Are Political and Charitable Giving Substitutes? Evidence from the United States

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Abstract

We provide evidence that individuals substitute between political contributions and charitable contributions, using micro data from the American Red Cross and Federal Election Commission. First, we find that foreign natural disasters, which are positive shocks to charitable giving, crowd out political giving. Second, we show that political advertisement campaigns, which are positive shocks to political giving, crowd out charitable giving. Our evidence suggests that individuals give to political and charitable causes to satisfy similar needs, and some of the drivers of charitable giving, such as other-regarding preferences, may be driving political giving too.

Keywords: charitable giving, political contributions, altruism, media.

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1 Introduction

Donations comprise a substantial fraction of household expenditures. In the United States, individual donations to charity and to political causes account for more than 2% of GDP (Giving USA, 2018; Federal Electoral Commission, 2017). These two types of giving, political and charitable, have a lot in common. For example, whereas a minority of very large donations might exert some influence, a typical donation from an individual is virtually never large enough to be influential on its own. Those who donate to charity are more likely to donate to politics, relative to those who do not (Yörük, 2015). Despite these commonalities, there is little research on the relation between charitable and political giving. In this paper, we fill this gap by studying whether charitable and political giving are substitutes.

The degree of crowding out between charitable and political giving can shed light on an open question in the social sciences: why do people give money to political campaigns? In the case of charitable giving, decades of research finds that its leading drivers are other-regarding preferences, such as impure altruism or warm-glow (e.g., Andreoni, 1989). In the case of political donations, however, there is still no such consensus. Some scholars propose that political donations, even small ones, are driven by strategic incentives (Bouton et al., 2018). Others argue that they fulfill a consumption role (Ansolabehere et al., 2003). We provide a new approach to answering this question: if political and charitable giving satisfy the same needs, individuals will behave as if charitable and political giving are substitutes.

We aim to answer this question using the data from the United States. We employ data on charitable donations to the American Red Cross (ARC) and data on political donations from the Federal Election Commission (FEC). These two giving categories are roughly comparable in magnitude: donations for disaster relief average $1.2 billion per year (Rooney, 2018), while individual contributions to political campaigns average $1.55 billion per year (Federal Electoral Commission, 2017).

Our identification strategy is based on shocks to the attractiveness of political and charitable giving. First, we measure if shocks that positively affect charitable giving crowd out political giving. Second, we study whether shocks that positively affect political giving crowd out charitable giving.

We start with the study of natural disasters that occur outside of the United States. Foreign natural disasters are unlikely to directly impact the financial means that U.S. households have

to give, because they occur outside of the country. On the other hand, these foreign disasters constitute a positive shock to charitable donations by U.S. households because they receive media coverage in the United States (Eisensee and Strömberg, 2007; Karlan et al., 2012; Cadena and Schoar, 2011).

According to anecdotal accounts, there is a significant increase in charitable giving concentrated in the six weeks after a large foreign natural disaster hits (Schwab, 2010; Rooney, 2018). Using data at the county-week level, we find strong support for these anecdotal accounts: in the six weeks following a large foreign natural disaster, donations to the American Red Cross increase by 27.2% (p-value=0.015). Next, we use the same specification to measure the effects of these natural disasters on political giving. If charitable and political giving are substitutes, we should observe a decline in political giving after the disasters hit. Consistent with this hypothesis, we estimate a 3.75% (p-value=0.043) decline in political donations in the six weeks following foreign natural disasters. Put differently, we find that an increase in charitable donations crowds out political donations by a factor of around 0.14 ($= \frac{3.75\%}{27.2\%}$).

To rule out alternative explanations, we conduct several robustness tests. We use the timing of the natural disasters as a falsification test in an event-study fashion. We show that charitable and political giving change right after a disaster, but they do not change in the weeks prior to the disaster. We also estimate the effects of disasters on placebo outcomes (individuals' spending on retail, groceries, and lottery tickets) and find estimates that, as expected, are precisely estimated and close to zero. Last, we show that our findings remain robust when using different time periods and when using different definitions of large natural disasters.

Next, we study a shock in the opposite direction: does charitable giving decline after a positive shock to political giving? We use political ads as shocks to the attractiveness of political giving. Just like the natural disasters, the political ads can act as reminders of political giving or increase the salience of the politician's need for contributions. To isolate exogenous variation in political advertising, we follow the identification strategy from Spenkuch and Toniatti (2018), Shapiro (2018) and Wang et al. (2018), exploiting sharp geographic discontinuities in advertisement markets. Specifically, we match counties across the boundaries of Nielsen's Designated Market Areas (DMAs). DMA boundaries are set in advance, independently of political races, and each has access to identical media outlets and advertising. Thus, two households that are in close proximity and similar in observable characteristics can receive a different number and type of political ads if they

are located on opposite sides of a DMA boundary. Because advertising spending is fixed within DMAs but varies between them, we can identify and isolate political information shocks.

We analyze the effects of political ads using monthly level data. We pair every county to their opposite county across the DMA boundary. As expected, we find that political ads act as positive shocks to political giving: political ad spending increases political giving by around 9.2% (p-value<0.001) relative to its paired county across the DMA boundary. If political giving and charitable giving are substitutes, we should expect that charitable giving declines in the aftermath of the political ad. Consistent with that hypothesis, we find that political ad spending decreases charitable giving by around 0.7% (p-value=0.015). In other words, we find that an increase in political donations crowds out charitable donations by a factor of 0.08 ($= \frac{0.7\%}{9.2\%}$).

This finding survives several robustness checks. For example, we use the timing of advertisement spending as a falsification test in an event-study fashion. Despite changes in political and charitable giving right after a political ad, there is no such effect in the weeks prior to the ad. And using micro-data on solicitation mailings from the American Red Cross, we show that the decline in charitable giving is not driven by a decline in outreach efforts by the charity.

The evidence of bi-directional crowding out suggests that charitable and political giving are substitutes to a degree that is statistically and economically significant. Strategic motives are unlikely to explain this crowd-out, as political donations do not improve outcomes for foreign disaster victims and donations to the American Red Cross do not improve election outcomes for candidates. Instead, our preferred interpretation for the crowding out between charitable and political giving is based on other-regarding preferences. In other words, individuals believe that their charitable and political contributions are alternative ways to help society: when one way becomes more attractive, it crowds out the other way.[1]

Our findings have some implications for policy makers and for researchers. One implication for policy makers is that policies designed to restrict or promote political donations might have consequences for charitable giving. For example, relaxing caps on individual political contributions could crowd out some charitable contributions. Thus, these unintended effects should be taken into account when comparing the costs and benefits of these policies. One implication for researchers is that shocks to one type of donation may be used as a source of exogenous variation in studying the effects of other types of donations. As a proof of concept, we measure the effect of political

[1]Moreover, our results may suggest that individuals have a mental account for giving that encompasses both charitable and political giving (Thaler, 1985, 1999; Hastings and Shapiro, 2013).

contributions on electoral outcomes using natural disasters as a source of exogenous variation in contributions. We find that, consistent with the logic in Ansolabehere et al. (2003), a decline in small, individual contributions improves the electoral prospects of incumbents.[2]

Our paper is related to a literature on the determinants of charitable and political giving. The literature on charitable giving emphasizes the role of other-regarding preferences such as altruism (Andreoni, 1989; Ottoni-Wilhelm et al., 2017; Becker, 1974; Gee and Meer, 2019) and warm-glow (Andreoni, 1989).[3] For political donations, however, there is no comparable consensus on the drivers of giving. Some studies attribute political donations to instrumental motives such as to influence the policies that benefits the donors the most (Snyder Jr, 1990; Grossman and Helpman, 1996; Mian et al., 2010; Bouton et al., 2018). Other studies claim that individual donations to politicians are driven by a consumption motive (Ansolabehere et al., 2003). We contribute to this literature by showing that individuals view political and charitable giving as substitutes. This finding suggests that other-regarding preferences, which have important roles in charitable giving, also may have important roles in political donations.

The two most closely related papers are Bertrand et al. (2018) and Yörük (2015). Bertrand et al. (2018) show that charitable giving is sometimes used as a means of political influence. For example, grants given to charitable organizations in a congressional district increase when that district's representative can influence relevant policies (e.g., by sitting on certain committees). Bertrand et al. (2018) also explore a connection between charitable giving and political giving, though the connection runs in the exact opposite direction. In other words, while Bertrand et al. (2018) shows that large charitable donations are sometimes used to influence politicians, our evidence suggests that small donors give to political campaigns to feel good about themselves.

To the best of our knowledge, Yörük (2015) is the only other study that investigates the re-

[2]On the one hand, the finding that extra outside spending can reduce, rather than exacerbate, the incumbency advantage in the U.S. is also consistent with Petrova et al. (2019). On the other hand, this finding contrasts with that of Avis et al. (2017), who show that after a policy change to limit campaign spending in Brazil, political competition increased by creating a larger pool of candidates, which also reduced the incumbency advantage.

[3]These theories suggest that charitable giving is a feel-good consumption item. There are, of course, other documented reasons why individuals give to charity, such as peer pressure (DellaVigna et al., 2012; Andreoni et al., 2017) and bragging rights (Glazer and Konrad, 1996; Harbaugh, 1998; Montano-Campos and Perez-Truglia, 2019)). Indeed, in addition to economics, giving is an important area of study in marketing and psychology (Jenni and Loewenstein, 1997; List and Lucking-Reiley, 2002; Kogut and Ritov, 2005; Landry et al., 2006; Shang and Croson, 2006; Small et al., 2007; Small and Simonsohn, 2007; Alpizar et al., 2008; Liu and Aaker, 2008).

lationship between charitable and political donations.[4] Studying household surveys of donations between 1990 and 2001, the author uses variations in income and itemized deductions in taxes to identify the relationship between charitable and political giving. The author concludes that these two types of donations are complementary, as a higher tax is associated with lower charitable giving and lower political giving. However, the main challenge for these results is that taxes can be associated with a host of unobservable factors such as wealth or altruism. Our study contributes by advancing the causal identification. Based on two natural experiments, we reach exactly the opposite conclusion: charitable and political giving are substitutes, not complements.

The rest of the paper is organized as follows. Section 2 describes the data sources. Section 3 presents the effects of foreign natural disasters on charitable and political giving. Section 4 discusses the effects of political ads on giving. Section 5 discusses the interpretation and implications of the findings. The last section concludes.

2 Data

In this section, we describe all the datasets and variable definitions used in the analysis.

Charitable Contributions. We use proprietary data from the American division of the Red Cross (RC).[5] RC is a humanitarian organization that provides emergency assistance, disaster relief, and disaster preparedness education in the United States and abroad. The dataset consists of records of individual donations made to the organization, with donor information anonymized. For each donor, we have data on their zip code, the date, and amount of donations, as well as any appeals or fundraising materials sent to them by RC. The data is available for 2006-2011.

Political Contributions. Political contributions dataset comes from Federal Elections Commission (FEC). The data are available at the individual level and the name and addresses of the individuals are listed, along with the date of the donation. We aggregate the data at the county level. The contributions are recorded and made public when an individual's contributions (over single or multiple giving occasions) exceed $200.

[4]Our paper is also related to the literature on the relationship between political campaigns and non-political expenditures, such as church donations (Hungerman et al., 2018) or commercial advertisements for consumer goods (Moshary, 2019; Moshary et al., 2019). Some literature also suggests that there is a fixed "altruism budget" when charitable donations and volunteering are taken into account (Andreoni et al., 1996; Brown et al., 2019).

[5]The dataset was made available by the Wharton Customer Analytics Initiative of the Wharton School of the University of Pennsylvania.

Foreign Natural Disasters. Since domestic disasters may result in negative economic shocks and therefore influence one's income and ability to donate, we focus on the information shocks associated with disasters that took place outside of the United States. We collect data on those disasters using the International Disasters Database (EM-DAT).[6] We focus on large disasters, defined as those resulting in 300 or more deaths. There are a variety of types of disasters such as earthquakes, floods, storms, and volcano eruptions.

Political Advertising. The data for political advertising is obtained from Wisconsin Advertising Project (for years before 2010) and its successor Wesleyan Media Project (for the 2010 and later years). We refer the reader to Fowler et al. (2015) for a detailed description of the data (as well as basic descriptive statistics). The source for this ad data is Kantar Media/CMAG. Kantar Media is a commercial firm, which specializes in providing detailed, real-time tracking information to corporate and political clients. These tracking data represent the most comprehensive and systematic collection on the content and targeting of political advertisements. The data include two types of information. First, frequency information tells when and where ads aired. It contains precise and detailed information on the date, time, market, station, and television show of each airing. Also, the cost of ads is reported. After receiving the data from CMAG, the Wesleyan Media Project processes and codes the ad tracking data from all 210 media markets in the United States. Project staff records the entity responsible for airing each political spot, distinguishing between those paid for by candidates, parties, and interest groups. Finally, the Wesleyan Media Project codes the content of each ad on an extensive battery of questions.[7]

Retail Spending. We use the Retail Scanner data of Nielsen, provided by University of Chicago's Kilts Center, to investigate the spending on other items for consumers. The data include purchases from all Nielsen-tracked categories, including food, nonfood grocery items, health and beauty aids, and select general merchandise. The data represent approximately 40,000 - 60,000 US households that continually provide information about the makeup of their households, the products they buy, as well as when and where they make purchases. The Retail Scanner Data consist of weekly purchase and pricing data generated from participating retail store point-of-sale systems in all US markets. Data include from approximately 35,000 grocery, drug, mass merchandiser, and

[6] According to the site, the database includes all disasters starting from 1900 until the present, conforming to at least one of the following criteria: 10 or more people dead; 100 or more people affected; the declaration of a state of emergency; or a call for international assistance.

[7] We also tried to use the full Kantar database to identify Red Cross TV ads. However, we identified only 76 instances of ARC ever running those ads on TV.

other stores. Products from all Nielsen-tracked categories are included in the data, such as food, nonfood grocery items, health and beauty aids, and select general merchandise.

Appendix A.1 provides detailed summary statistics on all the variables used for the analysis.

3 The Effects of Foreign Natural Disasters

We use the following specification:

$$Y_{c,t} = \alpha_1 \cdot I_t^{+0/+6} + \left[\alpha_2 \cdot I_t^{+7/+8} + \alpha_3 \cdot I_t^{-2/-1}\right] + \mathbf{X_{c,t}}\beta + \epsilon_{c,t} \quad (1)$$

The dependent variable $Y_{c,t}$ stands for either the total contributions to the Red Cross in county c and week t, or the corresponding total contributions to political campaigns. These dependent variables can take the value of zero, so we use inverse hyperbolic sine transformation instead of the logarithmic function (Burbidge et al., 1988) – as discussed below, our results are robust to alternative specifications.

The binary variable $I_t^{+0/+6}$ takes the value of 1 during the week of the disaster t and the following 6 weeks, thus α_1 captures the effect of a natural disaster on giving. We use a window of 6 weeks after the disaster because of the abundant anecdotal evidence that the effects of disasters on donations are concentrated in that time period. For example, (Schwab, 2010) claims that "disaster donations are typically (...) made within the six weeks following a disaster." And Rooney (2018) also argues that "most Americans who donate to support disaster relief (...) make these donations within six weeks of a big disaster."[8] To assess whether this time window is appropriate, we include the binary variable $I_t^{+7/+8}$, which takes the value 1 during the seventh and eight week after the disaster. Thus, α_2 measures if there are any substantial effects beyond the initial 6 weeks. Lastly, $I_t^{-2/-1}$ takes the value 1 during the two weeks before the start of the disaster. The coefficient α_3 provides an event-study falsification test, by measuring if there are any differences in contributions right before the disaster hits. If the timing of the disasters is truly exogenous, we should expect α_3 to be zero.

$\mathbf{X_{c,t}}$ is a vector of control variables: month-of-the-year dummies, year dummies and the time until the next election (to control for the fact that donations to politics are more likely to arrive closer to the election date), the number of mailings sent out by the Red Cross in the previous weeks

[8]This anecdotal evidence is also consistent with the findings from Eisensee and Strömberg (2007) that news media keep reporting about major foreign disasters during 40 days after the events.

(for charitable giving specifications) and county fixed effects. To take into account that the shock is essentially the same within every week, but standard errors within state might be correlated, we use two-way clustering by week and state.

The effects on charitable donations are presented in Table 1. The coefficient on $I_t^{+0/+6}$ from column (1) suggests that the charitable donations to RC increase by approximately 28.4% during the 6 weeks following a disaster. This effect is statistically significant at 1% level. In column (2), we add the variable $I_t^{-2/-1}$ for the event-study falsification test. The coefficient on $I_t^{+0/+6}$ remains almost the same in terms of its magnitude and statistical significance. On the contrary, the coefficient on $I_t^{-2/-1}$ is closer to zero and is statistically insignificant. This evidence supports the premise that the timing of the disasters is indeed as good as random. Column (3) also includes the variable $I_t^{+7/+8}$. The coefficient on this variable is smaller and statistically insignificant, indicating that, consistent with the anecdotal accounts, the effects on charitable contributions are concentrated in the first six weeks after the disaster hits.

In turn, columns (4)–(6) of the table show that the foreign natural disasters have a negative and significant effect on political contributions. The coefficient on $I_t^{+0/+6}$ from column (1) indicates that, in the six weeks after a disaster hits, there is an average decline in political giving of 3.75%. The coefficients on $I_t^{-2/-1}$ from columns (5)–(6) show that there are no pre-trends: these coefficients are closer to zero and statistically insignificant. Overall, the results in columns (4)–(6) show that natural disasters negatively affect political donations, suggesting that charitable donations crowd out political donations. In sum, Table 1 indicates that the foreign natural disasters increased RC donations but at the same time decreased political giving.

We can combine the estimates to quantify the degree of crowd out. The estimates presented above imply that charitable donations crowd out political donations by a factor of 0.14 ($= \frac{3.75\%}{27.2\%}$).

Next, we discuss a number of additional robustness checks. One potential concern is that there is some other factor going on that reduces income and thus spending across all giving and consumption categories. To rule out this confounding, we conducted a series of "placebo" tests with expenditures in other categories unrelated to giving.

Our main placebo outcome is based on retail expenditures, based on data from Nielsen. The results for this county-level outcome are summarized in Table 2. The coefficients imply that Nielsen expenditures, if anything, go up by 0.8% during the period after the disaster, with the coefficients having the opposite sign as predicted by the confounding factor and economically negligible in

magnitude. Due to the high statistical precision, these small coefficients are marginally statistically significant. Based on these numbers, we can rule out negative effects of up to 0.058%. This is consistent with negligible effect of disasters on overall patterns of retail spending. In sum, the evidence is not consistent with a simple budget constraint explanation.

Appendix A presents a number of additional robustness checks. We show that the results are robust when using time series data instead of county-level data (Appendix A.2) and show falsification tests based on two additional placebo outcomes that are available for the time series specification but unavailable for the county-level dataset (spending in lottery tickets and an additional measure of retail spending). And we show that the results are robust to a number of changes to the baseline specification, such as looking at the extensive vs. intensive margins (Appendix A.3), using alternative fatality thresholds for the definition of large natural disasters (Appendix A.4), excluding specific years from the time frame (Appendix A.5), excluding the number of RC mailings from the set of control variables (Appendix A.6), using a different time window after the disaster hits (Appendix A.7), and looking separately at contributions to Democratic and Republican campaigns (Appendix A.8).

4 The Effects of Political Advertising Shocks

Next, we carry out a similar exercise using political advertising as an information shock. Unlike natural disasters, spending on political advertising, therefore the arrival of political information shocks, is endogenous. A host of correlated unobservables may determine both the advertising spending and political contributions within a county. Thus, we cannot just interpret any OLS relationship between political advertising and different kinds of donations as causal evidence.

To address the identification issue, we use the fact that, since FCC gives local broadcasting licenses at the DMA level, a large number of ads are purchased at the DMA level (Goldstein and Freedman, 2002). DMAs do not follow administrative and political maps, but are rather determined according to the television stations a consumer of cable or satellite dish has access (Shapiro, 2018).[9] As a result, households within the same DMA are exposed to similar TV content and ads. The cross sectional variation due to discontinuous boundaries of DMAs allow individuals across DMA boundaries to be exposed to different frequency of political ads, resulting in a quasi-random source of variation in the political ads.

[9]Please see Shapiro (2018) and Spenkuch and Toniatti (2018) for details on the historical development of DMAs.

We focus on monthly, not weekly, data for two reasons. First, and most importantly, campaign ads have high degree of auto-correlation in weekly data. Thus, it is not possible to estimate a precisely timed effect with essentially a cross sectional source of exogenous variation.[10] Second, while some papers suggest that the impact of campaign advertising effect is short-lived (Gerber et al., 2011), others argue that some dynamic effects can last for six weeks (Hill et al., 2013), with Urban and Niebler (2014), similar to us, using monthly frequency.

We match counties across DMA boundaries based on their distance and then run a first differences regression, regressing donations on advertising spending.[11] We then run a first differences model with the outcome variable ΔY representing the difference between the total political contributions between the county pair pc in month t. We look at the dollar values of ads expenditures, employing logarithmic sine transformation, as we do with donations variables:[12]

$$\Delta Y_{pc,t} = \alpha_1 \Delta Log(D_{pc,t}^{+0/+1}) + \alpha_2 \Delta Log(D_{pc,t}^{-1}) + \theta \Delta \mathbf{X}_{pc,t} + \epsilon_{pc,t} \tag{2}$$

$\Delta Log(D_{pc,t}^{+0/+1})$ represents the difference in the total political advertising spending between the counties in pair pc in the first month following month t. Similar to (1), we also include the falsification term $\Delta Log(D_{pc,t}^{-1})$, corresponding to a shock happening in the future. $\mathbf{X}_{pc,t}$ is a vector of control variables that includes demographics characteristics and county pair and week fixed effects.

The results are presented in Table 3. Columns (1) and (2) show that political ads positively affect political donations, with the elasticity of 0.09: i.e. if the difference in political ads expenditures goes up by 10%, the corresponding difference in donations across DMA border is 0.9%. This estimate is consistent with relatively low persuasion rates obtained by the studies of political advertising (e.g., Spenkuch and Toniatti (2018)). The ads aired in the future do not affect current political (column (2)) or charitable (column (4)) donations. Next, we also observe that political ads negatively affect

[10]Note that Gordon and Hartmann (2013), Spenkuch and Toniatti (2018), and Wang et al. (2018) all argue that it can be problematic to estimate a precisely timed effect with cross-sectional source of variation. We have built in placebo tests in the baseline specification to deal with this concern.

[11]In particular, for each county pair that does not belong to the same DMA, we calculate the distance between them and then we looked at the pairs of counties that are closer than 10 miles from each other. The identification here assumes had the DMA boundary not fallen between the two counties randomly, they would be exposed to identical political information shocks. This methodology has been adopted by others before us (e.g., Shapiro, 2018).

[12]Since there is considerable variation in the prices of advertising between TV channels, day time vs. prime time advertisement options, and from one TV show to another within a given channel, we use dollar spending (as opposed to the number of ads aired or gross rating points) to better approximate the number of individuals which are exposed to the information shock. Typically, these two variables show a strong positive correlation.

charitable donations (columns (3) and (4)). The magnitude of the effect implies that 10% increase in the difference in political ads expenditures across the border leads to 0.07% decrease in charitable donations differential.

In sum, the results from Table 3 indicate that the political ads increase political giving and decrease charitable giving. Moreover, we combine the estimates to quantify the degree of crowd out. The estimates presented above imply that political donations crowd out charitable donations by a factor of 0.079 ($= \frac{0.73\%}{9.22\%}$). This crowding out factor is smaller than the corresponding estimate reported based on the natural disasters, but still in the same order of magnitude.[13]

In Table 3, we also estimate the impact of political ads on disaggregated retail expenses from Nielsen. We find that, consistent with the results for natural disasters, retail expenses do not negatively respond to political ads. The coefficient for the cross-border difference in political ads is 0.0581% for Nielsen expenditures in column (5), which is close to zero, statistically insignificant and also precisely estimated. As a result, we can rule out the negative effects of up to 0.17%. For the sake of comparison, our baseline coefficients from columns (1) and (3) imply effects of 9% and 0.77% on political giving and charitable giving, respectively.

Appendix A presents robustness checks. We show that results are robust to slight changes in the estimation window (Appendix A.9). Also, we explore whether the results are partially due to a strategic response from the Red Cross – i.e., the organization could have anticipated that increased political advertising will steal donors' attention away or will reduce individuals' budget for giving and, as a result, reduced the number of solicitations they send. We show that the data does not support that mechanism (Appendix A.10).

5 Discussion

In this section, we discuss the interpretation of our findings as well as some of their implications. We find that political and charitable giving crowd out each other. More specifically, we find that information shocks about natural disasters have a significant positive impact on charitable donations, however, they also have a smaller and a negative indirect impact on political donations. These

[13]There are at least two potential reasons why this ratio is different from the ratio for foreign natural disasters. First, the nature of the shocks is different, since political ads are anticipated, at least to some extent. Second, Red Cross contributions could be more sensitive to major TV events compared to political ones, thus the impact of different kinds of shocks could be asymmetric here.

results suggest that either an unobserved variable moves both political and charitable donations together but in opposite directions, or these two accounts of giving are considered substitutes by at least some individuals and move based on similar motivations.

One simple explanation for the observed crowding out is that giving to charitable and political causes are both motivated by the same type of other-regarding preferences. A pure altruism explanation for political giving is not consistent with the observed pattern, because donations, which increase the welfare of disaster victims, do not help politicians, and donations that reward domestic politicians do not increase the welfare of victims of a natural disaster abroad. Warmglow, however, can explain the observed substitution pattern. A number of studies provide empirical evidence that charitable giving is motivated by warmglow (Andreoni, 1989, 1995; Crumpler and Grossman, 2008). Similarly, DellaVigna et al. (2016) provide evidence that voting in elections is motivated by warmglow: an individual's desire to broadcast having taken an action. Such intrinsic motivations can also drive giving to political candidates because of the feel-good effect on the donor. Since charitable and political donations are imperfect substitutes, we can conclude that not all charitable or political donations are motivated by warmglow, but some are. People use both types of contributions to satisfy their other-regarding preferences, and have to allocate resources between the two in the presence of budget constraint. As a result, a shock to the "emotional attachment" to a specific cause (such as a natural disaster or a political ad) leads individuals to make a larger donations to this cause and and a smaller donation to the alternative cause. Another model that can explain the results is mental accounting (Thaler, 1985, 1999; Hastings and Shapiro, 2013). If charitable and political giving are bucketed under the same mental account, increased giving in one donation category would disproportionately crowd out other donation categories such as charitable giving.

Our evidence has implications for our understanding of the motivations behind political donations. Economists and political scientists have studied individual motivations for giving to politicians. A large part of the literature from these research studies remains inconclusive. A large part of the literature either assumes or argues that campaign contributions are made with some instrumental motivation. For small donations, however, the possibility of influencing a politician's policy position is practically impossible and thus this instrumental channel seems puzzling. Instead, our evidence supports the view that political donations are driven by other-regarding preferences. In the words of Ansolabehere et al. (2003): "political giving should be regarded as a form of con-

sumption not unlike giving to charities, such as the United Way or public radio." Last, our findings imply that researchers could use the substitutability between political and charitable giving for identifying the causal effects of these donations. In Appendix A.11 we provide a proof of concept, by using foreign disasters to measure the effects of campaign donations on electoral outcomes. The results suggest that higher campaign contributions hurt, rather than help, the electoral prospects of the incumbents.

6 Conclusions

We provide evidence that individuals see political donations and charitable donations as substitutes. Using data from the American Red Cross and the Federal Election Commission, we show that foreign natural disasters can act as information shocks to the need for charitable giving and thus decrease political contributions, and that political advertising can act as information shocks to the need for political contributions and thus decrease charitable donations. In other words, we provide evidence that political and charitable giving crowd out each other.

Our findings suggest that small political donations are not driven by instrumental motives. Instead, these donations may be driven by the same factors believed to drive charitable giving such as altruism and warm-glow. Our findings also imply that policies aimed at promoting or restricting one type of donation could have unintended consequences for other type of donations. For example, relaxing restrictions on campaign contributions could unintentionally result in lower charitable contributions. For fundraisers in the political and charitable sectors, or findings suggest that charitable organizations may expect electoral cycles to affect their fundraising efforts as political advertisements and campaigns encourage individuals to make political contributions.

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Table 1: Disaster Information Shocks, Charitable and Political Contributions

	Charitable Contributions			Political Contributions		
	(1)	(2)	(3)	(4)	(5)	(6)
$I^{+0/+6}$	0.284***	0.271***	0.302***	-0.0393**	-0.0407**	-0.0393**
	(0.0868)	(0.0903)	(0.0908)	(0.0183)	(0.0184)	(0.0187)
$I^{-2/-1}$		-0.0985	-0.0730		-0.0189	-0.0175
		(0.125)	(0.124)		(0.0225)	(0.0225)
$I^{+7/+8}$			0.219*			0.0150
			(0.117)			(0.0222)
Observations	740,280	740,280	740,280	1,077,215	1,077,215	1,077,215
R-squared	0.474	0.474	0.475	0.670	0.670	0.670
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Mailing Controls	Yes	Yes	Yes	Yes	Yes	Yes
Donations	All	All	All	All	All	All

Notes: * significant at the 10% level, ** at the 5% level, *** at the 1% level. Heteroscedasticity-robust standard errors, adjusted for clusters by state and week, in brackets. The dependent variable is aggregate Red Cross donations in a given county and week, transformed with inverse hyperbolic sine transformation ($y = log\left(x + (x^2 + 1)^{1/2}\right)$). Columns 1-3 include all observations, while columns 4-6 include only observations with non zero values of the dependent variable. Mailing controls include log of the numbers of mailings sent by Red Cross in the 3 months preceding donation. There are no observations with zero preceding mailings in the sample. The time period in 2006-2011. $I^{+0/+6}$ is a dummy, which equals 1 for the week of disaster and 6 weeks after that. $I^{+7/+8}$ is a dummy, which equals 1 for weeks 7 and 8 after the disaster, to allow for delayed effects. $I^{-2/-1}$ is a dummy, which equals 1 for weeks 1 and 2 preceding the disaster, to check for (placebo) anticipation effects.

Table 2: Disaster Information Shocks and Retail Expenditures

	Retail Expenses		
	(1)	(2)	(3)
$I^{+0/+6}$	0.00798*	0.00838*	0.00701
	(0.00468)	(0.00473)	(0.00478)
$I^{-2/-1}$		0.00332	0.00217
		(0.00580)	(0.00585)
$I^{+7/+8}$			-0.00966*
			(0.00526)
Observations	645,768	645,768	645,768
R-squared	0.844	0.844	0.844
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Expenses	All	All	All

Notes: * significant at the 10% level, ** at the 5% level, *** at the 1% level. Heteroscedasticity-robust standard errors, adjusted for clusters by week, in brackets. The dependent variable is aggregate retail expenses in a given county and week from Nielsen, transformed with inverse hyperbolic sine transformation ($y = log\left(x + (x^2+1)^{1/2}\right)$). $I^{+0/+6}$ is a dummy, which equals 1 for the week of disaster and 6 weeks after that. $I^{+7/+8}$ is a dummy, which equals 1 for weeks 7 and 8 after the disaster, to allow for delayed effects. $I^{-2/-1}$ is a dummy, which equals 1 for weeks 1 and 2 preceding the disaster, to check for (placebo) anticipation effects. ($y = log\left(x + (x^2+1)^{1/2}\right)$).

Table 3: Political Ads, Donations, and Nielsen Retail Expenditures

	Political Contributions		Charitable Contributions		Retail Expenses	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta(D_{pc,t}^{+0/+1})$	0.0922***	0.0907***	-0.00733**	-0.00779***	0.000581	0.000625
	(0.00961)	(0.00972)	(0.00302)	(0.00301)	(0.00139)	(0.00131)
$\Delta(D_{pc,t}^{-1})$		0.0125		0.00148		-0.000221
		(0.00745)		(0.00251)		(0.000663)
Observations	7,075	7,075	19,690	19,690	20,037	20,037
R-squared	0.876	0.876	0.589	0.589	0.448	0.448
County Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
RC Mailing Controls	No	No	Yes	Yes	No	No

Notes: * significant at the 10% level, ** at the 5% level, *** at the 1% level. Heteroscedasticity-robust standard errors, adjusted for clusters by state, in brackets. The results for political donations (columns 1 and 2) are estimated for the set of counties within the same congressional district, but located on different sides of corresponding DMA border. The dependent variable is the difference in aggregate political donations from FEC, charitable donations from RC, and retail expenses from Nielsen between two counties across the border in the same week, transformed with inverse hyperbolic sine transformation ($y = log\left(x + (x^2+1)^{1/2}\right)$). Independent variable is the difference in aggregate political ads expenditures across the border in the same week , transformed with inverse hyperbolic sine transformation ($y = log\left(x + (x^2+1)^{1/2}\right)$). The exact specification run is $\Delta Y_{pc,t} = \alpha_1 \Delta(D_{pc,t}^{+0/+1}) + \alpha_2 \Delta(D_{pc,t}^{-1}) + \theta \Delta \mathbf{X}_{pc} + \epsilon_{pc,t}$ with both differences taken for variables, transformed with inverse hyperbolic sine transformation.

Online Appendix: For Online Publication Only

A Additional Analysis and Robustness Checks

A.1 Summary Statistics

Tables A.1–A.4 provide summary statistics for the Red Cross and FEC data sets.

A.2 Time Series Version of the Effects of Disasters

As an alternative to the county-level results, we start with the time-series specification:

$$Y_t = \alpha_1 \cdot I_t^{+0/+6} + \left[\alpha_2 \cdot I_t^{+7/+8} + \alpha_3 \cdot I_t^{-2/-1}\right] + \mathbf{X_t}\beta + \epsilon_t \tag{A.1}$$

The dependent variable Y_t stands for either the total contributions to the Red Cross in week t or the total contributions to political campaigns. In the time series dataset, there are no zeroes so we can use the logarithm of contributions as dependent variable. The binary variable $I_t^{+0/+6}$ takes the value of 1 during the week of the disaster t and the following 6 weeks. The binary variable $I_t^{+7/+8}$ takes the value 1 during the seventh and eight week after the disaster. The variable $I_t^{-2/-1}$ takes the value 1 during the two weeks before the start of the disaster. $\mathbf{X_t}$ is a vector of control variables: month-of-the-year dummies, year dummies and the time until the next election (to control for the fact that donations to politics are more likely to arrive closer to the election date).

The timeline for disasters is shown in Figure A.1. The time series results are presented in Table A.5. The results for charitable donations are reported in columns (1)–(3), and the results for political donations are reported in columns (4)–(6). Column (1) suggests that the charitable donations to RC increase by approximately 41.7% during the 6 weeks following a disaster. This effect is statistically significant at 1% level. In column (2), we add the variable $I_t^{-2/-1}$ for the event-study falsification test. The coefficient on $I_t^{+0/+6}$ remains almost the same in terms of its magnitude and statistical significance. On the contrary, the coefficient on $I_t^{-2/-1}$ is closer to zero, has the opposite sign and is statistically insignificant. This evidence supports the premise that the timing of the disasters is indeed as good as random. Column (3) also includes the variable $I_t^{+7/+8}$. The coefficient on this variable is smaller and statistically insignificant, indicating that, consistent

with the anecdotal accounts, the effects on charitable contributions are concentrated in the first six weeks after the disaster hits. In sum, columns (1)–(3) show that foreign natural disasters constitute a positive shock to domestic charitable donations.

The time series results for the placebo effects are presented in Table A.6. With the time series dataset we can look at two additional placebo outcomes that are not available for the county-level dataset:

Redbook Retail Index. Johnson Redbook index data come from the website tradingeconomics.com and include measures of sales growth in the U.S. retail sales. The index is based on the sales data of around 9,000 large general merchandise retailers representing over 80% of the equivalent official retail sales series collected and published by the U.S. Department of Commerce.[14]

Lottery Purchases. We gather data on lottery purchases from lottoreport.com, which summarizes the total Mega Millions lottery sales from the states GA, IL, MD, MA, MI, NJ, NY, OH, TX, VA and WA.

The placebo effects are presented in Table A.6. There is not a significant decrease in these expenses following foreign natural disasters, since all the coefficients in the table are positive rather than negative, though not statistically significant. Based on these numbers, we can rule out negative effects of up to 1.1% decrease (for lottery tickets), 0.02% decrease (retail expenses based on Redbook), or 0.4% decrease (retail expenses based on Nielsen), thus the null effect is quite precisely estimated.

In turn, columns (4)–(6) of Table A.5 show that foreign natural disasters have a negative and significant effect on political contributions. The coefficient on $I_t^{+0/+6}$ from column (4) indicates that, in the six weeks after a disaster hits, there is an average decline in political giving of 17.2%.[15] The coefficients on $I_t^{-2/-1}$ from columns (5)–(6) show that there are no pre-trends: these coefficients are closer to zero and statistically insignificant. The coefficient on $I_t^{+7/+8}$ from column (6) indicates that the effects on political giving are also concentrated in the six weeks after the disaster hits. Overall, the results in columns (4)–(6) that natural disasters negatively affect political donations suggest that charitable donations crowd out political donations.

Table A.7 replicates Table A.5, however in columns (4)–(6) includes only the years for which the

[14]Source: https://tradingeconomics.com/united-states/redbook-index

[15]Note that one potential challenge for this specification is whether a domestic politician is using foreign natural disasters to emphasize the benefits of his or her policies to raise funds, but since the indirect effect is negative, this story is less likely to hold.

data from Red Cross is available. The results for political donations are larger in magnitudes, but are generally consistent with the results for the longer sample. Note that the results for the longer sample from Tables A.5 are thus more conservative. Also, note that the time-series and county-level results should not necessarily be equal in magnitude because of county-level heterogeneity in size and treatment effects.

A.3 Effects on the Number of Donors

Tables A.8 and A.9 test for the impact of disaster information shocks at the extensive margin, investigating if there is a change in the number of donors for RC and politicians, respectively. The evidence in the table is consistent with the evidence provided in Tables 1 and 3. In Table A.8 in all specifications given in columns (1)–(6), disaster information shock significantly increases the number of donors to RC, and in Table A.9 in all columns, the same shock decreases the number of donors to political donations within the 6-week period following a disaster.

A.4 Fatality Threshold

In the benchmark specifications, we assumed that charitable information shocks come from large disasters resulting in 300 fatalities at a minimum. As a robustness check, we vary the fatality threshold in the range of 240 to 360 fatalities in Table A.10. The results from these specifications show that, for both political and charitable donations, the coefficient of the disaster information shock for a period of 6 weeks after a disaster strikes is always significant and has the same sign with fatality threshold of 300. All specifications include the falsification check of the two weeks before the disaster date, and these coefficients are insignificant in all specifications. The magnitudes of the impact of disaster information shocks vary between 0.392 and 0.432 for charitable donations and between -0.174 and -0.134 for political contributions, indicating that the effect is fairly robust to disaster thresholds set in this range.

Table A.11 shows the robustness of the main results to small changes in the definition of a large foreign natural disaster and replicates the results from A.10 for the county-week analysis. The coefficients for charitable contributions range from 0.213 to 0.310 and are significant at least at the 5% level for all the modifications. The coefficients for political contributions range from -0.0487 to -0.0809, but they are less precisely estimated, with 1 out of 12 coefficients even losing statistical

significance at the conventional level. Out of remaining coefficients, 8 are significant at 5% level and 3 are significant at 10% level.

A.5 Data Time Period

Another concern is that the results may be driven by particular outliers, such as a year with many disasters or an intense political race. To assess the robustness of the results, Table A.12 reports our key specification excluding one year of data from the sample for each year in the study period. The coefficients of the information shock are significant for exclusion of each year, and for both the charitable and political contributions. If we reproduce the results leaving-one-year-out, we get similar results, with positive coefficients for charitable donations ranging from 0.278 to 0.565 (baseline coefficient being 0.432) and significant at least at 5% level, and with negative coefficients ranging from -0.146 to -0.208 (baseline coefficient being -0.174) and significant at least at 5% level. Moreover, we should note that all the falsification checks still remain insignificant.

A.6 RC Mailings as Control Variable

Table A.13 replicates Table 1 excluding RC's mailing controls, and demonstrates very similar results to this table, both in magnitudes and in significance.

A.7 Post-Disaster Window

Tables A.14 and A.15 show the robustness of the results to small changes in the definition of post-disaster window.

A.8 Heterogeneity of Effects of Disasters by Political Party

Despite some arguments in the literature that Republicans exhibit different patterns of charitable giving (Brooks, 2006), we were not able to identify any differences in the substitution effects by party. For instance, Table A.16 reports the impact of disasters on the donations to the Democrat and Republican politicians in time series analysis, separately. The coefficients (0.159 and 0.189) are too similar to be statistically different. Similarly, tables A.17 and A.18 report the results of county level analysis by party. The baseline coefficients (-0.335 and -0.348 in columns 1) are, again, very close in magnitudes. As a result, we were not able to identify partisan differences in responses.

A.9 Alternative Time Windows for the Political Ads

Table A.19 reproduces the main results on political advertising, but considering alternative windows after political ads were aired. To use slight modifications of estimation window, we go back to weekly data, with the results for 8 weeks after ads were aired approximately corresponding to baseline specification (Table 3). More specifically, our estimated model is $\Delta Y_{pc,t} = \alpha_1 \Delta Log(D_{pc,t}^{+0/+8}) + \alpha_2 \Delta Log(D_{pc,t}^{-2/-1}) + \theta \Delta \mathbf{X}_{pc,t} + \epsilon_{pc,t}$. We also report the results for 7 and 9 week window. The results are qualitatively robust. The magnitudes are smaller though, but that's mostly due to the fact that the dependent variable is constructed at the weekly rather than monthly level.

A.10 RC Mailings as Dependent Variable

Table A.20 compares the baseline elasticity coefficients from Table 3 with elasticity coefficients for RC mailings, showing that Red Cross was increasing rather than decreasing its mail fundraising efforts in times of political campaigns in places, most affected by political ads. To deal with this possibility, we estimated specification (2) but using the number of charitable mailings as the dependent variable. In Table A.20 we find that, on the contrary, Red Cross increases rather than decreasing its mailing activity in times of political campaigns in most affected places, with elasticity of mailings with respect to political ads expenditures being 4.1% (significant at 1% level). Thus, if anything, that would bias our estimates in Table 3 downward.

A.11 Disasters, Donations, and Electoral Outcomes

The relationships that we identify in the main body of the paper also allow us to study the impact of donations on the outcomes that they are supposed to affect. As a proof of concept, here we present the results of two stage analysis of political donations on the outcomes of the races they could affect. In particular, for the estimation we use the following three step procedure:

$$Charitable_{c,t} = \alpha_1 \cdot I_t^{+0/+6} + \left[\alpha_2 \cdot I_t^{+7/+8} + \alpha_3 \cdot I_t^{-2/-1}\right] + \mathbf{X_{c,t}}\beta_1 + \epsilon_{c,t} \tag{A.2}$$

$$Political_{c,t} = \delta_1 \cdot Charitable_{c,t} + \mathbf{X_{c,t}}\beta_2 + \zeta_{c,t} \tag{A.3}$$

$$Outcome_{d,y} = \gamma_1 \cdot \hat{Political}_{d,y} + \mathbf{S_{d,y}}\beta_3 + \eta_{d,y} \tag{A.4}$$

Here we first estimate the relationship between political and charitable donations at county-week level using an instrumental variable strategy. We then predict political donations from this model (equation A.3), essentially using variation in the timing of natural disaster and local relationship between charitable and political giving for prediction. Finally, we test how election-level outcomes (at district-year level) depend on political donations, predicted by the natural disasters (equation A.4). To compute standard errors in this nonstandard case, we use bootstrapped standard errors adjusted for clusters by state and year. Essentially, we test whether exogenous variation in political donations over the course of the campaign predicts a better or worse performance by the incumbents.

Table A.21 presents the results of the last stage of the estimation. Specifically, it demonstrates how the vote share and the likelihood of winning change based on the political donations predicted considering the interruptions from disasters which channel individual donations to charity. The table shows that lower aggregate donations improve, rather than hurt, the electoral prospects of incumbents, with vote share of challengers going up by 1.2 p.p. if political donations go up by 10 percent (column 1, coefficient significant at 1% level). Relatedly, the probability of winning by challenger goes up by 3.5 p.p. if political donations go up by 10 percent (column 2, coefficient is less precise, but is still significant at 10% level). Table A.22 runs the same specification, using the predicted political donations for the next political cycle instead, as a placebo specification. As expected, the effects found in Table A.21 disappear with this modification.

Overall, the results in Table A.21 are consistent with the idea that, in contrast to Avis et al. (2017), more money in politics hurt rather than help the electoral prospects of the incumbents. One potential explanation is that we observe Local Average Treatment Effect, i.e., we only see the changes in donations which are sensitive to the presence of natural disasters. And these kinds of donations can have different implications for donations from Political Action Committees or Special Interest Groups.

Figure A.1: Disasters from the first week of 2000 to the last week of 2014.

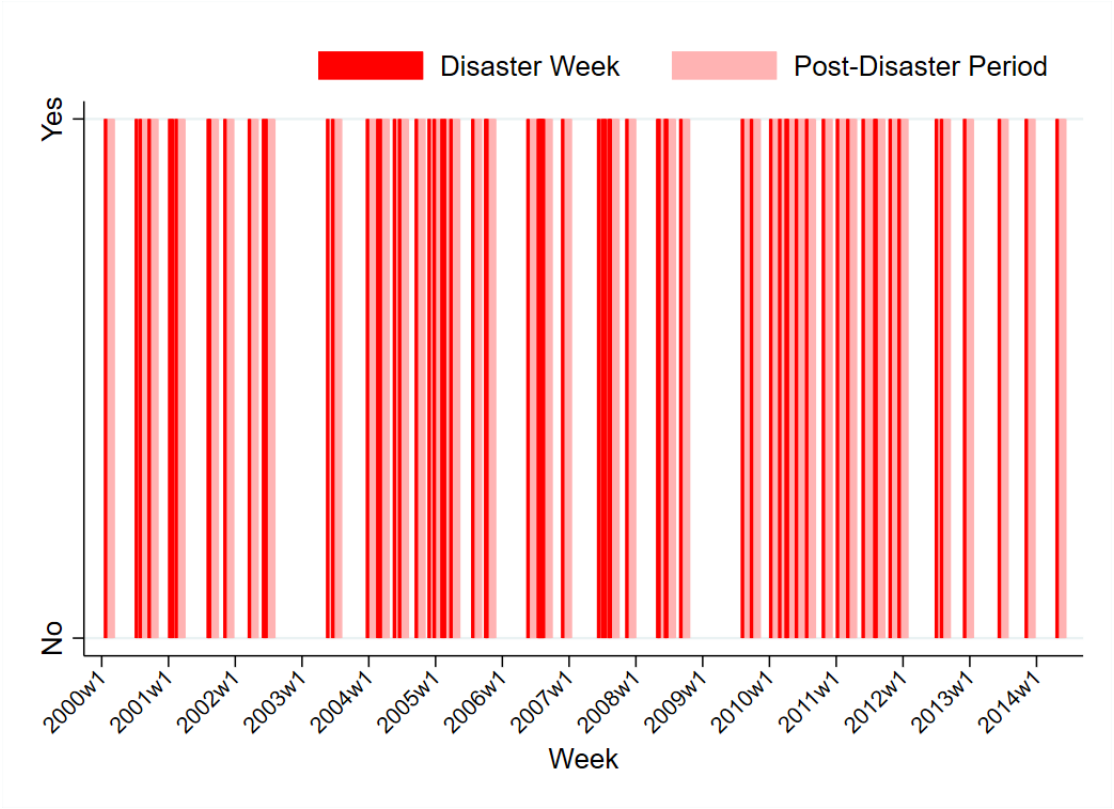


Table A.1: Summary Statistics for Variables Used in the Time Series Analysis

	N	Mean	SD	Median	Min	Max	Range
Log (Aggregate RC Donations)	300	11.55	0.97	11.61	7.65	14.71	06w1-11w40
Log (Aggregate Political Donations)	728	16.54	0.74	16.51	14.68	18.82	01w1-14w52
$I^{+0/+6}$	728	0.46	0.5	0	0	1	01w1-14w52
$I^{-2/-1}$	728	0.16	0.37	0	0	1	01w1-14w52
$I^{+7/+8}$	728	0.16	0.37	0	0	1	01w1-14w52
Distance to Elections	728	51.5	30.04	51.5	0	103	01w1-14w52
Log (Lottery Tickets Expenses)	441	17.44	0.46	17.3	16.76	19.11	03w28-11w52
Log (RedBook Index)	468	4.71	0.06	4.69	4.59	4.93	06w1-14w52
Log (Nielsen index)	415	4.52	0.09	4.5	4.37	4.93	07w1-14w51
Log (Aggregate Political Donations,Democrats)	728	14.99	0.89	15	12.2	17.45	01w1-14w52
Log (Aggregate Political Donations,Republicans)	728	15.13	0.75	15.17	12.85	17.05	01w1-14w52

Table A.2: Summary Statistics for Variables at the County Level

	N	Mean	SD	Median	Min	Max	Range
Aggregate RC donations, county	746417	1.38	2.34	0	0	12.46	06w1-11w40
No. of RC donations, county	746417	0.41	0.81	0	0	8.28	01w1-14w52
RC mailings in the past period	746417	0.42	0.68	0	0	5.27	06w1-11w40
$I^{+0/+6}$	1010109	0.47	0.5	0	0	1	01w1-14w52
$I^{-2/-1}$	1010109	0.16	0.37	0	0	1	01w1-14w52
$I^{+7/+8}$	1010109	0.17	0.38	0	0	1	01w1-14w52
Distance to Elections	1010109	56.64	30.11	59	0	103	01w1-14w52
Aggregate political donations, county	1010109	8.13	1.73	7.82	0	17.98	01w1-14w52
No. of political donations, county	1010109	2	1.28	1.44	0.88	9.09	01w1-14w52

Notes: All donations variables are computed with inverse hyperbolic sine transformation.

Table A.3: Summary Statistics for Variables at the County-Month Level

	N	Mean	SD	Median	Min	Max	Range
Difference in political donations in a county-pair-month	7075	2.15	13.5	2.56	-26.71	27.67	2008m2-2010m12
$\Delta(D^{+0/+1})$, political ad expenses in a county-pair-month, FEC sample	7075	1.4	12.6	0	-33.73	34.58	2008m2-2010m12
$\Delta(D^{-1})$, political ad expenses in a county-pair-month, FEC sample	7075	1.27	13.43	0	-35.56	35.62	2008m2-2010m12
Difference in RC donations in a county-pair-month	21480	0.41	5.95	0	-18.44	22.22	2008m2-2010m12
Difference in RC mailings in a county-pair-month	21480	0.32	4.18	0	-15.14	19.27	2008m2-2010m12
$\Delta(D^{+0/+1})$, political ad expenses in a county-pair-month, RC sample	21480	1.07	11.87	0	-34.58	34.58	2008m2-2010m12
$\Delta(D^{-1})$, political ad expenses in a county-pair-month, RC sample	21480	1.08	13.11	0	-35.56	35.62	2008m2-2010m12
Difference in Nielsen retail expenses in a county-pair-month	7075	0.09	2.04	0	-10.14	9.51	2008m2-2010m12

Notes: Unit of observations is county-pair-month. All donations and expenses variables are constructed with the use of inverse logarithmic sine transformation. The data on Congressional political advertising from Wisconsin Advertising Project is only available for 2008 and 2010 for the sample, for which Red Cross data is available.

Table A.4: Summary Statistics for Variables at the District-Year Level

	N	Mean	SD	Median	Min	Max	Range
Predicted logged aggregate political donations	2,456	15.85	1.07	15.93	11.69	17.67	2006-2010
Predicted future aggregate political donations, year t+1	2,456	15.39	1.21	15.43	10.85	17.74	2006-2010
Predicted future aggregate political donations, year t+2	1,615	15.98	1.04	16.16	12.77	17.67	2006-2008
Vote margin	2,437	0.27	0.19	0.26	0	0.93	2006-2010
Vote share, incumbents	1,148	0.66	0.13	0.65	0.34	1	2006-2010
Winning dummy, incumbents	1,167	0.92	0.27	1	0	1	2006-2010
Votes share, challengers	1,268	0.37	0.12	0.37	0.03	0.9	2006-2010
Winning dummy, challengers	1,269	0.16	0.37	0	0	1	2006-2010

Table A.5: Disaster Information Shocks and Contributions (Time Series)

	Charitable			Political		
	(1)	(2)	(3)	(4)	(5)	(6)
$I^{+0/+6}$	0.417***	0.428***	0.455***	-0.0877***	-0.0916***	-0.0904***
	(0.0937)	(0.0963)	(0.0999)	(0.0254)	(0.0254)	(0.0256)
$I^{+7/+8}$			0.176			0.0136
			(0.111)			(0.0304)
$I^{-2/-1}$		0.109	0.124		-0.0529	-0.0518
		(0.126)	(0.127)		(0.0327)	(0.0326)
Time Range	06w1-11w40	06w1-11w40	06w1-11w40	01w1-14w52	01w1-14w52	01w1-14w52
No. of Disasters	32	32	32	65	65	65
No. of Weeks	300	300	300	728	728	728

Notes: * significant at the 10% level, ** at the 5% level, *** at the 1% level. Heteroscedasticity-robust standard errors in parentheses. The dependent variables are constructed with natural log transformation. Controls included: month fixed effects, year fixed effects, distance to elections. The effect of disasters on Political Contributions is using the full sample of donations. $I^{+0/+6}$ is a dummy, which equals 1 for the week of disaster and 6 weeks after that. $I^{+7/+8}$ is a dummy, which equals 1 for weeks 7 and 8 after the disaster, to allow for delayed effects. $I^{-2/-1}$ is a dummy, which equals 1 for weeks 1 and 2 preceding the disaster, to check for (placebo) anticipation effects.

Table A.6: Effect of Natural Disasters on Placebo Outcomes: Lottery and Retail Activity

	Lottery			Retail Spending, Redbook			Retail Spending, Nielsen		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$I^{+0/+6}$	0.0312	0.0254	0.0272	0.00333	0.00358	0.00397	0.00313	0.00328	0.00254
	(0.0256)	(0.0246)	(0.0259)	(0.00215)	(0.00212)	(0.00215)	(0.00444)	(0.00439)	(0.00446)
$I^{+7/+8}$			0.0124			0.00269			-0.00427
			(0.0301)			(0.00226)			(0.00465)
$I^{-2/-1}$		-0.0576	-0.0566		0.00246	0.00269		0.00146	0.00100
		(0.0376)	(0.0374)		(0.00245)	(0.00247)		(0.00497)	(0.00502)
Time Range	06w1-11w40	06w1-11w40	06w1-11w40	06w1-11w40	06w1-11w40	06w1-11w40	07w1-11w40	07w1-11w40	07w1-11w40
No. of Disasters	32	32	32	32	32	32	25	25	25
No. of Weeks	300	300	300	300	300	300	248	248	248

Notes: * significant at the 10% level, ** at the 5% level, *** at the 1% level. Heteroscedasticity-robust standard errors in parenthesis. The dependent variables are constructed with natural log transformation. $I^{+0/+6}$ is a dummy, which equals 1 for the week of disaster and 6 weeks after that. $I^{+7/+8}$ is a dummy, which equals 1 for weeks 7 and 8 after the disaster, to allow for delayed effects. $I^{-2/-1}$ is a dummy, which equals 1 for weeks 1 and 2 preceding the disaster, to check for (placebo) anticipation effects.

Table A.7: Disaster Information Shocks and Contributions (time series), Same Time Period

	Charitable			Political		
	(1)	(2)	(3)	(4)	(5)	(6)
$I^{+0/+6}$	0.417***	0.428***	0.455***	-0.154***	-0.157***	-0.165***
	(0.0937)	(0.0963)	(0.0999)	(0.0408)	(0.0406)	(0.0420)
$I^{+7/+8}$			0.176			-0.0508
			(0.111)			(0.0433)
$I^{-2/-1}$		0.109	0.124		-0.0278	-0.0320
		(0.126)	(0.127)		(0.0467)	(0.0463)
Time Range	06w1-11w40	06w1-11w40	06w1-11w40	06w1-11w40	06w1-11w40	06w1-11w40
No. of Disasters	32	32	32	32	32	32
No. of Weeks	300	300	300	300	300	300

Notes: * significant at the 10% level, ** at the 5% level, *** at the 1% level. Heteroscedasticity-robust standard errors in parentheses. The dependent variables are constructed with natural log transformation. Controls included: month fixed effects, year fixed effects, distance to elections. $I^{+0/+6}$ is a dummy, which equals 1 for the week of disaster and 6 weeks after that. $I^{+7/+8}$ is a dummy, which equals 1 for weeks 7 and 8 after the disaster, to allow for delayed effects. $I^{-2/-1}$ is a dummy, which equals 1 for weeks 1 and 2 preceding the disaster, to check for (placebo) anticipation effects. In contrast to Table A.5, columns (4)–(6) of this table include only years for which the data from American Red Cross is available.

Table A.8: Disaster Information Shocks and Number of Charitable Contributions (County Level)

	Aggregate Charitable Contributions					
	(1)	(2)	(3)	(4)	(5)	(6)
$I^{+0/+6}$	0.284***	0.271***	0.302***	0.228***	0.237***	0.246***
	(0.0868)	(0.0903)	(0.0908)	(0.0515)	(0.0535)	(0.0541)
$I^{-2/-1}$		-0.0985	-0.0730		0.106	0.115
		(0.125)	(0.124)		(0.0802)	(0.0798)
$I^{+7/+8}$			0.219*			0.0627
			(0.117)			(0.0652)
Observations	740,280	740,280	740,280	205,976	205,976	205,976
R-squared	0.474	0.474	0.475	0.432	0.433	0.433
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Mailing Controls	Yes	Yes	Yes	Yes	Yes	Yes
Donations	All	All	All	Nonzero	Nonzero	Nonzero

Notes: * significant at the 10% level, ** at the 5% level, *** at the 1% level. Heteroscedasticity-robust standard errors, adjusted for clusters by state and week, in brackets. The dependent variable is aggregate Red Cross donations in a given county and week, transformed with inverse hyperbolic sine transformation ($y = log\left(x + (x^2 + 1)^{1/2}\right)$). Columns 1-3 include all observations, while columns 4-6 include only observations with non zero values of the dependent variable. Mailing controls include log of the numbers of mailings sent by Red Cross in the 3 months preceding donation. There are no observations with zero preceding mailings in the sample. The time period in 2006-2011. $I^{+0/+6}$ is a dummy, which equals 1 for the week of disaster and 6 weeks after that. $I^{+7/+8}$ is a dummy, which equals 1 for weeks 7 and 8 after the disaster, to allow for delayed effects. $I^{-2/-1}$ is a dummy, which equals 1 for weeks 1 and 2 preceding the disaster, to check for (placebo) anticipation effects.

Table A.9: Disaster Information Shocks and Number of Political Contributions (County Level)

	Political Contributions					
	(1)	(2)	(3)	(4)	(5)	(6)
$I^{+0/+6}$	-0.0375**	-0.0385**	-0.0363*	-0.0375**	-0.0385**	-0.0363*
	(0.0186)	(0.0188)	(0.0190)	(0.0186)	(0.0188)	(0.0190)
$I^{-2/-1}$		-0.0138	-0.0114		-0.0138	-0.0114
		(0.0226)	(0.0226)		(0.0226)	(0.0226)
$I^{+7/+8}$			0.0254			0.0254
			(0.0225)			(0.0225)
Observations	1,010,109	1,010,109	1,010,109	1,010,109	1,010,109	1,010,109
R-squared	0.653	0.653	0.653	0.653	0.653	0.653
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Mailing Controls	Yes	Yes	Yes	Yes	Yes	Yes
Donations	All	All	All	Nonzero	Nonzero	Nonzero

Notes: * significant at the 10% level, ** at the 5% level, *** at the 1% level. Heteroscedasticity-robust standard errors, adjusted for clusters by state and week, in brackets. The dependent variable is aggregate political donations to Congressional and Presidential candidates in a given county and week from Federal Election Commission, transformed with inverse hyperbolic sine transformation ($y = log\left(x + (x^2 + 1)^{1/2}\right)$). Columns 1-3 include all observations, while columns 4-6 include only observations with non zero values of the dependent variable. The time period in 2006-2011. $I^{+0/+6}$ is a dummy, which equals 1 for the week of disaster and 6 weeks after that. $I^{+7/+8}$ is a dummy, which equals 1 for weeks 7 and 8 after the disaster, to allow for delayed effects. $I^{-2/-1}$ is a dummy, which equals 1 for weeks 1 and 2 preceding the disaster, to check for (placebo) anticipation effects.

Table A.10: Robustness Check: Fatality Thresholds (Time Series)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Charitable Contributions			
$I^{+0/+6}$	0.432***	0.392***	0.406***	0.406***	0.432***	0.432***	0.432***
	(0.0964)	(0.0945)	(0.0985)	(0.0981)	(0.0964)	(0.0964)	(0.0964)
$I^{-2/-1}$	0.111	0.111	0.106	0.107	0.111	0.111	0.111
	(0.127)	(0.122)	(0.116)	(0.114)	(0.127)	(0.127)	(0.127)
				Political Contributions			
$I^{+0/+6}$	-0.174***	-0.134**	-0.138**	-0.137**	-0.174***	-0.174***	-0.174***
	(0.0458)	(0.0442)	(0.0450)	(0.0449)	(0.0458)	(0.0458)	(0.0458)
$I^{-2/-1}$	-0.0222	-0.00850	-0.0148	0.000514	-0.0222	-0.0222	-0.0222
	(0.0522)	(0.0526)	(0.0500)	(0.0490)	(0.0522)	(0.0522)	(0.0522)
Disaster Fatality Threshold	300	280	260	240	320	340	360
No. of Disaster Weeks	32	34	36	38	32	32	31
Observations	300	300	300	300	300	300	300

Notes: * significant at the 10% level, ** at the 5% level, *** at the 1% level. Heteroscedasticity-robust standard errors, adjusted for clusters by state and week, in brackets. The dependent variables are constructed with natural log transformation. Controls included: month fixed effects, year fixed effects, distance to elections. $I^{+0/+6}$ is a dummy, which equals 1 for the week of disaster and 6 weeks after that. $I^{+7/+8}$ is a dummy, which equals 1 for weeks 7 and 8 after the disaster, to allow for delayed effects. $I^{-2/-1}$ is a dummy, which equals 1 for weeks 1 and 2 preceding the disaster, to check for (placebo) anticipation effects. Columns (4)–(6) of this table include only years for which the data from American Red Cross is available.

Table A.11: Disaster Information Shocks and Political Contributions: Robustness to Disaster Thresholds (County Level)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Charitable Contributions													
$I^{+0/+6}$	0.271***	0.237***	0.215**	0.213***	0.310***	0.213***	0.310***	0.211***	0.271***	0.237***	0.271***	0.237***	0.271***	0.237***
	(0.0903)	(0.0535)	(0.0908)	(0.0545)	(0.0915)	(0.0580)	(0.0910)	(0.0576)	(0.0903)	(0.0535)	(0.0903)	(0.0535)	(0.0903)	(0.0535)
$I^{-2/-1}$	-0.0985	0.106	-0.107	0.0862	-0.0680	0.0828	-0.0698	0.0778	-0.0985	0.106	-0.0985	0.106	-0.0985	0.106
	(0.125)	(0.0802)	(0.118)	(0.0748)	(0.113)	(0.0725)	(0.112)	(0.0721)	(0.125)	(0.0802)	(0.125)	(0.0802)	(0.125)	(0.0802)
Observations	740,280	205,976	740,280	205,976	740,280	205,976	740,280	205,976	740,280	205,976	740,280	205,976	740,280	205,976
R-squared	0.474	0.433	0.473	0.431	0.474	0.431	0.474	0.431	0.474	0.433	0.474	0.433	0.474	0.433
Donations	All	Nonzero	All	Nonzero	All	Nonzero	All	Nonzero	All	Nonzero	All	Nonzero	All	Nonzero
	Political Contributions													
$I^{+0/+6}$	-0.0751**	-0.0809**	-0.0487	-0.0558*	-0.0610*	-0.0700**	-0.0611*	-0.0700**	-0.0751**	-0.0809**	-0.0751**	-0.0809**	-0.0751**	-0.0809**
	(0.0312)	(0.0307)	(0.0306)	(0.0298)	(0.0317)	(0.0305)	(0.0315)	(0.0303)	(0.0312)	(0.0307)	(0.0312)	(0.0307)	(0.0312)	(0.0307)
$I^{-2/-1}$	0.0193	0.0118	0.0347	0.0269	0.0323	0.0241	0.0342	0.0262	0.0193	0.0118	0.0193	0.0118	0.0193	0.0118
	(0.0336)	(0.0329)	(0.0334)	(0.0326)	(0.0320)	(0.0313)	(0.0313)	(0.0305)	(0.0336)	(0.0329)	(0.0336)	(0.0329)	(0.0336)	(0.0329)
Observations	465,898	465,503	465,898	465,503	465,898	465,503	465,898	465,503	465,898	465,503	465,898	465,503	465,898	465,503
R-squared	0.682	0.690	0.682	0.689	0.682	0.690	0.682	0.690	0.682	0.690	0.682	0.690	0.682	0.690
Donations	All	Nonzero	All	Nonzero	All	Nonzero	All	Nonzero	All	Nonzero	All	Nonzero	All	Nonzero
Fatality Threshold	300	300	280	280	260	260	240	240	320	320	340	340	360	360

Notes: * significant at the 10% level, ** at the 5% level, *** at the 1% level. Heteroscedasticity-robust standard errors, adjusted for clusters by state and week, in brackets. The dependent variable is aggregate political donations to Congressional and Presidential candidates in a given county and week from Federal Election Commission, transformed with inverse hyperbolic sine transformation ($y = log\left(x + (x^2+1)^{1/2}\right)$). Columns 1-3 include all observations, while columns 4-6 include only observations with non zero values of the dependent variable. The time period in 2006-2011. $I^{+0/+6}$ is a dummy, which equals 1 for the week of disaster and 6 weeks after that. $I^{+7/+8}$ is a dummy, which equals 1 for weeks 7 and 8 after the disaster, to allow for delayed effects. $I^{-2/-1}$ is a dummy, which equals 1 for weeks 1 and 2 preceding the disaster, to check for (placebo) anticipation effects.

Table A.12: Robustness Check: Exclusion of a Single Year (Time Series)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Charitable Contributions			
$I^{+0/+6}$	0.432***	0.427***	0.374***	0.365***	0.573***	0.278**	0.565***
	(0.0964)	(0.106)	(0.107)	(0.108)	(0.115)	(0.102)	(0.0981)
$I^{-2/-1}$	0.111	0.218	0.0119	0.150	0.199	-0.0607	0.104
	(0.127)	(0.142)	(0.137)	(0.148)	(0.135)	(0.125)	(0.131)
				Political Contributions			
$I^{+0/+6}$	-0.174***	-0.193***	-0.174***	-0.151**	-0.186***	-0.208***	-0.146**
	(0.0458)	(0.0494)	(0.0502)	(0.0534)	(0.0535)	(0.0532)	(0.0484)
$I^{-2/-1}$	-0.0222	-0.0377	-0.0233	0.000667	-0.0373	-0.0815	0.0240
	(0.0522)	(0.0561)	(0.0535)	(0.0587)	(0.0602)	(0.0609)	(0.0545)
Years Excluded	None	2006	2007	2008	2009	2010	2011
Observations	300	248	248	248	248	248	260

Notes: * significant at the 10% level, ** at the 5% level, *** at the 1% level. Heteroscedasticity-robust standard errors, adjusted for clusters by state and week, in brackets. The dependent variables are constructed with natural log transformation. Controls included: month fixed effects, year fixed effects, distance to elections. $I^{+0/+6}$ is a dummy, which equals 1 for the week of disaster and 6 weeks after that. $I^{+7/+8}$ is a dummy, which equals 1 for weeks 7 and 8 after the disaster, to allow for delayed effects. $I^{-2/-1}$ is a dummy, which equals 1 for weeks 1 and 2 preceding the disaster, to check for (placebo) anticipation effects.

Table A.13: Disaster Information Shocks and Charitable Contributions: No Mailing Controls Included (County Level)

	Charitable Contributions					
	(1)	(2)	(3)	(4)	(5)	(6)
$I^{+0/+6}$	0.260***	0.246**	0.279***	0.234***	0.243***	0.253***
	(0.0909)	(0.0943)	(0.0956)	(0.0506)	(0.0524)	(0.0530)
$I^{-2/-1}$		-0.130	-0.102		0.116	0.127
		(0.133)	(0.131)		(0.0824)	(0.0822)
$I^{+7/+8}$			0.254**			0.0751
			(0.117)			(0.0632)
Observations	746,417	746,417	746,417	206,120	206,120	206,120
R-squared	0.462	0.463	0.464	0.429	0.430	0.430
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Mailing Controls	No	No	No	No	No	No
Donantions	All	All	All	All	All	All

Notes: * significant at the 10% level, ** at the 5% level, *** at the 1% level. Heteroscedasticity-robust standard errors, adjusted for clusters by state and week, in brackets. The dependent variable is aggregate Red Cross donations in a given county and week, transformed with inverse hyperbolic sine transformation ($y = log\left(x + (x^2+1)^{1/2}\right)$). Columns 1-3 include all observations, while columns 4-6 include only observations with non zero values of the dependent variable. There are no observations with zero preceding mailings in the sample. The time period in 2006-2011. $I^{+0/+6}$ is a dummy, which equals 1 for the week of disaster and 6 weeks after that. $I^{+7/+8}$ is a dummy, which equals 1 for weeks 7 and 8 after the disaster, to allow for delayed effects. $I^{-2/-1}$ is a dummy, which equals 1 for weeks 1 and 2 preceding the disaster, to check for (placebo) anticipation effects.

Table A.14: Disaster Information Shocks and Charitable Contributions: Robustness to Window Lengths (County Level)

	Charitable Contributions											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$I^{+0/+5}$	0.235**	0.219**	0.261***				0.204***	0.220***	0.236***			
	(0.0919)	(0.0927)	(0.0919)				(0.0582)	(0.0559)	(0.0540)			
$I^{-2/-1}$		-0.0903	-0.0770		-0.0936	-0.0662		0.121	0.128		0.103	0.109
		(0.123)	(0.123)		(0.124)	(0.124)		(0.0796)	(0.0810)		(0.0817)	(0.0822)
$I^{+6/+8}$			0.219*						0.0814			
			(0.110)						(0.0670)			
$I^{+0/+7}$				0.322***	0.310***	0.326***				0.202***	0.211***	0.214***
				(0.0888)	(0.0915)	(0.0908)				(0.0531)	(0.0555)	(0.0554)
$I^{+8/+8}$						0.289**						0.0442
						(0.127)						(0.0761)
Observations	740,280	740,280	740,280	740,280	740,280	740,280	205,976	205,976	205,976	205,976	205,976	205,976
R-squared	0.473	0.473	0.474	0.474	0.474	0.475	0.431	0.432	0.433	0.430	0.431	0.431
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mailing Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Donations	All	All	All	All	All	All	Nonzero	Nonzero	Nonzero	Nonzero	Nonzero	Nonzero

Notes: * significant at the 10% level, ** at the 5% level, *** at the 1% level. Heteroscedasticity-robust standard errors, adjusted for clusters by state and week, in brackets. The dependent variable is aggregate Red Cross donations in a given county and week, transformed with inverse hyperbolic sine transformation ($y = log\left(x + (x^2+1)^{1/2}\right)$). Columns 1-3 include all observations, while columns 4-6 include only observations with non zero values of the dependent variable. Mailing controls include log of the numbers of mailings sent by Red Cross in the 3 months preceding donation. There are no observations with zero preceding mailings in the sample. The time period in 2006-2011. $I^{+0/+6}$ is a dummy, which equals 1 for the week of disaster and 6 weeks after that. $I^{+7/+8}$ is a dummy, which equals 1 for weeks 7 and 8 after the disaster, to allow for delayed effects. $I^{-2/-1}$ is a dummy, which equals 1 for weeks 1 and 2 preceding the disaster, to check for (placebo) anticipation effects.

Table A.15: Disaster Information Shocks and Political Contributions. Robustness to Window Lengths. (County level)

	Political Contributions											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$I^{+0/+5}$	-0.0787***	-0.0766**	-0.0845***				-0.0822***	-0.0812***	-0.0900***			
	(0.0285)	(0.0297)	(0.0308)				(0.0282)	(0.0294)	(0.0302)			
$I^{-2/-1}$		0.0149	0.0126		0.0211	0.0181		0.00729	0.00478		0.0136	0.0103
		(0.0347)	(0.0343)		(0.0335)	(0.0336)		(0.0340)	(0.0335)		(0.0328)	(0.0329)
$I^{+6/+8}$			-0.0403						-0.0449			
			(0.0290)						(0.0285)			
$I^{+0/+7}$				-0.0710**	-0.0687**	-0.0703**				-0.0772**	-0.0757**	-0.0774**
				(0.0310)	(0.0313)	(0.0311)				(0.0303)	(0.0306)	(0.0303)
$I^{+8/+8}$						-0.0284						-0.0304
						(0.0408)						(0.0404)
Observations	465,898	465,898	465,898	465,898	465,898	465,898	465,503	465,503	465,503	465,503	465,503	465,503
R-squared	0.682	0.682	0.682	0.682	0.682	0.682	0.690	0.690	0.690	0.690	0.690	0.690
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Donations	All	All	All	All	All	All	Nonzero	Nonzero	Nonzero	Nonzero	Nonzero	Nonzero

Notes: * significant at the 10% level, ** at the 5% level, *** at the 1% level. Heteroscedasticity-robust standard errors, adjusted for clusters by state and week, in brackets. The dependent variable is aggregate political donations to Congressional and Presidential candidates in a given county and week from Federal Election Commission, transformed with inverse hyperbolic sine transformation ($y = log\left(x + (x^2+1)^{1/2}\right)$). Columns 1-3 include all observations, while columns 4-6 include only observations with non zero values of the dependent variable. The time period in 2006-2011. $I^{+0/+6}$ is a dummy, which equals 1 for the week of disaster and 6 weeks after that. $I^{+7/+8}$ is a dummy, which equals 1 for weeks 7 and 8 after the disaster, to allow for delayed effects. $I^{-2/-1}$ is a dummy, which equals 1 for weeks 1 and 2 preceding the disaster, to check for (placebo) anticipation effects.

Table A.16: Republican vs Democratic Donations (Time Series)

		Political Contributions by Party	
	Total	Democratic	Republican
	(1)	(2)	(3)
$I^{+0/+6}$	-0.182***	-0.159**	-0.198***
	(0.0465)	(0.0519)	(0.0480)
$I^{+7/+8}$	-0.0528	-0.0286	-0.0694
	(0.0478)	(0.0532)	(0.0474)
$I^{-2/-1}$	-0.0266	-0.0118	-0.0392
	(0.0518)	(0.0537)	(0.0567)
Time Range	06w1-11w40	06w1-11w40	06w1-11w40
No. of Disasters	32	32	32
No. of Weeks	300	300	300

Notes: * significant at the 10% level, ** at the 5% level, *** at the 1% level. Heteroscedasticity-robust standard errors, adjusted for clusters by state and week, in brackets. The dependent variables are constructed with natural log transformation. Controls included: month fixed effects, year fixed effects, distance to elections. $I^{+0/+6}$ is a dummy, which equals 1 for the week of disaster and 6 weeks after that. $I^{+7/+8}$ is a dummy, which equals 1 for weeks 7 and 8 after the disaster, to allow for delayed effects. $I^{-2/-1}$ is a dummy, which equals 1 for weeks 1 and 2 preceding the disaster, to check for (placebo) anticipation effects. Columns (4)–(6) of this table include only years for which the data from American Red Cross is available.

Table A.17: Disaster Information Shocks and Political Contributions: Republicans

	Political Contributions (Republicans)					
	(1)	(2)	(3)	(4)	(5)	(6)
$I^{+0/+6}$	-0.335***	-0.319***	-0.348***	-0.364***	-0.353***	-0.386***
	(0.112)	(0.110)	(0.111)	(0.109)	(0.106)	(0.105)
$I^{-2/-1}$		0.129	0.102		0.0916	0.0612
		(0.113)	(0.112)		(0.108)	(0.105)
$I^{+7/+8}$			-0.196			-0.223*
			(0.118)			(0.114)
Observations	268,252	268,252	268,252	267,903	267,903	267,903
R-squared	0.499	0.500	0.500	0.502	0.502	0.503
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Mailing Controls	Yes	Yes	Yes	Yes	Yes	Yes
Donations	All	All	All	Nonzero	Nonzero	Nonzero

Notes: * significant at the 10% level, ** at the 5% level, *** at the 1% level. Heteroscedasticity-robust standard errors, adjusted for clusters by state and week, in brackets. The dependent variable is aggregate political donations to Congressional and Presidential candidates in a given county and week from Federal Election Commission, transformed with inverse hyperbolic sine transformation ($y = log\left(x + (x^2+1)^{1/2}\right)$). Columns 1-3 include all observations, while columns 4-6 include only observations with non zero values of the dependent variable. The time period in 2006-2011. $I^{+0/+6}$ is a dummy, which equals 1 for the week of disaster and 6 weeks after that. $I^{+7/+8}$ is a dummy, which equals 1 for weeks 7 and 8 after the disaster, to allow for delayed effects. $I^{-2/-1}$ is a dummy, which equals 1 for weeks 1 and 2 preceding the disaster, to check for (placebo) anticipation effects.

Table A.18: Disaster Information Shocks and Political Contributions: Democrats

	Political Contributions (Democrat)					
	(1)	(2)	(3)	(4)	(5)	(6)
$I^{+0/+6}$	-0.348**	-0.355**	-0.373**	-0.351**	-0.357**	-0.373**
	(0.141)	(0.143)	(0.142)	(0.141)	(0.143)	(0.141)
$I^{-2/-1}$		-0.0665	-0.0845		-0.0566	-0.0727
		(0.165)	(0.163)		(0.163)	(0.161)
$I^{+7/+8}$			-0.130			-0.116
			(0.139)			(0.136)
Observations	198,294	198,294	198,294	198,225	198,225	198,225
R-squared	0.552	0.552	0.552	0.555	0.555	0.555
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Mailing Controls	Yes	Yes	Yes	Yes	Yes	Yes
Donations	All	All	All	Nonzero	Nonzero	Nonzero

Notes: * significant at the 10% level, ** at the 5% level, *** at the 1% level. Heteroscedasticity-robust standard errors, adjusted for clusters by state and week, in brackets. The dependent variable is aggregate political donations to Congressional and Presidential candidates in a given county and week from Federal Election Commission, transformed with inverse hyperbolic sine transformation ($y = log\left(x + (x^2+1)^{1/2}\right)$). Columns 1-3 include all observations, while columns 4-6 include only observations with non zero values of the dependent variable. The time period in 2006-2011. $I^{+0/+6}$ is a dummy, which equals 1 for the week of disaster and 6 weeks after that. $I^{+7/+8}$ is a dummy, which equals 1 for weeks 7 and 8 after the disaster, to allow for delayed effects. $I^{-2/-1}$ is a dummy, which equals 1 for weeks 1 and 2 preceding the disaster, to check for (placebo) anticipation effects.

Table A.19: Political Advertising, Donations, and Nielsen Retail Expenditures: Robustness to Window Lengths

	(1) Political	(2) Political	(3) Political	(4) Charitable	(5) Charitable	(6) Charitable	(7) Retail	(8) Retail	(9) Retail
$\Delta(D^{+0/+7})$	0.00984***			-0.000885***			0.000127		
	(0.00133)			(0.000186)			(0.000198)		
$\Delta(D^{-2/-1})$	0.00329	0.00439	0.00542	0.000873	0.000448	0.000152	0.000129	0.000139	0.000136
	(0.00334)	(0.00336)	(0.00336)	(0.000845)	(0.000846)	(0.000844)	(0.000445)	(0.000437)	(0.000431)
$\Delta(D^{+0/+8})$		0.00869***			-0.000569***			0.000115	
		(0.00123)			(0.000177)			(0.000188)	
$\Delta(D^{+0/+9})$			0.00762***			-0.000348**			0.000117
			(0.00116)			(0.000170)			(0.000181)
Observations	14,871	14,871	14,871	91,290	91,290	91,290	14,871	14,871	14,871
R-squared	0.804	0.804	0.803	0.364	0.364	0.364	0.817	0.817	0.817
County Pair FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
RC Mailing Control				Yes	Yes	Yes			

Notes: * significant at the 10% level, ** at the 5% level, *** at the 1% level. Unit of observation is matched pair-week. Heteroscedasticity-robust standard errors, adjusted for clusters by state, in brackets. The results for political donations (columns 1 and 2) are estimated for the set of counties within the same congressional district, but located on different sides of corresponding DMA border. The dependent variable is the difference in aggregate political donations from FEC, charitable donations from RC, and retail expenses from Nielsen between two counties across the border in the same week, transformed with inverse hyperbolic sine transformation ($y = log\left(x + (x^2+1)^{1/2}\right)$). Independent variable is the difference in aggregate political ads expenditures across the border in the same week , transformed with inverse hyperbolic sine transformation ($y = log\left(x + (x^2+1)^{1/2}\right)$). The exact specification run is $\Delta Y_{pc,t} = \alpha_1 \Delta(D_{pc,t}^{+0/+8}) + \alpha_2 \Delta(D_{pc,t}^{-2/-1}) + \theta \Delta \mathbf{X}_{pc} + \epsilon_{pc,t}$ with both differences taken for variables, transformed with inverse hyperbolic sine transformation.

Table A.20: RC Mailings as Dependent Variable and Political Ads (County Level)

	(1) Political	(2) Political	(3) Charitable	(4) Charitable	(5) RC Mailings	(6) RC Mailings
$\Delta(D^{+0/+1})$	0.0922***	0.0907***	-0.00733*	-0.00779**	0.0418***	0.0398***
	(0.00961)	(0.00972)	(0.00374)	(0.00375)	(0.00436)	(0.00441)
$\Delta(D^{-1})$		0.0125		0.00148		0.00620
		(0.00745)		(0.00337)		(0.00402)
Observations	7,075	7,075	19,690	19,690	19,690	19,690
R-squared	0.876	0.876	0.589	0.589	0.694	0.694
County Pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
RC Mailing Controls			Yes	Yes	Yes	Yes

Notes: * significant at the 10% level, ** at the 5% level, *** at the 1% level. Heteroscedasticity-robust standard errors, adjusted for clusters by state, in brackets. The results for political and charitable donations are reproduced from Table 3 for the sake of comparison. The results for political donations (columns 1 and 2) are estimated for the set of counties within the same congressional district, but located on different sides of corresponding DMA border. The dependent variable is the difference in aggregate political donations from FEC, charitable donations from RC, and the number of RC mailings between two counties across the border in the same week, transformed with inverse hyperbolic sine transformation ($y = log\left(x + (x^2+1)^{1/2}\right)$). Independent variable is the difference in aggregate political ads expenditures across the border in the same week , transformed with inverse hyperbolic sine transformation ($y = log\left(x + (x^2+1)^{1/2}\right)$). The exact specification run is $\Delta Y_{pc,t} = \alpha_1 \Delta(D^{+0/+1}_{pc,t}) + \alpha_2 \Delta(D^{-1}_{pc,t}) + \theta \Delta \mathbf{X}_{pc} + \epsilon_{pc,t}$ with both differences taken for variables, transformed with inverse hyperbolic sine transformation. Columns 5 and 6 look at Red Cross mailings strategy in times of political campaigns and do not include the difference in mailings as a control.

Table A.21: Individual Political Donations and Electoral Outcomes, 2nd Stage (District Level)

	(1) Vote share Challengers	(2) Win Challengers	(3) Vote margin	(4) Vote share Incumbents	(5) Win Incumbents
Pol Donations, predicted by Disasters	0.123***	0.351*	-0.104	0.00605	-0.0309
	(0.0461)	(0.188)	(0.0664)	(0.0537)	(0.174)
Observations	1,243	1,244	1,244	1,136	1,164
R-squared	0.542	0.326	0.788	0.733	0.512
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: * significant at the 10% level, ** at the 5% level, *** at the 1% level. Heteroscedasticity-robust bootstrapped standard errors, adjusted for clusters by week, in brackets. The results of the second stage estimation are presented. To construct an independent variable, we first predict aggregate political donations from the model with charitable donations, instrumented by natural disasters, on the right hand side, with county, year, and month fixed effects included. We then aggregate obtained predicted values to state-Congressional cycle level to get "Pol Donations predicted by disasters" variable.

Table A.22: Future Individual Political Donations and Electoral Outcomes, 2nd Stage (District Level): Placebo Tests

	(1) Vote share Challengers	(2) Vote share Incumbents	(3) Win Challengers	(4) Win Incumbents	(5) Vote margin
Future Predicted Pol Donations	-0.00493	-0.0311	-0.109	0.0568	-0.0496*
	(0.0208)	(0.0236)	(0.0729)	(0.0560)	(0.0254)
Observations	1,243	1,136	1,244	1,164	1,244
R-squared	0.538	0.734	0.324	0.513	0.789
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: * significant at the 10% level, ** at the 5% level, *** at the 1% level. Heteroscedasticity-robust bootstrapped standard errors, adjusted for clusters by week, in brackets. The results of the second stage estimation are presented. To construct an independent variable, we first predict aggregate political donations from the model with charitable donations, instrumented by natural disasters, on the right hand side, with county, year, and month fixed effects included. We then aggregate obtained predicted values to state-Congressional cycle level to get "Pol Donations predicted by disasters" variable. $(y = log\left(x + (x^2 + 1)^{1/2}\right))$.