Extreme Weather and the Politics of Climate Change: a Study of Campaign Finance and Elections

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Abstract

In this paper, we study how extreme weather and natural disasters affect political outcomes such as campaign contributions and elections. Weather events associated with climate change may influence these outcomes by leading voters to re-evaluate the incumbent politician's environmental position. In a short-run analysis, we find that the number of online contributions to the Democratic Party increases in response to higher weekly temperature and that the effect is stronger in counties with more anti-environment incumbent politicians. In a medium-run analysis, we find evidence that when a natural disaster strikes, the election becomes more competitive if the incumbent has a more anti-environment stance: total campaign contributions increase for both candidates, though the increase is skewed towards the challenger; the race is more likely to be contested, and; the incumbent is less likely to be re-elected. Finally, we address alternative mechanisms and explanations for our results.

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1 Introduction

Public opinion on key issues is thought to play a crucial role in shaping policies and elections in a democracy. Therefore, it is important to understand what factors contribute to the formation of these opinions as well as their political ramifications. One such key issue is climate change, which has received significant policy attention for decades.

In the United States, both the public and legislators remain divided when it comes to climate change despite the scientific consensus on it. Many studies have examined factors that shape Americans' attitudes on this issue using survey data (Akerlof et al., 2013; Howe et al., 2015; Myers et al., 2013; Spence et al., 2011; Zaval et al., 2014). As weather anomalies and natural disasters become widely associated with climate change (IPCC, 2013), one recurring finding is that exposure to these events leads individuals to report a greater perception of climate change.[1]

Still, less is known about how weather anomalies may impact costly, real-world actions. People may misreport their true preferences due to social or strategic considerations, so surveys of stated beliefs can be misleading. Furthermore, it is unclear whether these extreme weather events can, through changes in beliefs, have real-world political consequences. Importantly, it remains an open question whether politicians will be held accountable for their positions on environmental issues as beliefs regarding climate get updated.[2]

In this paper, we present direct evidence of campaign finance and electoral responses to extreme weather events. We assemble a comprehensive dataset of extreme weather shocks, natural disasters, and U.S. House of Representative elections. These data allow us to examine various response margins, from campaign contributions to the competitiveness of elections and their outcomes. To understand whether environmental ideology is a driver of political support for candidates, we collect information on the environmental voting records of members of Congress to assess where they stand on the *anti-environment* to *pro-environment* spectrum.[3] Our key approach is to

[1]The reported change in perception can be due to a change in the belief about climate change or a change in the salience of the issue. In this research, we do not seek to disentangle the two channels but to understand the political consequence of the change in perception.

[2]One reason changes in beliefs might not lead to political consequences is that climate change may not always be a top policy priority (Davis and Wurth, 2003; Guber, 2001).

[3]These terms are used for concise communication with the reader and do not necessarily represent the views of the authors on these issues or the politicians involved.

test for differential effects of weather and disaster shocks based on the environmental stance of incumbent politicians. Our results document a margin of political behavior in this context that is, to the best of our knowledge, novel in the literature. They also shed light on the mechanisms through which public opinion may shape climate change adaptation and mitigation policies.

Our study follows the literature closely in terms of choosing regression frameworks and constructing measures of weather shocks. Previous studies can be classified into three categories. The first set of studies focuses on short-run weather shocks, over a period of a month or less (Egan and Mullin, 2012; Hamilton and Stampone, 2013; Joireman et al., 2010; Li et al., 2011; Zaval et al., 2014). The second set uses medium-run temperature shocks, over a period of a month to a year (Deryugina, 2013). The third set focuses on medium-run natural disaster shocks, also over a period of a month to a year (Lang and Ryder, 2016; Sisco et al., 2017; Spence et al., 2011). In accordance to this literature, we examine both short- and medium-run temperature variation as well as medium-run natural disaster shocks.

In the short-run analysis, we examine how weekly temperature shocks affect contributions to Democratic candidates through ActBlue, an online fundraising platform, during 2006-2012. The identification relies on two features. First, temperature shocks are measured by deviations of weekly mean temperature from the historical average in the same month and location, which eliminates most cross-sectional variation and seasonality that may be correlated with unobserved confounding factors. Second, we control for a rich set of fixed effects including county, week-in-sample, and state-by-election cycle. The results reveal an extensive-margin response: a 1 $^{\circ}$F increase in weekly average temperature has a contemporaneous effect of a 1.2% increase in the contribution rate, and a cumulative monthly effect of 2.7%. We do not detect any intensive-margin effect. When looking across incumbent characteristics such as party membership and environmental attitudes, we find a stronger response to temperature shocks among constituents with more anti-environment incumbents. Together, these results suggest that following a temperature shock, Democratic candidates are rewarded for their pro-environment stance, and especially when they are running against a more anti-environment incumbent.

In the medium-run analysis, we start by exploring how natural disasters in an election cycle interact with an incumbent's stance on environmental issues to influence both campaign finance and electoral outcomes. Our disaster definition is based on federal disaster declarations from the Federal Emergency Management Agency (FEMA), and we include only climate-related disasters. We examine the universe of political contributions to candidates of both parties in the U.S. House of Representatives elections during 1990-2012. We use two regression specifications. The first exploits variation in the incumbent's stance on environmental issues regardless of party affiliation ("cross-party specification" henceforth), while controlling for congressional district and state-by-election-cycle fixed effects. However, as large partisan divide exists in environmental as well as a myriad of non-environmental issues, the latter is correlated with the former and might drive the results. In light of this concern, we present results from a second specification which uses within-party variation ("within-party specification" henceforth). Under both specifications, we find that after a natural disaster, total fundraising and the number of donors in an election cycle is higher if the incumbent has a more anti-environment stance, and the effect is stronger for donations to challengers than to incumbents. Further, we find that after a disaster, the more anti-environment the incumbent is the higher the chance of a challenger entering the race, leading to a slightly lower re-election probability for the incumbent.

While our results are robust to using within-party variation, there might still be correlations between a politician's position on environmental issues and that on non-environmental, disaster-related issues, conditional on party affiliation. One notable possibility is the support for disaster relief. Past studies have shown that incumbents are rewarded for requesting and spending funds for disaster recovery (Healy and Malhotra, 2009; Healy et al., 2010; Gasper and Reeves, 2011; Chen, 2013). We test this possibility by examining disasters that are not related to climate change, such as tornadoes and earthquakes. We do not find evidence that these events induce differential electoral consequences for more anti-environment incumbents. In addition, we also examine the impacts of medium-run temperature shocks using a similar methodology. We classify election cycles as hot, normal, or cold based on the number of unusually high- or low-temperature days. While perceived to be indicative of the climate, these events are not related to disaster policy, nor do they usually invoke demand for incumbent action. We find that the magnitude and direction of the effects of hot weather events are similar to that of natural disasters. Cold weather events, on the other hand, are associated with effects that are small and opposite in sign. This suggests that people react differently to hot and cold weather anomalies in this context. These results complement the short-run analysis since we are able to examine the universe of contributions to House candidates, both Republican and Democrat, online and offline.

Taken together, our results suggest that an anti-environment voting record might be politically costly for the incumbent when an extreme weather event occurs. Short-run temperature shocks motivate spontaneous donations to the Democrats, and more so for Democratic challengers of a Republican incumbent. The medium-run analysis shows a similar pattern, where occurrences of natural disasters and extreme temperature events lead to stronger support for challengers in districts with a more anti-environment incumbent. People on both sides of the climate change debate may be galvanized by these events, either independently or as a response to the other side's actions, leading to a more competitive election.

This paper contributes to several research areas. Firstly, it is among the few existing studies that use a revealed preference approach to study the effects of weather shocks on people's beliefs about climate change. Previous studies have examined low-stake outcomes such as Google searches (Herrnstadt and Muehlegger, 2014; Lang and Ryder, 2016) and Twitter posts (Sisco et al., 2017; Moore et al., 2019). Li et al. (2011) show that respondents in a survey donated more money to an environmental charity if they thought that day was warmer than usual, although this donation came from the fee they were awarded for completing the study. The outcomes we study are more costly. They are also directly related to the political processes where, at least in principle, public opinions can shape policies.

Secondly, our results contribute to the current understanding of the motivations for political giving. Our results show that the number of spontaneous political contributions responds to short-run temperature shocks, but not the average amount. This is consistent with the mainstream view that individuals make campaign contributions for ideological reasons (Barber, 2016; Bonica, 2014; Ensley, 2009; Francia et al., 2003), and that they derive direct utility from contributing to their candidate of choice as if they were consuming an ideologically-motivated consumption good (Ansolabehere et al., 2003). Our findings are also consistent with the idea that online fundraising platforms like ActBlue have enabled such "political consumption" by significantly lowering transaction costs (Karpf, 2013). Our medium-run results provide insights into PAC contributions, whose motivation has not been unanimously agreed upon in the literature. While a prevalent theory is that PAC contributions have a *quid pro quo* nature, recent studies reveal that ideological considerations are also at play (Barber, 2016; Bonica, 2013, 2014, 2013; Snyder, 1990). Our evidence that PAC contributions also respond to natural disaster shocks lends further support to the ideological mechanism.

Thirdly, our results shed light on whether politicians are held accountable by constituents for their policy positions. On one hand, there is evidence to suggest that voters make seemingly irrational decisions, since same-day weather conditions or financial windfalls from lotteries have been shown to affect voting outcomes (Gomez et al., 2007; Bagues and Esteve-Volart, 2016; Meier et al., 2019). On the other hand, there is also evidence that incumbents are held partially accountable for their roles in disaster preparedness and post-disaster relief. For example, Arceneaux and Stein (2006) show that voters punish the incumbent mayor after a flood if they believed the city was responsible for flood preparation. Healy and Malhotra (2009) and Gasper and Reeves (2011) show that the electorates may punish or reward presidents and governors based on the delivery of disaster relief. Our analysis complements these studies by exploring legislative elections to the U.S. House of Representatives. We also go beyond the direct impacts of natural disasters to examine the broader issue of environmental ideology. Our results suggest that politicians are subject to electoral pressure on environmental issues. This finding is coherent with emerging evidence on changes in legislators' behaviors in response to a natural disaster. Herrnstadt and Muehlegger (2014) show that congresspersons are more likely to vote in favor of environmental legislation following natural disasters in their state. Gagliarducci et al. (2019) find an increased likelihood of sponsorship of green bills. While there are multiple possible channels for their results, a higher probability of being challenged could certainly put pressure on incumbents to change legislative behavior.

Finally, our findings also have important policy implications. Even though environmental issues are typically not front-and-center in U.S. elections, we demonstrate that the electorate is responsive to the salience of these issues. However, we caution that these responses may not be rational, since people may process shocks with psychological biases.[4] These responses may also reflect a suboptimal allocation of attention. Nevertheless, our findings suggest that approaches to raise issue salience by recounting relatable human experiences might have the potential to induce substantial changes in political behavior.

The remainder of this paper is organized as follows. Section 2 describes our data sources, while Section 3 describes our empirical strategy. In Section 4 we report and discuss the results. We conclude in Section 5.

[4] For example, Gallagher (2014) examines flood insurance take-up following flood events and finds a pattern indicative of availability bias or other forms of Bayesian learning with incomplete information.

2 Data

2.1 Database on Ideology, Money in Politics, and Elections

The political data we use come from the Database on Ideology, Money in Politics, and Elections (DIME) (Bonica, 2016). This database includes over 100 million campaign contributions made by individuals and organizations to candidates in local, state, and federal elections from 1979 to 2016. The main source of information is administrative records from the Federal Election Commission (FEC). In addition to campaign finance data, the database includes characteristics of the candidates receiving contributions, as well as information on election outcomes.[5]

For our study of the impact of short-run weather shocks on political campaign contributions, we use a subsample of the individual contributions data from DIME. The reason is that while individual contributions have dates assigned to them, these dates do not always match the contribution date. Instead, they may indicate the date the campaign or candidate filed these contributions. Since we are interested in people's response to short-run, time-varying weather shocks, we need accurate date information. To circumvent this problem, we focus on contributions made through the online fundraising platform ActBlue, since the reported date matches the date of the contribution in this sample. We discuss the implications of using ActBlue data in the following section.

For our study of the political consequences of natural disasters and medium-run weather shocks, we use the "recipients" file of the DIME database. This file contains information at the election cycle-by-candidate level and includes the total amount of funds raised by candidates from different sources, the seat sought, and the result of the election.

2.2 ActBlue

In our short-term study, we focus on campaign contributions made through ActBlue, which is an online fundraising platform for Democratic candidates. The site was founded in 2004 and its popularity rose quickly thereafter. In our sample, Act-

[5] For a detailed description of the database and data sources, please visit https://data.stanford.edu/dime.

Blue accounts for 4.3% of contributions and 0.8% of the total amount contributed to Democratic candidates.[6]

The main advantage of using ActBlue data is that the dates on ActBlue records are accurate, as they are electronically recorded at the time the contribution is made. Naturally, relying on accurate date information is crucial for estimating responses to short-run weather variations. Another advantage of using ActBlue is that the contributions made on the site are typically small in quantity (see Figure A2). For our purposes, these donations are very relevant, since they correspond to more spontaneous, lower-stake contribution decisions that may be affected by short-run weather variations.[7]

However, there are two concerns with using only ActBlue data for our short-run analysis. The first concern is that the lack of an established Republican equivalent of ActBlue leaves us with only donations to Democrats.[8] This feature of our data does not allow us to see how donations to Republicans would respond, which is a shortcoming of our strategy. However, we propose alternative methodologies in the following sections to address this concern. The second concern is that it is unclear whether using ActBlue data will yield results that are representative of how contributions to Democrats as a whole respond to weather shocks. Past studies have found that Internet donors tend to be much younger and give a smaller amount than the rest of the contributors, but are similar in terms of ideological positions (Wilcox, 2008; Karpf, 2013).[9] It should also be noted that these findings are from surveys conducted in the year 2000, while our main sample period is 2006-2012 when Internet use was more prevalent among the general population. In Appendix A, we show in more detail that ActBlue contributions and total Democratic contributions are highly correlated both over geographic areas and across time. For our purposes, even though Internet contributors may not be a mirror image of the general contributing population, focusing on these contributions allows

[6]Conversely, the total amount of contributions to Democrats is about 24 times the number of ActBlue contributions, and the total amount contributed to Democrats is 122 times the amount contributed through ActBlue. We keep these numbers in mind when assessing the magnitude of our coefficients later on.

[7]For an example of how contributions are made to Democratic candidates through ActBlue, see Figure A1.

[8]Rightroots, Big Red Tent, and Slatecard are examples, but their popularity has been far lower than ActBlue's.

[9]Specifically, Karpf (2013) suggests that the Internet brings about an increase in small donors by lowering transaction costs. They also suggest that this change has facilitated the flow of campaign funds towards more polarizing candidates. Meanwhile, Wilcox (2008) finds that Internet donors are much younger than other donors, but that those giving small amounts to Democrats online are actually similarly likely to consider themselves "ideologically extreme" as larger donors are.

us to hone in on lower-cost, spontaneous decisions that may be affected by weather variations.

2.3 League of Conservation Voters Scorecard

To capture the stance of incumbent politicians on environmental issues, we use the League of Conservation Voters (LCV) scorecard (also known as the *National Environmental Scorecard*). The LCV scorecard assigns percentage scores to U.S. congresspersons based on their voting records regarding environmental legislation introduced during a particular year.[10] According to the terminology used by the LCV, if a politician aligns with the LCV opinion on a vote, it is marked as a *pro-environment* action; conversely, if the politician does not align with the LCV on a vote, it is marked as an *anti-environment* action (League of Conservation Voters, 2007). For conciseness, in this paper, we will follow this terminology and refer to politicians who frequently align with the LCV as pro-environment and to those who don't as anti-environment.[11]

More specifically, LCV scores range from zero to one with pro- and anti-environment voting records on either side of the spectrum. In this paper, we subtract the original scores from one so that a score of zero indicates that the politician has disagreed with the LCV on 0% of the votes selected (pro-environment); conversely, a score of one indicates that the politician has disagreed with the LCV on 100% of the votes selected (anti-environment).[12]

There is a large divide in the LCV scores of Democrats versus Republicans, as shown in Figure 1. This is likely because politicians tend to vote along party lines when it comes to environmental issues. A majority of Democrats fall into the 0-0.25 range, meaning that they disagree with the LCV on less than 25% of the relevant votes. Likewise, most Republicans fall in the 0.75-1 range, meaning that they disagree with the LCV more than 75% of the time. However, there is still substantial within-party variation in environmental voting records. While the overall standard deviation of the LCV score is 0.32, the within-party standard deviation is 0.2.

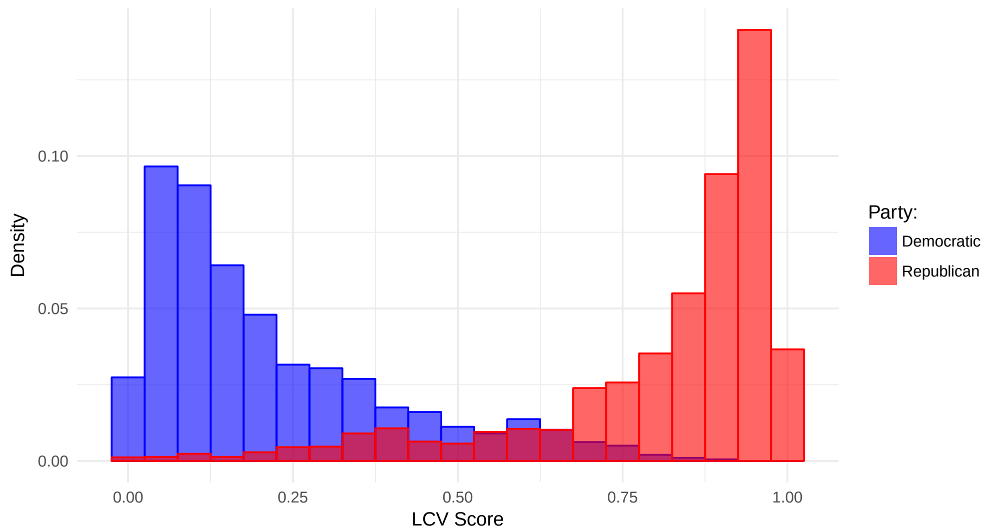
Additionally, the LCV score is an important indicator of whether the politician is a

[10] The legislation included in the scorecard arises from a consensus among leading environmental and conservation organizations in the U.S.

[11] Disclaimer: these terms are used to facilitate communication with the reader and do not necessarily represent the views of the authors on these issues or the politicians involved.

[12] For more information about the LCV scorecard, please visit the LCV website at http://scorecard.lcv.org/.

Figure 1: LCV score distribution by party affiliation



climate change denier. We obtain information on which congresspersons in the 112th caucus are climate change deniers from the site ThinkProgress.org.[13] Linking this information with LCV score data, we show that the probability of being a climate change denier is 51% for politicians with LCV scores above 0.5. Conversely, the probability of being a climate change denier for politicians with LCV scores below 0.5 is zero.

2.4 Weather Shocks

We obtain historical weather data from the Global Historical Climatology Network Daily (GHCN-D) database. This database contains daily observations of maximum temperature and precipitation from more than 8,000 weather stations throughout the United States during 1960-2014. Using this information, we construct measures of county-level weather.[14]

We construct two measures of daily temperature shocks, which we later aggregate over various time intervals for our analyses. The first measure is the daily deviation in maximum temperature from the historical climate normal in each county and month:

$$TmaxDev_{cmd} = Tmax_{cmd} - \overline{Tmax}_{cm}$$

[13] See the article "The Climate Zombie Caucus Of The 112th Congress" at https://thinkprogress.org/the-climate-zombie-caucus-of-the-112th-congress-2ee9c4f9e46/.

[14] If there is more than one weather station present in a given county, we take the average over all weather stations.

where c is county, m is month of year, and d is day-in-sample. $Tmax_{cmd}$ is the contemporaneous daily maximum temperature in county c. $\overline{Tmax}_{cm}$ is the long-run average of maximum temperature for this county in the same month, calculated over the 30 preceding years. The second measure is a pair of indicators for whether the maximum daily temperature is abnormally high or low, compared to historical temperature distributions:

$$TmaxLow_{5,cmd} = 1(Tmax_{cmd} \leq Tmax_{5,cm})$$

$$TmaxHigh_{5,cmd} = 1(Tmax_{cmd} \geq Tmax_{95,cm})$$

where $Tmax_{5,cm}$ is the 5th percentile of the distribution of maximum temperatures in the same county and month over the 30 preceding years, and $Tmax_{95,cm}$ is the corresponding 95th percentile. As a result, $TmaxLow_{5,cmd}$ is an indicator for whether the contemporaneous temperature is lower than the 5th percentile of the historical distribution, whereas $TmaxHigh_{95,cmd}$ indicates whether it is higher than the 95th percentile of that distribution.

For our short-run analysis at the county-week level, we aggregate these daily measures by week, to obtain our regressors of interest. We construct $TmaxDev_{cw}$, which is the average of $TmaxDev_{cmd}$ over the week and is our primary temperature shock measure. We also construct $TmaxHigh_{cw}$ and $TmaxLow_{cw}$, which are the sums over the week of $TmaxHigh_{5,cmd}$ and $TmaxLow_{5,cmd}$, respectively. Importantly, these measures capture different aspects of weather shocks. Further, we also construct similar measures of precipitation deviations which we use as controls in our regressions.

For our medium-run analysis, we first calculate the number of hot days, defined as those above the 95th percentile of the historical distribution, experienced by the average person in each congressional district and election cycle.[15] We then rank district-cycle observations by this variable and assign *hot* status to those cycles in the top quartile. Similarly, we assign *cold* status to a district-cycle if it is in the top quartile ranked by the number of cold days, defined as those below the 5th percentile of the historical distribution.

[15]The procedure makes use of the MABLE/Geocorr crosswalks developed by Missouri Census Data Center (2017), which partitions the population in a congressional district into its overlapping counties using Census data.

2.5 Natural Disasters

We obtain official disaster declaration data from the Federal Emergency Management Agency (FEMA) between 1990 and 2012. There are a total of 2,123 climate-related disasters, a large majority are storms (including hurricanes) and fires (table A1). Importantly, these official records contain the period of the incident and the specific counties affected. Most declarations are not statewide.

Because we analyze the impact of natural disasters at the congressional district level, we need to aggregate disaster status from counties to congressional districts. We first calculate the fraction of the population in a district who are residing in counties hit by disasters.[16] A congressional district is considered to be hit by a disaster if that fraction exceeds 50%. This might not be the exact threshold at which natural disasters become salient politically and thus could lead to measurement error. However, the majority of district-cycle observations in our data have a fraction of the population affected of either zero or one, so adjustments to the threshold would not have a substantial impact on our results.

3 Empirical Framework

Existing studies suggest that climate change perception is affected by personal experiences and there are multiple possible relevant time frames and types of weather events. Following this literature, we examine the impacts of weather shocks both in both the short and medium run, as well as the medium-run impacts of natural disasters. In this section, we outline our empirical strategy for doing so.

3.1 Short-Run Weather Impacts

We first analyze the impact of weekly weather shocks on contributions to Democrats through ActBlue. Since Democratic candidates tend to be more pro-environment than non-Democratic candidates, we expect these donations to increase in response to weather shocks as people's perceptions of climate change elevate.

[16] This procedure also uses MABLE/Geocorr crosswalks (Missouri Census Data Center, 2017).

The estimating equations takes the following form:

$$Y_{cw} = \gamma' Weather_{cw} + \delta_w + \delta_c + \delta_{se} + \varepsilon_{cw} \tag{1}$$

where c is county, w is week-in-sample, s is state, and e is election cycle. Y_{cw} is the outcome of interest from ActBlue records, which can be either (1) the contribution rate (the per capita number of contributions), or (2) the average amount per contribution. Furthermore, $Weather_{cw}$ is a vector of weather variables, which includes measures of temperature conditions as the key regressors and those of precipitation conditions as controls. Our coefficients of interest are the ones in γ corresponding to the temperature variables.

We use three different specifications of $Weather_{cw}$ in our main analysis. The first specification includes temperature and precipitation shocks in the same week:

$$Weather_{cw} = [TmaxDev_{cw}, PrcpDev_{cw}]^T.$$

The shocks are defined as deviations from long-run climate normals, as discussed in Section 2.4. To allow for a delayed effect of the temperature shock on contributions, we add four lags of both temperature and precipitation shocks to our second specification:

$$Weather_{cw} = [TmaxDev_{cw}, ..., TmaxDev_{c,w-4}, PrcpDev_{cw}, ..., PrcpDev_{c,w-4}]^T.$$

This specification captures delayed impacts of weather shocks occurring during the past month. The third specification uses the average of shocks in the current and previous week:

$$Weather_{cw} = [\overline{TmaxDev}_{c,w}, \overline{PrcpDev}_{c,w}]^T$$

where $\overline{TmaxDev}_{c,w} = \frac{1}{2}(TmaxDev_{cw} + TmaxDev_{c,w-1})$, and $\overline{PrcpDev}_{c,w}$ is similarly defined.

All specifications include week-in-sample (δ_w), county (δ_c), and state-by-election cycle (δ_{se}) fixed effects. The county fixed effects absorb time-invariant factors in each county such as general political preferences and contribution behavior. The week-in-sample fixed effects control for confounding national events and the exponential growth of the platform itself. Finally, the state-by-cycle fixed effects account for slower-moving changes across states, such as whether the current president is politically aligned with the state or new policies adopted by the state. We cluster standard errors at the county level.

Aside from the main specifications outlined above, we also consider four extensions. First, we estimate the effects of positive and negative temperature deviations separately as people might respond to them differently. Second, we estimate effects separately for each quarter of the election cycle to study how these vary with the progression of campaigns. Third, we consider alternative measures of our independent variables by focusing on counts of extreme temperature events instead of average temperature. Fourth, we extend our main regressions to allow for heterogeneous effects depending on the environmental stance of the incumbents in the contributor's place of residence, to rule out unobservable confounding factors that may drive all contributions across time and location, and not only those that are environmentally motivated. More specifically, we examine whether the response to weather shocks is stronger for counties where the majority of the population lives in districts represented by anti-environment incumbents.[17] For more details on these additional specifications, see Appendix B.

3.2 Medium-Run Natural Disaster Impacts

Aside from studying weather shocks, we are interested in how fundraising and elections are affected by natural disasters in the medium run. Specifically, we study how this relationship varies depending on the environmental stance of the incumbent politician. Our sample contains races for the U.S. House of Representatives during election cycles 1990-2012. We study campaign finance outcomes, such as total funds raised and the fraction that goes to the challenger. We also examine electoral outcomes such as the probability of the incumbent being challenged, getting re-elected, etc.

One concern we have to address is that natural disasters may have significant effects on campaign contributions and other political outcomes through channels unrelated to environmental preferences and beliefs. For example, following the September 11 terror attacks, individuals substituted away from campaign contributions and towards charitable giving.[18] We expect this to be relevant for natural disasters as well since they often entail tragic consequences and loss of property.

To address the above concern, our research design consists in comparing congressional districts experiencing natural disasters whose incumbent politicians have an anti-environment voting record to other districts experiencing natural disasters but

[17] This is what we would expect as long as the Democratic candidates receiving contributions on ActBlue are more pro-environment on average.

[18] "Despite Terrorism, Candidates Make Slow Return to Fundraising.", The Hill. October 24, 2001. www.hillnews.com/102401.

whose incumbents exhibit pro-environment voting records. By studying differential impacts by the environmental stance of incumbents, we hope to isolate the environmental preference mechanism. Specifically, the regression equation takes the following form:

$$Y_{de} = \beta_1 Disaster_{de} + \beta_2 LCV_{de} + \beta_3 Disaster_{de} \times LCV_{de} + \delta_d + \delta_{se} + \varepsilon_{de} \tag{2}$$

where Y_{de} is an outcome for a race in congressional district d during election cycle e; $Disaster_{de}$ is an indicator variable for whether the congressional district has experienced a major disaster, as defined in Section 2.5; LCV_{de} is the LCV score of the incumbent;[19] and δ_d and δ_{se} are fixed effects for congressional district and state-by-election cycle, respectively. We cluster standard errors at the state level.

Our coefficient of interest is β_3. This coefficient should be interpreted as the difference in the outcome of a disaster-struck congressional district whose incumbent congressperson has the most anti-environment voting record ($LCV = 1$), and the outcome of a similar, disaster-struck congressional district whose incumbent congressperson has the most pro-environment voting record possible ($LCV = 0$). Given that a one-unit difference in the LCV score is a very large difference, we suggest scaling our estimates by the standard deviation of the LCV score in interpretation. Since the standard deviation of the LCV score is 0.2, we interpret our coefficients by dividing them by five.[20]

While the LCV score captures precisely the political dimension we care about, it is important to consider how it relates to party affiliation. As we can see in Figure 1, the LCV score is closely related to party affiliation. This raises a limitation of model (2): following a natural disaster, if people react differently to incumbents from different parties for non-environmental reasons, then the coefficient of interest would be picking up on these factors as well. To address this issue, we propose an extension of the above model. The proposed model is:

$$\begin{aligned} Y_{de} = &\beta_1 Disaster_{de} + \beta_2 LCV_{de} + \beta_3 Disaster_{de} \times LCV_{de} + \\ &\beta_4 R_{de} + \beta_5 Disaster_{de} \times R_{de} + \delta_d + \delta_{se} + \varepsilon_{de} \end{aligned} \tag{3}$$

where all variables are defined as in model (2) and we have now added R_{de}, an indicator

[19]In order to incorporate all available information at the time of the race, we average the LCV score of politicians for that election cycle and all past election cycles, using this measure throughout in our regressions.

[20]We propose to use the standard deviation of LCV score after controlling for the politician's party, which is 0.2. Without controlling for the politician's party the standard deviation is 0.32.

variable for whether the incumbent is a Republican, as well as an interaction of this variable with $Disaster_{de}$. Our coefficient of interest is still β_3, which is now identified using variation in the LCV score within the incumbent's political party.

It is important to note that model (3) comes with both advantages and disadvantages over model (2). The main advantage, as previously discussed, is that it addresses the concern that people may respond to disasters differently depending on the incumbent party for reasons unrelated to the environment. The disadvantage is that the model does not make use of of meaningful cross-party variation in environmental stances, which is perhaps the most visible and available to people when making decisions. Therefore, we consider these models to be complementary and keep these features in mind when interpreting results.

3.3 Medium-Run Weather Impacts

Campaign contributions and elections may also respond to shocks to medium-run temperature. Since people may respond to hot- and cold-weather shocks differently, we estimate their effects separately. Using the same notation as in the natural disasters section, we study the impact of medium-run weather as follows:

$$\begin{aligned} Y_{de} =& \beta_1 Hot_{de} + \beta_2 Cold_{de} + \beta_3 LCV_{de} + \beta_4 Hot_{de} \times LCV_{de} + \\ & \beta_5 Cold_{de} \times LCV_{de} + \delta_d + \delta_{se} + \varepsilon_{de}. \end{aligned} \tag{4}$$

Hot_{de} and $Cold_{de}$ are indicators for whether the election cycle was particularly hot or cold for a given district in an election cycle, constructed as described in Section 2.4. Aside from including these variables, we also add their interaction with the LCV score, following our earlier models. All fixed effects are as previously defined. Standard errors are clustered by state.

Our coefficients of interest are β_4 and β_5. As before, we interpret these coefficients as the difference in the outcome of a congressional district undergoing an unusually hot (cold) cycle, whose incumbent congressperson has the most anti-environment voting record ($LCV = 1$), and the outcome of a similar district whose incumbent congressperson has the most pro-environment voting record possible ($LCV = 0$). Again, we divide them by five in interpretation. Finally, it is straightforward to extend this methodology to make use of within-party variation in the LCV score following a disaster, by adding R_{de} and its interaction with LCV as in model (3) above.

4 Results

In this section, we present our results in three parts: (1) short-run temperature impacts on ActBlue contributions, (2) medium-run natural disaster impacts on campaign contributions and election outcomes, and (3) medium-run temperature impacts on the same set of outcomes as in (2).

4.1 Short-Run Weather Impacts

In the short-run analysis, we investigate how ActBlue contributions are affected by temperature shocks in the current and previous weeks. We examine two outcomes. The first outcome is the contribution rate, defined as the number of contributions per million people in a county. This variable captures extensive-margin responses, i.e. whether temperature shocks motivate more or fewer contributions. The second outcome is the average amount per contribution, calculated as the total amount contributed divided by the number of contributions for each county-week. Absent any extensive-margin responses, this outcome measures intensive-margin responses, i.e. whether temperature shocks motivate larger or smaller donations from regular contributors. However, if extensive-margin responses are present, this outcome captures both the intensive-margin responses and potential changes in the composition of contributors.

In our sample period of 2006-2012, each county receives around \$150 per week (Table A2). ActBlue contributions are usually small: the average donation amount is \$13.2. Meanwhile, the mean weekly temperature deviation from the historical normals is 0.45 °F, showing a warming trend. This pattern is also illustrated by the extreme temperature bins, as the number of extremely hot days exceeds the number of extremely cold ones.[21]

Table 1 reports estimates from equation (1). Columns (1)-(3) focus on responses in the contribution rate. In Column (1), the main weather variable is temperature shock in the current week.[22] The estimate is positive and significant at the 1% level. A 1 °F increase in weekly temperature is associated with 0.19 additional contributions per million people (1.2% D.V. mean).[23] In Column (2), we augment the model with

[21]Extremely hot days are those above the 95th percentile of the historical distribution, while extremely cold days are those below the 5th percentile of that distribution.

[22]The deviation in precipitation is also included in the model as a control. Both temperature and precipitation shocks are constructed as the deviation from 30-year normal, as detailed in Section 2.4.

[23]$\widehat{\gamma_0}/D.V.Mean = 0.186/15.40 \approx 1.2\%$.

Table 1: Actblue donation responses to short-run temperature shocks

Dep. Var.	Count/1M pop			Average amount		
	(1)	(2)	(3)	(4)	(5)	(6)
TmaxDev (current week)	0.186***	0.134***		0.0163	0.0129	
	(0.0574)	(0.0449)		(0.0471)	(0.0461)	
TmaxDev (1-week lag)		0.103***			-0.0426	
		(0.0355)			(0.0343)	
TmaxDev (2-week lag)		0.0540***			0.0547	
		(0.0166)			(0.0411)	
TmaxDev (3-week lag)		0.0721***			0.0352	
		(0.0246)			(0.0346)	
TmaxDev (4-week lag)		0.0547**			-0.0348	
		(0.0231)			(0.0323)	
TmaxDev (2-week avg.)			0.287***			-0.00740
			(0.0832)			(0.0545)
N	944172	935201	941672	944172	935201	941672
R^2	0.209	0.204	0.209	0.0539	0.0539	0.0539
D.V. Mean	15.42	15.42	15.42	13.15	13.15	13.15
County F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Week F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State-cycle F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Notes: point estimates from equation (1) are shown. The dependent variable in columns (1)-(3) is the number of contributions per 1 million people, and that in columns (4)-(6) is the average amount per contribution. The sample consists of ActBlue contributions by week and county. Standard errors are clustered by county. Statistical significance: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

four lags of temperature deviations. This specification allows us to examine whether temperature deviations from previous weeks might affect contemporaneous contributions. The estimated dynamics have two remarkable features. First, the estimates are across-the-board positive and significant. This pattern is inconsistent with a harvesting mechanism, where a temperature shock simply shifts the timing of contributions but not the overall amount. Instead, these effects could represent a net increase in contributions. Second, the impact of a temperature shock appears to decay over time, as the estimates are lower for temperature deviations that took place longer ago. The contemporaneous effect is smaller than in Column (1), but the cumulative effect is larger: a 1 °F increase in weekly temperature is associated with a cumulative effect of 0.42 additional contributions per million population, or a 2.7% increase in the contribution rate relative to the mean.[24] The comparison between Columns (1) and (2) suggests that omitting temperature lags might have led us to overestimate the contemporaneous effect and underestimate the overall effects of a temperature shock. In Column (3), we take the average of deviations in these two weeks and use it as our main independent variable. As expected, the estimate is again positive and significant at the 1% level.

In Columns (4)-(6), we re-estimate our models using the average contribution amount as the outcome variable. In this case, all estimates are small and statistically insignificant, with no recognizable pattern. This could mean that temperature shocks do not induce intensive-margin responses or changes in contributor composition that are strong enough to be statistically detectable. It is also possible that these changes go in opposite directions and cancel each other out.

We also estimate several variants of equation (1). In Table A3, we estimate the effects of positive and negative shocks separately. This is implemented by replacing each deviation regressor above with a pair of variables that separately capture the absolute values of its positive and negative components.[25] The results show that the observed effects are mainly driven by variation in positive shocks. In Table A4, we report estimates based on alternative measures of temperature shocks. These are a pair of variables counting the number of extremely hot/cold days in a week. Such extreme temperature events might be more salient than the average temperature. Again, we find effects on the contribution rate but not the other two outcomes. One more extremely hot day in a week is associated with a contemporaneous increase of 0.35 contributions per million people (2.3% D.V. mean). The cumulative effect over a month is an increase of 7% of the mean.[26] On the flip side, one more extremely cold day reduces the contribution rate by 6.6% in the current week and 15.8% cumulatively. This finding stands in contrast with our results above using average temperature deviations, where we find no impact from negative shocks. The difference might be explained by psychological factors, that an extremely cold day might be more salient than a slightly colder spell. It could also be due to the political discourse surrounding cold-weather events.[27] In fact, it is consistent with Roxburgh et al. (2019), who examine climate change discourse on social media and find evidence of a lesser public understanding of

[24] $(\widehat{\gamma_0} + ... + \widehat{\gamma_4})/MeanD.V. = (0.134 + 0.103 + 0.054 + 0.072 + 0.055)/15.40 \approx 2.7\%$.

[25] For more details on the specification, see Appendix B.

[26] $\widehat{\gamma_0}/D.V.Mean = 0.353/15.40 \approx 2.3\%$.

[27] Examples include "Inhofe brings snowball on Senate floor as evidence globe is not warming", CNN, https://www.cnn.com/2015/02/26/politics/james-inhofe-snowball-climate-change/index.html and "Why is the cold weather so extreme if the Earth is warming?", the New York Times, https://www.nytimes.com/interactive/2019/climate/winter-cold-weather.html.

how climate change may influence cold weather events when compared with tropical storms.

Taken together, our results suggest that the impact of temperature shocks is concentrated on motivating more instances of political giving to Democrats but not a larger average amount. This finding is consistent with a mechanism where a positive temperature shock leads people to feel more politically aligned with Democratic candidates, due to either a stronger belief on climate change or greater attention to the issue. However, there are also alternative explanations that are unrelated to environmental reasons. For example, it is known that weather can change voting behavior through psychological channels (Meier et al., 2019). It might also affect time use or the expediency of online versus other contribution channels.[28]

To address these concerns and shed light on the mechanisms behind our results, we examine heterogeneous effects based on incumbent characteristics.[29] To enhance statistical power, we build on the specification reported in Column (3)/(6) of Table 1, using a two-week average deviation as the main measure of temperature shock. We add an interaction term of the temperature variable with one of two incumbent characteristics: (1) population-weighted mean LCV score (mean = 0.672); (2) whether over half of the population has a Republican incumbent (mean = 62.2%).[30] We are interested in the coefficient associated with the interaction term as it shows how the effects of weather shocks vary according to incumbent characteristics.[31] In this analysis, we restrict our sample to competitive races.

The results are reported in Table 2. As before, we find a positive and significant effect of temperature deviations on the contribution rate, but not on the average amount. Importantly, the interaction term shows that the effect on contributions is larger when the incumbent has a more unfavorable view of environmental protection or is a Republican. The scale is important relative to the baseline effect (Column (3), Table 1).

[28] Section 4.4 presents a detailed discussion of the alternative mechanisms.

[29] We do not observe which candidates receive the contribution in the ActBlue data, only the place of residence of the donor. This limits our investigation to incumbent characteristics. While many contributions are directed to candidates outside of the district of residence of the contributor, we think this is a meaningful margin of giving behavior to study. For example, environmentally motivated donors may look to other congressional district races if the district they reside in is a very safe seat held by an anti-environment politician.

[30] The summary statistics suggest that the counties in our sample tend to have incumbents who are unfavorable to environmental protection and more likely to be Republicans. This could be due to people supporting a Democratic challenger being more active in online contributions than those supporting a Democratic incumbent.

[31] For more details on the specification, see Appendix B.

Table 2: Heterogeneous effects by incumbent characteristics

Dep. Var.	(1) Count/1M pop	(2) Avg. amount	(3) Count/1M pop	(4) Avg. amount
TmaxDev (2-week avg.)	0.193**	-0.115	0.228**	-0.102
	(0.0975)	(0.118)	(0.103)	(0.0748)
LCV	10.30**	2.016		
	(4.658)	(1.318)		
TmaxDev × LCV	0.152**	0.128		
	(0.0681)	(0.110)		
Republican			5.336**	0.764
			(2.674)	(0.854)
TmaxDev × Republican			0.107***	0.117**
			(0.0373)	(0.0557)
R^2	0.207	0.0550	0.207	0.0551
N	830316	830316	830316	830316
D.V. Mean	12.29	11.09	12.29	11.09
County F.E.	Yes	Yes	Yes	Yes
Week F.E.	Yes	Yes	Yes	Yes
State-cycle F.E.	Yes	Yes	Yes	Yes

Notes: point estimates from equation (8) are shown. The dependent variable in columns (1)-(3) is the number of contributions per 1 million people, and that in columns (4)-(6) is the average amount per contribution. The temperature shock measure is the average temperature deviation in the current and past week. Standard errors are clustered by county. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Column (1) shows that, when the mean LCV score increases by one standard deviation, the scale of the positive effect goes up by 10.6% of the average effect.[32] Further, the effect of temperature shocks in Republican-dominated counties is 37.3% larger than in Democrat-dominated ones, according to Column (2).[33] These results suggest that people make compensatory contributions when politicians ideologically different from them are elected in their district.[34]

We also examine how effects vary based on the progression of campaigns. We include an interaction term of the two-week temperature measure with a set of eight

[32]LCV incremental effect: $SD(\overline{LCV}) \times \widehat{\beta}_3/\widehat{\beta}_1 = 0.2 \times 0.152/0.287 \approx 10.6\%$.

[33]Republican incremental effect: $\widehat{\beta}_3/\widehat{\beta}_1 = 0.107/0.287 \approx 37.3\%$.

[34]This is also consistent with the coefficients on the incumbent characteristics, which are all positive and significant when looking at contribution rates. Since we have controlled for county fixed effects, this parameter identifies the increase in the contribution rate corresponding to an increase in anti-environment or Republican incumbents within a county.

indicators for quarters in the election cycle, which yields a separate estimate for each quarter. The results are plotted in Figure A3 and reported in Table A5. The results reveal a new finding previously masked in our main estimates. The positive effect of high-temperature shocks on contribution rate is the largest in the last quarter leading up to the election. In the same quarter, we also observe a negative impact of temperature shocks on the average contribution amount. This is consistent with a selection mechanism where heat shocks draw in more small-amount contributions.

Lastly, we perform a back-of-the-envelope calculation to infer the effects of temperature shocks on total Democratic contributions using estimates based on ActBlue contributions. This calculation allows us to gauge the actual magnitudes of our previous estimates. In our sample, the total number of Democratic contributions is 24 times that of ActBlue contributions, and the total amount is 122 times larger. Using these numbers and our estimates in Table 1, we find that the contemporaneous effect of a 1 °F increase in weekly mean temperature corresponds to a total increase of 3.2 contributions or $215.6 per million people per week.[35] The corresponding cumulative effects are 10 contributions and $672.6. It should be noted that this calculation relies on the assumption that total Democratic donations and ActBlue donations react similarly to weather shocks. In reality, we may expect ActBlue donations to react more strongly given the small and spontaneous nature of these contributions, meaning that these calculations are likely to represent upper bounds on the actual effects.

4.2 Medium-Run Natural Disaster Impacts

In this section, we study the impact of natural disasters on campaign finance and elections. This analysis complements the previous results, as we explicitly account for politicians' environmental attitudes and include contributions to both Democratic and Republican candidates. As suggested by previous studies, natural disasters can draw public attention to climate change (Lang and Ryder, 2016; Sisco et al., 2017) and they also bring about political ramifications for the incumbents (Arceneaux and Stein, 2006; Gasper and Reeves, 2011; Healy and Malhotra, 2009). Building on this literature, we hypothesize that anti-environment leaning incumbents will be held accountable for their environmental stance when a natural disaster strikes, leading to increased support for challengers. However, we do not necessarily expect support for these incumbents to remain unchanged, since they may intensify their fundraising efforts as a response

[35] Δ number of contribution $= \widehat{\gamma_0} \times ratio(Dem/ActB) = 0.134 \times 24 = 3.22$. Δ total amount $= \Delta$ number of contributions $\times$ average amount $\times ratio(Dem/ActB) = 0.134 \times 13.19 \times 122 = 215.63$.

to the increased support for challengers. In other words, we are agnostic about what happens to incumbent support.

Our sample includes House of Representative races during the 1990-2012 election cycles. Summary statistics for the sample can be found in the bottom panel of Table A2. Out of the races in our data, 73% are competitive, 17.2% are uncontested, and the remaining 9.8% are open races. When studying campaign finance outcomes, we focus on all races where the incumbent is seeking re-election.[36] The incumbents enjoy large advantages when they run: both the number of donors and the total amount of funds raised are much higher for them than for challengers.

We examine how the impact of a natural disaster varies depending on the environmental voting record of the incumbent politician (LCV score). We run regressions that follow the specifications in equations (2) and (3). When interpreting the magnitude of our coefficients, we divide them by five so that they correspond to the effect of a one-standard-deviation difference in the LCV score of a candidate.[37]

We start by studying the effects of natural disasters on the amount of funds raised during the election. Panel A of Table 3 contains the results using the cross-party specification described in equation (2). Column (1) shows that total fundraising following a natural disaster is higher in districts with more anti-environment incumbents. More precisely, a one-standard-deviation increase in the LCV score of the incumbent translates to a $99,000 increase in total fundraising during a cycle (7.4% D.V. mean), when a natural disaster strikes. Next, columns (2) and (3) break down the sources and show that funds from PACs go up by about $24,000 (4.9% D.V. mean) and funds from individuals go up by about $49,000 (7.0% D.V. mean). In columns (4)-(6), we assess whether there is increased support for challengers, incumbents, or both. In column (4), we find that a one-standard-deviation increase in the LCV score of the incumbent translates to a $43,000 (13.6% D.V. mean) increase in fundraising by challengers during a cycle, when a natural disaster strikes. This result substantiates the hypothesis of increased support for challengers in races with anti-environment incumbents. In column (5), we find that a one-standard-deviation increase in the LCV score of the incumbent also translates to a $56,000 (5.5% D.V. mean) increase in fundraising by incumbents following a natural disaster. These results are consistent with the hypothesis that incumbents may react to the strengthened support for the challengers and

[36] For races without a challenger in the general election, we collect data on campaign finance for any potential challenger in the earlier stage. Since the viability of the challenger might be an endogenous outcome in our setting, we seek to avoid selection bias by constructing the sample this way.

[37] The within-party standard deviation of the LCV score is 0.2.

Table 3: The effects of natural disasters on amount raised ($1,000)

	(1) Total	(2) Total (PAC)	(3) Total (Ind.)	(4) Challenger	(5) Incumbent	(6) Share (C)
			Panel A: Cross-Party Specification			
Disaster	-316.7***	-72.15***	-164.8***	-138.9***	-177.7***	-0.0371***
	(65.65)	(19.30)	(47.88)	(36.72)	(50.96)	(0.0137)
LCV	-227.7	-96.76**	-24.12	-186.8*	-40.88	-0.0369
	(246.6)	(36.00)	(213.5)	(101.8)	(171.1)	(0.0263)
Disaster × LCV	495.9***	118.3***	244.9**	216.6***	279.3***	0.0587**
	(149.1)	(29.62)	(97.23)	(76.73)	(93.24)	(0.0231)
R^2	0.468	0.588	0.439	0.341	0.490	0.328
			Panel B: Within-Party Specification			
Disaster	-312.1***	-69.96***	-163.3***	-136.2***	-175.9***	-0.0359***
	(64.12)	(18.61)	(47.18)	(35.74)	(50.54)	(0.0129)
LCV	233.3	137.6	116.1	111.2	122.1	0.106
	(405.7)	(115.4)	(316.9)	(211.3)	(259.1)	(0.0629)
Disaster × LCV	482.7***	112.5***	239.8**	209.5***	273.2***	0.0555**
	(146.5)	(29.27)	(95.48)	(75.56)	(91.09)	(0.0219)
Republican	-171.3	-14.40	-144.4	8.602	-180.0	0.0203
	(265.2)	(51.40)	(170.2)	(179.0)	(120.0)	(0.0370)
Republican × LCV	-187.6	-176.2	45.50	-253.9	66.32	-0.139
	(455.9)	(127.2)	(277.0)	(300.6)	(228.5)	(0.0855)
R^2	0.469	0.590	0.439	0.342	0.490	0.330
N	4328	4328	4328	4328	4328	4419
Mean D.V.	1326.2	481.0	702.5	319.3	1007.0	0.176
State-cycle F.E.	Yes	Yes	Yes	Yes	Yes	Yes
C.D. F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Notes: point estimates from equations (2) and (3) are shown. The dependent variable in columns (1)-(5) is the amount of money raised in an election cycle from different sources in a given district, expressed in thousands of dollars. The dependent variable in column (6) is the share of total funds raised by the challengers. Standard errors are clustered at the State level. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

increase fundraising efforts themselves. Furthermore, although fundraising increases more in absolute terms for the incumbents than the challengers, the increase is much more important for the challengers in relative terms. This is evident when comparing the effects against their respective dependent variable means. This is also confirmed in column (6), where we formally test whether the share of funds going to challengers is higher when the incumbent leans anti-environment. A one-standard-deviation increase in the LCV score is associated with a 1.2 p.p. increase in the share of funds going to challengers when a natural disaster strikes, over a baseline of 17.6 p.p., when a natural disaster strikes. Next, Panel B of Table 3 reports the results of our within-party specification described in equation (3). We find very similar estimates in terms of magnitude and statistical significance to those in Panel A. This reassures us that the set of fixed effects in the model is able to properly control for variation in environmental positions driven purely by partisanship.

We also examine the number of donors to challengers and incumbents and report these estimates in Table A6 in the appendix. We find qualitatively similar results as above. Following a natural disaster, a one-standard-deviation increase in the LCV score of the incumbent translates to 89 additional donors when there is a natural disaster. The increase is again skewed toward the challenger at a scale similar to the case of total funds raised. Furthermore, these results are also robust to using within-party variation.

Next, we take the analysis a step further by exploring how natural disasters affect election outcomes. There are several reasons to expect a differential impact based on the incumbent's environmental stance. First, the campaign finance consequences of natural disasters shown above may, in turn, affect electoral outcomes. Second, natural disasters may provide a stronger motivation for prospective challengers to enter the race if the incumbent is more anti-environment. Third, natural disasters may prompt issue voting and directly influence the results of the election. Therefore, it is important to not only examine the outcome of the election, but also its type. We focus on the following four outcomes: whether the election is competitive (i.e. there is a challenger), whether the incumbent runs unopposed, whether there is an open seat election (i.e. the incumbent does not run for re-election), and whether the incumbent is re-elected.

The results of this analysis are in Table 4. Again, the estimates in Panel A and B are very similar and we discuss them together. When it comes to the election type, we can see that if the incumbent in a disaster-struck district has a higher LCV score, they are more likely to face a challenger in the race (column (1)). For a one-standard-

Table 4: The effects of natural disasters on elections

	(1) Competitive	(2) Unopposed	(3) Open Seat	(4) Incumbent Win
	Panel A: Cross-Party Specification			
Disaster	-0.0112	0.0320	-0.0208	0.0427*
	(0.0238)	(0.0198)	(0.0178)	(0.0230)
LCV	-0.130***	0.0575	0.0724*	0.103**
	(0.0449)	(0.0384)	(0.0389)	(0.0458)
Disaster × LCV	0.135***	-0.125***	-0.0105	-0.0651**
	(0.0387)	(0.0405)	(0.0259)	(0.0253)
R^2	0.263	0.313	0.221	0.277
	Panel B: Within-Party Specification			
Disaster	-0.0118	0.0311	-0.0193	0.0415*
	(0.0230)	(0.0197)	(0.0174)	(0.0229)
LCV	-0.255**	-0.0921	0.347***	-0.0284
	(0.111)	(0.0892)	(0.0637)	(0.0708)
Disaster × LCV	0.136***	-0.122***	-0.0148	-0.0623**
	(0.0367)	(0.0400)	(0.0257)	(0.0251)
Republican	-0.126	-0.00472	0.130***	-0.0365
	(0.0779)	(0.0645)	(0.0356)	(0.0380)
Republican × LCV	0.241*	0.128	-0.369***	0.148*
	(0.142)	(0.128)	(0.0573)	(0.0816)
R^2	0.261	0.313	0.227	0.277
N	4824	4824	4824	4328
Mean D.V.	0.729	0.173	0.0978	0.951
State-Cycle F.E.	Yes	Yes	Yes	Yes
C.D. F.E.	Yes	Yes	Yes	Yes

Notes: point estimates from equations (2) and (3) are shown. The dependent variable in columns (1)-(3) is the probability of a congressional race being of a certain type (competitive, unopposed, open seat). The dependent variable in column (4) is the probability that the incumbent is re-elected. Columns (1)-(3) include all elections and column (4) excludes open seat elections. Standard errors are clustered at the State level. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

deviation increase in the LCV score, the probability of the race being competitive following a disaster increase by 2.7 p.p (3.7% D.V. mean). As a result, the effect on the incumbent running unopposed is negative and similar in magnitude (column (2)). The probability of an open seat election taking place is unaffected (column (3)). Importantly, these results are in line with our hypothesis of increased support for challengers, as the presence of challengers is often contingent on the underlying support. Potential challengers may join the race simply because of the increased funds they are able to raise, or because they recognize an opportunity to run on a pro-environment platform given the incumbent's record. As for the election outcome, we examine the impacts on the incumbent's re-election probability in column (4). The estimates show a lower probability of an incumbent win following natural disasters if the incumbent has an anti-environment voting record. Specifically, for a one-standard-deviation difference in the LCV score, this effect is about 1.3%.

4.3 Medium-Run Temperature Impacts

In this section, we focus on the impact of temperature shocks on medium-run political outcomes. Temperature shocks are different from natural disasters for a number of reasons. First, temperature shocks can be either hot weather shocks or cold weather shocks, each with their own possible ramifications. While people may interpret extremely hot weather as evidence of climate change, this may not be the case for extremely cold weather. We have shown some suggestive evidence in the short-run analysis that some may interpret cold shocks as evidence against climate change. Second, temperature shocks may be less salient than natural disasters, in part because the latter often results in property damage and extensive news coverage. To capture the medium-run temperature shocks, we define a pair of indicator variables based on the number of extremely hot/cold days experienced by a congressional district in an election cycle (see Section 2.4 for more details). In line with our previous analysis, we follow equation (4) and interpret the interaction terms to see how the effects of weather events vary with the LCV score.

Table A7 in the appendix reports results on campaign funds, and Table A8 reports those on the number of donors. For abnormally hot cycles, the results resemble those of natural disasters. Again, the impact of having a hot cycle for a more anti-environment incumbent is an increase in the competitiveness of the election, illustrated by an overall increase in campaign funds and the number of donors. Also similar to natural disasters,

Table 5: The effects of extreme temperature on elections

	(1) Competitive	(2) Unopposed	(3) Open Seat	(4) Incumbent Win
	Panel A: Cross-Party Specification			
Hot	-0.0566	0.0413	0.0153	0.0247
	(0.0343)	(0.0294)	(0.0187)	(0.0181)
LCV	-0.0491	-0.00846	0.0576*	0.0800**
	(0.0437)	(0.0380)	(0.0324)	(0.0348)
Hot × LCV	0.0684	-0.0833*	0.0148	-0.0700**
	(0.0494)	(0.0422)	(0.0337)	(0.0262)
Cold	0.0315	-0.000230	-0.0313*	-0.00197
	(0.0267)	(0.0269)	(0.0181)	(0.0218)
Cold × LCV	-0.0683	0.0520	0.0163	0.00203
	(0.0479)	(0.0313)	(0.0338)	(0.0254)
R^2	0.260	0.312	0.221	0.276
	Panel B: Within-Party Specification			
Hot	-0.0545	0.0421	0.0124	0.0253
	(0.0339)	(0.0290)	(0.0192)	(0.0180)
LCV	-0.161	-0.164	0.325***	-0.0544
	(0.121)	(0.105)	(0.0641)	(0.0644)
Hot × LCV	0.0650	-0.0838**	0.0188	-0.0715***
	(0.0492)	(0.0412)	(0.0334)	(0.0262)
Cold	0.0320	-0.000981	-0.0310	-0.00226
	(0.0274)	(0.0270)	(0.0184)	(0.0218)
Cold × LCV	-0.0696	0.0524*	0.0172	0.00223
	(0.0489)	(0.0308)	(0.0352)	(0.0257)
Republican	-0.127	-0.00482	0.132***	-0.0390
	(0.0812)	(0.0672)	(0.0351)	(0.0383)
Republican × LCV	0.234	0.135	-0.368***	0.155*
	(0.146)	(0.132)	(0.0579)	(0.0817)
R^2	0.261	0.314	0.227	0.279
N	4874	4874	4874	4397
Mean D.V.	0.729	0.173	0.0978	0.951
State-Cycle F.E.	Yes	Yes	Yes	Yes
C.D. F.E.	Yes	Yes	Yes	Yes

Notes: point estimates from equation (4) are shown. The dependent variable in columns (1)-(3) is the probability of a congressional race being of a certain type (competitive, unopposed, open seat). The dependent variable in column (4) is the probability that the incumbent is re-elected. Columns (1)-(3) include all elections and column (4) excludes open seat elections. Standard errors are clustered by state. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the challengers to more anti-environment incumbents account for a higher fraction of funds and donors when the cycle has more abnormally hot events. In contrast, the effects of abnormally cold events are very small throughout.

In Table 5, we directly explore the effects of extreme temperatures on election outcomes. For hot cycles, the effects point in the same direction as natural disasters. Races are more likely to be competitive and less likely to be uncontested, while the probability of an incumbent win is lowered by a similar amount. While some of the estimates are smaller and not as statistically significant, the pattern is telling. In the case of cold cycles, some of these relationships appear to be reversed but most estimates are not statistically significant.

Overall, high-temperature events in the medium run appear to have a similar effect as climate-related natural disasters. Low-temperature events, on the other hand, are not found to have any notable effect.[38] We consider this as suggestive evidence that these two types of shocks are perceived differently.

4.4 Mechanisms and Limitations

Throughout this paper, we have proposed a mechanism of environmental policy preference as the driver of our results. In this mechanism, extreme weather events lead people to feel more politically aligned with a more pro-environment politician, or less so with a more anti-environment politician. This could be due to a stronger belief about climate change or greater attention to the issue. However, there may still be other possible explanations for these results. In this section, we address limitations and alternative mechanisms, discussing them in the context of our findings.

One alternative explanation for our results regarding weather shocks and campaign finance is time use. Weather shocks affect time use, which, in turn, may affect giving behavior. This is especially relevant for online giving, since if weather leads people to spend more time indoors then this could expose them to more opportunities for online giving. Importantly, if time spent indoors is driving our results, then results should be similar for hot weather shocks and cold weather shocks since it has been shown that both types of shock can lead to more time spent indoors (Graff Zivin and Neidell, 2014). However, in both short-run and medium-run analyses, we find that hot and cold events generally have different, sometimes opposite effects on campaign contributions.

[38] When we compare these results with the short run, it seems that high-temperature events have more consistent impacts, while low-temperature ones are not as powerful in the medium run.

Therefore, time spent indoors is not likely to account for our results.

In the case of natural disasters, an important alternative mechanism is that of factors that are correlated with the LCV score but unrelated to incumbents' stances on environmental issues. For example, if pro-environment candidates are also more willing to pass disaster relief packages for those affected, this may explain the increase in funds and support for these candidates following disasters. While this is a possibility, we argue that these factors are not likely to be driving our results for three reasons. First, we study the effects of natural disasters using a within-party specification, since policy positions on several issues are determined along party lines. We find very similar estimates under this specification, despite party affiliation being perhaps the most visible source of information on politicians' environmental positions. Second, the observed effects of abnormally hot weather in the short and medium-run are in the same direction as those of natural disasters, and there is no obvious policy position regarding hot weather other than a politician's stance on environmental issues. This is especially true in the case of short-run weather variations. Third, we also examine the electoral impacts of natural disasters that are not connected to climate change, such as tornadoes and earthquakes (see Table A9). If the incumbent's policy position on disaster relief is indeed a major confounding factor, we would expect the response to these disasters to go in the same direction. Instead, we find very different and statistically insignificant estimates.

Finally, there might be other psychological explanations for our results. For example, Meier et al. (2019) explore the link between rainy weather, risk aversion, and voting for status quo candidates. This link between short term weather and emotions could be a confounder to the extent that emotions affect individuals' incentives to make political campaign contributions. However, we observe similar patterns in the medium term, as well as stronger short-term effects in counties with more anti-environment incumbents, so our results cannot be entirely driven by the emotional consequences of short-run weather.

5 Conclusion

In this paper, we study the impacts of extreme weather events on campaign contributions and electoral outcomes in the United States. As these events are often considered signs of climate change, our analyses place particular emphasis on testing for differential constituent responses based on the incumbent politician's views on environmental issues. In a short-run analysis, we find that weekly temperature shocks lead to a higher number of online donations to Democratic candidates, especially in counties with a greater share of anti-environment incumbents. In a medium-run analysis, we find evidence that natural disasters lead to increased overall competitiveness in congressional races where the incumbent is more anti-environment: fundraising increases for both candidates, though skewed toward the challenger; the challenger is more likely to enter the general election; and finally, the incumbent is less likely to win.

The most plausible mechanism for our results is one where voters adjust or express their environmental policy preferences. The results in this paper suggest that politicians' policy positions on environmental issues are taken into account by people when responding to extreme weather events, and that these responses may have political consequences. Further, these findings suggest additional mechanisms for results in previous studies showing that, following natural disasters in their state, congresspersons are more likely to vote in favor of environmental legislation (Herrnstadt and Muehlegger, 2014) and sponsor green bills (Gagliarducci et al., 2019). Put together, these behaviors from constituents, candidates, and legislators are consistent with a representative democracy at work. As the salience of climate change in U.S. politics has grown significantly since 2012, we believe the mechanism in this paper will play a much more important role in ultimately bridging the gap between the scientific consensus on climate change and the political acceptance of it.

The findings in this paper pose a series of additional questions and possible extensions. Firstly, a question raised by this work is whether the politicians themselves react to the salience of climate change by adjusting their narratives when it comes to speeches and soliciting contributions. Secondly, an important player which is missing from our analysis are environmental advocacy groups. Future research should focus on the role these groups play in disseminating information and forming opinions following extreme weather events. Finally, it is an open question whether the behavior observed here generalizes to other policy areas in which the event of interest has a stochastic component, like terrorism or gun violence.

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Appendix

Figures

Figure A1: Example of an ActBlue donation

Figure A2: Distribution of individual ActBlue donation amounts

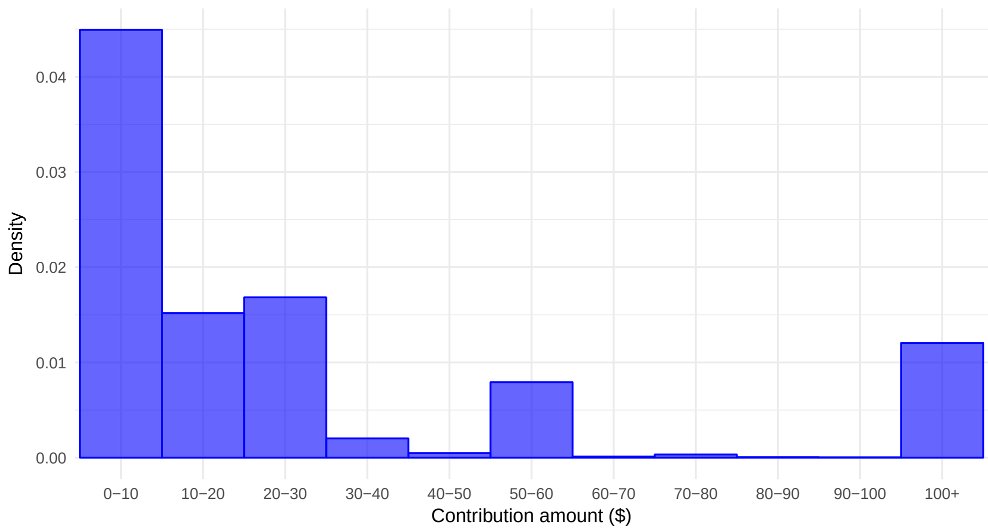
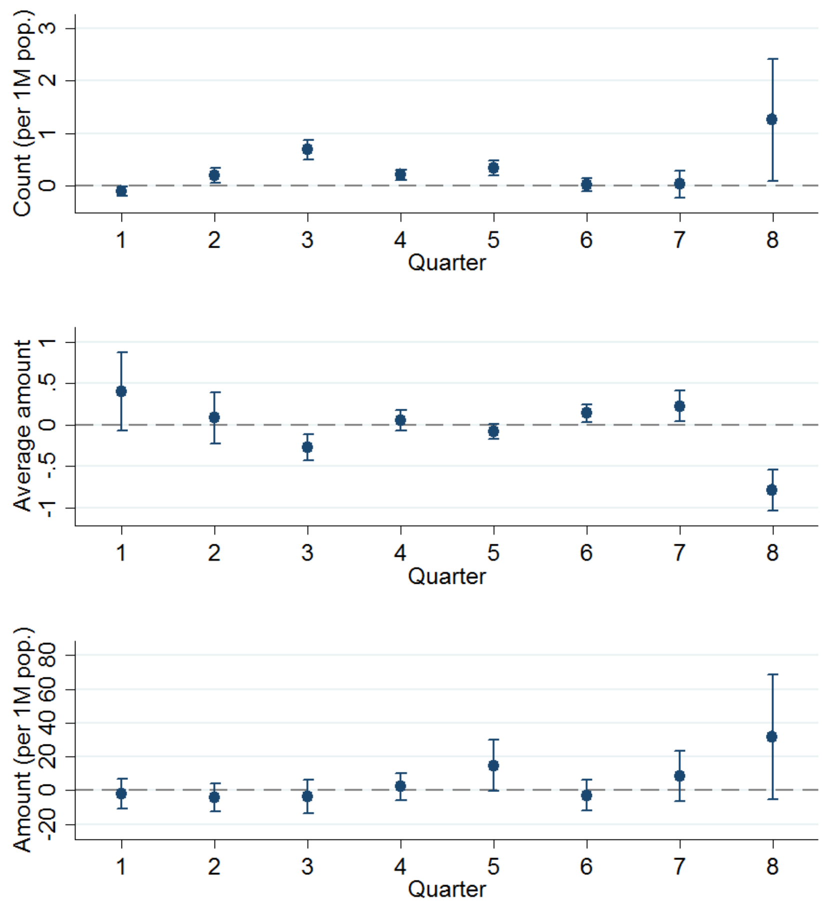


Figure A3: Variations of estimates across quarters in election cycle



Notes: Point estimates from equation (9) and 95 percent confidence intervals are shown. The outcome variables, as displayed next to the y-axis, are based on ActBlue records. Standard errors are clustered by county. All regressions control for county, week-in-sample, and state-by-cycle fixed effects.

Tables

Table A1: FEMA Disaster Declarations, 1990-2012

Type	Number of Declarations	County-Year Observations
A. Climate-related disasters		
Storm	985	21,265
Fire	775	2,525
Flood	178	3,198
Snow	176	4,438
Drought	5	178
Total	2,119	31,604
B. Other disasters		
Tornado	41	480
Earthquake	19	80
Other	23	308
Total	83	868

Notes: this table shows a summary of natural disasters in the sample. Some disaster types are re-classified into broader categories: “Storm” includes ”Coastal Storm”, ”Hurricane”, and ”Severe Storm(s)”; “Snow” also includes “Freezing”, “Severe Ice Storm”; “Earthquake” also includes “Tsunami”, “Other” also includes “Dam/Levee Break”, “Fishing Losses”, “Mud/Landslide”, “Human Cause”, “Terrorist”, and “Toxic Sbustances”.

Table A2: Summary Statistics

Variable	N	Mean	Std. Dev.	Min.	Max.
ActBlue, 2006-2012 (county-week)					
Amount ($)	938,040	151.29	2057.95	0	583663.8
Count	938,040	2.42	23.07	0	5315
Count (per 1M pop)	938,040	15.46	137.29	0	38848.92
Average amount ($)	938,040	13.17	125.53	0	32500
Population	938,040	110414.5	336717	403	9974868
Mean LCV	830,316	0.672	0.322	0	0.980
Republican incumbent	830,316	0.622	0.485	0	1
Short-run Weather, 2006-2012 (county-week)					
Tmax dev. (F)	938,040	0.449	6.621	-37.60	37.51
Tmax positive dev. (F)	938,040	2.789	4.038	0	37.51
Tmax negative dev. (F)	938,040	-2.343	3.806	-37.60	0
Tmax low (< 5th pctile)	938,040	0.318	0.785	0	7
Tmax high (> 95th pctile)	938,040	0.473	1.066	0	7
Prcp dev. (1/10mm)	936,836	0.0843	13.642	-49.91	540.93
Natural Disasters, 1990-2012 (congressional district-cycle)					
Num. donors (C)	4,397	221.58	1034.96	0	27122
Receipts ($1,000) (C)	4,397	319.19	675.39	0	9825.57
Num. donors (I)	4,397	495.95	1051.15	0	43718
Receipts ($1,000) (I)	4,397	1004.72	996.30	6.623	25894.72
Receipts PACs ($1,000)	4,397	480.09	390.98	0	3177.194
Receipts Ind. ($1,000)	4,397	701.61	954.70	0.825	23770.43
Competitive election	4,874	0.730	0.444	0	1
Unopposed election	4,874	0.172	0.378	0	1
Open race election	4,874	0.0979	0.297	0	1
LCV score	4,874	0.508	0.362	0	1
Republican incumbent	4,874	0.482	0.500	0	1
Incumbent wins	4,874	0.858	0.349	0	1
Disaster indicator (climate)	4,874	0.568	0.495	0	1
Disaster indicator (non-climate)	4,874	0.048	0.214	0	1
Hot indicator	4,874	0.250	0.433	0	1
Cold indicator	4,874	0.250	0.433	0	1

Table A3: Positive and negative temperature shocks on ActBlue contributions

	(1)	(2)
Dep. Var.	Count/1M pop	Avg. amount
Positive Tmax deviation		
Current week	0.274***	-0.0704
	(0.0982)	(0.0522)
1-week lag	0.110***	-0.0746
	(0.0289)	(0.0591)
2-week lag	0.165***	0.0720
	(0.0411)	(0.0587)
3-week lag	0.173***	-0.0964**
	(0.0366)	(0.0424)
4-week lag	0.124***	-0.0348
	(0.0330)	(0.0385)
Negative Tmax deviation		
Current week	-0.0154	0.0956
	(0.0309)	(0.0594)
1-week lag	0.0948	-0.00318
	(0.0736)	(0.0385)
2-week lag	-0.0701*	0.0405
	(0.0408)	(0.0506)
3-week lag	-0.0362	0.175**
	(0.0315)	(0.0754)
4-week lag	-0.0286	-0.0307
	(0.0308)	(0.0595)
N	935201	935201
R^2	0.204	0.0539
D.V. Mean	15.40	13.19
County F.E.	Yes	Yes
Week F.E.	Yes	Yes
State-cycle F.E.	Yes	Yes

Notes: point estimates from equation (6) are shown. The dependent variable in columns (1)-(3) is the number of contributions per 1 million people, and that in columns (4)-(6) is the average amount per contribution. The sample consists of ActBlue contributions by week and county. Standard errors are clustered by county. Statistical significance: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table A4: The effect of extreme temperature events on ActBlue contributions

	(1)	(2)
Dep. Var.	Count/1M pop	Avg. amount
High-temp (> p95) days		
Current week	0.353*	-0.0430
	(0.183)	(0.138)
1-week lag	0.211**	0.0580
	(0.0915)	(0.187)
2-week lag	0.224***	0.215
	(0.0816)	(0.211)
3-week lag	0.277**	-0.0584
	(0.135)	(0.126)
4-week lag	0.01000	-0.0316
	(0.159)	(0.125)
Low-temp (< p5) days		
Current week	-1.020***	-0.318
	(0.368)	(0.229)
1-week lag	-0.641*	0.176
	(0.336)	(0.182)
2-week lag	-0.0825	-0.0628
	(0.188)	(0.211)
3-week lag	-0.315*	-0.140
	(0.187)	(0.220)
4-week lag	-0.372**	0.442
	(0.170)	(0.368)
N	936954	936954
R^2	0.203	0.0539
D.V. Mean	15.40	13.18
County F.E.	Yes	Yes
Week F.E.	Yes	Yes
State-cycle F.E.	Yes	Yes

Notes: point estimates from equation (7) are shown. The dependent variable in columns (1)-(3) is the number of contributions per 1 million people, and that in columns (4)-(6) is the average amount per contribution. The sample consists of ActBlue contributions by week and county. Standard errors are clustered by county. Statistical significance: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table A5: Heterogeneous effects across quarters in election cycle

Dep. Var.	(1) Amount/1M pop	(2) Count/1M pop	(3) Avg. amount
TmaxDev (2-week) ×			
Q1 (Dec-Feb)	-1.901	-0.114**	0.401*
	(4.431)	(0.0492)	(0.241)
Q2 (Mar-May)	-4.271	0.183**	0.0861
	(4.233)	(0.0722)	(0.158)
Q3 (Jun-Aug)	-3.407	0.681***	-0.273***
	(5.062)	(0.0926)	(0.0781)
Q4 (Sep-Nov)	2.314	0.200***	0.0543
	(4.076)	(0.0511)	(0.0619)
Q5 (Dec-Feb)	14.83*	0.324***	-0.0768*
	(7.697)	(0.0729)	(0.0465)
Q6 (Mar-May)	-2.968	0.0100	0.142**
	(4.634)	(0.0631)	(0.0555)
Q7 (Jun-Aug)	8.640	0.0234	0.223**
	(7.540)	(0.131)	(0.0946)
Q8 (Sep-Nov)	31.66*	1.256**	-0.795***
	(18.83)	(0.596)	(0.126)
N	941672	941672	941672
R^2	0.0734	0.209	0.0540
D.V. Mean	639.7	15.42	13.15
County F.E.	Yes	Yes	Yes
Week F.E.	Yes	Yes	Yes
State-cycle F.E.	Yes	Yes	Yes

Notes: point estimates from equation (9) are shown, which allows the estimates to differ by quarter-in-cycle. The dependent variables in columns (1)-(3) are the total amount of ActBlue contributions per 1 million people, the number of contributions per 1 million people, and the average amount per contribution, respectively. The sample consists of ActBlue contributions by week and county. Standard errors are clustered by county. Statistical significance: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table A6: The effects of natural disasters on the number of donors

	(1) Total	(2) Challenger	(3) Incumbent	(4) Share (C)
	Panel A: Cross-Party Specification			
Disaster	-231.7**	-6.885	-224.8***	-0.0308*
	(100.3)	(60.77)	(66.95)	(0.0182)
LCV	-470.3	27.09	-497.4	0.00842
	(446.9)	(123.6)	(358.9)	(0.0330)
Disaster × LCV	444.9**	136.6	308.3**	0.0553*
	(201.0)	(95.44)	(136.7)	(0.0299)
R^2	0.391	0.421	0.329	0.329
	Panel B: Within-Party Specification			
Disaster	-232.3**	-5.859	-226.5***	-0.0292*
	(100.1)	(59.81)	(66.99)	(0.0173)
LCV	-558.3	179.0	-737.2	0.195***
	(618.0)	(190.2)	(529.7)	(0.0576)
Disaster × LCV	445.7**	135.6	310.1**	0.0512*
	(200.3)	(92.70)	(136.5)	(0.0285)
Republican	-111.9	228.7	-340.6**	0.0450
	(289.1)	(201.5)	(142.3)	(0.0349)
Republican × LCV	196.5	-378.7*	575.2**	-0.203**
	(389.6)	(221.5)	(279.4)	(0.0839)
R^2	0.391	0.422	0.329	0.331
N	4328	4328	4328	4416
D.V. Mean	720.1	222.5	497.6	0.183
State-cycle F.E.	Yes	Yes	Yes	Yes
C.D. F.E.	Yes	Yes	Yes	Yes

Notes: point estimates from equations (2) and (3) are shown. The dependent variable in columns (1)-(3) is the number of donors in an election cycle from different sources in a given district. The dependent variable in column (4) is the share of total donors corresponding to the challengers. Standard errors are clustered by state. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: The effects of extreme temperature on amount raised ($1,000)

Dep. Var.	(1) Total	(2) Total (PAC)	(3) Total (Ind.)	(4) Challenger	(5) Incumbent	(6) Share (C)
			Panel A: Cross-Party Specification			
Hot	-325.8***	-53.41**	-203.2***	-133.9*	-192.0***	-0.0341***
	(113.8)	(24.64)	(71.62)	(79.52)	(50.68)	(0.0117)
LCV	-46.03	-37.05	43.33	-100.2	54.18	-0.0188
	(181.9)	(38.12)	(153.5)	(65.73)	(134.6)	(0.0235)
Hot × LCV	441.9**	49.61	292.6**	139.8	302.1**	0.0515**
	(197.8)	(31.81)	(126.4)	(104.9)	(134.3)	(0.0201)
Cold	54.89	6.353	52.27	3.661	51.23	-0.0165
	(113.0)	(22.98)	(90.73)	(61.27)	(60.36)	(0.0188)
Cold × LCV	-0.0962	-8.546	11.89	22.41	-22.50	0.0130
	(169.4)	(34.67)	(127.9)	(81.57)	(118.6)	(0.0267)
R^2	0.467	0.587	0.439	0.341	0.490	0.327
			Panel B: Within-Party Specification			
Hot	-324.9***	-53.31**	-202.4***	-133.9*	-191.0***	-0.0342***
	(112.6)	(24.45)	(70.82)	(79.10)	(50.08)	(0.0113)
LCV	439.9	201.5*	195.9	206.0	233.9	0.126*
	(374.0)	(114.3)	(276.3)	(207.9)	(240.3)	(0.0702)
Hot × LCV	437.4**	49.27	288.7**	140.1	297.3**	0.0519**
	(196.4)	(31.54)	(125.3)	(103.3)	(134.5)	(0.0197)
Cold	59.12	6.945	55.57	3.814	55.30	-0.0168
	(115.7)	(23.58)	(92.73)	(61.80)	(61.80)	(0.0186)
Cold × LCV	-9.782	-11.42	6.349	19.49	-29.27	0.0121
	(169.5)	(34.10)	(129.9)	(82.03)	(118.5)	(0.0262)
Republican	-170.8	-15.89	-143.9	7.372	-178.2	0.0223
	(267.3)	(51.08)	(174.1)	(176.6)	(124.9)	(0.0374)
Republican × LCV	-212.5	-180.3	34.11	-262.4	49.85	-0.145*
	(457.0)	(127.5)	(279.1)	(295.0)	(238.4)	(0.0854)
R^2	0.468	0.589	0.440	0.342	0.491	0.330
N	4328	4328	4328	4328	4328	4419
D.V. Mean	1326.2	481.0	702.5	319.3	1007.0	0.176
State-cycle F.E.	Yes	Yes	Yes	Yes	Yes	Yes
C.D. F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Notes: point estimates from equation (4) are shown. The dependent variable in columns (1)-(5) is the amount of money raised in an election cycle from different sources in a given district, expressed in thousands of dollars. The dependent variable in column (6) is the share of total funds raised by the challengers. Standard errors are clustered by state. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: The effects of extreme temperature on the number of donors

Dep. Var.	(1) Total	(2) Challenger	(3) Incumbent	(4) Share (C)
	A. Cross-Party Specification			
Hot	-331.5**	-240.9***	-90.55	-0.0441***
	(132.6)	(84.11)	(76.58)	(0.0155)
LCV	-338.8	-6.974	-331.9	0.0222
	(302.9)	(121.7)	(244.1)	(0.0234)
Hot × LCV	638.0***	393.7**	244.4**	0.0559*
	(222.7)	(163.1)	(100.3)	(0.0278)
Cold	110.1	-21.62	131.8	-0.0235
	(212.8)	(68.63)	(155.9)	(0.0200)
Cold × LCV	-107.3	52.53	-159.9	0.0164
	(318.3)	(101.6)	(246.1)	(0.0369)
R^2	0.392	0.423	0.329	0.330
	B. Within-Party Specification			
Hot	-330.9**	-242.2***	-88.74	-0.0443***
	(133.1)	(83.18)	(78.23)	(0.0150)
LCV	-389.9	155.8	-545.7	0.211***
	(476.6)	(213.3)	(409.8)	(0.0674)
Hot × LCV	635.2***	400.3**	234.9**	0.0570**
	(220.3)	(161.3)	(98.26)	(0.0274)
Cold	112.3	-26.65	139.0	-0.0243
	(216.3)	(70.07)	(157.8)	(0.0197)
Cold × LCV	-109.7	57.47	-167.1	0.0157
	(322.7)	(102.9)	(249.5)	(0.0360)
Republican	-102.7	238.4	-341.0**	0.0472
	(291.9)	(199.0)	(151.8)	(0.0348)
Republican × LCV	157.1	-401.4*	558.5*	-0.209**
	(389.9)	(211.1)	(290.9)	(0.0831)
R^2	0.392	0.424	0.330	0.334
Observations	4328	4328	4328	4416
D.V. Mean	720.1	222.5	497.6	0.183
State-cycle F.E.	Yes	Yes	Yes	Yes
C.D. F.E.	Yes	Yes	Yes	Yes

Notes: point estimates from equation (4) are shown. The dependent variable in columns (1)-(3) is the number of donors in an election cycle from different sources in a given district. The dependent variable in column (4) is the share of total donors corresponding to the challengers. Standard errors are clustered by state. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: The effects of other natural disasters on elections

	(1) Competitive	(2) Unopposed	(3) Open Seat	(4) Incumbent Win
	Panel A: Cross-Party Specification			
Disaster	0.0273	0.0579	-0.0852**	0.0214
	(0.0599)	(0.0549)	(0.0360)	(0.0166)
LCV	-0.0463	-0.0196	0.0659**	0.0630
	(0.0367)	(0.0282)	(0.0275)	(0.0383)
Disaster × LCV	-0.105	0.0698	0.0349	0.00987
	(0.0867)	(0.0832)	(0.0496)	(0.0224)
R^2	0.260	0.312	0.221	0.275
	Panel B: Within-Party Specification			
Disaster	0.0249	0.0530	-0.0779**	0.0181
	(0.0595)	(0.0554)	(0.0364)	(0.0173)
LCV	-0.161	-0.173*	0.334***	-0.0701
	(0.111)	(0.0965)	(0.0578)	(0.0670)
Disaster × LCV	-0.101	0.0744	0.0263	0.0144
	(0.0841)	(0.0843)	(0.0487)	(0.0227)
Republican	-0.128	-0.00376	0.132***	-0.0363
	(0.0802)	(0.0671)	(0.0357)	(0.0383)
Republican × LCV	0.236	0.131	-0.367***	0.151*
	(0.145)	(0.130)	(0.0578)	(0.0818)
R^2	0.260	0.312	0.222	0.276
N	4824	4824	4824	4328
D.V. Mean	0.729	0.173	0.0978	0.951
State-cycle F.E.	Yes	Yes	Yes	Yes
C.D. F.E.	Yes	Yes	Yes	Yes

Notes: point estimates from equations (2) and (3) are shown. The dependent variable in columns (1)-(3) is the probability of a congressional race being of a certain type (competitive, unopposed, open seat). The dependent variable in column (4) is the probability that the incumbent is re-elected. Columns (1)-(3) include all elections and column (4) excludes open seat elections. Standard errors are clustered by state. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A Comparing ActBlue and overall contributions

In this section, we further explore the representativeness of ActBlue contributions. We would ideally correlate changes over time in ActBlue donations to changes in non-ActBlue donations, given that we exploit time-varying weather shocks in our analysis. However, there are two difficulties associated with doing this. First, as stated above, the date information for the non-ActBlue data is unreliable. Second, ActBlue was founded in 2004 and has become more popular since then, meaning that the trend of donations made through ActBlue will likely differ from the trend of overall Democratic donations. However, even though exploiting the time dimension may be difficult, we can explore whether ActBlue data do a good job of explaining the cross-section of total donations to Democrats. In order to do this, we regress total donation amounts and counts at the state-by-election cycle level on ActBlue donations and counts. If the cross-section of ActBlue donations is representative of the total Democratic cross-section, it should have high explanatory power. Additionally, to account for the fact that ActBlue becomes more popular over time and may represent a larger portion of total donations, we let our coefficients vary by election cycle in alternative regressions.

The results of these regressions are in Table A10. The first two columns refer to the total amount contributed and the next two refer to the number of of contributions. As can be seen in column (1), simply including the amount donated through ActBlue is a strong predictor of total donations, leading to an R^2 of 0.74. When we allow the effect to vary by election cycle, as in column (2), the explanatory is even higher, with an R^2 of 0.86. When we consider counts of donations instead of amounts donated, the fit is slightly better, with an R^2 of 0.83 and 0.88 in columns (3) and (4), respectively. Finally, an interesting feature of Table A10 is the time-varying estimates in columns (2) and (4). The estimates for earlier years tend to be larger than in later years, revealing that over time the portion of ActBlue donations in total Democratic donations is rising.[39]

[39] It is worth pointing out that this trend stabilizes during the 2012 election cycle.

Table A10: Predicting total Democratic donations using ActBlue donations

Dep. Var.	Amount		Number	
	(1)	(2)	(3)	(4)
ActBlue	85.33***		14.67***	
	(5.63)		(1.30)	
ActBlue × 2006		209.93***		32.58***
		(24.98)		(8.14)
ActBlue × 2008		99.09***		21.95***
		(6.14)		(2.97)
ActBlue × 2010		57.51***		12.15***
		(6.32)		(2.44)
ActBlue × 2012		111.23***		14.63***
		(6.55)		(1.00)
Observations	200	200	200	200
R^2	0.74	0.86	0.83	0.88

Notes: the above table includes point estimates from various OLS regressions of the amount and number of donations to Democrats from all sources, to the amount and donations from ActBlue sources. All regressions include an intercept term. Standard errors are clustered at the state level. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Additional Specifications in the Short-Run Analysis

This section lists additional regression specifications for the short-run analysis that are not included in Section 3.1. Recall that the main specification (equation (1)) takes the form

$$Y_{cw} = \gamma' Weather_{cw} + \delta_w + \delta_c + \delta_{se} + \varepsilon_{cw}. \tag{5}$$

In Table A3, we use the following set of weather variables:

$$\begin{aligned} Weather_{cw} = [&TmaxDev^{+}_{cw}, ..., TmaxDev^{+}_{c,w-4}, \\ &TmaxDev^{-}_{cw}, ..., TmaxDev^{-}_{c,w-4}, \\ &PrcpDev_{cw}, ..., PrcpDev_{c,w-4}]^{T} \end{aligned} \tag{6}$$

where $TmaxDev^{+} = TmaxDev \times (TmaxDev > 0)$ and $TmaxDev^{-} = TmaxDev \times (TmaxDev < 0)$. This specification allows us to estimate the effects of positive and negative deviations separately. In Table A4, we use an alternative set of weather variables:

$$\begin{aligned} Weather_{cw} = [&TmaxHigh_{cw}, ..., TmaxHigh_{c,w-4}, \\ &TmaxLow_{cw}, ..., TmaxLow_{c,w-4}, \\ &PrcpDev_{cw}, ..., PrcpDev_{c,w-4}]^{T}, \end{aligned} \tag{7}$$

where $TmaxHigh_{cw}$ is the total number of days in week w when the maximum temperature exceeds 95th percentile of the historical distribution in the month, and $TmaxLow_{cw}$ counts days with temperature below the 5th percentile.

In Table 2, we use the two-week average of temperature shocks as the main measure and interact it with incumbent characteristics:

$$\begin{aligned} Y_{cw} = &\beta_1 \overline{TmaxDev}_{c,w} + \beta_2 IncChar + \beta_3 \overline{TmaxDev}_{c,w} \times IncChar + \\ &\gamma \overline{PrcpDev}_{c,w} + \delta_w + \delta_c + \delta_{se} + \varepsilon_{cw}, \end{aligned} \tag{8}$$

where $\overline{TmaxDev}_{c,w} = \frac{1}{2}(TmaxDev_{cw} + TmaxDev_{c,w-1})$, and $\overline{PrcpDev}_{c,w}$ is similarly defined. $IncChar$ is an incumbent characteristic of interest. We examine two characteristics: (1) LCV score; (2) party affiliation. Our coefficient of interest is β_3, which shows how effects of temperature shocks vary based on the incumbent characteristic.

For Figure A3 and Table A5, we use the following specification:

$$Y_{cw} = \sum_{t=1}^{8} \beta_t \overline{TmaxDev}_{c,w} \times Q_t + \gamma \overline{PrcpDev}_{c,w} + \delta_w + \delta_c + \delta_{se} + \varepsilon_{cw}, \tag{9}$$

where $\overline{TmaxDev}_{c,w}$ and $\overline{PrcpDev}_{c,w}$ are defined as above. Q_t is a set of eight indicators for quarters in the election cycle. This specification allows us to obtain a separate estimate for each quarter-in-cycle.