age (Treatment)	37.666	3.444	37.5	55.7	28.2	–0.009
Rural–Urban (Control)	3.418	1.717	3	6	1	-
Rural–Urban (Treatment)	3.427	1.658	4	6	1	0.006
Democratic 2008 (Control)	0.577	0.494	1	1	0	-

Democratic 2008 (Treatment)	0.582	0.493	1	1	0	0.011

Table B3: Two TP Groups

Values of Weights (IPW)	Mean	Sd	p50	Max	Min	SMD
Control	3.022	0.992	2.834	8.562	1.614	-
Treatment	1.497	0.221	1.451	2.61	1.157	-
Unweighted Values						
Percent White (Control)	49.840	31.823	57.4	96.6	0.026	-
Percent White (Treatment)	59.772	29.776	69.6	95.8	0.098	0.325
Median Income (Control)	$55,972	$16,572	$52,893	$125,675	$23,773	-
Median Income (Treatment)	$57,906	$15,752	$54,034	$129,821	$31,368	0.120
Median Age (Control)	36.927	3.800	37.1	51.1	26	-
Median Age (Treatment)	38.016	3.330	37.8	55.7	28.2	0.305
Rural–Urban (Control)	3.419	1.794	3	6	1	-
Rural–Urban (Treatment)	3.432	1.605	4	6	1	0.007
Democratic 2008 (Control)	0.674	0.469	1	1	0	-
Democratic 2008 (Treatment)	0.539	0.499	1	1	0	–0.277
Weighted Values						
Percent White (Control)	57.085	30.541	67.8	96.6	0.026	-
Percent White (Treatment)	56.689	30.849	67.246	95.8	0.098	–0.013
Median Income (Control)	$57,294	$16,714	$53,746	$125,675	$23,773	-
Median Income (Treatment)	$57,315	$15,619	$53,673	$129,821	$31,368	0.001
Median Age (Control)	37.788	3.842	38.1	51.1	26	-
Median Age (Treatment)	37.701	3.335	37.5	55.7	28.2	–0.024
Rural–Urban (Control)	3.416	1.768	3	6	1	-
Rural–Urban (Treatment)	3.432	1.624	4	6	1	0.009
Democratic 2008 (Control)	0.575	0.494	1	1	0	-
Democratic 2008 (Treatment)	0.582	0.492	1	1	0	0.014

Table B4: 3 TP Groups (used in main analysis due to best balance - Table 2)

Values of Weights (IPW)	Mean	Sd	p50	Max	Min	SMD
Control	2.601	0.982	2.287	10.171	1.302	-
Treatment	1.631	0.318	1.565	4.232	1.12	-
Unweighted Values						
Percent White (Control)	37.911	33.622	33.500	96.6	0.026	-
Percent White (Treatment)	48.000	36.305	62.925	95.8	0.098	0.288
Median Income (Control)	$54,555	$16,778	$51,647	$125,675	$19,311	-
Median Income (Treatment)	$54,992	$15,244	$51,700	$129,821	$25,630	0.273
Median Age (Control)	36.591	3.956	36.7	51.1	22.3	-
Median Age (Treatment)	37.929	3.468	37.8	55.7	21.0	0.360
Rural–Urban (Control)	3.443	1.846	3	6	1	-
Rural–Urban (Treatment)	3.408	1.551	4	6	1	–0.021
Democratic 2008 (Control)	0.682	0.466	1	1	0	-
Democratic 2008 (Treatment)	0.524	0.500	1	1	0	–0.327
Weighted Values						
Percent White (Control)	44.607	35.029	48	96.6	0.026	-
Percent White (Treatment)	44.234	36.398	56.1	95.8	0.098	–0.010
Median Income (Control)	$54,584	$16,216	$51,738	$125,675	$19,311	-
Median Income (Treatment)	$54,751	$15,353	$51,576	$129,821	$25,630	0.010
Median Age (Control)	37.598	4.045	37.7	51.1	22.3	-
Median Age (Treatment)	37.480	3.542	37.4	55.7	21.0	–0.031
Rural–Urban (Control)	3.416	1.81	3	6	1	-
Rural–Urban (Treatment)	3.421	1.585	4	6	1	0.003
Democratic 2008 (Control)	0.570	0.495	1	1	0	-
Democratic 2008 (Treatment)	0.580	0.494	1	1	0	0.021

Table B5: Four TP Groups

Values of Weights (IPW)	Mean	Sd	p50	Max	Min	SMD
Control	2.271	1.090	1.916	11.900	1.196	-
Treatment	1.801	0.530	1.660	4.889	1.097	-
Unweighted Values						
Percent White (Control)	48.600	30.106	51.575	96.6	0.260	-
Percent White (Treatment)	62.891	29.629	72.800	95.8	0.098	0.475
Median Income (Control)	$57,353	$16,782	$53,969	$125,675	$23,773	-
Median Income (Treatment)	$57,185	$15,436	$53,400	$129,821	$31,683	–0.010
Median Age (Control)	36.773	3.700	36.8	51.1	26	-
Median Age (Treatment)	38.372	3.24	38.2	55.7	28.2	0.462
Rural–Urban (Control)	3.396	1.865	3	6	1	-
Rural–Urban (Treatment)	3.453	1.493	4	6	1	0.034
Democratic 2008 (Control)	0.682	0.466	1	1	0	-
Democratic 2008 (Treatment)	0.504	0.500	1	1	0	–0.366
Weighted Values						
Percent White (Control)	57.160	29.857	65.512	96.6	0.260	-
Percent White (Treatment)	56.612	32.165	68.700	95.8	0.098	–0.017
Median Income (Control)	$56,772	$15,873	$53,617	$125,675	$23,773	-
Median Income (Treatment)	$57,018	$15,824	$53,194	$129,821	$31,683	0.016
Median Age (Control)	37.952	3.973	38.1	51.1	26	-
Median Age (Treatment)	37.803	3.238	37.6	55.7	28.2	–0.041
Rural–Urban (Control)	3.410	1.822	3	6	1	-
Rural–Urban (Treatment)	3.433	1.547	4	6	1	0.014
Democratic 2008 (Control)	0.560	0.497	1	1	0	-
Democratic 2008 (Treatment)	0.574	0.495	1	1	0	0.028

Table B6: Five TP Groups

Values of Weights (IPW)	Mean	Sd	p50	Max	Min	SMD
Control	1.907	0.809	1.642	9.375	1.116	-
Treatment	2.114	0.764	1.877	6.256	1.108	-
Unweighted Values						
Percent White (Control)	49.646	29.873	55.100	96.6	0.26	-
Percent White (Treatment)	64.270	29.716	74.136	95.8	0.98	0.490
Median Income (Control)	$57,867	$17,397	$54,202	$129,821	$23,773	-
Median Income (Treatment)	$56,567	$14,335	$53,160	$124,627	$31,368	–0.082
Median Age (Control)	36.876	3.689	36.80	51.5	26	-
Median Age (Treatment)	38.544	3.112	38.4	55.7	29.8	0.489
Rural–Urban (Control)	3.390	1.875	3	6	1	-
Rural–Urban (Treatment)	3.470	1.398	4	6	1	0.048
Democratic 2008 (Control)	0.658	0.475	1	1	0	-
Democratic 2008 (Treatment)	0.500	0.500	0	1	0	–0.325
Weighted Values						
Percent White (Control)	56.909	29.578	65.3	96.6	0.26	-
Percent White (Treatment)	56.465	33.010	69.5	95.8	0.98	–0.014
Median Income (Control)	$56,871	$16,377	$53,324	$129,821	$23,773	-
Median Income (Treatment)	$56,906	$14,906	$53,512	$124,627	$31,368	0.002
Median Age (Control)	37.943	4.052	37.8	51.5	26	-
Median Age (Treatment)	37.874	3.096	37.7	55.7	29.8	–0.019
Rural–Urban (Control)	3.437	1.831	4	6	1	-
Rural–Urban (Treatment)	3.442	1.470	4	6	1	0.003
Democratic 2008 (Control)	0.567	0.496	1	1	0	-
Democratic 2008 (Treatment)	0.571	0.495	1	1	0	0.008

Table B7: Six TP Groups

Values of Weights (IPW)	Mean	Sd	p50	Max	Min	SMD
Control	2.411	1.046	2.092	8.561	1.157	-
Treatment	1.444	0.190	1.398	2.324	1.166	-
Unweighted Values						
Percent White (Control)	50.068	29.976	56.249	96.6	0.026	-
Percent White (Treatment)	65.300	29.421	75.315	95.8	0.17	0.512
Median Income (Control)	$57,583	$17,152	$53,970	$129,821	$23,773	-
Median Income (Treatment)	$56,815	$14,391	$53,367	$124,627	$31,368	–0.048
Median Age (Control)	36.984	3.686	36.9	51.5	26	-
Median Age (Treatment)	38.579	3.075	38.4	55.7	29.8	0.470
Rural–Urban (Control)	3.370	1.865	3	6	1	-
Rural–Urban (Treatment)	3.507	1.352	4	6	1	0.084
Democratic 2008 (Control)	0.672	0.494	1	1	0	-
Democratic 2008 (Treatment)	0.462	0.499	0	1	0	–0.433
Weighted Values						
Percent White (Control)	56.776	29.575	65.300	96.6	0.026	-
Percent White (Treatment)	56.318	33.503	69.964	95.8	0.17	–0.014
Median Income (Control)	$56,915	$16,302	$53,336	$129,821	$23,773	-
Median Income (Treatment)	$56,809	$14,854	$53,367	$124,627	$31,368	–0.007
Median Age (Control)	37.892	3.998	37.700	51.5	26	-
Median Age (Treatment)	37.883	3.089	37.800	55.7	29.8	–0.003
Rural–Urban (Control)	3.432	1.825	4	6	1	-
Rural–Urban (Treatment)	3.430	1.435	4	6	1	–0.001
Democratic 2008 (Control)	0.569	0.494	1	1	0	-
Democratic 2008 (Treatment)	0.570	0.495	1	1	0	0.001

Robustness Checks

The below section is the results of our robustness checks. Alongside our main analyses we conduct multiple robustness checks, namely; moving the boundary for the number of Tea Party groups required to be considered in the treatment group, only including the distinct sub-components of our treatment variable—activist presence and candidate presence—as our treatment, restricting primaries to challengers who received at least twenty-five percent of the vote, restricting primary challengers to those who filed campaign receipts with the Federal Election Committee (FEC), using static weights based on 2008 districts, extending our treatment period to include primaries in 2016, repeating our analysis of legislator position using 2018 as the post-treatment period, using lagged versions of our dependent variables, including the alternative dependent variable as a confounding variable, and using doubly robust estimators. The results of these robustness checks give us greater confidence in our main findings, with an effect found in almost all models.

The results in Table C1 point in the theorized direction regardless of how many Tea Party groups we require for a district to be considered in our treatment group though this effect decreases in size and loses significance when we consider one or two groups as sufficient to be considered treated, largely due to a lack of data in the control group.

Table C1: Presidential Vote Share – Robustness Check using different #TP Groups

	1+ TP Groups	2+ TP Groups	4+ TP Groups	5+ TP Groups	6+ TP Groups
2016 (Time)	0.174	0.065	–0.509	–0.299	–0.277
	(0.798)	(0.811)	(0.769)	(0.674)	(0.600)
Factionalism (Treatment)	4.610***	5.496***	5.798***	5.897***	6.145***
	(1.620)	(1.545)	(1.414)	(1.356)	(1.365)
Diff-in-diff	0.429	0.912	2.298*	2.784**	2.742***
	(1.041)	(1.132)	(1.219)	(1.154)	(1.010)
Observations	870	870	870	870	870
R-squared	0.022	0.035	0.052	0.061	0.066
Mean Control 2008	42.58	42.28	43.08	43.37	43.65
	(1.439)	(1.348)	(1.124)	(0.999)	(0.938)
Mean Treated 2008	47.19	47.77	48.87	49.26	49.80
	(0.744)	(0.755)	(0.858)	(0.917)	(0.992)
Diff 2008	4.610	5.496	5.798	5.897	6.145
	(1.620)	(1.545)	(1.414)	(1.356)	(1.365)
Mean Control 2016	42.76	42.34	42.57	43.07	43.38
	(1.689)	(1.609)	(1.431)	(1.270)	(1.195)
Mean Treated 2016	47.80	48.75	50.66	51.75	52.26
	(0.878)	(0.877)	(0.957)	(1.034)	(1.093)
Diff 2016	5.040	6.408	8.097	8.681	8.887
	(1.903)	(1.832)	(1.722)	(1.637)	(1.619)

The results in Table C2 remain significant in the theorized direction regardless of how many Tea Party groups we require for a district to be considered in our treatment group. The substantive size of the effect decreases slightly when a single Tea Party group is considered as a treated district.

Table C2: Representative Position – Robustness Check using different #TP Groups

	1+ TP Groups	2+ TP Groups	4+ TP Groups	5+ TP Groups	6+ TP Groups
2016 (Time)	0.050	0.041	0.033	0.041	0.048
	(0.034)	(0.034)	(0.029)	(0.031)	(0.030)
Factionalism (Treatment)	0.041	0.054	0.074*	0.082*	0.077*
	(0.047)	(0.046)	(0.044)	(0.044)	(0.044)
Diff-in-diff	0.087**	0.112**	0.149***	0.158***	0.153***
	(0.043)	(0.044)	(0.043)	(0.046)	(0.046)
Observations	870	870	870	870	870
R-squared	0.021	0.029	0.047	0.056	0.054
Mean Control 2008	–0.041	–0.046	–0.044	–0.040	–0.030
	(0.041)	(0.039)	(0.033)	(0.031)	(0.029)
Mean Treated 2008	0.001	0.008	0.029	0.042	0.048
	(0.024)	(0.025)	(0.029)	(0.031)	(0.033)
Diff 2008	0.041	0.054	0.073	0.082	0.077
	(0.048)	(0.046)	(0.044)	(0.044)	(0.044)
Mean Control 2016	0.010	–0.005	-0.012	0.001	0.018
	(0.042)	(0.040)	(0.035)	(0.033)	(0.032)

Mean Treated 2016	0.138	0.161	0.211	0.242	0.249
	(0.027)	(0.027)	(0.031)	(0.034)	(0.036)
Diff 2016	0.128	0.166	0.223	0.240	0.231
	(0.050)	(0.049)	(0.047)	(0.047)	(0.048)

Table C3 and Table C4 show the main results if we independently use the two components of our main treatment variable as the treatment condition. In Table C3, we use the presence of three Tea Party groups as our treatment. For both outcomes, our effect size retains significance and increases substantively, likely due in part to the imbalance between the numbers of treatment and control districts, shown in Table B1.

Table C3: Tea Party Groups (Activist Presence) as Treatment

	Pres Vote Share	Leg Position
2016 (Time)	–3.972**	–0.040
	(1.723)	(0.060)
3+ TP Groups (Treatment)	8.891***	0.079
	(2.350)	(0.065)
Diff-in-diff (Time x Treatment)	5.641***	0.191***
	(1.946)	(0.065)
Observations	870	870
R-squared	0.150	0.06
Mean Control 2008	38.55	–0.074
	(2.228)	(0.061)
Mean Treated 2008	47.44	0.005
	(0.748)	(0.023)
Diff 2008	8.891	0.079
	(2.350)	(0.065)
Mean Control 2016	34.58	–0.114
	(1.722)	(0.071)
Mean Treated 2016	49.11	0.156
	(0.832)	(0.025)
Diff 2016	14.53	0.270
	(1.913)	(0.075)

In Table C4, we present our results only using Tea Party primaries as our treatment condition. In this case, our results for H1 are completely removed and essentially zero. The rightward movement of voters therefore appears more closely connected to the presence of activist groups in a given district than of factional candidates in congressional primaries. Our finding for H2 remains substantively significant, suggesting that legislative primaries are important in their ability to pressure parties at the elite level.

Table C4: TP Primary (Candidate Presence) Only as Treatment

	Pres Vote Share	Leg Position
2016 (Time)	0.529	0.048
	(0.690)	(0.034)
TP Primary 10-14 (Treatment)	4.644***	0.032
	(1.642)	(0.048)
Diff-in-diff (Time x Treatment)	–0.149	0.087**
	(0.773)	(0.042)

Observations	870	870
R-squared	0.020	0.019
Mean Control 2008	42.32	–0.037
	(1.463)	(0.042)
Mean Treated 2008	46.97	–0.005
	(0.745)	(0.024)
Diff 2008	4.644	0.032
	(1.642)	(0.048)
Mean Control 2016	42.85	0.011
	(1.695)	(0.042)
Mean Treated 2016	47.35	0.130
	(0.894)	(0.027)
Diff 2016	4.495	0.119
	(1.916)	(0.050)

In Table C5 we restrict our analyses only to primary elections where the second-placed candidate received more than twenty-five percent of the vote. The effect remains present in both models despite the smaller size of the treatment group.

Table C5: Only Including Primaries Where Non-Winner Receives 25 percent of Votes

	Pres Vote Share	Leg Position
2016 (Time)	–0.482	0.032
	(0.735)	(0.029)
Factionalism (>25%) (Treatment)	5.080***	0.026
	(1.413)	(0.043)
Diff-in-diff (Time x Treatment)	1.953*	0.154***
	(1.178)	(0.044)
Observations	870	870
R-squared	0.037	0.031
Mean Control 2008	43.21	–0.025
	(1.136)	(0.033)
Mean Treated 2008	48.29	0.001
	(0.841)	(0.028)
Diff 2008	5.080	0.026
	(1.413)	(0.043)
Mean Control 2016	42.73	0.007
	(1.421)	(0.035)
Mean Treated 2016	49.76	0.187
	(0.942)	(0.031)
Diff 2016	7.034	0.180
	(1.705)	(0.047)

In Table C6, we only include primaries where the losing candidate in Republican primaries filed an FEC report, suggesting they raised a minimum of $5,000. Both models retained significance.

Table C6: Only Including Primaries Where Non-Winner Files FEC Report

		Pres Vote Share	Leg Position
2016 (Time)		–0.319	0.033
		(0.736)	(0.030)
Factionalism (Treatment)	w/receipts	6.292***	0.067
		(1.392)	(0.044)

Diff-in-diff (Time x Treatment)	1.523	0.141***
	(1.106)	(0.044)
Observations	870	870
R-squared	0.053	0.042
Mean Control 2008	42.74	–0.041
	(1.139)	(0.034)
Mean Treated 2008	49.04	0.026
	(0.800)	(0.027)
Diff 2008	6.292	0.067
	(1.392)	(0.043)
Mean Control 2016	42.43	–0.008
	(1.440)	(0.036)
Mean Treated 2016	50.24	0.200
	(0.900)	(0.030)
Diff 2016	7.815	0.208
	(1.698)	(0.046)

Not all primary challengers are equally threatening. In Table C7, we restrict inclusion in our treatment to those Tea Party-supported primary candidates that can be considered 'quality'. For simplicity, we use Jacobson's (1978, 1989) definition of quality as being candidates who have previously held elected public office. All primary candidates were hand coded as quality by one of the authors using Vote Smart, Ballotpedia, and biographical information on candidates' websites. Our results for H1 lose significance when we restrict treatment in this way, though remain in the theorized direction. Our results for H2, perhaps unsurprisingly, increase in substantive size, suggesting that incumbents are more responsive to quality Tea Party-supported challengers, and that quality Tea Party-supported candidates are more likely to enter Congress.

Table C7: Only Including Primaries with 'Quality' Tea Party Candidate

	Pres Vote Share	Leg Position
2016 (Time)	0.093	0.052**
	(0.415)	(0.024)
Factionalism w/'Quality' (Treatment)	10.246***	0.140***
	(1.327)	(0.049)
Diff-in-diff (Time x Treatment)	1.387	0.272***
	(0.969)	(0.058)
Observations	870	870
R-squared	0.147	0.158
Mean Control 2008	43.80	–0.039
	(0.795)	(0.024)
Mean Treated 2008	54.05	0.101
	(1.062)	(0.042)
Diff 2008	10.25	0.140
	(1.327)	(0.049)
Mean Control 2016	43.90	0.013
	(0.973)	(0.025)
Mean Treated 2016	55.53	0.424
	(1.074)	(0.045)
Diff 2016	11.63	0.411
	(1.449)	(0.052)

One potential counter-argument to our findings is that 2010 was an unusual year, with many Tea Party candidates standing in primary elections and the party performing unusually well in a 'wave' election that November. Our results are consistent if we only consider the 2012 and 2014 primaries within our treatment, as shown in Table C8.

Table C8: Only Including 12-14 Primaries as Treatment

	Pres Vote Share	Leg Position
2016 (Time)	–0.345	0.053*
	(0.553)	(0.028)
Factionalism: 12-14 only (Treatment)	6.061***	0.070
	(1.313)	(0.043)
Diff-in-diff (Time x Treatment)	1.375*	0.116***
	(0.825)	(0.043)
Observations	870	870
R-squared	0.051	0.040
Mean Control 2008	43.34	–0.038
	(0.984	(0.029)
Mean Treated 2008	49.40	0.032
	(0.869)	(0.031)
Diff 2008	6.061	0.070
	(1.313)	(0.043)
Mean Control 2016	42.99	0.015
	(1.211)	(0.032)
Mean Treated 2016	50.43	0.202
	(0.992)	(0.033)
Diff 2016	7.436	0.186
	(1.565)	(0.046)

The weights in Table C9 use data from 2008 only. Control districts were matched to treatment districts with similar characteristics. If no treatment district was sufficiently similar, the district was removed from the dataset, giving a smaller sample size. In addition, because these weights are 'fixed' to a congressional district number, they could not change over time, meaning that if redistricting altered the configurations of districts in a state (as it did for example in California), the weight could not be reallocated. In addition, districts that were only created following redistricting were unable to be included in this analysis. These constraints led us to use the IPW weighting in our main analysis and give us caution over the below results. The removal of districts and potentially incorrect weighting based on outdated district numbers remove the significance in H2 but we note that the direction of the relationship is the same (and significant at the $p<0.1$ level in the presidential vote share model).

Table C9: Alternative Weighting Using 2008 Fixed Weights

	Pres Vote Share	Leg Position
2016 (time)	–1.630	0.081*
	(1.435)	(0.044)
Factionalism (treatment)	4.178***	0.133**
	(1.484)	(0.055)
Diff-in-diff	3.676*	0.054
	(2.097)	(0.054)

Observations	789	789
R-squared	0.044	0.051
Mean Control 2008	44.77	–0.067
	(0.994)	(0.049)
Mean Treated 2008	48.95	0.066
	(1.101)	(0.026)
Diff 2008	4.178	0.133
	(1.484)	(0.055)
Mean Control 2016	43.14	0.014
	(1.035)	(0.049)
Mean Treated 2016	50.99	0.201
	(1.060)	(0.029)
Diff 2016	7.853	0.187
	(1.481)	(0.057)

In Table C10 we conduct our analyses using all Tea Party-aligned candidates within our treatment rather than restricting inclusion only to those candidates in contested primaries. Making this change moved twenty-eight districts from our control to our treatment group. Most of these were unchallenged Republican incumbents, who adopted the Tea Party label and then didn't face a primary challenger in 2010, 2012, or 2014. We theorize that this group moved rightward solely through adaptation and successfully prevented being 'primaried' by adopting the Tea Party label. This group included notable figures such as Jim Jordan and Steve King. Other districts were unchallenged Tea Party candidates running against Democrats in districts where no contested primary took place due to lack of interest, usually due to a perceived lack of competitiveness in the November general election. As expected, our findings hold including these districts and for both models, the size of rightward movement increased.

Table C10: All TP Candidates (not just contested primaries)

	Pres Vote Share	Leg Position
2016 (time)	–0.399	0.012
	(1.413)	(0.040)
Factionalism – any TP candidate	6.786***	0.074*
	(1.464)	(0.041)
Diff-in-diff	1.843	0.154***
	(2.077)	(0.058)
Observations	870	870
R-squared	0.061	0.046
Mean Control 2008	41.65	–0.055
	(0.996)	(0.028)
Mean Treated 2008	48.43	0.019
	(1.072)	(0.030)
Diff 2008	6.786	0.074
	(1.464)	(0.041)
Mean Control 2016	41.25	–0.043
	(1.003)	(0.028)
Mean Treated 2016	49.88	0.185
	(1.079)	(0.030)
Diff 2016	8.629	0.228
	(1.473)	(0.041)

We also coded 2016 primaries as featuring a 'Tea Party' candidate. We followed the same method as outlined in the main paper, though official endorsements or associations with the Tea Party were scarcer in this election cycle. The inclusion of the 2016 cycle produced results that included no gap during our analysis, with every primary election included in either our pre-treatment, treatment, or post-treatment period. Including Tea Party primaries from 2016 moved eighteen districts from our control to our treatment group. The results in Table C11 are broadly consistent with our main findings, though H1 loses significance.

Table C11: Including 2016 'Tea Party' Primaries

	Pres Vote Share inc. 2016 Primaries	Leg Position inc. 2016 Primaries
2016 (Time)	–0.916	0.009
	(1.426)	(0.041)
Factionalism inc. 2016 (Treatment)	5.566***	0.041
	(1.463)	(0.042)
Diff-in-diff (Time x Treatment)	2.361	0.156***
	(2.085)	(0.060)
Observations	870	870
R-squared	0.047	0.033
Mean Control 2008	42.60	–0.028
	(0.995)	(0.029)
Mean Treated 2008	48.17	0.013
	(1.072)	(0.031)
Diff 2008	5.566	0.041
	(1.463)	(0.042)
Mean Control 2016	41.69	–0.019
	(1.022)	(0.029)
Mean Treated 2016	49.61	0.178
	(1.079)	(0.031)
Diff 2016	7.927	0.197
	(1.486)	(0.043)

In Table C12 we repeat our analysis for H2 using positions from the 116th Congress as the post-treatment period. This period did not start with an election in which Trump featured on the ballot and serves as further evidence that we are capturing an effect of factional pressure separate from the Trump phenomenon.

Table C12: H2 with 116th Congress (2019–2021) as Post

	Leg Position 116th Post
2016 (Time)	–0.017
	(0.041)
Factionalism (Treatment)	0.067
	(0.042)
Diff-in-diff (Time x Treatment)	0.105*
	(0.060)
Observations	870
R-squared	0.023
Mean Control 2008	–0.046
	0.029

Mean Treated 2008	0.021
	0.031
Diff 2008	0.067
	0.042
Mean Control 2016	–0.062
	0.029
Mean Treated 2016	0.109
	0.031
Diff 2016	0.171
	0.042

An alternative explanation for district-level change is the replacement of incumbent representatives with comparative more extreme alternatives. The below models include three indicators of representative replacement corresponding with the number of times a district elected a new representative (one, two, or three or more new members) between our pre and post periods; we use no replacement as our base category.[15] We do so to address the possibility that any effects are the result of the increasingly routine replacement of moderate members with comparatively extreme representatives (Theriault 2006). The below models in Table C13 therefore use the following specification:

$$Y_{it} = \alpha + \lambda^{2016}{}_{t} + \gamma^{\text{Factionalism}}{}_{i} + \delta^{(2016\text{*Factionalism})}{}_{it} + \beta_1{}^{\text{Partisanship}}{}_{it} + \beta_2{}^{\text{Replacement}}{}_{it} + \varepsilon_{it}$$

Our findings in Table C13 remain significant even when we control for representative replacement, and representative replacement is not a significant coefficient in either of our models. This gives us confidence that we are not simply capturing the effect of new, more extreme, representatives replacing long-serving moderates.

Table C13: Legislator Replacement

	Pres Vote Share New Rep Model	Leg Position New Rep Model
2016 (time)	–0.697	0.035
	(0.808)	(0.031)
Factionalism (treatment)	5.296***	0.066
	(1.450)	(0.044)
Diff-in-diff	2.066*	0.129***
	(1.186)	(0.043)
New Representative (1)	2.675	0.016
	(1.779)	(0.045)
New Representative (2)	3.866*	–0.010
	(2.073)	(0.062)
New Representative (3+)	1.169	–0.071
	(3.235)	(0.081)
Observations	870	870
R-squared	0.055	0.038
Mean Control 2008	41.45	–0.048

[15] Given our pre-period measures positions in the 111th Congress we do not include replacements in 2008 primary or general elections, we include replacements in special elections during the 111th Congress. Given our analysis concludes in the 115th Congress we include replacement in 2016 primary or general election but not in special elections during the 115th Congress.

	(1.538)	(0.045)
Mean Treated 2008	46.74	0.018
	(1.268)	(0.038)
Diff 2008	5.296	0.066
	(1.450)	(0.044)
Mean Control 2016	40.75	–0.014
	(1.827)	(0.046)
Mean Treated 2016	48.11	0.181
	(1.340)	(0.040)
Diff 2016	7.362	0.195
	(1.760)	(0.047)

In Table C14 we include lagged versions of dependent variables in each model, as expected the lagged versions of each dependent variable are highly significant predictors of our outcomes. Our model for H1 loses significance and decreases substantively in size, our model for H2 also decreases in substantive size but remains statistically significant, giving further confidence in our findings for this analysis.

Table C14: Lagged Dependent Variables as Controls

	Pres Vote Share - Lagged Model	Leg Position - Lagged Model
2016 (time)	2.679***	–0.010
	(0.961)	(0.016)
Factionalism (treatment)	-0.031	–0.008
	(1.046)	(0.018)
Diff-in-diff	1.337	0.047**
	(1.102)	(0.023)
Lagged DV	89.044***	0.943***
	(2.678)	(0.013)
Observations	870	870
R-squared	0.731	0.879
Mean Control 2008	0.810	–0.014
	(1.635)	(0.014)
Mean Treated 2008	0.779	–0.022
	(1.601)	(0.011)
Diff 2008	–0.031	–0.008
	(1.046)	(0.018)
Mean Control 2016	3.489	–0.027
	(1.060)	(0.011)
Mean Treated 2016	4.794	0.015
	(1.387)	(0.009)
Diff 2016	1.306	0.039
	(0.696)	(0.015)

Table C15 presents the main results with the inclusion of the alternative dependent variable as an additional control. Our model for H2 retains significance in the theorized direction, though our model for H1 is non-significant and the direction is reversed. These models further suggest the greater robustness of our finding for H2 than H1.

Table C15: Alternative Dependent Variable as Control

	Pres Vote Share inc. leg position	Leg Position inc. pres vote share
2016 (time)	–1.502*	0.049*

	(0.837)	(0.029)
Factionalism (treatment)	4.133***	–0.047
	(1.240)	(0.038)
Diff-in-diff	–1.007	0.086**
	(1.141)	(0.038)
Alternative DV	24.048***	0.020***
	(1.109)	(0.001)
Observations	870	870
R-squared	0.501	0.495
Mean Control 2008	43.74	–0.890
	(1.012)	(0.045)
Mean Treated 2008	47.87	–0.937
	(0.708)	(0.050)
Diff 2008	4.133	–0.047
	(1.240)	(0.038)
Mean Control 2016	42.24	–0.841
	(1.024)	(0.041)
Mean Treated 2016	45.36	–0.802
	(0.529)	(0.050)
Diff 2016	3.126	0.039
	(1.171)	(0.031)

As we were writing this paper, academic discourse around the optimal estimator for conducting DiD analyses has been ongoing. Without wishing to make any methodological commentary about approaches to DiD studies, we are keen to demonstrate that our findings are not an artifact of the estimator used. Table C15 presents our results using a variety of estimators, including Sant'Anna and Zhao's (2020) doubly robust estimator. Under most of the below estimators, our results are substantively unchanged.

Table C16: Alternative DiD Estimators

	Pres Vote Share	Legislator Position
Doubly Robust IPW	2.032*	0.126***
	(1.179)	(0.043)
Doubly Robust Improved Estimator	2.032*	0.126***
	(1.179)	(0.043)
Regression Augmented Estimator	2.032*	0.126***
	(1.179)	(0.043)
Abadie (2005) IPW Estimator	2.309	0.127***
	(2.801)	(0.043)
IPW and Regression Adjustment Estimator	2.032*	0.126***
	(1.179)	(0.043)

We acknowledge that our approach to 'controlling' for partisanship uses a rather blunt instrument (partisan control of the district in 2008). We use this approach in our main analysis given the endogeneity issues inherent with using more granular controls and approaches. Here, we present two alternative models that attempt to further control for partisan differences across districts. We include the additional variables as separate controls rather than in our propensity score estimation strategy given the endogeneity issues identified.

In the first set of models, we construct an index of district partisanship based on House results in the final two cycles prior to treatment. The partisan index takes the value 1 if the Republican candidate won the district with over 60 percent of the vote in 2006 and 2008; takes the value 2 if the Republican candidate won the district in both 2006 and 2008 (not achieving 60 percent of the vote); takes the value 3 if neither party won the district in both elections; takes the value 4 if the Democratic candidate won the district in both 2006 and 2008; and takes the value 5 if the Democratic candidate won the district with over 60 percent of the vote in both cycles. Unsurprisingly, this variable is negatively correlated with both outcomes. In both cases, the substantive size of our DiD effect is reduced, and in the case of H1 some significance is lost. In H2 significance is retained and the substantive size is only reduced by around one-third.

As an even more granular approach to partisanship, we include 2008 PVI scores from the Cook Political Report. These scores are essentially lagged versions of our DV in the case of H1 (the scores are estimated using presidential vote shares in 2000 and 2004) and so it is unsurprising that our effect once again loses significance in this model, though, again, the relationship is in the theorized direction. For H2, our results remain substantively significant.

Table C17: Including Pretreatment Partisan Index & 2008 PVI as Controls

	Pres Vote Share (Partisan Index)	Legislator Position (Partisan Index)	Pres Vote Share (2008 PVI)	Legislator Position (2008 PVI)
2016 (time)	–0.213	0.053**	–0.525	0.040
	(0.860)	(0.023)	(0.918)	(0.026)
Factionalism (treatment)	5.161***	0.043**	0.377	–0.096***
	(1.263)	(0.019)	(1.068)	(0.028)
Diff-in-diff	0.951	0.082**	1.449	0.109***
	(1.169)	(0.034)	(1.152)	(0.036)
Partisan Index	–5.234***	–0.215***	-	-
	(0.404)	(0.006)		
2008 PVI	-	-	0.813***	0.025***
			(0.039)	(0.001)
Observations	870	870	870	870
R-squared	0.332	0.630	0.560	0.619
Mean Control 2008	60.57	0.692	46.43	0.070
	(1.745	0.030	0.878)	(0.022)
Mean Treated 2008	65.73	0.735	46.81	–0.027
	(1.387)	(0.024)	(0.575)	(0.017)
Diff 2008	5.161	0.043	0.377	–0.096
	(1.263)	(0.019)	(1.068)	(0.028)
Mean Control 2016	60.36	0.745	45.90	0.109
	(1.898)	(0.034)	(1.096)	(0.021)
Mean Treated 2016	66.47	0.870	47.73	0.122
	(1.370)	(0.030)	(0.594)	(0.020)
Diff 2016	6.112	0.125	1.826	0.012
	(1.466)	(0.035)	(1.287)	(0.030)

Placebo Tests

As discussed in the main text, we also conduct independent placebo tests for treatment (Table C18) and time (Table C19). We present our results for the treatment placebo in Table C18, and show the confidence intervals around the means in Figure C1 (H1) and Figure C2 (H2). For each hypothesis, we use an alternative indicator of partisanship as the placebo treatment. For H1, we consider districts that were represented by a Republican in the House of Representatives after the 2008 election as our treatment condition. For H2, we consider districts that had a Republican lean according to 2008 PVI scores as treated. In each case, these conditions represent the best endogenous approximation of district partisanship available. For both hypotheses, the treatment conditions are, as expected, highly significant, but our DiD coefficients in each case are non-significant. These null results indicate that our main findings are not simply a byproduct of district partisanship or general over-time trends but are instead the result of concerted action by the Tea Party faction at the activist and candidate level.

Figure C1: Treatment Placebo H1

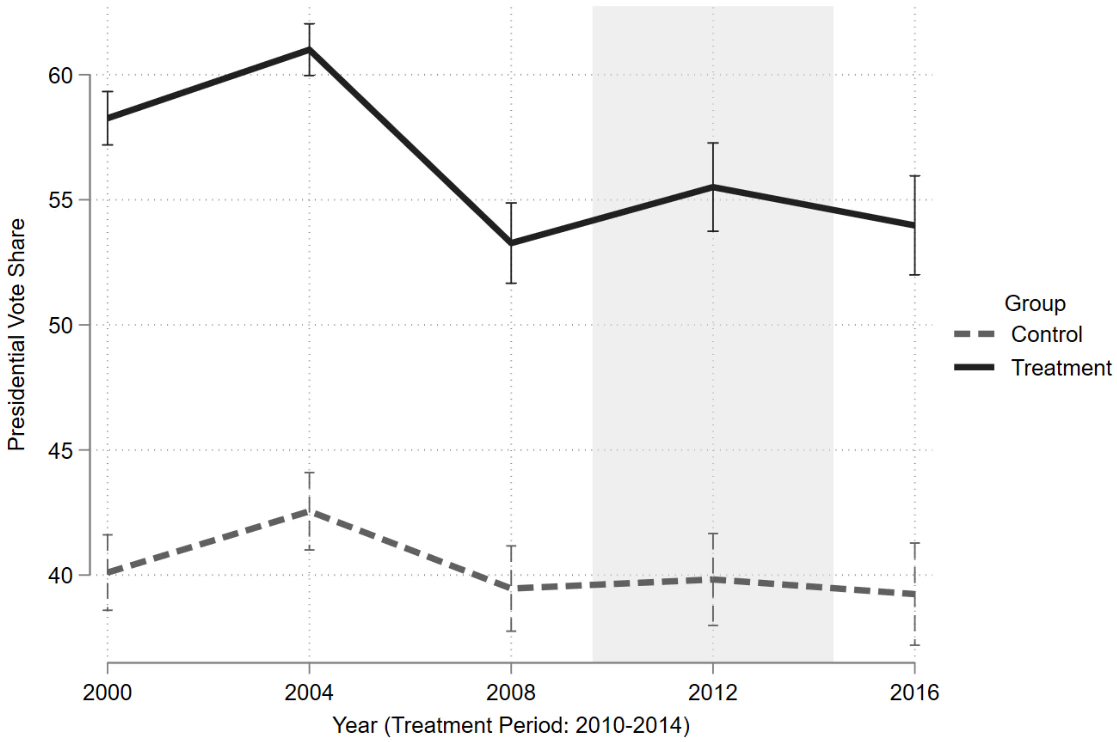


Figure C2: Treatment Placebo H2

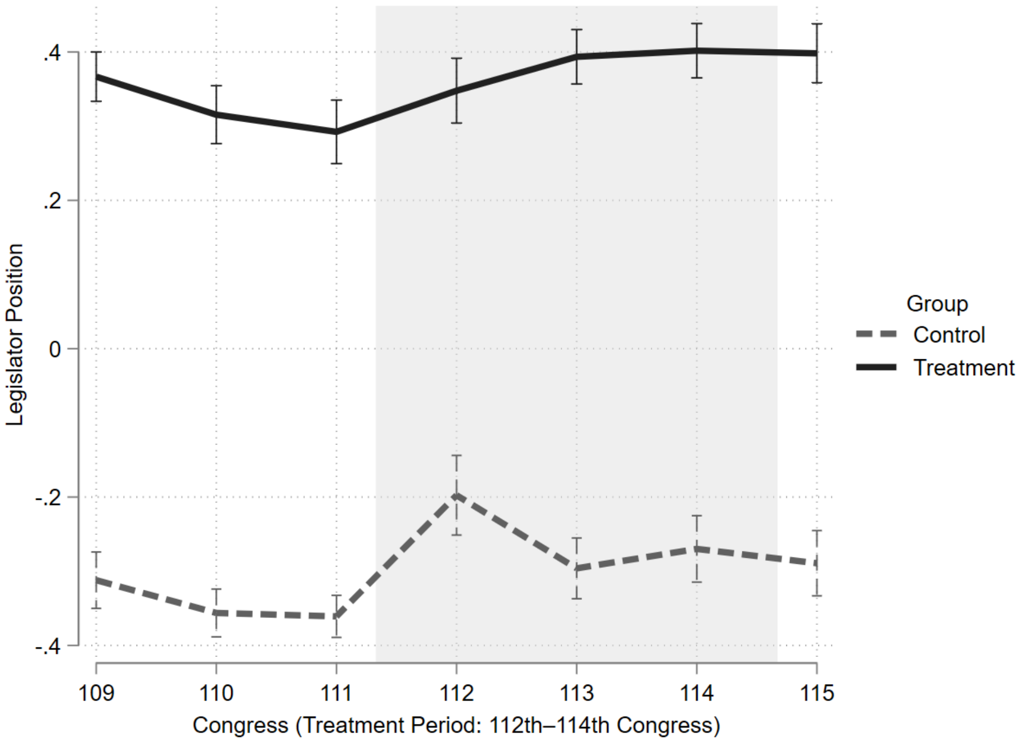


Table C18: Placebo Treatment (2008 Partisanship)

	Pres Vote Share	Legislator Position
2016 (Time)	–0.223	0.072***
	(0.453)	(0.025)
Republican Held District 2008 (Treatment H1)	13.808***	-
	(1.342)	
Republican Lean PVI 2008 (Treatment H2)	-	0.653***
		(0.031)
Diff-in-diff (Time x Treatment)	0.930	0.034
	(0.871)	(0.037)
Observations	870	870
R-squared	0.202	0.565
Mean Control 2008	39.46	–0.361
	(0.908	0.020)
Mean Treated 2008	53.27	0.292
	(0.988)	(0.023)
Diff 2008	13.81	0.653
	(1.342)	(0.031)
Mean Control 2016	39.24	–0.289
	(1.081)	(0.023)
Mean Treated 2016	53.98	0.398
	(1.222)	(0.021)
Diff 2016	14.74	0.687
	(1.631)	(0.032)

We present the results of our time placebo in Table C19. Here, we simply randomize the date of each observation within our dataset. As expected, our DiD coefficient is non-significant and close to zero. This result gives further confidence that we are not simply observing general differences between our treatment and control districts across the entire period but are instead being produced via the theorized mechanism of factional activity in the Tea Party era.

Figure C3: Timing Placebo H1

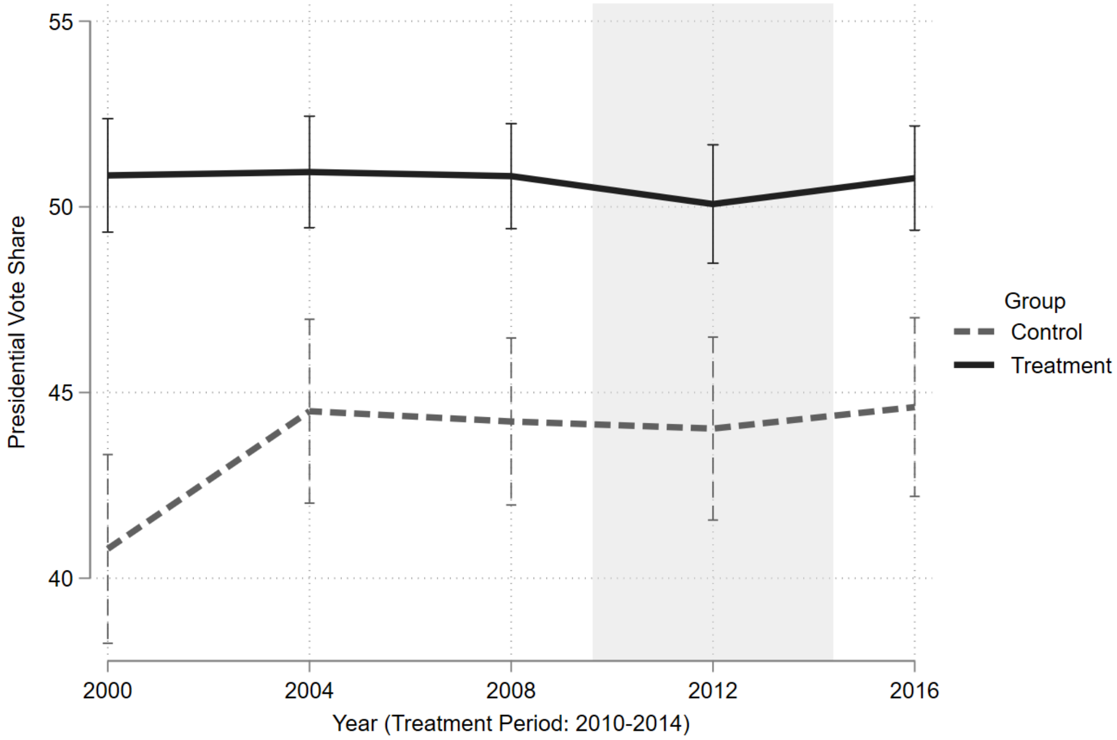


Figure C4: Timing Placebo H2

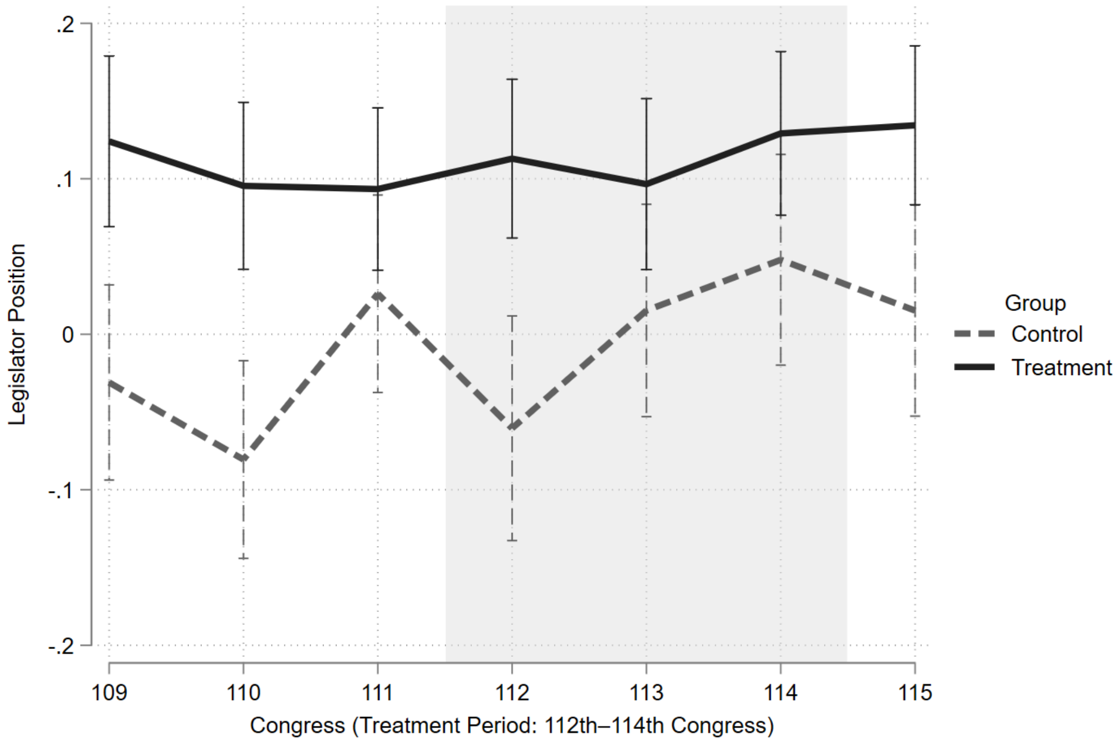


Table C19: Placebo Timing (Date Randomization)

	Pres Vote Share	Legislator Position
2016 (Time: Randomized)	0.388	–0.011
	(1.333)	(0.047)
Factionalism (Treatment)	6.607***	0.067
	(1.675)	(0.053)
Diff-in-diff (Time x Treatment)	–0.443	0.052
	(1.726)	(0.061)
Observations	870	870
R-squared	0.051	0.013
Mean Control 2008	44.22	0.026
	(1.393)	(0.041)
Mean Treated 2008	50.83	0.093
	(0.946)	(0.034)
Diff 2008	6.607	0.067
	(1.675)	(0.053)
Mean Control 2016	44.61	0.015
	(1.564)	(0.046)
Mean Treated 2016	50.77	0.134
	(0.973)	(0.033
Diff 2016	6.164	0.119
	(1.839)	(0.057)