

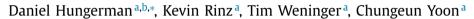
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Political campaigns and church contributions[☆]





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ABSTRACT

We combine a new dataset of weekly Catholic church donations with a new dataset of presidential-election campaign stops to explore the impact of stops on donations. We find that stops increase donations, with a campaign stop generating 2 percent more donations in the following week. Our results suggest that this effect is of short duration. Using a well-known list of politically-motivated words, we find that this effect does not appear to vary based on the political language used by the parish. Our results underscore the contemporary political dimension of US religiosity and the elemental relationship between religious and political events more generally.

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1. Introduction

The scale of US presidential campaigns has become dramatically larger than even a generation ago; in the past 20 years expenditures on presidential campaigns have increased nearly 5-fold.¹ How do these campaigns impact individuals and communities? A large body of scholarship has taken up this question. Work has especially focused on how campaigns affect political participation (see Green and Schwam-Baird (2016), for a recent review), but scholars have also investigated whether campaigns affect communities' social engagement outside of political participation, with mixed conclusions (e.g., Rahn et al. (2004); Banducci and Karp, 2003; Coleman and Manna (2000)).

In this paper, we explore how the electoral process impacts pro-social behavior, and in particular how campaign stops made by candidates impact religious donations. Some prior work has considered the effects of campaign activity on other types of donations, for example, Barton et al. (2016) and Perez-Truglia and Cruces (2017). More generally, recent work in economics has considered the importance of social context (such as "the power of the ask") in motivating giving (Andreoni et al., 2017; DellaVigna et al., 2012). Several factors motivate our extension of this work to religious donations.

First, religiosity remains an important activity, with most Americans professing a belief in God and attending worship with some frequency (Lipka, 2013; 2015), and with religion continuing to make up by far the largest component of all charitable giving. Second, religion appears to be an institution closely related to political participation. Individuals' religiosity is

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¹ Using data from the Federal Election Committee, Galka (2016) reports the 2016 campaign involved \$857 million in expenditures, while the 1996 campaign had \$182 million, an increase of about 470%. Barton et al. (2014) report that expenditures for all 2010 US federal elections were nearly \$4 billion.

an extremely strong predictor of a person's likelihood to vote and their political attitudes (Chen and Lind, 2016; Zada et al., 2016); and some work (Gerber et al., 2016) has concluded that the effect of religion on voting behavior is causal. Scholars have also noted that the communal aspects of worship represent an elemental connection between religion and other social events that, in the words of Émile Durkheim, "sustain and reaffirm the collective feelings and ideas that constitute (a society's) unity and its personality" (2008, pg 322).² Relating political activity to religious activity then is a project that touches on long-standing ideas of religiosity, but the potential connection between religious and political activity has also become especially relevant in recent years in the US, where religious participation appears to be increasingly politically motivated, and political identification and religious identification have become increasingly connected (Campbell and Putnam, 2012; Hout and Fischer, 2014).

For this reason, the study of the connection between explicitly political events and religious activity is particularly timely and further involves unique policy considerations. The relationship between politicking and religiosity has come under renewed discussion in the context of the Johnson Amendment, which threatens the tax-exempt status of churches if they endorse or oppose particular political candidates. Religious groups' enthusiasm for eliminating this amendment appears mixed, with some "thrilled" by the idea but many religious groups opposing it (Goodstein and Shear, 2017).

This conflicted response mirrors the inherent uncertainty in whether campaign activity could benefit churches. The implications of past work are not entirely clear: on the one hand, if campaigns (for instance) promote tastes for social participation, or let individuals acquire information or social contacts conducive to future religiosity, then campaign activity could increase religious participation. On the other hand, as mentioned above, studies have found mixed results (including small or zero effects) of campaigns on pro-social attitudes. Campaigns could lower religious participation if, for example, individuals have limited time for socially-focused activities and campaign participation "crowds out" religious participation.³ Moreover, recent studies have shown that other activities such as education, while itself likely important for promoting social capital, may lower religious participation (Becker and Woessman, 2017; Cesur and Mocan, 2014; Hungerman, 2014a; Mocan and Pogorelova, 2014). Similarly, Durkheim (2008) argues that scientific thought and religious thought have critical similarities, and this may lead religious thought to fade away as scientific thought progresses.⁴ But in truth all of this work is tangential to our topic; we know of no extant work that explores the issue we consider here.⁵

This may in part be explained by data limitations. Churches and other congregations typically do not report information to any federal census or survey. While well-known surveys such as the General Social Survey ask individuals questions on their religiosity, the annual periodicity and relatively small sample sizes of these surveys make them not ideal for our topic. Further, perhaps surprisingly, we also know of no available dataset with detailed information on national campaign activity even for the most recent presidential elections.

We overcome these challenges by constructing two new datasets. First, we construct a dataset of weekly church donations from a sample of hundreds of Catholic churches from across the United States. This data was obtained from the weekly service bulletins published by these churches on their websites over a period of several years. Importantly, along with a church's exact location, these bulletins almost always include weekly donations collected, which we use as our measure of religious activity. Further, they include as a potential datasource the text of the bulletin itself. Our data includes both donations made to each parish and also a measure of the political content of the words in each bulletin. We discuss this dataset more below.

Using a wide variety of sources, we then construct a dataset of presidential-campaign stops during the fall of 2015. Fortunately, the campaign featured a large number of candidates, giving us a very high amount of variation in stops across communities and across time. Our data includes all stops made by the top 11 candidates in the presidential race from September 1st, 2015, through December 31st of that year. Overall, we identify a total of 864 distinct campaign stops, where we observe the location, exact date, and candidate at the stop.

Of course, campaign stops are not randomly made but rather reflect (presumably) careful strategic thinking by candidates and campaign managers. If certain communities are more likely to get campaign stops than others, which is obviously true, then care should be taken that differences in religious behavior observed in towns receiving campaign stops are driven by the campaign stops and not the underlying characteristics of the towns. We exploit the high-frequency and years-long availability of our data to non-parametrically control for differences between the observations that see a campaign stop and those that do not. We find evidence that campaign stops tend to occur in communities with naturally lower levels of donations, all else equal. This difference appears to be driven by cross sectional (rather than temporal) variation, and to primarily be driven by differences across states, rather than within them. We describe our methodology and these differences more below.

² Durkheim considers *corroboree* and other events held by Australian Aboriginals as examples, but he also relates religious activities to events that are patriotic and political. He asks, "What essential difference is there between an assembly of Christians commemorating the principal moments in the life of Christ... and a meeting of citizens commemorating the institution of a new moral charter or some great event in national life?" (ibid).

³ Even the authority Alexis de Tocqueville, whose extensive and nuanced writings often emphasized the beneficial aspects of religion for democracy, warns that the democratic process could undermine certain aspects of religious practices: "Another truth seems clear to me: religions must attend less to external practices in democratic times than in all others." He argues that during these times men "are naturally led to attach only a secondary importance to the details of worship" (de Tocqueville (2012); pg 750). Tocqueville' s observation specifically concerns external practices or "small observances" of faith, and whether his argument would apply to religious participation in the present day is an open question.

⁴ See part 2 of his Conclusions for this discussion.

⁵ However, we do know of important work relating religious participation to electoral outcomes, (e.g., Bhalotra et al. (2014); Meyersson (2014)).

Controlling for these differences, we find that a campaign stop made by a presidential candidate leads to an increase in collections for nearby churches the following week. The typical increase is moderately large: about 2% of total collected weekly revenue for each campaign stop. The result does not appear to be driven by churches in any particular state. Using a list of politically motivated words developed by Gentzkow and Shapiro (2010), we also look at how our effect varies by the political language used within the church bulletins, but we do not find strong differences across parishes with differing political content (e.g., using words favored by Democrats or Republicans) in their bulletins. We also explore whether our effects vary by the candidates themselves.

Our findings are relevant for past and future work in several ways. First, our results provide novel evidence of the connection between religious activity and explicitly political activity, underscoring the "elemental" similarities between religious and political events as well as the contemporary political dimension of US religiosity. More generally, our results support the conclusion that campaigns affect non-campaign behavior. This matters for prior work on the effects of campaigns, and also for work on how social contexts can affect pro-social behavior. Most recent work in economics in this latter area (Andreoni et al., 2017; DellaVigna et al., 2012; Knutsson et al., 2013; Trachtman et al., 2015) explores the costs individuals incur to avoid solicitation. But our study considers how campaign activity affects donations that likely occur days afterwards and could easily be avoided. Our findings suggest that future work should consider the importance of social context in settings beyond those typically considered when studying "the power of the ask." That said, we note that the nature of our study does not allow us to identify what it is about campaigns that increases donations, although we find evidence against some plausible explanations suggested by prior work.

For example, we find little evidence that this effect endures. In this sense, our findings do not fit the same conclusions as those reached by the excellent work of Madestam et al. (2013). Their paper shows that attendance at a Tea Party rally on Tax Day (April 15), 2009, had important impacts on social behavior. They conclude that the local, enduring effects from rallies fits Zuckerman's (2005) "social logic of politics" wherein the rallies' effects depend upon social networks, mobilization, and/or habit formation that lead to enduring effects over time. In contrast, our effects appear to be quite short-lived and become imprecise and statistically insignificant in a matter of weeks. This result also suggests that studies on campaign events and public-goods contributions (such as DellaVigna (2010), which looks at events in the 2008 presidential campaign and monthly organ donations) should be sure to use sufficiently high-frequency data.

Our work makes several other contributions to research on campaigns and on church/state relations. First, while scholars as noted above have shown an interest in how campaigns effect social outcomes, we do not know of any work that looks at religious participation as an outcome; our novel focus on religion is useful to work on elections and social outcomes given the critical role of churches in fostering social cohesion and important social outcomes.⁶ Second, many prior studies have focused on campaigns and self-reported measures of trust, an outcome that is certainly quite important but one that may not accurately reflect observed (rather than self-reported) outcomes. Third, we focus on an aspect of campaigns that is quite well-known to citizens but may be sometimes overlooked in the vast elections literature: campaign stops.⁷ Fourth, we take both our bulletin data and our campaign data as unique and potentially useful new resources that may be of interest to scholars in the future.

The next section discusses our bulletin and campaign data. Section 3 describes our empirical methodology. Section 4 lays out results, and Section 5 concludes.

2. Bulletin and campaign data

2.1. Bulletin data

Our bulletin data provides weekly information on church donations to a national sample of Catholic churches, or parishes. The term *parish*, which will be used repeatedly in what follows, refers to a local Catholic church as well as any related facilities, such as a school, under the supervision of a particular pastor.

We are aware of a small amount of research using weekly church data, most notably the studies by Olson (2008) and by Jannaccone and Everton (2004); the former tracks Protestant churches in one Midwestern city in 2004 and the latter tracks attendance at four churches for several years in the 1990s and early 2000s. Moreover, while a large literature has focused on the social importance of parishes, even annual Catholic data with financial information is difficult to find in prior scholarship.⁸

To construct our dataset, we first obtained a list of US parish Web sites from www.masstimes.org and depth of 3, ie, we downloaded the parish's homepage, visited all the links on the page, all of the links of links, and all of the links-of-links. This process collected millions of Web pages but also videos, images, and pdf documents. To keep

⁶ Examples of the important social role played by churches include Franck and Iannaccone (2014), Bentzen (2016), Chen and Lind (2016); Dills and Hernandez-Julian (2014); Gill (2004); Hungerman (2014b); Pope et al. (2014); see lyer (2016) for a discussion.

⁷ This is not to say that no prior work has been done on campaign stops; some examples include Strömberg (2008) and Wood (2016).

⁸ Much of this literature has focused on the notably better outcomes produced by Catholic schools (Altonji et al., 2005; Evans and Schwab, 1995) and schools' impacts on economic diversity (see Section 5 of Black and Sokoloff (2006)). Other work has considered the impact of parishes on charitable activity more generally, such as Bottan and Perez-Truglia (2015). For a discussion of the challenges of obtaining parish financial data, see Hungerman et al. (2017).

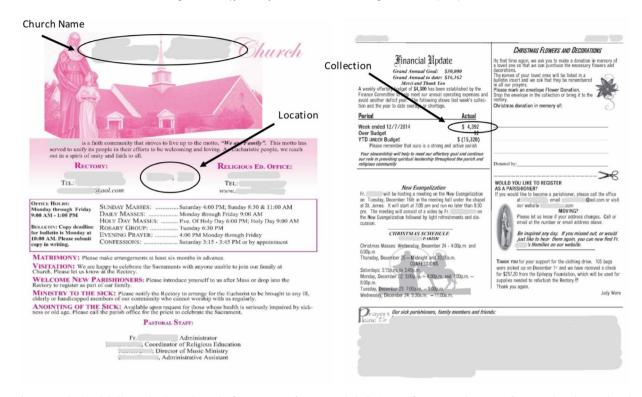


Fig. 1. Sample church bulletin. The above shows the first two pages from a sample bulletin. Specific names and contact information have been redacted.

from downloading enormous files we limited restricted files to be less than 5MB in size, and discarded all non-pdf files. We ran this Web crawling process once every four weeks through January 2016, at which point our server ran out of disk space for storing documents. In total we collected 836,458 pdf documents comprising 947GBs. Further, not all Web sites had pdfs, and not all pdfs collected from Web sites were church bulletins. Non-bulletin files collected included general school/event forms, flyers, passages from the Bible, and speeches from pastors. It is often easy for a person to distinguish bulletins from non-bulletins, but harder for a machine to do so. We threw out pdfs that did not contain the word 'bulletin' in the filename. This resulted in 79,560 parish bulletins.

Fig. 1 shows an example of a church bulletin. Names and contact information have been redacted. The figure shows the first two pages (this bulletin was in total four pages). As in this figure, most bulletins are weekly, contain parish address information, and contain information on total donations. These are the key pieces of information we required for our study. Bulletins often contain other interesting pieces of donation information, such as (here) the weekly target collection amount. Other items frequently reported include the fraction of money budgeted towards a particular project, such as a capital campaign, or the total collected throughout the year to date. However, there is little uniformity in the reporting of these other items across parishes, and so we focus on the total collected for all purposes by the parish in a given week for our variable. Also, bulletins do not typically report attendance, so that the total donations number we focus on could be driven by the number of people attending worship changing, or by the same number of people changing how much they give. We will not be able to separate these two behaviors.

Collecting information from these bulletins presented some challenges. While easy to view, the collection amount in Fig. 1 is in a table that could be difficult to identify as the object of interest using machine reading. To deal with these challenges, we hired workers from Amazon Mechanical Turk (ie, turkers) to extract donation amounts and bulletin metadata. Based on our available funding, we began with a random sample of about 1500 bulletins and asked 75 turkers to extract information from 20 bulletins each. Entries were checked for accuracy by a research assistant prior to paying for data entry. The same challenges is a superior of the collection amount in Fig. 1 is in a table that could be difficult to identify as the object of interest using machine reading. To deal with these challenges, we hired workers from Amazon Mechanical Turk (ie, turkers) to extract donation amounts and bulletin metadata.

⁹ Note also that there could be two "dates" in the bulletin; the date the bulletin was published, and the date the collection was taken, which typically is from the week before. Fig. 1 shows the date of collection but we have omitted the date of publication from the figure (which in this case was reported on page 3). When writing our instructions for data extraction, we paid special care to explicitly clarify how date should be recorded. We further subsequently checked entries to ensure that the "correct" date was entered. We believe virtually all bulletins in our study do not confuse these dates.

¹⁰ We particularly thank our research assistant Kathleen Ryan for her work on this.

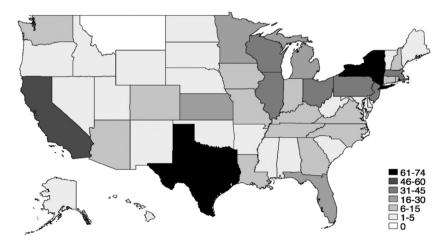


Fig. 2. Number of parishes by state.

From the initial extraction effort we identified parish URLs with usable bulletins; we then crowdsourced all bulletins found from these parish URLs.

This left us with a "raw" dataset of 40,950 observations. Next, we removed bulletins that did not report the amount of donations, that reported donations from multiple parishes or from multiple locations within a single parish, and those that did not report weekly donations. We then re-verified the location of each parish, the dates and the donations in our data. We finally identified 712 unique parishes in 25,775 observations between May 2008 and Jan 2016. For the main regression sample, we will (as discussed more below) restrict our data to a date range from 2014 and September through December of 2015 (but we report results from a larger range as well). This provides us with a dataset of 10,187 observations with 549 unique parishes.

Fig. 2 shows the locations of parishes in our dataset. This sample includes 49 states, excluding only Montana. It should be kept in mind that our results come from a sample of all US parishes, and in particular from parishes that have websites (although almost all parishes have websites). Further, as discussed below, for some estimates we focus on a subset of 237 of these parishes, although we report results for the full sample as well. But whether our results would extend to other religious faiths we cannot say.

Table 1 shows some descriptive statistics by counties for (a) the entire United States, (b) the 712 parishes in the data with usable bulletins and (c) the subsample of these parishes observed in 2014 and the fall of 2015. The means are taken from the 2010 Decennial Census, and (excepting the last row) are unweighted. Standard deviations are in brackets. The first few rows show that the counties included in our sample are reasonably close to the average county in the United States in terms of the percent white, Hispanic, under 18, or over 65. The average county population of our sample is greater than the average population in the whole U.S. This is unsurprising in that larger-population counties are more likely to have more parishes and thus more likely to be sampled. The last row of means weights by population, thus comparing the population for the average *individual* in each type of county. Here the differences are a bit closer, but again suggest that the average person in the parish-sample counties lives in a more populous county than does the average person overall.

We will also explore whether campaign effects vary by the political content in the bulletins themselves. First, we converted the pdf bulletins to text files using "pdftotext" which is a command line tool for Linux/Mac. Then, we searched each file for occurrences of highly political words, as given in Gentzkow and Shapiro (2010).¹² Aside from being well-known, Gentzkow and Shapiro's list has the benefit of being produced independently of the current project, lessening concerns that we selected words for study with an eye to procuring a particular result. Out of 150 phrases used more often by Democrats and 150 phrases used more often by Republicans as identified by Gentzkow and Shapiro, we identified 118 political phrases in our bulletins in the full sample, 51 democratic and 67 republican. In Appendix Table A.1, we give a list of the 10 most commonly observed democratic and republican phrases in our bulletins.

¹¹ Our dataset is an unbalanced panel dataset; not all weeks within a date range are necessarily reported for every parish.

¹² Gentzkow and Shapiro identify political words by examining the text of speeches given by congressional Republicans and Democrats, identifying words that are frequently used by one party's politicians but not the other.

Table 1Descriptive Statistics.

	Whole U.S.	Parishes with Usable Data	Parishes Observed in 2014 & Fall of 2015
Average % Population of Whites	82.88	79.68	78.24
	[16.85]	[15.01]	[15.51]
Average % Population of Hispanics	8.28	11.05	11.66
	[13.19]	[12.31]	[12.48]
Average % Population of Persons under 18 years	23.42	23.57	23.65
	[3.38]	[2.97]	[2.97]
Average % Population of Persons 65 years and over	15.88	13.93	13.76
	[4.19]	[3.76]	[3.55]
Average Population	98,233	422,526	473,013
	[312901]	[749225]	[813604]
Weighted Average Population	1,094,601	1,747,700	1,868,129
	[1891638]	[2334891]	[2402593]
Number of Counties	3143	396	324

The source for Table 1 is 2010 U.S. Census Summary File 1, a 100 percent sample of the whole population of the U.S., provided by the U.S. Census Bureau. Standard deviations are presented in brackets below the means. In our sample, we identified 396 unique counties where 712 parishes are located for the usable-data sample presented in Column 2 and 324 unique counties from 549 parishes for the main-period-of-study sample presented in Column 3. The White population here refers to a person who marked only the White category on the questionnaire. The Hispanic population refers to a person of Hispanic or Latino origins regardless of race. The averages are the (unweighted) average of each county's population except for the final row, which is weighted by county's population.

2.2. Campaign data

Our goal is to see how weekly collections reported in church bulletins change when a presidential candidate visits a community. Perhaps surprisingly, we know of no rigorous effort that tracked and collated the campaign stops of presidential candidates in the most recent election. Given this, we undertook our own collection effort.¹³

The campaign featured a large number of prospective Republican candidates and relatively few Democratic candidates. We focused on campaign stops made by any Republican candidate that polled in the top 5 of the republican field during the time period of September 1, 2015 to December 31, 2015. ¹⁴ On the Democratic side, only Hillary Clinton and Bernie Sanders were included as no other candidate drew significant polling numbers. In total, we use nine Republican and two Democratic candidates. ¹⁵ Here, the term "campaign stop" typically refers to public events held by one of these 11 candidates: speeches, town hall meetings, and meet and greet sessions. ¹⁶

As no single central repository of campaign stops exists, we instead used a wide variety of sources to assemble our data. First, some regional news sources reported all stops in a given area. The New England Cable News kept track of all campaign stops made in New Hampshire, the Des Moines Register kept track of stops in Iowa, and the Governing Under the Influence Website¹⁷ tracked all stops in both Iowa and New Hampshire. The South Carolina Republican Party Website tracked stops in South Carolina, and the Reno Gazette-Journal tracked campaign visits throughout Nevada. In a few instances we also consulted Google News to verify the locations of a particular stop on a particular day.

Next, for each candidate we also used information sources specific to that candidate's campaign to track events. Different campaigns reported their campaign stops in different ways, and in a few cases a particular form of social media was most helpful: YouTube (Trump), Instagram (Bush and Rubio), a campaign website (Clinton and Sanders), or Twitter (Christie, Paul and Fiorina). We also made candidate-specific searches in search engines and in some instances directly communicated with individuals working on campaigns to verify the details of a campaign stop. Our use of a variety of sources allowed us to cross check our efforts with the regional cites above to verify the comprehensiveness of each individual source.

Our resultant campaign database, which is reported in its entirety in Appendix Table A.2 contains 864 stops, covering 34 states and the District of Columbia. The first four states to hold primaries or caucuses, all of which took place in February 2016, saw the most visits from presidential candidates during the last four months of 2015. By far the most visited states were Iowa and New Hampshire, with 262 and 326 events, respectively. South Carolina (75) and Nevada (40) were the next most visited states. The places candidates visited most outside of this group were the District of Columbia (20) and Florida

¹³ We specifically thank our research assistant Eric Fein for his effort here.

¹⁴ This was determined using the site realclearpolitics.com. Real Clear Politics compiles polling data from 8 sources including CNN, USA Today, Suffolk, Pew Research and Quinnipiac.

¹⁵ The Republican candidates included are Jeb Bush, Ben Carson, Chris Christie, Ted Cruz, Carly Fiorina, John Kasich, Rand Paul, Marco Rubio, and Donald Trump.

¹⁶ Candidates also sometimes made stops at the homes of private citizens (for example, wealthy potential donors). We typically did not include visits to private homes unless these visits included events that were open to a large audience.

¹⁷ This is a non-partisan education project of the American Friends Service Committee (a Quaker Organization that promotes lasting peace with justice as a practical expression of faith in action).

(18). This raises the issue of how the effect of campaign stops can best be studied methodologically. We turn to that question next.

3. Methodology

To motivate our methodology, suppose that parish donations could be described as:

$$lngive_{pwc} = \alpha + \beta campaign_{wc} + \gamma X_c + \delta X_w + \rho_w + \phi_c + \theta_p + f(X_c, X_w, \mu_c, \rho_w) + \epsilon_{pwc}$$
(1)

where $\ln give_{pwc}$ is the log of total donations made to parish p in week w in community c. The variable $campaign_{wc}$ is a measure of campaign activity, such as the number of campaign stops made in community c in the prior week. The matrices X_c and X_w represent observable attributes of a community and week in the year that may be relevant for donations, such as population characteristics (in X_c) or an indicator for whether a certain week includes the observance of a holiday (in X_w), and the vectors γ and δ are coefficients. Beyond controlling for the linear effects of observables, there may be unobserved determinants of church activity across communities and at different times of the year, captured by the effects ρ_w and ϕ_c , as well as a fixed-effect and a time-varying residual for the parish, respectively denoted by θ_p and ϵ_{pwc} . The term $f(X_c, X_w, \mu_c, \rho_w)$ represents the possibility that community and week-of-the year characteristics, both observed and unobserved, could interact in complex ways. If it these interactions impact both religious donations and candidates' decisions to visit, then in a regression of donations on campaign activity and the observables X_c and X_w , the coefficient β would be biased. Note that because of the f term, even with a full set of fixed effects β could still be biased if f were not controlled for. But the functional form of f is unknown.

To address this concern, we take the 52-week difference of our data, so that outcomes in a given week one year are subtracted from the same week the next year. Letting Δ denote the 52-week difference, Eq. 1 then becomes:

$$\Delta lngive_{pwc} = \beta \Delta campaign_{wc} + \Delta \epsilon_{pwc}$$
 (2)

where all other terms are differenced out, so that we can estimate β in a way that allows for variation related to a given week, and to a given parish and community, and even to potentially complex interactions between these variables. Eq. 2 represents our baseline estimation model, although we consider several extensions. These include a non-differenced OLS estimation of 2, an estimation of 2 that allows for time trends, and non-differenced fixed-effect estimation.

While we take Eq. 2 as a strong starting point, we note several concerns that could persist in its estimation. First, some "intermediate" time effects could be longer than a week but shorter than a year in duration during the sample. For example, if a factory opens 6 months after our first observation, and a candidate arrives 6 months later to tout the factory's successful start, and the factory raises the incomes (and hence donations) of parish-goers, then the observed campaign effect could be driven in part by the factory. For our analysis, we can further exploit the week-by-week variation in our data to see if campaign stops especially matter in the weeks closest to the stop. Enduring anticipatory increases in donations before a stop, or enduring increases after a stop, could raise the concern that our estimates are driven by intermediate dynamic effects. (Although such results could also fit certain depictions of how campaigns could impact religious behavior.) If our effects are strongest immediately before or after a campaign stop, however, it is evidence against this sort of effect.

A related concern is that there is an unobserved transitory effect on a certain week that drives donations and campaigns. For example, perhaps a state fair is held in a given week, and this both increases donations in a parish and increases the likelihood of a candidate arriving. Since such events are, by assumption, never observed to the econometrician, we cannot nor could we ever entirely rule out the possibility of their occurrence. In response to this, we first note that a result of our analysis below is that the effects of campaigns are short-lived, and this story would likely only strengthen this conclusion. Additionally, several factors give us confidence that our results are not driven by this "state-fair" type of story. First, our qualitative observation from constructing our campaign data is that most campaign stops are not timed to coincide with other standalone events. One could instead wonder whether the candidates we observe driving our estimates ran their campaigns differently than other candidates. We further note that we find similar estimates for candidates (in particular, for Hillary Clinton and Donald Trump) whose entire campaign strategies appear to have been extraordinarily different (e.g., Bloomberg News, 2016; Sheridan (2016)). Taken together, the immediate and dynamic effects of campaign stops, the pattern of results observed across candidates and campaigns, and the qualitative nature of most campaign stops work in combination to support the robustness of our results.

To estimate Eq. 2, we need to combine our two datasets. In so doing, we define campaign stops as close by if they occur within 25 miles of a given parish. The pattern of results presented in our baseline estimates is not sensitive to this choice, though using shorter distances does lead to larger point estimates.

 $^{^{18}}$ These interactions could further depend on parish characteristics ϕ in our methodology; this is omitted from the function f in 1 for brevity.

¹⁹ Related to this point is the issue that campaign stops could affect donations "mechanically" if they are held on Sundays (although plausibly this would work against the positive effect we find), as Sunday is a key day for worship (and making donations) for many churchgoers. In fact, almost none of the campaign stops happen on Sundays. Below we show results varying the temporal "distance" of the campaign stop to worship.

²⁰ We also attempted in a limited away to quantify this qualitative impression. Two of our campaign-stop sources, the Des Moines Register and the New England Cable News, provided brief descriptions of the nature of each campaign stop. While only for two states, these two sources include a large number of stops (over 500) and so we used their descriptions to identify stops that appeared to be held as part of a larger event (e.g., a parade). The vast majority of events–over 80 percent–were *not* described as related to any other event.

Table 2Baseline effects of campaigns.

	Baseline (1)	Time Trend (2)	Campaign Dummy (3)	Levels Collections (4)	OLS (5)	All Years (6)
Campaign Stops	0.0204	0.0199	0.0845	126	-0.078	0.0213
	[0.00291]	[0.00313]	[0.0425]	[32]	[0.0148]	[0.00325]
Observations	2375	2375	2375	2375	2375	3229
Differenced Data?	Yes	Yes	Yes	Yes	No	Yes
Trend Coefficient	No	Yes	No	No	No	Yes
Dependent Variable	Logs	Logs	Logs	Levels	Logs	Logs
Key Regressor?	Count of	Count of	Campaign Stops	Count of	Count of	Count of
-	Campaign Stops	Campaign Stops	Dummy	Campaign Stops	Campaign Stops	Campaign Stops
All Years?	No	No	No	No	No	Yes

The table shows regressions of weekly church collections, logged, on a count variable for the number of nearby political campaigns in the prior week. Standard errors, clustered by city, are in brackets. The mean of the dependent variable is 10,764 and the mean number of campaign stops is 0.14 and in a week with a campaign stop the mean number is about 2.5.

In combining our two datasets and employing the specification in Eq. 2, our estimates will necessarily be driven by parishes with bulletins available 52 weeks apart that see a campaign stop. Further, since our campaign data covers September through December of 2015, but not the earlier months of 2015, we omit observations from the earlier months of 2015 as we do not have campaign information. The resulting sample consists of 2375 bulletins, from 237 parishes. The distribution of parishes in this sample is close to our larger sample–in Fig. A.1, we replicate the map from Fig. 2 using just these 237 parishes; the two figures are similar. We also can use a larger sample by checking our results in non-52-week differenced data and we do so below.

The total number of campaign stops in the baseline sample is 349. There are 60 parishes in this sample that see at least one campaign stop, and a total of 142 parish/weeks in the data where at least one campaign stop occurs. In weeks in which a campaign stop occurs, the median number of nearby stops is 1, and the mean is about 2.45. The stops are reasonably widespread, covering 20 states, including several events in states not typically regarded as "critical" primary battlegrounds.²¹ We also observe a number of stops for almost all of our different candidates.²² In the next section we discuss how these stops affect reported donations.

4. Results

Table 2 presents our baseline estimates. The dependent variable in the initial columns is logged donations, the unit of observation is a parish bulletin (ie, a parish/week), the specification is given by Eq. 2, and robust standard errors, clustered by city, are reported in brackets. The sample includes all parish data from 2014 and from September through December of 2015. The key dependent variable is the number of nearby campaign stops in the week prior to the Sunday when donations were made.

The coefficient suggests that, for each presidential campaign stop, donations increase by about 2 percent. The mean collection amount in the sample is 10,764 so the implied effect is a little over \$200. As mentioned above, in weeks where a stop occurs the mean number of stops is about 2.5, so in the average campaign-stop week a parish's donations increase by about 5 percent or \$500, a moderate but non-trivial effect. As mentioned before, this effect reflects both changes in the number of attenders and per-attender donation generosity.²³

The next column allows for a time trend by adding back the α constant to Eq. 2; the results are essentially the same as before (we report more aggressive trend control results momentarily). Column 3 simply uses a dummy variable for whether any campaign stop occurred, rather than the number of stops, as the key regressor. The coefficient is slightly larger in its implied effect. In Column 4, the dependent variable is now donations in levels, rather than logs; the result is slightly smaller but nonetheless qualitatively similar to the baseline estimate, suggesting that each campaign stop raises donations by about \$130.

In column 5, we report OLS results using non-differenced data. This regression returns to using total campaign stops and using logged donations (although the results are similar with levels donations). The estimates now are negative and

as a "treatment on the treated" style effect. In this analysis the unit of observation is best understood as a parish, rather than an individual.

²¹ The likelihood we observe a stop depends upon the likelihood of a stop as well as the likelihood that we observe a parish in a community. States with observed stops include Arizona (1 stop), California (6), Connecticut (1), Florida (1), Georgia (3), Iowa (9), Illinois (19), Indiana (1), Massachusetts (19), Maryland (22), New Hampshire (155), New Jersey (23), New York (43), Ohio (2), Pennsylvania (3), South Carolina (12), Tennessee (2), Texas (6), Virginia (15), and Wisconsin (6). We discuss below the sensitivity of our results to dropping different states; our results are not driven by any one state.

²² An exception is Ben Carson; we only observe 4 stops by Carson in our matched data. We observe 38 for Trump, 25 for Bush, 18 for Rubio, 11 for Cruz, 100 for Clinton, 54 for Sanders, 24 for Christie, 11 for Paul, 37 for Kasich, and 27 for Fiorina. Again, we discuss effects for different candidates more below.

²³ We also of course lack information on the number of worshippers involved in any way with a campaign stop, so that we cannot interpret this result

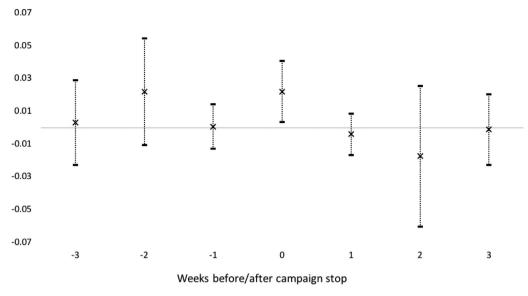


Fig. 3. Effects before and after campaign stops. The figure shows the coefficients and 95% confidence intervals for the regression in column 6 of Table 5.

Table 3 Alternate specifications.

Panel A: Dropping	g Iowa and New Han	npshire		
	From Table 2 (1)	No New Hampshire (2)	No Iowa (3)	No New Hampshire & No Iowa (4)
Campaign Stops	0.0204 [0.00291]	0.0283 [0.0158]	0.0205 [0.00297]	0.0294 [0.0167]
Observations	2375	2323	2368	2316
Panel B: Alternat	e Controls			
	Month Dummies	Month & State Dummies	City & Year Dummies	Month, City & Year Dummies
	(1)	(2)	(3)	(4)
Campaign Stops	0.0176	0.02	0.0201	0.0173
	[0.00301]	[0.00359]	[0.0115]	[0.0113]
Observations	3229	3229	3229	3229
Panel C: Alternat	e Controls on Undif	ferenced Data		
	Month Dummies	Month & State Dummies	City & Year Dummies	Month, City & Year Dummies
	(1)	(2)	(3)	(4)
Campaign Stops	-0.0366 [0.0194]	0.0543 [0.0103]	0.016 [0.0078]	0.015 [0.0076]
Observations	13036	13036	13036	13036

The tables shows regressions of weekly church collections on a count variable for the number of nearby political campaigns in the prior week. Standard errors, clustered by city, are in brackets. The first panel shows results from the baseline regression in Table 2, dropping lowa and/or New Hampshire. In panel B, month, state, and year dummies are added (as the data is 52-week differenced, these variables have a different interpretation than in levels data). In the final panel these specifications are repeated for data that is not differenced.

significant. This indicates that campaign stops are more likely to occur near parishes with below-average donation amounts, but that this is driven by fixed differences in parish donations over time. Returning to the specification used in column 2, in the final column we redo the estimate in column 2 but now include all available years of data before 2014. (Redoing this estimate on the baseline specification yields the same result.) Observations observed in 2013 are differenced off of 2012 bulletins, so that these new observations are taken from bulletins available online several years after they were produced. There are relatively few such observations (854, raising the total sample size to 3,229) and they may come from a non-random subsample of our parishes. However, including these years does not alter our estimates.

Table 2 thus suggests that campaign stops lead to higher donations at worship the following week. Table 3 produces a number of different robustness tests for these results. In the first panel we redo the baseline estimate but show that the

Table 4 Alternate durations for campaigns.

	2015-2014 (1)	2015-2014, with Trend (2)	All Years, with Trend (3)
Campaign Stops	0.0204	0.0199	0.0213
	[0.00291]	[0.00313]	[0.00325]
Campaign Stops-past 5 days	0.0231	0.0225	0.0241
	[0.00319]	[0.00335]	[0.00346]
Campaign Stops-Past 10 days	0.0168	0.0166	0.0175
	[0.00182]	[0.00204]	[0.00213]
Campaign Stops-past 15 days	0.0143	0.0141	0.0149
	[0.00122]	[0.00148]	[0.00151]
Observations	2375	2375	3229

The table shows regressions of weekly church collections on different count variables for the number of nearby political campaigns in the prior week. Standard errors, clustered by city, are in brackets. Each coefficient is from a separate regression. Row 1 reports the baseline results using total campaign stops in the prior week.

Table 5Before and after campaign stops.

	(1)	(2)	(3)	(4)	(5)	(6)
3 Weeks Before	-	-	-	-	-0.0228	0.00298
					[0.0705]	[0.0132]
2 Weeks Before	-	-	-0.0489	0.0168	-0.0489	0.022
			[0.0895]	[0.0130]	[0.0896]	[0.0166]
1 Week Before	0.0329	0.00919	0.0329	0.00172	0.032	0.000596
	[0.0437]	[0.00361]	[0.0437]	[0.00729]	[0.0505]	[0.00694]
Campaign Stops	0.024	0.0121	0.0204	0.0165	0.0238	0.022
	[0.00338]	[0.00717]	[0.00373]	[0.00676]	[0.00376]	[0.00953]
1 Week After	-0.0138	0.00767	-0.0238	-0.00525	-0.0228	-0.00406
	[0.0431]	[0.00618]	[0.0441]	[0.00650]	[0.0441]	[0.00644]
2 Weeks After	-	-	-0.0201	-0.00804	-0.0926	-0.0175
			[0.103]	[0.0146]	[0.0833]	[0.0219]
3 Weeks After	-	-	-	-	-0.0288	-0.00117
					[0.0641]	[0.0110]
Identify with in-between weeks?	No	Yes	No	Yes	No	Yes
Observations	2,226	2,226	2,093	2,093	1,932	1,932

Regressions are on the difference of logged collection revenue, and include a constant. The first column reports a coefficient for a one-week lead on campaign stops prior to the first observed stop, and a coefficient lagged to one week after the last observed stop. Column 2 redoes this regression but the lead and lag variables are based on all weeks and all campaign stops, e.g., the "one week before" coefficient is the one-week lead of campaign stops. The difference in the columns will be driven by the use of "in between" observations for identifying the coefficients. Columns 3 and 4 use two leads/lags, and columns 5 and 6 use three leads/lags. When using (e.g.) 2 lags and leads, we drop the last 2 weeks of the sample and the first 2 weeks of the sample, as we do not have recorded campaign data for those weeks outside the sample.

Table 6Effects by political words in bulletins and political party of candidate.

	All Bulletins (1)	Democratic Bulletin (2)	Republican Bulletin (3)	All Bulletins (4)	Democratic Bulletin (5)	Republican Bulletin (6)
Campaign Stops	0.0204 [0.00291]	-0.0315 [0.0849]	0.0154 [0.0102]	-	-	-
Democratic Stops	-	-	-	0.0326 [0.0189]	0.00136 [0.141]	0.0168 [0.0189]
Republican Stops	-	-	-	0.0168 [0.00286]	-0.069 [0.0585]	0.0125 [0.0157]
Observations	2,375	180	581	2,375	180	581

In columns 1, 2, and 3, each coefficient is from a different regression where logged donations is th dependent variable. In each column, the sample changes based on whether all bulletins are used (column 1), from parishes that use democratic words but never use republican words (2), or ever use republican but never democratic (3). In the last three columns the regressions are repeated but now the coefficient on campaign stops is broken apart by whether stops were made by a democratic candidate or republican candidate.

Table 7Results by candidate.

	Trump	Clinton	Christie	Rubio	Bush
Campaign Stops	0.0329	0.05	0.16	0.122	0.0815
	[0.0420]	[0.0305]	[0.00674]	[0.0750]	[0.00833]
	Cruz	Sanders	Kasich	Paul	Fiorina
Campaign Stops	0.0319	0.0618	0.0544	0.00857	0.0394
	[0.0385]	[0.0265]	[0.00607]	[0.0443]	[0.00654]

The table shows the effects of campaign stops on parish collections by specific candidate. Each cell is from a separate regression, on 2375 observations. Results are differenced as in other tables and standard errors are in brackets. The top panel includes the two eventual nominees, Trump (a Presbyterian), Clinton (Methodist), the three Catholic candidates. The bottom panel includes other non-Catholic and non-nominee candidates.

results are robust to dropping lowa and New Hampshire, the two states whose primaries receive outsize political attention and who get a high number of campaign stops. As shown in the table, our results are similar, and in fact slightly larger, if we drop these estimates. (The increase in the coefficient would be consistent, e.g., with a "campaign fatigue" scenario for these states where the large volume of campaigns diminishes the impact of the marginal campaign on donations.) In Appendix Fig. A.2 we present a histogram where we drop each state in our sample in turn; we find that our results are not driven by any one state with nearly all estimates staying quite close to our baseline 0.02 coefficient.

In Panel B of Table 3, we include a variety of fixed-effect controls. (As our data is differenced these controls have a different interpretation than with non-differenced data; here a fixed effect captures a fixed rate of difference, akin to a trend estimate in a regression on non-differenced data). The results use all years of data to help in identifying the fixed effects separately.²⁴ Even when including aggressive city, year, and month dummies, our result is qualitatively close to before. (Note city and year controls would subsume the state and year controls in column 2, and that the month effects are identified separately from year effects since we have multiple years.)

In the last panel, we redo the specifications in panel B but now we report estimates from non-differenced data. The first column shows a negative coefficient, which is unsurprising given the OLS estimate shown in Table 2 earlier. Once a geographic fixed effect is included, even a state fixed effect as in column 2, the coefficient becomes positive. The similarity of column 1 to the earlier OLS, the change from column 1 to column 2, and the slightly smaller effects in columns 3 and 4, indicate that (a) campaign stops happen in places with naturally lower donations, that (b) the fixed component driving this lower donation amount is geographical rather than temporal (else column 1 here would not be negative), and that (c) this geographic variation is primarily across states, rather than within states (else the final columns would be larger in size than column 2).²⁵ The table also shows that our results are similar when using a specification with a much larger sample than our main specification allows.²⁶ Overall, the main takeaway from Table 3 is that the positive effect documented in the baseline is robust to a number of different samples and specifications.

All of these results have used campaign stops in the prior week as the key regressor. While a week is a natural timespan to consider, Table 4 presents results using alternate measures of time. The first row for comparison's sake presents results using the prior week. Row 2 uses stops from the past 5 days, row 3 uses 10, and row 4, 15. The first column uses the standard sample, column 2 includes a trend control, and column 3 uses all years. In all cases, the table shows a clear pattern: the strongest results are observed from stops in the past 5 days, and the results grow steadily weaker as stops from further back in time are added. This suggests that the effects of campaign stops diminish over time.

Table 5 develops the possibility of dynamic effects of campaign stops further, including lag and lead coefficients to capture effects pre-stop and post-stop. For many observations, stops may occur several weeks in a row; raising a conceptual question of how to handle, e.g., a bulletin observed two weeks before a stop and two weeks after an earlier stop. The first column reports a coefficient for a one-week lead on campaign stops prior to the first observed stop, and a coefficient lagged one week after the last observed stop. Column 2 redoes this regression but the lead and lag variables are based on all weeks and all campaign stops. That is, the regression in column 2 is:

$$\Delta \ln give_{pwc} = \alpha_1 F(\Delta campaign_{wc}) + \beta \Delta campaign_{wc} + b_1 L(\Delta campaign_{wc}) + \Delta \epsilon_{pwc}$$
(3)

where terms are defined as in Eq. (2) and the functions F() and L() represent one-week lead and lag operators, respectively. In Table 5, the "one week before" coefficient corresponds to the coefficient for the one-week lead of differenced campaign stops, α_1 . Column 1 uses Eq. (3) except that F() is set to zero for all weeks except the week prior to the first observed campaign stop, and L() is set to zero for all weeks except the week following the last observed stop. The difference in the

²⁴ Results using the baseline sample are qualitatively similar, although smaller and less precise in columns 3 and 4.

²⁵ The smaller coefficients in the last two columns suggest that while states are *negatively* selected for campaigns, communities within states are *positively* selected, else city effects would make the coefficients larger still. Clearly, the negative-across-state effect dominates, so that when both effects are controlled for the coefficient remains positive, unlike the OLS result.

²⁶ We cannot expand the main sample, but we can limit this larger sample; limiting to the same period or even the exact same bulletins as the main result produces qualitatively similar estimates.

columns will be driven by the use of "in between" observations for identifying the coefficients. Columns 3 and 4 use two leads/lags, and columns 5 and 6 use three leads/lags.

The story told across the columns is similar: we consistently see a significant and positive effect from "contemporaneous" campaign stops, where the "contemporaneous" week refers to stops in the 7 days before a collection is taken (as defined in the earlier tables). There are almost no statistically significant effects observed either before or after the week of a campaign stop, and indeed several of lag/lead coefficients are negative.²⁷ The results from the final column in Table 5 are illustrated in Fig. 3, where for the weeks leading up to and following a campaign stop each coefficient and 95% confidence interval is depicted. Overall, the results in Table 5 and Fig. 3 fail to provide any evidence that campaign effects endure over time, and instead suggest that our observed effects are short lived. This contrasts with the Tea-Party effects observed in Madestam et al. (2013), who document strongly persistent effects over time. We discuss this more in the conclusions.

One might wonder whether the political leanings of a congregation, or of a candidate, matter for these effects. We begin our investigation of this in Table 6. The three columns of Table 6 shows results by the inferred political leaning of the parish, which we base, as described earlier, on whether a parish (a) uses a democratic word *and* never uses a republican word ("democratic" parishes, for short) or ever uses a republican word and never uses a democratic work ("republican" parishes).²⁸ Overall, the first three columns show little evidence that the appearance of politically-loaded language in a bulletin is related to how donations respond to campaign stops.

The last three columns redo this analysis but break apart campaign stops by the political party of the candidate. Column 4 uses all stops; the coefficient is somewhat bigger for democratic candidates but not significantly so. Turning to the last two columns, we again fail to find any clear or compelling pattern for how political language in bulletins corresponds to the effects of campaign stops. It is perhaps noteworthy that the republican parishes have a positive coefficient for republican stops while democratic parishes have a negative coefficient, but none of these coefficients is significant and we take this observation as suggestive at best. These results do not rule out heterogeneity in responses to campaigns that is based on other types of politically motivated language; church leaders and legislators could simply use different politically motivated words when discussing political issues. But the results here find little evidence of variation based on the well-known list of words produced by Gentzkow and Shaprio.

Further, it is possible that within political party some candidates have different effects than others. Table 7 investigates this by reporting regressions (including a time trend, as in column 2 of Table 2) where campaign stops are specific to a particular candidate. As mentioned earlier, we observe several campaign stops for most candidates, allowing this comparison across many politicians.²⁹ The top panel in Table 7 begins with the eventual nominees, Trump and Clinton. Although these candidates were markedly different in their policy positions, demeanor, campaign strategies, and the details of many of their campaign stops, both produce similar (and statistically insignificant) coefficients. The next three candidates in the top panel (Christie, Rubio, Bush) report the largest coefficients of all candidates, and in all three cases they are at least marginally significant. Do these three candidates have anything in common? Yes-they are all Catholic, and they are the only Catholic candidates. Overall, the differences in candidates across the table are statistically significant: a joint test that the coefficients are equal in Table 7 is strongly rejected (p < 0.001).30 One could also regress donations on all stops by Table 7 candidates and add a variable for stops made by Catholic candidates and a variable for stops made by the eventual nominees; the coefficients on these latter two variables would indicate the differential effect between these groups of candidates. This regression yields a main coefficient of -0.02 (se = 0.02), a nominee coefficient of 0.049 (0.030) and a Catholic coefficient of 0.101 (0.056), so that the coefficients indicate that stops by Catholic candidates generate the largest increases in donations and that the difference between Catholics and other candidates is significant (p = 0.073). However, a Wald test that the Catholic-stops coefficient and the nominee-stops coefficient are equal cannot be rejected.³¹ We thus take the relatively large coefficients for Catholic candidates in Table 7 as suggestive.

Overall the results of Tables 2, 3, 4, 5, 6, and 7 show that a campaign stop leads to an immediate, moderately-sized, and short-lived increase in church donations the following week. Political words in bulletins do not appear to strongly predict responses to campaign stops (although this result is tempered by our smaller sample sizes), but we find suggestive evidence

²⁷ Unsurprisingly, given the results in this table, if one were to redo the main estimates using *weekly* differenced data, those results are typically close to zero and statistically insignificant. Of course, our main specification avoids any confounding factors of dynamic effects and controls for seasonality as discussed earlier.

²⁸ We also considered results using alternate definitions of Democratic and Republican bulletins, such as whether a parish *ever* uses a democratic word or ever uses a republican word. This could make sense as parishes might use language or undertake arguments meant to persuade or otherwise appeal to voters of both parties. Those results are also statistically insignificant.

²⁹ Since Carson was only observed four times, we omit him from the table. The coefficient on Carson's stops is 0.248 [se = 0.005].

³⁰ Since each coefficient is from its own regression, we performed this test via Seemingly Unrelated Regression to allow for nonzero covariances between the estimates

 $^{^{31}}$ We performed other tests (such as combining all non-Catholic candidates together, rather than splitting out nominees and others), and while these tests often indicated a continued significant difference between Catholics and other candidates, we found that in some specifications the significance of the difference between Catholic and non-Catholic candidates could be sensitive to the distance used for defining whether campaign stops were near a parish. As with the baseline estimates, smaller distances generated stronger results, but using larger distances often produced tests that could not reject the null of no difference between Catholic and non-Catholic candidates. Using the baseline specification, one cannot reject that Catholic candidates have the same effect as all non-Catholic candidates (p = 0.284).

that our results are the largest for Catholic candidates. We take these results are notable for both future scholarship and policy; we turn to implications in the conclusion.

5. Conclusion

Combining a new dataset of parish donation activity with a new dataset on presidential-election campaign stops for the fall of 2015, this paper explores the impact of stops on church donations. We find that stops increase donations, with each campaign stop leading to 2 percent more donations in the following week. Our results suggest that this effect is of short duration. Using a well-known list of politically-motivated words we find that our effect does not appear to vary based on the political language used by the parish.

As mentioned above, our results have several implications. First, they highlight the need for further discussion of the dynamic effects of political activity. The dynamic effects identified here appear different than the strongly persistent effects identified for Tea Party rallies in Madestam, Shoag, Veuger, and Yanagizawa-Drott's work. However, the rally they study was intended to foster a long-term political movement, while the effect we identify is incidental to the campaign stop, so that the results are potentially harmonious. Our results do raise the possibility, however, that commonly-used outcomes such as post-election surveys of self-reported trust in the government may quickly dissipate. Scholars investigating the effects of campaigns in the future should take care to consider dynamic effects. Work could also study the dynamics of how campaign stops raise *campaign* donations, but we do not know of a high-frequency, highly-localized datasource on donations that could be used to match campaign donations to the campaign-stops data we have collected here.

Next, our work suggests that the response of religious donations to campaign stops varies across candidates, so that the impacts of policy changes to allow political activity within churches could depend upon what type of candidates campaign and potentially what type of congregations are nearby. However, without data on non-Catholic congregations, we cannot explore this idea fully. But our results do highlight the possibility that, with increasingly sophisticated campaigns and the policy-driven potential for greater campaign activities within churches, candidates in the future might more closely organize their campaign activity in conjunction with religious observance. Whether religious endorsements would matter for candidates is unclear although prior work (e.g., Garthwaite and Moore (2012)) has explored the potential importance of non-political endorsements of candidates.

Next, our results document the importance of social context in affecting giving, but differs from most prior work in this area. Rather than studying how consumers avoid solicitations to give, we study how one social event affects a donation made days later (but not weeks later). Our results suggest that further research is needed to understand the various ways that social contexts can influence giving. Future work could also refine the donative activities considered. Our results here cannot distinguish increased donations from greater attendance versus greater donative generosity of churchgoers. Moreover, while donations are obviously a critical aspect of religious life, one might wonder whether campaigns affect other, more qualitative measures of religiosity. This topic, as well as the above implications, represent excellent areas for future work.

Appendix A

Table A1Political phrases used most often in bulletins.

Rank	Democratic Words	Frequency	Republican Words	Frequency
1	senior citizens	1150	boy scouts	1600
2	credit card	696	human life	1515
3	african american	296	ten commandments	236
4	low income	243	post office	215
5	poor people	140	third time	108
6	civil rights	107	stem cell	95
7	living in poverty	57	natural gas	78
8	million americans	36	embryonic stem	75
9	child labor	33	immigration reform	72
10	minimum wage	32	food program	68

Table A2Campaign Stops by Candidate, Date, and Location.

Date	Trump	Trump2	Bush	Bush2	Bush3	Rubio	Rubio2	Rubio3	Date
9/1/15 9/2/15	Norwood, NH					Carson City, NV Oklahoma City,	Fallon, NV	Yerrington, NV	9/1/15 9/2/15
						OK			
)/3/15			Hampton, NH	Laconia, NH		Chattenooga, TN			9/3/15
)/4/15									9/4/15
)/5/15						San Juan, Puerto Rico			9/5/15
0/6/15									9/6/15
)/7/15						Charleston, SC	Milford, NH		9/7/15
)/8/15	Washington DC					Hooksett, NH	Keene, NH		9/8/15
/9/15	Washington, DC		Exeter. NH	Calama NIII					9/9/15
/10/15			Manohester, NH	Salem, NH Londonderry, NH		Ankeny, IA			9/10/1
)/11/15)/12/15	Boone, IA		Manonester, Nn	Londonderry, Nn		Iowa City, IA	Ames, IA		9/11/1 9/12/1
/12/13	bootie, iA					iowa City, iA	Allies, IA		9/12/1
)/14/15	Dallas, TX								9/14/1
)/15/15	Dallas, 17								9/15/1
)/16/15	Simi Valley, CA					Simi Valley, CA			9/16/1
11	(Debate)					(Debate)			-//
9/17/15	Rochester, NH					(=====)			9/17/15
9/18/15	,					Mackinac Island,			9/18/15
, .,						MI			-, -,
9/19/15	Des Moines, IA		Athens, GA			Mackinac Island, MI			9/19/15
9/20/15									9/20/15
9/21/15			Mason City, IA			Atlanta, GA			9/21/1
9/22/15			Cedar Falls, IA	Cedar Rapids, IA					9/22/1
9/23/15	Columbia, SC		Gladbrook, IA						9/23/1
9/24/15									9/24/1
)/25/15	Oklahoma City, OK	Washington, DC				Washington DC			9/25/1
)/26/15									9/26/1
/27/15									9/27/1
)/28/15	New York, NY					The Villages, FL			9/28/1
9/29/15			Portsmouth, NH						9/29/1
9/30/15	Keene, NH		Manchester, NH	Bedford, NH					9/30/1
10/1/15						Cedar Falls, IA			10/1/1
10/2/15			Greenville, SC			Dubuque, IA			10/2/1
10/3/15	Franklin, TN								10/3/1
10/4/15						Dubuque, IA			10/4/1
10/5/15									10/5/15
10/6/15			Davenport, IA			Bedford, NH	Manchester, NH		10/6/1
10/7/15	Waterloo, IA		Oskaloosa, IA			Wolfeboro, NH	Dover, NH		10/7/15
10/8/15			Indianola, IA			Las Vegas, NV	Summerlin, NV		10/8/15
10/9/15	Namana CA		Vecusille TN			Las Vegas, NV	Enterprise, NV		10/9/15
10/10/15	Norcross, GA		Knoxville, TN			North Las Vegas, NV	Boulder City, NV		10/10/
	Knoxville, TN								10/11/
	Manchester, NH								10/12/
0/13/15			Manchester, NH	Keene, NH					10/13/
	Richmond, VA		Concord, NH	Lebanon, NH		Derry, NH	Porsmouth, NH		10/14/
10/15/15 10/16/15	Tyngsborough,		Concord, NH			Philedelphia, PA Salem, OH	Pittsburg, PA		10/15/1 10/16/1
	MA								
10/17/15			Portsmouth, NH			Portsmouth, NH			10/17/1
10/18/15									10/18/1
	Anderson, SC					Called A City			10/19/
10/20/15			Dama NU	North Let Ver		Salt Lake City, UT			10/20/
10/21/15	Burlington, IA		Reno, NV	North Las Vegas, NV					10/21/
10/22/15	Minusi F		Manus Pl						10/22/
υ/23/15	Miami, FL		Mount Pleasant, SC						10/23/
0/24/15	Jackson, FL		- -						10/24/
0/25/15	y								10/25/
	Atkinson, NH								10/26/
	Sioux City, IA		El Dorado						10/27/
	J.		Springs, CO						
0/28/15	Boulder, CO		Boulder, CO			Boulder, CO			10/28/
, ., -	(Debate)		(Debate)			(Debate)			-, -,
10/29/15	Reno, NV		New London, NH	Portsmouth, NH		•			10/29/
10/23/13									

Table A2 (continued)

Date	Trump	Trump2	Bush	Bush2	Bush3	Rubio	Rubio2	Rubio3 I	Date
10/30/15			Portsmouth, NH			Orange City, IA	Sioux City, IA		10/30/15
10/31/15	Norfolk, VA		Des Moines, IA			Des Moines, IA	Mason City, IA		10/31/15
11/1/15			Wolfboro, NH						11/1/15
11/2/15			Orlando, FL						11/2/15
11/3/15	New York, NY		Rye, NH	Raymond, NH					11/3/15
11/4/15	Concord, NH		Manchester, NH	Hollis, NH	Wolfeboro, NH	Nashua, NH	Manchester, NH		11/4/15
11/5/15			North Conway, NH	Somersworth, NH		Concord, NH			11/5/15
11/6/15									11/6/15
11/7/15									11/7/15
11/8/15									11/8/15
11/9/15	Springfleild, IL					Burlington, WI			11/9/15
11/10/15	Milwaukee, WI (Debate)					Milwaukee, WI (Debate)			11/10/15
11/11/15	Manchester, NH		Johnston, IA	Atlantic, IA	Waukee, IA	Davenport, IA			11/11/15
11/12/15	Fort Dodge, IA		Tuftonboro, NH			Columbia, SC			11/12/15
	Orlando, FL		Franklin, NH	Orlando, FL		Orlando, FL			11/13/15
11/14/15	Beaumont, TX								11/14/15
11/15/15									11/15/15
	Knoxville, TN								11/16/15
11/17/15			Florence, SC	Charleston, SC					11/17/15
11/18/15			Bedford, NH						11/18/15
	Newton, IA		Manchester, NH	Londonderry, NH					11/19/15
	Spartanburg, SC					Des Moines, IA			11/20/15
	Birmingham, AL					Des Moines, IA			11/21/15
11/22/15									11/22/15
	Columbus, OH								11/23/15
	Myrtle Beach, SC		Gaffney, SC			Charleston CC			11/24/15
11/25/15						Charleston, SC			11/25/15
11/26/15									11/26/15
11/27/15	Camanata FI		Charlerilla MC						11/27/15
	Sarasota, FL		Starkville, MS						11/28/15
11/29/15	Massa CA		Casas Islas IA			Laconia. NH	Date NIII		11/29/15
	Macon, GA Waterville Valley, NH		Goose Lake, IA Waterloo, IA			Guntersville, AL	Rye, NH		11/30/15 12/1/15
12/2/15	Manassas, VA		Goose Lake, IA						12/2/15
12/2/15	New York, NY		Waterloo, IA	Newton, IA					12/2/15
12/4/15	Raleigh, NC		Dubuque, IA	recvetori, in		Greenland, NH	Concord, NH		12/4/15
12/5/15	Davenport, IA	Spencer, IA	Dubuque, IA			Greemand, Wi	Concord, IVII		12/5/15
12/6/15	Darenport, II.	openeer,							12/6/15
12/7/15	Mount Pleasant,								12/7/15
12/0/15	SC		Hooksett, NH	Manchester NU					12/0/15
12/8/15 12/9/15				Manchester, NH					12/8/15 12/9/15
	Portsmouth, NH		Manchester, NH Milford, NH			Ames, IA	West Des Moines		12/9/13
							IA		
	Des Moines, IA		_			Iowa City, IA			12/11/15
	Aiken, SC		Derry, NH			Greenville, SC			12/12/15
12/13/15									12/13/15
	Las Vegas, NV					Green Valley, NV			12/14/15
12/15/15	M 47					A I	Manual No.		12/15/15
	Mesa, AZ					Ankeny, IA	Manchester, NH		12/16/15
12/17/15						Knoxville, IA	Muscatine, IA		12/17/15
12/18/15	Codar Danida 74		Evotor NIII	Contoneed NII	Windham NII	Dubuque, IA	Andorson CC		12/18/15
	Cedar Rapids, IA		Exeter, NH	Contoocook, NH	Windham, NH	Spartanburg, SC	Anderson, SC		12/19/15
12/20/15	Crand Danida Mi		Nashua, NH			Partlett NIII	Dochaster NIII		12/20/15
12/21/15	Grand Rapids, MI		Alton, NH Conway, MA	Berlin, NH	Littleton, NH	Bartlett, NH Berlin, NH	Rochester, NH North Conway,		12/21/15 12/22/15
10/00/11						Tinden	NH		10/00/4-
12/23/15						Littleton, NH	Franklin, NH		12/23/15
12/24/15									12/24/15
12/25/15									12/25/15
12/26/15									12/26/15
12/27/15	Nachua NIII		Ocala El						12/27/15
12/28/15	Nashua, NH		Ocala, FL			Clinton IA	Waterles IA		12/28/15
12/20/15	Council Bluffs, IA					Clinton, IA	Waterloo, IA		12/29/15
	Hilton Haad CC		Lavington CC						
12/30/15	Hilton Head, SC		Lexington, SC			Newton, IA			12/30/15
		2000000000000	Lexington, SC			Newton, IA			12/30/15

Table A2 (continued)

0/1/15 0/2/15 0/2/15 0/2/15 0/3/15 0/3/15 0/4/15 0/6/15 0/6/15 0/7/15 0/8/15 0/9/15 0/10/15 0/11/15 0/13/15 0/13/15 0/16/15 0/17/15	Seabrook, NH Houston, TX Fort Worth, TX Grayson, KY Washington, DC Simi Valley, CA Des Moines, IA Urbandale, IA	Concord, NH Tyler, TX	San Juan, Puerto Rico Portsmouth, NH Newton, IA Cedar Rapids, IA Washington, DC Columbus, OH Washington, DC Decorah, IA Staten Island, NY Nashua, NH	Milwaukee, WI			9/1/15 9/2/15 9/2/15 9/3/15 9/4/15 9/5/15 9/6/15 9/8/15 9/8/15 9/10/15 9/10/15 9/11/15 9/12/15 9/13/15 9/14/15
)/3/15)/4/15)/5/15)/5/15)/5/15)/5/15)/7/15)/8/15)/10/15)/11/15)/13/15)/14/15)/15/15)/15/15)/18/15)/18/15)/19/15)/19/15)/20/15)/22/15	Fort Worth, TX Grayson, KY Washington, DC Simi Valley, CA Des Moines, IA	Tyler, TX	Rico Portsmouth, NH Newton, IA Cedar Rapids, IA Washington, DC Columbus, OH Washington, DC Decorah, IA Staten Island, NY Nashua, NH	Milwaukee, Wl			9/3/15 9/4/15 9/5/15 9/6/15 9/7/15 9/8/15 9/9/15 9/10/15 9/11/15 9/12/15 9/13/15 9/14/15
0/4/15 0/5/15 0/6/15 0/6/15 0/7/15 0/8/15 0/9/15 0/10/15 0/11/15 0/11/15 0/15/15 0/15/15 0/16/15 0/16/15 0/18/15 0/19/15 0/20/15 0/21/15	Grayson, KY Washington, DC Simi Valley, CA Des Moines, IA	Tyler, TX	Rico Portsmouth, NH Newton, IA Cedar Rapids, IA Washington, DC Columbus, OH Washington, DC Decorah, IA Staten Island, NY Nashua, NH	Milwaukee, WI			9/4/15 9/5/15 9/6/15 9/7/15 9/8/15 9/9/15 9/10/15 9/11/15 9/12/15 9/13/15 9/14/15
0 5 15 0 6 15 1 7 15 0 8 15 0 9 15 0 10 15 1 11 15 0 12 15 0 13 15 0 15 15 0 15 15 0 16 15 0 17 15 0 19 15 0 20 15 0 21 15 0 22 15	Washington, DC Simi Valley, CA Des Moines, IA		Rico Portsmouth, NH Newton, IA Cedar Rapids, IA Washington, DC Columbus, OH Washington, DC Decorah, IA Staten Island, NY Nashua, NH	Milwaukee, WI			9/5/15 9/6/15 9/7/15 9/8/15 9/9/15 9/10/15 9/11/15 9/12/15 9/13/15 9/14/15
0/6/15 1/7/15 1/8/15 1/8/15 1/9/15 1/10/15 1/11/15 1/13/15 1/13/15 1/14/15 1/15/15 1/16/15 1/16/15 1/18/15 1/19/15 1/20/15 1/20/15 1/22/15	Washington, DC Simi Valley, CA Des Moines, IA		Portsmouth, NH Newton, IA Cedar Rapids, IA Washington, DC Columbus, OH Washington, DC Decorah, IA Staten Island, NY Nashua, NH	Milwaukee, WI			9/6/15 9/7/15 9/8/15 9/9/15 9/10/15 9/11/15 9/12/15 9/13/15 9/14/15
0/7/15 1/8/15 1/8/15 1/8/15 1/9/15 1/10/15 1/11/15 1/12/15 1/14/15 1/15/15 1/16/15 1/18/15 1/18/15 1/19/15 1/19/15 1/20/15 1/22/15	Washington, DC Simi Valley, CA Des Moines, IA		Cedar Rapids, IA Washington, DC Columbus, OH Washington, DC Decorah, IA Staten Island, NY Nashua, NH	Milwaukee, WI			9/7/15 9/8/15 9/9/15 9/10/15 9/11/15 9/12/15 9/13/15 9/14/15
0/7/15 1/8/15 1/8/15 1/8/15 1/9/15 1/10/15 1/11/15 1/12/15 1/14/15 1/15/15 1/16/15 1/18/15 1/18/15 1/19/15 1/19/15 1/20/15 1/22/15	Washington, DC Simi Valley, CA Des Moines, IA		Washington, DC Columbus, OH Washington, DC Decorah, IA Staten Island, NY Nashua, NH	Milwaukee, WI			9/7/15 9/8/15 9/9/15 9/10/15 9/11/15 9/12/15 9/13/15 9/14/15
8 15 9 15 10 15 11 15 11 15 12 15 13 15 15 15 15 15 16 15 18 15 18 15 19 15 20 15 22 15	Washington, DC Simi Valley, CA Des Moines, IA		Washington, DC Columbus, OH Washington, DC Decorah, IA Staten Island, NY Nashua, NH	Milwaukee, WI			9/8/15 9/9/15 9/10/15 9/11/15 9/12/15 9/13/15 9/14/15
0/9/15 1/10/15 1/10/15 1/12/15 1/12/15 1/13/15 1/14/15 1/15/15 1/15/15 1/17/15 1/18/15 1/19/15 1/19/15 1/20/15 1/22/15	Washington, DC Simi Valley, CA Des Moines, IA		Columbus, OH Washington, DC Decorah, IA Staten Island, NY Nashua, NH	Milwaukee, WI			9/9/15 9/10/15 9/11/15 9/12/15 9/13/15 9/14/15
0/10/15 1/11/15 1/11/15 1/13/15 1/13/15 1/14/15 1/15/15 1/15/15 1/17/15 1/18/15 1/19/15 1/20/15 1/22/15 1/22/15	Simi Valley, CA Des Moines, IA		Columbus, OH Washington, DC Decorah, IA Staten Island, NY Nashua, NH	Milwaukee, WI			9/10/15 9/11/15 9/12/15 9/13/15 9/14/15
)/11/15)/12/15)/12/15)/13/15)/14/15)/15/15)/16/15)/16/15)/18/15)/19/15)/20/15)/21/15)/22/15	Des Moines, IA		Washington, DC Decorah, IA Staten Island, NY Nashua, NH	,			9/11/15 9/12/15 9/13/15 9/14/15
0/12/15 1/13/15 1/13/15 1/15/15 1/16/15 1/16/15 1/18/15 1/19/15 1/20/15 1/21/15 1/22/15 1/22/15	Des Moines, IA		Decorah, IA Staten Island, NY Nashua, NH				9/12/15 9/13/15 9/14/15
)(13/15)(14/15)(15/15)(15/15)(16/15)(17/15)(18/15)(19/15)(20/15)(21/15)(22/15)(23/15	Des Moines, IA		Decorah, IA Staten Island, NY Nashua, NH				9/13/15 9/14/15
0/14/15 0/15/15 1/16/15 0/17/15 0/18/15 0/18/15 0/20/15 0/20/15 0/22/15	Des Moines, IA		Decorah, IA Staten Island, NY Nashua, NH				9/14/15
0/15/15 0/16/15 0/16/15 0/18/15 0/18/15 0/20/15 0/20/15 0/22/15 0/22/15	Des Moines, IA		Staten Island, NY Nashua, NH				
0/16/15 0/17/15 0/18/15 0/19/15 0/20/15 0/21/15 0/22/15	Des Moines, IA		Nashua, NH				3/13/13
)/17/15 0/18/15 0/19/15 0/20/15 0/21/15 0/22/15 0/23/15	Des Moines, IA		Nashua, NH				9/16/15
0/18/15 0/19/15 0/20/15 0/21/15 0/22/15 0/23/15				Laconia NU	Concord NU		
)/19/15)/20/15)/21/15)/22/15)/23/15				Laconia, NH	Concord, NH		9/17/15
0/20/15 0/21/15 0/22/15 0/23/15			Durham, NH	Portland, ME	Plymouth, NH		9/18/15
0/21/15 0/22/15 0/23/15	Urbandale, IA		Manchester, NH				9/19/15
)/22/15)/23/15							9/20/15
0/23/15			Baton Rouge, LA	Little Rock, AK			9/21/15
			Des Moines, IA				9/22/15
)/24/15							9/23/15
							9/24/15
)/25/15	Washington, DC						9/25/15
/26/15	Thompson, IA	Hampton, IA					9/26/15
/27/15	Urbandale, IA		Los Angeles, CA				9/27/15
)/28/15	,		San Francisco, CA				9/28/15
)/29/15			Charlotte, NC				9/29/15
0/30/15			New York, NY				9/30/15
0/1/15			Belmont, MA	Boston, MA			10/1/15
	Nashua, NH	Salem, NH	Davie, FL	North Palm	Fort Lauderdale,	Miami Beach, FL	
0/2/15	Nasiiua, INFI		Davie, FL	Beach, FL	FL	iviiaiiii beacii, FL	10/2/15
0/3/15	Hooksett, NH	Laconia, NH	Washington, DC				10/3/15
0/4/15	Wolfeboro, NH						10/4/15
0/5/15	Kalamazoo, MI		Manchester, NH				10/5/15
0/6/15			Davenport, IA	Muscatine, IA			10/6/15
0/7/15			Mt. Vernon, IA	Council Bluffs, IA			10/7/15
0/8/15			Washington, DC				10/8/15
0/9/15	Nashua, NH		Washington, DC				10/9/15
0/10/15	rasita, iii		rrasimgton, De				10/10/15
0/11/15							10/11/15
0/12/15			Lea Verse NV				10/12/15
0/13/15			Las Vegas, NV				10/13/15
0/14/15			Las Vegas, NV				10/14/15
0/15/15			San Antonio, TX	Houston, TX			10/15/15
0/16/15			Keene, NH	Nashua, NH			10/16/15
0/17/15	Contoocook, NH		Birmingham, AL	Hoover, AL			10/17/15
0/18/15							10/18/15
0/19/15							10/19/15
0/20/15							10/20/15
0/21/15							10/21/15
0/22/15			Washington, DC				10/22/15
0/23/15	Glenwood, IA	Council Bluffs, IA	Washington, DC	Alexandria, VA			10/23/15
0/24/15	Marshalltown, IA	Waterloo, IA	Des Moines, IA	•			10/24/15
0/25/15		,	New York, NY				10/25/15
0/26/15							10/26/15
0/27/15			Morristown, NJ				10/27/15
0/28/15	Boulder, CO		Manchester, NH	Bartlett, NH	Meredith, NH		10/28/15
	boulder, CO				IVICICUIUI, INFI		
0/29/15			Berlin, NH	Littleton, NH			10/29/15
0/30/15	Doc Mains - 14	Almon IA	Atlanta, GA	Charleston, SC			10/30/15
0/31/15	Des Moines, IA	Akron, IA	Charleston, SC				10/31/15
1/1/15			ol :				11/1/15
1/2/15			Chicago, IL	Evanston, IL			11/2/15
1/3/15			Coralville, IA	Grinnell, IA			11/3/15
1/4/15			Sacramento, CA	Los Angeles, CA			11/4/15
1/5/15			Los Angeles, CA	St. Helena, CA			11/5/15
1/6/15	Des Moines, IA		Rock Hill, SC				11/6/15
1/7/15			Orangeburg, SC	Columbia, SC			11/7/15
1/8/15			5				11/8/15
1/9/15			Windham, NH	Nashua, NH			11/9/15
1/10/15	Milwaukee, WI		Derry, NH	Hanover, NH	Buffalo, NY		11/10/15
				Hallovel, INFI	Dullalo, INI		
1/11/15	Kingston, NH		New York, NY				11/11/15
1/12/15	Concord, NH						11/12/15
1/13/15							11/13/15 Intinued on next p

Table A2 (continued)

Date	C	Cruz	Cruz2		Clinton	Clin	ton2	Clinton3		Clinton4	Date	
11/14/15		Greenville, SC			Des Moines,	IA					11/1	
11/15/15		Ayrtle Beach, S			Ames, IA						11/1	
11/16/15	C	Okatie, SC	Charles	ston, SC							11/1	
11/17/15					Dallas, TX						11/1	
11/18/15					Nov. Vonl. N	v					11/1	
11/19/15	г	os Moinos IA			New York, N Louisville, K		nnhic TN	Nashville,	TNI		11/1	
11/20/15 11/21/15		Des Moines, IA Clear Lake, IA			Charleston, S		nphis, TN	inasiiviiie,	111		11/2 11/2	
11/21/15		lear Lake, IA			Clinton, IA	C					11/2	
11/23/15					Reno, NV	Car	son City, NV				11/2	
1/24/15					Boulder, CO		iver, CO				11/2	
1/25/15											11/2	
11/26/15											11/2	6/15
11/27/15											11/2	
11/28/15		Creston, IA	Lamon		_						11/2	
1/29/15		Des Moines, IA		dorf, IA	Boston, MA		nchester, NH				11/2	
1/30/15	C	Coralville, IA	Clinton	i, iA	Washington,		vy Chase, MD				11/3	
2/1/15 2/2/15					Montgomery Orlando, FL		mi Beach, FL notosassa, FL	Winderme	ro El	Jacksonville, FL	12/1 12/2	
2/2/13 2/3/15					Nashua, NH		nchester, NH	Dover, NH		Boston, MA	12/2	
2/4/15	I	ohnston, IA			Sioux City, I/		ichester, ivii	Dover, Mir		DOSTOII, IVIA	12/3	
2/5/15		Des Moines, IA	Cedar	Rapids, IA	ir city, ir						12/5	
2/6/15	-			,,	Washington,	DC Alex	kandria, VA				12/6	
2/7/15	C	Greenville, SC			Washington,		ings Mills, MD				12/7	
2/8/15					Salem, NH						12/8	
2/9/15					Waterloo, IA		andale, IA				12/9	
2/10/15					New York, N						12/1	
2/11/15					Tulsa, OK	St.	Louis, MO				12/1	
2/12/15											12/1	
2/13/15					Dunalden NI						12/1	
2/14/15 2/15/15					Brooklyn, NY Minneapolis,						12/1 12/1	
2/15/15	T	as Vegas, NV			Omaha, NE		a City, IA	Mason City	, 1Δ	New York, NY	12/1	
2/17/15	S	ummerlin Sou V	ıth,		Omana, NE	iow	a City, in	Wason City	,, 111	New Tork, IVI	12/1	
2/18/15	•	••									12/1	8/15
2/19/15					New York, N	Y Mai	nchester, NH				12/1	9/15
2/20/15												0/15
2/21/15											12/2	
2/22/15					Keota, IA							2/15
2/23/15											12/2	4/15
2/24/15 2/25/15												5/15
2/26/15												6/15
2/27/15												7/15
2/28/15												8/15
2/29/15					Portsmouth,	NH Ber	lin, NH					9/15
2/30/15												0/15
2/31/15											12/3	1/15
1/15	Sanders	Sanders2	Sanders3	Sanders4	Christie	Christie2	Christie3	Paul Jefferson,	Paul2 Berlin, NH	Paul3 North	Paul4	Date 9/1/1
2/15								NH Freedom,	Wolfboro,	Conway, NH Laconia, NH		9/1/1
-, 13		O	West		Littleton,	Lancaster,	Berlin, NH	NH Manchester,	NH	Eucoma, 1411		9/3/1
3/15	Grinnell. IA	Ottuma. IA			NH	NH	,	NH				-1-1-
/3/15	Grinnell, IA	Ottuma, IA	Burlington, IA									
/3/15 /4/15	Muscatine,	Cedar	Burlington,		North	Contoocook						9/4/1
4/15	Muscatine, IA		Burlington,		North Conway, NH		, Concord, NH					
4/15 5/15	Muscatine,	Cedar	Burlington,									9/5/1
4/15 5/15 6/15	Muscatine, IA Altoona, IA Manchester,	Cedar Rapids, IA Amherst,	Burlington,									9/5/1 9/6/1
4/15 5/15 6/15 7/15	Muscatine, IA Altoona, IA	Cedar Rapids, IA	Burlington, IA		Conway, NH							9/5/1: 9/6/1: 9/7/1:
4/15 5/15 6/15 7/15 8/15	Muscatine, IA Altoona, IA Manchester,	Cedar Rapids, IA Amherst,	Burlington, IA									9/5/1: 9/6/1: 9/7/1: 9/8/1:
4/15 5/15 6/15 7/15 8/15 9/15	Muscatine, IA Altoona, IA Manchester,	Cedar Rapids, IA Amherst,	Burlington, IA		Conway, NH							9/5/1 9/6/1 9/7/1 9/8/1 9/9/1
25/15 25/15 26/15 27/15 28/15 29/15 20/15	Muscatine, IA Altoona, IA Manchester, NH	Cedar Rapids, IA Amherst,	Burlington, IA		Conway, NH			Indianola	Ames IA			9/5/1: 9/6/1: 9/7/1: 9/8/1: 9/9/1: 9/10/
25/15 25/15 26/15 27/15 28/15 29/15 20/15	Muscatine, IA Altoona, IA Manchester,	Cedar Rapids, IA Amherst,	Burlington, IA		Conway, NH			Indianola, IA	Ames, IA			9/5/1 9/6/1 9/7/1 9/8/1 9/9/1 9/10/
25/15 16/15 16/15 17/15 18/15 19/15 10/15 11/15	Muscatine, IA Altoona, IA Manchester, NH	Cedar Rapids, IA Amherst, NH	Burlington, IA		Conway, NH			Indianola, IA		A Ames. IA		9/5/1 9/6/1 9/7/1 9/8/1 9/9/1 9/10/ 9/11/
25/15 16/15 16/15 17/15 18/15 19/15 10/15 11/15	Muscatine, IA Altoona, IA Manchester, NH	Cedar Rapids, IA Amherst,	Burlington, IA		Conway, NH				Nevada, IA	A Ames, IA		9/5/1 9/6/1 9/7/1 9/8/1 9/9/1 9/10/ 9/11/
25/15 16/15 16/15 17/15 18/15 19/15 10/15 11/15	Muscatine, IA Altoona, IA Manchester, NH Atlanta, GA Columbia,	Cedar Rapids, IA Amherst, NH	Burlington, IA		Conway, NH			IA	Nevada, IA	A Ames, IA		9/5/1: 9/6/1: 9/7/1: 9/8/1: 9/9/1: 9/10/ 9/11/
	Muscatine, IA Altoona, IA Manchester, NH Atlanta, GA Columbia,	Cedar Rapids, IA Amherst, NH	Burlington, IA		Conway, NH			IA Marshalltowi	Nevada, IA	A Ames, IA		9/4/1: 9/5/1: 9/6/1: 9/7/1: 9/8/1: 9/9/1: 9/10/ 9/11/: 9/12/

Table A2 (continued)

D .)		0 1 0		et : .:	ol 1 .1 =	al		p. 10	D 10	D 14	ъ.
Date 9/14/15	Sanders Lynchburg,	Sanders2 Manassas,	Sanders3	Sanders4	Christie Manchester,	Christie2	Christie3	Paul	Paul2	Paul3	Paul4	Date 9/14/15
	VA	VA			NH							9/14/15
9/15/15												9/15/15
9/16/15								Carson City	Lac Vocas	Dono NV	Elv. NV	9/16/15
9/17/15								Carson City, NV	NV	Reno, NV	Ely, NV	9/17/15
9/18/15	New York, NY							Henderson, NV				9/18/15
9/19/15	Manchester, NH	NH										9/19/15
9/20/15	Seabrook, NH	Portsmouth, NH	Exeter, NH	Durham, NH								9/20/15
9/21/15 9/22/15												9/21/15 9/22/15
9/23/15								Rock Hill, SC	Columbia, SC	Spartanburg,		9/23/15
9/24/15										SC		9/24/15
9/25/15	Portsmouth, NH				Nashua, NH			Manchester, NH	Hudson, NH	Salem, NH		9/25/15
9/26/15	Des Moines, IA				Loudon, NH	Concord, NH	Derry, NH	Henniker, NH	Brookline, NH			9/26/15
9/27/15	Waukee, IA	Des Moines, IA	Fort Dodge, IA	Mason City								9/27/15
9/28/15 9/29/15	Chicago, IL		111		Alden, IA Des Moines,							9/28/15 9/29/15
9/30/15					IA							9/30/15
10/1/15												10/1/15
10/2/15												10/2/15
0/3/15	Springfield,	Boston, MA										10/3/15
0/4/15	MA											10/4/15
0/4/15 0/5/15												10/4/15 10/5/15
0/6/15												10/6/15
10/7/15					Hampstead,							10/7/15
10/8/15					NH Manchester, NH	NH Belmont, NH						10/8/15
10/9/15	Tucson, AZ				Henniker, NH			Manchester, NH	Nashua, NH			10/9/15
10/10/15	Boulder, CO				NH			NH				10/10/1
10/11/15	bounder, co											10/11/1
10/12/15					Manchester,			Cedar	Mt. Vernon,			10/12/1
10/13/15	NV Las Vegas,				NH			Rapids, IA Davenport,	IA Dubuque,	IA West Des	Cedar Falls,	10/13/1
10/13/13	NV							IA Sioux City,	IA Storm Lake,	Moines, IA Des Moines,	IA	10/13/1
40/45/45	Angeles, CA							IA	IA	IA		40/45/4
10/15/15					Newport, NH Manchester,	Redford		Manchester,				10/15/1
10/17/15					NH	NH		NH Hooksett,	Contoocook,			10/17/1
10/18/15	Iowa City,	Fort						NH Dalton, NH	NH	NH		10/18/1
10/19/15	IA Oskaloosa, IA	Madison, IA										10/19/1
10/20/15 10/21/15					Newton, IA	Des Moines,						10/20/15 10/21/15
10/22/15 10/23/15		Davenport,				IA						10/22/1 10/23/1
.0 23 13	Washington, DC											10/23/1
	Des Moines, IA											10/24/1
0/25/15	Des Moines, IA											10/25/1
10/26/15	New York, NY											10/26/1
10/27/15	New York, NY											10/27/1
											(continued on	

Table A2 (continued)

Date	Sanders	Sanders2	Sanders3	Sanders4	Christie	Christie2	Christie3	Paul	Paul2	Paul3	Paul4	Date
10/28/15	Fairfax, VA	Washington,										10/28/1
10/29/15 10/30/15		DC Nashua, NH	Derry, NH		Council	Orange City,		Des Moines,				10/29/15 10/30/15
10/31/15	NH Concord, NH	Warner, NH	Lebanon, NH		Bluffs, IA Des Moines, IA	IA		IA Newton, IA	Des Moines, IA			10/31/1
11/1/15 11/2/15								Durham,				11/1/15 11/2/15
11/3/15 11/4/15								NH				11/3/15 11/4/15
11/5/15	Concord, NH				Nashua, NH	Somersworth NH	ı,					11/5/15
11/6/15	Rock Hill, SC				Concord, NH	Hanover, NH		Spartanburg,				11/6/15
11/7/15	Rock Hill, SC	Columbia, SC	Aiken, SC		Plymouth, NH	Bedford, NH		Sc				11/7/15
11/8/15	Las Vegas, NV											11/8/15
	Las Vegas, NV											11/9/15
11/10/15 11/11/15					Bettendorf,	Muscatine,	Coralville,	Council	Des Moines,	Ames, IA		11/10/15 11/11/15
11/12/15	NH				IA Cedar Rapids, IA	IA Anamosa, IA	IA Robins, IA	Bluffs, IA Johnston, IA	IA Altoona, IA	Winterset, IA		11/12/15
11/13/15					Cedar Falls, IA	Johnston, IA	Nevada, IA	Concord, NH	Somersworth NH	Portsmouth,		11/13/15
11/14/15 11/15/15	Des Moines,	Indianola,						Des Moines,	1411			11/14/15 11/15/15
11/16/15	IA Cleveland,	IA						IA				11/16/15
11/17/15 11/18/15 11/19/15	ОН											11/17/15 11/18/15 11/19/15
	Washington, DC Charleston,							Des Moines,				11/20/15
	SC Charleston,	Columbia,	Orangeburg,		Stratham,	Windham,	Manchester,	IA				11/21/15
	SC St. Helena,	SC Savannah,	SC		NH Bedford,	NH	NH	IA				11/22/15
11/23/15 11/24/15	SC Atlanta, GA	GA			NH							11/23/15 11/24/15
11/25/15 11/26/15												11/25/15 11/26/15
11/27/15 11/28/15												11/27/15 11/28/15
	Manchester, NH											11/29/1
11/30/15					Concord, NH	Loudon, NH						11/30/15
12/1/15					Londonderry, NH	Concord, NH						12/1/15
12/2/15												12/2/15
12/3/15 12/4/15					West Des Moines, IA	Jefferson, IA	Fort Dodge, IA	Waukee, IA	Fort Dodge, IA	Mason City, IA	Cedar Falls, IA	12/3/15 12/4/15
12/5/15	Keene, NH	Plymouth, NH				Iowa Falls, IA		Waterloo, IA	Cedar Falls, IA	Cedar Rapids, IA		12/5/15
12/6/15	Washington, DC									• •		12/6/15
12/7/15 12/8/15	Baltimore,											12/7/15 12/8/15
12/9/15	MD										(continued on	12/9/15 next page

Table A2 (continued)

)													
Date	Sanders	Sanders2	Sanders3	Sanders	4 Christ	ie	Christie	e2 C	Christie3	Paul	Paul2	Paul3	Paul4	Date
12/10/15 12/11/15					Wolfe	boro,				Keene, NH	Rindge, NH			12/10/15 12/11/15
12/12/15	Anamosa,	Clinton, IA	Dubuque,	Waterlo	NH o, Weare	, NH				Nashua, NH		Manchester, NH		12/12/15
12/13/15	IA Waterloo, IA	Mount Vernon, IA	IA Davenport, IA	IA							INFI	NH		12/13/15
	Nashua, NH Rochester,		Dover, NH											12/14/15 12/15/15
12/16/15	NH Washington									Reno, NV	Las Vegas, NV			12/16/15
12/17/15	DC													12/17/15
12/18/15 12/19/15	Manchester,				Exete	, NH	Derry, l		Bedford,					12/18/15 12/19/15
12/20/15	NH				Mancl NH	nester,	Peterbo		ΝΗ					12/20/15
12/21/15	Sioux City, IA				Hollis	NH	NH Pelham	ı, NH N	New ondon, NH					12/21/15
12/22/15	Storm Lake, IA	Carroll, IA	Harlan, IA	Council Bluffs, L	Portsr A NH	nouth,		L	ondon, rur					12/22/15
12/24/15 12/25/15 12/26/15	Chicago, IL Reno, NV													12/23/15 12/24/15 12/25/15 12/26/15 12/27/15
12/28/15	North Las Vegas, NV													12/28/15
	Muscatine, IA	Davenport, IA			Musca IA	itine,	Iowa Ci IA	ity,						12/29/15
	Burlington, IA	Keokuk, IA	Ottumwa, IA											12/30/15
12/31/15	Knoxville, IA	Des Moines, IA	•											12/31/15
	Carson (Carson2 Ca	arson3 Ca	rson4	Kasich	Kasich	2 K	asich3	Kasich4	Fiorina	Fiorina2	Fiorina3	Fiorina4	Date
9/1/15 9/2/15					Henniker, NH	New Londo	W n, NH Le N							9/1/15 9/2/15
9/3/15 9/4/15 9/5/15								••		Amherst, NH	Manchester, NH	, Sandown, NH		9/3/15 9/4/15 9/5/15
9/6/15 9/7/15					Rye, NH	Milford	d, NH Sa	alem, N	Н	Derry, NH Concord,		ł		9/6/15 9/7/15
9/8/15					Concord,	Brookl	ine,			NH				9/8/15
9/9/15 9/10/15 9/11/15					NH	NH								9/9/15 9/10/15 9/11/15
	Aiken, SC				Manchester, NH	Raymo NH	ond, D	over, NI	H Stratham NH	, Chicheste NH	, Stratham, NH	Dover, NH		9/12/15
9/13/15										Alton, NH	Pembroke, NH	Glen, NH		9/13/15
9/14/15 9/15/15														9/14/15 9/15/15 9/16/15 9/17/15 9/18/15 9/19/15 9/20/15 9/21/15
9/16/15 9/17/15 9/18/15 9/19/15 9/20/15 9/21/15														3/21/13
9/17/15 9/18/15 9/19/15 9/20/15 9/21/15 9/22/15										Charleston SC	Beach, SC			9/22/15
9/17/15 9/18/15 9/19/15 9/20/15 9/21/15 9/22/15 9/23/15											Beach, SC			9/22/15 9/23/15
9/17/15 9/18/15 9/19/15 9/20/15 9/21/15 9/22/15 9/23/15										SC Lexington SC Spartanbu	Beach, SC Rock Hill, SC			9/22/15
9/17/15 9/18/15 9/19/15 9/20/15					Hilton Head Island, SC	l			Davenpo IA	SC Lexington SC Spartanbu SC	Beach, SC Rock Hill, SC		9/25/15	9/22/15 9/23/15

Table A2 (continued)

Date	Carson	Carson2	Carson3	Carson4	Kasich	Kasich2	Kasich3	Kasich4	Fiorina	Fiorina2	Fiorina3	Fiorina4	Date
9/26/15					Sioux City, IA	Council Bluffs, IA			Iowa City, IA	Arlington, IA	1		9/26/1
9/27/15													9/27/1
/28/15													9/28/1
/29/15													9/29/1
/30/15	Exeter, NH	Durham, NH	Portsmouth, NH	, New Castle, NH	Davenport, IA	Cedar Rapids, IA							9/30/1
0/1/15	West Des Moines, IA												10/1/1
0/2/15	Des Moines IA	Ankeny, IA			Concord, NH	Goffstown, NH	Manchester, NH		Aiken, SC	Mt Pleasant, SC	,		10/2/1
10/3/15									Hooksett, NH	Hudson, NH	Portsmout NH	h,	10/3/1
10/4/15									Rye, NH	Windham, NH			10/4/1
10/5/15									Manchester, NH	, Nashua, NH	Bedford, N	Н	10/5/1
10/6/15													10/6/1
10/7/15													10/7/1
0/8/15													10/8/1
0/9/15					Stratham, NH								10/9/1
	Columbia, SC												10/10/
10/11/15													10/11/
0/12/15					Manchester, NH								10/12/
0/13/15					Bow, NH	Tilton, NH	Littleton, NH						10/13/
0/14/15					NH	Tuftonboro, NH			C====== IA	Mindon			10/14/
0/15/15					Nashua, NH				Spencer, IA	Heights, IA Grinnell, IA			10/15
0/16/15									Pleasant Hill, IA		Monticalla		10/16
0/17/15									Cedar Rapids, IA	Waterloo, IA	IA	,	10/17
10/18/15													10/18/
0/19/15													10/19
0/20/15													10/20
0/21/15 0/22/15					Hanover,	Newport,							10/21 10/22
0/23/15					NH Manchester,	NH Milford, NH			Beaufort, SC	Hilton Head	,		10/23
0/24/15	Ames, IA	West Des	Waterloo,	Dubuque,	NH		NH			SC			10/24
0/25/15		Moines, IA	IA	IA									10/25
0/25/15 0/26/15													10/25 10/26
0/20/15 0/27/15													10/27
0/28/15													10/28
0/29/15													10/29
)/30/15									Orange City				10/30
/31/15									IA	Des Moines,	. Indianola.	IA	10/31
/1/15									IA Oskaloosa,	IA	,		11/1/
/2/15					Des Moines,				IA Oskaloosa,				11/2/
1/3/15					IA Dubuque,				IA				11/3/
1/4/15					IA								11/4/
1/5/15					Durham, NH	Londonderr NH	y,		Concord, NH	Newport, NH			11/5/
1/6/15					Concord, NH	Hopkinton, NH			Manchester, NH	, Milford, NH	Dover, NH		11/6/
					***				Franklin, NH	Bedford, NH	Londonder	ту,	11/7/
1/7/15											NILI		
1/7/15											NH		11/8/1
											NH		11/8/ 11/9/ 11/10

Table A2 (continued)

Date	Carson	Carson2	Carson3	Carson4	Kasich	Kasich2	Kasich3	Kasich4	Fiorina	Fiorina2	Fiorina3	Fiorina4	Date
11/11/15				West Columbia, SC	Hilton Head Island, SC								11/11/15
11/12/15				3C	Exeter, NH	Concord, NH			Onawa, IA	Harlan, IA			11/12/1
11/13/15	Greenville, SC				Hudons, NH	Laconia, NH	I		Council Bluffs, IA	Corning, IA	Greenfield, IA		11/13/1
11/14/15 11/15/15	Las Vegas,												11/14/15 11/15/15
11/16/15	NV Green Valley, NV								Plymouth, NH				11/16/15
11/17/15	vancy, ivv								Concord, NH				11/17/15
11/18/15									Henniker, NH	Keene, NH			11/18/1
11/19/15	Columbia, SC				Spartanburg	Charleston, ,SC							11/19/15
11/20/15	Concord, NH				SC Hollis, NH				Des Moines	,			11/20/1
11/21/15		Tipton, IA	Wilton, IA	Davenport, IA	Berlin, NH	Sanbornville	Dover, NH e,		Dike, IA				11/21/1
11/22/15						NH			Wilton, IA				11/22/1
	Pahrump, NV								Des Moines, IA	, Council Bluffs, IA	Sioux City, IA		11/23/1
11/24/15 11/25/15 11/26/15 11/27/15 11/28/15 11/29/15 11/30/15					Ames, IA	Cedar			Greenville,	Anderson,			11/24/1: 11/25/1: 11/26/1: 11/27/1: 11/28/1: 11/29/1: 11/30/1:
12/1/15						Rapids, IA			SC Columbia, SC	SC West Columbia,	Charleston, SC		12/1/15
12/2/15	Rock Hill, SC	Spartanburg	.,							SC			12/2/15
12/3/15		SC			Salem, NH								12/3/15
12/4/15					Manchester, NH	NH							12/4/15
	Waterloo, IA	Cedar Rapids, IA			Claremont, NH	New London, NH	I		Cedar Rapids, IA				12/5/15
12/6/15 12/7/15									Coon Rapids, IA Cedar				12/6/15 12/7/15
12/8/15					Myrtle				Rapids, IA Des Moines				12/8/15
12/9/15					Beach, SC				IA Lebanon,				12/9/15
12/10/15					Manchester,				NH Concord,	Bedford, NH	Derry, NH		12/10/1
12/11/15	Burlington, IA	Moravia, IA			NH Keene, NH	Peterboroug	Bedford, gh)H		NH Manchester, NH	Nashua, NH	Exeter, NH		12/11/1
12/12/15 12/13/15 12/14/15 12/15/15						NH							12/12/1: 12/13/1: 12/14/1: 12/15/1:
	Elko, NV	Las Vegas, NV	Carson City, NV		Ankeny, IA				Reno, NV				12/16/1
	McGregor, IA	Mason City, IA	Siony City		Waterloo, IA	Des Moines IA	•		Clinton IA	Dubuque, IA	Davor		12/17/1
	IA	Orange City, IA Harlan, IA	IA							Washington	IA		12/18/1
	Nashua, NH		Bluffs, IA		Manchester.	Portsmouth			IA	IA	,		12/19/1
	Manchester,				NH	NH Rochester,			Mt.	Pawleys			12/21/1
	NH	NH			NH	NH	NH		Pleasant, SC Florence, SC	Island, SC			12/22/1

Table A2 (continued)

Date	Carson	Carson2	Carson3	Carson4	Kasich	Kasich2	Kasich3	Kasich4	Fiorina	Fiorina2	Fiorina3	Fiorina4	Date
12/23/	15												12/23/15
12/24/	15												12/24/15
12/25/	15												12/25/15
12/26/	15												12/26/15
12/27/1	15												12/27/15
12/28/	15				Manchest NH	er, Derry, NH							12/28/15
12/29/	15				Nashua, N	NH Keene, NH	ł						12/29/15
12/30/	15												12/30/15
12/31/1	15												12/31/15

Note: this list contains all recorded campaign including those not matched to our own sample of parish bulletins. There are multiple columns for candidates as candidates sometimes made more than one stop in a day.

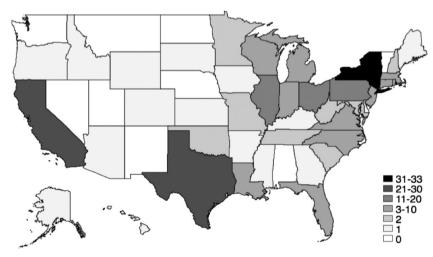


Fig. A1. Distribution of Parishes in Baseline Estimates.

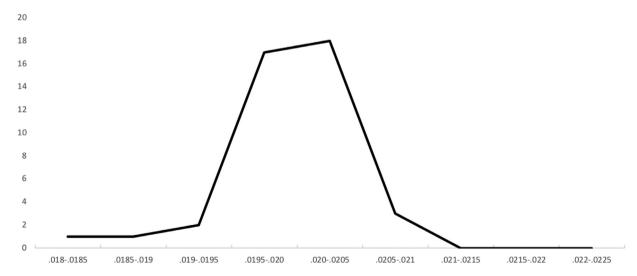


Fig. A2. Results Dropping Each State, Except New Hampshire.

The figure presents a histogram of coefficients from a regression of church collections on campaigns with each state dropped. All regressions difference data and include bulletins from 2014 and 2015 and include a constant. The y axis shows the number of regressions that produced a campaign coefficient in a given bin. The baseline coefficient, including all states, is 0.0204. All coefficients from this exercise are statistically significant. Results dropping New Hampshire are reported in Table 3 and produce a coefficient of 0.0273, which would be to the right of the above picture.

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