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

Yanjun Liao*† Pablo Ruiz Junco*

September 2021

Abstract

This paper studies how extreme weather and natural disasters affect 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, with a larger effect in counties with more anti-environment incumbent politicians. In a medium-run analysis, we find that, when a natural disaster strikes, the election becomes more competitive if the incumbent leans more anti-environment: total campaign contributions increase for both candidates and 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. These results suggest that extreme weather events carry a moderate electoral penalty for anti-environment incumbents during 1990-2012. This mechanism will likely play a more important role as the public awareness of climate change continues to increase.

JEL Classification: D72, D91, Q54.

Keywords: climate change beliefs, natural disasters, campaign finance, elections.

*We thank Julie Cullen, Mark Jacobsen, Julian Betts, Richard Carson, James Fowler, Joshua Graff Zivin, David Victor, Stefano Carratini, Frances Moore, participants at the UCSD environmental economics seminar, the SEA 2019 annual meetings, and the ASSA 2020 annual meetings for valuable comments and feedback. We thank Adam Bonica for making the data for this project easily accessible and for assistance with understanding the data sources.

†Resources for the Future. Email: yliao@rff.org.

1 Introduction

Public opinion on key issues is thought to play a crucial role in shaping policies and elections in a democracy. It is important to understand the factors contributing to the formation of these opinions and their political ramifications. This paper focuses on the issue of climate change, which has received significant policy attention in the last three decades. In the United States, both the public and legislators remain divided on climate change despite the scientific consensus on it.

Many studies have examined factors that shape Americans' attitudes on climate change 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. Surveys of stated beliefs can be misleading if people misrepresent their true preferences due to social or strategic considerations. Changes in stated beliefs do not necessarily correspond to changes in behavior. Importantly, it remains an open question whether politicians will be held accountable for their environmental positions since environmental and climate issues are not always a top priority (Davis and Wurth, 2003; Guber, 2001).

In this paper, we present 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 multiple 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.[2] Our key approach is to test for differential effects of weather and disaster shocks based on the environmental stance of incumbent politicians. Our results show a margin of political behavior in this context that is, to the best of our knowledge, novel in the litera-

[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] 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.

ture. They also uncover mechanisms through which public opinion may shape U.S. climate policies.

Our study follows the literature closely in choosing regression frameworks and constructing measures of weather shocks. Previous studies can be classified into three categories. The first set of papers study short-run weather shocks within a month or less (Joireman et al., 2010; Li et al., 2011; Egan and Mullin, 2012; Hamilton and Stampone, 2013; Zaval et al., 2014). The second set examines 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 (Spence et al., 2011; Lang and Ryder, 2016; Sisco et al., 2017). Motivated by the literature, we study all three types of 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 show an extensive-margin response: a 1 °F increase in weekly average temperature corresponds to a 1.2% increase in the contribution rate within the week and a cumulative effect of 2.7% over a five-week period. We do not detect any intensive-margin effect. Furthermore, we find a stronger response to temperature shocks among constituents with more anti-environment incumbents. Overall, these results suggest that a higher temperature shock favors Democratic candidates–who typically lean pro-environment–especially when they are running against a more anti-environment incumbent.

In the medium-run analysis, we first explore 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), from which we identify 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. Our regression specification captures the differential effect of natural disasters on elections based on the incumbent's stance on environmental issues, conditional on congressional district and state-by-election-cycle fixed effects. However, as large partisan divide exists not only in environment but also many non-environmental issues, an estimate based on cross-party variation in environmental stance might pick up additional effects from such partisanship. It might also be biased if the incumbent's environmental stance is correlated with other incumbent or district characteristics that affect the electorates' evaluation of the incumbent after a disaster. To account for these correlations, we control for a set of district and incumbent characteristics and their interaction with natural disasters. These characteristics include, of the incumbent, demographics and party affiliation, and of the district, demographics and measures of rurality. We find that after a natural disaster, total fundraising 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, a politician's position on environmental issues might still be correlated with her position on non-environmental, disaster-related issues, conditional on party affiliation and other characteristics. One notable possibility is her support for disaster relief. Past studies show that incumbents are rewarded for requesting and spending funds for disaster recovery (Healy and Malhotra, 2009; Healy et al., 2010a; Gasper and Reeves, 2011; Chen, 2013). We test this possibility by examining disasters that are not perceived to be related to climate change, such as tornadoes and earthquakes.[3] 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 similar regressions. 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 likely to invoke disaster relief or other 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

[3]As of now, scientists have not been able to establish a clear connection between climate change and tornadoes, as the relationship is theoretically ambiguous and empirically undetected (National Academies of Sciences, Engineering, and Medicine, 2016). Brooks et al. (2014) shows that variability of tornadoes has increased since the 1970s but not the frequency. Likewise, there has been no evidence that climate change can trigger earthquakes strong enough to be detectable by human (https://climate.nasa.gov/news/2926/can-climate-affect-earthquakes-or-are-the-connections-shaky/). Neither have been mentioned in the IPCC 5th Assessment Report (IPCC, 2013), and hence are unlikely to be perceived by the public to be related to climate change.

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 Democrats, and more so for Democratic challengers of a Republican incumbent. The medium-run analysis shows a consistent pattern, where occurrences of natural disasters and extreme temperature events lead to stronger support for challengers running against 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. These findings are consistent with emerging evidence on changes in legislators' behaviors in response to a natural disaster in their district. 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 other possible explanations for their results, a more challenging re-election would put pressure on incumbents to change legislative behavior.

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. Most of these studies examine low-stake outcomes such as Google searches (Herrnstadt and Muehlegger, 2014; Lang, 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, but this donation came from the payment they received for completing the study.[4] The outcomes analyzed in this paper are costlier and directly related to the political processes where, at least in principle, public opinions can shape policies.

Secondly, this paper is closely related to an extensive literature on retrospective voting (see Healy and Malhotra (2013) for a review). This literature focuses on testing whether voters punish or reward politicians for events that occurred while they were in office. In particular, past studies have shown that incumbents are held partially accountable for their roles in disaster preparedness and post-disaster relief. For example, voters punish the incumbent

[4] In a related paper, Jacobsen (2011) shows that Al Gore's documentary "An Inconvenient Truth" caused a 50% relative increase in the purchase of voluntary carbon offsets in neighborhoods close to the theatres. This suggests people can take costly climate action when provided with a strong stimulus.

mayor after a flood if they believed the city was responsible for flood preparation (Arceneaux and Stein, 2006). Similarly, delivery of disaster relief affects voter turnout and outcomes in presidential and gubernatorial elections (Healy and Malhotra, 2009; Gasper and Reeves, 2011; Chen, 2013).[5] Our analysis complements these studies in three ways. First, we explore legislative elections to the U.S. House of Representatives. Second, we examine campaign finance in addition to election outcomes. Third, we 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.

Thirdly, our results contribute to understanding 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 voters make campaign contributions for ideological reasons (Francia et al., 2003; Ensley, 2009; Bonica, 2014; Barber, 2016), and that they derive direct utility from such contributions as if they were consuming an ideologically-motivated consumption good (Ansolabehere et al., 2003). In addition, our medium-run analysis find a similar response in PAC contributions as in individual contributions, adding to the evidence that PAC contributions are also motivated by ideological considerations instead of being *quid pro quos* by nature (Snyder, 1990; Bonica, 2013, 2014, 2013; Barber, 2016).

Finally, our findings also have real-world implications for climate policy. Even though environmental issues have not been front-and-center in U.S. elections, we demonstrate that the electorate is responsive to the salience of these issues.[6] Our results suggest that approaches to raise issue salience by recounting relatable human experiences might have the potential to induce substantial changes in political behavior. Moreover, as the prominence of climate issues in politics is rising in the U.S.,[7] the mechanism we identify will also become more relevant. In particular, there is now increasing recognition of the political cost of continued climate denial.[8]

[5] Re-analysis by Gallagher (2020) has cast doubt on part of the findings in Gasper and Reeves (2011), but still suggests the electorates are responsive.

[6] We caution that these responses may not be entirely rational, since people might process shocks with psychological bias. There is also evidence to suggest that voting outcomes are affected by irrelevant events such as same-day weather patterns, a recent college football game or financial windfalls from lotteries (Gomez et al., 2007; Healy et al., 2010b; Bagues and Esteve-Volart, 2016; Achen and Bartels, 2017; Meier et al., 2019). Overall, however, the public is under-adopting the scientific consensus on climate change.

[7] For example, there have been numerous public discussions inspired by the proposal of a Green New Deal and Jay Inslee's 2020 presidential campaign built primarily on climate issues.

[8] See, for example, "Findings and Insighs on GOP Climate Strategy", Luntz Global Partners, https://www.eenews.net/assets/2019/06/13/document_daily_01.pdf, or "Recent Polling on Youth

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

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 contributions data in DIME mainly come from administrative records of the Federal Election Commission (FEC). The FEC requires each committee of a House of Representative candidate to file quarterly reports, disclosing all contributions exceeding $200 and those adding up to over $200 from an individual. The database also contains candidate characteristics and election outcomes.[9]

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 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, where 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 weather shocks in the medium run, 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.

Voters", Benenson Strategy Group and GS Strategy Group, https://climateaccess.org/system/files/BSG%20LCV_Polling%20Youth.pdf.

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

2.2 ActBlue

In our short-run analysis, 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, ActBlue accounts for 4.3% of contributions and 0.8% of the total amount contributed to Democratic candidates.[10]

The main advantage of using ActBlue data is the accuracy of the recorded dates, 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. A second advantage is that ActBlue captures small contributions well (see Figure A3 for a histogram of ActBlue contribution amounts). In contrast, other records contain mostly contributions exceeding $200 for an individual. Such smaller donations reflect spontaneous, low-stake decisions[11] that are more likely to be affected by short-run weather shocks.

However, there are two concerns with using only ActBlue data for our short-run analysis. First, the lack of an established Republican equivalent of ActBlue leaves us with only donations to Democrats.[12] Thus, we are not able to see how donations to Republicans would respond. We propose alternative methodologies below to address this concern. The second concern is that it is unclear whether using ActBlue data will yield results that are representative of all contributions to Democrats. Past studies have found that Internet donors tend to be younger and give a smaller amount than the rest of the contributors, but are similar in terms of ideological positions (Wilcox, 2008; Karpf, 2013).[13] 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 us to hone in on lower-cost, spontaneous decisions that may be affected by weather shocks. Moreover, as online donors are economically more representative

[10] 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 use these numbers when assessing the magnitude of our coefficients later on.

[11] For an example of how contributions are made to Democratic candidates through ActBlue, see Figure A2.

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

[13] Specifically, Karpf (2013) suggests that the Internet brings about an increase in small donors by lowering transaction costs. Meanwhile, Wilcox (2008) finds that Internet donors are 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.

of the American electorate than traditional offline donors (Graf et al., 2004; Malbin, 2013), their contribution behavior might also be informative of how politicians are perceived among a broader population.

2.3 League of Conservation Voters Scorecard

To capture the position 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.[14] 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.[15]

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).[16]

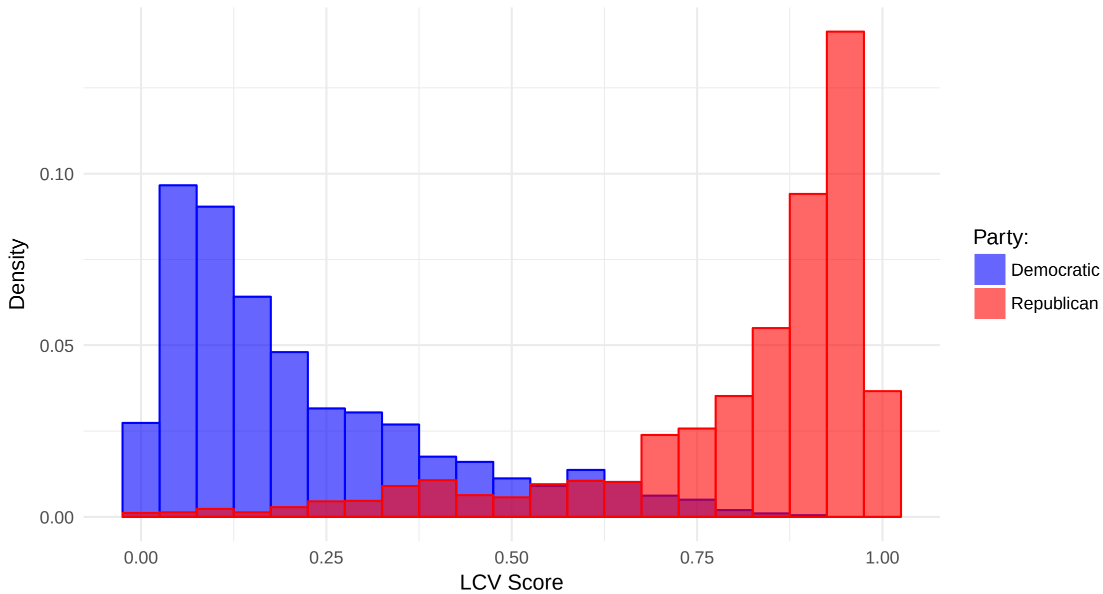
There is a large divide in the LCV scores of Democrats versus Republicans, as shown in Figure 1. A majority of Democrats fall into the 0-0.25 range, meaning that they disagree with the LCV on less than 25% of the relevant votes. Likewise, most Republicans fall in the 0.75-1 range, meaning that they disagree 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.

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

[15] 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.

[16] For more information about the LCV scorecard, visit http://scorecard.lcv.org/.

Figure 1: LCV score distribution by party affiliation



Notes: this figure shows the histogram of incumbents' LCV scores by party affiliation. Throughout this paper, we use this "inverted" LCV score, which has been subtracted from one.

Additionally, the LCV score is an important indicator of whether the politician is a climate change denier. We obtain records of climate change deniers in the 112th caucus from the site ThinkProgress.org.[17] 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.[18]

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

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

We construct two measures of daily temperature shocks, which we later aggregate over the appropriate 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:

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

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:

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

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

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, $TmaxLow_{cmd}$ is an indicator for whether the contemporaneous temperature is lower than the 5th percentile of the historical distribution, whereas $TmaxHigh_{cmd}$ 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 use as the main regressors. Specifically, our primary temperature measure is $TmaxDev_{cw}$, which is the average of $TmaxDev_{cmd}$ over the week. For robustness, we also use the alternative measures $TmaxHigh_{cw}$ and $TmaxLow_{cw}$, the weekly sum of $TmaxHigh_{cmd}$ and $TmaxLow_{cmd}$, respectively. We also construct similar measures of precipitation deviations to use as controls in the regressions.

For our medium-run analysis, we similarly calculate the number of abnormally hot days, defined as those above the 95th percentile of the district-specific historical distribution, experienced by the average person in each congressional district and election cycle.[19] 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

[19] The procedure and all similar ones below 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.

ranked by the number of cold days, defined as those below the 5th percentile of the historical distribution.

2.5 Natural Disasters

High-profile recognition for the scientific link between climate change and natural hazards can be traced back to as early as the first Assessment Report of the IPCC in 1990 (Tegart et al., 1990). We obtain data on disaster declarations between 1990 and 2012 from the Federal Emergency Management Agency (FEMA). There are a total of 1,943 climate-related disasters, a large majority are storms (including hurricanes) and fires (see Table A1). Importantly, these official records contain the period of the incident and the specific counties affected. Most declarations are not statewide.

As we analyze the impact of natural disasters at the congressional district level, we aggregate disaster status from counties to congressional districts. We first calculate the fraction of the population in a district who are residing in a county hit by a disaster. 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. Based on this definition, almost 95% of congressional districts have experienced at least one climate-related disaster during the sample period. As shown in Figure A4, total disaster exposure is not geographically concentrated, and there is also substantial within-state variation in the vast majority of states.

Federal disaster declarations provide a comprehensive record of major natural disasters across types. The declarations are primarily based on damage assessments. For example, FEMA relies on a single criterion – a per capita damage indicator – for recommending declarations for Public Assistance (PA), its largest post-disaster aid program (U.S. Government Accountability Office, 2012).[20] In addition, Gagliarducci et al. (2019) finds that FEMA declarations correspond well to actual trajectories of hurricanes and objective measures of

[20] Specifically, FEMA recommends PA to the president when the per capita damage exceeds a predetermined threshold. See https://www.fema.gov/assistance/public/applicants/per-capita-impact-indicator for information on the thresholds used in recent years.

intensity. However, one might still worry that declarations are politically motivated and therefore endogenous to our outcomes (Garrett and Sobel, 2003). When we discuss our empirical framework below, we will address this issue further and explain why we think this concern is outweighed by the advantage of using a comprehensive set of disasters spanning broad geographic areas.

2.6 District and Incumbent Characteristics

For district-level demographics and incumbent characteristics, we use data from Historical Congressional Legislation and District Demographics 1972-2014 (Foster-Molina, 2017). This dataset covers standard demographic variables that measure the income, race, and education level in each district for each Congress, as well as the age, gender, and race of the corresponding incumbent.

We also include two measures of rurality of the district. The first is the fraction of population living in non-metro counties as defined by the Rural-Urban Continuum Codes.[21] Under this classification scheme, a non-metro county is some combination of open countryside, rural towns, and urban areas with populations below 50,000. The second measure is the employment share in agriculture and mining from the Quarterly Census of Employment and Wages (QCEW), which we aggregate from county to congressional district level.

3 Empirical Framework

Existing studies suggest that climate change perception is affected by personal experiences of weather events over different time frames. Following this literature, we examine the impacts of weather shocks in both the short and medium run, as well as natural disasters in the medium run. In this section, we describe our empirical strategy.

[21] Data available at https://www.ers.usda.gov/data-products/rural-urban-continuum-codes.aspx. We use the 1993 edition of the data.

3.1 Short-Run Weather Impacts

We first analyze the impact of weekly weather shocks on ActBlue contributions to Democrats. 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. We also 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.[22]

The basic 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. The term Y_{cw} represents 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. The term $Weather_{cw}$ is a vector of weather variables including temperature measures as the key regressors and precipitation measures as controls.

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. The second specification adds four lags of both temperature and precipitation shocks:

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

This specification captures the delayed impacts of past weather shocks for up to a month.[23] The third specification uses the average deviation in the current and previous week:

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

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

[23] We also run a version of this distributed lag model with twelve lags to explore the dynamics further.

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 political ideology and contribution behavior. The week-in-sample fixed effects control for national events and the exponential growth of the platform. 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 and changes in policies or economic conditions in the state. We cluster standard errors at the county level.

Next, we extend the basic specification to estimate heterogeneous effects based on the environmental stance of the incumbents. This allows us to rule out unobservable confounding factors that may drive all contributions across time and location, and not only those that are environmentally motivated. To enhance statistical power, we use the two-week average of temperature shocks as the main measure and interact it with the incumbent's LCV score:

$$\begin{aligned} Y_{cw} = &\beta_1 \overline{TmaxDev}_{c,w} + \beta_2 LCV + \beta_3 \overline{TmaxDev}_{c,w} \times LCV \\ &+ \gamma \overline{PrcpDev}_{c,w} + \delta_w + \delta_c + \delta_{se} + \varepsilon_{cw}, \end{aligned} \tag{2}$$

where $\overline{TmaxDev}_{c,w} = \frac{1}{2}(TmaxDev_{cw} + TmaxDev_{c,w-1})$, and $\overline{PrcpDev}_{c,w}$ is similarly defined. Our coefficient of interest is β_3, which captures how the effect of temperature shocks varies based on the incumbent's LCV. We estimate this equation using the full sample as well as on separate subsets of counties based on the incumbent's party.

3.2 Medium-Run Natural Disaster Impacts

In the medium run, we study how fundraising and elections are affected by natural disasters. In particular, we examine 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 examine campaign finance outcomes such as total funds raised and the fraction that goes to the challenger and electoral outcomes such as the probability of the incumbent being challenged, getting re-elected, and so on.

One concern we have 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.[24] We expect this to be relevant for natural disasters as well since they often entail tragic consequences and loss of property.

To address this concern, our research design compares congressional districts experiencing natural disasters whose incumbent politicians have an anti-environment voting record to other districts experiencing natural disasters but whose incumbents exhibit pro-environment voting records. By studying differential impacts by the environmental stance of incumbents, we can isolate the environmental preference mechanism. Specifically, the regression equation takes the following form:

$$\begin{aligned} Y_{de} =& \beta_1 Disaster_{de} + \beta_2 LCV_{de} + \beta_3 Disaster_{de} \times LCV_{de} \\ &+ \gamma_1' Char_{de} + \gamma_2' Disaster_{de} \times Char_{de} + \delta_d + \delta_{se} + \varepsilon_{de} \end{aligned} \tag{3}$$

where Y_{de} is an outcome in 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.[25] $Char_{de}$ is a vector of characteristics of the congressional district and the incumbent. 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 represents the difference in the outcome of a disaster-stricken congressional district whose incumbent congressperson has the most anti-environment voting record ($LCV = 1$), and the outcome of a similar, disaster-stricken 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 (0.2) in interpretation.[26]

The identification of β_3 requires accounting for factors that correlate with the LCV score of the incumbent. In our specification, the district fixed effects control for cross-sectional variation in disaster risk and political preference. The state-by-cycle fixed effects control for

[24] "Despite Terrorism, Candidates Make Slow Return to Fundraising.", The Hill. October 24, 2001.

[25] 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.

[26] 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.

political alignment of the state and the president, which is important given past findings on politically motivated aid decisions (Garrett and Sobel, 2003). It also controls for a changing policy and economic environment. However, one might still be concerned about the correlation between the LCV score and the party affiliation and other characteristics of the incumbent. If, following a disaster, people react differently to incumbents from different parties for non-environmental reasons, then β_3 would pick up the effect of the party. Similarly, demographic changes following a disaster might also create such effects. To address this concern, we control for a list of incumbent and district characteristics and their interaction with the disaster indicator. These characteristics are, for the incumbent, party affiliation, gender, race and ethnicity; and for the district, the median income, percent of population with bachelor's degree or above, percent of white population, percent of nonmetro population, employment share in agriculture and mining, and the Gini index.

Another major concern is that presidential disaster declarations might be endogenous to political outcomes. A disaster declaration is at the president's discretion and does not require congressional approval. Consistent with this rule, Garrett and Sobel (2003) find a higher likelihood for disaster declarations in a presidential election year and in states of electoral importance to the president, but no evidence of an effect due to political alignment of the governor or congressional members with the president.[27] It seems unlikely that House representatives directly exert political influence on the declaration process in a way that is correlated with their environmental ideology. However, this could still bias our estimates downward if declarations in swing states during election years represent less severe disasters than usual. To investigate this issue, we will run a robustness check excluding cycles in which a president seeks re-election.

3.3 Medium-Run Weather Impacts

Campaign contributions and elections may also respond to shocks to medium-run temperature. We estimate the effects of hot- and cold-weather shocks separately using the following specification:

$$\begin{aligned} Y_{de} =& \beta_1 Hot_{de} + \beta_2 Cold_{de} + \beta_3 LCV_{de} + \beta_4 Hot_{de} \times LCV_{de} + \beta_5 Cold_{de} \times LCV_{de} \\ &+ \gamma_1' Char_{de} + \gamma_2' Hot \times Char_{de} + \gamma_3' Cold \times Char_{de} + \delta_d + \delta_{se} + \varepsilon_{de}. \end{aligned} \tag{4}$$

[27]Later studies, including Sylves and Búzás (2007), Reeves (2011), and Kousky et al. (2018), have invariably emphasized the discretionary role and political motivation of the president in disaster declarations.

The notations are similar to before. 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. We also interact these indicators with the LCV score to estimate the differential effects. Other controls and 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.

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) robustness checks and extensions of the medium-run analysis, including the impacts of medium-run temperature shocks.

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 contribution amount divided by the number of contributions in 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.

In our sample period of 2006-2012, each county received around $150 per week (Table A2). ActBlue contributions are usually small: the average donation amount is $13.2. Meanwhile,

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

Dep. Var.	Count/1 million 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)
Precipitation Dev.	Yes	Yes	Yes	Yes	Yes	Yes
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
N	944172	935201	941672	944172	935201	941672
R^2	0.209	0.204	0.209	0.0539	0.0539	0.0539
D.V. Mean	15.45	15.40	15.42	13.13	13.19	13.15

Notes: estimates on temperature deviations 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. The estimates on precipitation deviations from these regressions are reported in Table A3. Standard errors are clustered by county. Statistical significance: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

the mean weekly temperature deviation from the historical normals is 0.45 °F, showing a warming trend. There are also more days of extreme heat than extreme cold.[28]

Table 1 reports estimates from equation (1). Columns (1)-(3) focus on responses in contribution rates. Column (1) shows the current week's temperature is positively associated with contribution rates, and the estimate is statistically significant.[29] A 1 °F increase in weekly

[28]Days of extreme heat are those above the 95th percentile of the historical distribution, and extreme cold refers to those below the 5th percentile.

[29]The deviation in precipitation is also included in the model as a control. Both temperature and precip-

temperature is associated with 0.19 additional contributions per million people (1.2% D.V. mean).[30] Alternatively, this is 1.3 additional contributions per million people (8% D.V. mean) for a one-standard-deviation (6.62 °F) increase in weekly temperature deviation. In column (2), we add four lags of temperature deviations to examine whether temperature shocks from previous weeks affect current contributions.[31] The estimates are positive and significant across-the-board, suggesting that positive temperature shocks increase contributions for up to four weeks after. Together, they show a larger cumulative effect: a 1 °F increase in weekly temperature is associated with a cumulative effect of 0.42 additional contributions per million population (2.7% D.V. mean), or 2.8 additional contributions per million population for a one-standard-deviation increase in weekly temperature deviation. In column (3), we use the average temperature deviation in the current week and the week before as our main regressor and again find the estimate to be positive and significant at the 1% level. In columns (4)-(6), we re-estimate these models using the average contribution amount as the outcome variable. Here, all estimates are small and statistically insignificant. This could mean that temperature shocks do not motivate people to contribute more each time. It is also possible that regular contributors do give more, but this effect is offset when the additional contributions are smaller.

Table A3 reports the estimates on precipitation shocks from these same regressions. Precipitation shocks appear to have a positive contemporaneous effect on contribution rates but negative lagged effects. As a result, the effect of a precipitation shock over two weeks is close to zero and statistically insignificant. These effects are qualitatively different from those of temperature shocks and might be better explained by other channels such as time use.[32] In general, it is unclear whether voters are well aware of the connection between abnormal precipitation patterns and climate change during the study period.

We also estimate several variants of equation (1) to explore differences in the effects of heat and cold shocks (see Appendix B for a detailed discussion of these results). We find that heat shocks are the main driver of the effects observed above, but an extremely cold day also reduces contributions. This suggests that extreme cold is a salient event that might

itation shocks are constructed as the deviation from 30-year normal, as detailed in Section 2.4.

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

[31] To further explore the dynamic effects, we plot the estimates from a version of this regression with twelve distributed lags in Figure A5. These results show that the temperature effect tapers off after four lags, which is why we include four lags in the main result.

[32] For example, raining can lead to more indoor time and internet use, which might shift future donations forward. Thus, it can explain the harvesting pattern we observe.

have been interpreted as evidence *against* climate change, which is consistent with existing studies on public opinions (Roxburgh et al., 2019). This interpretation might be due to the political discourse surrounding cold-weather events.[33]

Taken together, our results suggest that the impact of temperature shocks is concentrated on motivating more instances of political giving to Democrats. 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, weather might change political behavior for psychological reasons. It might also affect time use or the expediency of online versus other contribution channels.[34]

To understand the motivation behind these temperature-driven contributions, we estimate how the temperature effect differs based on the incumbent's LCV score.[35] Specifically, we estimate equation (2) with the contribution rate as the main outcome. The results are reported in Table 2. Column (1) includes all counties in the sample. As before, we find a positive and significant effect of temperature deviations on contribution rates. Importantly, the incumbent's LCV score has a positive interaction effect with temperature deviations, which means the temperature effect is more pronounced when the incumbent leans more anti-environment. The scale of this interaction effect is important relative to the baseline effect (column (3), Table 1). 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.[36] In columns (2) and (3), we estimate this model separately on counties with a Democratic incumbent and those with a Republican incumbent, respectively. In counties with Democratic incumbents, temperature shocks uniformly increase ActBlue contributions to the incumbents regardless of their environmental position, likely because Democratic incumbents are generally more pro-

[33] Anecdotes 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.

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

[35] 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.

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

Table 2: Heterogeneous effects by incumbent's environmental position

Count/1 million pop	(1) Full Sample	(2) D Incumbent	(3) R Incumbent
TmaxDev (2-week avg.)	0.193**	0.305**	-0.146
	(0.0975)	(0.126)	(0.115)
Incumbent LCV	10.30**	-3.439	-2.992
	(4.658)	(12.75)	(5.471)
TmaxDev × Incumbent LCV	0.152**	-0.0992	0.487***
	(0.0681)	(0.111)	(0.176)
Precipitation Dev.	Yes	Yes	Yes
County F.E.	Yes	Yes	Yes
Week F.E.	Yes	Yes	Yes
State-Cycle F.E.	Yes	Yes	Yes
N	830316	313890	516426
R^2	0.207	0.244	0.246
Mean D.V.	12.29	14.22	11.12

Notes: estimates from equation (2) are shown. Column (1) is based on the full sample, columns (2) and (3) are based on counties with a Democratic incumbent and those with a Republican incumbent, respectively. The dependent variable is the number of contributions per 1 million population. The temperature shock measure is the average temperature deviation in the current and past week. "Incumbent LCV" is a score indicating the incumbent's environmental position. It ranges from 0 to 1, 0 being the most pro-environment and 1 the most anti-environment (inverted from the original scale). Standard errors are clustered by county. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

environment than their challengers. For Republican incumbents, the picture is very different: the more they lean anti-environment, temperature shocks motivate more ActBlue contributions to their Democratic challengers. These results provide support that the temperature effect we observe is indeed motivated by environmental ideology.

We also examine how the temperature effect vary based on the progression of campaigns. We interact the two-week temperature measure with indicators of each quarter in the election cycle, which estimates the temperature effect separately for each quarter. These estimates are plotted in Figure A6 and show heterogeneous effects 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 effect of temperature shocks on total Democratic contributions from these estimates based on ActBlue contributions. In our sample, the total number of Democratic contributions is 24 times that of ActBlue contributions and the total amount is 122 times. 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.[37] The corresponding cumulative effects are 10 contributions and $672.6. We note the important caveat that these calculations assume a similar reaction to weather shocks in total Democratic donations and ActBlue donations. In reality, we may expect ActBlue donations to have a stronger response given their nature of small, spontaneous donations. Therefore, these calculations likely represent upper bounds on the actual effect.

To sum up, in this section we show that short-run temperature shocks lead to a stronger support for Democrats. In particular, such responses change according to the incumbent's party and environmental position, suggesting that they are motivated by environmental policy preferences. Since online donors are more representative of the American electorate than traditional offline donors, this mechanism might also have broader implications for political volunteering, voting, and ultimately electoral outcomes. We next turn to a medium-run analysis to explore how this mechanism affects election dynamics.

4.2 Medium-Run Natural Disaster Impacts

In this section, we study the impacts 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. Previous studies find that 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 the environmental stance of the incumbent will come under more scrutiny when a natural disaster strikes. Therefore, we expect an anti-environment incumbent will face a more competitive electoral landscape

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

Table 3: The effect of natural disasters on log amount raised

	(1) Total Funds	(2) PAC	(3) Individual	(4) Challenger	(5) Incumbent	(6) Share (C)
Disaster	-0.175***	-0.218***	-0.166***	-0.365**	-0.132***	-0.0348**
	(0.0357)	(0.0444)	(0.0479)	(0.154)	(0.0248)	(0.0133)
Incumbent LCV	-1.250	-1.197	-0.552	-6.178	-0.470	-0.143
	(1.455)	(1.541)	(1.686)	(4.910)	(1.173)	(0.390)
Disaster × Incumbent LCV	0.255***	0.296***	0.215**	0.904***	0.186***	0.0515**
	(0.0657)	(0.0677)	(0.0824)	(0.302)	(0.0489)	(0.0228)
District Char. × Disaster	Yes	Yes	Yes	Yes	Yes	Yes
State-Cycle F.E.	Yes	Yes	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.636	0.628	0.636	0.423	0.707	0.338
N	4307	4307	4307	4307	4307	4397
Mean D.V. (levels)	1330.1	482.0	704.8	320.7	1009.5	0.177

Notes: estimates from equation (3) are shown. In columns (1)-(5), the dependent variable is the (IHS-transformed) amount of campaign funds of the category indicated in the top panel. In column (6), the dependent variable is the share of total funds raised by the challenger. The bottom panel reports the mean of each dependent variable in levels. "Incumbent LCV" is a score indicating the incumbent's environmental position. It ranges from 0 to 1, 0 being the most pro-environment and 1 the most anti-environment (inverted from the original scale). Standard errors are clustered at the state level. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

than the status quo.

Our sample consists of House of Representative races in election cycles from 1990 to 2012. Summary statistics for the sample are reported in the bottom panel of Table A2. In our data, 73% of the races are competitive, 17.2% 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.[38] The incumbents enjoy large advantages when they run: the total amount of funds raised is typically much higher for them than for challengers and they win 95% of the time.

We study how the effects of a natural disaster vary depending on the environmental voting record of the incumbent by estimating equation (3). Table 3 reports the results on campaign

[38] 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.

finance outcomes. Column (1) shows that the effect of a natural disaster on total fundraising ranges from a decrease of 17.5% in districts with the most pro-environment incumbent (LCV = 0) to an increase of 8% with the most anti-environment incumbent (LCV = 1).[39] Among districts hit by a disaster, a one-standard-deviation increase in the LCV score of the incumbent is associated with a 5.1% increase in total fundraising or about $67,800 more when multiplied by the average amount.[40] Next, columns (2) and (3) break down the sources by PACs versus individuals and show a similar pattern in both. Among disaster-stricken districts, a one-standard-deviation increase in the incumbent's LCV score is associated with 6% more funds from PACs and 4.3% more funds from individuals. In columns (4)-(6), we break down the increase by the recipient. Column (4) shows a one-standard-deviation increase in the LCV score of the incumbent translates to a 18% increase (about $57,600) in fundraising by the challenger, on average, when a natural disaster strikes. The corresponding increase in funds for the incumbent is smaller at 3.7% (about $37,300). In column (6), we formally test whether the share of funds going to challengers is higher when the incumbent leans anti-environment. The estimate suggests that a one-standard-deviation increase in the LCV score is associated with a 1 p.p. increase in the share of funds going to challengers when a natural disaster strikes, over a baseline of 17.7 p.p.

More competitive elections generally attract more resources on both sides. The above pattern is consistent with a more competitive race for anti-environment incumbents in the wake of a disaster. As their challengers garner more support, incumbents also ramp up fundraising in response. Nonetheless, the gain in funds and support is much more significant for the challengers. This result aligns with the hypothesis that a disaster can motivate greater support for challengers who run against more anti-environment incumbents.

Next, we take the analysis a step further by exploring the impact on 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 affect electoral outcomes. Second, natural disasters may motivate 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. Below, we examine 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

[39] The effect of a disaster is given by $0.255 \times LCV - 0.175$.

[40] The within-party standard deviation of the LCV score is 0.2. The effect of one-standard-deviation increase in LCV is thus given by $25.5\% \times 0.2 = 5.1\%$.

Table 4: The effect of natural disasters on elections

	(1) Competitive	(2) Unopposed	(3) Open Seat	(4) Incumbent Win
Disaster	0.000930	0.0196	-0.0205	0.0394
	(0.0255)	(0.0218)	(0.0167)	(0.0242)
Incumbent LCV	-1.304**	0.970**	0.334	0.365
	(0.529)	(0.415)	(0.345)	(0.376)
Disaster × Incumbent LCV	0.108***	-0.0966**	-0.0112	-0.0588**
	(0.0394)	(0.0428)	(0.0249)	(0.0289)
District Char. × Disaster	Yes	Yes	Yes	Yes
State-Cycle F.E.	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes
N	4801	4801	4801	4307
R^2	0.276	0.317	0.251	0.290
Mean D.V.	0.731	0.171	0.0979	0.951

Notes: estimates from equation (3) are shown. In columns (1)-(3), the dependent variable is an indicator of the congressional race to be of a certain type (competitive, unopposed, open seat). The dependent variable in column (4) is an indicator of the incumbent getting re-elected. Columns (1)-(3) include all elections and column (4) excludes open seat elections. "Incumbent LCV" is a score indicating the incumbent's environmental position. It ranges from 0 to 1, 0 being the most pro-environment and 1 the most anti-environment (inverted from the original scale). Standard errors are clustered at the state level. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

not run for re-election), and whether the incumbent is re-elected.

Table 4 shows these results. For the most pro-environment incumbents, disasters do not appear to change the nature of the race or the incumbent's chances of winning, as indicated by the coefficients on the disaster indicator. However, these effects change significantly for incumbents that lean more anti-environment. Column (1) shows that they are more likely to face a challenger when disaster strikes. For a one-standard-deviation increase in the LCV score, the probability of the race being competitive following a disaster increases by 2.2 p.p. The next two columns show a corresponding decrease in the probability of an uncontested race and no change in the probability of an open seat election. 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 enter 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. Finally, consistent with the previous results, in column (4) we find a lower probability of winning for incumbents with an anti-environment voting record. Specifically, for a one-standard-deviation change in the LCV score, the probability decreases by 1.2 p.p. While this effect is not large in absolute terms, it represents a substantial change in the odds of winning for challengers, for whom the probability of winning is only 5% on average.

4.3 Robustness and Extension of the Medium-Run Analysis

In this section, we report a series of robustness checks and extensions of our main findings in the medium-run analysis. For brevity, we will focus on four key outcomes throughout this section: the log of total funds raised, the share of funds going to the challenger, the probability of the race being competitive, and the probability of an incumbent win.

Robustness: Binned LCV Score

The main specification in equation (3) assumes the effect of disasters changes linearly with the LCV score. Here, we relax this assumption by estimating a specification where the LCV score is replaced by four indicators for equal-length bins of its value.[41] This specification allows the effect of disasters to change in a more flexible way with the LCV score. Figure A7 plots the coefficients on the interaction terms for the four key outcomes. We find that the estimates show larger disaster effects for bins with higher LCV values and the pattern is roughly linear. This lowers our concern of mis-specification in the main results.

Robustness: Accounting for Politically-Motivated Declarations

We also run a robustness check to explore the issue of politically-motivated disaster declarations as discussed in Section 3. In particular, past studies show that the main source of political influence over declarations is the president's re-election incentives (Garrett and Sobel, 2003; Gasper, 2015). In light of this, we re-estimate equation (3) in a sample that excludes cycles in which a president is seeking re-election. These results are reported in Table A4. We find slightly larger estimates on total contributions, the challenger share

[41] See equation (B2) in Appendix C for this specification.

of the contribution, and the probability of a competitive race, which is consistent with a downward bias from including less severe disasters in presidential re-election cycles. The estimate on the probability of incumbent getting re-elected is slightly smaller and no longer statistically significant, which is also partly due to lower statistical power. Nevertheless, the overall pattern is similar to before, which suggests that our results are not driven by political motivation.

Robustness: Heterogeneous Effects over Time

We also examine how these effects evolve over time, as the public's attention on climate change has changed substantially during the study period. Looking at the same outcomes, we estimate another version of equation (3) where we interact the main regressors with indicators for three periods: 1990-1996, 1998-2004, and 2006-2012.[42] Figure A8 plots the coefficients on the period-wise differential effects of disasters based on the incumbent LCV score. Notably, the effects are concentrated in the last period for all outcomes, which coincides with the rapid increase in the usage of climate keywords after 2005 captured by Google Ngram Viewer (see Figure A1). This supports that the salience of climate change is an important factor in the political ramifications of climate-related disasters.

Extension: Extreme Temperature Events

Another extension is to estimate the medium-run effect of temperature shocks. Temperature shocks are different from natural disasters for a number of reasons. First, temperature shocks can be either hot or cold weather shocks and they might be interpreted differently. Second, temperature shocks may be less salient than natural disasters, in part because they do not usually result 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). The estimation follows equation (4).

These results are reported in Table 5. An abnormally hot cycle does not appear to affect an anti-environment incumbent significantly more in terms of total funds raised in the race or the probability of being challenged, as shown in columns (1) and (3), respectively. However,

[42] See equation (B3) in Appendix C for this specification.

Table 5: The medium-run effects of extreme temperature events

	(1) Total Funds	(2) Share (C)	(3) Competitive	(4) Incumbent Win
Hot	-0.0848	-0.0340***	-0.0509	0.0294
	(0.0555)	(0.0104)	(0.0394)	(0.0177)
Incumbent LCV	-1.155	-0.121	-1.266**	0.347
	(1.450)	(0.399)	(0.527)	(0.382)
Hot × Incumbent LCV	0.0904	0.0502**	0.0195	-0.0820***
	(0.0896)	(0.0198)	(0.0576)	(0.0259)
Cold	0.0165	-0.0189	-0.0168	0.0216
	(0.0449)	(0.0185)	(0.0285)	(0.0236)
Cold × Incumbent LCV	-0.0326	0.0131	-0.0325	-0.00634
	(0.0665)	(0.0260)	(0.0383)	(0.0356)
District Char. × Disaster	Yes	Yes	Yes	Yes
State-Cycle F.E.	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes
N	4307	4397	4801	4307
R^2	0.634	0.338	0.274	0.291
Mean D.V.	1330.1	0.177	0.731	0.951

Notes: estimates from equation (4) are shown. The dependent variable is the (IHS-transformed) total amount of campaign funds in column (1), the share of total funds raised by the challenger in column (2), an indicator of the congressional race being competitive in column (3), and an indicator of the incumbent getting re-elected in column (4). "Incumbent LCV" is a score indicating the incumbent's environmental position. It ranges from 0 to 1, 0 being the most pro-environment and 1 the most anti-environment. The bottom panel reports the mean of each dependent variable in levels, including the amount of total funds raised in column (1). Standard errors are clustered by state. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the results in columns (2) and (4) show that challengers in these race do obtain a larger share of funds and have a higher chance of winning the race. In contrast, the coefficients for cold cycles are much smaller and statistically insignificant.

Overall, these results suggest that extreme heat events are not as politically salient as natural disasters - there is no evidence that more prospective challengers are motivated to enter the race. However, we do find favorable effects of extreme heat events for challengers already in the run against anti-environmental incumbents. Extreme cold events, on the other hand, appears to be perceived differently from extreme heat, echoing our short-run results.[43]

Extension: Non-Climate Disasters

We also examine the electoral impacts of natural disasters that are not perceived to be connected to climate change, such as tornadoes and earthquakes, as a placebo test. We do so by augmenting equation (3) to estimate the effect of these other disasters separately from that of climate-related ones:

$$\begin{aligned} Y_{de} =& \beta_1 Disaster_{de} + \beta_2 LCV_{de} + \beta_3 Disaster_{de} \times LCV_{de} + \beta_4 NonClim_{de} \\ &+ \beta_5 NonClim_{de} \times LCV_{de} + \gamma_1' Char_{de} + \gamma_2' Disaster_{de} \times Char_{de} + \delta_d + \delta_{se} + \varepsilon_{de}. \end{aligned} \tag{5}$$

In the above equation, $Disaster_{de}$ now indicates all disasters instead of just the climate-related ones before, and $NonClim_{de}$ indicates disasters not connected to climate change.[44] Thus, the first three coefficients have the same interpretation as before, while β_4 and β_5 capture the effect of non-climate disasters *relative to* that of climate-related ones.

These results are reported in Table 6. Similar to before, we find that climate-related disasters lead to more competitive elections for anti-environment incumbents. Non-climate disasters, however, do not seem to carry a similar penalty. For all outcomes, its interaction with the LCV score goes in the opposite direction. In most cases, this difference is statistically significant and large enough to reverse the punishing effect.

An important caveat in interpreting these results is that there are only a small number of non-climate disasters. We therefore caution against making a strong inference from these patterns. Instead, we view them as suggestive evidence that non-climate disasters might have different political ramifications for the incumbent from those of climate-related ones.

[43] 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.

[44] Snow events are not included in this analysis because, while supported by climate science, the connection between snow storms and climate change is not widely known to the public. Results (available upon request) with snow events counted in either category are qualitatively similar to the ones shown here.

Table 6: The effects of non-climate natural disasters

	(1) Total Funds	(2) Share (C)	(3) Competitive	(4) Incumbent Win
Disaster	-0.174***	-0.0310**	-0.00322	0.0439*
	(0.0367)	(0.0128)	(0.0253)	(0.0246)
Incumbent LCV	-1.283	-0.151	-1.325**	0.371
	(1.460)	(0.392)	(0.530)	(0.376)
Disaster × Incumbent LCV	0.264***	0.0459**	0.129***	-0.0651**
	(0.0639)	(0.0216)	(0.0412)	(0.0290)
Non-Climate	0.177*	0.0490*	0.0344	-0.00344
	(0.102)	(0.0261)	(0.0584)	(0.0246)
Non-Climate × Incumbent LCV	-0.363***	-0.0821**	-0.175**	0.0492**
	(0.0936)	(0.0336)	(0.0812)	(0.0242)
District Char. × Disaster	Yes	Yes	Yes	Yes
State-Cycle F.E.	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes
N	4307	4397	4801	4307
R^2	0.636	0.338	0.277	0.290
Mean D.V.	1330.1	0.177	0.731	0.951

Notes: estimates from equation (5) are shown. The dependent variable is the (IHS-transformed) total amount of campaign funds in column (1), the share of total funds raised by the challenger in column (2), an indicator of the congressional race being competitive in column (3), and an indicator of the incumbent getting re-elected in column (4). "Incumbent LCV" is a score indicating the incumbent's environmental position. It ranges from 0 to 1, 0 being the most pro-environment and 1 the most anti-environment. The bottom panel reports the mean of each dependent variable in levels, including the amount of total funds raised in column (1). Standard errors are clustered by state. Statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.4 Mechanisms and Limitations

Throughout this paper, we have proposed a mechanism of environmental policy preference as the driver of our results. Under 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 discuss limitations and alternative mechanisms in the context of our findings.

One alternative explanation for our results on 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 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). Instead, we find that hot and cold events have different, sometimes opposite, effects on campaign contributions. 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. However, there are three reasons to believe this is not the main driver of our results. First, we control for a range of incumbent and district characteristics to account for important differences in policy positions along these dimensions. 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. Third, if the incumbent's policy position on disaster relief is indeed a major confounding factor, we would expect the responses to disasters that are not connected to climate change to go in the same direction. Instead, we find the effects of these disasters to be close to null and statistically different from those of climate-related disasters.

In light of the literature on the political economy of FEMA's operation, one might also be concerned that disaster declarations are endogenous to political outcomes and might bias our results. There are two possible endogenous channels. First, the main source of political influence over declarations comes from the president's bid for re-election, which itself have down-ballot implications for House elections (Garrett and Sobel, 2003; Gasper, 2015). However, we find similar effects after excluding those cycles of presidential re-elections. The second channel is through aid distribution, which can be influenced by congresspeople serving on Stafford Act oversight committees. However, such influence no longer exists after FEMA was re-organized to become affiliated with DHS in 2003 (Sobel et al., 2007). This is inconsistent with our finding that the disaster effect is, in fact, largely driven by post-2004 cycles. Therefore, our main results are unlikely to be driven by the endogeneity of disaster declarations.

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-run weather and emotions could be a confounder to the extent that emotions affect individuals' incentives to make political campaign contributions. However, this does not explain the differential effects based on the incumbents' environmental stance found in both the short- and medium-run analysis. It is unlikely that our findings are 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 associated with 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, and more so when the incumbent leans anti-environment. In a medium-run analysis, we find evidence that natural disasters lead to greater 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.

These findings suggest that extreme weather events carry different political consequences for politicians with different environmental positions. The most plausible mechanism is one where voters adjust or express their environmental policy preferences in response to these events. Further, these findings suggest that electoral pressure is a plausible reason for congresspersons to change their behavior following natural disasters in their state, such as being 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 illustrate democratic forces at work. As the salience of climate change in U.S. politics has grown significantly since 2012, the mechanism in this paper will likely play a 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 missing from our analysis are environmental advocacy groups. Future research should focus on the role these groups play in disseminating information and forming public opinions following extreme weather events. Finally, it would be interesting to explore whether the behavior observed here generalizes to other policy domains in which the event of interest has a stochastic component, like terrorism or gun violence.

References

Achen, C. H. and Bartels, L. M. (2017). *Democracy for realists: Why elections do not produce responsive government*, volume 4. Princeton University Press.

Akerlof, K., Maibach, E. W., Fitzgerald, D., Cedeno, A. Y., and Neuman, A. (2013). Do people "personally experience" global warming, and if so how, and does it matter? *Global Environmental Change*, 23(1):81–91.

Ansolabehere, S., de Figueiredo, J. M., and Snyder, James M., J. (2003). Why is there so little money in u.s. politics? *Journal of Economic Perspectives*, 17(1):105–130.

Arceneaux, K. and Stein, R. M. (2006). Who is held responsible when disaster strikes? the attribution of responsibility for a natural disaster in an urban election. *Journal of Urban Affairs*, 28(1):43–53.

Bagues, M. and Esteve-Volart, B. (2016). Politicians' luck of the draw: Evidence from the spanish christmas lottery. *Journal of Political Economy*, 124(5):1269–1294.

Barber, M. (2016). Donation motivations: Testing theories of access and ideology. *Political Research Quarterly*, 69(1):148–159.

Bonica, A. (2013). Ideology and interests in the political marketplace. *American Journal of Political Science*, 57(2):294–311.

Bonica, A. (2014). Mapping the ideological marketplace. *American Journal of Political Science*, 58(2):367–386.

Bonica, A. (2016). Database on ideology, money in politics, and elections: Public version 2.0 [computer file]. *Stanford, CA: Stanford University Libraries.* Available at: https://data.stanford.edu/dime.

Brooks, H. E., Carbin, G. W., and Marsh, P. T. (2014). Increased variability of tornado occurrence in the united states. *Science*, 346(6207):349–352.

Chen, J. (2013). Voter partisanship and the effect of distributive spending on political participation. *American Journal of Political Science*, 57(1):200–217.

Davis, F. L. and Wurth, A. H. (2003). Voting preferences and the environment in the american electorate: The discussion extended. *Society & Natural Resources*, 16(8):729–740.

Deryugina, T. (2013). How do people update? the effects of local weather fluctuations on beliefs about global warming. *Climatic Change*, 118(2):397–416.

Egan, P. J. and Mullin, M. (2012). Turning personal experience into political attitudes: The effect of local weather on americans' perceptions about global warming. *The Journal of Politics*, 74(3):796–809.

Ensley, M. J. (2009). Individual campaign contributions and candidate ideology. *Public Choice*, 138(1/2):221–238.

Foster-Molina, E. (2017). Historical Congressional Legislation and District Demographics 1972-2014.

Francia, P. L., Green, J. C., Herrnson, P. S., Powell, L. W., and Wilcox, C. (2003). *The Financiers of Congressional Elections: Investors, Ideologues, and Intimates*. Columbia University Press.

Gagliarducci, S., Paserman, M. D., and Patacchini, E. (2019). Hurricanes, climate change policies and electoral accountability. Technical report, National Bureau of Economic Research.

Gallagher, J. (2020). Natural disasters that cause no damage: Retrospective voting and a reanalysis of 'make it rain'.

Garrett, T. A. and Sobel, R. S. (2003). The political economy of fema disaster payments. *Economic Inquiry*, 41(3):496–509.

Gasper, J. T. (2015). The politics of denying aid: An analysis of disaster declaration turndowns. *Journal of Public Management & Social Policy*, 22(2):7.

Gasper, J. T. and Reeves, A. (2011). Make it rain? retrospection and the attentive electorate in the context of natural disasters. *American Journal of Political Science*, 55(2):340–355.

Gomez, B. T., Hansford, T. G., and Krause, G. A. (2007). The republicans should pray for rain: Weather, turnout, and voting in us presidential elections. *Journal of Politics*, 69(3):649–663.

Graf, J., Reeher, G., Malbin, M. J., and Panagopoulos, C. (2004). Small donors and online giving. *Institute for Politics, Democracy and the Internet*.

Graff Zivin and Neidell (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics*, 32(1):1–26.

Guber, D. L. (2001). Voting preferences and the environment in the american electorate. *Society & Natural Resources*, 14(6):455–469.

Hamilton, L. C. and Stampone, M. D. (2013). Blowin' in the wind: Short-term weather and belief in anthropogenic climate change. *Weather, Climate, and Society*, 5(2):112–119.

Healy, A. and Malhotra, N. (2009). Myopic voters and natural disaster policy. *American Political Science Review*, 103(3):387–406.

Healy, A. and Malhotra, N. (2013). Retrospective voting reconsidered. *Annual Review of Political Science*, 16:285–306.

Healy, A., Malhotra, N., et al. (2010a). Random events, economic losses, and retrospective voting: Implications for democratic competence. *Quarterly Journal of Political Science*, 5(2):193–208.

Healy, A. J., Malhotra, N., and Mo, C. H. (2010b). Irrelevant events affect voters' evaluations of government performance. *Proceedings of the National Academy of Sciences*, 107(29):12804–12809.

Herrnstadt, E. and Muehlegger, E. (2014). Weather, salience of climate change and congressional voting. *Journal of Environmental Economics and Management*, 68(3):435–448.

Howe, P. D., Mildenberger, M., Marlon, J. R., and Leiserowitz, A. (2015). Geographic variation in opinions on climate change at state and local scales in the usa. *Nature Climate Change*, 5(6):596.

IPCC (2013). *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Jacobsen, G. D. (2011). The al gore effect: an inconvenient truth and voluntary carbon offsets. *Journal of Environmental Economics and Management*, 61(1):67–78.

Joireman, J., Truelove, H. B., and Duell, B. (2010). Effect of outdoor temperature, heat primes and anchoring on belief in global warming. *Journal of Environmental Psychology*, 30(4):358–367.

Karpf, D. (2013). The internet and american political campaigns. In *The Forum* (Vol. 11, No. 3, pp. 413–428). De Gryuter.

Kousky, C., Michel-Kerjan, E. O., and Raschky, P. A. (2018). Does federal disaster assistance crowd out flood insurance? *Journal of Environmental Economics and Management*, 87:150–164.

Lang, C. (2014). Do weather fluctuations cause people to seek information about climate change? *Climatic Change*, 125(3-4):291–303.

Lang, C. and Ryder, J. D. (2016). The effect of tropical cyclones on climate change engagement. *Climatic Change*, 135(3-4):625–638.

League of Conservation Voters (2007). National environmental scorecard, first session of the 115th congress. Available at: https://scorecard.lcv.org/.

Li, Y., Johnson, E. J., and Zaval, L. (2011). Local warming: Daily temperature change influences belief in global warming. *Psychological Science*, 22(4):454–459.

Malbin, M. J. (2013). Small donors: Incentives, economies of scale, and effects. In *The Forum*, volume 11, pages 385–411. De Gruyter.

Meier, A. N., Schmid, L., and Stutzer, A. (2019). Rain, emotions and voting for the status quo. *European Economic Review*, 119:434–451.

Missouri Census Data Center (2017). MABLE/Geocorr 90/2k/14: Geographic Correspondence Engine.

Moore, F. C., Obradovich, N., Lehner, F., and Baylis, P. (2019). Rapidly declining remarkability of temperature anomalies may obscure public perception of climate change. *Proceedings of the National Academy of Sciences*, 116(11):4905–4910.

Myers, T. A., Maibach, E. W., Roser-Renouf, C., Akerlof, K., and Leiserowitz, A. A. (2013).

The relationship between personal experience and belief in the reality of global warming. *Nature Climate Change*, 3(4):343.

National Academies of Sciences, Engineering, and Medicine (2016). *Attribution of extreme weather events in the context of climate change*. National Academies Press.

Reeves, A. (2011). Political disaster: Unilateral powers, electoral incentives, and presidential disaster declarations. *The Journal of Politics*, 73(4):1142–1151.

Roxburgh, N., Guan, D., Shin, K. J., Rand, W., Managi, S., Lovelace, R., and Meng, J. (2019). Characterising climate change discourse on social media during extreme weather events. *Global Environmental Change*, 54:50–60.

Sisco, M. R., Bosetti, V., and Weber, E. U. (2017). When do extreme weather events generate attention to climate change? *Climatic Change*, 143(1-2):227–241.

Snyder, J. M. (1990). Campaign contributions as investments: The U.S. House of Representatives, 1980-1986. *Journal of Political Economy*, 98(6):1195–1227.

Sobel, R. S., Coyne, C. J., and Leeson, P. T. (2007). The political economy of fema: did reorganization matter? *Journal of Public Finance and Public Choice*, 25(2-3):151–167.

Spence, A., Poortinga, W., Butler, C., and Pidgeon, N. F. (2011). Perceptions of climate change and willingness to save energy related to flood experience. *Nature Climate Change*, 1(1):46.

Sylves, R. and Búzás, Z. I. (2007). Presidential disaster declaration decisions, 1953–2003: What influences odds of approval? *State and Local Government Review*, 39(1):3–15.

Tegart, W. J., Sheldon, G. W., Griffiths, D. C., et al. (1990). Climate change. The IPCC impacts assessment.

U.S. Government Accountability Office (2012). *Improved Criteria Needed to Assess a Jurisdiction's Capability to Respond and Recover on Its Own*. Available at: http://www.gao.gov/assets/650/648162.pdf.

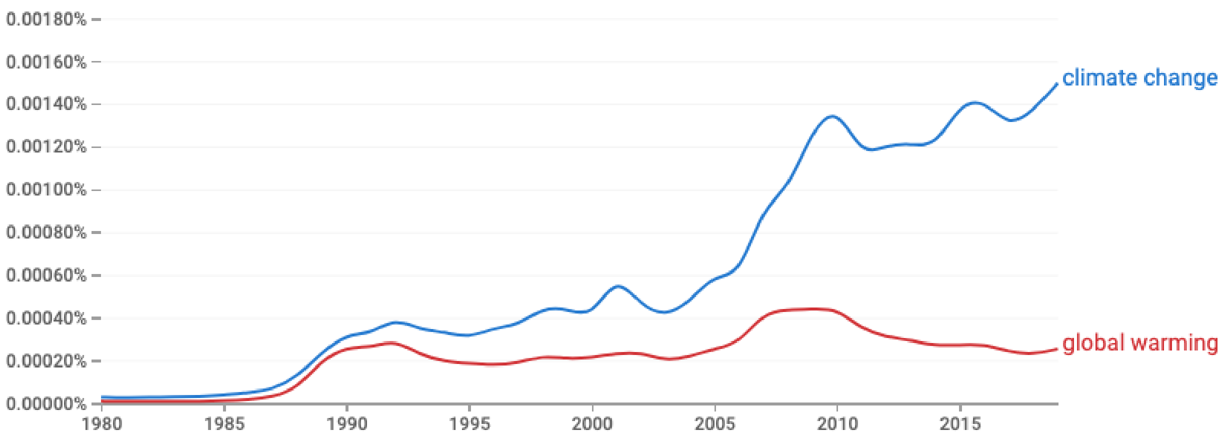
Wilcox, C. (2008). Internet fundraising in 2008: A new model? In *The Forum* (Vol. 6, No. 1). De Gryuter.

Zaval, L., Keenan, E. A., Johnson, E. J., and Weber, E. U. (2014). How warm days increase belief in global warming. *Nature Climate Change*, 4(2):143.

Appendix

Figures

Figure A1: Time series of climate keywords in Google Ngram Viewer



Notes: this figure shows the relative occurrences of keywords "climate change" and "global warming" in sources printed in Google's text corpora in English between 1980 and 2012.

Figure A2: Example of ActBlue donation interface

Figure A3: Distribution of individual ActBlue donation amounts

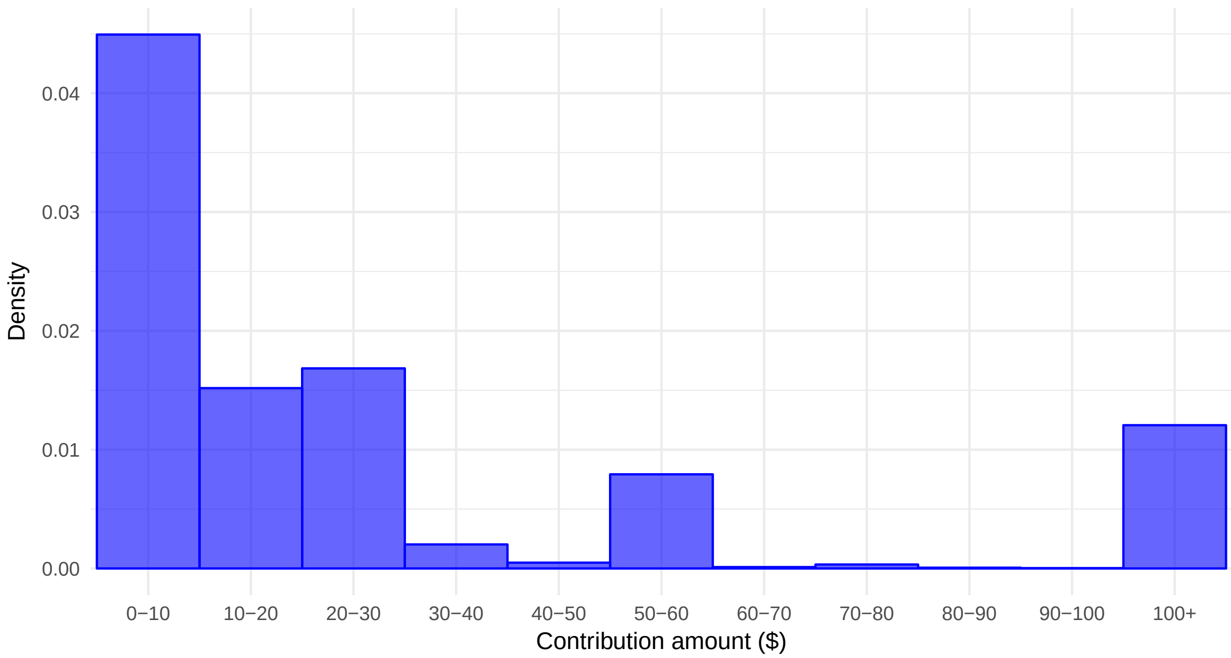
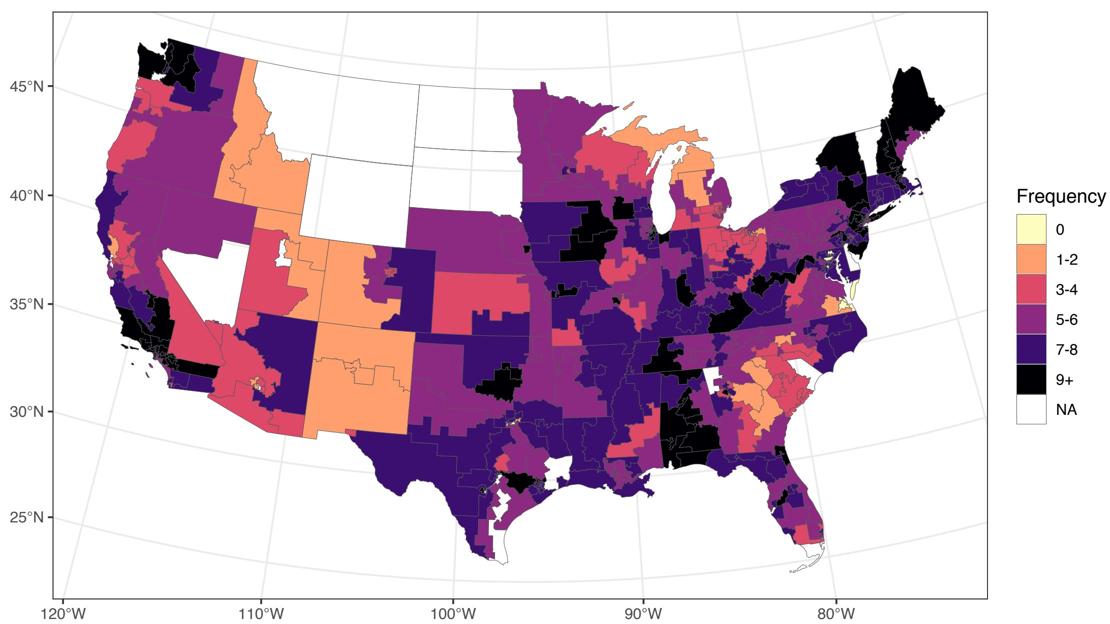
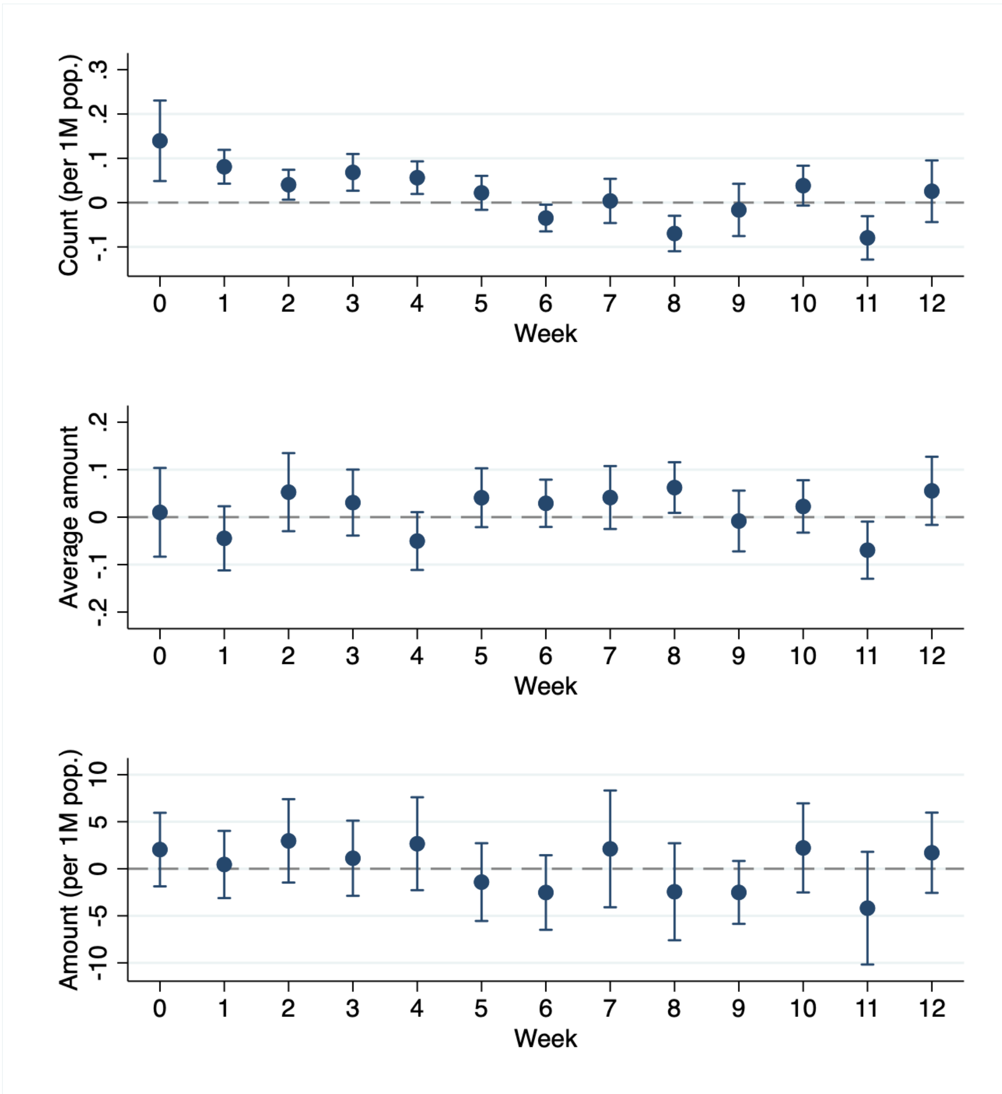


Figure A4: Disaster exposure across congressional districts



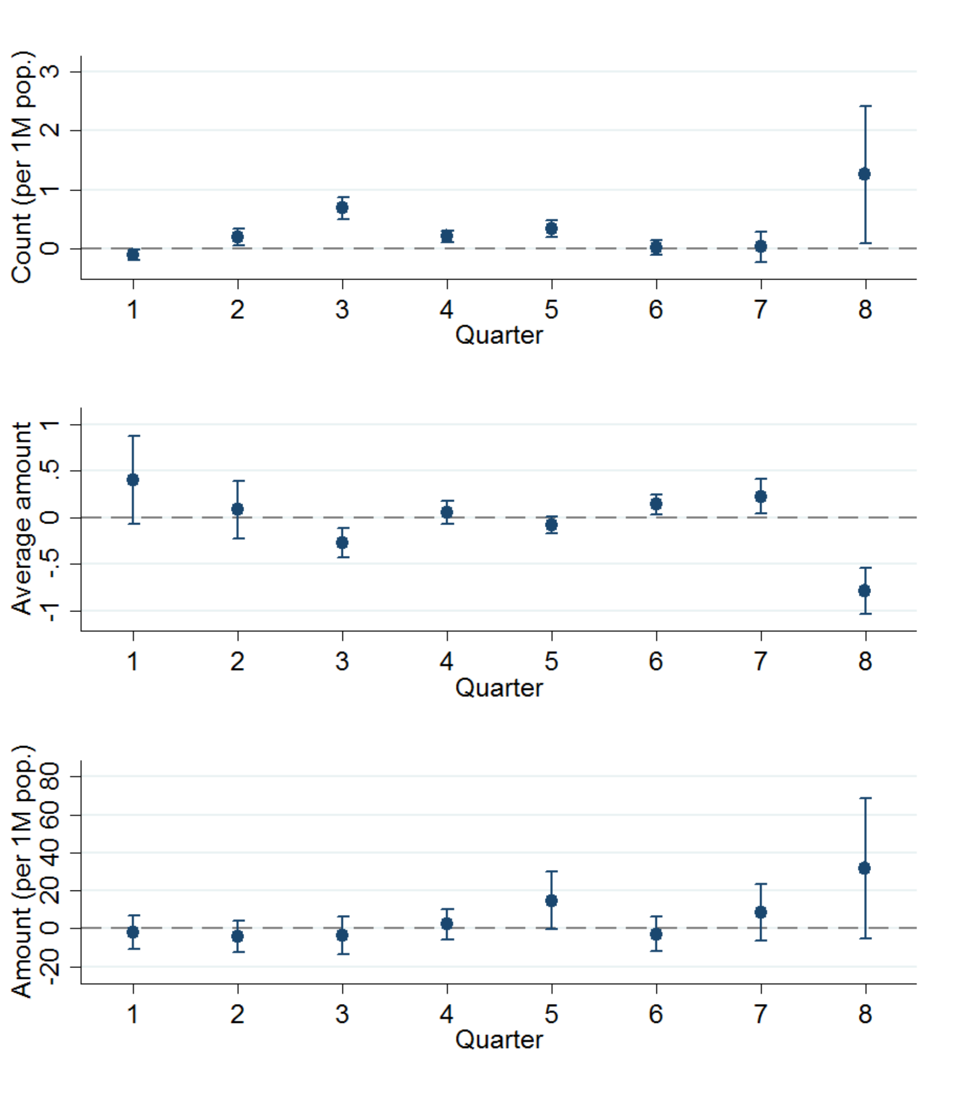
Notes: this map shows the number of cycles when each congressional district is hit by a climate-related disaster in the data.

Figure A5: Distributed lags of short-run temperature effect on ActBlue donations



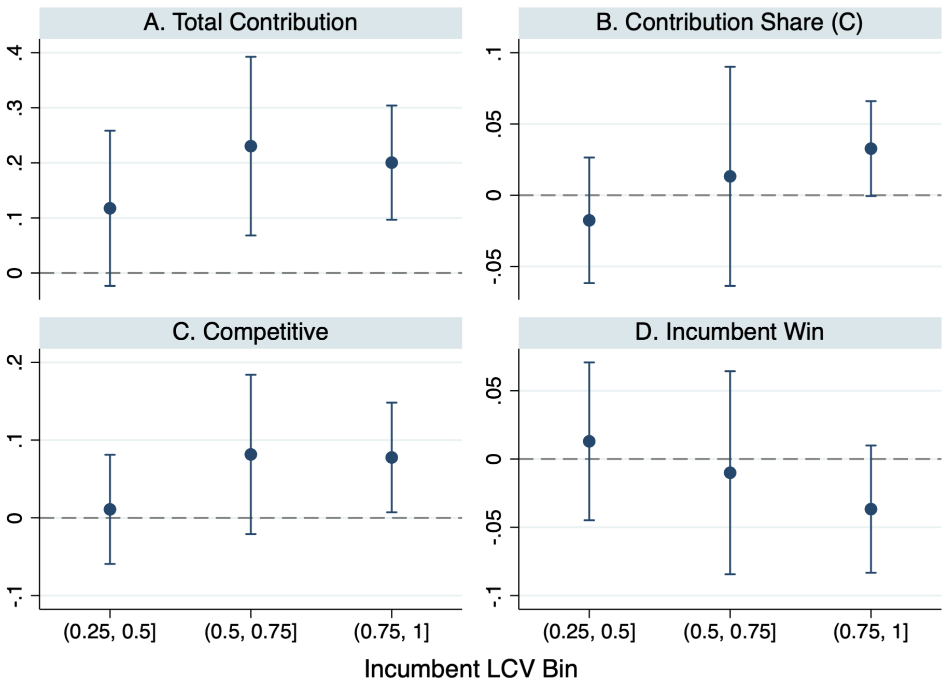
Notes: this figure shows the point estimates and their 95% confidence intervals from equation (1) but with twelve lags instead of four. The outcome variables, as displayed next to the y-axis, are based on ActBlue records. Standard errors are clustered by county. All regressions control for precipitation, county, week-in-sample, and state-by-cycle fixed effects.

Figure A6: Variation of estimates across quarters in election cycle



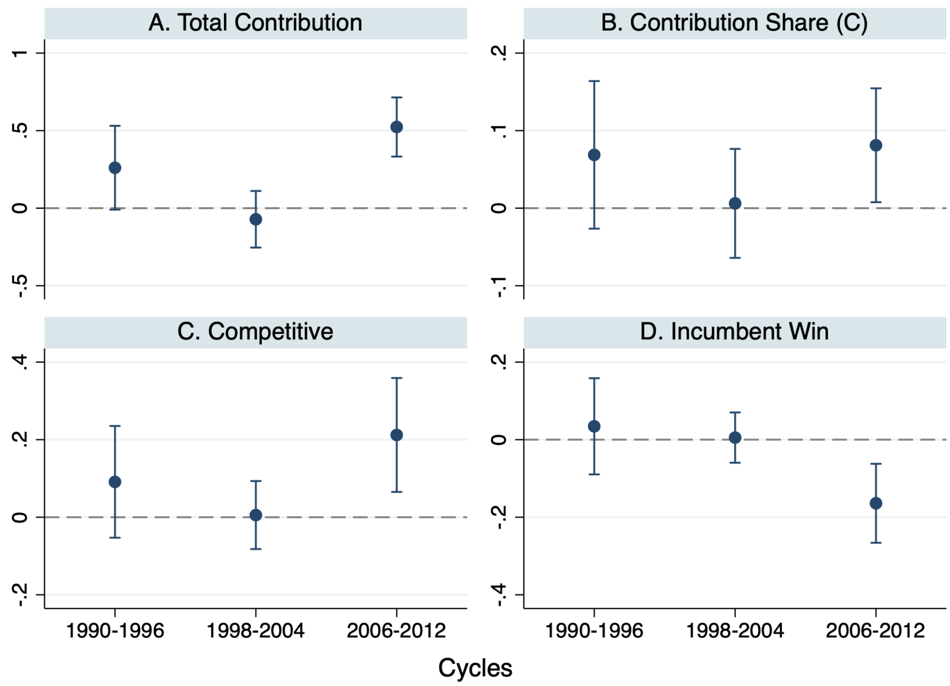
Notes: this figure shows the point estimates from equation (B1) and their 95 percent confidence intervals. The outcome variables, as displayed next to the y-axis, are based on ActBlue records. Standard errors are clustered by county. All regressions control for precipitation, county, week-in-sample, and state-by-cycle fixed effects.

Figure A7: The effects of natural disasters by incumbent LCV bin



Notes: these regressions follow equation (B2), which divides incumbents into four LCV bins and separately estimate bin-wise disaster effects. The point estimates on interaction terms between the disaster indicator and LCV bins are shown with their 95% confidence intervals. The dependent variables in panels A and B correspond to those in columns (1) and (6) of Table 3, and those in panels C and D correspond to columns (1) and (4) of Table 4, respectively. Panels A and B are based on all elections, and panels C and D exclude open seat elections. The effects are relative to the omitted category of the most pro-environment incumbents who have a LCV score below 0.25. All regressions control for differential disaster effects based on district and incumbent characteristics (including party affiliation), as well as state-by-cycle and district fixed effects. Standard errors are clustered by state.

Figure A8: The effects of natural disasters over time



Notes: these regressions follows equation (B3), which groups the twelve election cycles into three periods (1990-1996, 1998-2004, and 2006-2012) and estimate period-wise disaster effects. The point estimates for the period-wise interaction between disaster and LCV score are shown with their 95% confidence intervals. The dependent variables in panels A and B correspond to those in columns (1) and (6) of Table 3, and those in panels C and D correspond to columns (1) and (4) of Table 4, respectively. Panels A and B include all elections, and panels C and D exclude open seat elections. All regressions control for differential disaster effects based on district and incumbent characteristics (including party affiliation), as well as state-by-cycle and district fixed effects. Standard errors are clustered by state.

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
Drought	5	178
Total	1,943	27,166
B. Non-climate disasters		
Tornado	41	480
Earthquake	19	80
Other	23	308
Total	83	868
C. Ambiguous		
Snow*	176	4,438

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 Substances".

* Snow events are scientifically linked to climate change, but it is not widely known to the public during the sample period.

Table A2: Summary statistics

Variable	N	Mean	Std. Dev.	Min.	Max.
ActBlue, 2006-2012 (county-week)					
Amount ($)	938,040	151.29	2057.95	0	583663.8
Count	938,040	2.42	23.07	0	5315
Count (per 1 million pop)	938,040	15.46	137.29	0	38848.92
Average amount ($)	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)					
Receipts ($1,000) (C)	4,397	319.19	675.39	0	9825.57
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
Incumbent 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 - climate	4,874	0.52	0.5	0	1
Disaster - non-climate	4,874	0.16	0.37	0	1
Hot cycle	4,874	0.250	0.433	0	1
Cold cycle	4,874	0.250	0.433	0	1
Median income	4,870	42573.89	16684.31	7453	109168
Percent bachelor's degree	4,870	24.07	9.91	4.14	65.7
Percent white	4,870	68.82	23.17	2.22	98.81
Percent metro population	4,869	0.8	0.26	0	1
Percent ag. employment	4,846	0.02	0.03	0	0.24
Gini index	4,870	0.46	0.04	0.34	0.61
Age of incumbent	4,872	53.45	10.06	26	87
Gender of incumbent	4,872	1.87	0.33	1	2
Black incumbent	4,872	0.08	0.28	0	1
Hispanic incumbent	4,871	0.05	0.21	0	1

*: this is the"inverted" (subtracted from 1) LCV score used in the analysis.

Table A3: Actblue donation responses to short-run precipitation shocks

Dep. Var.	Count/1 million pop			Average amount		
	(1)	(2)	(3)	(4)	(5)	(6)
PrcpDev (current week)	0.0207***	0.0161***		-0.0180*	-0.0176	
	(0.00537)	(0.00586)		(0.0108)	(0.0112)	
PrcpDev (1-week lag)		-0.0193*			-0.00612	
		(0.0112)			(0.00850)	
PrcpDev (2-week lag)		-0.0141			0.00615	
		(0.00890)			(0.0110)	
PrcpDev (3-week lag)		-0.0252***			-0.0150	
		(0.00680)			(0.00931)	
PrcpDev (4-week lag)		-0.00542			-0.0199*	
		(0.00518)			(0.0105)	
PrcpDev (2-week avg.)			0.000599			-0.0245
			(0.0125)			(0.0158)
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
N	944172	935201	941672	944172	935201	941672
R^2	0.209	0.204	0.209	0.0539	0.0539	0.0539
D.V. Mean	15.45	15.40	15.42	13.13	13.19	13.15

Notes: estimates on precipitation deviations 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. The estimates on temperature variables from these regressions are reported in Table 1. Standard errors are clustered by county. Statistical significance: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table A4: The effects of natural disasters excluding presidential re-elections

	(1) Total Funds	(2) Share (C)	(3) Competitive	(4) Incumbent Win
Disaster	-0.172***	-0.0437***	0.00249	0.0489*
	(0.0440)	(0.0151)	(0.0320)	(0.0279)
Incumbent LCV	-0.559	-0.0893	-1.712**	0.601
	(1.391)	(0.369)	(0.699)	(0.473)
Disaster × Incumbent LCV	0.235***	0.0666**	0.139**	-0.0474
	(0.0774)	(0.0286)	(0.0640)	(0.0349)
District Char. × Disaster	Yes	Yes	Yes	Yes
State-Cycle F.E.	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	Yes	Yes
N	2930	2975	3216	2930
R^2	0.666	0.368	0.327	0.353
Mean D.V.	1310.0	0.164	0.717	0.950

Notes: estimates from equation (3) are shown. The sample excludes all election cycles when a president is seeking re-election. The dependent variables is the (IHS-transformed) total amount of campaign funds in column (1), the share of total funds raised by the challenger in column (2), an indicator of the congressional race being competitive in column (3), and an indicator of the incumbent getting re-elected in column (4). "Incumbent LCV" is a score indicating the incumbent's environmental position. It ranges from 0 to 1, 0 being the most pro-environment and 1 the most anti-environment (inverted from the original scale). 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. 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 A5. 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 A5 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.[45]

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

Table A5: 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: this table shows 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 Short-Run Analysis: Variants of the Main Results

Recall that the main specification in the short-run analysis is given by equation (1):

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

where $Weather_{cw}$ is a vector of weather variables. In this section, we present results based on two additional specifications of $Weather_{cw}$.

First, we want to estimate the effects of heat and cold shocks separately. We do so by including separate measures of positive and negative temperature deviations:

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

where

$$TmaxDev^{+} = TmaxDev \times (TmaxDev > 0)$$

and

$$TmaxDev^{-} = TmaxDev \times (TmaxDev < 0).$$

These results are reported in Table B1. We can see that our main results on contribution rates are largely driven by heat shocks, while cold shocks have small and insignificant effects.

Next, we switch to alternative measures of extreme temperature events:

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

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. Such extreme temperature events might be more salient than average temperature.

These estimates are shown in Table B2. Again, we only find effects on contribution rates. One more day of extreme heat in a week is associated with a contemporaneous increase

Table B1: 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)
Precipitation Dev.	Yes	Yes
County F.E.	Yes	Yes
Week F.E.	Yes	Yes
State-Cycle F.E.	Yes	Yes
N	935201	935201
R^2	0.204	0.0539
D.V. Mean	15.40	13.19

Notes: 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 B2: The effect of extreme temperature events on ActBlue contributions

Dep. Var.	(1) Count/1M pop	(2) 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)
Precipitation Dev.	Yes	Yes
County F.E.	Yes	Yes
Week F.E.	Yes	Yes
State-Cycle F.E.	Yes	Yes
N	936954	936954
R^2	0.203	0.0539
D.V. Mean	15.40	13.18

Notes: 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: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

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.[46] On the flip side, an extreme-cold day reduces the contribution rate by 6.6% in the current week and 15.8% cumulatively.

C Additional Regression Specifications

This section lists additional regression specifications that are not included in Section 3.

C.1 Short-Run Analysis

In Figure A6, we use the following specification:

$$Y_{cw} = \sum_{t=1}^{8} \beta_t \overline{TmaxDev}_{c,w} \times Q_t + \gamma \overline{PrcpDev}_{c,w} + \delta_w + \delta_c + \delta_{se} + \varepsilon_{cw}, \tag{B1}$$

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.

C.2 Medium-Run Analysis

In Figure A7, we use the following specification:

$$\begin{aligned} Y_{de} =& \beta_1 Disaster_{de} + \sum_{j=1}^{4} (\beta_2^j LCVBin_{de}^j + \beta_3^j Disaster_{de} \times LCVBin_{de}^j) \\ &+ \gamma_1' Char_{de} + \gamma_2' Disaster_{de} \times Char_{de} + \delta_d + \delta_{se} + \varepsilon_{de}, \end{aligned} \tag{B2}$$

where $LCVBin_{de}^j$ denotes a set of indicators for the LCV score to be in one of four bins: [0, 0.25], (0.25, 0.5], (0.5, 0.75], and (0.75, 1]. This specification allows the disaster effect to change more flexibly with the LCV score.

[46] $\widehat{\gamma}_0 / D.V.Mean = 0.353/15.40 \approx 2.3\%$.

In Figure A8, we use the following specification:

$$\begin{aligned} Y_{de} = &\sum_{k=1}^{3} Period_{de}^{k} \times (\beta_1^k Disaster_{de} + \beta_2^k LCV_{de} + \beta_3^k Disaster_{de} \times LCV_{de}) \\ &+ \gamma_1' Char_{de} + \gamma_2' Disaster_{de} \times Char_{de} + \delta_d + \delta_{se} + \varepsilon_{de}, \end{aligned} \tag{B3}$$

where $Period_{de}^{k}$ denotes a set of indicators for the election cycle to be in one of three periods: 1990-1996, 1998-2004, 2006-2012. This specification allows the disaster effect and its relationship with the incumbent's environmental stance to change over time.