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

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11th March 2021

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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. Furthermore, those who donate to charity are also more likely to donate to politics than those who do not (Yörük, 2015), suggesting that there might be a common motive behind both types of donations. Nonetheless, there is little research on the relation between charitable and political giving. In this paper, we fill this gap by studying whether other-regarding preferences could drive both.

Understanding whether there is a common rationale behind charitable and political giving can shed light on an open question in the social sciences: why do people give money to political campaigns? For 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 research question: if political and charitable giving satisfy the same needs, individuals will behave as if charitable and political giving are substitutes, and increased donation in one type will crowd out donations in the other domain.

We investigate the relationship between political and charitable giving via a set of online experiments and using observational data on charitable donations to the American Red Cross (ARC) and data on political donations from the Federal Election Commission (FEC). First, we recruited 3000 subjects on the online platform Mechanical Turk and elicited preferences towards i) donating to ARC, ii) donating to political candidates, or iii) keeping the money for themselves. We then randomly assigned them to a "charitable information" condition where they were reminded of the mission of ARC, or a "political information" condition where they were reminded of the importance of upcoming elections, or to a "no information" control where they received no information, and re-elicited their preferences. We find strong support that, relative to the no information condition, those who received a message about the ARC increased their charitable giving, and decreased their political giving, with charitable giving going up by 4.58 pp and political giving going down by 1.82 pp. Similarly, those who were assigned to the "political information" treatment increased political giving by 2.47 pp, and decreased charitable giving by 1.69 pp. In two follow-up experiments, we show that these findings generalize to two alternate charitable organizations, the American Cancer Society and Feeding America. These results are consistent with the hypothesis that political and charitable donations are close substitutes.

While the experiments provide a clear understanding of the relationship between political and charitable donations, they may at the same time lack external validity. The experimental estimates of elasticity of substitution could also be very different from those in real life. We next take our hypotheses to observational data from ARC and FEC. [1,2] Note that 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). We use data on natural disasters outside of the United States as an unexpected shock to the need for charitable giving. Foreign natural disasters are unlikely to directly impact the financial means of U.S. households of giving. On the other hand, these disasters receive media coverage in the United States (Eisensee and Strömberg, 2007).[3] Consistently with anecdotal accounts (Schwab, 2010; Rooney, 2018), we find that the increase in charitable giving is concentrated in the six weeks after a large foreign natural disaster hits. In our data, we estimate that in the six weeks following a large foreign natural disaster, donations to the American Red Cross increase by 28.9% (p-value less than 0.001). At the same time, consistent with our experimental

[1] A number of reasons make the Red Cross an almost ideal case for our investigation. First, American Red Cross is the largest (by income) non-religious disaster-relief organization. We do not think the charitable organizations which focus on a narrower domain (e.g., combating cancer, alcoholism, drug abuse) can be a good testing ground, as it is not clear what kind of shocks drive their donations. In the observational analysis, to study the relationship between political and charitable donations, we make use of informational shocks that shift the price of giving to politics or charity. Ideally, these shocks should create a need to donate in a timely manner, arrive on a somewhat frequent basis to create enough time-series variation, and should not impact the ability of giving by the donors. The arrival of natural disasters outside of the U.S. as information shocks is suitable because disaster response (unlike other causes such as raising funds to cure cancer or ending hunger) requires timely response from donors, receives ample media coverage to generate a response from the donors, and does not correlate with the ability of giving of the donors. We also do not anticipate religious charitable organizations to provide a good testing ground because they may draw donations from a small set of individuals who regularly donate as they attend to, say, church services, rather than donating based on a need or informational shocks. Second, we would like to use data from a charity with a high name recognition (Briones et al., 2011), but not close to one of the political parties, and out of those ARC is probably the most recognizable one. Among the organizations that provide disaster relief, American Red Cross is the largest by the number of donations and revenue and is listed to be highly recognized by donors (see e.g. Charity Navigator 2020).

[2] We also have access to limited data from the Catholic Relief Services (CRS). When we use data from the CRS, we find qualitatively similar results.

[3] Information about natural disasters can serve as a reminder to give money to disaster relief, similar to reminders for loan repayments (Cadena and Schoar, 2011; Karlan et al., 2012).

results, we estimate a 7.4% decline in political donations during the period following foreign natural disasters (p-value less than 0.001). Put differently, we find that an increase in charitable donations crowds out political donations by a factor of around 0.26 ($= \frac{7.4\%}{28.9\%}$, p-value less than 0.001).

To rule out some alternative explanations, we conduct several robustness tests. First, we use the timing of the natural disasters as a falsification test in an event-study fashion and show that charitable and political giving do not change during the weeks prior to the disaster. We also find that the effects of disasters on placebo outcomes (individuals' spending on retail, groceries, and lottery tickets) are close to zero and mostly precisely estimated. We did not find any evidence of political ads responding to natural disasters. Our findings remain robust to using different time periods of data and different definitions of natural disasters.

Next, we study a shock in the opposite direction: does charitable giving decline after a positive shock to political giving? We use spatial differences in political ads as generating quasi-random heterogeneity in the attractiveness of political giving. Just like natural disasters, political ads can act as reminders of political giving or increase the salience of the need for political contributions. To isolate exogenous variation in political advertising, we follow the identification strategy from Spenkuch and Toniatti (2018) and Shapiro (2018), exploiting sharp geographic discontinuities in advertisement markets. Specifically, we match counties across the boundaries of Nielsen's Designated Market Areas (DMAs).[4] Two households that are in close proximity and similar in observable characteristics can receive different numbers and types 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 month-level data, and pair every county to their neighboring county across the DMA boundary. We find that political ads positively affect political giving: 100% increase in spending on political ads increases political donations by around 9.07% (p-value<0.001) relative to its paired county across the DMA boundary. Consistent with experimental results, we find that a 100% increase in spending on political ads leads to a decrease in charitable giving by around 0.77% (p-value=0.044). In other words, we find that an increase in political donations crowds out charitable donations by a factor of 0.08 ($= \frac{0.77\%}{9.07\%}$, p-value 0.052).

These results survive a number of 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

[4]Note that DMA boundaries are set in advance, independently of political races, and each has access to identical cable channels and identical advertising.

charitable giving right after a political ad, there is no such effect in the weeks prior to the ad. Also, using micro-data on solicitation mailings from the ARC, we show that the decline in charitable giving is not driven by a decline in outreach efforts by the charity.

Overall, the results from the experiments and observational data imply that charitable and political giving are substitutes. Our preferred interpretation of these results is based on other-regarding preferences; some individuals feeling a warmglow from making charitable and political contributions, as alternative ways to help society. When one way becomes more attractive, it crowds out the other way.[5] Note that throughout the paper we mostly rely on the data from ARC as an example of a large charitable organization with high brand recognition. We show that the results for other charities, such as American Cancer Society, Feeding America, and Catholic Relief Services are qualitatively consistent with the results from the Red Cross. Based on these findings, we argue that our results are likely to be generalizable to other charities which do not hold strong connections to political parties.[6]

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. Another 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 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. On the one hand, the finding that additional 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

[5] 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).

[6] We expect the results from ARC to generalize to non-political charitable organizations for a number of reasons. First, American Red Cross is the largest (by income) non-religious disaster-relief organization. It is also the largest by the number of donations and is listed to be highly recognized by donors (see e.g. Charity Navigator 2020), implying that donations to ARC capture the donation preferences of a large number of individuals. Moreover, it is not close to one of the political parties, making the results less organization- or ideology-specific and more generalizable to other organizations.

also reduced the incumbency advantage.

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).[7] 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 benefit 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 an important role in driving charitable giving, may also have an important role in driving political donations.

The two closely related papers are Bertrand et al. (2018) and Yörük (2015). Bertrand et al. (2018) show that charitable giving can be 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 results are consistent with some small donors giving to political campaigns for the feel-good effect.

To the best of our knowledge, Yörük (2015) is the only other study that investigates the relationship between charitable and political donations.[8] Studying household surveys of donations between 1990 and 2001, the author uses variations in income and itemized deductions in taxes across states to identify the relationship between charitable and political giving. Author concludes that these two types of donations are complementary, documenting that charitable donors are more likely to give

[7]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).

[8]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, 2020; 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).

money to politics, using imputed household-specific tax rate as an instrument for charitable giving. The main challenge for these results is that taxes could be associated with a host of unobservable household-specific factors, such as wealth or altruism. Our study contributes to the literature by advancing the causal identification and reaches exactly the opposite conclusion. In particular, in three laboratory and two natural experiments, we show that charitable and political giving are substitutes, not complements. Thus, our paper represents a reversal of the earlier findings in the literature.

The rest of the paper is organized as follows. In Section 2, we provide a theoretical model to explain the relationship between political and charitable giving. Next, in Section 3, we provide experimental evidence for the relationship between political and charitable donations. Section 4 describes the data sources and Section 5 presents the effects of foreign natural disasters on charitable and political giving using data from ARC. Section 6 discusses the effects of political ads on giving. Section 7 presents robustness exercises. Section 8 discusses the interpretation and implications of the findings and concludes.

2 A Simple Model of Donations

Consider the following constant elasticity of substitution (CES) utility function according to which donors determine the optimal donation amounts:

$$\max_{g_c, g_p, C} U(g_c, g_p) = \left(\frac{\alpha_c}{\alpha_c + \alpha_p + 1} g_c^\rho + \frac{\alpha_p}{\alpha_c + \alpha_p + 1} g_p^\rho + \frac{1}{\alpha_c + \alpha_p + 1} C^\rho\right)^{\frac{1}{\rho}}$$

$$\text{s.t. } p_c g_c + p_p g_p + C \leq B$$

where $g_c \geq 0$ is the amount of charitable giving, $g_p \geq 0$ is the amount of political giving, $C \geq 0$ is other spending, and $B > 0$ is the budget of the donor. Each account of giving can yield more utility depending on the relative salience of the need, which are defined by $\frac{\alpha_c}{\alpha_c+\alpha_p+1}$ for the relative importance of giving to charity, $\frac{\alpha_p}{\alpha_c+\alpha_p+1}$ for the relative importance of giving to politics, and $\frac{1}{\alpha_c+\alpha_p+1}$ for the relative importance of other consumption. We assume that $\alpha_c, \alpha_p > 0$. The prices of each type of donation are $p_c > 0$ and $p_p > 0$ and are allowed to be the same or different. In this utility expression, the magnitude of ρ indicates whether the donation amounts are substitutes or complements. We will show that when $\rho < 1$, charitable and political giving are substitutes.

Proposition 1. *When $\rho < 1$,*

(i) $\frac{\partial g_c}{\partial \alpha_c} > 0$ *and* $\frac{\partial g_p}{\partial \alpha_c} < 0$. *Moreover,* $\frac{\partial g_p}{\partial \alpha_p} > 0, \frac{\partial g_c}{\partial \alpha_p} < 0$. *Put differently, an information shock to political giving increases the donations to own-type of giving, but decreases donations to other-type giving.*

(ii) $\frac{\partial C}{\partial \alpha_c} < 0$ *and* $\frac{\partial C}{\partial \alpha_p} < 0$. *A positive information shock to either type of donation decreases other-type spending. Moreover,* $\frac{\partial g_p}{\partial \alpha_c} < \frac{\partial C}{\partial \alpha_c} < 0$ *when* $\left(\frac{p_p}{\alpha_c}\right)^{\frac{1}{1-\rho}} < 1$, and $\frac{\partial g_c}{\partial \alpha_p} < \frac{\partial C}{\partial \alpha_p}$ when $\left(\frac{p_c}{\alpha_p}\right)^{\frac{1}{1-\rho}} < 1$.

For a formal proof of this proposition, see Appendix B. The utility model above can explain how each donation category responds to information shocks. Specifically, donations to political and charitable giving increase with positive information shocks of own-type and decrease with positive information shocks of the other type. While the model also predicts other type of spending to respond to information shocks, the magnitude of these shocks can be much smaller relative to the response in either type of donation, thus suggesting that people mostly think of different kinds of donations as substitutes within this category of expenses. This is the key empirical prediction that we are going to test empirically: information shock to a particular type of giving reduces donations to other type giving without sizable effect for spending of the other kinds.

3 Experimental Evidence

3.1 Research Design

We start by running an experiment to investigate the relationship between charitable and political donations. We recruited 3,000 subjects on Amazon's MTurk. First, all MTurkers were asked to allocate a $1 bonus to one of three conditions: keep to self, donate to a Republican or Democratic candidate, or donate to the American Red Cross as the charity. After this first elicitation, we notified the subjects that they may be randomly selected to receive a message, and then we randomly assigned them with equal probability to one of three treatments: No Info (respondents were told they were not selected to receive a message and asked to proceed with the survey), Charitable Information (i.e., a message stressing the importance of the work done by Red Cross), and Political Information (i.e., a message stressing the importance of the upcoming elections in the state of Georgia Senate race in 2021). We then re-elicited their spending choices.

The experiment ran between December 11th to December 24th, 2020. The survey was advertised as a 5-minute survey about donations. Participation in the MTurk Survey was restricted to respondents located within the U.S., who self-reported to be U.S. citizens and over 18 years old. The median respondent took about 3 minutes to complete the survey. Towards the end of the survey, we introduced an attention check, similar to the one used in Bottan and Perez-Truglia (2017). A total of 99% of the respondents passed the attention check. After removing those who failed the attention check, we ended up with 2980 subjects. The payment scheme was on par with other MTurk surveys (Bottan and Perez-Truglia, 2020). Participants received a fixed fee of $0.5 for participation. The researchers made contributions in the amounts chosen by the respondents to political candidates and to charity, therefore there were no deception.

3.2 Results

We next present the experimental results. We test for the following hypotheses: (i) relative to the No Information group, charitable donations in the Charitable Info group will increase, and the political giving will decrease (ii) relative to the No Info group, in the Political Info group the political donations will go up and the charitable giving will go down.

Table 1 shows balance in baseline characteristics by treatment group. Column (1) corresponds to the average characteristics for the whole subject pool, while columns (2) through (4) present the pre-treatment characteristics by respondents that were randomly assigned to the No Info, Charitable Info, and Political Info treatment groups, respectively. Column (5) reports the p-values for the test that the average of each characteristic is equal across these three treatment groups. The results show that, consistent with a successful random assignment, individuals were balanced in their observable characteristics across treatment groups, with the exception that the likelihood of being married and having children being marginally statistically different.[9] According to Table 1, 50% of the subjects were female, the average age was 40, 47% (24%) self-identified as a Democrat (Republican). 73% (19%) of the subjects indicated that they donated to political (charitable) campaigns over the past 12 months.

In Figure 1, we present the changes in the donation amount under each treatment condition. Panels (a) and (b) provide a test for our first hypothesis: relative to the "No Info" group, those who received a message about American Red Cross increased their charitable giving and decreased their

[9]These two characteristics being significant out of the twelve tested is consistent with spurious correlation.

political donations, calculated as the percent change with respect to the first time. In terms of the magnitudes, relative to the no-info condition, the Charitable Info treatment increased charitable giving by 4.58 pp (panel (a)) and decreased political giving by 1.82 pp (panel (b)). We interpret this finding as implying that each additional dollar in charitable giving crowds out roughly 40 cents ($= \frac{1.82}{4.58}$) of political giving (p-value<0.001) – i.e., they are seen as close substitutes. Panels (c) and (d) demonstrate a similarly strong crowd-out of charitable giving for people exposed to political information. Relative to the No Info group, in the Political Info treatment, there was a statistically significant (p-value<0.001) increase in political donations. Relative to the No Info condition, Political Info treatment increased political giving by 2.47 pp (panel (c)) and decreased charitable giving by 1.69 pp (panel (d)), indicating that each additional dollar in political giving crowds out roughly 68 cents ($= \frac{1.69}{2.47}$) of charitable giving – once again, suggesting that the two types of donation are close substitutes, consistent with our second hypothesis.

Table 2 reports the OLS specifications to estimate the effect of treatments with different sets of controls. In all specifications, we control for the initial (i.e., pre-randomization) allocation to improve power (McKenzie, 2012). Columns (1)–(3) report the benchmark estimates of the treatment effects on charitable giving (column (1)), political giving (column (2)) and consumption (i.e., amount that participants allocated to themselves, in column (3)). The dependent variables are measured in percentage point units, taking the value 0 if a subject decided to allocate 0 cents for a corresponding category and 100 if the subject allocated the whole dollar to the corresponding category. On average, respondents split the dollar in 19.92 pp for charity, 11.95 for political donations to a party of their choice, and 68.12 pp for consumption. The results suggest that the charitable info treatment increased charitable giving by an average of 4.3 pp, which was “financed” by a decrease of 1.769 in political giving and a decrease of 2.538 in consumption. In other words, the charitable shock crowded out political giving, but it crowded out consumption too. In turn, the political info treatment increased political giving by 2.415 pp, which was “financed” by a decrease of 1.812 in charitable giving and decrease of 0.603 in consumption. Put differently, the political giving shock crowded out charitable giving much more strongly. In what follows, we will describe the results pertaining to additional experiments we ran with other charitable organizations.

3.3 Replication with Other Charitable Organizations

To test the generalizability of our results to other charitable organizations, we replicated the experimental design described in Section 3.1 with two alternative organizations: American Cancer Society, that raises funds to aid cancer patients and to their families, and Feeding America, that provides food aid to families with low income. We chose these organizations because both are among the largest organizations by revenue, operate nationally, and are well-known, allaying the concerns that individuals may hesitate to donate due to lack of familiarity with the organization. We recruited participants online on Amazon's Mechanical Turk (MTurk) with the same fee structure described in Section 3.1. Likewise, the researchers made donations in the amounts chosen by the respondents to political candidates and to the relevant charities, implying that there was no deception. The first experiment ran between January 4th to January 6th, 2021, and the latter ran between January 5th to January 6th, 2021. Both experiments were advertised as a 5-minute survey about donations. The median respondent took about 4 minutes to complete the survey in both. The design was the same as in the main experiment, with the difference that participants were given the choice to donate to the charity selected for their respective experiment (i.e., American Cancer Society and Feeding America, respectively, in each experiment). As before, participants under the Charitable Information condition received a note about the importance of the work of the relevant charity (see Appendix C for the information provided under this condition). These results are summarized in columns (4)-(9) of Table 2 and are consistent with the results for American Red Cross described earlier: charitable information treatment reduced donations to politics (columns 5 and 8), while political information treatment reduced donations to corresponding charity (columns 4 and 7). We discuss these results in more details in sections A.1 and A.2 in the Appendix, see also Figures A.1 and A.2.

While suggestive, the experimental evidence has some limitations. However useful, laboratory is a low-stakes and artificial setting, so it is not fully clear if people would behave in the same way with larger stakes and in a natural environment. Thus, in the next sections, we provide evidence from two natural experiments that complements the experimental evidence we present. While causal identification in natural experiments necessarily rely on some assumptions, it nevertheless makes up for it by providing a high-stake, lab-free, natural environment to test the relationship between political and charitable giving.

4 Natural Experiments: Data

We will next describe the natural experiments we used to test the relationship between political and charitable donations, starting with describing the data sets and variable definitions used in the analysis.

Charitable Contributions from American Red Cross. We use proprietary data from the American division of the Red Cross (RC). 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 data set comes from the 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. Regulation requires all donations of \$200 and above to be reported by political candidates, while donations below \$200 are reported only on a voluntary basis, and most of them are not reported. In the analysis, we check if our results are robust to looking at donations from a specific subcategory, including below \$50, \$50-\$200, \$200-\$1000, \$1000-\$3000, \$3000-\$5000, above \$5000. We collected the data for 2001-2014, though the majority of our analysis is carried out for the period 2006-2011, since this is period over which charitable giving data is available.

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).[10] We focus on large disasters, defined as those resulting in 300 or more deaths, however, we also carry out robustness checks with other fatality thresholds. Various disasters such as earthquakes, floods, storms, and volcano

[10] 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.

eruptions are included in the data. Throughout the analysis, we also provide controls for tropical storms, originated abroad but affecting the US directly (hits of homeland) or indirectly (close call, Mexico, Cuba, Haiti, Dominican Republic, Puerto Rico, Bermuda).

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.[11] This data is available for 2004-2012, excluding 2006.

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 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.3 provides detailed summary statistics on all the variables used for the analysis.

[11] 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 in some media markets.

5 The Effects of Foreign Natural Disasters

In the first natural experiment, we test how charitable and political donations respond to foreign disaster information shocks. Foreign disasters arrive unexpectedly, receive media coverage in the U.S., and therefore act as reminders for the need to donate to disaster relief. More importantly, these disasters take place in other parts of the world, so they are unlikely to impact donors' financial means of giving directly. 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 subsequently, 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."[12] 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. And, for illustrative purposes, Figure 2, panel (a), presents a timeline for the foreign disasters on a weekly basis.

[12] 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, thus there are several reasons to consider the window of 6 weeks. In Section 7.3, we show that the results are robust to post disaster window definition being slightly longer or shorter.

$\mathbf{X_{c,t}}$ is a vector of control variables: month-of-the-year dummies, year dummies, 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 (for charitable giving specifications), and county fixed effects.[13] 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 3. The coefficient on $I_t^{+0/+6}$ from column (1) suggests that the charitable donations to RC increase by approximately 28.9% 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.[14]

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 (4) indicates that, in the six weeks after a disaster hits, there is an average decline in political giving of 7.4%. 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 3 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 0.26 ($= \frac{7.4\%}{28.9\%}$). We also estimate p-value (<0.001) and

[13] Note that the variation in key variable of interest (dummy for the weeks right after disasters) comes at the weekly level, and there is no cross-sectional variation in this variable. Thus, unfortunately, we can't use week fixed effects, as those would be perfectly collinear with our variable of interest. Accordingly, we double cluster standard errors by state (to account for potential spatial correlation) and week (to take into account that disaster shock is the same for the whole country). Alternatively, in what follows we present the results of time series analysis with all political and charitable contributions collapsed to the country level.

[14] Note that we include a separate control for tropical storms close to the United States, which could affect the United States directly. Our results are robust to the exclusion of these controls, see Table A.7, or to repeating the analysis using only observations without zero donations (Table A.17).

confidence intervals (95% confidence interval is [0.192; 0.298]) for this elasticity using seemingly unrelated regressions approach.[15]

Next, we discuss a number of additional robustness checks. One potential concern is that an unobservable factor drives both the reduction in 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, using data from Nielsen at the county-level. The results for this outcome are summarized in Table 4. The coefficients for Nielsen expenditures are positive but not statistically significant. The point estimate ranges from 0.0051 to 0.0063. Based on these numbers and corresponding 90% confidence intervals, we can rule out negative effects of up to 0.0027. 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, as otherwise disasters would lead to a decrease in other spending.

Note that political donations are typically larger in size than charitable donations, at least in our data. In Figure 3, we report the results for disasters affecting donations separately for different amounts, for those below \$50, \$50-\$200, \$200-\$1000, \$1000-\$3000, \$3000-\$5000, and above \$5000. Our results seem to be the strongest for donations above \$200 and below \$3000. We generally expect our results to be stronger for smaller donations, as those are closer to typical political donations. However, per FEC guidelines, political candidates are required to itemize only political contributions over \$200. Donations below \$200 are voluntarily reported, and the data for many of these donations is missing, thus these results should be interpreted with caution. Nevertheless, with all the caveats above, our coefficients are negative and significant at 10% level even for donations \$50-\$200.[16]

Appendix A and Section 7 present a number of additional robustness checks. We show that the results are robust when using time series data instead of county-level data (Section 7.1) 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 excluding the number of RC mailings from the

[15]More specifically, we use delta method for non linear combination of parameters following seemingly unrelated regressions estimation and its nlcom implementation in STATA.

[16]We also estimated our specification for donations to Political Action Committees, and the results (reported in Figure A.3) look qualitatively similar, but noisier. See subsection 7.6 for more details.

set of control variables (Appendix A.9), looking at the extensive vs. intensive margins (Appendix A.5), using alternative fatality thresholds for the definition of large natural disasters (Appendix A.6), excluding specific years from the time frame (Appendix A.7) or extending the time period of analysis for political donations (Appendix A.10), using a different time window after the disaster hits (Section 7.3), looking separately at contributions to Democratic and Republican campaigns (Appendix A.8), and exclusion of county-weeks that have zero donations (Appendix A.9). We also report the detailed results for the various donations amounts reported in Figure 3 (Appendix A.14).

6 The Effects of Political Advertising

Next, we carry out a similar exercise using political advertising as an information shock. Unlike natural disasters, spending on political advertising, and its consequent political information shocks, are 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 to (Shapiro, 2018).[17] 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. For illustrative purposes, Figure 2.b presents a map (reproduced from Spenkuch and Toniatti (2018)) with the DMA and county boundaries for the state of Illinois.

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, we cannot argue that political ads constitute abrupt information shocks, as we could for natural disasters. 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

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

Niebler (2014), similar to us, using monthly frequency, thus using monthly data seems to follow the pre-existing practices.

We match counties across DMA boundaries based on their distance and then run a first differences regression, regressing donations on advertising spending.[18] 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:[19]

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

$\Delta Log(D_{pc,t}^{+0/+1})$ 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 county pair, year, and month-of-the-year fixed effects. [20,21]

The results from this specification are presented in Table 5. Columns (1) and (2) show that political ads positively affect political donations, with the estimates for α_1 ranging from 0.091 to 0.092: i.e., if the difference in political ads expenditures goes up by 10%, the corresponding difference in political donations across DMA border is 0.9%. This estimate is consistent with the relatively low persuasion rates reported in 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 charitable donations (columns (3) and (4)). The magnitude of the effect implies that 10% increase

[18] In particular, for each county pair that does not belong to the same DMA, we take all possible county pairs that share the same border and, for political donations, belong to the same Congressional district. The identification here assumes that, had the DMA boundary not fallen between the two counties for quasi random reasons, orthogonal to the dynamics of political/charitable donations, they would be exposed to identical political advertising. This methodology has been adopted by others before us (e.g., Shapiro, 2018).

[19] 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.

[20] Note that an alternative way to implement border discontinuity analysis is estimating the panel specification at the county-month level, with county-pair fixed effects. A potential problem with this approach is counting several counties multiple times, as they repeat in multiple county-pairs as the best matching county to other counties. Spenkuch and Toniatti (2018), for example, implemented this alternative approach, and, correspondingly, had to use some of their counties several times in their estimation. We chose the first difference model as a more conservative approach, where every county-pair enters the estimation exactly once.

[21] We alternatively control for county-pair-year and month fixed effects in Table A.19 in the Appendix for robustness. Unfortunately, we cannot control for county-pair-month fixed effects as this is our unit of observation.

in the difference in political ads expenditures across the border leads to 0.77% decrease in charitable donations differential.

In sum, the results from Table 5 indicate that 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 0.08 ($= \frac{0.77\%}{9.07\%}$). This crowding out factor is smaller than the corresponding estimate reported based on the natural disasters, but still in the same order of magnitude.[22] We also estimate p-value (0.052) and confidence intervals (95% interval being [-.0007; 0.146]) for this elasticity value using seemingly unrelated regressions approach.

In columns 5-6 of Table 5, 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 0.00046 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 0.22% decline. For sake of comparison, our baseline coefficients from columns (1) and (3) imply effects of 9.2% and 0.73% on political giving and charitable giving, respectively.

In Section A, we show that the results are robust to small changes in the estimation window size (Subsection 7.4). 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, reduce the number of solicitations they send. We show that the data does not support that mechanism (Subsection 7.5).

[22] 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, for instance, since political ads are anticipated to some extent. Second, Red Cross contributions could be more sensitive to major TV events compared to political donations, thus the impact of shocks could be asymmetric.

7 Additional and Robustness Checks

7.1 Time Series Analysis (Effect of Disasters & Other Spending Placebos)

As an alternative to the county-level results, we estimate the following time-series specification:

$$Y_t = \alpha_1 \cdot I_t^{+0/+6} + \left[\alpha_2 \cdot I_t^{+7/+8} + \alpha_3 \cdot I_t^{-2/-1}\right] + \mathbf{X_t}\beta + \epsilon_t \tag{3}$$

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 zero observations, thus we can use the logarithm of contributions as the 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 time until the next election (to control for the possibility that donations to politics are more likely to arrive closer to the election date).

The time series results are presented in Table 6. 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 39.7% 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 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.

In turn, columns (4)–(6) of Table 6 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 15.3%.[23] 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) indicating that natural disasters negatively affect political donations suggest that charitable donations crowd out political donations.

Using the time series dataset, we can also look at two additional placebo outcomes that are not available for the county-level dataset: a second retail spending index (Redbook) and spending on Mega Millions lottery.

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.[24]

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. Spending on lotteries are informative in an additional way relative to spending on retail in that since these purchases are hedonic in their nature.

The placebo tests for the above two outcomes, as well as that for the aggregate spending data from Nielsen, are presented in Table 7. 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 1.7% decrease (for lottery tickets), 0.02% (retail expenses based on Redbook), or 0.62% (retail expenses based on Nielsen). While the results with lottery tickets are noisier and, therefore, should be interpreted with caution, the null effects for the latter two outcomes are quite precise and resemble precisely estimated zeroes. These findings are consistent with the claim that crowding out of one type of donations by another type is unlikely to be explained by a simple budget constraint story (in fact, as we discuss below, a more likely explanation for the observed substitution is warm-glow as a common motivation for some people to donate, or mental accounting of setting a shared budget for political and charitable donations).

[23] A potential threat for this specification is a domestic politician using foreign natural disasters to raise funds, such as emphasizing the benefits of the policies he or she is advocating. However, since the indirect effect of disasters on political donations is negative, this story is not consistent with data.

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

Table A.18 replicates columns 4-6 of Tables 3 and 6, but includes a longer time period over which the data on political donations is available. The results are larger in magnitude compared to those in the original tables but are consistent with them. [25]

7.2 Political Ads and Natural Disasters

Table 8 reproduces the main results on disasters, but using political ads as the dependent variable. More specifically, we test whether political ad spending responds to foreign natural disasters. We find that neither of the effects in Table 8 are significant for the first 8 weeks after a disaster, and, if anything, the coefficients of interest are positive rather than negative. Thus, this relationship, if any, is unlikely to explain why political donations respond to natural disasters. The most likely reason for this null finding is that political ads are paid months in advance, and it is difficult for candidates/parties to adjust the purchased times/time slots in response to unexpected foreign disasters.

7.3 Post-Disaster Window

Tables 9 and 10 show the robustness of the charitable donation results to small changes of one to two weeks in the definition of post-disaster window. Qualitatively, our results are robust to these small changes.

7.4 Alternative Time Windows for the Political Ads

Table 11 reproduces the main results on political advertising, but considering alternative windows after political ads were aired. To make small modifications to the estimation window, we go back to weekly data, focusing on the 8 weeks after ads were aired in our baseline specification (whose results were reported in Table 5). Specifically, estimated model is $\Delta Y_{pc,t} = \alpha_1 \Delta Log(D_{pc,t}^{+0/+8}) + \alpha_2 \Delta Log(D_{pc,t}^{-2/-1}) + \theta \Delta \mathbf{X}_{pc,t} + \epsilon_{pc,t}$, where $\Delta Log(D_{pc,t}^{+0/+8})$ is the difference in logged political ad spending between the county-pair pc in the following 8 week period and $\Delta Log(D_{pc,t}^{-2/-1})$ is the difference in logged ad spending in the previous two weeks period. We also report the results for 7 and 9 week windows. The results are qualitatively robust while the magnitudes are smaller. This

[25] 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.

is mostly due to the fact that the dependent variable is constructed at weekly, rather than monthly level.

7.5 RC Mailings as Dependent Variable

It is plausible that the substitution between political and charitable donations is due to a change in the donation solicitation strategy of ARC in periods and regions of political races, rather than donor motivations. In Table 12, we estimated specification (2) using the number of charitable mailings sent by ARC in the as the dependent variable. We find that, ARC had higher, rather than lower, mailing activity with higher political ads, with an elasticity of mailings with respect to political ad spending estimated at 4.1% (significant at 1% level). Therefore, a change in the solicitation strategy of ARC driving the substitution results is not consistent with what the data show. If anything, these results indicate that our estimates in Table 5 would be biased downward.

7.6 Donations to Political Action Committees (PAC) and non-PAC Committees

In our benchmark specification, we focus on donations from individuals to political candidates, however, a number of donations are made to Political Action Committees (PACs) and other committees. Because donations to PACs are subject to different regulations than donations to candidates, we do not expect individuals to view the two types of donations the same. Individuals with strategic motivations may choose to donate to PACs since there are fewer restrictions on PAC donations, and therefore such donations may not respond to disaster information shocks like individual donations do. We use data on contributions to PACs from Bonica (2019) (for details see Bonica (2014)) and replicate specification 1, where the left hand side is now contributions to PACs. We also replicate our baseline analysis, using (non-representative) data on individual donations below \$200.

Table A.23 summarizes the results of these checks. Panel A reports the results for all political donations to candidates, altogether (column 1) or separately for donations below \$50, \$50-\$200, \$200-\$1000, \$1000-\$3000, \$3000-\$5000, above \$5000 (columns 2-7). These results repeat those reported in Figure 3 and are largely consistent with our baseline results (Table 3). Panels B-D of the table repeat the exercise for all political committees (Panel B), PACs (Panel C), and non-PAC committees (Panel D). We see that the coefficient for column 1 for the dummy for the 6 weeks following the natural disaster is negative and statistically significant at the 5% level across all the specifications where the total amount is on the left-hand side. The magnitude of the coefficient is also consistent across all the specifications. We also run this specification breaking down by donation brackets (i.e., below $50, $50-200, $200-1000, $1000-3000, $3000-5000, and above $5000). For sake of illustration, we also report the corresponding coefficients of interest (α_2), as well as their 90% and 95% confidence intervals in Figure A.3. We cannot reject the null hypothesis that there was no change in political donations to various political committees in the six weeks following the natural disaster for any amount of donation but for the $1000-3000 bracket, where the point coefficient is around -0.05. Therefore, it is likely that the donations to political committees (including PACs) are have different motives than individual donations, such as influencing policy outcomes, as noted by Bertrand et al. (2018).

7.7 Catholic Relief Services Data

Finally, to test the robustness of our findings, we replicate our key tables using proprietary data from the Catholic Relief Services (CRS). CRS is an international humanitarian agency of the Catholic community in the United States whose aim is to provide relief at times of disaster, civil conflict, and disease and poverty. While its aid efforts resemble that of ARC, CRS is different in its denominational nature and religious affiliation. Therefore, it is not clear ex ante if our findings can generalize to an organization such as CRS. Table A.24 presents the results from CRS, running specification 1, similar to Table 3. The coefficient on $I^{+0/+6}$ from column (1) suggests that the charitable donations to CRS increase by approximately 12.4% during the 6 weeks following a disaster and this effect is significant at 5% level. In column (2), we add the variable $I^{-2/-1}$ for the event-study falsification test and the coefficient on $I^{+0/+6}$ remains very similar in magnitude. The coefficient on $I^{-2/-1}$ is close to zero and is statistically insignificant, suggesting again that the timing of the disasters is indeed as good as random. In column (3), the coefficient on the variable $I_t^{+7/+8}$ is smaller, however significant, indicating that, while charitable contributions are concentrated in the first six weeks, at least for some types of donations, some intertemporal shift in giving may be possible. These results should be interpreted with caution, since in contrast to ARC, we do not know much about the data generating process for CRS. Regardless, the results using CRS data are largely consistent with the results using ARC data.

Second, we also relate CRS data to political ads (Table A.25). Our results are consistent with the results reported in columns (1) and (2) of Table 5, as political ads seem to significantly decrease donations to CRS. Point estimate is 0.012, which is smaller than the results using ARC data, but consistent with CRS data set being noisier and more patchy compared to ARC data. Overall, the results in Tables A.24 and A.25 suggest that our results are not stylized facts only relevant to ARC donations and are likely to be generalizable to number of other disaster relief charities.

8 Discussion and Conclusions

In this paper, 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, as well as from experiments, 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 have implications for our understanding of the motivations behind political donations. Economists and political scientists have studied individual motivations for giving to politicians. 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 to influence policy outcomes. 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, pg.118): "political giving should be regarded as a form of consumption not unlike giving to charities, such as the United Way or public radio."

Our preferred interpretation for our results is that both forms of giving can be partially motivated by warm-glow for some people. A pure altruism explanation as a common motivation is not consistent with the observed pattern of substitution, since disaster-driven donations increase the victims' welfare, but do not help politicians, and conversely, donations that reward domestic politicians do not increase the welfare of victims of a natural disaster taking place in another country. Warmglow, the feel-good effect of giving, can explain the observed substitution pattern.[26] Therefore small political donations, for some individuals, may be driven by the same motivations that drive charitable giving.

An alternative explanation is budget constraint considerations. If budget is a binding constraint for individuals, after making one type of donation, they may be inclined to spend less on other goods and services, including on other donations. However, a budget constraint explanation would imply that budget is a binding constraint for an average donor. Moreover, placebo estimates for disaggregated consumer expenditures from Nielsen, as well as county-level results for Redbook retail index and lottery ticket expenses, seem to argue against this possibility.

The evidence from American Cancer Society, Feeding America, and Catholic Relief Services suggest that our results are generalizable to a number of charitable organizations and causes. Notice, that we cannot fully rule out the possibility of information shocks increasing donations to some charities, at the expense of others. However, even though the composition of charitable giving across various organizations may be influenced by natural disasters or political ads, it is unlikely that the total amount of non-political charitable giving would go down after disasters (or go up in places with more exposure to political ads), given the evidence we provide for multiple charitable organizations. It is also possible that people just shift the timing of their donations, rather than changing the composition of their donations. Our experimental results speak against this possibility since we see evidence of substitution even though thee subjects participated in the experiment only once.

Our findings are important as they show 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, our findings suggest that

[26] 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 not all political donations are motivated by warmglow, but some are. People use both types of contributions to satisfy their other-regarding preferences, and allocate their resources between the two under a budget constraint. As a result, a shock to the "emotional attachment" to a specific cause (such as a natural disaster or a political ad) motivates individuals to make a larger donation to this cause and a smaller donation to the alternative cause. Another model that can explain our 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.

charitable organizations may expect electoral cycles to affect their fundraising efforts as political advertisements and campaigns encourage individuals to make political contributions. Similarly, disaster shocks could have implications for aggregate political donations over the course of the campaign.

Researchers can use our results on the substitutability between political and charitable giving for identifying the causal effects of donations and related policies on other outcomes. In Appendix A.13 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. Future research can utilize this proof of concept to study the impact of various policies regarding political or charitable donations on other outcomes of interest.

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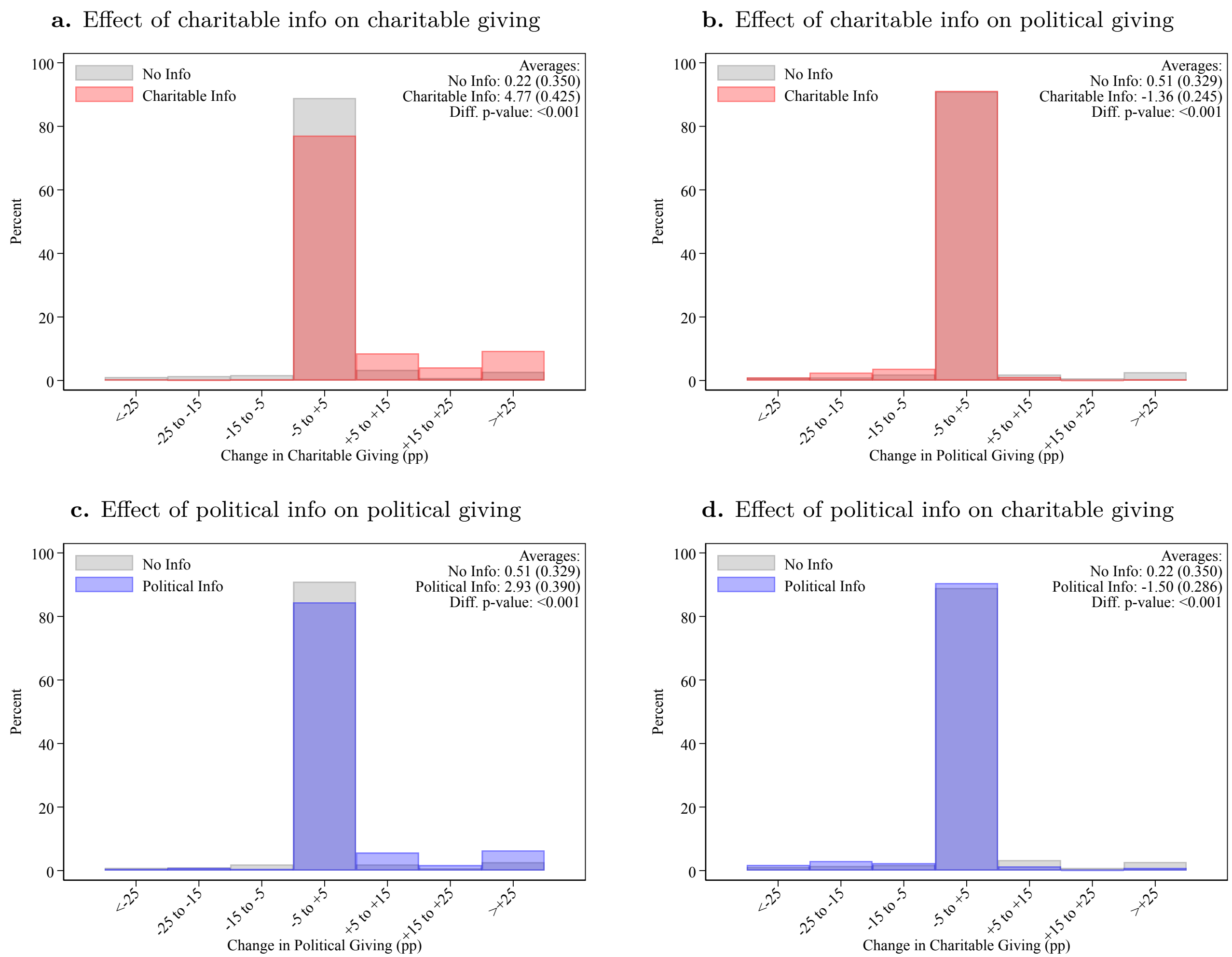
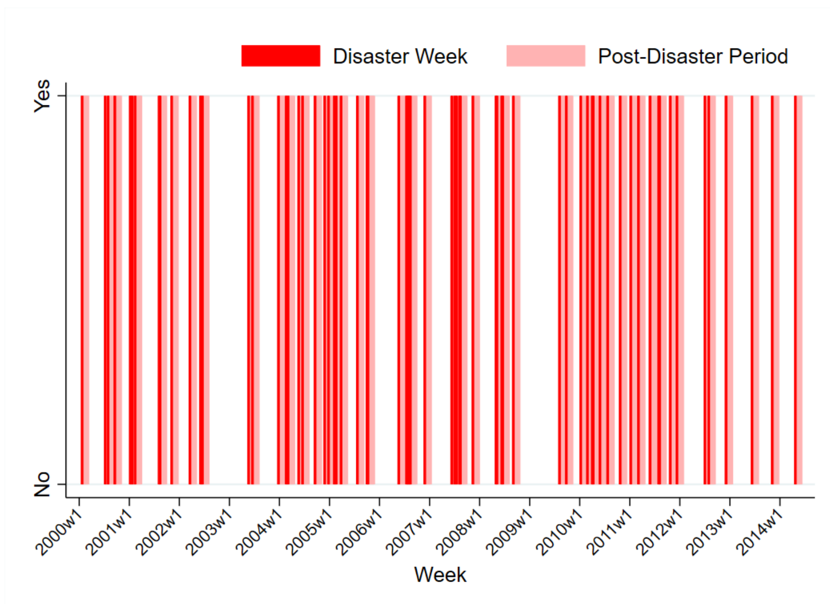
Figure 1: Results from the Experiment in Histograms (American Red Cross)



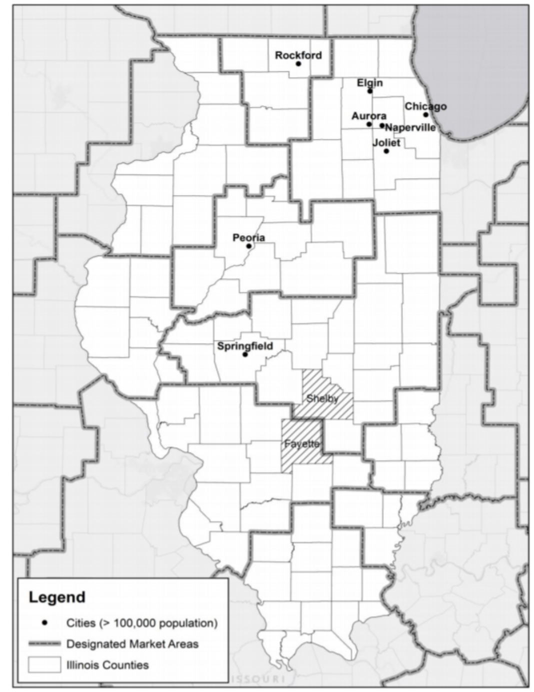
Notes: The panels show the results of the experiment described in Section 3 using American Red Cross as the source of charitable organization. Panels (a) and (b) show the distribution of changes in charitable and political giving if given additional charitable information in comparison with their no additional information counterparts, respectively. Panels (c) and (d) show the distribution of changes in political and charitable giving if given additional political information in comparison with their no additional information counterparts. Average changes in donations reported with standard errors in parentheses.

Figure 2: Institutional Context for the Natural Experiments

a. Large Foreign Natural Disasters over Time

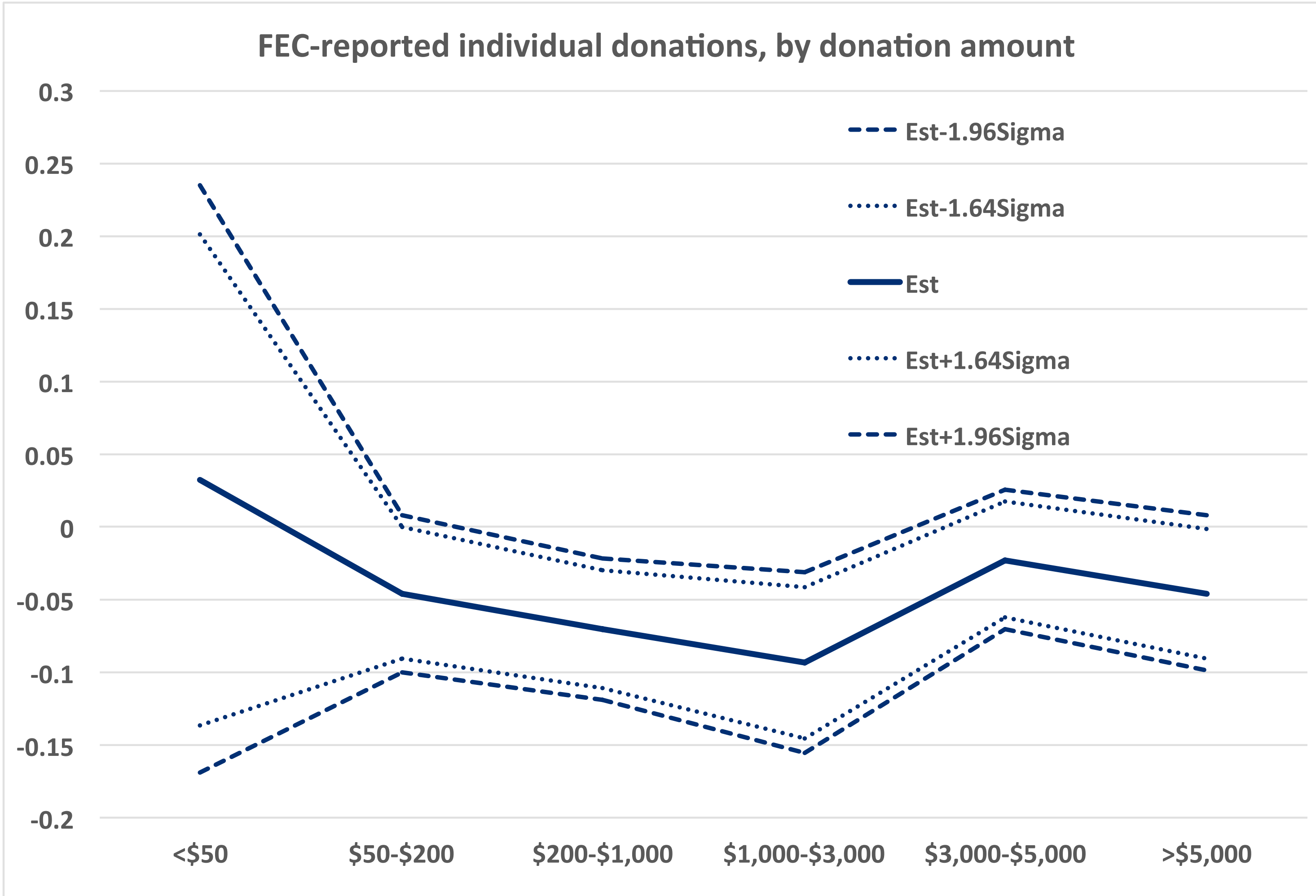


b. Counties and Media Markets in the State of Illinois



Notes: Panel (a) shows the weekly time series of large foreign natural disasters in 2000-2014. The darker red bars indicate that there was a disaster in that week, while the lighter red bars indicate that there had been a disaster in recent weeks. Panel (b) is a reproduction from Spenkuch and Toniatti (2018). It shows the boundaries for counties and media markets in the state of Illinois, as well as the cities with a population of more than 100,000.

Figure 3: Individual donation sensitivities to disaster, by political donation amount



Notes: The graph plots the coefficients of $I^{+0/+6}$ of the identification regressing the amount of donations to the Federal Election Commission on the three dummies $I^{+0/+6}$, $I^{+7/+8}$and $I^{-2/-1}$, which respectively equal 1 for the week of disaster and 6 weeks after that, for weeks 7 and 8 after the disaster, and for a week and two weeks before the disaster. The regression also controls for the county, year, and month fixed effects. We also control for tropical storms, originated abroad but affecting the US directly (hits of homeland) or indirectly (close call, Mexico, Cuba, Haiti, Dominican Republic, Puerto Rico, Bermuda). 6 regressions were run by different dollar amounts of donations, where the regressions include individuals that donate less than $50, $50-$200, $200-$1000, $3000-$5000, and more than $5000 respectively. The regressions are reported in Panel A, Table A.23 in the Appendix.

Table 1: Summary Statistics and Randomization Balance for Experiment (American Red Cross)

	All	Information Treatment			
	(1)	(2) None	(3) Char.	(4) Pol.	(5) p-value
Female (=1)	0.50	0.52	0.51	0.49	0.48
	(0.01)	(0.02)	(0.02)	(0.02)	
Age (in years)	40.03	39.95	39.69	40.47	0.39
	(0.23)	(0.39)	(0.40)	(0.41)	
Democrat (=1)	0.47	0.46	0.47	0.47	0.72
	(0.01)	(0.02)	(0.02)	(0.02)	
Republican (=1)	0.24	0.25	0.22	0.23	0.29
	(0.01)	(0.01)	(0.01)	(0.01)	
White (=1)	0.75	0.75	0.74	0.76	0.54
	(0.01)	(0.01)	(0.01)	(0.01)	
African-American (=1)	0.10	0.11	0.10	0.09	0.23
	(0.01)	(0.01)	(0.01)	(0.01)	
Hispanic (=1)	0.05	0.04	0.05	0.05	0.75
	(0.00)	(0.01)	(0.01)	(0.01)	
Asian (=1)	0.10	0.09	0.10	0.09	0.71
	(0.01)	(0.01)	(0.01)	(0.01)	
Married (=1)	0.44	0.47	0.43	0.42	0.06
	(0.01)	(0.02)	(0.02)	(0.02)	
Has Children (=1))	0.46	0.48	0.43	0.47	0.09
	(0.01)	(0.02)	(0.02)	(0.02)	
Char. Don. in Past 12 Months (=1)	0.73	0.73	0.73	0.73	0.96
	(0.01)	(0.01)	(0.01)	(0.01)	
Pol. Don. in Past 12 Months (=1)	0.19	0.18	0.19	0.20	0.64
	(0.01)	(0.01)	(0.01)	(0.01)	
Observations	2,980	994	996	990	

Notes: * significant at the 10% level, ** at the 5% level, *** at the 1% level. The table summarizes the characteristics of subjects in the American Red Cross experiment described in Section 3. First column demonstrates the randomization for all subjects, columns (2), (3), and (4) summarize characteristics of the subjects randomized into the "No Info," "Charitable Info" and "Political Info" conditions, respectively. Column (5) reports the p-value for the test that the average of each characteristic is equal across these three treatment groups.

Table 2: Political and Charitable Information Shocks and Contributions (American Red Cross Experiment)

	Red Cross			American Cancer Society			Feeding America		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Char.	Pol.	Cons.	Char.	Pol.	Cons.	Char.	Pol.	Cons.
Treatment Dummies:									
Charitable Info (=1)	4.307***	-1.769***	-2.538***	3.284***	-1.412***	-1.871**	2.416***	-1.430***	-0.986
	(0.540)	(0.394)	(0.584)	(0.868)	(0.483)	(0.882)	(0.715)	(0.514)	(0.767)
Political Info (=1)	-1.812***	2.415***	-0.603	-1.798**	1.392**	0.405	-1.942***	0.581	1.361*
	(0.441)	(0.505)	(0.552)	(0.787)	(0.669)	(0.764)	(0.677)	(0.670)	(0.712)
Mean Dep. Var.	19.92	11.95	68.12	18.83	11.29	69.87	20.39	9.95	69.66
Observations	2,980	2,980	2,980	1,025	1,025	1,025	840	840	840

Notes: * significant at the 10% level, ** at the 5% level, *** at the 1% level. The table summarizes the coefficients to political and charitable information shocks in the experiments described in Section 3. Columns (1)-(3) report the change in charitable donations, political donations, and consumption (i.e., bonus kept) where American Red Cross was the charity of donation. Columns (4) - (6) follow the format of the first three columns for the experiment where American Cancer Society was the charity of choice, and columns (7) – (9) do the same for the experiment where the charitable organization was Feeding America. First row in the table reports the results for assignment to a "Charitable Info" condition relative to assignment to "No Info" (control) condition. The second row reports the results for the "Political Info" treatment relative to the "No Info" (control) condition.

Table 3: Disaster Information Shocks, Charitable and Political Contributions

	Charitable Contributions			Political Contributions		
	(1)	(2)	(3)	(4)	(5)	(6)
$I^{+0/+6}$	0.289***	0.276***	0.304***	-0.0741**	-0.0711**	-0.0722**
	(0.0884)	(0.0925)	(0.0922)	(0.0314)	(0.0322)	(0.0331)
$I^{-2/-1}$		-0.0940	-0.0712		0.0236	0.0227
		(0.126)	(0.124)		(0.0335)	(0.0336)
$I^{+7/+8}$			0.218*			-0.00800
			(0.119)			(0.0325)
Observations	740,280	740,280	740,280	465,898	465,898	465,898
R-squared	0.474	0.474	0.475	0.682	0.682	0.682
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	No	No	No
Disaster 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 or political donations in a given county and week, transformed with inverse hyperbolic sine transformation ($y = log\left(x + (x^2+1)^{1/2}\right)$). Political donations come from Federal Election Commission . Mailing controls include log of the numbers of mailings sent by Red Cross in the 3 months preceding donation and only apply to columns (1)-(3). 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. We control for tropical storms, originated abroad but affecting the US directly (hits of homeland) or indirectly (close call, Mexico, Cuba, Haiti, Dominican Republic, Puerto Rico, Bermuda).

Table 4: Disaster Information Shocks and Retail Expenditures

	Retail Expenditures (Nielsen)		
	(1)	(2)	(3)
$I^{+0/+6}$	0.00610	0.00626	0.00519
	(0.00470)	(0.00474)	(0.00477)
$I^{-2/-1}$		0.00122	0.000332
		(0.00563)	(0.00569)
$I^{+7/+8}$			-0.00832
			(0.00533)
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
Disaster Controls	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 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. We control for tropical storms, originated abroad but affecting the US directly (hits of homeland) or indirectly (close call, Mexico, Cuba, Haiti, Dominican Republic, Puerto Rico, Bermuda).

Table 5: Political Ads, Donations, and Nielsen Retail Expenditures

	(1) Political	(2) Political	(3) Charitable	(4) Charitable	(5) Retail	(6) Retail
$\Delta LogD^{+0/+1}$	0.0922***	0.0907***	-0.00733*	-0.00779**	0.000468	0.000523
	(0.0118)	(0.0119)	(0.00374)	(0.00375)	(0.00158)	(0.00153)
$\Delta LogD^{-1}$		0.0125		0.00148		-0.000468
		(0.00959)		(0.00337)		(0.000928)
Observations	7,075	7,075	19,690	19,690	7,075	7,075
R-squared	0.876	0.876	0.589	0.589	0.823	0.823
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			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 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 period. Independent variable is the difference in aggregate political ads expenditures across the border in the same month. The exact specification run is $\Delta Y_{pc,t} = \alpha_1 \Delta Log(D^{+0/+1}_{pc,t}) + \alpha_2 \Delta Log(D^{-1}_{pc,t}) + \theta \Delta \mathbf{X}_{pc} + \epsilon_{pc,t}$, with differences taken for variables transformed with inverse hyperbolic sine transformation.

Table 6: Disaster Information Shocks and Contributions (Time Series)

	Charitable			Political		
	(1)	(2)	(3)	(4)	(5)	(6)
$I^{+0/+6}$	0.397***	0.407***	0.433***	-0.153***	-0.156***	-0.163***
	(0.0960)	(0.0995)	(0.103)	(0.0408)	(0.0405)	(0.0419)
$I^{+7/+8}$			0.180			-0.0511
			(0.112)			(0.0434)
$I^{-2/-1}$		0.0877	0.102		-0.0265	-0.0306
		(0.127)	(0.128)		(0.0473)	(0.0469)
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
Disaster Controls	Yes	Yes	Yes	Yes	Yes	Yes

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. Time period is 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. We control for tropical storms, originated abroad but affecting the US directly (hits of homeland) or indirectly (close call, Mexico, Cuba, Haiti, Dominican Republic, Puerto Rico, Bermuda).

Table 7: Effect of Natural Disasters on Placebo Outcomes: Lottery and Retail Activity

	Lottery			Retail-RedBook			Retail-Nielsen		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$I^{+0/+6}$	0.0326	0.0261	0.0279	0.00324	0.00351	0.00391	0.00215	0.00217	0.00145
	(0.0269)	(0.0257)	(0.0271)	(0.00221)	(0.00218)	(0.00221)	(0.00462)	(0.00458)	(0.00464)
$I^{+7/+8}$			0.0123			0.00270			-0.00421
			(0.0300)			(0.00225)			(0.00466)
$I^{-2/-1}$		-0.0569	-0.0559		0.00240	0.00262		0.000150	-0.000293
		(0.0367)	(0.0365)		(0.00244)	(0.00247)		(0.00490)	(0.00493)
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
Disaster Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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. We control for tropical storms, originated abroad but affecting the US directly (hits of homeland) or indirectly (close call, Mexico, Cuba, Haiti, Dominican Republic, Puerto Rico, Bermuda).

Table 8: Political Advertising and Natural Disasters

	(1) Political Ads	(2) Political Ads
$I^{+0/+1}$	0.101	0.118
	(0.138)	(0.212)
I^{-1}		0.0504
		(0.113)
Observations	7,075	5,401
R-squared	0.872	0.883
County Pair FE	Yes	Yes
Year FE	Yes	Yes
Month FE	Yes	Yes

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. Time period is 2006-2011. $I^{+0/+1}$ is a dummy that equals 1 if there was at least one natural disaster during the one month period following the disaster. I^{-1} is a dummy which equals 1 for the one month preceding the disaster, to check for (placebo) anticipation effects. We control for tropical storms, originated abroad but affecting the US directly (hits of homeland) or indirectly (close call, Mexico, Cuba, Haiti, Dominican Republic, Puerto Rico, Bermuda).

Table 9: Disaster Information Shocks and Charitable Contributions: Robustness to Window Lengths (County Level)

	(1)	(2)	(3)	(4)	(5)	(6)
			Charitable Contributions			
$I^{+0/+5}$	0.232**	0.215**	0.248**			
	(0.0932)	(0.0942)	(0.0934)			
$I^{+0/+7}$				0.311***	0.298***	0.311***
				(0.0888)	(0.0916)	(0.0913)
$I^{-2/-1}$		-0.0940	-0.0875		-0.103	-0.0782
		(0.124)	(0.124)		(0.125)	(0.125)
$I^{+6/+8}$			0.209*			
			(0.115)			
$I^{+8/+8}$						0.282**
						(0.126)
Observations	740,280	740,280	740,280	740,280	740,280	740,280
R-squared	0.473	0.473	0.474	0.474	0.474	0.475
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
Disaster 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 ($y = log\left(x + (x^2 + 1)^{1/2}\right)$). 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 is 2006-2011. $I^{i/j}$ is a dummy, which equals 1 from i^{th} week after the disaster to j^{th} weeks after that. $I^{-2/-1}$ is a dummy, which equals 1 for weeks 1 and 2 preceding the disaster, to check for (placebo) anticipation effects. We control for tropical storms, originated abroad but affecting the US directly (hits of homeland) or indirectly (close call, Mexico, Cuba, Haiti, Dominican Republic, Puerto Rico, Bermuda).

Table 10: Disaster Information Shocks and Political Contributions. Robustness to Window Lengths. (County level)

	(1)	(2)	(3)	(4)	(5)	(6)
	Political Contributions					
$I^{+0/+5}$	-0.0753**	-0.0722**	-0.0800**			
	(0.0296)	(0.0311)	(0.0321)			
$I^{+0/+7}$				-0.0689**	-0.0659**	-0.0674**
				(0.0313)	(0.0317)	(0.0316)
$I^{-2/-1}$		0.0189	0.0167		0.0259	0.0230
		(0.0348)	(0.0344)		(0.0333)	(0.0334)
$I^{+6/+8}$			-0.0404			
			(0.0290)			
$I^{+8/+8}$						-0.0264
						(0.0409)
Observations	465,898	465,898	465,898	465,898	465,898	465,898
R-squared	0.682	0.682	0.682	0.682	0.682	0.682
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
Disaster 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 aggregated political donations in a given county and week from Federal Election Commission, transformed with inverse hyperbolic sine transformation ($y = log\left(x + (x^2+1)^{1/2}\right)$). The time period is 2006-2011. $I^{i/j}$ is a dummy, which equals 1 from i^{th} week after the disaster to j^{th} weeks after that. $I^{-2/-1}$ is a dummy, which equals 1 for weeks 1 and 2 preceding the disaster, to check for (placebo) anticipation effects. We control for tropical storms, originated abroad but affecting the US directly (hits of homeland) or indirectly (close call, Mexico, Cuba, Haiti, Dominican Republic, Puerto Rico, Bermuda).

Table 11: 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
$\Delta LogD^{+0/+7}$	0.0125***			-0.000884***			0.000111		
	(0.00148)			(0.000186)			(0.000202)		
$\Delta LogD^{+0/+8}$		0.0111***			-0.000568***			0.000100	
		(0.00139)			(0.000177)			(0.000192)	
$\Delta LogD^{+0/+9}$			0.00987***			-0.000347**			0.000103
			(0.00132)			(0.000170)			(0.000184)
$\Delta LogD^{-2/-1}$	0.00298	0.00435	0.00550	0.000871	0.000446	0.000151	0.000112	0.000122	0.000118
	(0.00355)	(0.00357)	(0.00357)	(0.000846)	(0.000847)	(0.000844)	(0.000441)	(0.000434)	(0.000428)
Observations	23,754	23,754	23,754	91,290	91,290	91,290	14,871	14,871	14,871
R-squared	0.784	0.784	0.784	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
Disaster Controls	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, 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 8 weeks, transformed with inverse hyperbolic sine transformation $(y = log\left(x + (x^2+1)^{1/2}\right))$. The exact specification run is $\Delta Y_{pc,t} = \alpha_1 \Delta Log(D^{+0/+8}_{pc,t}) + \alpha_2 \Delta Log(D^{-2/-1}_{pc,t}) + \theta \Delta \mathbf{X}_{pc} + \epsilon_{pc,t}$ with differences taken for variables transformed with inverse hyperbolic sine transformation.

Table 12: RC Mailings as Dependent Variable and Political Ads (County Level)

	(1) RC Mailing	(2) RC Mailing
$\Delta LogD^{+0/+1}$	0.0418***	0.0398***
	(0.00436)	(0.00441)
$\Delta LogD^{-1}$		0.00620
		(0.00402)
Observations	19,690	19,690
R-squared	0.694	0.694
County Pair FE	Yes	Yes
Year FE	Yes	Yes
Month FE	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 dependent variable is the difference in the number of RC mailings between two counties across the border in the same month, 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 month transformed with inverse hyperbolic sine transformation ($y = log\left(x + (x^2+1)^{1/2}\right)$). The exact specification run is $\Delta Y_{pc,t} = \alpha_1 \Delta Log(D^{+0/+1}_{pc,t}) + \alpha_2 \Delta Log(D^{-1}_{pc,t}) + \theta \Delta \mathbf{X}_{pc} + \epsilon_{pc,t}$ with differences taken for variables transformed with inverse hyperbolic sine transformation.

Online Appendix: For Online Publication Only

A Additional Analysis and Robustness Checks

A.1 Results for American Cancer Society Experiment

In the experiment with American Cancer Society, we recruited 1098 participants. After focusing on the responses until and including the Georgia State primary and removing those who failed the attention check (Bottan and Perez-Truglia, 2020), we ended up with 1025 subjects.[27] Table A.1 breaks down the average characteristics we used in the randomization by treatment group. Column (1) corresponds to the average characteristics for the whole subject pool, while columns (2) through (4) present the pre-treatment characteristics by respondents that were randomly assigned to the No Info, Charitable Info, and Political Info treatment groups. Column (5) reports the p-values for the null hypothesis that the average of each characteristic is equal across these three treatment groups. Consistent with random assignment, participants in the three treatment conditions did not significantly differ in observable characteristics at conventional significance levels. The only exceptions were the share of Democratic voters (p-value 0.10), and Hispanics (p-value 0.11) which were marginally different from each other. Similarly to the main experiment sample described in 3.1, we found that the sample was almost split equally between female (49%) and men; the average age was 40.54 years old; 52% (28%) of the respondents identified as Democrat (Republican); and 29% (76%) had donated to a political (charitable) organization in the past 12 months.

In Figure A.1, we present the distribution of percent changes in donation amounts in the second elicitation with respect to the first elicitation, under each treatment condition. The top two panels show the results for the Charitable Info treatment group, compared to the No Info condition. Panel (a) shows that, relative to the No Info group, those who received the positive message about the American Cancer Society increased their allocation to charitable giving. Likewise, in Panel (b) (top-right figure), we see that being exposed to information about the American Cancer Society increased donation to it, relative to not receiving any information. We also find treatment effect magnitudes

[27] Notice that the experiment ran between January 4th to January 6th. The Georgia State Primary took place on January 5th. Since it is possible that some subjects felt it is less beneficial to donate after this date, we focus on the respondents from January 4th and 5th. Results do not change if we focus on January 4th alone, January 4th and 5th, or all days. However, we do see that the political information condition generates a weaker response in the experiments closer to the election date, which is a verification that the subjects indeed took into account the importance of the political need in their donations.

similar to the findings in Figure 1: the "Charitable Info" treatment increased charitable giving by 2.82 pp (panel (a)), and decreased political giving by 1.39 pp (panel (b)) relative to the no-info condition. Panel (b) shows that the increase in donations for the American Cancer Society came at the expense of donations to political candidates i.e., relative to the No Info group, in the Charitable Info participants' political donations declined significantly (p-value<0.001). The magnitude of the crowd-out was 49% ($= \frac{1.39}{2.82}$), meaning that, for each extra cent that the Charitable Info group donated to the American Cancer Society in the second elicitation, they decreased the political donations by 49 cents. Similarly, Panels (c) and (d) demonstrate a strong crowd-out of charitable giving when subjects were exposed to political information. Relative to the No Information group, in the Political Information treatment there was a statistically significant (p-value<0.05) increase of 1.72 pp in political donations (Panel (c)), and a statistically significant (p-value<0.05) decrease, equal to 2.20 pp, in charitable donations (Panel (d)). The implied crowd-out was 80 cents ($= \frac{1.72}{2.20}$), further suggesting that participants see the two forms of giving as very close substitutes.

In columns (4)-(6) of Table 2 we report results from the same experiment when running OLS regressions, which allows us to control for baseline allocation to increase precision. We first notice that the No Information group donated 18.83% of their bonus to charitable giving, 11.29% to political parties, and 69.87% to their own consumption, a very similar allocation to the one in the main experiment (Columns (1) to (3)). In terms of treatment effects, in Column (4) we report results when the outcome of interest is the percent change in donation to the American Cancer Society in the second elicitation relative to the first (pre-Treatment) elicitation. We see that the Charitable Information treatment resulted in an increase in donations to the charity by 3.284 pp (p-value<0.001) relative to the baseline allocation, while –at the same time– decreasing donations to the political party of choice by 1.412 pp (Column (5)) and reducing the share devoted to their own consumption by 1.871 pp (p-value = 0.05). The Political Information treatment, by contrast, caused a decrease in charitable giving to the American Cancer Society by 1.798 pp (p-value = 0.05), while it increased political donations by 1.392 pp (p-value = 0.05). Interestingly, in the case of the Political Information treatment, we do not see a statistically significant crowd-out of own consumption - if anything, participants increased their own consumption, but the coefficient is imprecisely estimated. Overall, the results are qualitatively and quantitatively consistent with the main experiment.

A.2 Results from Donations to Feeding America Experiment

In our last experiment, we selected FeedingAmerica as the designated charity for donations. We recruited 937 participants. After focusing on the responses until, and including, the day of the Georgia State primary, and removing those who failed the attention check, we were left with a sample size of 840 participants. In line with the two experiments described above, Table A.2 shows that participants were well balanced in terms of observable characteristics across the three treatment conditions. In Column (1) of Table A.2, we show the average characteristics for the entire sample, while Columns (2) to (4) report the averages for each treatment group (No Info, Charitable Info, and Political Info, respectively). Finally, Column (5) reports the p-values for the null hypothesis of equality of the three sample means. We cannot reject the null hypothesis of equality for any of the observable characteristics we considered. Reassuringly, the sample is also similar in observable characteristics to the participants in the main experiment, and in the American Cancer Society Experiments: it comprised 48% of female participants, with an average age of 40.81 years, 50% of whom self-identified as Democrats, and 29% as Republicans. In line with the other samples, a large majority had donated to charities in the previous 12 months (76%), while 30% had donated to a political party.

The results of these experiments are remarkably similar to the American Red Cross and the American Cancer Society ones. Figure A.2, similarly to Figures 1 and A.1, shows the distribution of the percent changes in donations in the second elicitation, relative to the first elicitation, under each treatment condition. In Panels (a) and (b) we see that, relative to the No Information group, participants who received a message about the importance of Feeding America's work increased their charitable giving by 2.63 pp on average and decreased political donations by 1.54 pp, with both results being statistically different from the No Information group (p-value < 0.01). The implied crowd-out was 59% ($= \frac{1.54}{2.63}$). Panels (c) and (d), instead, plots the distribution of the percent change in donations among the Political Treatment group, and compare it to the No Information group. We see that the former group increased their donations to their political party of choice by 0.60 pp on average, in the expected direction but imprecisely estimated, while decreasing charitable giving to Feeding America by 2.07 pp, and the latter effects were significantly different from the No Info group (p-value < 0.01).

Turning to the OLS results, Columns (7) to (9) in Table 2 shows the coefficients for each treatment effect dummy on the allocation to Feeding America (Column (7)), political party (Column

(8)), or own consumption (Column (9)). We see that, relative to the No Information group, participants who received information on the importance of Feeding America's work were 2.416 pp (p-value<0.001) more likely to donate to the same charity, and 1.430 pp (p-value<0.001) less likely to donate to a political party. By contrast, those who received Political Information, were 1.942 pp less likely (p-value<0.001) to reallocate money to Feeding America in the second elicitation. Albeit imprecisely estimated, we also see that participants in the Political Information treatment arm were more likely to increase donations to their political party, which is consistent with our hypothesis.

A.3 Summary Statistics

Tables A.3–A.6 provide summary statistics for the Red Cross and FEC data sets.

A.4 Excluding Controls

Table A.7 test for the impact of disaster information shocks without including controls for tropical storms in the Caribbean. i.e. natural disasters potentially close to the US. Similarly, Table A.8 replicates columns 1-3 of Table A.8 excluding RC's mailing controls, while Table A.9 replicates columns 1-2 of Table 5 excluding these controls. For every robustness exercise reported in this section, the results are very similar, both in magnitudes and in significance, to our baseline results.

A.5 Effects on the Number of Donors

Table A.10 tests 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 3 and 5. In columns (1)–(3), disaster information shock significantly increases the number of donors to RC, while in columns (4)-(6), the same shock decreases the number of donors to political donations within the 6-week period following a disaster.

A.6 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.11. 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 0.373 and 0.407 for charitable donations and between -0.156 and -0.097 for political contributions, indicating that the effect is fairly robust to disaster thresholds set in this range.

Table A.12 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.11 for the county-week analysis. The coefficients for charitable contributions range from 0.216 to 0.310 and are significant at least at the 5% level for all the modifications. The coefficients for political contributions range from -0.0448 to -0.0711, but they are less precisely estimated, with 1 out of 7 coefficients even losing statistical significance at the conventional level. Out of remaining coefficients, 4 are significant at 5% level and 2 are significant at 10% level.

A.7 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.13 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 0.258 to 0.557 (baseline coefficient being 0.407) and significant at least at 5% level, and with negative coefficients ranging from -0.138 to -0.195 (baseline coefficient being -0.163) and significant at least at 5% level. Moreover, we should note that all the falsification checks still remain insignificant.

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.14 reports the impact of disasters on the donations to the Democrat and Republican politicians in time series analysis, separately. The coefficients (0.146 and 0.190) are too similar to be statistically different. Similarly, tables A.15 and A.16 report the results of county level analysis by party. The baseline coefficients (-0.331 and -0.332 in columns 1) are, again, very close in magnitudes. As a result, we were not able to identify partisan differences in responses.

A.9 Excluding County-Weeks with Zero Donations

Table A.17 replicates the results from Table 3 excluding all observations with zero aggregated donations. The results are very close in terms of magnitudes and statistical significance.

A.10 Extending Time Period for Political Donations

Throughout the paper, we perform the analysis for 2006-2011, as those are the years for which the data on ARC is available, and we want to make sure that the time period for ARC analysis and the rest of the paper is comparable. However, the data for political donations are available for a longer time period, more specifically for 2001-2014. In Table A.18 we perform the analysis with the dependent variable as political donations during 2001-2014, with columns (1)-(3) replicating the columns (4)-(6) of 3 (county-level analysis), and columns (4)-(6) replicating the columns (4)-(6) of Table 6 (time series analysis). With this modification, the magnitudes in this new table are smaller than the corresponding magnitudes for 2006-2011, which could be due to imperfect data coverage for earlier years. Nevertheless, the coefficients remain negative and statistically significant (for the weeks following natural disasters) in all the specifications in this table (columns 1-6).

A.11 Adding County-Year Fixed Effects for Border Discontinuity Analysis

Table A.19 replicates the results from Table 5 with adding county pair-year and month fixed effects. The results are close in terms of magnitudes and statistical significance to the original results (if anything, the magnitudes get larger with this modification).

A.12 Oil Prices as Shocks to Budget Constraint

In Table A.20, we estimate the effect of purely economic shocks on donations. We did not find a lot of precisely estimated results. However, the coefficient for oil price change on ARC donations is negative and significant at 10%. While the corresponding coefficient for political donations is also negative, it is not significant at the conventional levels. If we interpret these magnitudes at their face value, the effect of one standard deviation change in oil prices is comparable with the effect of disasters on charitable donations, but is almost 10 times smaller than the effect of disasters on political donations. Thus, these findings are not consistent with the changes in budget constraint driving our results.

A.13 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:

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

$$Political_{c,t} = \delta_1 \cdot Charitable_{c,t} + \mathbf{X_{c,t}}\beta_2 + \zeta_{c,t} \tag{A.2}$$

$$Outcome_{d,y} = \gamma_1 \cdot Polit\hat{i}cal_{d,y} + \mathbf{S_{d,y}}\beta_3 + \eta_{d,y} \tag{A.3}$$

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.2), 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.3). 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 such donations can have different implications for donations from Political Action Committees or Special Interest Groups.

A.14 Disasters and Political donations, by Donation Amount Subcategory

In this subsection, we report the results for the effect of natural disasters on individual political donations, by subcategory. Table A.23 summarizes the results of these checks. Panel A reports the results for all political donations to individual, all together (column 1) or separately for donations below \$50, \$50-\$200, \$200-\$1000, \$1000-\$3000, \$3000-\$5000, above \$5000 (columns 2-7). These results repeat those reported in Figure 3 and are largely consistent with our baseline results (Table 3). Panels B-D of the table repeats the exercise for all political committees (panel B), PAC committees (Panel C), and non-PAC committees (Panel D). For the sake of illustration, we also report the corresponding coefficients (α_2) of interest as well as the 90% and 95% confidence intervals in Figure A.3. We cannot reject the null hypothesis that there was no change in political donations to various political committees in the six weeks following the natural disaster for any amount of donation but for the \$1000-3000 bracket, where the point coefficient being around-0.05.

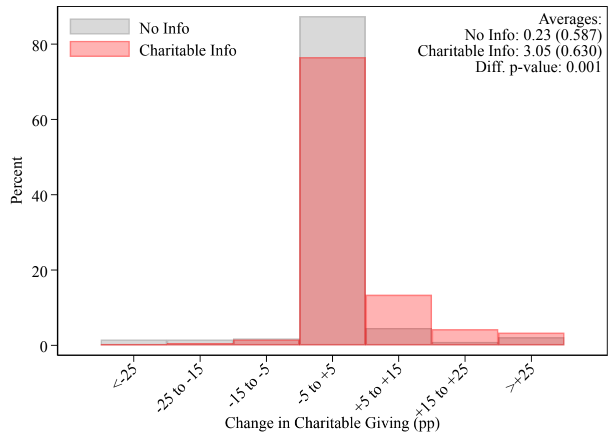
A.15 Results with Catholic Relief Services

Table A.24 replicates the results from Table 3 using the data from Catholic Relief Services (CRS) as a dependent variable. The findings are generally consistent with the findings for ARC, though the coefficients are naturally different (CRS budget is at least 7 times smaller than ARC). The only difference is that for CRS the effect of being 7-8 weeks after a disaster is negative rather than position (significant at 10% in both cases). However, we do not know if this is explained by changes in marketing by CRS, as we unfortunately do not know much about CRS data generating process (in comparison, we know that ARC sends marketing materials to people in their database regularly).

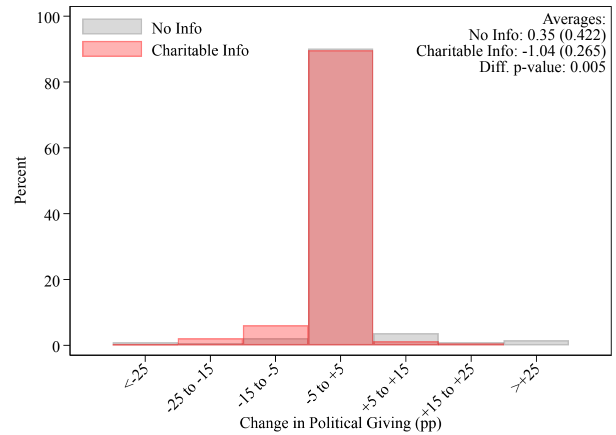
Similarly, Table A.25 replicates the results from Table 5 using CRS data. The coefficients are negative and significant at 5% level, though the magnitudes are different from the magnitudes in Table 5, which could be explained by different propensity of CRS to be active in neighboring counties.

Figure A.1: Results from the Experiment in Histograms (American Cancer Society)

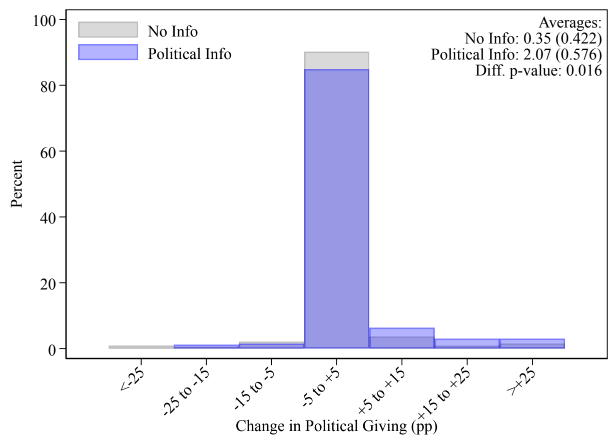
a. Effect of charitable info on charitable giving



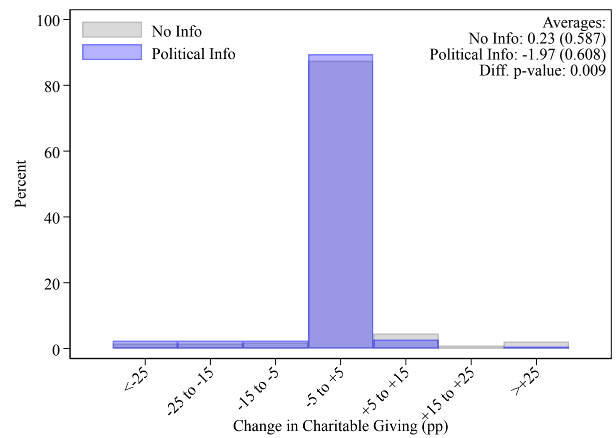
b. Effect of charitable info on political giving



c. Effect of political info on political giving



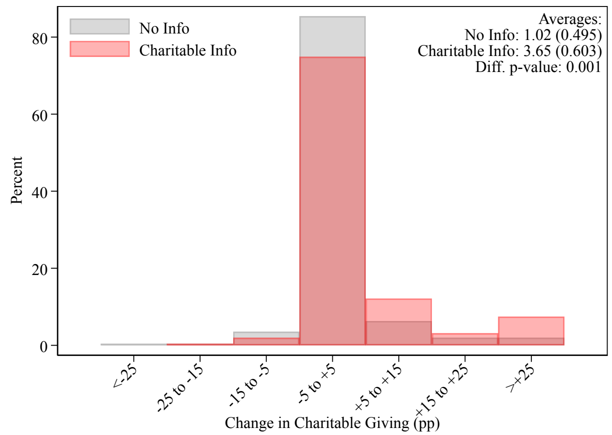
d. Effect of political info on charitable giving



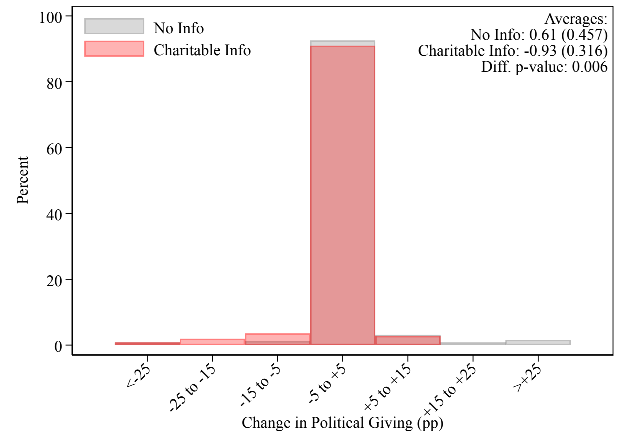
Notes: The panels show the results of the replication of the experiment described in Section 3 using American Cancer Society as the charity. Panels (a) and (b) show the distribution of changes in charitable and political giving if given additional charitable information in comparison with their no additional information counterparts, respectively. Panel (c) and (d) show the distribution of changes in political and charitable giving if given additional political information in comparison with their no additional information counterparts, respectively. Average changes in donations reported with standard errors in parentheses.

Figure A.2: Results from the Experiment in Histograms (Feeding America)

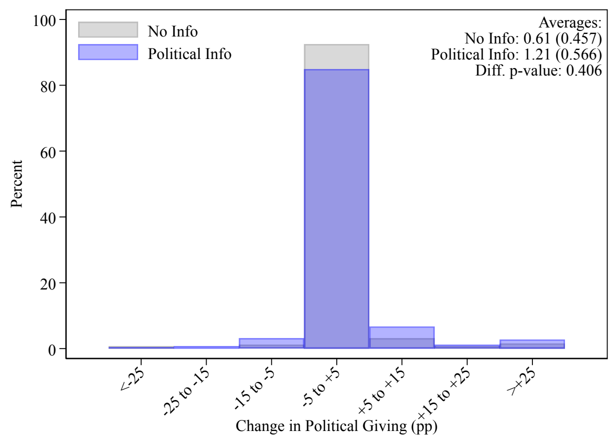
a. Effect of charitable info on charitable giving



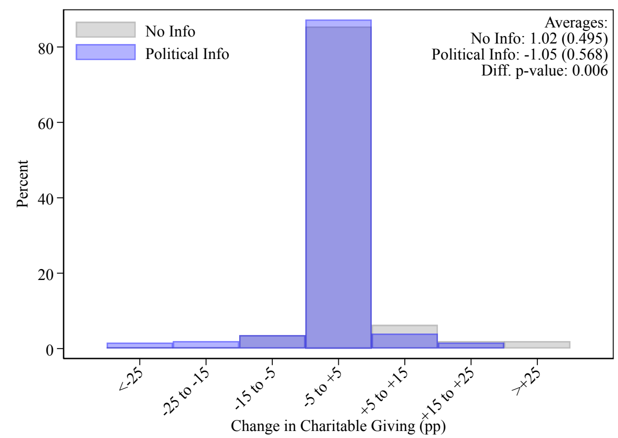
b. Effect of charitable info on political giving



c. Effect of political info on political giving

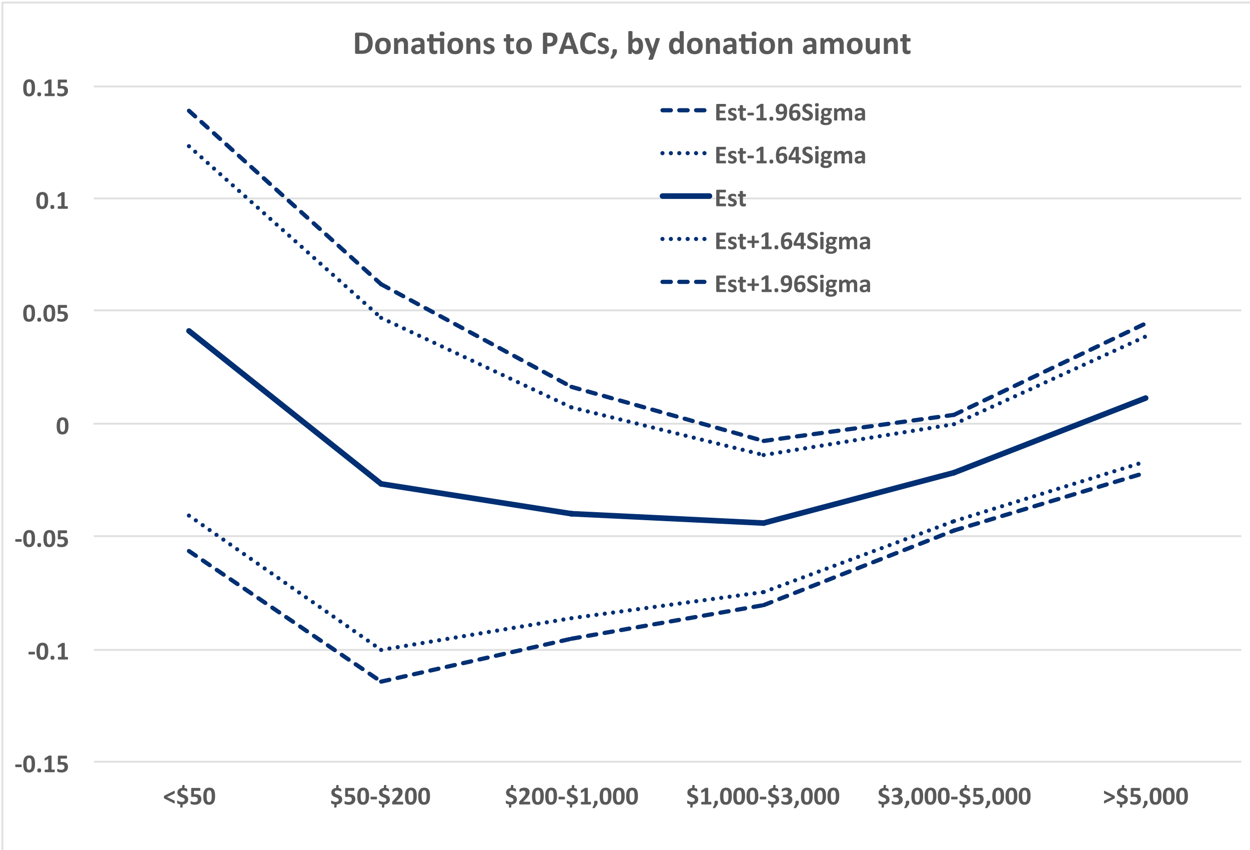


d. Effect of political info on charitable giving



Notes: The panels show the results of the replication of the experiment described in Section 3 using Feeding America as the charity. Panels (a) and (b) show the distribution of changes in charitable and political giving if given additional charitable information in comparison with their no additional information counterparts, respectively. Panel (c) and (d) show the distribution of changes in political and charitable giving if given additional political information in comparison with their no additional information counterparts, respectively. Average changes in donations reported with standard errors in parentheses.

Figure A.3: Natural Disaster Shocks and Donations to Political Action Committees, by amount



Notes: The graph plots the coefficients of $I^{+0/+6}$of the identification regressing the amount of donations to Political Action Committees on the three dummies $I^{+0/+6}$, $I^{+7/+8}$and $I^{-2/-1}$, which respectively equal 1 for the week of disaster and 6 weeks after that, for weeks 7 and 8 after the disaster, and for a week and two weeks before the disaster. The regression also controls for the county, year, and month fixed effects. Solid line provides the point estimates, dashed line corresponds to the 90% confidence interval, and the dotted line corresponds to the 95% confidence interval. We also control for tropical storms, originated abroad but affecting the US directly (hits of homeland) or indirectly (close call, Mexico, Cuba, Haiti, Dominican Republic, Puerto Rico, Bermuda). 6 regressions were run by different dollar amounts of donations, where the regressions include individuals that donate less than $50, $50-$200, $200-$1000, $3000-$5000, and more than $5000 respectively. The regressions are reported in Panel C, Table A.23 in the Appendix.

Table A.1: Summary Statistics and Randomization Balance for Experiment (American Cancer Society)

	All	Information Treatment			
	(1)	(2) None	(3) Char.	(4) Pol.	(5) p-value
Female (=1)	0.49	0.47	0.48	0.52	0.43
	(0.02)	(0.03)	(0.03)	(0.03)	
Age (in years)	40.54	40.05	40.64	40.92	0.66
	(0.41)	(0.66)	(0.72)	(0.72)	
Democrat (=1)	0.52	0.54	0.55	0.47	0.10
	(0.02)	(0.03)	(0.03)	(0.03)	
Republican (=1)	0.28	0.26	0.27	0.31	0.45
	(0.01)	(0.02)	(0.02)	(0.02)	
White (=1)	0.78	0.76	0.78	0.78	0.75
	(0.01)	(0.02)	(0.02)	(0.02)	
African-American (=1)	0.07	0.07	0.06	0.08	0.47
	(0.01)	(0.01)	(0.01)	(0.01)	
Hispanic (=1)	0.05	0.03	0.07	0.05	0.11
	(0.01)	(0.01)	(0.01)	(0.01)	
Asian (=1)	0.09	0.11	0.07	0.08	0.30
	(0.01)	(0.02)	(0.01)	(0.01)	
Married (=1)	0.51	0.54	0.50	0.47	0.18
	(0.02)	(0.03)	(0.03)	(0.03)	
Has Children (=1))	0.54	0.52	0.53	0.56	0.61
	(0.02)	(0.03)	(0.03)	(0.03)	
Char. Don. in Past 12 Months (=1)	0.76	0.74	0.79	0.76	0.30
	(0.01)	(0.02)	(0.02)	(0.02)	
Pol. Don. in Past 12 Months (=1)	0.29	0.29	0.30	0.28	0.80
	(0.01)	(0.02)	(0.02)	(0.02)	
Observations	1,025	340	341	344	

Notes: * significant at the 10% level, ** at the 5% level, *** at the 1% level. This table breaks down the average characteristics we used for randomization by treatment group in the experiment using American Cancer Society as the charity. Column (1) reports the average characteristics for the whole subject pool. Columns (2) through (4) present the pre-treatment characteristics by respondents that were randomly assigned to the No Info, Charitable Info, and Political Info treatment groups. Column (5) reports the p-values for the null hypothesis that the average of each characteristic is equal across these three treatment groups.

Table A.2: Summary Statistics and Randomization Balance for Experiment (Feeding America)

	All	Information Treatment			
	(1)	(2) None	(3) Char.	(4) Pol.	(5) p-value
Female (=1)	0.48	0.48	0.49	0.48	0.93
	(0.02)	(0.03)	(0.03)	(0.03)	
Age (in years)	40.81	41.23	40.48	40.71	0.77
	(0.43)	(0.78)	(0.73)	(0.74)	
Democrat (=1)	0.50	0.48	0.54	0.50	0.33
	(0.02)	(0.03)	(0.03)	(0.03)	
Republican (=1)	0.29	0.30	0.29	0.29	0.96
	(0.02)	(0.03)	(0.03)	(0.03)	
White (=1)	0.78	0.78	0.79	0.75	0.46
	(0.01)	(0.02)	(0.02)	(0.03)	
African-American (=1)	0.06	0.07	0.05	0.07	0.50
	(0.01)	(0.02)	(0.01)	(0.02)	
Hispanic (=1)	0.05	0.04	0.05	0.05	0.90
	(0.01)	(0.01)	(0.01)	(0.01)	
Asian (=1)	0.09	0.07	0.10	0.11	0.33
	(0.01)	(0.02)	(0.02)	(0.02)	
Married (=1)	0.53	0.50	0.53	0.55	0.45
	(0.02)	(0.03)	(0.03)	(0.03)	
Has Children (=1))	0.55	0.51	0.58	0.56	0.25
	(0.02)	(0.03)	(0.03)	(0.03)	
Char. Don. in Past 12 Months (=1)	0.76	0.73	0.79	0.76	0.34
	(0.01)	(0.03)	(0.02)	(0.03)	
Pol. Don. in Past 12 Months (=1)	0.30	0.32	0.28	0.30	0.60
	(0.02)	(0.03)	(0.03)	(0.03)	
Observations	840	282	281	277	

Notes: * significant at the 10% level, ** at the 5% level, *** at the 1% level. This table breaks down the average characteristics we used for randomization by treatment group in the experiment using Feeding America as the charity. Column (1) reports the average characteristics for the whole subject pool. Columns (2) through (4) present the pre-treatment characteristics by respondents that were randomly assigned to the No Info, Charitable Info, and Political Info treatment groups. Column (5) reports the p-values for the null hypothesis that the average of each characteristic is equal across these three treatment groups.

Table A.3: 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.4: 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
Difference in CRS donations	5,056	857.681	6178.819	0	212525.3		

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

Table A.5: 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.6: 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.7: Disaster Information Shocks, Charitable and Political Contributions, without US disaster controls

	(1)	(2)	(3)	(4)	(5)	(6)
	Charitable Contributions			Political Contributions		
$I^{+0/+6}$	0.284***	0.271***	0.302***	-0.0773**	-0.0751**	-0.0763**
	(0.0868)	(0.0903)	(0.0908)	(0.0306)	(0.0312)	(0.0321)
$I^{-2/-1}$		-0.0985	-0.0730		0.0193	0.0184
		(0.125)	(0.124)		(0.0336)	(0.0337)
$I^{+7/+8}$			0.219*			-0.00853
			(0.117)			(0.0325)
Observations	740,280	740,280	740,280	465,898	465,898	465,898
R-squared	0.474	0.474	0.475	0.682	0.682	0.682
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	No	No	No
Disaster Controls	No	No	No	No	No	No
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 or political donations in a given county and week, transformed with inverse hyperbolic sine transformation ($y = log\left(x + (x^2+1)^{1/2}\right)$). Political donations come from Federal Election Commission. Mailing controls include log of the numbers of mailings sent by Red Cross in the 3 months preceding donation and only apply to columns (1)-(3). 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. In this table, we do NOT include controls for tropical storms, originated abroad but affecting the US directly (hits of homeland) or indirectly (close call, Mexico, Cuba, Haiti, Dominican Republic, Puerto Rico, Bermuda).

Table A.8: Disaster Information Shocks and Charitable Contributions: No Mailing Controls Included.

	Charitable Contributions					
	(1)	(2)	(3)	(4)	(5)	(6)
$I^{+0/+6}$	0.278***	0.262***	0.295***	0.203***	0.211***	0.221***
	(0.0919)	(0.0959)	(0.0949)	(0.0511)	(0.0538)	(0.0542)
$I^{-2/-1}$		-0.116	-0.0884		0.0834	0.0935
		(0.131)	(0.129)		(0.0832)	(0.0830)
$I^{+7/+8}$			0.261**			0.0690
			(0.118)			(0.0620)
Observations	746,417	746,417	746,417	206,12	206,12	206,12
R-squared	0.463	0.463	0.464	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	No	No	No	No	No	No
Disaster 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 ($y = log\left(x + (x^2+1)^{1/2}\right)$). 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. We control for tropical storms, originated abroad but affecting the US directly (hits of homeland) or indirectly (close call, Mexico, Cuba, Haiti, Dominican Republic, Puerto Rico, Bermuda).

Table A.9: Political Ads and American Red Cross (ARC) Contributions. No Mailing Controls included.

	(1) Charitable	(2) Charitable
$\Delta LogD^{+0/+1}$	-0.00654*	-0.00705*
	(0.00355)	(0.00363)
$\Delta LogD^{-1}$		0.00160
		(0.00335)
Observations	19,690	19,690
R-squared	0.589	0.589
County Pair FE	Yes	Yes
Year FE	Yes	Yes
Month FE	Yes	Yes
Mailing Controls	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 period. Independent variable is the difference in aggregate political ads expenditures across the border in the same month. The exact specification run is $\Delta Y_{pc,t} = \alpha_1 \Delta Log(D^{+0/+1}_{pc,t}) + \alpha_2 \Delta Log(D^{-1}_{pc,t}) + \theta \Delta \mathbf{X}_{pc} + \epsilon_{pc,t}$, with differences taken for variables transformed with inverse hyperbolic sine transformation.

Table A.10: Disasters and Numbers of Charitable and PoliticalContributions (County Level)

	Number of Charitable Contributions			Number of Political Contributions		
	(1)	(2)	(3)	(4)	(5)	(6)
$I^{+0/+6}$	0.0823***	0.0802**	0.0892***	-0.0700***	-0.0690***	-0.0711***
	(0.0290)	(0.0312)	(0.0312)	(0.0237)	(0.0243)	(0.0247)
$I^{-2/-1}$		-0.0146	-0.00724		0.00817	0.00648
		(0.0441)	(0.0436)		(0.0254)	(0.0254)
$I^{+7/+8}$			0.0702*			-0.0144
			(0.0392)			(0.0256)
Observations	740,280	740,280	740,280	465,898	465,898	465,898
R-squared	0.586	0.586	0.587	0.794	0.794	0.794
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	No	No	No
Disaster 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 the number of 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. We control for tropical storms, originated abroad but affecting the US directly (hits of homeland) or indirectly (close call, Mexico, Cuba, Haiti, Dominican Republic, Puerto Rico, Bermuda).

Table A.11: Robustness Check: Fatality Thresholds (Time Series)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Charitable Contributions						
$I^{+0/+6}$	0.407***	0.373***	0.392***	0.391***	0.407***	0.407***	0.407***
	(0.0995)	(0.0953)	(0.0983)	(0.0978)	(0.0995)	(0.0995)	(0.0995)
$I^{-2/-1}$	0.0877	0.0888	0.0802	0.0821	0.0877	0.0877	0.0877
	(0.127)	(0.122)	(0.117)	(0.114)	(0.127)	(0.127)	(0.127)
	Political Contributions						
$I^{+0/+6}$	-0.156***	-0.0975*	-0.109**	-0.106**	-0.156***	-0.156***	-0.156***
	(0.0405)	(0.0380)	(0.0384)	(0.0385)	(0.0405)	(0.0405)	(0.0405)
$I^{-2/-1}$	-0.0265	0.00146	-0.00738	0.0166	-0.0265	-0.0265	-0.0265
	(0.0473)	(0.0484)	(0.0458)	(0.0467)	(0.0473)	(0.0473)	(0.0473)
Time Range	06w1-11w40	06w1-11w40	06w1-11w40	06w1-11w40	06w1-11w40	06w1-11w40	06w1-11w40
Disaster Threshold	300	280	260	240	320	340	360
No. of Disasters	32	34	36	38	32	32	31
No. of Weeks	300	300	300	300	300	300	300
Disaster Controls	Yes	Yes	Yes	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 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. $I^{-2/-1}$ is a dummy, which equals 1 for weeks 1 and 2 preceding the disaster, to check for (placebo) anticipation effects. We control for tropical storms, originated abroad but affecting the US directly (hits of homeland) or indirectly (close call, Mexico, Cuba, Haiti, Dominican Republic, Puerto Rico, Bermuda).

Table A.12: Disaster Information Shocks and Political Contributions: Robustness to Disaster Thresholds (County Level)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Charitable Contributions						
$I^{+0/+6}$	0.310***	0.309***	0.216**	0.276***	0.276***	0.276***	0.276***
	(0.0916)	(0.0922)	(0.0911)	(0.0925)	(0.0925)	(0.0925)	(0.0925)
$I^{-2/-1}$	-0.0703	-0.0684	-0.106	-0.0940	-0.0940	-0.0940	-0.0940
	(0.113)	(0.113)	(0.118)	(0.126)	(0.126)	(0.126)	(0.126)
Observations	740,280	740,280	740,280	740,280	740,280	740,280	740,280
R-squared	0.474	0.474	0.473	0.474	0.474	0.474	0.474
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mailing Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Donations	All	All	All	All	All	All	All
Fatality Threshold	240	260	280	300	320	340	360
	Political Contribution						
$I^{+0/+6}$	-0.0592*	-0.0590*	-0.0448	-0.0711**	-0.0711**	-0.0711**	-0.0711**
	(0.0319)	(0.0321)	(0.0315)	(0.0322)	(0.0322)	(0.0322)	(0.0322)
$I^{-2/-1}$	0.0393	0.0374	0.0394	0.0236	0.0236	0.0236	0.0236
	(0.0313)	(0.0322)	(0.0337)	(0.0340)	(0.0340)	(0.0340)	(0.0340)
Observations	465,898	465,898	465,898	465,898	465,898	465,898	465,898
R-squared	0.682	0.682	0.682	0.682	0.682	0.682	0.682
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mailing Controls	No	No	No	No	No	No	No
Donations	All	All	All	All	All	All	All
Disaster Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fatality Threshold	240	260	280	300	320	340	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 aggregated 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. We control for tropical storms, originated abroad but affecting the US directly (hits of homeland) or indirectly (close call, Mexico, Cuba, Haiti, Dominican Republic, Puerto Rico, Bermuda).

Table A.13: Robustness Check: Exclusion of a Single Year (Time Series)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Charitable Contributions							
$I^{+0/+6}$	0.407***	0.386***	0.352**	0.343**	0.557***	0.258*	0.548***
	(0.0995)	(0.108)	(0.109)	(0.109)	(0.119)	(0.108)	(0.101)
$I^{-2/-1}$	0.0877	0.172	-0.000335	0.115	0.185	-0.0748	0.0883
	(0.127)	(0.145)	(0.135)	(0.147)	(0.137)	(0.124)	(0.132)
Political Contributions							
$I^{+0/+6}$	-0.163***	-0.176***	-0.165**	-0.148**	-0.169**	-0.195***	-0.138**
	(0.0459)	(0.0502)	(0.0503)	(0.0535)	(0.0536)	(0.0538)	(0.0481)
$I^{-2/-1}$	-0.0107	-0.0175	-0.0177	0.00628	-0.0202	-0.0713	0.0325
	(0.0520)	(0.0563)	(0.0524)	(0.0591)	(0.0599)	(0.0609)	(0.0547)
Years Excluded	None	2006	2007	2008	2009	2010	2011
No. of Disasters	32	25	26	27	30	25	27
No. of Weeks	300	248	248	248	248	248	260
Disaster Controls	Yes	Yes	Yes	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 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. $I^{-2/-1}$ is a dummy, which equals 1 for weeks 1 and 2 preceding the disaster, to check for (placebo) anticipation effects. We control for tropical storms, originated abroad but affecting the US directly (hits of homeland) or indirectly (close call, Mexico, Cuba, Haiti, Dominican Republic, Puerto Rico, Bermuda).

Table A.14: Republican vs Democratic Donations (Time Series)

	Total Amount	By Party: Democrat Amount	By Party: Republican Amount
	(1)	(2)	(3)
$I^{+0/+6}$	-0.171***	-0.146**	-0.190***
	(0.0466)	(0.0519)	(0.0485)
$I^{+7/+8}$	-0.0548	-0.0311	-0.0709
	(0.0466)	(0.0518)	(0.0466)
$I^{-2/-1}$	-0.0151	0.00194	-0.0309
	(0.0517)	(0.0544)	(0.0559)
Time Range	06w1-11w40	06w1-11w40	06w1-11w40
No. of Disasters	32	32	32
No. of Weeks	300	300	300
Disaster Controls	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 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. We control for tropical storms, originated abroad but affecting the US directly (hits of homeland) or indirectly (close call, Mexico, Cuba, Haiti, Dominican Republic, Puerto Rico, Bermuda).

Table A.15: Disaster Information Shocks and Political Contributions: Republicans

	(1)	(2)	(3)	(4)	(5)	(6)
	Political Contribution to Republicans					
$I^{+0/+6}$	-0.331***	-0.311***	-0.342***	-0.367***	-0.354***	-0.389***
	(0.113)	(0.112)	(0.113)	(0.108)	(0.106)	(0.105)
$I^{-2/-1}$		0.136	0.109		0.0905	0.0587
		(0.118)	(0.117)		(0.110)	(0.107)
$I^{+7/+8}$			-0.194			-0.223*
			(0.118)			(0.113)
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	No	No	No	No	No	No
Disaster 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 aggregated 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. We control for tropical storms, originated abroad but affecting the US directly (hits of homeland) or indirectly (close call, Mexico, Cuba, Haiti, Dominican Republic, Puerto Rico, Bermuda).

Table A.16: Disaster Information Shocks and Political Contributions: Democrats

	(1)	(2)	(3)	(4)	(5)	(6)
	Political Contribution to Democrats					
$I^{+0/+6}$	-0.332**	-0.338**	-0.356**	-0.335**	-0.340**	-0.356**
	(0.142)	(0.143)	(0.142)	(0.142)	(0.143)	(0.142)
$I^{-2/-1}$		-0.0473	-0.0653		-0.0372	-0.0533
		(0.165)	(0.163)		(0.163)	(0.161)
$I^{+7/+8}$			-0.126			-0.112
			(0.138)			(0.136)
Observations	198,294	198,294	198,294	198,225	198,225	198,225
R-squared	0.552	0.552	0.553	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	No	No	No	No	No	No
Disaster 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 aggregated 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. We control for tropical storms, originated abroad but affecting the US directly (hits of homeland) or indirectly (close call, Mexico, Cuba, Haiti, Dominican Republic, Puerto Rico, Bermuda).

Table A.17: Disaster Information Shocks, Charitable and Political Contributions, excluding County-Weeks with Zero donations

	Charitable Contributions			Political Contributions		
	(1)	(2)	(3)	(4)	(5)	(6)
$I^{+0/+6}$	0.208***	0.215***	0.224***	-0.0799**	-0.0780**	-0.0797**
	(0.0519)	(0.0548)	(0.0553)	(0.0308)	(0.0315)	(0.0322)
$I^{-2/-1}$		0.0764	0.0855		0.0149	0.0135
		(0.0818)	(0.0814)		(0.0326)	(0.0326)
$I^{+7/+8}$			0.0639			-0.0119
			(0.0648)			(0.0320)
Observations	205,976	205,976	205,976	465,503	465,503	465,503
R-squared	0.434	0.435	0.435	0.690	0.690	0.690
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	No	No	No
Disaster Controls	Yes	Yes	Yes	Yes	Yes	Yes
Donations	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 or political donations in a given county and week, transformed with inverse hyperbolic sine transformation ($y = log\left(x + (x^2+1)^{1/2}\right)$). Political donations come from Federal Election Commission. Mailing controls include log of the numbers of mailings sent by Red Cross in the 3 months preceding donation and only apply to columns (1)-(3). 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. We control for tropical storms, originated abroad but affecting the US directly (hits of homeland) or indirectly (close call, Mexico, Cuba, Haiti, Dominican Republic, Puerto Rico, Bermuda).

Table A.18: Disaster Information Shocks and Political Contributions, 2001-2014

	Political Contributions, County Level			Political Contributions, Time Series		
	(1)	(2)	(3)	(4)	(5)	(6)
$I^{+0/+6}$	-0.0377**	-0.0387**	-0.0364*	-0.0864***	-0.0901***	-0.0897***
	(0.0186)	(0.0187)	(0.0189)	(0.0292)	(0.0293)	(0.0296)
$I^{-2/-1}$		-0.0133	-0.0110		-0.0481	-0.0478
		(0.0226)	(0.0226)		(0.0363)	(0.0362)
$I^{+7/+8}$			0.0251			0.00423
			(0.0225)			(0.0369)
Observations	1,010,109	1,010,109	1,010,109	730	730	730
R-squared	0.653	0.653	0.653	0.782	0.783	0.783
County FE	Yes	Yes	Yes	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Disaster 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 or political donations in a given county and week, transformed with inverse hyperbolic sine transformation ($y = log\left(x + (x^2+1)^{1/2}\right)$). Political donations come from Federal Election Commission. Mailing controls include log of the numbers of mailings sent by Red Cross in the 3 months preceding donation and only apply to columns (1)-(3). $I^{+0/+6}$ 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. We control for tropical storms, originated abroad but affecting the US directly (hits of homeland) or indirectly (close call, Mexico, Cuba, Haiti, Dominican Republic, Puerto Rico, Bermuda).

Table A.19: Political Ads, Donations, and Nielsen Retail Expenditures. County-Pair x Year Fixed Effects included.

	(1) Political	(2) Political	(3) Charitable	(4) Charitable	(5) Retail	(6) Retail
$\Delta LogD^{+0/+1}$	0.0855***	0.0854***	-0.0117**	-0.0112**	0.00155	0.00155
	(0.0125)	(0.0126)	(0.00449)	(0.00446)	(0.00125)	(0.00125)
$\Delta LogD^{-1}$		0.00720		-0.00252		-0.000537
		(0.00911)		(0.00344)		(0.000714)
Observations	7,005	7,005	19,690	19,690	7,005	7,005
R-squared	0.887	0.887	0.628	0.628	0.894	0.894
County Pair x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	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 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 period. Independent variable is the difference in aggregate political ads expenditures across the border in the same month The exact specification run is $\Delta Y_{pc,t} = \alpha_1 \Delta Log(D_{pc,t}^{+0/+1}) + \alpha_2 \Delta Log(D_{pc,t}^{-1}) + \theta \Delta \mathbf{X}_{pc} + \epsilon_{pc,t}$, with differences taken for variables transformed with inverse hyperbolic sine transformation.

Table A.20: Oil Price Shocks, Charitable, and Political Contributions

	Charitable Contributions		Political Contributions	
	(1)	(2)	(3)	(4)
Top 5% Oil Price Decline	0.151		-0.0203	
	(0.154)		(0.0572)	
Top 5% Oil Price Growth	-0.146		0.0599	
	(0.126)		(0.0654)	
Oil Price Weekly Change		-3.234*		-0.120
		(1.787)		(0.598)
Observations	740,280	740,280	465,898	465,898
R-squared	0.471	0.472	0.682	0.682
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Mailing Controls	Yes	No	No	No
Disaster Controls	Yes	Yes	Yes	Yes
Donations	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 or political donations in a given county and week, transformed with inverse hyperbolic sine transformation ($y = log\left(x + (x^2+1)^{1/2}\right)$). Political donations come from Federal Election Commission ($200 and above). Mailing controls include log of the numbers of mailings sent by Red Cross in the 3 months preceding donation and only apply to columns (1)-(3). The time period in 2006-2011. We control for tropical storms, originated abroad but affecting the US directly (hits of homeland) or indirectly (close call, Mexico, Cuba, Haiti, Dominican Republic, Puerto Rico, Bermuda). Oil price data is Crude Oil Prices: West Texas Intermediate (WTI, Cushing, Oklahoma, Dollars per Barrel, Weekly, Not Seasonally Adjusted) is from FRED. Top 5% Oil Price Decline (Growth) is a dummy equal to one if the week is belong to the bottom (top) 5% of oil price changes (defined as $log(Oil_t/Oil_{t-1})$) in the sample. Oil Price Weekly Change is defined as $log(Oil_t/Oil_{t-1})$.

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. ($y = log\left(x + (x^2+1)^{1/2}\right)$).

Table A.23: Disaster Information Shocks & Political Contributions to Individuals and Committees

	(1) All	(2) Below $50	(3) $50-$200	(4) $200-$1000	(5) $1000-$3000	(6) $3000-$5000	(7) Above $5000
Panel A.	Donations by individuals to candidates						
$I^{+0/+6}$	-0.0802**	0.0325	-0.0458	-0.0706***	-0.0936***	-0.0226	-0.0459*
	(0.0332)	(0.103)	(0.0276)	(0.0250)	(0.0317)	(0.0244)	(0.0271)
$I^{-2/-1}$	0.0221	0.112	-0.0250	0.0154	0.0126	0.0532**	-0.0161
	(0.0345)	(0.0982)	(0.0261)	(0.0259)	(0.0330)	(0.0252)	(0.0306)
$I^{+7/+8}$	-0.0138	0.0632	-0.0517*	-0.0233	-0.0114	0.00376	-0.0127
	(0.0324)	(0.115)	(0.0273)	(0.0257)	(0.0298)	(0.0210)	(0.0327)
Observations	468,831	38,790	12,524	429,998	223,704	21,544	45,789
R-squared	0.683	0.193	0.179	0.738	0.660	0.349	0.460
Panel B.	Donations by individuals to All Political Committees						
$I^{+0/+6}$	-0.0733**	0.0117	-0.0408	-0.0370	-0.0507**	-0.00805	-0.158
	(0.0343)	(0.0358)	(0.0326)	(0.0240)	(0.0193)	(0.0178)	(0.129)
$I^{-2/-1}$	-0.0158	0.0390	-0.00958	-0.00248	-0.0116	-0.00587	0.00783
	(0.0387)	(0.0387)	(0.0349)	(0.0282)	(0.0213)	(0.0158)	(0.136)
$I^{+7/+8}$	-0.0476	0.0118	-0.0352	-0.0256	-0.0181	-0.0191	-0.324*
	(0.0427)	(0.0401)	(0.0373)	(0.0304)	(0.0236)	(0.0220)	(0.183)
Observations	803,521	661,821	537,007	402,847	150,280	20,566	67,398
R-squared	0.670	0.744	0.755	0.725	0.629	0.285	0.279
Panel C.	Donations by individuals to PACs						
$I^{+0/+6}$	-0.0979**	0.0409	-0.0266	-0.0396	-0.0444**	-0.0218	0.0110
	(0.0404)	(0.0499)	(0.0450)	(0.0285)	(0.0186)	(0.0131)	(0.169)
$I^{-2/-1}$	-0.0253	0.0765	0.00581	0.00333	-0.00585	0.000803	0.218
	(0.0450)	(0.0516)	(0.0461)	(0.0324)	(0.0211)	(0.0175)	(0.154)
$I^{+7/+8}$	-0.0432	0.0555	-0.00380	-0.0248	-0.0161	-0.00781	-0.201
	(0.0444)	(0.0575)	(0.0481)	(0.0307)	(0.0201)	(0.0141)	(0.222)
Observations	566,731	441,272	334,470	245,878	88,771	9,200	35,011
R-squared	0.602	0.693	0.709	0.653	0.561	0.237	0.256
Panel D.	Donations by individuals to non-PAC Political Committees						
$I^{+0/+6}$	-0.0704**	-0.00492	-0.0505*	-0.0363	-0.0428**	0.00804	-0.262*
	(0.0347)	(0.0339)	(0.0279)	(0.0230)	(0.0194)	(0.0211)	(0.143)
$I^{-2/-1}$	-0.0276	0.0129	-0.0261	-0.00778	-0.0127	-0.00607	-0.0975
	(0.0365)	(0.0339)	(0.0288)	(0.0251)	(0.0192)	(0.0174)	(0.134)
$I^{+7/+8}$	-0.0572	-0.0131	-0.0510	-0.0282	-0.0201	-0.0235	-0.258
	(0.0438)	(0.0337)	(0.0338)	(0.0309)	(0.0242)	(0.0239)	(0.182)
Observations	696,925	556,415	452,592	321,840	108,140	13,854	49,565
R-squared	0.634	0.691	0.699	0.671	0.530	0.236	0.258
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Donations	All	All	All	All	All	All	All

Notes: * significant at the 10% level, ** at the 5% level, *** at the 1% level. Dependent variables are amount and number of donations to all political action committees. Controls included: county fixed effects, month fixed effects, year fixed effects. $I^{+0/+6}$ 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. Data for political contributions are from Bonica (2019).

Table A.24: Disaster Information Shocks and Contributions to Catholic Relief Services (CRS)

	(1)	(2)	(3)	(4)	(5)	(6)
$I^{+0/+6}$	0.112**	0.111**	0.0982**	0.106**	0.106**	0.0923*
	(0.0491)	(0.0487)	(0.0485)	(0.0491)	(0.0487)	(0.0485)
$I^{-2/-1}$		-0.00127	-0.0122		-0.00253	-0.0137
		(0.0625)	(0.0623)		(0.0625)	(0.0622)
$I^{+7/+8}$			-0.0920*			-0.0941*
			(0.0496)			(0.0496)
Observations	381,574	381,574	381,574	381,149	381,149	381,149
R-squared	0.654	0.654	0.655	0.658	0.658	0.658
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	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 donations to Catholic Relief Services in a given county and week, transformed with inverse hyperbolic sine transformation ($y = log\left(x + (x^2+1)^{1/2}\right)$). 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. We control for tropical storms, originated abroad but affecting the US directly (hits of homeland) or indirectly (close call, Mexico, Cuba, Haiti, Dominican Republic, Puerto Rico, Bermuda).

Table A.25: Political Advertising Shocks and Contributions to Catholic Relief Services (CRS)

	(1) Charitable	(2) Charitable
$\Delta LogD^{+0/+1}$	-0.0127**	-0.0134**
	(0.00626)	(0.00647)
$\Delta LogD^{-1}$		-0.00552
		(0.00342)
Observations	5,056	5,056
R-squared	0.862	0.862
County Pair x Year FE	Yes	Yes
Month FE	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 dependent variable is the difference in aggregate charitable donations to Catholic Relief Services (CRS). Independent variable is the difference in aggregate political advertising expenditures of paired counties across the DMA border in the same month. The exact specification is $\Delta Y_{pc,t} = \alpha_1 \Delta Log(D_{pc,t}^{+0/+1}) + \alpha_2 \Delta Log(D_{pc,t}^{-1}) + \theta \Delta \mathbf{X}_{pc} + \epsilon_{pc,t}$, with first differences taken for variables transformed with inverse hyperbolic sine transformation.

B Proof of Propositions

For simplicity of expressions, let $\beta_c \equiv \frac{\alpha_p}{\alpha_c+\alpha_p+1}$ for the relative importance of giving to charity, $\beta_p \equiv \frac{\alpha_p}{\alpha_c+\alpha_p+1}$ for the relative importance of giving to politics, and $\frac{1}{\alpha_c+\alpha_p+1} \equiv 1-\beta_p-\beta_c$ for other giving. Then we can rewrite the expression as

$$\begin{aligned} \max_{g_c,g_p,C} U(g_c,g_p) =& (\beta_c g_c^\rho + \beta_p g_p^\rho + (1-\beta_p-\beta_c)C^\rho)^{\frac{1}{\rho}} \\ \text{s.t. } & p_c g_c + p_p g_p + C \leq B \end{aligned} \tag{B.1}$$

The optimal giving to each account can be determined from writing down the Lagrangian:

$$\mathcal{L} = ((1-\beta_p-\beta_c)C^\rho + \beta_c g_c^\rho + \beta_p g_p^\rho)^{\frac{1}{\rho}} + \lambda(B - p_c g_c - p_p g_p - C),$$

and by calculating the first order conditions with respect to the donation amounts (g_c, g_p) and other spending (C):

$$\frac{\partial \mathcal{L}}{\partial g_c} = \beta_c g_c^{\rho-1}\left(\beta_c g_c^\rho + \beta_p g_p^\rho + (1-\beta_p-\beta_c)C^\rho\right)^{\frac{1}{\rho}-1} - \lambda p_c = 0 \tag{B.2}$$

$$\frac{\partial \mathcal{L}}{\partial g_p} = \beta_p g_p^{\rho-1}\left(\beta_c g_c^\rho + \beta_p g_p^\rho + (1-\beta_p-\beta_c)C^\rho\right)^{\frac{1}{\rho}-1} - \lambda p_p = 0 \tag{B.3}$$

$$\frac{\partial \mathcal{L}}{\partial C} = (1-\beta_p-\beta_c)C^{\rho-1}\left(\beta_c g_c^\rho + \beta_p g_p^\rho + (1-\beta_p-\beta_c)C^\rho\right)^{\frac{1}{\rho}-1} - \lambda = 0 \tag{B.4}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = B - p_c g_c - p_p g_p - C = 0. \tag{B.5}$$

From the first two expressions above, we can write

$$\frac{\beta_c g_c^{\rho-1}}{p_c} = \frac{\beta_p g_p^{\rho-1}}{p_p}$$

Using equations (1) and (3), we can write:

$$g_c = \left(\frac{p_c}{\beta_c}(1-\beta_p-\beta_c)\right)^{\frac{1}{\rho-1}} C$$

Using equations (2) and (3), we can write:

$$g_p = \left(\frac{p_p}{\beta_p}(1-\beta_p-\beta_c)\right)^{\frac{1}{\rho-1}} C$$

and plugging into (4)

$$B - \left(p_c\left(\frac{p_c}{\beta_c}(1-\beta_p-\beta_c)\right)^{\frac{1}{\rho-1}} + p_p\left(\frac{p_p}{\beta_p}(1-\beta_p-\beta_c)\right)^{\frac{1}{\rho-1}} + 1\right) C = 0$$

Solving for C yields:

$$C^* = B\frac{1}{\left(p_c\left(\frac{p_c}{\beta_c}(1-\beta_p-\beta_c)\right)^{\frac{1}{\rho-1}}+p_p\left(\frac{p_p}{\beta_p}(1-\beta_p-\beta_c)\right)^{\frac{1}{\rho-1}}+1\right)} = B\frac{1}{\left(p_c\left(\frac{p_c}{\alpha_c}\right)^{\frac{1}{\rho-1}}+p_p\left(\frac{p_p}{\alpha_p}\right)^{\frac{1}{\rho-1}}+1\right)}$$

Plugging this expression in equations () and (), we obtain:

$$g_c^* = B\frac{1}{\left(p_c+p_p\left(\frac{p_p}{\alpha_p}\frac{\alpha_c}{p_c}\right)^{\frac{1}{\rho-1}}+\left(\frac{p_c}{\alpha_c}\right)^{\frac{1}{1-\rho}}\right)}$$

$$g_p^* = B\frac{1}{\left(p_p+p_c\left(\frac{p_c}{\alpha_c}\frac{\alpha_p}{p_p}\right)^{\frac{1}{\rho-1}}+\left(\frac{p_p}{\alpha_p}\right)^{\frac{1}{1-\rho}}\right)}$$

Proof. We then investigate how the relative shock to one type of giving influences the donations to own- and other-type giving. Notice that when $\rho<1$, $\frac{\partial g_c}{\partial\alpha_c} = -\frac{B\left(\frac{p_c}{\alpha_c}\right)^{\frac{1}{\rho-1}}\left(p_p\left(\frac{p_p}{\alpha_p}\right)^{\frac{1}{\rho-1}}+1\right)}{\alpha_c(\rho-1)\left(p_c\left(\frac{p_c}{\alpha_c}\right)^{\frac{1}{\rho-1}}+p_p\left(\frac{p_p}{\alpha_p}\right)^{\frac{1}{\rho-1}}+1\right)^2} > 0$ and $\frac{\partial g_p}{\partial\alpha_p} = -\frac{B\left(\frac{p_p}{\alpha_p}\right)^{\frac{1}{\rho-1}}\left(p_c\left(\frac{p_c}{\alpha_c}\right)^{\frac{1}{\rho-1}}+1\right)}{\alpha_p(\rho-1)\left(p_p\left(\frac{p_p}{\alpha_p}\right)^{\frac{1}{\rho-1}}+p_c\left(\frac{p_c}{\alpha_c}\right)^{\frac{1}{\rho-1}}+1\right)^2} > 0$,

$\frac{\partial g_c}{\partial\alpha_p} = \frac{B\left(\frac{p_c}{\alpha_c}\right)^{\frac{1}{\rho-1}}\left(\frac{p_p}{\alpha_p}\right)^{\frac{\rho}{\rho-1}}}{(\rho-1)\left(p_c\left(\frac{p_c}{\alpha_c}\right)^{\frac{1}{\rho-1}}+p_p\left(\frac{p_p}{\alpha_p}\right)^{\frac{1}{\rho-1}}+1\right)^2} < 0$ and $\frac{\partial g_p}{\partial\alpha_c} = \frac{B\left(\frac{p_c}{\alpha_c}\right)^{\frac{\rho}{\rho-1}}\left(\frac{p_p}{\alpha_p}\right)^{\frac{1}{\rho-1}}}{(\rho-1)\left(p_c\left(\frac{p_c}{\alpha_c}\right)^{\frac{1}{\rho-1}}+p_p\left(\frac{p_p}{\alpha_p}\right)^{\frac{1}{\rho-1}}+1\right)^2} < 0.$

The derivative of other type of spending with respect to information shocks to charitable giving is also negative when $\rho<1$,

$\frac{\partial C}{\partial\alpha_c} = \frac{B\left(\frac{p_c}{\alpha_c}\right)^{\frac{\rho}{\rho-1}}}{(\rho-1)\left(p_c\left(\frac{p_c}{\alpha_c}\right)^{\frac{1}{\rho-1}}+p_p\left(\frac{p_p}{\alpha_p}\right)^{\frac{1}{\rho-1}}+1\right)^2} < 0$ and $\frac{\partial C}{\partial\alpha_p} = \frac{B\left(\frac{p_p}{\alpha_p}\right)^{\frac{\rho}{\rho-1}}}{(\rho-1)\left(p_c\left(\frac{p_c}{\alpha_c}\right)^{\frac{1}{\rho-1}}+p_p\left(\frac{p_p}{\alpha_p}\right)^{\frac{1}{\rho-1}}+1\right)^2} < 0$

However notice that the magnitude of the change can be lower than the magnitude of change in response to the same parameter, if $\frac{\partial C}{\partial\alpha_c} < \frac{\partial g_p}{\partial\alpha_c}$, or if

□

$$\frac{B\left(\frac{p_c}{\alpha_c}\right)^{\frac{\rho}{\rho-1}}}{(\rho-1)\left(p_c\left(\frac{p_c}{\alpha_c}\right)^{\frac{1}{\rho-1}}+p_p\left(\frac{p_p}{\alpha_p}\right)^{\frac{1}{\rho-1}}+1\right)^2} < \frac{B\left(\frac{p_c}{\alpha_c}\right)^{\frac{\rho}{\rho-1}}\left(\frac{p_p}{\alpha_p}\right)^{\frac{1}{\rho-1}}}{(\rho-1)\left(p_c\left(\frac{p_c}{\alpha_c}\right)^{\frac{1}{\rho-1}}+p_p\left(\frac{p_p}{\alpha_p}\right)^{\frac{1}{\rho-1}}+1\right)^2}$$

which holds if $\left(\frac{p_p}{\alpha_p}\right)^{\frac{1}{\rho-1}} > 1$ holds. A similar expression can be written for $\frac{\partial C}{\partial\alpha_p} < \frac{\partial g_c}{\partial\alpha_p}$.

C Experimental Instructions

CONSENT & IRB (REMOVED TO MAINTAIN ANONYMITY)

We will begin by asking you a few background questions. Please indicate your gender:

- ◯ Female
- ◯ Male
- ◯ Other

How old are you?

[ ]

Are you a U.S. citizen?

- ◯ Yes
- ◯ No

The researchers have a $1 budget, and you get to decide how to split that amount between the following four categories.

The researchers can: (1.) give part of the budget to you in the form of a bonus payment through Mturk. (2.) add part of the funds as a charitable contribution to the Red Cross; or donate to a political candidate in the upcoming state of Georgia runoff elections taking place in January 2021, outcome of which will determine which party controls the U.S. Senate. Researchers can (3.) add part of the funds as a contribution to a Democratic Party candidate, or (4.) add part of the funds as a contribution to a Republican Party candidate.

Making this choice is your main task in this study. Whatever allocation you choose will be implemented by the researchers. Please decide how to allocate the $1 budget (note that your answers must sum up to 100%):

Bonus payment for you	0	%
Donation to the Red Cross	0	%
Donation to a Democratic party candidate	0	%
Donation to a Republican party candidate	0	%
Total	0	%

Next, a group of individuals participating in this survey will be randomly chosen to receive some information.

Please continue to the next screen to find out if you will be selected to receive information.

TREATMENT: (AMERICAN RED CROSS) CHARITABLE INFORMATION CONDITION

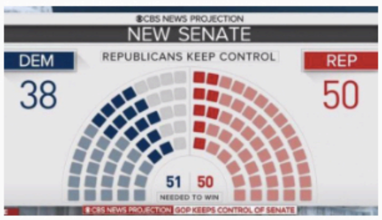
You have been randomly selected to receive the following information:

The American Red Cross shelters, feeds and provides emotional support to victims of disasters; supplies about 40 percent of the nation's blood; teaches skills that save lives; provides international humanitarian aid; and supports military members and their families. The Red Cross is a not-for-profit organization that depends on volunteers and the generosity of the American public to perform its mission.

Please proceed to the next screen to continue with the survey.

TREATMENT: POLITICAL INFORMATION CONDITION

You have been randomly selected to receive the following information:



The 2020 U.S. Senate election in Georgia was held on November 3, 2020, to elect the member of the U.S. Senate to represent the state of Georgia, concurrently with the 2020 U.S. presidential election. No candidate received a majority of the vote, and so the top two finishers, Republican David Perdue and Democratic Jon Ossoff, will advance to a runoff election on January 5, 2021. Since Georgia's other U.S. Senator, Johnny Isakson, announced his resignation in 2019, a concurrent special election for the Class III seat has taken place; it will also be decided in a January 5 runoff. The outcome of the contests will either swing the Senate majority to Democrats, handing President-elect Joe Biden power to carry out his policy agenda or leave Republicans in majority, allowing them to influence his plans.

Please proceed to the next screen to continue with the survey.

CONTROL: NO INFORMATION CONDITION

You have not been randomly selected to receive any information.

Please proceed to the next screen to continue with the survey.

You are asked to re-answer the following question from before.

The researchers have a $1 budget, and you get to decide how to split that amount between the following four categories.

The researchers can: (1.) give part of the budget to you in the form of a bonus payment through Mturk. (2.) add part of the funds as a charitable contribution to the Red Cross; or donate to a political candidate in the upcoming state of Georgia runoff elections taking place in January 2021, outcome of which will determine which party controls the U.S. Senate. Researchers can (3.) add part of the funds as a contribution to a Democratic Party candidate, or (4.) add part of the funds as a contribution to a Republican Party candidate.

Making this choice is your main task in this study. Whatever allocation you choose will be implemented by the researchers. Please decide how to allocate the $1 budget (note that your answers must sum up to 100%):

Bonus payment for you	0 %
Donation to the Red Cross	0 %
Donation to a Democratic party candidate	0 %
Donation to a Republican party candidate	0 %
Total	0 %

Have you made any charitable contributions in the past 12 months?

- ○ Yes
- ○ No

Have you made any contributions to a political campaign or political party in the past 12 months?

- ○ Yes
- ○ No

In politics, as of today, do you consider yourself a Republican, a Democrat, or an independent?

- ◯ Democrat
- ◯ Republican
- ◯ Independent

Which of the following best describes your ethnicity?

- ◯ White
- ◯ Black or African American
- ◯ Asian or Native Hawaiian and other Pacific Islander
- ◯ American Indian or Alaska Native
- ◯ Hispanic or Latino origin

What is your marital status?

- ◯ Single
- ◯ Married
- ◯ Separated/Divorced
- ◯ Widower

Do you have kids?

- ◯ Yes
- ◯ No

Recent research on decision making shows that choices are affected by the context in which they are made. Differences in how people feel, in their previous knowledge, experience, and in their environment can influence the choices they make. To help us understand how people make decisions, we are interested in information about you. Specifically, whether you actually take the time to read the instructions. If you don't, some results may fail to tell us very much about decision making in the real world. To help us confirm that you have read these instructions, please ignore the question about how you are feeling. Instead, only check the "none of the above" option. Thank you very much.

☐ Interested	☐ Hostile	☐ Nervous
☐ Distressed	☐ Enthusiastic	☐ Determined
☐ Excited	☐ Proud	☐ Attentive
☐ Upset	☐ Irritable	☐ Jittery
☐ Strong	☐ Alert	☐ Active
☐ Scared	☐ Inspired	☐ None of the above

In your opinion, were the questions included in this survey easy or difficult to understand?

- ◯ Easy to understand
- ◯ Neither easy nor difficult
- ◯ Difficult to understand

Please write down your MTurk ID

Feel free to share any comments with us below. For example, let us know if there is a question you did not understand.

TREATMENT FOR THE AMERICAN CANCER SOCIETY EXPERIMENT

(ALL OTHER QUESTIONS REMAIN IDENTICAL)

You have been randomly selected to receive the following information:

The American Cancer Society (ACS) is a nationwide voluntary health organization dedicated to eliminating cancer. Established in 1913, ACS offers programs and services to help the more than 1.4 million cancer patients diagnosed each year in this country, and the 14 million cancer survivors – as well as their family and friends.

Please proceed to the next screen to continue with the survey.

TREATMENT FOR THE FEED AMERICA EXPERIMENT

(ALL OTHER QUESTIONS REMAIN IDENTICAL)

You have been randomly selected to receive the following information:

The Feeding America network is the nation's largest domestic hunger-relief organization, working to connect people with food and end hunger. Feeding America network of food banks feed 40 million people at risk of hunger, including 12 million children and 7 million seniors. Donors, staff, and volunteers all play an important role in their efforts to end hunger in the United States.

Please proceed to the next screen to continue with the survey.

D Designated Market Areas (DMA) Border Discontinuity Research Design

To perform a border discontinuity analysis, we use the following steps. First, we identify all counties in the United States which share a physical border, but belong to different DMAs. Next, for the analysis of political donations, we exclude the county pairs that belong to different congressional districts. We exclude the counties that are not within the same congressional district, because otherwise we cannot meaningfully compare the patterns of political ads and the patterns of political donations to Congressional candidates. After these steps, we identified 987 distinct county pairs. These county pairs are our spatial units of observation.

Our key independent variable is spending on Congressional political ads, by DMA-month, obtained from the Wisconsin advertising project. We use inverse hyperbolic sine transformation (SINE) for dollar spending on ads. We estimate the specification given in equation (2) in Section 6. We use monthly aggregates of spending on ads for two reasons. First, spending on ads may be measured with error and monthly aggregates are more precise in this sense than the weekly estimates. Second, weekly ad spending exhibits high levels of autocorrelation for a disaggregated analysis to be meaningful. For the monthly analysis, we exclude the months with no previous data on ads, as we are not able to estimate the effect of pre-trend (columns 2 and 4 of Table 5) there, and we want the samples in columns 1 and 3 (2 and 4) of Table 5 to be comparable.

In our baseline specification (Table 5), we use estimates for the same time period as for when our RC data is available (2006-2011), to make sure that we are comparing the behavior of people during the same time period. We only include counties with non-zero presence of the Red Cross, according to our data (3032 out of 3143 (in 2010) counties in the United States), as only donations sent in pre-paid envelopes are part of ARC original data. To make sure that our results are not driven by different intensity of Red Cross fundraising campaigns, we control for the difference in ARC mailings across the border. Our results are virtually identical in the absence of this control.