The Behavioral Consequences of Public Appeals: Evidence on Campaign Fundraising from the 2018 Congressional Elections

SHU FU and WILLIAM G. HOWELL

Whereas the preponderance of studies on public appeals evaluates their impacts on mass public opinion, we investigate behavioral responses—in particular, the willingness of donors to contribute to candidates for public office. As appeals, we identify and code the online messages from all 2018 candidates for Congress, winners and losers alike, about both Donald Trump himself and his signature policy initiative, immigration reform; and as behavioral responses, we track candidates' daily itemized fundraising totals. What Republican candidates for Congress say about Trump, we find, bears significantly on their ability to raise money. In the immediate aftermath of complimenting the president, Republicans secured a modest increase in fundraising; when they criticized him, however, they promptly suffered a substantial decline. We do not observe comparable evidence for Democratic candidates. Our findings are robust to a wide variety of measurement and modeling strategies, and expand our understanding of the political stakes of public appeals.

Keywords: public appeals, interbranch messaging, social media, campaign fundraising, congressional elections

When presidents and members of Congress speak, who listens? And what changes as a result? Substantial bodies of research evaluate the efficacy of public appeals (for reviews on the relevant presidency literature, see Edwards 2009; Eshbaugh-Soha 2016; Eshbaugh-Soha and Collins 2015). Nearly without exception, these studies assess the effects of what political elites say on the contents of mass public opinion, with some reporting modestly positive evaluations (see, e.g., Barrett 2004; Brace and Hinckley 1992; Cavari 2013), others highlighting the possibility of a backlash (Cameron and Park 2011; Lee 2008),

Shu Fu is a PhD candidate in political science at the University of Chicago. His research interests include the American presidency, executive–legislative relations, communications, distributive politics, causal inference, and text as data methods. **William G. Howell** is the Sydney Stein Professor in American Politics at the University of Chicago, where he holds appointments in the Harris School, political science department, and college. He has written widely on separation-of-powers issues and American political institutions, especially the presidency.

Presidential Studies Quarterly
Vol. 50, No. 2, June 2020, 325–347
DOI: 10.1111/psq.12645

and many more reporting null effects (Edwards 2003; 2009; Franco, Grimmer, and Lim 2018; Simon and Ostrom 1989).

The intended audience of at least some public appeals, however, may not be the general public. And the intended purpose may have very little to do with persuasion. Rather, these appeals may be directed to specific groups with an eye toward altering not thought but behavior. In the context of a political campaign, the relevant audience for some elite appeals may consist of the most politically engaged American citizens and the relevant outcome may concern their willingness to donate.

To investigate such possibilities, we identified every instance in which a candidate for Congress in 2018 either retweeted Donald Trump or posted a message on Twitter or Facebook that addressed Trump's signature policy initiative, immigration reform. We then hand-coded these appeals to identify the subset that clearly supported or opposed the president. Using Federal Election Commission (FEC) data on campaign donations, we subsequently estimated a series of fixed effects models that leverage within-candidate, within-day changes in fundraising to gauge behavioral consequences of public appeals.

Our findings reveal an interesting asymmetry. In the immediate aftermath of complimenting the president, Republican candidates experience a slight increase in campaign fundraising. But when these same members speak out against Trump, their fundraising drops precipitously—at least in the short term. Among Democratic candidates, however, the consequences of online appeals are not nearly so clear. Though some models yield statistically significant correlations between messaging and campaign donations, these results tend to be sporadic and fragile. In the main, we do not observe any clear or consistent evidence that Democratic appeals on Trump meaningfully bear upon their fundraising.

The models estimated in this article isolate the short-term effects of a specific class of public appeals on candidate fundraising within the context of a single electoral cycle. As a consequence, it is difficult to know whether the findings on offer mask other, longer-term, and possibly cumulative effects of Democratic appeals, or whether they speak to general differences between the two parties. What is clear, though, is that even some of the shortest and most targeted of public appeals—direct messages sent to online followers—can have important behavioral consequences for at least some potential donors.

We proceed as follows. The first section characterizes the relevant literatures on public appeals and congressional elections, and the subsequent two sections summarize our data and describe general patterns of congressional appeals about the president. We then present our identification strategy, the results it yields, and a variety of extensions and robustness checks. The final sections discuss possible interpretations of our findings and conclude.

Literature Review

Two broad literatures motivate the empirical investigations in this article. One focuses on the efficacy of appeals made by presidents and legislators to the American public; the other investigates the politics of congressional campaigns. In this section, we review each and characterize how its insights inform the analyses that follow.

Scholars of the presidency have long recognized how presidents communicate with the American public (Kernell 1986; Tulis 1987). The significance of such communications, though, is a matter of ongoing dispute. Some studies present evidence that presidential appeals have the potential to reshape the contents of public opinion (see, e.g., Cavari 2013). The preponderance of evidence on offer, however, suggests that the actual capacity of presidents to successfully break through the din of media chatter and voter indifference and thereby alter public opinion is either limited in scope (see, e.g., Eshbaugh-Soha and Peake 2011; Rottinghaus 2010) or altogether nonexistent (Edwards 2003; 2009; Franco, Grimmer, and Lim 2018; Simon and Ostrom 1989).

Presidents, however, hardly hold monopoly rights on public appeals. From Fenno (1978) to Grimmer (2013), congressional scholars have documented the ways in which legislators invest time and resources to communicate with their constituencies (see also Grimmer, Westwood, and Messing 2014; Lipinski 2004; Quinn et al. 2010; Yiannakis 1982). Some of this literature is purely descriptive in nature, seeking to characterize, for instance, differences in congressional speeches between the two major parties (e.g., Gentzkow, Shapiro, and Taddy 2019). A handful of studies, however, examine the efficacy of these appeals. And like the work on presidential appeals, these studies investigate the effects of congressional appeals on various aspects of voters' opinions about their representatives, such as name recognition (Cain, Ferejohn, and Fiorina 1987) and impressions of influence (see Grimmer, Westwood, and Messing 2014, chapters 4 and 5).

Whether its protagonist is a president or legislator, however, all of this research focuses on incumbent politicians and their efforts to persuade the public either about their own individual merits or those of the policies they support when governing. Three features of these literatures, as such, warrant some discussion. First, the preponderance of studies focus on the dyadic relationship between a politician and her constituents. The presidential appeals literature focuses on the interaction between presidents and their national audience, and the congressional appeals literature emphasizes communication between a representative and her constituents. But the exchange of messages between presidents and legislators receives very little attention by either. To be sure, some experiential work investigates how mass opinion is formed and altered by the competing political messages sent by the president and Congress (Chong and Druckman 2010; Howell and Kriner 2013; Lupia 1994). And more recent scholarship documents the intermittent willingness of members of Congress to either affirm, oppose, or keep silent in the aftermath of presidential appeals (Fu 2020). Outside of these exceptions, however, the dynamic and contested nature of interbranch appeals receives very little systematic attention.

Second, none of the existing scholarship assesses the impacts of presidential or congressional appeals on outcomes among the general public, apart from changes in opinion.[1] Though scholars have taken an increasingly expansive view of public opinion (see, e.g., Howell, Porter, and Wood 2020), it is what people think, and not what people do, that captures the attention of scholars trying to assess the efficacy of public appeals. As a consequence, the downstream behavioral outcomes of public appeals remain unexamined—even as certain kinds of appeals, particularly those issued over social media, are not

1. Of course, a substantial body of work assesses the effects of public appeals on the behavior of elected officials (see, e.g., Canes-Wrone 2006).

even intended to change mass public opinion. Rather, by political strategists' own accounting, at least some of these appeals are meant to attract prospective donors. As Vincent Harris, a digital strategist for Senator Rand Paul's (R-KY) campaign, notes, "Twitter has been a successful avenue of fundraising for campaigns" (Bykowicz 2015). Especially since teaming up with mobile payment companies like Square, say others, "Twitter becomes much more attractive to candidates because it's an easy way to generate campaign dollars" (Wagner 2015). Public appeals on this platform are not intended to sway mass public opinion. Rather, their primary purpose, say some users, is to raise money in the context of a campaign.

This leads to the third feature of the existing research on public appeals: the vast majority of studies on the subject focus exclusively on the actions of incumbent politicians in office. Generally, the background setting in which appeals are made is a bill under formal consideration or unilateral directive requiring public justification. None of this research, however, accounts for the public appeals of competing candidates—incumbents and challengers alike—in an electoral setting.

This is not to say that the dynamics of congressional campaigns have been altogether ignored. To the contrary, a substantial body of scholarship investigates the dynamics of political campaigns, wherein Fenno famously noted, "our representative form of government begins and ends" (1996, 9). And much of this research evaluates various aspects of the communication strategies of competing candidates. Important work, for instance, has been conducted on position taking (Ansolabehere, Snyder, and Stewart 2001; Burden 2004), issue ownership (Budge and Farlie 1983; Petrocik 1996), and the politics of "going negative" (Druckman, Kifer, and Parkin 2010). The rhetorical strategies candidates employ, of course, further depend upon the structural positions they assume within a race. And so, scholars have shown, a candidate's status as incumbent or challenger informs numerous aspects of her campaign behavior (Jacobson 2004, 91–98; Trent and Friedenberg 2008), as does the competitiveness of the race itself (Kahn and Kenney 2004).

Like the presidential and congressional literatures on public appeals, however, scholarship on public appeals within the context of congressional campaigns tends to focus on the ability of candidates to change public opinion. Persuasion—whether by reference to the content of a political opinion or its salience—is the presumed objective of campaign messaging. By integrating and extending prior work on the subject, for instance, Druckman, Kifer, and Parkin (2009) stipulate that a major purpose of campaign communication is to shape the relevant criteria on which voters form their opinions toward candidates. They draw supporting evidence on this point from a rich public opinion literature, including research on priming (Miller and Krosnick 1996), heuristics (Riker 1996), and political polling (Druckman, Jacobs, and Ostermeier 2004; Jacobs and Shapiro 1994). Here again, the behavioral consequences of candidate appeals—their willingness to canvass on behalf of candidates, join their campaigns, or donate—receive considerably less scholarly attention (but for exceptions, see Minozzi et al. 2015; Valenzuela and Michelson 2016).

There is, of course, a modest literature on campaign fundraising (see, e.g., Squire 1995; Stratmann 2005). And this literature has done a nice job of documenting changes to the federal campaign finance system that, scholars recognize, have generated huge windfalls in campaign spending from political action committees (PACs; Denzau and Munger 1986; Fouirnaies and Hall 2014; Kolodny 2011). A variety of scholars also have sought to clarify the various benefits such spending ostensibly purchases, whether it be votes, access, or something altogether different (Li 2018; Powell and Grimmer 2016; Romer and Snyder 1994). Scholars also have paid attention to the behaviors of individual donors, who are more ideologically extreme and tend to give money to ideologically aligned candidates in congressional and presidential races (Barber, Canes-Wrone, and Thrower 2017; 2019; Hill and Huber 2017). This literature, however, has less to say about the strategic appeals that candidates for office issue in their ongoing efforts to fundraise. The possibility that what candidates raise in funds depends on what they say in public remains unexamined.

Data

To investigate the relationship between congressional candidates' public communications and fundraising, we rely on three types of data: (1) originally collected and coded social media posts from Twitter and Facebook; (2) information on congressional candidates' political backgrounds and the districts they represent; and (3) raw FEC donations, with itemized political contributions compiled by Adam Bonica (2018). In this section, we summarize each of these three data sources.

As social media data, we collected all 875,261 tweets and 194,346 Facebook messages posted by the 1,260 candidates running for a seat in Congress between January 1 and election day in 2018. Candidates include 1,134 individuals running for the House of Representatives and 126 individuals running for the Senate. In total, 396 were incumbents, 700 were challengers, and the remaining 84 competed in open races.

To identify the messages that specifically related to the president, we culled the aggregated data in two ways. First, we identified all retweets of messages from Donald Trump's Twitter account (@realDonaldTrump), some of which included comments from the congressional candidate (N = 3,091), and some of which did not (N = 1,938). We then hand-coded these retweets to identify the subset that clearly supported or opposed Trump. All retweets without comment were coded as support; the remainder were coded according to the valence of their accompanying comments. Supportive retweets with comments reiterated or praised a component of Trump's original tweet. Opposing retweets admonished or dismissed a component of Trump's tweet.[2] Retweets that had no clear valence were excluded from the analysis.

2. As an example of a supportive retweet with comment, Rep. Daniel Donovan (R-NY11) noted: "President Trump got done what others couldn't. I was proud to support this important legislation that will empower Americans & save lives. http://t.co/B1FIxBPqrc." An illustrative example of an opposing retweet comes from Amy McGrath (D-KY), who posted, "When will Republicans in office stand up to this president when they know he is wrong? When? #CountryoverParty http://t.co/iMnxs3WoTE." The vast majority of messages were overwhelmingly positive or negative in their orientation. For the handful of cases that included both supporting and opposing sentiments, we coded the message according to its dominant valence.

The second subset of messages focused on Trump's signature policy issue: immigration. Using keyword searches,[3] we identified 4,551 tweets and 3,142 Facebook posts on immigration policy. We then hand-coded each of these messages according to its support for or opposition to Trump's position on the issue. In this instance, the relevant reference was Trump's immigration policy, and not immigration per se. Supporting statements, therefore, praised or promoted some aspect of Trump's immigration policy. Opposing statements, by contrast, either criticized or outright rejected Trump's immigration policy.[4] Here again, messages that lacked a clear valence were omitted from the analysis.

Following conventions in the congressional elections literature (Canes-Wrone, Brady, and Cogan 2002; Jacobson 2004), we also gathered political information about each candidate. We categorized each candidate as Democratic, Republican, or member of a third party. As our measure of ideology, we collected each candidate's campaign finance (CF) score (Bonica 2014), which is estimated from patterns of donations, and hence is available for winning and losing candidates alike. We also gathered information on Trump's two-party vote share in the 2016 presidential election in the district or state that each candidate sought to represent.

For donations, we rely on the FEC's raw database with itemized political contributions. Each observation is a donation record that identifies its date of receipt, amount, and information about the recipient and contributor. With these data, we generated a candidate-by-day donation panel, which can be further disaggregated into individual and PAC donors and according to in-state and out-of-state donations.[5]

Patterns of Social Media Appeals on Trump

In total, 774 congressional candidates (or 60% of the sample) retweeted at least one of Trump's tweets during the 11 months leading up to the election. Of these retweets, 2,456 supported Trump and 1,950 opposed him. Unsurprisingly, patterns of

3. Keywords include "immigration," "immigrant," "border," "wall," "illegal," "undocumented," "caravan," "daca," *or* "dreamer"; *and* "trump," "president," *or* "potus." All messages were preprocessed into lowercase.

4. As an example of a supportive message on Trump's immigration policy, Rep. Vern Buchanan (R-FL16) tweeted: "The President did the right thing by signing an executive order to keep families together at the border. Children should not be separated from their parents. We can still enforce the laws and secure the border without causing undue hardship to young children." An example of an opposing message on immigration comes from Rep. Bill Foster (D-IL11), who issued a Facebook post: "This announcement is another example of the President's attempt to walk away from the principles that made this country great and to instill fear in the immigrant community and the individuals who lawfully seek asylum in our country."

5. From the outset, it is important to recognize one limitation of the donation data. In the FEC raw data, the donation date is actually "the date of receipt," which is the date the candidate, the campaign committee, or an agent acting on their behalf actually received the contribution. (See "Federal Election Commission Campaign Guide: Congressional Candidates and Committees," June 2014, https://www.fec.gov/resources/cms-content/documents/candgui.pdf#page=32.) The date of receipt is distinct from the date a contribution is made, which is when the contributor relinquished control over the contribution by either delivering or mailing it to the candidate, the committee, or their agent. We are not able to distinguish the contributions that are made online, for which the dates of disbursement and receipt should be identical, from those made through traditional mail, which may incur some delay. Given that most donations are made during the week, however, we expect such delays will be relatively small.

retweeting overwhelmingly fell along party lines: the lion's share of support came from Republican candidates, and almost all opposition came from Democratic candidates. Among Democrats, 2.7% of retweets were positive and 97.3% were negative. Among Republicans, by contrast, 99.1% were positive, and just 0.9% were negative.

Similar patterns are observed in candidates' immigration appeals. In total, 642 candidates (or 51% of the sample) issued at least one tweet or Facebook message on Trump's immigration policy. Of these messages, 5,812 criticized Trump's policy and 1,408 supported some aspect of it. Here again, the distribution of negative and positive messages broke almost exclusively along partisan lines, with the preponderance of negative messages coming from Democratic candidates, and Republicans furnishing most positive messages.

Figure 1 tracks the average daily volume of Republican and Democratic public appeals over the course of the election year. At a reasonably steady rate, both parties retweeted Trump throughout the period of investigation. In the final month of the election season, Republicans ratcheted up their retweets, whereas Democrats held steady. Over the course of the entire time series, though, spikes in appeals from one or another party can be detected, as on May 10 when Trump tweeted, "On behalf of the American people, WELCOME HOME" and included a video of the triumphant return of three Americans released by North Korea, a message that was retweeted by numerous Republican candidates; or on September 13, when Trump tweeted, "3,000 people did not die in the two hurricanes that hit Puerto Rico. When I left the Island, AFTER the storm had hit, they had anywhere from 6 to 18 deaths," a message that drew harsh criticism from Democratic candidates for misreporting the actual number of Hurricane Maria casualties.

Patterns of Republican and Democratic candidates' appeals on immigration look somewhat different. As can be seen in the lower panel of Figure 1, Democratic candidates persistently issued more appeals on immigration than did Republicans. Across the two parties, however, the daily average volumes of these appeals track one another reasonably closely. On many of those days when Democratic candidates issued a large number of messages on immigration, their Republican rivals followed suit. For instance, the biggest spike of congressional responses comes on June 20, when Trump signed an executive order on family separation, which drew more than 150 opposing messages from Democratic candidates and more than 60 supporting messages from Republicans.

Figure 2 shows how the valences of congressional appeals correspond with Trump's vote share in a candidate's district or state in the 2016 presidential elections and with the candidate's ideology. In each panel, observations represent a summary measure of each candidate's messaging behavior. The y-axis in each plot indicates the percentage of a candidate's messages that either support or oppose Trump himself (column A) or his immigration policy (column B).[6] The x-axis of each row represents Trump's 2016 vote share (row 1) or a measure of candidate ideology (row 2). In all panels, larger dots indicate more messages sent, smaller dots indicate fewer, and those candidates who did not issue any pertinent messages are excluded from the analysis. Separate nonparametric locally estimated scatterplot smoothing (LOESS) is performed for each party, with observations weighted by the number of messages.

6. We measure candidates' attitudes toward Trump as follows: (Number of Positive Messages – Number of Negative Messages) / (Number of Positive Messages + Number of Negative Messages).

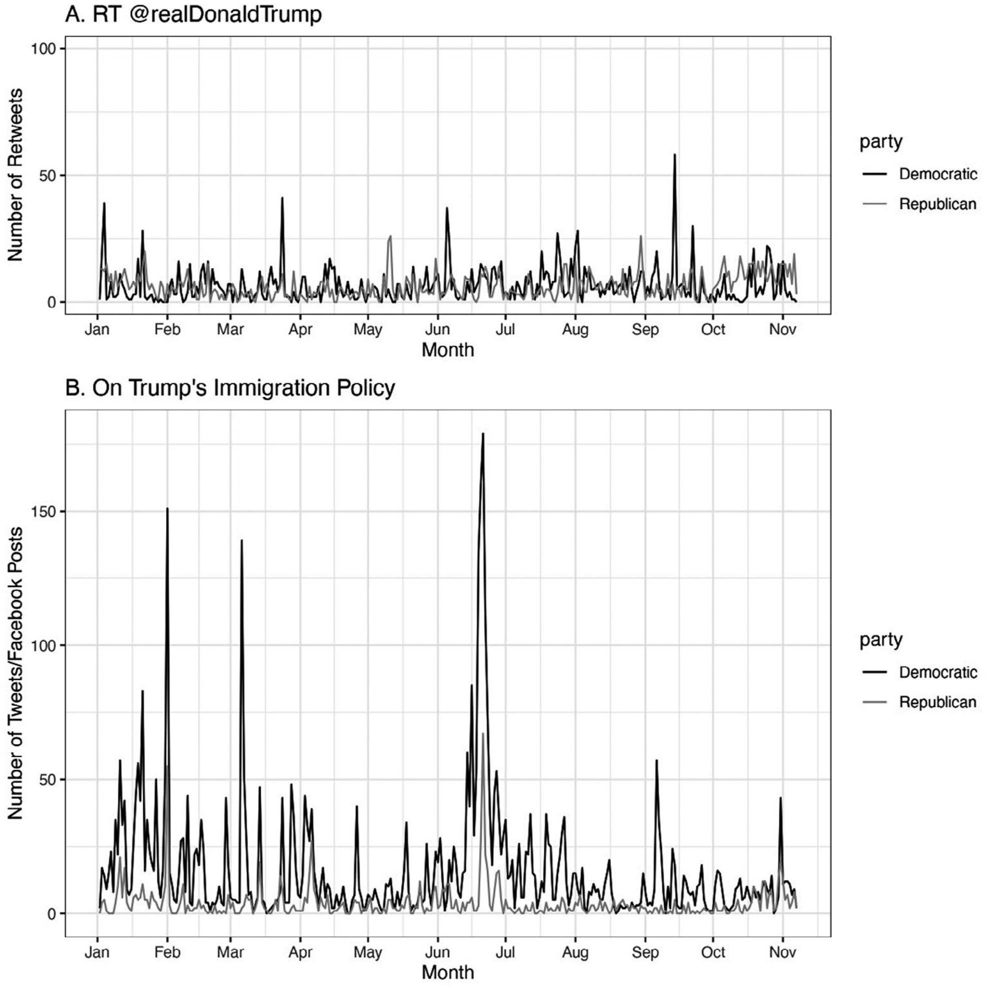

FIGURE 1. Daily Candidate's Messaging Behavior in the 2018 Midterm Election.

Interestingly, we see persistently flat fit lines for candidates from both parties, regardless of Trump's past performance in their districts or states or their ideology. Regardless of how Trump performed in the last election, Republican candidates for Congress supported Trump when retweeting him. Similarly, we do not observe any meaningful intraparty variation in retweeting behavior among candidates with different ideologies. Liberal Republicans are no more likely to criticize Trump than are conservative Republicans, and likewise for Democrats.

The results shift somewhat when surveying candidates' appeals on immigration. Republican candidates from districts and states in which Trump performed poorly in the 2016 elections were less likely to support Trump's immigration policy; and those Democratic candidates who posted supportive messages about Trump's immigration policy tended to come from jurisdictions in which Trump performed relatively well in the

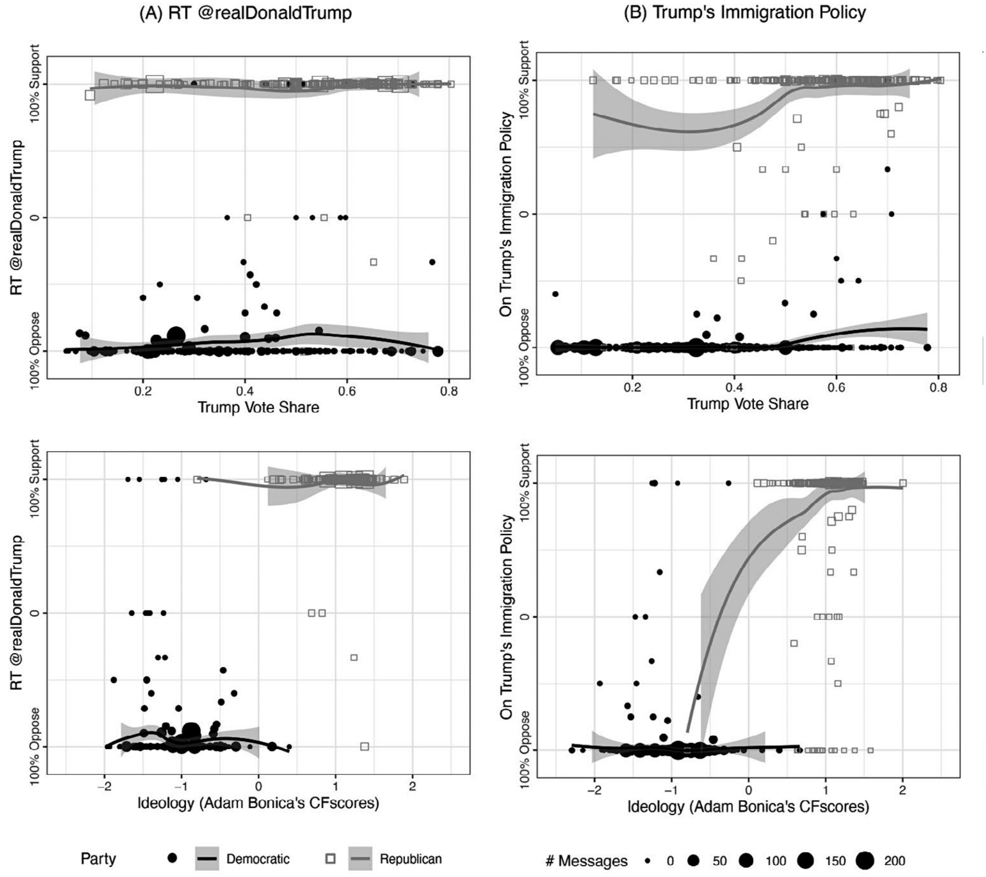

FIGURE 2. How Partisanship, Electoral Connection, and Ideology Map into Candidates' Trump-Related Appeals.

Note: Black solid dots identify candidates from the Democratic Party, and gray hollow squares identify candidates from the Republican Party. The size of each dot or square reflects the number of messages sent. Smooth fit lines are drawn by locally estimated scatterplot smoothing, weighted by number of messages. In row 1, the *x*-axis represents Trump's two-party vote share in the 2016 presidential election in the political jurisdiction in which the candidate seeks office. In row 2, the *x*-axis is each candidate's campaign finance score.

previous presidential election. Among moderate Republicans, meanwhile, we find some evidence of partisan convergence; though here again, the trend among Democrats appears altogether flat.

Expectations

How should a candidate's online appeals affect her short-term fundraising? Much, of course, depends upon the underlying interests and motivations of her prospective donors, which we do not directly observe. We can, however, offer some reasonable inferences about them. During the 2018 congressional elections, we suggest, Republican donors were principally concerned with maintaining their party's unity and strength. For them, keeping the party intact and in power constituted the immediate goal of the midterm elections. As Brad Todd, a GOP consultant, notes, "Strategically, it's a no brainer. The President has a brand that transcends the party. A pro-Trump message has 'no downside' among partisan GOP voters, and is pure 'upside' for that part of the Trump vote that is skeptical of both parties" (Gilbert 2018). Democratic donors, meanwhile, stood squarely opposed to the interests of Republicans. For Democrats, the core objective of the midterm elections was to take back one or both chambers of Congress. And to do that, they needed to highlight the many offenses and failures of the sitting president (see, e.g., Hook 2017).

From this general characterization of donor interests, reasonably clear expectations follow about the behavioral consequences of public appeals. Republican candidates who come out and support their president and his policies ought to be rewarded by their donor base. But when Republican candidates criticize their party's leader, and thereby open rifts within their party's ranks, punishments should swiftly follow. Democratic donors, meanwhile, ought to respond in an entirely complementary fashion. For them, criticisms of Trump warrant heightened financial support, whereas statements of support demand the withholding of funds. And provided punishments and rewards are administered within, but not across, party lines,[7] the aggregate effects of public appeals should follow directly from the expected changes in donation patterns among a candidate's copartisan followers.

Empirical Strategy

To estimate the relationship between congressional candidates' appeals and fundraising, we exploit within-candidate daily variation in donations. Our panel consists of all Democratic and Republican candidates through the primaries and general elections. (Third-party candidates are excluded from the analysis.) Individuals are tracked as long as they remain active candidates either for their party's nomination (during the primary elections) or the congressional seat (during the general election). The final data set consists

7. For several reasons, we think this supposition is likely. To begin, the bulk of communication within our sample occurs within parties. On Twitter and Facebook, Republican constituents (and potential donors) tend to follow Republican candidates, just as Democrats follow Democrats. As a result, most constituents do not even receive the messages sent by candidates from the opposing party. For the small number who do, meanwhile, changes in donation patterns are likely to be quite constrained. It is possible, of course, that some donors may be prompted to give even more to their preferred candidate after reading a particularly troubling message from her opponent. Given the general patterns of campaign fundraising, however, these donors are unlikely to be prompted to give across party lines (see also Barber, Canes-Wrone, and Thrower 2017; Hill and Huber 2017). Those entities and individuals who make a habit of supporting both Democrats and Republicans, such as corporate PACs seeking access or influence to whomever wins office, are unlikely to be especially concerned about the content of online appeals (Li 2018). For all of these reasons, then, variation in fundraising that is associated with public appeals is likely to depend upon the changes in behavior of copartisan donors.

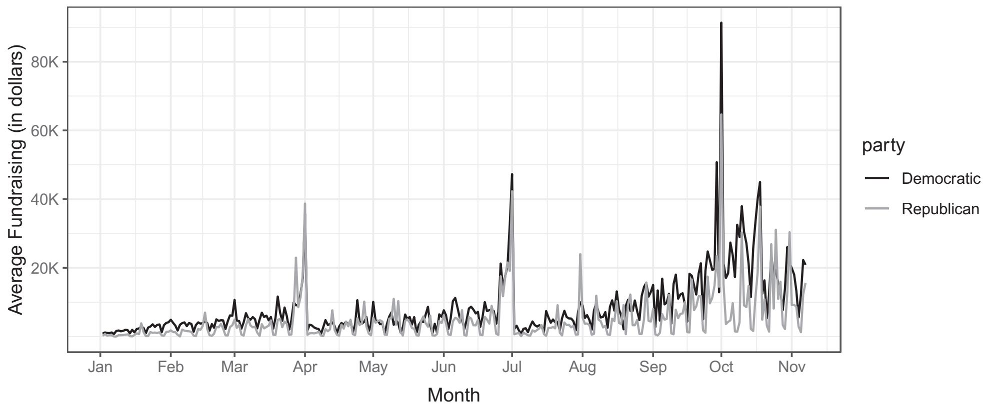

FIGURE 3. Average Daily Candidates' Fundraising in the 2018 Midterm Election.

of an 11-month unbalanced panel of daily appeals and fundraising for every congressional candidate from a major party during the 2018 midterm elections.

We use a generalized differences-in-differences design to estimate the degree to which daily donations correspond with congressional candidates' messages about Trump. Specifically, we estimate the following models:

$$\begin{aligned}\log\left(Receipts_{i,t}+1\right) &= \alpha_i+\delta_t+\boldsymbol{\beta}_1 Support_{i,t-k}+\boldsymbol{\beta}_2 Support_{i,t-k}\times Party_i+\boldsymbol{\beta}_3 Oppose_{i,t-k} \\ &\quad +\boldsymbol{\beta}_4 Oppose_{i,t-k}\times Party_i+\epsilon_{i,t}\end{aligned} \tag{1}$$

$$\begin{aligned}\log\left(Receipts_{i,t}+1\right) &= \alpha_i+\delta_{t\times party\times state}+\boldsymbol{\beta}_1 Support_{i,t-k}+\boldsymbol{\beta}_2 Support_{i,t-k}\times Party_i+\boldsymbol{\beta}_3 Oppose_{i,t-k} \\ &\quad +\boldsymbol{\beta}_4 Oppose_{i,t-k}\times Party_i+\epsilon_{i,t}\end{aligned} \tag{2}$$

where the dependent variable in both is the amount of itemized donations received by candidate i on day t. Because the distribution of receipts is right-skewed, we take the natural log of donation receipts. Given the nonindependence of observations within congressional races, we cluster at the race level.

In model (1), we include candidate fixed effects, $\boldsymbol{\alpha}_i$, in order to control for observed and unobserved time-invariant attributes that may affect candidate fundraising. To account for time trends, we also include day fixed effects, $\boldsymbol{\delta}_t$. In model (2), $\boldsymbol{\delta}_{t\times party\times state}$ represents a vector of day-by-party-by-state fixed effects, which account for the possibility that donations received by candidates in different parties and in different states may track different time trends. Both fixed effects structures account for secular trends in campaign donations that, as Figure 3 shows, reveal consistent and significant declines on weekends, spikes at the end of each quarter, and marked increases during the final 2 months of the campaign.

Support and *Oppose* indicate the daily number of retweets issued by a candidate that either support or oppose Trump; or, in separate models, the daily number of tweets and

Facebook posts that support or oppose Trump's immigration policy. Because these messages can be expected to have different effects for Republican and Democratic candidates, we interact *Support* and *Oppose* with candidates' partisanship indicator, *Party*, which equals 1 if a candidate is Democratic and 0 if Republican. The constitutive term *Party* is subsumed by the candidate fixed effects. For convenience of comparison and clarity of presentation, we present separate estimates by party and message valence. Thus, in the following results section, our four independent variables are denoted as *Support by Republican*, *Support by Democrat*, *Oppose by Republican*, and *Oppose by Democrat*.[8]

The salience of Trump-related messages might reasonably endure for a couple of days, so we add lags in the model. Each β represents a vector of coefficients for the independent variable and its lags, denoted by the subscript $t-k$. Here, k = 0, 1, 2, or 3, and so our models include a contemporaneous measure of candidate messaging as well as 1-day, 2-day, and 3-day lags.[9] We purposefully include different lags in the same regression, instead of running them separately, in order to mitigate inference problems associated with overlapping effects.

Main Results

Table 1 reports our main results. Columns (1) and (2) display the results for candidates' retweets of Trump, and columns (3) and (4) show the results for immigration messages. Odd columns include candidate and day fixed effects, as in Equation (1); even columns present results from the more restrictive candidate and day-by-party-by-state fixed effects models, as in Equation (2).

We find no evidence that Democratic candidates' propensities to support or oppose the president correlate with their ability to fundraise. Regardless of whether Democratic candidates support or oppose Trump himself or his immigration policy, we recover consistently null results. Given the differential propensities of Democratic candidates to send messages of support and opposition to the president, the results associated with Democratic support are less precisely estimated than those associated with Democratic opposition. None, however, even approach standard thresholds of statistical significance.

Among Republican candidates for Congress, by contrast, we do find evidence of a meaningful relationship between public appeals and short-term fundraising. Republican candidates who praised Trump in their retweets of him raised significantly more money—on the order of 11% to 16%—both that day and the one that followed. Those candidates who sent messages that supported Trump's immigration policies raised 14% to 17% more money two days later. We also find some evidence of costs associated with criticizing the president. Three days after criticizing Trump in a retweet and one day after

8. For example, if Candidate A, who is a Republican, has two positive retweets about Trump and zero negative retweets on a day, the main variables of interest here for this observation are *Support by Rep* = 2, *Support by Dem* = 0, *Oppose by Rep* = 0, and *Oppose by Dem* = 0.

9. To account for anticipatory effects of messages on fundraising, in our extensions we add an equivalent set of leads to the model.

TABLE 1
Estimated Effects of Candidates' Online Appeals on Fundraising

	Dependent Variable: Log Daily Receipts			
	Retweet @realDonaldTrump		*Trump's Immigration Policy*	
	(1)	*(2)*	*(3)*	*(4)*
Support by Rep	0.165***(0.048)	0.116* (0.047)	0.251*** (0.071)	0.173* (0.087)
Lag 1	0.169** (0.055)	0.141* (0.059)	0.116 (0.074)	0.061 (0.080)
Lag 2	−0.021 (0.044)	−0.016 (0.046)	0.160** (0.062)	0.142* (0.071)
Lag 3	−0.044 (0.048)	−0.010 (0.053)	−0.008 (0.065)	0.020 (0.064)
Support by Dem	−0.030 (0.220)	0.137 (0.262)	0.439 (0.410)	0.943 (0.573)
Lag 1	0.055 (0.259)	0.037 (0.290)	0.265 (0.379)	0.378 (0.457)
Lag 2	−0.170 (0.277)	−0.244 (0.311)	0.225 (0.399)	0.413 (0.468)
Lag 3	−0.418 (0.450)	−0.614 (0.481)	−0.023 (0.373)	0.177 (0.453)
Oppose by Rep	0.367 (0.789)	0.027 (0.722)	0.918 (0.477)	0.866 (0.473)
Lag 1	−0.676 (0.504)	−0.749 (0.592)	−1.198** (0.383)	−1.071** (0.372)
Lag 2	−0.567 (0.533)	−0.440 (0.540)	−0.328 (0.395)	−0.381 (0.392)
Lag 3	−0.986* (0.471)	−1.646***(0.400)	0.716 (0.373)	0.482 (0.375)
Oppose by Dem	−0.062 (0.053)	−0.071 (0.056)	−0.004 (0.034)	−0.004 (0.035)
Lag 1	−0.060 (0.068)	−0.059 (0.070)	0.061 (0.035)	0.056 (0.033)
Lag 2	−0.000 (0.058)	−0.033 (0.061)	0.022 (0.029)	−0.019 (0.029)
Lag 3	−0.104* (0.052)	−0.130* (0.056)	0.041 (0.034)	−0.013 (0.033)
Fixed Effects	Day, Candidate	Day × Party × State, Candidate	Day, Candidate	Day × Party × State, Candidate
Observations	289,696	289,696	289,696	289,696
R^2	.550	.614	.550	.614

Note: Standard errors are clustered by congressional race.
*p < .05; **p < .01; ***p < .001.

sending a message that opposed the president's immigration policy, Republican candidates registered statistically significant decreases in fundraising. The magnitude of these declines, what is more, is roughly 5 to 10 times as large as the gains observed for online appeals that supported the president.

Substantively, we know from our data that the average daily donations received by a Republican candidate is around $5,000, as shown in Table S1 in the supporting information. The positive reward associated with standing by the president, as such, is $500 to $800, whereas the magnitude of the punishment associated with opposing him is more than $2,500. Given that most individual donors contribute less than $200,[10] the effects we find on fundraising are nontrivial.

Campaign contributions, of course, can come from very different donors, and the sensitivity of these different donors to candidates' online appeals may systematically vary from one to another. We therefore reestimate our models after disaggregating overall funds into those that come from PACs and those that come from individuals. In so doing, we find that our main results associated with Republican online appeals are most pronounced for individual donations. Take a look at Table 2. Among Democrats, we find a couple of idiosyncratic correlations that are statistically significant, which is hardly surprising given the sheer number of quantities being estimated in our models. For the most part, though, we continue to observe null relationships. Among Republicans, however, the positive rewards associated with supporting Trump and his immigration policy, as well as the punishments associated with opposing the president, are most apparent among individual donors. With the exception of one negative and statistically significant correlation associated with the three-day lag on opposition to a Trump tweet, all of the estimated correlations of Republican online behavior and PAC donations are statistically insignificant.

We also reran our models after disaggregating donors into those who are from the same states in which candidates are running and those who reside in other states. As shown in Table 3, we find that our main effects for Republican candidates hold for both in-state donors and out-of-state donors. However, when Republican candidates issue appeals on immigration policy, the positive effects associated with supporting Trump largely come from the out-of-state donors, whereas the negative effect associated with criticizing Trump's policy is primarily driven by in-state donors. When disaggregating the data in this way, we also observe some evidence that Democratic candidates who publicly oppose Trump's immigration policy are rewarded the following day with more out-of-state donations.

Robustness Checks

Our main results are robust to a variety of alternative measurement and modeling specifications. First and foremost, our core findings hold when we add an equivalent set of

10. Open Secrets, Center for Responsive Politics, offers helpful summaries of contribution patterns. For details, see https://www.opensecrets.org/elections-overview/large-vs-small-donations?cycle=2018&type=M.

TABLE 2
Distinguishing Individual and PAC Donations

	Dependent Variable: Log Daily Receipts			
	Retweet @realDonaldTrump		*Trump's Immigration Policy*	
	Individual	*PACs*	*Individual*	*PACs*
	(1)	(2)	(3)	(4)
Support by Rep	0.088 (0.051)	0.058 (0.049)	0.194* (0.086)	-0.052 (0.080)
Lag 1	0.153** (0.057)	0.048 (0.042)	0.090 (0.079)	0.011 (0.071)
Lag 2	−0.017 (0.044)	−0.050 (0.040)	0.089 (0.073)	0.041 (0.065)
Lag 3	−0.001 (0.049)	−0.007 (0.042)	0.021 (0.061)	−0.036 (0.073)
Support by Dem	−0.230 (0.272)	1.027* (0.438)	0.502 (0.428)	1.798* (0.818)
Lag 1	−0.117 (0.272)	0.310 (0.381)	0.511 (0.480)	0.311 (0.544)
Lag 2	−0.348 (0.306)	0.540 (0.406)	0.178 (0.439)	0.084 (0.661)
Lag 3	−0.661 (0.616)	0.098 (0.478)	0.307 (0.457)	−0.434 (0.576)
Oppose by Rep	−0.035 (0.712)	−0.010 (0.502)	0.838 (0.487)	0.633 (0.470)
Lag 1	−0.540 (0.594)	−0.415 (0.376)	−1.127** (0.363)	−0.392 (0.241)
Lag 2	−0.847* (0.397)	0.433 (0.450)	−0.125 (0.378)	−0.245 (0.266)
Lag 3	−1.252*** (0.337)	−1.441*** (0.412)	0.268 (0.387)	-0.104 (0.422)
Oppose by Dem	−0.080 (0.050)	−0.083 (0.096)	−0.003 (0.029)	0.042 (0.046)
Lag 1	−0.079 (0.053)	0.027 (0.089)	0.029 (0.027)	0.065 (0.043)
Lag 2	−0.067 (0.053)	0.080 (0.085)	−0.019 (0.031)	−0.031 (0.042)
Lag 3	−0.153* (0.061)	0.019 (0.074)	−0.003 (0.026)	−0.026 (0.037)
Fixed Effects	Day × Party × State, Candidate	Day × Party × State, Candidate	Day × Party × State, Candidate	Day × Party × State, Candidate
Observations	289,696	289,696	289,696	289,696
R^2	.618	.400	.618	.400

Note: Standard errors are clustered by congressional race.
*p < .05; **p < .01; ***p < .001.

TABLE 3
Distinguishing In-State and Out-of-State Donations

	Dependent Variable: Log Daily Receipts			
	Retweet @realDonaldTrump		*Trump's Immigration Policy*	
	In-State	*Out-of-State*	*In-State*	*Out-of-State*
	(1)	*(2)*	*(3)*	*(4)*
Support by Rep	0.112* (0.048)	0.115 (0.069)	0.144 (0.083)	0.056 (0.079)
Lag 1	0.162** (0.061)	0.100* (0.046)	0.028 (0.078)	0.113 (0.074)
Lag 2	−0.042 (0.045)	0.008 (0.050)	−0.006 (0.065)	0.156* (0.066)
Lag 3	−0.014 (0.056)	0.053 (0.049)	0.051 (0.075)	0.016 (0.060)
Support by Dem	−0.182 (0.235)	0.382 (0.338)	0.292 (0.385)	0.688 (0.695)
Lag 1	0.094 (0.367)	−0.298 (0.289)	−0.200 (0.362)	0.802 (0.522)
Lag 2	−0.460 (0.315)	0.424 (0.343)	-0.073 (0.377)	0.562 (0.453)
Lag 3	−0.508 (0.605)	0.010 (0.357)	0.529 (0.434)	−0.466 (0.312)
Oppose by Rep	−0.251 (0.700)	0.145 (0.785)	0.449 (0.444)	0.973 (0.552)
Lag 1	0.498 (0.703)	−1.866*** (0.281)	−1.008*** (0.299)	−0.562 (0.320)
Lag 2	−0.346 (0.335)	−0.170 (0.491)	−0.171 (0.337)	−0.036 (0.368)
Lag 3	−0.927** (0.323)	−1.762*** (0.466)	0.293 (0.425)	−0.063 (0.360)
Oppose by Dem	−0.121* (0.050)	−0.036 (0.071)	0.012 (0.030)	0.043 (0.038)
Lag 1	−0.092 (0.053)	-0.013 (0.071)	0.043 (0.029)	0.083* (0.037)
Lag 2	−0.086 (0.051)	0.002 (0.069)	−0.019 (0.032)	−0.030 (0.032)
Lag 3	−0.188** (0.058)	−0.043 (0.063)	−0.017 (0.028)	−0.001 (0.033)
Fixed Effects	Day × Party × State, Candidate	Day × Party × State, Candidate	Day × Party × State, Candidate	Day × Party × State, Candidate
Observations	289,696	289,696	289,696	289,696
R^2	.576	.579	.576	.579

Note: Standard errors are clustered by congressional race.
*$p < .05$; **$p < .01$; ***$p < .001$.

three-day leads of the key independent variable, which allow us to relax the parallel trends assumption in difference-in-difference estimators and thereby account for any anticipatory effects associated with strategic appeals (see Table S2 in the supporting information). We have estimated models that vary the length of either the lags and leads included in the models (Table S3 in the supporting information). Rather than count the total number of positive and negative messages, we also have estimated models that simply note whether any such messages were posted on a given day (see Table S4 in the supporting information). In all of these regressions, our main results appear largely unchanged.

Recognizing that candidates face different opponents and electorates in different stages of congressional elections, we also estimated separate models for the primaries and general elections (Table S5 in the supporting information). Here, the results differ somewhat. As before, we do not find any systematic association between Democratic candidates' messages on Trump and their fundraising, regardless of the stages of elections. For Republican candidates, however, the effects appear to be concentrated in the primary stages. In the general elections, the effects attenuate in magnitude, perhaps because of the truncated time series and restrictive fixed effects structure. We also note that the one aberrant finding regarding Republican criticisms of Trump is estimated on an extremely small number of observations.[11]

Congressional candidates, of course, send numerous tweets and post Facebook messages every week, and their general online presence may inform the willingness of donors to give to their campaigns. After controlling for the total number of other tweets sent by a candidate each day and its lags (see Table S6 in the supporting information), we find our main effects for Republican candidates still hold in the candidate and day fixed effects models, although they attenuate somewhat in models that include the more restrictive fixed effects structure. Interestingly, the coefficients associated with the total number of tweets are positive and statistically significant in the first period and then fade over time. Specifically, one additional tweet, regardless of its content, corresponds with a statistically significant 1.5% increase in fundraising on the same day that the message is sent, a 0.4% increase the next day, and zero thereafter.

Our results also do not appear to be an artifact of a handful of outlier observations. We can observe in Figure 2 that donations reliably peak at the end of each quarter, when candidates push to increase their fundraising numbers and, by extension, their perceived electoral strength. We therefore reestimated the same models but excluded the final day of each quarter. As shown in Table S7 in the supporting information, our results are almost identical to the main results. The correlations between candidates' online appeals and fundraising are hence pretty general throughout the campaign and election year, and they are not driven by big donation days.

Recall, finally, that we assume retweets of Trump without any comment constitute endorsements. And there is good reason to code the data thusly, as fully 99% of direct retweets come from Republican candidates for Congress. Nonetheless, when we restrict

11. In the general stage of elections, we only observe four retweets with criticisms from just three Republican candidates (Adam Kinzinger, Ron J. Bassilian, and Justin Amash), all of whom were competing in swing districts.

our analysis to the subset of retweets that explicitly comment on the content of Trump's original tweet, we recover similar estimates. As shown in Table S8 in the supporting information, the positive effects are concentrated in the direct retweet subset, which is how Republican candidates overwhelmingly express their allegiance to Trump. The point estimates for Republican candidates' retweets with positive comments are similar in magnitude but, given the smaller number of observations, are less precisely estimated. Given their considerably larger magnitude, the negative effects for Republicans who criticize Trump in their retweets are statistically significant. Interestingly, when disaggregating the data in this way, we also observe some evidence that Democrats received fewer donations two days after directly retweeting Trump.

Discussion

The findings presented here reveal a general and unexpected asymmetry between the two parties. When examining the immediate effects of individual appeals on candidate fundraising, we consistently observe significant correlations among Republicans. These effects, moreover, reliably conform to the content of the appeals: praise of Trump and his policies elicit small increases in fundraising, whereas opposition comes at a steep cost. We do not observe any consistent relationship, however, between the patterns of Democratic messaging and candidate fundraising.

What should we make of these findings? It is possible, of course, that they speak to certain limitations of our research design. Given the volume and rapidity of online appeals and the complexity of the larger political communication environment, our ability to estimate causal effects—if available at all—is confined to individual tweets and Facebook messages over relatively short periods of time. Perhaps multiple messages sent over longer periods of time ultimately convince some donors to give (when they otherwise would not) or to conserve (when they otherwise would give). The null results reported here, therefore, may belie cumulative effects associated with candidates' social media activities. It is possible, for instance, that Democrats' appeals alter fundraising patterns outside of the narrow three-day window we consider. It also is possible that the accumulation of multiple messages informs the willingness of Democratic donors to contribute to congressional candidates. All that we can say, just now, is that we find very little evidence that individual online appeals issued by Democratic candidates for Congress affected their immediate ability to raise money for their campaigns.

The study's sample frame may also be a contributing factor. Notice that all of the tweets and Facebook messages that we examine directly implicate either Trump himself or his signature policy priority, immigration. They come at a time, moreover, when Trump had assumed the mantle of party leader in the face of widespread and acute criticism—from Democrats, of course, but also from significant portions of the media, cultural elites, foreign nations, and plenty more political opponents. The findings here, therefore, may reflect a larger insistence that Republicans close ranks behind their beleaguered president. To do their part, Republican donors doled out minor rewards for

Republican candidates who praised the president, and they administered harsher punishments to those who dared cross him. In less turbulent times, perhaps, Republican donors may assume a more accommodating posture toward candidate communications.

It is also possible, though, that we have uncovered patterns that do in fact apply more broadly, and that speak to the more general efforts of each party to maintain discipline within its ranks. Democratic donors, for their part, may not have seen public appeals on Trump as a litmus test for financial giving. For them, allegiance to different political paragons—say, Nancy Pelosi or Barack Obama—may have mattered more. Minor acts of political heresy, under this telling, depend upon the subject under question. When it concerns one of your own, attention—and with it, consequences—spikes. But across party lines, the lines of accountability may blur.

With the sample of public appeals before us here, we cannot distinguish among these various explanations. Future research, however, should be well positioned to do so. By collecting and coding additional online appeals about subjects beyond Trump, and by tracking the patterns of social media communication during other elections, we may gain further insight into how the patterns of results documented here map onto larger political strategies. And we have good reason to conduct this research. Rather than being scripted exercises of campaign performance, public appeals about the president appear to have immediate consequences for at least one party's candidates. When Republican candidates talk about Trump, at least some key constituents—prospective donors—take notice; and they change their behavior as a consequence.

Conclusion

The existing literatures on presidential and congressional appeals, by and large, evaluate their singular effects on the contents of public opinion. Numerous studies document the limited ways in which a mass public updates its views either about public policies or its elected officials in the aftermath of hearing from them. Communication, in this setting, flows directly from the mouths of incumbents to the ears of constituents.

To study the politics of public appeals, we take a slightly different tack. To begin, we evaluate what political actors say about each other, or more specifically, what congressional candidates say about the president. We do so, moreover, by evaluating public appeals issued through social media in an electoral setting. And rather than track the contents of public opinion, we investigate the behavioral consequences of public appeals—in particular, the willingness of donors to contribute to candidates' campaigns.

In so doing, we find evidence of a striking asymmetry between Democratic and Republican appeals. We observe only limited, and then only sporadic, evidence that the messaging of Democratic candidates registered with their prospective donors. Among Republican candidates, however, a very different pattern emerged. Within just a couple of days of issuing appeals that compliment either Trump himself or his signature policy initiative, immigration reform, members enjoyed an immediate bump in their campaign contributions. When they criticized either, however, they promptly experienced a sharp decline.

These findings have a number of strengths. They derive from a research design that leverages variation in public appeals within members and that nets out common temporal shocks. Rather than depend upon selected surveys that rely on respondents' self-reported opinions and behaviors, we cull administrative data on actual campaign donations throughout the entirety of a midterm election. And the results, we show, are robust to a wide variety of model and measurement specifications.

Our study, though, also has limits. Neither the content nor timing of congressional appeals was randomly administered; as such, we confront all of the standard inferential challenges associated with observational data. The analytic focus of our inquiry, meanwhile, remains deliberately narrow. Though we can assess the immediate effects of individual public appeals, we are poorly equipped to take stock of their cumulative or longer-term consequences for fundraising. And by examining a selected set of online appeals within the context of a single congressional election season, we may miss the significance of larger communication trends that do not immediately implicate either the president or immigration policy.

Still, based on just the evidence before us, some provisional conclusions are warranted. Though public appeals may not ultimately persuade public opinion writ large, they also are not entirely innocuous. The things that at least Republican candidates for Congress say about Trump, after all, seem to have attracted the attention of at least some key supporters. And perhaps most importantly, the stakes of public appeals are not confined to what people think. They carry over to what people do, with documented consequences for the capacity of congressional candidates to raise money for their campaigns.

References

Ansolabehere, Alan I., James M. Snyder, and Charles Stewart III. 2001. "Candidate Positioning in U.S. House Elections." *American Journal of Political Science* 45 (1): 136–59.

Barber, Michael, Brandice Canes-Wrone, and Sharece Thrower. 2017. "Ideologically Sophisticated Donors: Which Candidates Do Individual Contributors Finance?" *American Journal of Political Science* 61 (2): 271–88.

Barber, Michael, Brandice Canes-Wrone, and Sharece Thrower. 2019. "Campaign Contributions and Donors' Policy Agreement with Presidential Candidates." *Presidential Studies Quarterly* 49 (4): 770–97.

Barrett, Andrew W. 2004. "Gone Public: The Impact of Going Public on Presidential Legislative Success." *American Politics Research* 32 (3): 338–70.

Bonica, Adam. 2014. "Mapping the Ideological Marketplace." *American Journal of Political Science* 58 (2): 367–86.

Bonica, Adam. 2018. *Database on Ideology, Money in Politics, and Elections: Public version 2.0 {Computer file}*. Stanford, CA: Stanford University Libraries.

Brace, Paul, and Barbara Hinckley. 1992. *Follow the Leader*. New York: Basic Books.

Budge, Ian, and Dennis Farlie. 1983. "Party Competition—Selective Emphasis or Direct Confrontation? An Alternative View with Data." In *Western European Party Systems*, eds. Hans Daadler and Peter Mair. Beverly Hills, CA: Sage, 267–305.

Burden, Berry. 2004. "Candidate Positioning in U.S. Congressional Elections." *British Journal of Political Science* 34 (2): 211–37.

Bykowicz, Julie.2015. "Twitter Dives into Campaign Fundraising." *PBS New Hour*, September 15. https://www.pbs.org/newshour/economy/twitter-takes-dive-campaign-fundraising.

Cain, Bruce, John Ferejohn, and Morris Fiorina. 1987. *The Personal Vote: Constituency Service and Electoral Independence*. Cambridge, MA: Harvard University Press.

Cameron, Charles, and Lee-Kwang Park. 2011. "Going Public When Opinion Is Contested: Evidence from Presidents' Campaigns for Supreme Court Nominees, 1930–2009." *Presidential Studies Quarterly* 41 (3): 442–70.

Canes-Wrone, Brandice. 2006. *Who Leads Whom? Presidents, Policy, and the Public*. Chicago: University of Chicago Press.

Canes-Wrone, Brandice, David W. Brady, and John F. Cogan. 2002. "Out of Step, Out of Office: Electoral Accountability and House Members' Voting." *American Political Science Review* 96 (1): 127–40.

Cavari, Amnon. 2013. "The Short-Term Effect of Going Public." *Political Research Quarterly* 66 (2): 336–51.

Chong, Dennis, and James Druckman. 2010. "Dynamic Public Opinion: Communication Effects over Time." *American Political Science Review* 104 (4): 663–80.

Denzau, Arthur T., and Michael C. Munger. 1986. "Legislators and Interest Groups: How Unorganized Interests Get Represented." *American Political Science Review* 80 (1): 89–106.

Druckman, James N., Lawrence R. Jacobs, and Eric Ostermeier. 2004. "Candidate Strategies to Prime Issues and Image." *The Journal of Politics* 66 (4): 1205–27.

Druckman, James N., Martin J. Kifer, and Michael Parkin. 2009. "Campaign Communications in U.S. Congressional Elections." *American Political Science Review* 103 (3): 343–66.

Druckman, James N., Martin J. Kifer, and Michael Parkin. 2010. "Timeless Strategy Meets New Medium: Going Negative on Congressional Campaign Web Sites, 2002–2006." *Political Communication* 27 (1): 88–103.

Edwards, George C., III. 2003. *On Deaf Ears: The Limits of the Bully Pulpit*. New Haven, CT: Yale University Press.

Edwards, George C., III. 2009. *The Strategic President: Persuasion and Opportunity in Presidential Leadership*. Princeton, NJ: Princeton University Press.

Eshbaugh-Soha, Matthew. 2016. "Going Public and Presidential Leadership." *Oxford Research Encyclopedia of Politics*. https://doi.org/10.1093/acrefore/9780190228637.013.57.

Eshbaugh-Soha, Matthew, and Jeffrey S. Peake. 2011. *Breaking through the Noise: Presidential Leadership, Public Opinion, and the News Media*. Stanford, CA: Stanford University Press.

Eshbaugh-Soha, Matthew, and Paul M. Collins Jr. 2015. "Presidential Rhetoric and Supreme Court Decisions." *Presidential Studies Quarterly* 45 (4): 633–52.

Fenno, Richard. 1978. *Home Style: House Members in Their Districts*. Reading, MA: Addison Wesley.

Fenno, Richard. 1996. *Senators on the Campaign Trail: The Politics of Representation*. Norman: University of Oklahoma Press.

Fouirnaies, Alexander, and Andrew Hall. 2014. "The Financial Incumbency Advantage: Causes and Consequences." *The Journal of Politics* 76 (3): 711–24.

Franco, Annie, Justin Grimmer, and Chloe Lim. 2018. "The Limited Effect of Presidential Public Appeals." Working Paper. Department of Political Science, Stanford University.

Fu, Shu. 2020. "Against and Alongside the Bully Pulpit: How Members of Congress Publicly Respond to Presidential Appeals." Working Paper. Department of Political Science, University of Chicago.

Gentzkow, Matthew, Jesse M. Shapiro, and Matt Taddy. 2019. "Measuring Group Differences in High-Dimensional Choices: Method and Application to Congressional Speech." *Econometrica* 87 (4): 1307–40.

Gilbert, Craig. 2018. "Donald Trump Once Divided Republicans; Ads for Midterms Signal That's No Longer True." *USA Today*, May 17. https://www.usatoday.com/story/news/politics/2018/05/17/republican-midterm-ads-dominated-praise-donald-trump/618532002/.

Grimmer, Justin. 2013. *Representational Style in Congress: What Legislators Say and Why It Matters*. New York: Cambridge University Press.

Grimmer, Justin, Sean Westwood, and Solomon Messing. 2014. *The Impression of Influence: Legislator Communication, Representation, and Democratic Accountability*. Princeton, NJ: Princeton University Press.

Hill, Seth J., and Gregory A. Huber. 2017. "Representativeness and Motivations of the Contemporary Donorate: Results from Merged Survey and Administrative Records." *Political Behavior* 39 (1): 3–29.

Hook, Jenet.2017. "Democrats Are United Against Trump, Divided on Everything Else." *Wall Street Journal*, October 26. https://www.wsj.com/articles/democrats-struggle-with-their-own-tea-party-moment-1509031265.

Howell, William G., and Douglas Kriner. 2013. "Political Elites and Public Support for War." In *Congress Reconsidered*, eds. Lawrence C. Dodd and Bruce I. Oppenheimer. Vol. 10. Washington, DC: Congressional Quarterly Press, 377–400.

Howell, William G., Ethan Porter, and Thomas J. Wood. 2020. "Making a President: Performance, Public Opinion, and the Transmutation of Donald J. Trump." *Journal of Political Institutions and Political Economy* 1 (1): 137–58.

Jacobs, Lawrence R., and Robert Y. Shapiro. 1994. "Issues, Candidate Image, and Priming: The Use of Private Polls in Kennedy's 1960 Presidential Campaign." *American Political Science Review* 88 (3): 527–40.

Jacobson, Gary. 2004. *The Politics of Congressional Elections*. 6th ed. New York: Pearson Longman.

Kahn, Kim Fridkin, and Patrick J. Kenney. 2004. *No Holds Barred: Negativity in U.S. Senate Campaigns*. Upper Saddle River, NJ: Pearson, Prentice-Hall.

Kernell, Samuel. 1986. *Going Public: New Strategies of Presidential Leadership*. Washington, DC: CQ Press.

Kolodny, Robin. 2011. "Campaign Finance in Congressional Elections." In *The Oxford Handbook of the American Congress*, eds.Eric Schickler and Frances E. Lee. New York: Oxford University Press, 215–38.

Lee, Frances E. 2008. "Dividers, Not Uniters: Presidential Leadership and Senate Partisanship, 1981–2004." *The Journal of Politics* 70 (4): 914–28.

Li, Zhao. 2018. "How Internal Constraints Shape Interest Group Activities: Evidence from Access-Seeking PACs." *American Political Science Review* 112 (4): 792–808.

Lipinski, Daniel. 2004. *Congressional Communication: Content and Consequences*. Ann Arbor: University of Michigan Press.

Lupia, Arthur. 1994. "Shortcuts versus Encyclopedias: Information and Voting Behavior in California Insurance Reform Elections." *American Political Science Review* 88 (1): 63–76.

Miller, Joanne M., and Jon A. Krosnick. 1996. "News Media Impact on the Ingredients of Presidential Evaluations." In *Political Persuasion and Attitude Change*, eds. Diana C. Mutz, Paul M. Sniderman, and Richard A. Brody. Ann Arbor: University of Michigan Press, 79–100.

Minozzi, William, Michael A. Neblo, Kevin M. Esterling, and David M. J. Lazer. 2015. "Field Experiment Evidence of Substantive, Attributional, and Behavioral Persuasion by Members of Congress in Online Town Halls." *Proceedings of the National Academy of Sciences* 112 (13): 3937–42.

Petrocik, John R. 1996. "Issue Ownership in Presidential Elections, with a 1980 Case Study." *American Journal of Political Science* 40 (3): 825–50.

Powell, Eleanor Neff, and Justin Grimmer. 2016. "Money in Exile: Campaign Contributions and Committee Access." *The Journal of Politics* 78 (4): 974–88.

Quinn, Kevin, Burt L. Monroe, Michael Colaresi, Michael H. Crespin, and Dragomir R. Radev. 2010. "How to Analyze Political Attention with Minimal Assumptions and Costs." *American Journal of Political Science* 54 (1): 209–28.

Riker, William H. 1996. *The Strategy of Rhetoric: Campaigning for the American Constitution*. New Haven, CT: Yale University Press.

Romer, Thomas, and James M. Snyder. 1994. "An Empirical Investigation of the Dynamics of PAC Contributions." *American Journal of Political Science* 38 (3): 745–69.

Rottinghaus, Brandon. 2010. *The Provisional Pulpit: Modern Presidential Leadership of Public Opinion*. College Station: Texas A&M University Press.

Simon, Dennis M., and Charles W. Ostrom Jr. 1989. "The Impact of Televised Speeches and Foreign Travel on the Presidential Approval." *Public Opinion Quarterly* 53 (1): 58–82.

Squire, Peverill. 1995. "Candidates, Money, and Voters—Assessing the State of Congressional Elections Research." *Political Research Quarterly* 48 (4): 891–917.

Stratmann, Thomas. 2005. "Some Talk: Money in Politics. A (Partial) Review of the Literature." *Public Choice* 124 (1–2): 135–56.

Trent, Judith S., and Robert V. Friedenberg. 2008. *Political Campaign Communication*. New York: Rowman and Littlefield.

Tulis, Jeffrey K. 1987. *The Rhetorical Presidency*. Princeton, NJ: Princeton University Press.

Valenzuela, Ali A., and Melissa R. Michelson. 2016. "Turnout, Status, and Identity: Mobilizing Latinos to Vote with Group Appeals." *American Political Science Review* 110 (4): 615–30.

Wagner, Kurt. 2015. "Twitter and Square Are Partnering So People Can Donate to Politicians through Tweets." *CNBC*, September 15. https://www.cnbc.com/2015/09/15/twitter-and-square-are-partnering-so-people-can-donate-to-politicians-through-tweets.html.

Yiannakis, Diana Evans. 1982. "House Members' Communication Styles: Newsletter and Press Releases." *The Journal of Politics* 44 (4): 1049–71.

Supporting Information

Additional supporting information may be found in the online version of this article at the publisher's web site:

The Behavioral Consequences of Public Appeals:

Evidence on Campaign Fundraising from the 2018 Congressional Elections

Shu Fu and William G. Howell

Online Appendix – Supplementary Materials

Contents

Table A.1: Summary Statistics

Variable	Obs.*	Mean	S.D.	Min	Max
Donation Data					
Daily Receipts	292,651	6,741	61,477	-210,498	8,030,548
Daily Receipts (R)	140,248	4,947	72,563	-10,800	8,030,548
Daily Receipts (D)	152,403	8,391	49,054	-210,498	6,001,250
Log Daily Receipts	292,651	3.785	4.094	0	15.899
Log Daily Receipts (R)	140,248	2.758	3.897	0	15.899
Log Daily Receipts (D)	152,403	4.730	4.044	0	15.607
Messaging Data					
A. RT @realDonaldTrump					
Daily Support by Rep	1421	0.00659	0.119	0	13
Daily Support by Dem	50	0.00018	0.015	0	2
Daily Oppose by Rep	17	0.00001	0.008	0	2
Daily Oppose by Dem	1643	0.00667	0.096	0	6
B. Trump's Immigration Policy					
Daily Support by Rep	859	0.00381	0.081	0	11
Daily Support by Dem	23	0.00009	0.010	0	2
Daily Oppose by Rep	46	0.00017	0.014	0	3
Daily Oppose by Dem	3498	0.0175	0.185	0	9

Note: Summary statistics for messaging data are based on non-zero observations, which are equivalent to the total number of messages sent by candidates.

Table A.2: Estimated Effects with Leads (7-day Range)

	Dependent Variable: Log Daily Receipts			
	Retweet @realDonaldTrump		Trump's Immigration Policy	
	(1)	(2)	(3)	(4)
--- lead3	0.054 (0.047)	0.089 (0.054)	-0.088 (0.077)	0.007 (0.087)
--- lead2	0.109** (0.041)	0.108* (0.045)	0.011 (0.063)	0.019 (0.069)
--- lead1	0.109* (0.045)	0.045 (0.051)	0.102 (0.075)	0.016 (0.084)
Support by Rep	0.127** (0.049)	0.086 (0.047)	0.247*** (0.073)	0.167 (0.089)
--- lag 1	0.144* (0.061)	0.122 (0.062)	0.109 (0.077)	0.053 (0.083)
--- lag 2	-0.060 (0.051)	-0.051 (0.053)	0.169* (0.068)	0.160* (0.075)
--- lag 3	-0.078 (0.049)	-0.038 (0.053)	-0.009 (0.065)	0.014 (0.064)
--- lead3	0.178 (0.315)	0.325 (0.401)	0.487 (0.291)	0.774 (0.459)
--- lead2	0.540 (0.288)	0.565* (0.277)	-0.171 (0.339)	-0.062 (0.431)
--- lead1	0.299 (0.326)	0.497 (0.333)	0.863 (0.464)	0.937 (0.491)
Support by Dem	-0.032 (0.220)	0.135 (0.261)	0.388 (0.420)	0.912 (0.581)
--- lag 1	0.038 (0.264)	0.034 (0.295)	0.240 (0.367)	0.347 (0.450)
--- lag 2	-0.170 (0.284)	-0.274 (0.317)	0.230 (0.400)	0.422 (0.469)
--- lag 3	-0.408 (0.450)	-0.620 (0.481)	-0.016 (0.371)	0.189 (0.451)
--- lead3	-1.041* (0.492)	-1.045* (0.475)	0.330 (0.491)	0.431 (0.478)
--- lead2	-0.737** (0.260)	-1.262*** (0.367)	-0.321 (0.297)	-0.184 (0.287)
--- lead1	0.066 (0.675)	-0.308 (0.489)	1.139** (0.415)	0.991* (0.452)
Oppose by Rep	0.376 (0.781)	0.062 (0.720)	0.907 (0.467)	0.845 (0.460)
--- lag 1	-0.649 (0.486)	-0.747 (0.576)	-1.201** (0.386)	-1.081** (0.373)
--- lag 2	-0.446 (0.549)	-0.283 (0.555)	-0.341 (0.403)	-0.413 (0.399)
--- lag 3	-0.930* (0.446)	-1.504*** (0.402)	0.675 (0.378)	0.438 (0.384)
--- lead3	0.029 (0.063)	-0.034 (0.064)	0.017 (0.027)	-0.053 (0.030)
--- lead2	-0.053 (0.056)	-0.048 (0.057)	0.048 (0.029)	0.004 (0.029)
--- lead1	-0.119* (0.048)	-0.158** (0.055)	0.097** (0.034)	0.062 (0.035)
Oppose by Dem	-0.058 (0.054)	-0.065 (0.057)	-0.019 (0.032)	-0.012 (0.034)
--- lag 1	-0.057 (0.068)	-0.053 (0.070)	0.064 (0.035)	0.065* (0.032)
--- lag 2	0.004 (0.057)	-0.025 (0.060)	0.020 (0.029)	-0.016 (0.029)
--- lag 3	-0.104* (0.052)	-0.125* (0.056)	0.038 (0.033)	-0.011 (0.033)
Fixed Effects	Day, Candidate	Day x Party x State, Candidate	Day, Candidate	Day x Party x State, Candidate
Observations	286,741	286,741	286,741	286,741
R^2	0.551	0.615	0.551	0.615

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$. Standard errors are clustered by congressional race.

Table A.3: Estimated Effects with Leads (5-day Range)

	Dependent Variable: Log Daily Receipts			
	Retweet @realDonaldTrump		Trump's Immigration Policy	
	(1)	(2)	(3)	(4)
--- lead2	0.118** (0.043)	0.123** (0.046)	-0.0004 (0.062)	0.020 (0.068)
--- lead1	0.120* (0.049)	0.070 (0.055)	0.097 (0.075)	0.018 (0.085)
Support by Rep	0.129* (0.056)	0.089 (0.054)	0.236** (0.072)	0.162 (0.087)
--- lag 1	0.134* (0.058)	0.118* (0.056)	0.109 (0.075)	0.057 (0.082)
--- lag 2	-0.063 (0.057)	-0.035 (0.057)	0.156* (0.062)	0.146* (0.071)
--- lead2	0.536 (0.286)	0.559* (0.274)	-0.142 (0.351)	-0.033 (0.432)
--- lead1	0.303 (0.325)	0.497 (0.333)	0.874 (0.464)	0.962* (0.491)
Support by Dem	-0.038 (0.220)	0.131 (0.259)	0.383 (0.419)	0.900 (0.579)
--- lag 1	0.039 (0.257)	0.049 (0.288)	0.236 (0.364)	0.346 (0.445)
--- lag 2	-0.174 (0.285)	-0.280 (0.319)	0.224 (0.396)	0.427 (0.464)
--- lead2	-0.843** (0.270)	-1.436*** (0.377)	-0.315 (0.303)	-0.169 (0.293)
--- lead1	0.005 (0.669)	-0.383 (0.463)	1.153** (0.414)	1.006* (0.450)
Oppose by Rep	0.427 (0.773)	0.130 (0.724)	0.900 (0.467)	0.844 (0.461)
--- lag 1	-0.714 (0.482)	-0.810 (0.559)	-1.192** (0.386)	-1.070** (0.375)
--- lag 2	-0.559 (0.552)	-0.419 (0.546)	-0.286 (0.390)	-0.350 (0.387)
--- lead2	-0.057 (0.055)	-0.055 (0.056)	0.053 (0.030)	0.003 (0.029)
--- lead1	-0.117* (0.048)	-0.157** (0.055)	0.101** (0.034)	0.061 (0.035)
Oppose by Dem	-0.064 (0.053)	-0.069 (0.057)	-0.016 (0.033)	-0.010 (0.034)
--- lag 1	-0.059 (0.067)	-0.056 (0.069)	0.062 (0.035)	0.060 (0.032)
--- lag 2	0.002 (0.056)	-0.030 (0.060)	0.024 (0.030)	-0.018 (0.030)
Fixed Effects	Day, Candidate	Day x Party x State, Candidate	Day, Candidate	Day x Party x State, Candidate
Observations	288,795	288,795	288,711	288,711
R^2	0.549	0.613	0.549	0.613

Note: *p<0.05; **p<0.01; ***p<0.001. Standard errors are clustered by congressional race.

Table A.4. Estimated Effects with Measures of Dichotomous Support and Opposition

	Dependent Variable: Log Daily Receipts			
	Retweet @realDonaldTrump		Trump's Immigration Policy	
	(1)	(2)	(3)	(4)
Support by Rep	0.331*** (0.085)	0.256** (0.093)	0.372** (0.121)	0.246 (0.126)
--- lag 1	0.189** (0.071)	0.130 (0.074)	0.223 (0.115)	0.121 (0.130)
--- lag 2	-0.013 (0.083)	0.002 (0.084)	0.200* (0.098)	0.172 (0.108)
--- lag 3	0.003 (0.102)	0.069 (0.105)	-0.043 (0.102)	0.022 (0.098)
Support by Dem	-0.005 (0.234)	0.172 (0.270)	0.519 (0.508)	1.111 (0.645)
--- lag 1	0.106 (0.299)	0.053 (0.339)	0.381 (0.447)	0.482 (0.520)
--- lag 2	-0.231 (0.336)	-0.277 (0.375)	0.284 (0.487)	0.409 (0.544)
--- lag 3	-0.620 (0.487)	-0.862 (0.504)	-0.029 (0.468)	0.185 (0.526)
Oppose by Rep	0.762 (0.699)	0.329 (0.713)	1.286** (0.494)	1.190* (0.534)
--- lag 1	-0.509 (0.385)	-0.586 (0.518)	-1.413** (0.485)	-1.256** (0.480)
--- lag 2	-0.366 (0.408)	-0.235 (0.430)	-0.240 (0.498)	-0.306 (0.503)
--- lag 3	-0.853* (0.402)	-1.724*** (0.500)	0.727 (0.468)	0.467 (0.450)
Oppose by Dem	-0.075 (0.069)	-0.088 (0.071)	-0.026 (0.056)	-0.005 (0.058)
--- lag 1	-0.141 (0.079)	-0.145 (0.083)	0.151** (0.055)	0.147** (0.054)
--- lag 2	-0.044 (0.073)	-0.084 (0.076)	0.043 (0.051)	-0.033 (0.051)
--- lag 3	-0.153* (0.073)	-0.202** (0.079)	0.065 (0.051)	-0.028 (0.050)
Fixed Effects	Day, Candidate	Day x Party x State, Candidate	Day, Candidate	Day x Party x State, Candidate
Observations	289,780	289,780	289,696	289,696
R^2	0.550	0.614	0.550	0.614

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$. Standard errors are clustered by congressional race. Here, the independent variables are dichotomous—that is, coded 0 if no messages of support (or opposition) are sent, and 1 if at least one such message is sent.

Table A.5. Estimated Effects in Different Election Stages

	Dependent Variable: Log Daily Receipts			
	Retweet @realDonaldTrump		Trump's Immigration Policy	
	Primary (1)	**General** (2)	**Primary** (3)	**General** (4)
Support by Rep	0.127 (0.079)	0.065 (0.053)	0.245* (0.107)	0.110 (0.149)
--- lag 1	0.042 (0.071)	0.179 (0.097)	0.007 (0.100)	0.163 (0.141)
--- lag 2	-0.031 (0.085)	-0.053 (0.058)	0.129 (0.093)	0.200 (0.108)
--- lag 3	-0.057 (0.099)	0.120* (0.060)	0.043 (0.091)	0.004 (0.115)
Support by Dem	0.166 (0.467)	0.248 (0.317)	1.012 (0.894)	0.824 (0.455)
--- lag 1	0.350 (0.439)	-0.217 (0.373)	0.934 (0.633)	-0.286 (0.523)
--- lag 2	-0.430 (0.424)	0.122 (0.537)	0.235 (0.712)	0.636 (0.389)
--- lag 3	-0.928 (0.637)	-0.105 (0.405)	0.275 (0.782)	0.187 (0.321)
Oppose by Rep	-0.676 (0.677)	2.978*** (0.747)	0.227 (0.532)	1.803* (0.848)
--- lag 1	-0.741 (0.702)	-0.394 (0.684)	-0.993*** (0.284)	-1.773 (0.940)
--- lag 2	-0.554 (0.665)	0.387 (0.620)	-0.654 (0.409)	-0.214 (0.833)
--- lag 3	-1.857*** (0.496)	-0.605 (0.468)	0.356 (0.486)	0.223 (0.696)
Oppose by Dem	-0.084 (0.071)	-0.032 (0.111)	0.015 (0.043)	-0.087 (0.056)
--- lag 1	-0.160* (0.080)	0.088 (0.109)	0.042 (0.039)	0.037 (0.049)
--- lag 2	-0.026 (0.072)	-0.005 (0.083)	-0.024 (0.037)	-0.055 (0.054)
--- lag 3	-0.122 (0.077)	-0.096 (0.080)	-0.027 (0.042)	-0.034 (0.055)
Fixed Effects	Day x Party x State, Candidate	Day x Party x State, Candidate	Day x Party x State, Candidate	Day x Party x State, Candidate
Observations	166,097	123,683	166,056	123,640
R^2	0.598	0.660	0.598	0.660

Note: *p<0.05; **p<0.01; ***p<0.001. Standard errors are clustered by congressional race.

Table A.6: Estimated Effects when Controlling for Number of Daily Tweets by Candidates

	Dependent Variable: Log Daily Receipts			
	Retweet @realDonaldTrump		Trump's Immigration Policy	
	(1)	(2)	(3)	(4)
Support by Rep	0.095 (0.057)	0.057 (0.056)	0.233** (0.072)	0.158 (0.087)
--- lag 1	0.126* (0.064)	0.104 (0.066)	0.104 (0.073)	0.050 (0.080)
--- lag 2	-0.051 (0.051)	-0.042 (0.052)	0.156* (0.061)	0.140 (0.072)
--- lag 3	-0.073 (0.056)	-0.033 (0.060)	-0.009 (0.066)	0.021 (0.063)
Support by Dem	-0.087 (0.219)	0.088 (0.260)	0.338 (0.413)	0.829 (0.574)
--- lag 1	0.054 (0.257)	0.037 (0.288)	0.253 (0.370)	0.343 (0.451)
--- lag 2	-0.197 (0.276)	-0.270 (0.313)	0.171 (0.406)	0.366 (0.475)
--- lag 3	-0.434 (0.453)	-0.628 (0.484)	-0.057 (0.376)	0.155 (0.456)
Oppose by Rep	0.369 (0.781)	0.026 (0.715)	0.894 (0.478)	0.842 (0.474)
--- lag 1	-0.673 (0.499)	-0.749 (0.587)	-1.215** (0.384)	-1.087** (0.372)
--- lag 2	-0.580 (0.531)	-0.452 (0.538)	-0.340 (0.393)	-0.391 (0.391)
--- lag 3	-1.013* (0.477)	-1.674*** (0.401)	0.704 (0.374)	0.472 (0.375)
Oppose by Dem	-0.086 (0.054)	-0.090 (0.056)	-0.019 (0.034)	-0.015 (0.035)
--- lag 1	-0.083 (0.069)	-0.078 (0.072)	0.050 (0.035)	0.047 (0.033)
--- lag 2	-0.016 (0.058)	-0.046 (0.061)	0.015 (0.029)	-0.025 (0.029)
--- lag 3	-0.119* (0.052)	-0.142* (0.056)	0.037 (0.034)	-0.016 (0.033)
# Daily Tweets	0.015*** (0.002)	0.013*** (0.002)	0.015*** (0.002)	0.013*** (0.002)
--- lag 1	0.004* (0.002)	0.004* (0.002)	0.005* (0.002)	0.004* (0.002)
--- lag 2	-0.001 (0.002)	-0.0003 (0.002)	-0.001 (0.002)	-0.0004 (0.002)
--- lag 3	0.001 (0.002)	0.00004 (0.002)	0.001 (0.002)	-0.0001 (0.002)
Fixed Effects	Day, Candidate	Day x Party x State, Candidate	Day, Candidate	Day x Party x State, Candidate
Observations	289,696	289,696	289,696	289,696
R^2	0.550	0.614	0.550	0.614

Note: *p<0.05; **p<0.01; ***p<0.001. Standard errors are clustered by congressional race.

Table A.7: Estimated Effects when Excluding Final Day of each Fundraising Quarter

	Dependent Variable: Log Daily Receipts			
	Retweet @realDonaldTrump		Trump's Immigration Policy	
	(1)	(2)	(3)	(4)
Support by Rep	0.170*** (0.049)	0.117* (0.048)	0.261*** (0.072)	0.181* (0.088)
--- lag 1	0.172** (0.054)	0.142* (0.059)	0.120 (0.074)	0.062 (0.081)
--- lag 2	-0.024 (0.044)	-0.019 (0.046)	0.156* (0.062)	0.140* (0.071)
--- lag 3	-0.061 (0.048)	-0.021 (0.052)	-0.022 (0.066)	0.001 (0.064)
Support by Dem	-0.027 (0.220)	0.139 (0.262)	0.437 (0.410)	0.943 (0.573)
--- lag 1	0.058 (0.259)	0.039 (0.290)	0.260 (0.380)	0.376 (0.459)
--- lag 2	-0.167 (0.277)	-0.241 (0.311)	0.216 (0.402)	0.411 (0.469)
--- lag 3	-0.416 (0.448)	-0.612 (0.480)	0.078 (0.375)	0.225 (0.468)
Oppose by Rep	0.386 (0.790)	0.046 (0.723)	1.001* (0.486)	0.946* (0.480)
--- lag 1	-0.658 (0.506)	-0.731 (0.594)	-1.190** (0.382)	-1.065** (0.370)
--- lag 2	-0.550 (0.534)	-0.423 (0.542)	-0.317 (0.396)	-0.372 (0.393)
--- lag 3	-0.967* (0.473)	-1.627*** (0.402)	0.729 (0.373)	0.493 (0.375)
Oppose by Dem	-0.065 (0.055)	-0.073 (0.057)	-0.003 (0.035)	-0.002 (0.036)
--- lag 1	-0.058 (0.069)	-0.058 (0.072)	0.062 (0.035)	0.055 (0.032)
--- lag 2	-0.005 (0.058)	-0.039 (0.061)	0.021 (0.029)	-0.020 (0.029)
--- lag 3	-0.102 (0.053)	-0.127* (0.057)	0.036 (0.034)	-0.020 (0.034)
Fixed Effects	Day, Candidate	Day x Party x State, Candidate	Day, Candidate	Day x Party x State, Candidate
Observations	286,899	286,899	286,899	286,899
R^2	0.548	0.612	0.548	0.612

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$. Standard errors are clustered by congressional race.

Table A.8. Effects of Retweeting Trump on Candidates' Fundraising

	Dependent Variable: Log Daily Receipts			
	Direct Retweet		**Retweet with Comments**	
	(1)	(2)	(3)	(4)
Support by Rep	0.169** (0.057)	0.125* (0.054)	0.160 (0.119)	0.056 (0.143)
--- lag 1	0.202** (0.068)	0.198** (0.069)	0.042 (0.122)	-0.121 (0.124)
--- lag 2	-0.020 (0.049)	-0.031 (0.053)	-0.078 (0.133)	-0.009 (0.139)
--- lag 3	-0.009 (0.050)	0.016 (0.055)	-0.274* (0.139)	-0.196 (0.150)
Support by Dem	0.240 (0.683)	-0.039 (0.799)	-0.055 (0.227)	0.177 (0.270)
--- lag 1	-0.150 (0.644)	-0.432 (0.922)	0.078 (0.282)	0.102 (0.305)
--- lag 2	-1.099 (0.606)	-1.613* (0.700)	-0.015 (0.294)	-0.057 (0.326)
--- lag 3	0.269 (0.727)	-0.770 (1.131)	-0.531 (0.500)	-0.588 (0.528)
Oppose by Rep	--	--	0.365 (0.789)	0.023 (0.722)
--- lag 1	--	--	-0.680 (0.505)	-0.748 (0.593)
--- lag 2	--	--	-0.563 (0.531)	-0.429 (0.537)
--- lag 3	--	--	-0.976* (0.469)	-1.648*** (0.398)
Oppose by Dem	--	--	-0.062 (0.053)	-0.071 (0.056)
--- lag 1	--	--	-0.060 (0.068)	-0.059 (0.071)
--- lag 2	--	--	-0.0004 (0.058)	-0.033 (0.061)
--- lag 3	--	--	-0.103* (0.052)	-0.130* (0.056)
Fixed Effects	Day, Candidate	Day x Party x State, Candidate	Day, Candidate	Day x Party x State, Candidate
Observations	289,696	289,696	289,696	289,696
R^2	0.550	0.614	0.550	0.614

Note: *p<0.05; **p<0.01; ***p<0.001. Standard errors are clustered by congressional race.