Agglomeration and Parochial Giving Induce Disparity in Aid for Natural Disasters*

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Abstract

Public and private transfers provide ex-post support to victims of extreme events, but the social insurance value of these transfers depends on how closely they align with victim need. We study transfers through the largest private and public providers of disaster aid using the donations database of the American Red Cross (ARC) and expenditure records of the Federal Emergency Management Agency (FEMA). We focus on aid and donations in the aftermath of deadly tornadoes, which are local and unpredictable. Donations decrease with time and distance from the tornado and increase with its severity and with the donor- and affected-area incomes. We find no in-group biases, but the dollar value of donations is far greater when a tornado strikes a high-income area than when one strikes a low-income area. This disparity arises mostly because higher-income tornado sites are located near larger and higher-income populations, and we find the same pattern in donations to local charities. This agglomeration effect suggests a role for coordinated redistribution, but we find almost no progressivity in tornado-related FEMA aid: FEMA's rebuilding aid to counties is not progressive, and its assistance to individuals is not sufficiently progressive to offset the disparities in donations.

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1 Introduction

Natural disasters are becoming more frequent and more severe (IPCC, 2021). Households' insurance coverage is typically insufficient to cover rebuilding costs (e.g., United Policyholders, nd; Wagner, 2022; Cookson, Gallagher and Mulder, 2024), and over 6 million households in the US lack any homeowners insurance (Cornelissen, Heller and DeLong, 2024). In addition to rebuilding, many disaster victims require temporary shelter and medical support. Some of the gap is filled by social insurance and government disaster aid (e.g., Kousky, 2013; Deryugina, 2017). But another potentially important source of informal insurance is charitable giving: institutional donors contribute roughly $1.7 billion annually to disaster relief (Center for Disaster Philanthropy, 2024), and about 30 percent of US households report making disaster-related donations each year (Bergdoll et al., 2019).

Whether charitable donations are an effective insurance mechanism depends on their distributional properties. Billings, Gallagher and Ricketts (2022), Raker (2023), and Begley et al. (2024) have documented disparities in insurance coverage, government disaster aid, and government post-disaster loans, respectively. Donor preferences for giving to certain victims may ameliorate or worsen disparities in government support. Evidence on this question is limited because few datasets measure donations to different causes or recipients. We develop a research design that incorporates a large number of disasters and connects donations to each of them, allowing us to estimate donations as a function of the characteristics of the affected areas and to provide evidence on the nature of prosocial behavior and preferences.

We estimate donation responses to deadly tornadoes—a local and unpredictable natural disaster—using transaction-level data from the American Red Cross (ARC). The dataset includes the date, ZIP Code, and fund name for each transaction and encompasses nearly $20 billion in donations in 1989–2017. Our empirical strategy controls for time and location effects, identifying donation responses to each disaster from relative within-location changes when a tornado strikes nearby. We employ an estimator that imposes no structure on treatment-effect heterogeneity (Borusyak, Jaravel and Spiess, 2024), allowing us to describe

how the charitable response varies with disaster severity, the characteristics of both donor and affected areas, and the physical and temporal proximity between the disaster and donors. Consistent estimates can be obtained for weighted averages of observation-level treatment effects, allowing us to (1) convert responses of log donations per ZIP Code into aggregate dollars donated and (2) conduct inference on disparities in amounts donated across different disasters.

When a fatal tornado strikes, donations from surrounding areas increase quickly and substantially relative to donations from areas farther away. We find a strong distance gradient, consistent with parochial altruism, with significant effects within at least 150 miles of tornado sites and for at least 5 weeks after the tornado. The response increases with tornado severity, consistent with altruism or greater media attention, and it declines noticeably with distance to the tornado site. This proportional response (in terms of log donations) is substantially larger for donations to ARC funds earmarked for specific disasters, suggesting that donation patterns may constrain the ARC's ability to reallocate funds across events based on relative need. The proportional response is increasing in the income of the donor area, but it also increases in the income of the affected area, consistent with differences in media coverage.

Natural disasters in the US are one setting in which the dollar value of donations is comparable to the value of government aid.[1] Such decentralization can lead to disparities if there is in-group bias, and we test for this with respect to income and the share of white residents. For each of these, we consider the interaction of the value of the characteristic for a donor area with its value in affected areas, controlling for uninteracted values. We find no evidence of in-group bias with regard to race or income. In fact, log donations of high-income donor areas respond relatively more when a nearby tornado strikes lower-income areas. All of our results are robust to a host of controls, including multiple measures of tornado severity, the distance between donors and the affected area, and indicators for whether the tornado struck within the donors' own media market or state. High-income

[1]Both FEMA and the ARC have distributed several billion dollars per year over our sample period.

areas' relatively large response when a tornado affects low-income areas provides suggestive evidence of distributional preferences.

Because high-income areas provide the majority of donations and respond more strongly to low-income affected areas, we might expect to find that donations are decreasing in the income of affected areas. Instead, we find that donations are *increasing* in the income of affected areas. A fatal tornado that strikes areas in the bottom tercile of the income distribution attracts average donations of $600,000 from donors within 100 miles and $2 million from within 200 miles. For tornadoes that strike areas in the top tercile of income, the corresponding estimates are more than $1 million larger. We show that the disparity in donation amounts arises largely due to the geographic distributions of population and income, combined with the tendency to give locally. Areas surrounding high-income affected areas contain larger populations, higher incomes, and higher baseline giving than areas surrounding lower-income affected areas. This unexpected form of agglomeration economies results in a distribution of giving that, based on the proportional responses, appears less supportive of low-income areas than donors themselves may have intended.

The mechanism of our finding is not specific to the ARC. Using IRS data collected from the information returns that charitable organizations file annually, we test whether similar patterns hold for other charitable organizations. The lower frequency of this data and the fact that most organizations are not engaged in disaster relief reduces statistical power for estimating an average effect. We instead focus on the marginal effect of tornado fatalities on donations, exploiting variation in tornado severity and the fact that donors respond more to tornadoes causing more fatalities. As with the ARC, we find that far more is donated following an additional fatality in a high-income area than one in a lower-income area.

We then test whether the disparity in donations is offset by government aid, using expenditure data from the Federal Emergency Management Agency (FEMA), the government body providing the largest amount of aid for disaster victims. We find that FEMA's public aid—awarded to communities for debris cleanup and rebuilding public buildings and

infrastructure—is unrelated to local area income, while individual assistance for uninsured losses is slightly decreasing in local area income. Overall, FEMA expenditure appears to offset no more than a small fraction of the disparity in private donations to the ARC, let alone to other charities.

Our results imply that donations tend to exacerbate pre-existing inequality and that reallocating funds between disasters offers a potential Pareto improvement that would be preferred ex ante by donors and potential recipients. However, charities' reallocation of donations is limited by a legal requirement to adhere to donor intent, and 42 percent of the disaster-related donations in our ARC data are restricted by the donor to specific disasters. A former head of the ARC described donor restrictions as a "straitjacket" for ARC and other large charities, although the organization has been accused of reallocating funds in the past.[2] We cannot measure the degree to which ARC reallocates funds, but our estimates inform the degree to which it or the government should do so. If we assume that the donations to organizations located near the disaster are not redistributed, since these organizations are generally local and smaller than the ARC, then national organizations would need to provide far more aid to lower-income areas to achieve levels comparable to the private donations made to high-income areas.

Our study is, to our knowledge, the first to examine how affected-area demographics influence large-scale charitable giving. Donations to the ARC average $500 million–$1 billion annually, reaching the same order of magnitude as the $3.7 billion per year of disaster aid provided by FEMA and $0.4 billion per year provided by the US Department of Housing and Urban Development (DeBarge et al. 2018). Private transfers thus provide a meaningful share of the support for natural disaster victims in the US, and evidence suggests that much of the private response is not diversion of funds that would have been given to other causes

[2]See, for example, https://www.washingtonpost.com/archive/politics/2001/11/19/red-cross-has-pattern-of-diverting-donations/7e2b0187-690f-4432-a7ad-040b5c67979d/ and https://edition.cnn.com/2001/US/11/06/rec.charity.hearing/index.html. Backlash over the repurposing of funds donated after the Sept. 11 terrorist attacks was one reason for the resignation of the president of the ARC at that time (https://edition.cnn.com/2001/US/11/06/rec.charity.hearing/index.html).

so much as an increase in total giving.[3]

Victim characteristics can influence donations because identity has been shown to impact behavior in many contexts (Tajfel et al., 1971; Kalin and Sambanis, 2018; Charness and Chen, 2020; Shayo, 2020). Previous research has explored how racial diversity affects public good provision and participation (Alesina, Baqir and Easterly, 1999; Alesina and La Ferrara, 2000; Vigdor, 2004). Charitable donations potentially offer a more direct measure of preferences, but evidence is limited by the lack of datasets that connect donors with recipients or describe the identity of either. For charitable donations in dictator games, Fong and Luttmer (2009) and Fong and Luttmer (2011) find that the race of pictured recipients in a fundraiser have detectable but small effects on donations. Cookson, Gallagher and Mulder (2023) find income-based disparities in donations among appeals posted on GoFundMe following the 2021 Marshall Fire in Colorado. We believe that our study is the first to test for donor preferences for certain groups in charitable giving on a national scale. Through a comprehensive analysis of millions of donations, we quantify how demographic and geographic factors shape donation patterns. Rather than test for particular donor preferences, such as warm glow or pure altruism (e.g., Andreoni, 1989; Ottoni-Wilhelm, Vesterlund and Xie, 2017), we focus on amounts given relative to the characteristics of affected areas and show that disparities in these amounts appear to contradict donor preferences. Our quasi-experimental design, which leverages variation in the timing, location, and severity of disasters, contributes to the time-series evidence from international disasters (e.g., Yildirim et al., 2020; Scharf, Smith and Ottoni-Wilhelm, 2022; Jayaraman, Kaiser and Teirlinck, 2023).

The rest of the paper is organized as follows. Section 2 describes our data and provides brief background information on tornadoes and the US disaster aid process. Section 3 outlines our empirical strategy. We present the results in Section 4 and conclude in Section 5.

[3]Deryugina and Marx (2021) use annual data from the IRS to show that a fatal tornado strike in one's state increases deducted donations to *all* causes and does not reduce receipts of other charities located near the donors. Meer (2017) finds no evidence of substitution between teacher requests for funding in donorschoose.org data.

2 Data

2.1 Tornadoes and affected-area characteristics

Tornadoes are rapidly rotating columns of air that form over land, typically during thunderstorms. They generally have much higher wind speeds than other extreme events, including hurricanes, and thus cause significantly more damage conditional on a strike. Tornadoes occur relatively frequently, but their spatial extent and temporal duration is typically small.[4] Unlike some disasters that can be forecast days ahead of time, the formation of tornadoes is very difficult to predict. Tornado watches are issued when atmospheric conditions are conducive to tornado formation, but whether and exactly where a tornado will form cannot be forecast with any reasonable accuracy. Although some areas are more tornado-prone, and tornadoes are most common in the spring, the timing of a tornado strike is as good as random, conditional on the location and time of year.

We obtain data on tornado paths from the Storm Prediction Center of the National Oceanic and Atmospheric Administration (NOAA) for the years 1989–2016. For each recorded tornado, the data contain the coordinates of the start and end points, the estimated tornado width, as well as the reported number of injuries, fatalities, property damage, and crop damage.[5] Over 90% of the tornadoes recorded during our time period cause very little damage and do not kill or injure anyone, and we do not expect such tornadoes to prompt a meaningful giving response. We therefore focus our analysis on 572 tornadoes that caused fatalities over this time period. The median number of fatalities among these tornadoes is 1, and the total number of tornado-related fatalities in 1989–2016 is 2013. Fatalities should be measured with the least error and are a meaningful proxy for a tornado that has a non-trivial

[4] According to tornado path data, which provides estimated tornado width and length, between 1989 and 2016, all 32,575 US tornadoes—including ones that caused little or no damage—affected about 18 thousand square miles, which is only about 0.6% of the continental US's land area.

[5] The data also contain a severity rating between 0 and 5 based on the Enhanced Fujita Scale, which is a function of observed property damage. Given the additional variables reported in the tornado database, this variable does not add further information. There are polygon map files that depict tornado paths more precisely, but these exist only for about 45 fatal tornadoes in our sample.

impact.

A key goal of our paper is to estimate how donations vary with affected-area characteristics. Because tornadoes affect relatively small areas, even ZIP-level characteristics may yield a noisy measure of who was affected. We thus use demographic information at the smallest level available in publicly accessible data—Census block for race and population and Census block group for median income. We first merge the tornado path data with 2010 Census shapefiles to determine the affected Census blocks. We then use mappings between 2010 and 2000 Census blocks and between 2010 and 1990 Census blocks to determine which Census blocks were affected by pre-2010 tornadoes.[6] Taking the estimated tornado width into account, we assign each tornado-block combination the demographics from the most recent Census year preceding the tornado year (e.g., tornadoes occurring between 2000 and 2009 will be assigned 2000 Census demographics). Tornadoes from 1989, the first year in the sample, are assigned 1990 Census demographics. Because income is no longer available in the 2010 Census, we use data from the 2011-2016 American Community Survey for years 2012 and later. For tornadoes occurring in 2001-2011, we use the 2000 Census income data. Finally, we convert income to 2024 dollars.

For each tornado, we then calculate the total population, total black population, total white population, and average median income (weighted by each block's population) across all the affected Census blocks/Census block groups. Finally, we calculate the percent of the affected population that is white and the percent that is black (with other racial groups forming an implicit "other" category).

Even with the most spatially granular data available, some measurement error in affected-area demographics is unavoidable for several reasons. First, many Census blocks are likely only partially affected. Second, while a linear path approximates many tornadoes well, some follow curved trajectories. Third, even with perfect mapping of a tornado's path

[6]Shapefiles for 2000 Census blocks exist, but 1990 Census block shapefiles are very low-quality. For consistency, we therefore limit the spatial merge to the 2010 Census and use crosswalks to determine affected blocks for earlier Census years.

to individual dwellings and household demographics, the precise damage to each building remains uncertain. These factors likely bias our results toward detecting no heterogeneity, meaning any observed heterogeneity should be interpreted as a lower bound.

2.2 Red Cross donations and donor-area characteristics

We obtain donation-level data from the American Red Cross (ARC)—the largest and most prominent disaster-relief charity in the US—from January 1, 1989 through May 24, 2017. The ARC supports victims of natural disasters by providing essential emergency goods and services—such as food, clean water, shelter, family reunification, and mental health services—as well as direct financial assistance in some cases.[7] The data contain the donor's 5-digit ZIP Code and the exact donation date, allowing us to compile daily donations by ZIP Code and merge in ZIP-level demographics from the most recent US Census. We convert donations to 2024 dollars. To calculate the physical distance between donors and tornado-affected areas, we compute the minimum distance between ZIP Code centroids and the path of the tornado, interpolated from its start and end coordinates provided in the NOAA data. The spatial distribution of total donations to the ARC is shown in Appendix Figure A.1.

Appendix Figure A.2 shows daily donations averaged over 1989–2017 (panel (a)) and daily log donations averaged over the same time period (panel (b)). Donations are greatest on December 31, most likely because donors must give before a year ends to obtain an income tax deduction for that year. Giving in levels is also high in the fall—during peak hurricane season—and is relatively low in the spring, when tornadoes are most common.[8] In contrast, mean log giving (panel (b)) is much more stable throughout the year, indicating that the fall pattern is driven by rare events that generate a very large charitable response.

Outlier events that trigger giving can confound estimation of the effects of tornadoes

[7] https://www.redcross.org/donations/how-the-red-cross-spends-your-donations.html

[8] In principle, our econometric approach can also used to study the giving response to hurricanes and other natural disasters. Hurricanes affect much larger areas than tornadoes, however, and their spatial boundaries are less clear, making it much harder to precisely quantify affected areas and their demographics. Other disasters affecting smaller areas—like floods—lack high-resolution impact data.

occurring around the same time. We define outlier weeks by regressing our outcome on a quadratic time trend and week-of-year dummies. We exclude periods with at least two consecutive weeks with residuals greater than 1.95, based on visual inspection, and two weeks after any of these outliers. This removes 41 weeks (2.8% of the sample) that fall within 5 continuous spans of time.[9] We restrict the sample period for our analysis by dropping these 28 weeks (1.9 percent of the sample). Results for average or total effects are similar whether or not we include these periods. We then focus on the restricted sample because the omitted periods can produce large biases in heterogeneity analyses.

The ARC data also contain the name of the fund to which the donation was made, allowing us to classify donations into broad fund types. We assign each fund to one of several categories reflecting the intended use of the donation: unrestricted funds that can be deployed flexibly across needs, disaster-specific funds earmarked for particular events or types of disasters, international funds supporting activities outside the US, and other restricted funds tied to non-disaster programs or purposes.

Finally, as a proxy for donor characteristics, we obtain income and demographic information for each 5-digit ZIP Code from the US Census, which publishes Census data at the ZIP Code Tabulation Area (ZCTA), largely equivalent to US ZIP Codes. As in Deryugina and Marx (2021), we make these units consistent over time by combining any ZIP Codes that were merged or separated, as detailed in the US Postal Bulletins.

2.3 Other charities

The ARC responds to disasters across the country, but other organizations may also offer support to victims when a disaster strikes near them. To estimate tornadoes' effect on charitable donations to local organizations, we use the IRS Exempt Organizations Business Master File (EOBMF) and annual Financial Extracts.[10] To obtain tax-exempt status under

[9] The 5 spans follow Hurricane Andrew in 1992, Sept 11 of 2001, the Indian Ocean Tsunami in 2004, Hurricane Katrina in 2005, and the Haiti earthquake in 2010.

[10] These datasets are archived by the National Center for Charitable Statistics.

section 501(c)3 of the tax code, organizations must describe their organizational mission in an application to the Internal Revenue Service (IRS). The EOBMF contains the set of all organizations that have been granted exempt status and includes a categorization of their declared missions according to the National Taxonomy of Exempt Entities (NTEE) codes. We merge this information with the annual Form 990 that charities above a size threshold must file annually (Marx, 2019). We drop observations that fall below that year's threshold level of gross receipts to eliminate the selected sample of voluntary filers.

After merging the annual files we prepare the data in several steps. We drop observations that are missing a ZIP Code or the date that the fiscal year ended, and we drop those with contributions that are nonpositive or missing.[11] Multiple observations for an organization-date combination can arise if charities file multiple returns for the same date or are sampled more than once. We drop all observations in the same organization-date combination if the ZIP Code or contribution amounts conflict. If there is no conflict then we keep one of the observations. To address likely typos in ZIP Codes, we replace any ZIP Code that does not match its lead and lagged value if those match each other.

Merging the charity data with other datasets enables our analysis. Rather than use self-reported state, we use the charity's ZIP Code and obtain the corresponding state from the ESRI 2010 ZIP Code centroid data. As with the ARC data, we use the Postal Bulletin data to combine ZIP Codes into time-invariant superZIPs. We use the fiscal year of each observation to merge to ZIP-by-month versions of the tornado data, each identifying the worst tornado occurring within X miles, for X in 10, 20, 30. We identify the worst tornado within the observation's tax year and drop fiscal years with multiple fatal tornadoes to avoid ambiguity in tornado severity and the income of affected areas. As with the ARC data, we use the CPI to inflate the value of contributions to 2024 dollar values.

A handful of restrictions to this dataset produce our final analysis sample. We drop a small number of observations with a fiscal year shorter than 12 months to make contributions

[11] Contributions include donations from individuals as well as grants or other support. We drop observations with zero contributions because these are likely to be errors.

more comparable over time. Similarly, we drop a small share of observations with fiscal years ending in months other than June or December to make timing more comparable across organizations. We drop years after 2017 to match the coverage of the ARC data and drop years 1997-1999, when much of the sample is missing. Lastly, for estimation purposes, we drop treated observations with no untreated pre-period year.

2.4 Disaster aid

We obtain data on federal disaster aid from the Federal Emergency Management Agency (FEMA) for disasters occurring in 2002–2016. When a natural or man-made event threatens to overwhelm state and local resources, the state governor can request a major disaster declaration.[12] FEMA assesses damage and makes a recommendation, but the ultimate decision is up to the US President. In practice, the most extreme events receive a major disaster declaration almost immediately. Very few disaster declaration requests are denied, although governors likely consider the probability of approval when deciding whether to request a declaration. Once a major disaster is declared, the included counties become eligible for funds for debris cleanup and to repair public buildings and infrastructure ("public aid"), funds to individuals for temporary housing and repairs ("individual aid"), or both.[13]

FEMA data do not track aid disbursement over time but report total aid given for a particular disaster declaration. Because public aid is given to local governments, it is only reported at the county level, while records of individual aid are available at the ZIP Code level. We consider a declaration tornado-related if either the incident type or the incident description mention a tornado. Although the date of the disaster is listed in the major disaster declaration, the dates in tornado-related declarations do not always line up perfectly with the date of the tornado, in part because declarations can include multiple extreme events (e.g., tornadoes and flooding). For this reason, we attribute to each tornado

[12] See https://www.fema.gov/pdf/rrr/dec_proc.pdf for more details.

[13] 73% of 893 major disaster declarations in our data provide public aid only; 22% provide both public and individual aid; 4% provide individual aid only; a handful (9 declarations) provide neither.

all funds associated with a tornado-related declaration and given to a tornado-affected ZIP Code or county within a month of the tornado date.

During our time period, tornado-related major disasters received $1.9 billion in Individual Assistance and $5.5 billion in Public Assistance (2017 dollars), comprising 8.5% of total individual assistance and 7.3% of total public assistance given over this time period. In our sample, 44% of ZIP Codes affected by a fatal tornado received some Individual Assistance, and 38% of affected counties received some Public Assistance.

2.5 Descriptive statistics

Table 1 shows summary statistics for the 568 fatal tornadoes in our sample. The average tornado affected 30 square miles and about 7 Census blocks, killed 3.6 people, injured 33 people, and caused $50 million in damage (2024 dollars). The affected Census blocks contained on average 1,460 people total, of whom 84% were white and 11% were black. The average median income in the tornado-affected area is $52,000. Importantly, there is substantial heterogeneity in the characteristics of the affected areas. For example, over 10 percent of tornadoes affected areas with no black populations, but 10 percent of them affected areas that were more than 40% black. Similarly, the 10th percentile of median income is $34,000, and the 90th percentile is more than double that ($73,000).

In Figure 1, we depict the spatial distribution of these tornadoes alongside median household income, both at the ZIP Code and tornado level. Fatal tornadoes manifest predominantly in the Midwest and Southeastern regions, with sporadic occurrences along the East Coast. There is substantial spatial heterogeneity in both the affected-area income and in the median household income of potential donor areas surrounding the areas that were affected.

Table 2 shows the partial correlations between tornado and affected-area characteristics (population, median income, urbanicity and percent black). Unsurprisingly, affected-area population is significantly correlated with fatalities, injuries, and losses. Conditional on the other characteristics, affected-area income is not significantly correlated with any tornado

characteristics. Point estimates suggest that tornadoes affecting urban areas cause more losses and casualties, but the standard errors are large. Fatalities are marginally lower in areas with a larger share of black individuals. Overall, these patterns suggest that affected-area median income is as good as random with respect to tornado characteristics, conditional on the other affected-area characteristics. Nonetheless, we probe the robustness of our estimates to detailed controls for tornado severity and affected-area population.

Table 3 shows the correlations between the characteristics of donor areas and nearby fatal tornadoes (within 100 miles).[14] The unit of observation is a donor-ZIP-Code-tornado (such that ZIP Codes that are near multiple tornadoes in non-overlapping time periods appear multiple times). We regress tornado fatalities, injuries, losses, or distance from the donor ZIP Code on donor population, income, urbanicity, and percent black. Donor population is uncorrelated with nearby fatalities or injuries but positively correlated with losses. More populous donor areas are also slightly closer to fatal tornadoes, conditional on being within 100 miles (column (4)). Donor median income is *negatively* correlated with fatalities, injuries, losses, and distance. In other words, higher-income donor areas are more likely to be near less severe tornadoes, which should bias us toward finding giving falling with donor income. However, because higher-income donor areas are also slightly closer, controlling for distance to the tornado could be important. The partial correlation with a donor urbanicity indicator is not significant for any tornado characteristic. Finally, areas with a higher share of black individuals are more likely to be near less severe tornadoes (as measured by injuries and losses) and to be slightly further from them.

3 Empirical framework

We use a difference-in-difference design, comparing donation changes in ZIP Codes that are near fatal tornadoes to donation changes in ZIP Codes that are further away. We expect that

[14] Online Appendix Table A.1 shows analogous correlations for donor areas located within 200 miles of tornado-affected areas.

people who live closer to the location of a tornado will donate more to the ARC in response to the tornado compared to those located further away. Closer donors could give more if they are more aware of the tornado or because they feel a closer affinity to those who are affected (Enke, Rodríguez-Padilla and Zimmermann, 2023). Our identification assumption is that, conditional on ZIP Code and time fixed effects, the occurrence of a tornado is a random event. This assumption is highly plausible, as, conditional on the location and time of year, tornado occurrence is very difficult to predict.

Even with this simple framework, however, we are faced with two key choices: (1) how large a radius around the affected area to consider and (2) over what time window to allow donations to respond to tornado occurrence. A small radius (e.g., 25 miles) may miss a donation response farther away, for example. However, a large radius (e.g., 1000 miles) may yield noisy estimates and lead to a large number of overlapping events, complicating our difference-in-difference strategy. We address these issues with a data-driven approach, selecting our preferred radius and time window empirically and showing the robustness of our estimates to alternative choices.

3.1 Marginal treatment effects

A traditional two-way fixed effects estimator would imply the following estimating equation:

$$y_{zt} = \sum_{s=-p}^{K} \delta_s T^R_{z,t-s} + \alpha_z + \gamma_t + \varepsilon_{zt}. \tag{1}$$

The outcome, y_{zt}, is equal to $max(0, ln(d_{zt}))$, where d_{zt} is total donations to the ARC from ZIP Code z in week t. We use this transformation because donations are skewed and zero donations are common (about 54 percent of ZIP-weeks). The functional form follows recommendations by Chen and Roth (2024) to assign an explicit value to the extensive margin, and we set its value to zero because the first dollar donated is worth no more than other dollars. Note that any donations of $1 or less—which are highly likely to be errors—

will also be set to zero. We are interested in how these donations are affected by a fatal tornado, $T^R_{z,t-s}$, occurring in week $t-s$ within radius R of a donor ZIP Code. To account for spatial correlation of treatment, we cluster standard errors at the 3-digit ZIP Code level.

The key coefficients of interest are δ_s, which capture the effect of tornadoes on donations from p weeks before the tornado through K weeks after. Given the definition of y_{zt}, coefficients can be interpreted as percentage changes in donations. Testing that $\delta_s = 0$ for future tornadoes ($s < 0$) allows us to verify that the tornado-unaffected observations in our sample are valid counterfactuals with similar trends in donations. Estimating equation (1) for different values of R measures how donors respond over space.

Recent papers in the difference-in-difference literature have shown that treatment effect heterogeneity can lead to bias in estimated treatment effects when the regression involves using earlier-treated units as controls for later-treated units (Roth et al., 2023). This so-called "forbidden comparison" can also lead to spurious pre-trends even in cases where the treatment is exogenous. We therefore use the method developed by Borusyak, Jaravel and Spiess (2024) (hereafter "BJS"), which involves estimating time and unit fixed effects using not-yet-treated or never-treated observations and then using those estimates as the time and unit fixed effects for the treated observations. Other papers have proposed alternative solutions to avoid the forbidden comparison, but Borusyak, Jaravel and Spiess (2024): (1) allow for the estimation of event-specific treatment effects, which is useful for our goal of heterogeneity analysis, and (2) prove that their estimator offers maximal efficiency, at least in the case of homoskedastic errors.

Because tornadoes can arise repeatedly in or near a particular location, we use a simple algorithm to adapt this heterogeneity-robust estimator to a setting with repeated treatments. Such estimators have mostly been used to study events that are likely to have long-lasting effects, such as new state policies, and assume that each unit experiences at most a one-time change in treatment status. Unlike policy changes, however, it is plausible that disasters only have a temporary effect on the donations of those not directly affected, which we verify

by examining lags of the tornado variable. If effects end within a certain number of weeks, then we can define distinct, non-overlapping time periods for each area that is ever treated and incorporate fixed effects for each of these ZIP-time periods.

We define treatment as a fatal tornado within radius R of a given ZIP Code that is not preceded by a fatal tornado within radius R of any ZIP within the relevant 3-digit ZIP Code in the previous $p + K + 1$ weeks. The restriction depends on the 3-digit ZIP Code because this is the level at which we cluster standard errors and is meant to be conservative. The partition of time for each ZIP Code ensures that our estimation window contains the full length of the pre-treatment period of interest (p weeks) followed by the full length of the post-treatment period of interest (K weeks plus the week of the tornado). Whenever there are more than $p + K + 1$ weeks between two qualifying tornadoes, we assign the "extra" weeks to the pre-period to maximize the precision with which our fixed effects are estimated. Any fatal tornado that occurs less than $p+K+1$ weeks after another is not used to estimate treatment effects.[15]

Partitioning the sample and employing the BJS estimator yields an equation similar to equation (1) above:

$$y_{zt} = \sum_{s=-p}^{K} \delta_{ze,s} T^{R}_{ze,t-s} + \alpha_{ze} + \gamma_t + \varepsilon_{zt}. \tag{2}$$

The two differences are that (1) treatment effects can vary with each ZIP-Code-by-event unit ze and time period, i.e. with each observation, and (2) ZIP Code fixed effects α_z are replaced by ZIP-Code-by-event fixed effects α_{ze}. In addition to clustering standard errors at the 3-digit ZIP Code level, we make use of leave-out standard errors that do not depend on a unit's own residual, a conservative option that the authors recommend when there are treatment dates with a small number of treated clusters.

[15] For example, suppose a fatal tornado occurs within R miles of a given 3-digit ZIP Code in weeks 25 and 70 of the sample. For $p = 10$ and $K = 15$, our algorithm will assign that ZIP Code's data in weeks 1-40 to one ZIP-time period and will assign data in weeks 41-85 to another ZIP-time period, with ZIP Code fixed effects being specific to each time period.

This estimator yields similar average effects to the two-way fixed effects estimation of equation (1) in our setting, but it imposes no structure on treatment effect heterogeneity. Standard errors can be obtained for weighted sums of the observation-level estimates $\delta_{ze,s}$, allowing us to test for treatment effect heterogeneity by, for example, comparing the average effect of tornadoes that struck higher-income areas to that of tornadoes that struck lower-income areas. Such comparisons rely on a further ceteris paribus assumption, and we therefore show versions of our heterogeneity analyses that use the Frisch-Waugh-Lovell Theorem to partial out the influence of other variables such as the number of fatalities caused by the tornado.[16] We test for heterogeneous effects in weeks 0 through 5 after a tornado, when effects are largest and most precisely estimated, to show how the dollars donated vary with the characteristics of tornadoes and the areas where they strike.

3.2 Total resources transferred

Estimates from equation (2) quantify relative increases in donations from a donor ZIP Code. These coefficients can be translated to estimates of the effect on dollars donated. In our context, these dollar-valued estimates demonstrate the importance of measuring resources transferred, both overall and as a function of affected-area characteristics.

Equation (2) can be inverted to obtain the dollar-valued treatment effect. The equation implies that actual donations, d^1_{zet}, can be written as a function of estimated counterfactual donations, $\widehat{d^0_{zet}}$, that would have been made to the ARC had there not been a tornado s weeks earlier. For all treated observations there is an s for which $T^R_{ze,t-s} = 1$, and if we allow counterfactual log donations to take negative values (i.e. donation amounts between \$0 and \$1), then the function is $max(0, ln(d^1_{zet})) = \widehat{ln(d^0_{zet})} + \widehat{\delta_{ze,s}}$. This can be rearranged to obtain d^1_{zet} explicitly in terms of the observed d^1_{zet} and coefficient estimate to obtain the dollar-valued effect $d^1_{zet} - d^0_{zet}$. Subtracting the estimated coefficient from each side gives

[16] To estimate treatment effects as a function of a high-income dummy ι_e and constant η, partialling out the effect of fatalities f_e, we would obtain $\hat{\iota_e}$ and $\hat{\eta}$ as residuals from regression each of these variables on the other and f_e, then weight each by the sum of its squared residuals.

$\widehat{ln(d^0_{zet})} = max(0, ln(d^1_{zet})) - \widehat{\beta_{zet}}$, and then exponentiating both sides of the equation yields $\widehat{d^0_{zt}} = exp(max(0, ln(d^1_{zet}) - \widehat{\beta_{zet}})$. This gives the counterfactual level of donations, which can be subtracted from the observed level to obtain the estimated dollar-valued treatment effect for the observation. To obtain this from the estimation, we define a weight that for each observation takes the value $(\widehat{d^1_{zt}} - \widehat{d^0_{zt}})/\widehat{\delta_{sze}}$ so that the multiplication of this weight by the coefficient estimate

3.3 Effects on local charities

We estimate effects of nearby fatal tornadoes on donations to other charities in largely the same way that we estimate effects on ARC donations. We again use the estimator of Borusyak, Jaravel and Spiess (2024) to obtain heterogeneous treatment effect estimates. Because we are interested in donations to more local charities, we conduct this analysis at the 5-digit ZIP Code level. We define treatment as a fatal tornado occurring within 10 miles of the charitable organization. We follow a similar algorithm for defining event-by-organization fixed effects, in this case estimating contemporaneous effects in the year of treatment given the coarse nature of Form 990 data. Our regression includes these fixed effects and year dummies, and leave-out standard errors are clustered by 3-digit ZIP Code. We estimate effects on log contributions and on dollars contributed to charities by tercile of income in the areas struck by the tornado.

3.4 FEMA aid analysis

Recall that FEMA reports disaster aid fundamentally differently from how donations are reported by the ARC. We do not observe the disbursement of aid over time but rather total aid given to an area. Individual aid (IA) is reported at the ZIP-Code-by-declaration level. Public assistance (PA) is reported at the county-by-declaration level. Declaration-level information includes the dates the disaster begins and ends, the date of the declaration, and a brief description (e.g., "Tornadoes"). Because tornadoes may be accompanied by

other adverse weather events, we do not necessarily expect the disaster date to correspond perfectly to the date of the tornado. In rare cases, a county or ZIP Code may be affected by multiple tornadoes in the same week, making it difficult to distinguish which of the two events triggered the aid.[17] For this reason, we first aggregate fatal tornado information to the ZIP-Code-by-week and county-by-week level to merge with IA and PA data, respectively. We then attribute all aid associated with declarations where the incident date is within one week of the tornado date to that tornado *unless* another tornado occurs following the tornado in question, in which case the aid is assigned to the subsequent tornado.[18]

Our primary estimating equation focuses on how disbursed aid correlates with affected-area characteristics:

$$asinh(Aid_{gt}) = Char'_{g,c(t)}\beta + \alpha_f + \gamma_y + \varepsilon_{gt}, \tag{3}$$

where g is geography (either ZIP Code or county) and t is year-week. The variable $Char_{g,c(t)}$ corresponds to some characteristic(s) of the tornado-affected area, where $c(t)$ refers to the closest Census preceding year-week t. Affected-area characteristics are determined based on Census blocks, as described in Section 2. We also control for fatality fixed effects and year fixed effects (α_f and γ_y, respectively). Thus, the relationship between affected-area characteristics and aid will be conditional on the number of tornado fatalities.

[17] If multiple tornadoes affect a county in close succession, the *total* damage will likely be the determining factor behind the decision to declare a major disaster.

[18] For example, suppose tornado 1 affects a county in week w, tornado 2 affects the county in week $w+1$, and tornado 3 affects the same county in week $w+4$ (note: three tornadoes in such a short span never happens in practice). Major disaster declarations are issued for incidents occurring in weeks $w+1$ and weeks $w+3$. The first declaration is assigned to tornado 2 because it is the most recent tornado preceding the declaration, while the second one is assigned to tornado 3.

4 Results

4.1 Spatial and temporal patterns of donations to the ARC

It is ex-ante unclear whether the disparities documented in the realms of crowdfunding and disaster loans and grants should carry over into charitable donations. Donors are able to select a specific recipient with crowdfunding but not with general charitable giving, although the funding will often be framed as going to a particular set of victims. Disaster loans and grants are governed by different processes and rules than charitable giving. Moreover, donors could be deliberately trying to offset any perceived inequality in the former through their charitable donations. Alternatively, any inequality in disaster aid may not be salient or the donors may view patterns of such aid as a signal of where need is greatest and exacerbate any inequalities in aid with correlated giving. Finally, Red Cross outreach efforts, which presumably increase donations, could be a function of unmet need.

Panel (a) of Figure 2 shows how donations within 100 miles of the tornado-affected ZIP Code evolve over time, as measured by the number of weeks since the tornado. Giving increases immediately and persistently, although the magnitude falls with time. The largest response occurs in the week of the tornado and the subsequent week, when giving increases by almost 45%.[19] Because a tornado can occur on any day of the week, on average only half of the week of the tornado is treated. Adjusting for this fact implies similar responses in that week and the week after. Two to five weeks after the tornado, giving is 17-30% higher, and the response is generally falling with the number of weeks since the tornado. After 15 weeks, giving returns to baseline. The persistence of elevated giving for over three months following a fatal tornado may be due to a number of factors, such as awareness of continued rebuilding efforts, repeated ARC solicitations, recurring donations set up in response to the tornado, or increased awareness of natural disasters. In Appendix Figure A.3, we show that

[19] We calculate the percent change in giving s weeks following a tornado as $e^{\widehat{\delta_s}} - 1$, where $\widehat{\delta_s}$ is the estimated average response s weeks after a tornado, calculated from equation (2). Other percent changes are calculated similarly.

our estimates are very similar when we extend the pre-period to be 10 weeks and the post-period to be 25 weeks. Appendix Figure A.4 shows that the temporal pattern is qualitatively similar but less pronounced when we widen the radius of the area that we consider treated.

Panel (b) of Figure 2 separates the giving response by fund type. Donations to both restricted and unrestricted funds rise, but a much larger—more than twice as large in relative terms—increase is seen for restricted funds. This pattern suggests that the ARC faces meaningful constraints with respect to at least some of the disaster giving. By contrast, donations to international causes, which could in principle be crowded out by the occurrence of a nearby fatal tornado, are virtually unaffected.

Figure 3 shows the average coefficient within 100 miles of the tornado-affected area 0-5 weeks after a fatal tornado, binned by the natural log of fatalities (panel (a)) or the natural log of property damage, in 2024 dollars (panel (b)).[20] In both cases, the donation response is clearly increasing with severity, although the slope with respect to fatalities is steeper, possibly due to less measurement error in this variable.

Figure 4 shows the response by distance to the tornado-affected area.[21] The strongest relative response is observed by donors living within 20 miles: their giving increases by over 60%. The relative response falls monotonically with distance, and donors who are 100 miles away from the fatal tornado site give only about 12% more. In Appendix Figure A.5, we broaden the definition of treatment to include any fatal tornado within 200 miles, and find no significant response by donors further than 150 miles away from the tornado sites.[22] While these estimates strongly suggest that people are not moral universalists, an alternative explanation is that those living further away are simply less aware of the tornado. Note that

[20] We use equally spaced fatality bins but also impose the restriction that the bottom three bins correspond to 1, 2, and 3 fatalities, respectively. We group log fatalities in this way because the distribution is extremely right-skewed. Although there is also skewness in log property damage, it is less extreme, and we therefore have 20 bins for this variable.

[21] We exclude giving by ZIP Codes located within 10 miles of the tornado-affected areas, where giving directly to individuals or other organizations is likely to be more common.

[22] Estimates for greater distances are noisier than in our main figure because our estimation strategy omits subsequent fatal tornadoes within a given radius if they occur within 15 weeks of another fatal tornado. This becomes increasingly likely as we increase the radius around the donor ZIP Code of interest.

these patterns do not automatically imply that the majority of *dollars* donated to the ARC in response to the tornado come from those living very close to the affected area, as there are naturally more areas that are further away from the site of the tornado.

4.2 Income in affected areas

Our heterogeneity analysis first studies how the charitable response to tornadoes varies with the characteristics of the residents of tornado-affected areas. Table 4 shows the average response by affected-area income in weeks 0-5 within 100 miles, with a variety of controls. Compared to the bottom income tercile, the second income tercile generates a response that's 17-20 percentage points larger when we include the most rigorous controls. The top income tercile also consistently generates an 8-10 percentage-point larger giving response compared to the bottom tercile, but we can't always rule out that the responses differ. Differences between the second and third tercile are largely insignificant. Appendix Figure A.6 shows that the giving response has a similar distance gradient for each of these income terciles.

Next, we estimate the total dollars donated, following the approach described in Section 3.2. Table 5 shows estimates of the dollar value of donations, both overall and by income tercile. On average, about $1.2 million is donated per tornado by donors living within 100 miles (Panel A), and about $2.8 million is donated by donors living within 200 miles (Panel B). Within 100 miles, only about half of the average amount is donated for tornadoes that strike areas in the lowest tercile of income of tornado sites. Donations for tornadoes in high-income areas were more than 3.5 times the amount donated for low-income areas, and the differences between terciles are statistically significant. Middle-income areas attract about $200,000 more in donations than low-income areas. Figure **??** shows total donations as a more flexible function of affected-area incomes using a finer partition of its distribution.[23] Panel B of Table 5 shows that the difference in absolute donations between the low-income and

[23] After calculating the total dollars donated by donors living within 100 miles in response to each tornado, we construct 40 bins of the median income of the tornado-affected area with an equal number of tornadoes in each one. The figure plots average donations against the average income in each bin.

high-income areas are similar when we compare donations within 200 miles of affected areas, although total donations to both sets of affected areas are higher, and average donations to tornadoes affecting low-income areas are now about 80% of the overall average.

The highly unequal pattern of donations is surprising considering the relatively small differences in donation responses shown in Table 4. Despite these similar percentage changes, donations could favor higher-income areas if there is a higher level of baseline giving around these areas. Figure 6 shows that this is the case. Annual donations to the ARC are much greater in the areas surrounding higher-income tornado sites. Those within 100 miles of the top income tercile of tornado-affected areas give more than three times as much, on average, as areas surrounding the bottom tercile. This implies that the similar percentage effects on donations result in more dollars donated when tornadoes strike high-income areas. The higher year-round giving within 100 miles of higher-income areas likely arises because both population and income levels are higher in these areas (Appendix Figures A.7-A.9).

Another possibility is that the mean responses shown in Table 4 obscure heterogeneity with respect to the income of the donor area. Table 6 shows the marginal response 0-5 weeks following a fatal tornado by *donor* income. The mean donor income by tercile is \$32,293 (tercile 1), \$47,584 (tercile 2), and \$70,052 (tercile 3). Appendix Table A.2 provides additional detail. The estimates consistently indicate that donations from middle- or high-income areas increase by more in relative terms than donations from low-income areas. Middle- and high-income donors respond nearly identically, with no statistically significant differences between them. In aggregate, however, higher-income areas donate more than lower-income area (Table 7), due to the latter having higher baseline donations.

Finally, we consider interactions between donor and affected-area income. If there is in-group favoritism, then this would contribute to the disparity in dollars donated because of the greater baseline donations and responsiveness of higher-income donor areas. Figure 7 plots the responses when we split affected-area income by its median and donor-area income by decile. Rather than in-group favoritism, we find that low-income areas are relatively more

responsive when tornadoes hit high-income areas, while high-income areas give more when tornadoes strike low-income areas. The significance of this pattern is confirmed in Table 8, in which we find a negative interaction between donor-area income and the indicator for a high-income site. The magnitude is sizable, ranging from 16 to 25 percentage points in the more rigorous specifications. The result is robust to a variety of controls, and it implies that out-group favoritism actually reduces the overall regressivity of dollars donated.

4.3 Other charities

We next examine whether the agglomeration pattern in donations to ARC also applies to other charities. While ARC is large enough to potentially reallocate some funds between recipients, most charities are smaller than ARC, and those located in a disaster site would be unlikely to send funds elsewhere.

Estimating effects on other charities in annual data requires a consideration of statistical power. Only 0.2 percent of charities have the NTEE code for "Disaster Preparedness & Relief Services," and the vast majority of charities would likely see no effect on donations, though we cannot know a priori which charities would be affected. In addition, the average coefficient for the ARC over weeks 0-5 is about 0.25, as can be seen in Figure 2, which implies an effect of less than 0.03 at the annual frequency with which we observe other charities. For these reasons we would expect an annual effect on charities that is orders of magnitude smaller than 0.03. An estimate of the average effect using the charities data (not presented) gives a standard error of 0.0043, meaning that we would barely obtain statistical significance with an estimate 30 percentage as large as that of the ARC, an implausibly large effect.

To enhance statistical power in estimating effects on other charities we exploit the variation in tornado severity. The Borusyak, Jaravel and Spiess (2024) estimator allows us to conduct inference on treatment effects as a function of other variables, and we do so using tornado fatalities. Based on the distributions of fatalities affecting areas in the income terciles that we examined for ARC, we restrict attention to the range of common support

from 0 to 25 fatalities. We estimate Equation 2 and present the effects of log fatalities in each income tercile on the average organization's log contributions. We again use the Delta Method for estimates of dollars donated per fatal tornado in each income tercile. Our main analysis defines treatment as a deadly tornado within 20 miles, and we show robustness to varying this radius.

Results are presented in Table 9. The first column presents a basic specification with fixed effects for each organization and year. Coefficients on log fatalities are positive but are largest for income tercile 3. This translates to a large estimate of $11 million per fatal tornado in an area with income in tercile 3, whereas estimated dollar-valued effects for terciles 1 and 2 are smaller and not statistically significant. The columns of the table show that this pattern is robust to dropping the largest 10 percent of organizations in terms of average contributions (which are likely to have more locations than the single address reported on Form 990) or to fully interacting the year fixed effects with any of organization size decile dummies, organization mission dummies, ZIP-Code-first-digit dummies, or state dummies. The last specification is the most demanding, and it reduces the estimate for tercile 3 to $7 million per fatal tornado, but this remains significantly larger than the dollars provided when tornadoes strike lower-income areas.

We conclude that the income disparity in donations to ARC is present and even more pronounced for other charities. To explore heterogeneity, we estimate elastic net regressions of the estimated treatment effects on log fatalities and their interaction with indicators for each of the major NTEE categories. Results vary somewhat with hyperparameters but most often select only the "Mental Health & Crisis Intervention" organizations as receiving a relatively large donation response. We also check the robustness of the estimates to definitions of treatment based on different distances. Appendix Table A.4 shows that dollar values are smaller when we only consider charities to be treated if they are within 10 miles of the tornado path, while Appendix Table A.5 shows that they are similar for a 30-mile treatment radius to those for a 20-mile treatment radius, together indicating that most of the response

flows to charities within roughly 20 miles.

4.4 FEMA aid

Figure 8 compares FEMA aid to tornado-affected areas to estimated donations to the ARC attributable to the same set of tornadoes (using a 100-mile radius around the tornado-affected area). We do this by income ventiles, calculated within-sample. We take the maximum of zero and the natural log of FEMA aid and ARC donations and then calculate the population-weighted mean for each income bin, but the results are very similar if we apply the natural log transformation after calculating the mean and/or consider the unweighted mean. Likewise, ARC donations within 200 or 300 miles of the tornado site have very similar relationships with income as those within 100 miles.

There is suggestive evidence that public assistance (PA) is somewhat regressive, with areas in higher income bins receiving higher levels of public aid (slope = 0.044). This relationship is not statistically significant, however. The relationship between ARC donations and income is more positively sloped (slope = 0.14, $p = 0.058$), and combining the two sources of aid unsurprisingly yields a positive but insignificant aid-income relationship (slope = 0.15, $p = 0.14$).

By contrast, there is suggestive evidence that individual assistance (IA) from FEMA is progressive, with areas in higher-income bins receiving less (slope = -0.11, $p = 0.16$). The pattern of donations to the ARC (slope = 0.14, $p = 0.001$) counteract this progressivity, however, and the overall aid-income relationship is positive but not statistically significant (slope = 0.062, $p = 0.14$).

Table 10 conducts a more rigorous investigation of federal disaster aid's distributional properties by estimating equation (3) for Public Assistance (PA). There is no significant relationship between PA and the racial composition of an area. Unsurprisingly, more populated areas receive more aid. As in Figure 8, there is no statistically significant relationship between the affected area's median income and PA, either in isolation or when jointly estimated

with population and race characteristics.

Table 11 shows a parallel set of results for Individual Assistance (IA). Again, racial composition is uncorrelated with the amount of aid received, but higher-population affected areas receive more assistance. After accounting for the population and racial composition of an area, wealthier areas receive less assistance, confirming the visual evidence in Figure 8.[24]

5 Conclusion

Charitable giving plays a vital role in funding disaster relief efforts across the United States. We use detailed data from donations to the American Red Cross to shed light on the determinants of charitable giving by studying how donors respond to the socioeconomic characteristics and proximity of areas affected by deadly tornadoes. Geographic proximity is the strongest predictor of the relative giving response, even at distances such that donors are unlikely to know any of the victims personally. We find heterogeneity in how donors respond to income levels of the affected area in terms of relative giving and in the responses of higher- versus lower-income donor areas.

Agglomeration of donors and a tendency to give locally result in areas with higher incomes attracting a disproportionate amount of post-disaster giving. This finding demonstrates that disparities along a particular dimension do not require donors to have explicit preferences for one group but can arise indirectly due to other forces that shape social and geographic proximity. While large organizations may be able to reallocate some donations between causes, many donations are explicitly restricted, and the mechanism applies not only to ARC donations but also to local charities. As with donations to the ARC, donations to local charities are far greater when a tornado strikes a high-income area. These patterns suggest a role for redistribution, but resources provided by FEMA are not nearly progressive enough to offset the disparity in donations.

[24] We find no significant relationship between an area's income and the probability of PA or IA eligibility (as specified in the major disaster declaration), conditional on year and fatality fixed effects.

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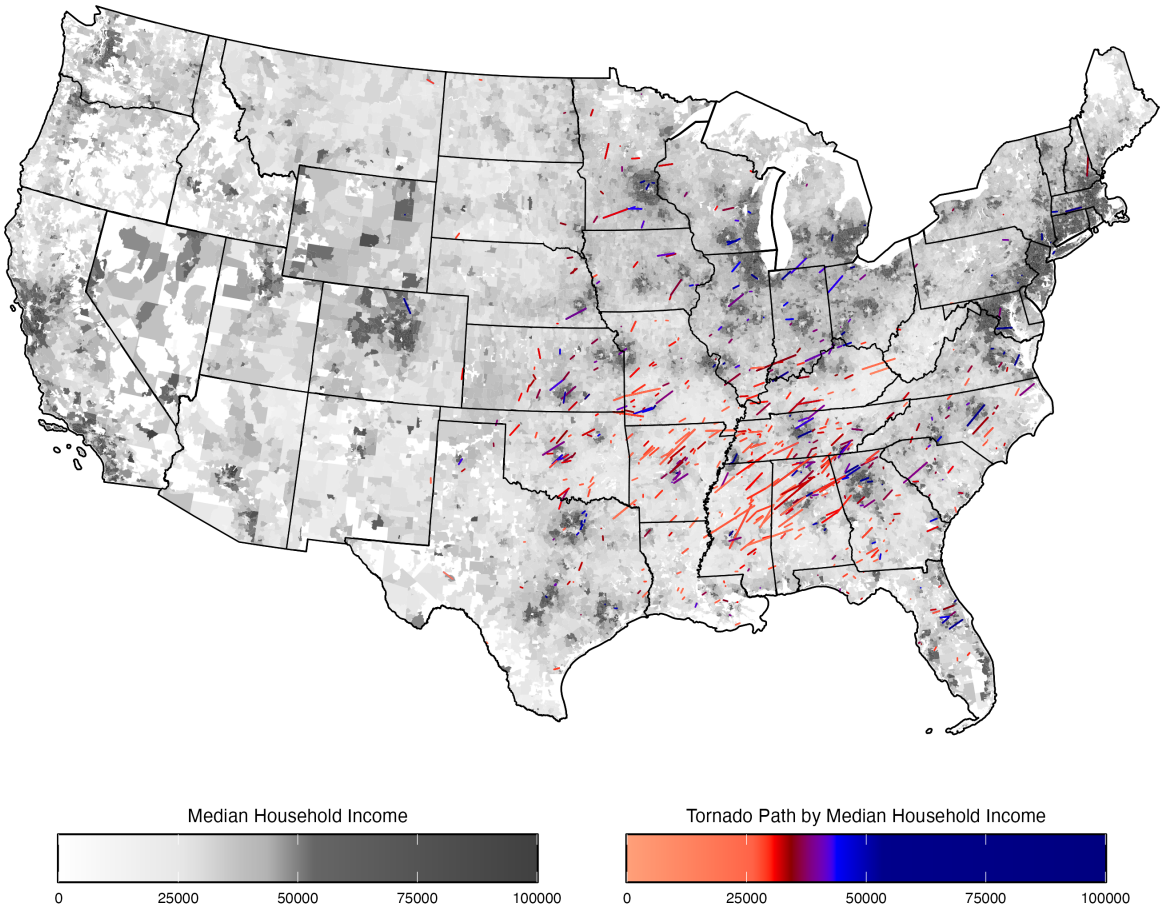
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Figures

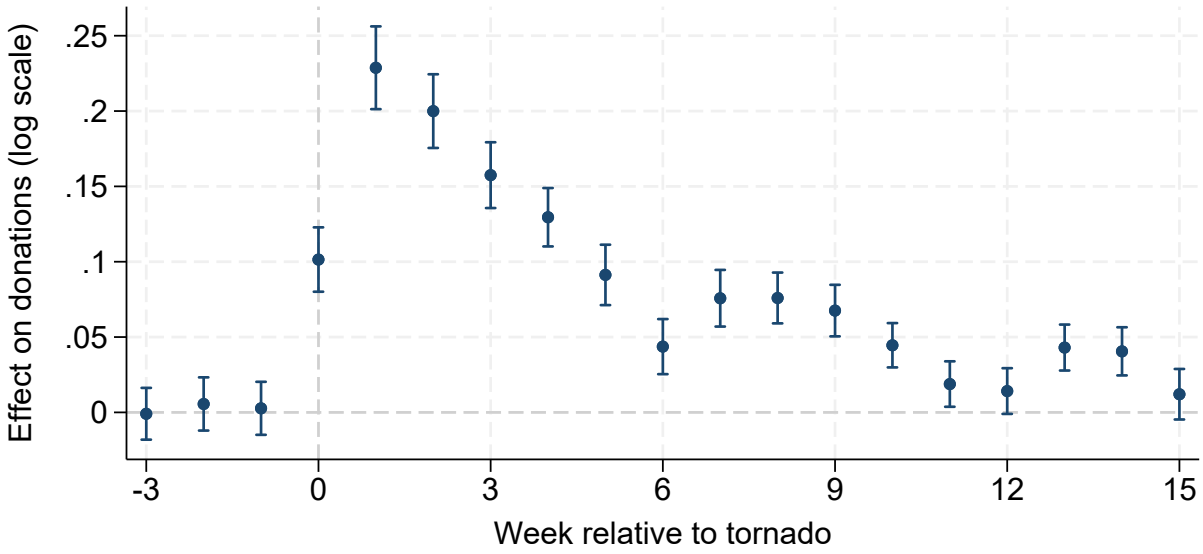
Figure 1: Paths of fatal tornadoes



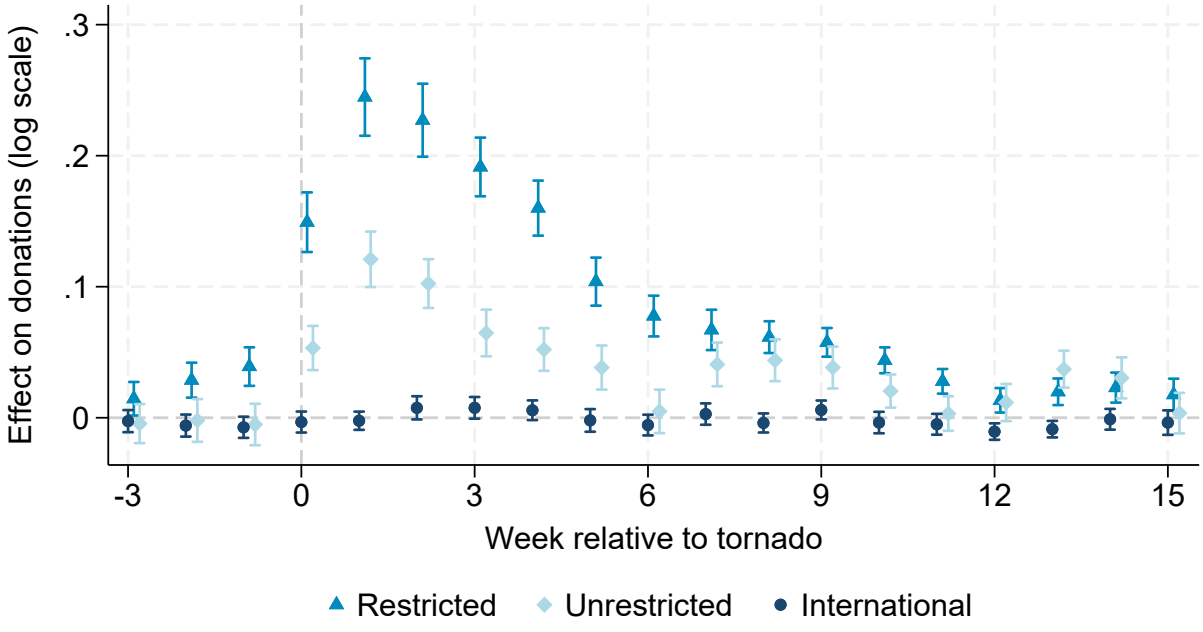
Notes: This figure shows (a) the paths of tornadoes that occurred in 1989–2016 and caused at least one fatality and (b) the median household incomes of affected Census blocks and of US ZIP Codes. Median household income at the ZIP Code level is from the 2000 Census and is top-coded at $100,000.

Figure 2: Temporal response of donations

(a) Overall



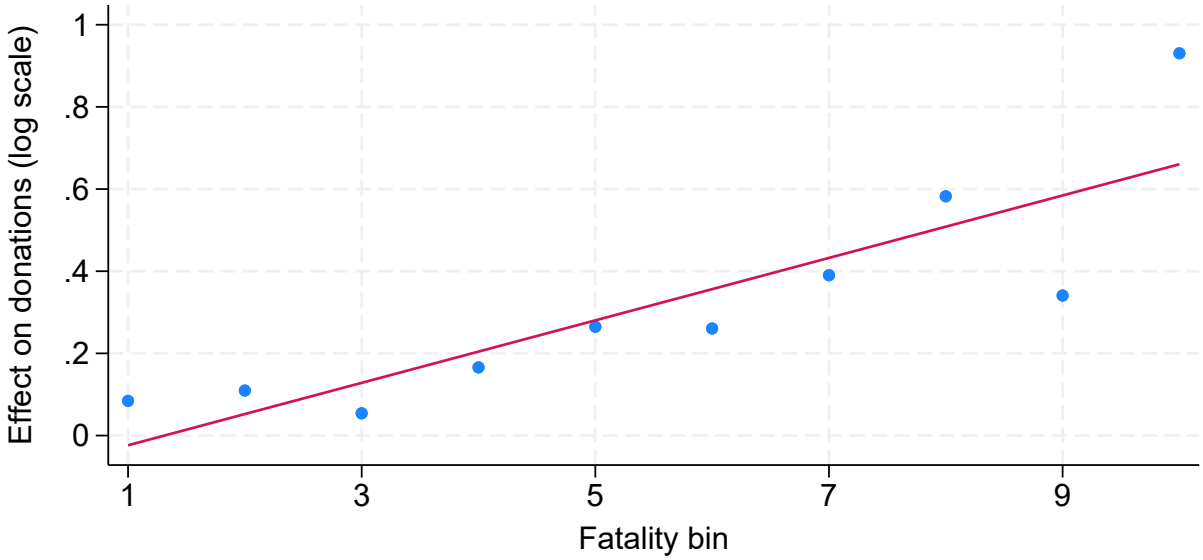
(b) By designation



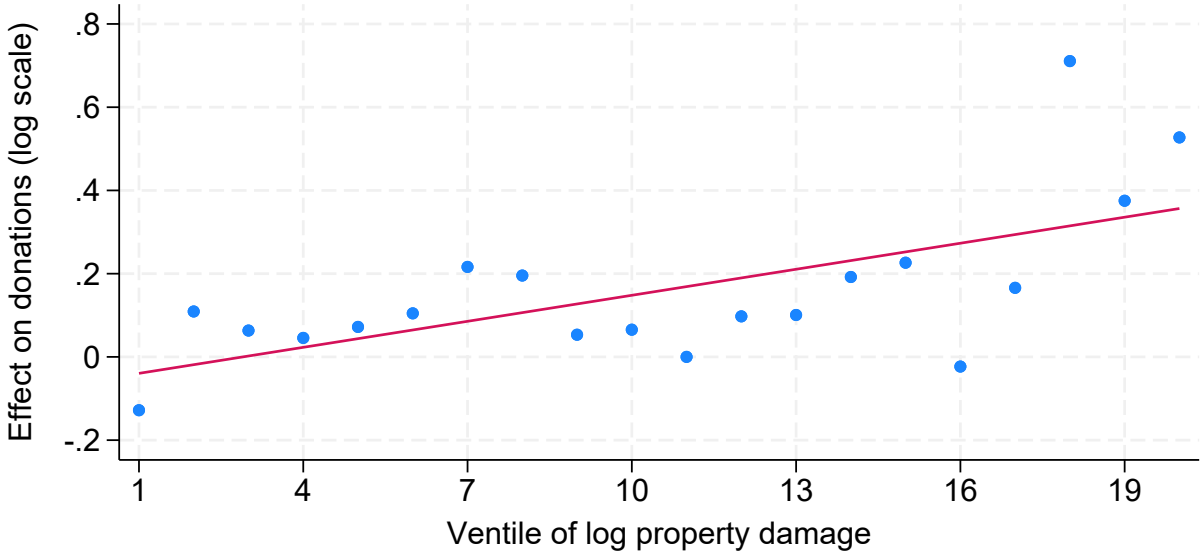
Notes: This figure shows point estimates and 95 percent confidence intervals for the giving response over time. Treatment is defined as being within 100 miles of a fatal tornado. Standard errors are clustered by 3-digit ZIP Code.

Figure 3: Response of donations by tornado severity

(a) Fatalities

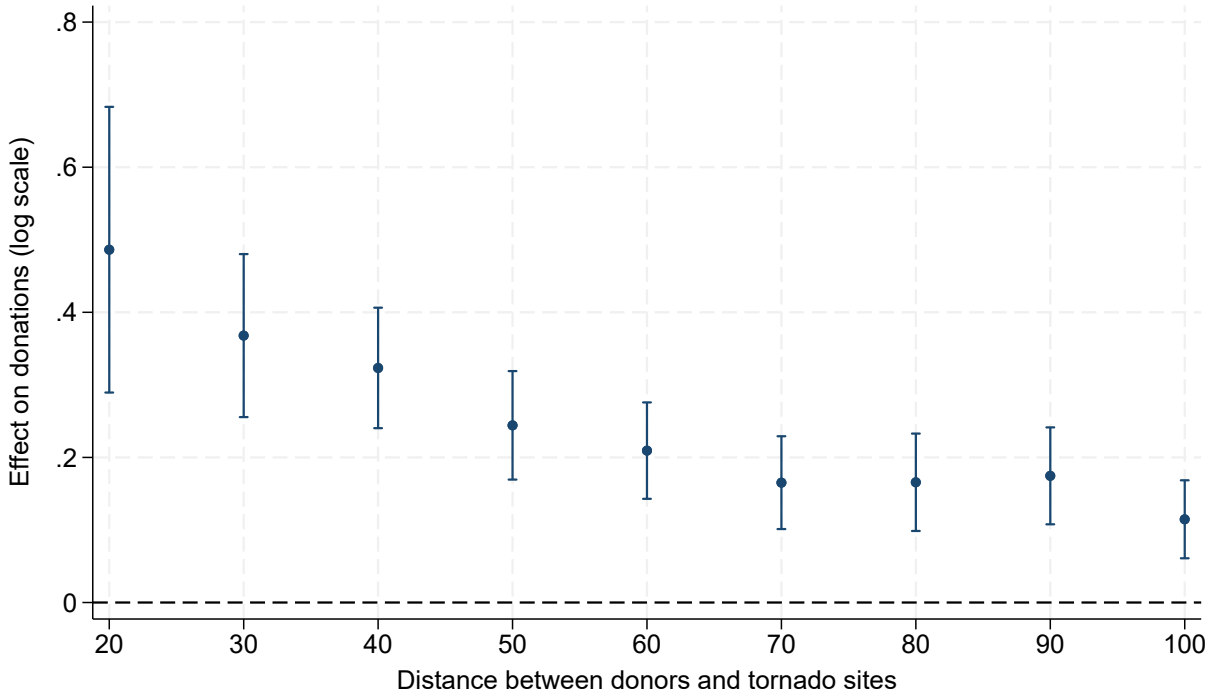


(b) Damage



Notes: This figure shows estimates of the relative giving response within 100 miles and 15 weeks of a fatal tornado by binned tornado severity, as measured by (a) the natural log of fatalities or (b) the natural log of damage. We utilize 11 bins for fatalities and 20 bins for property damage. Fatality bins 1–3 correspond to the number of fatalities (e.g., the first bin corresponds to tornadoes with 1 fatality); the remaining bins are quantiles for higher numbers of fatalities. Property damage bins are ventiles.

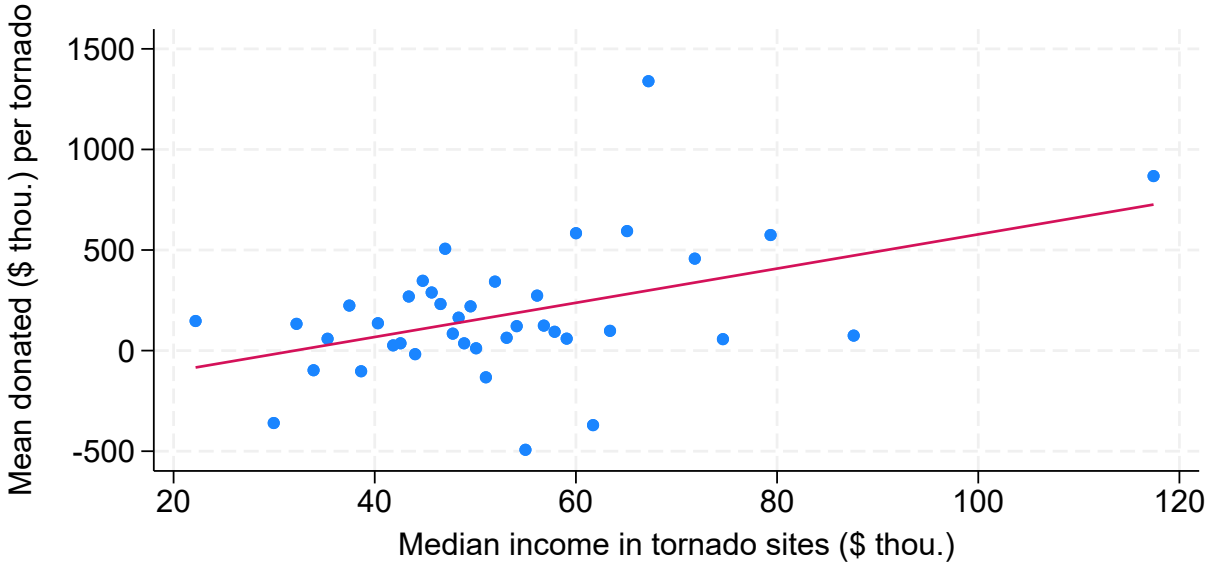
Figure 4: Donation response by distance



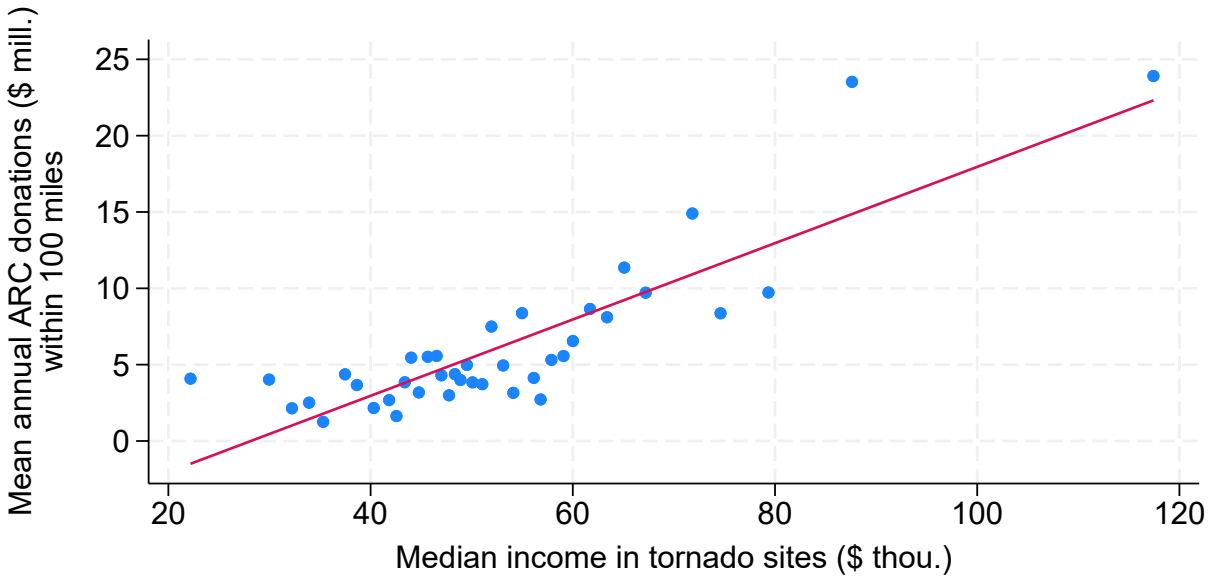
Notes: This figure shows estimated coefficients, averaged over all observations within 10-mile bins of distance between donors and affected areas.

Figure 5: Donations by income in tornado sites

(a) Dollars donated in response to tornadoes

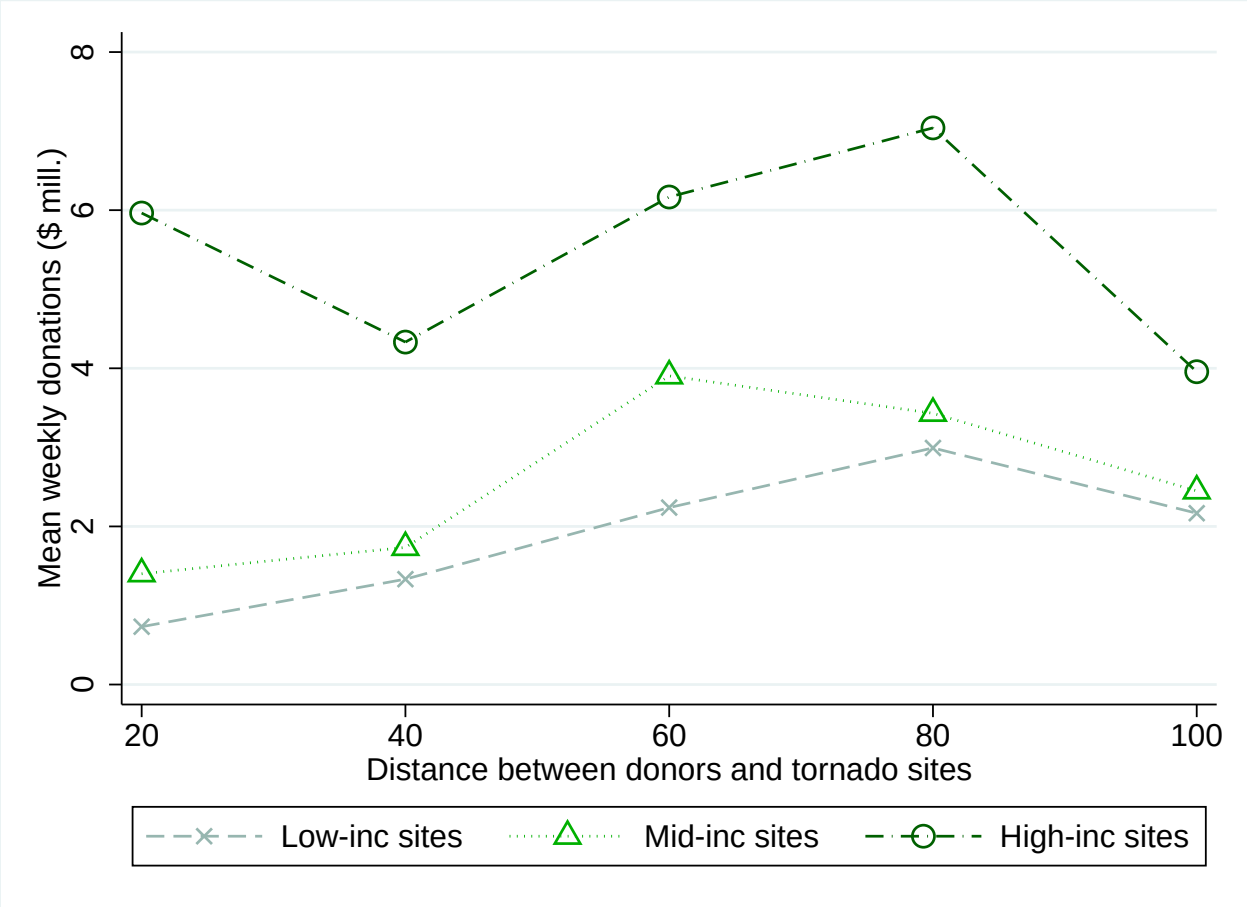


(b) Year-round donations



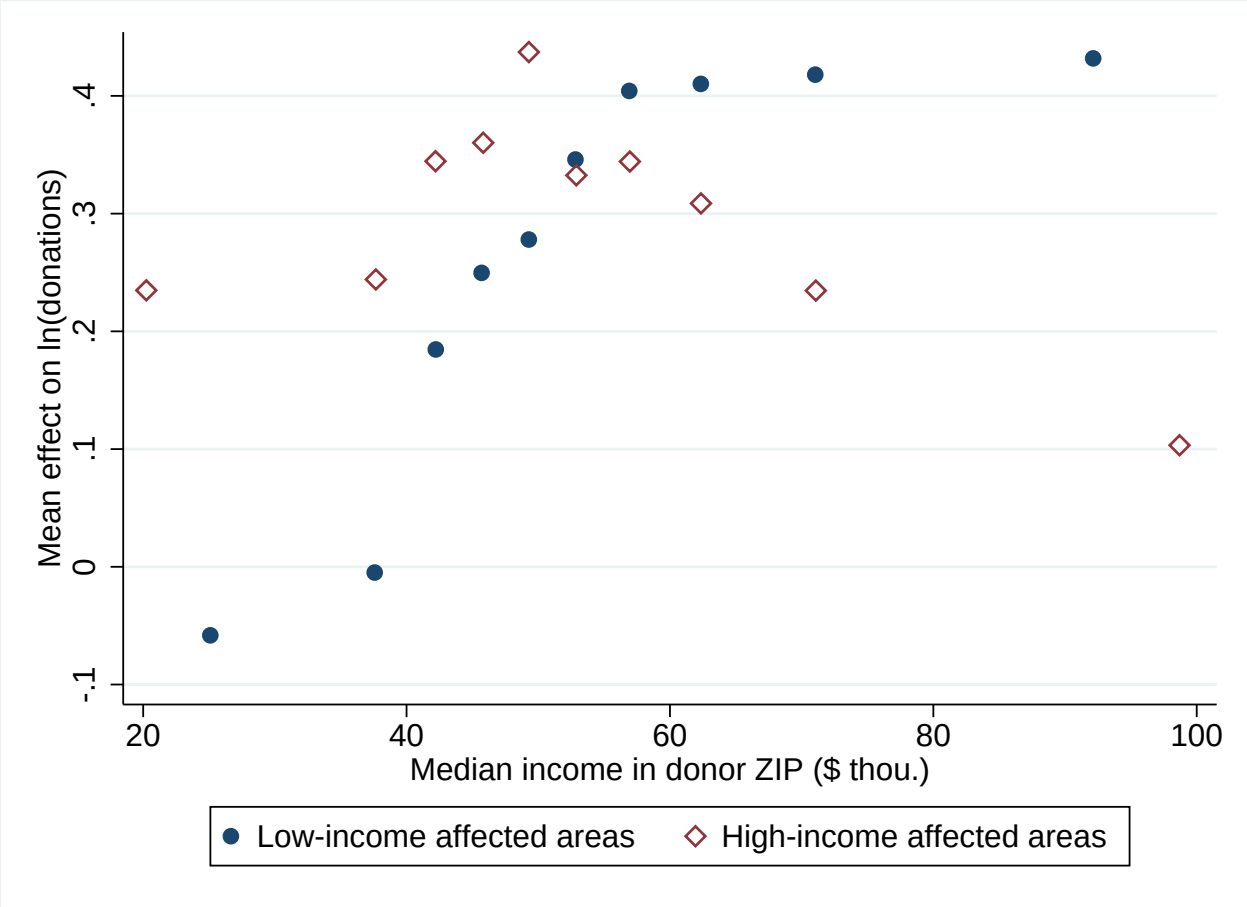
Notes: Panel (a) shows estimates of dollars donated in response to tornadoes, calculated from coefficients as described in the text. Panel (b) shows average annual dollars donated by ZIP Codes within 100 miles of areas ever struck by a fatal tornado. In both panels, each mark represents the sum within a bin for a quantile of income in affected areas.

Figure 6: Year-round donations by distance from tornado sites



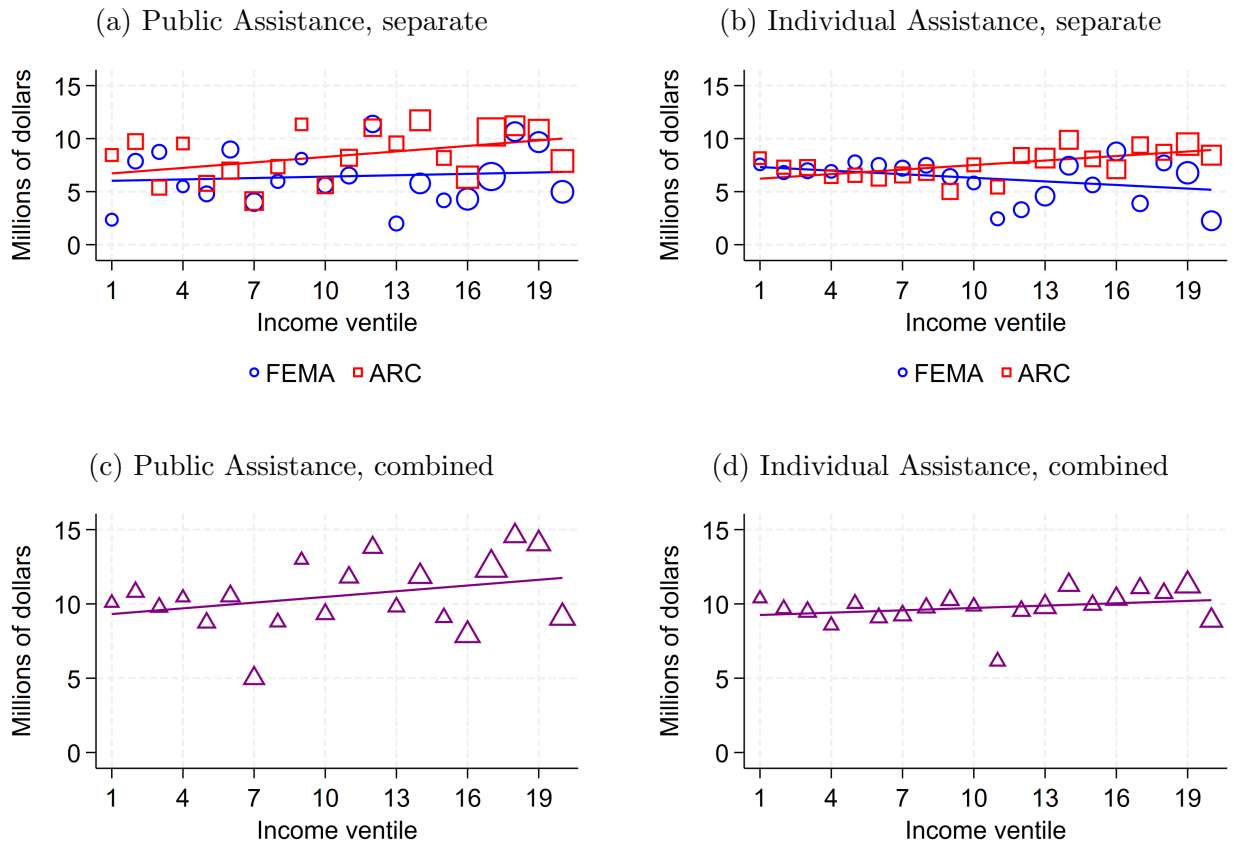
Notes: This figure shows annual dollars donated, averaged within 10-mile bins of distance between donors and affected areas for each tercile of the overall distribution of income in affected areas.

Figure 7: Dollars donated by income in tornado sites and donor areas



Notes: This figure shows estimated coefficients for tornadoes within 100 miles over the past 0-5 weeks, averaged within decile bins of donor-area income and whether affected-area income is above or below median.

Figure 8: Donations to the ARC and FEMA aid by income ventile



Notes: This figure shows average FEMA aid and estimated ARC donations by donors living within 100 miles of the tornado-affected area by affected areas' median income. Plots labeled "Public Assistance" use county-level public aid information; plots labeled "Individual Assistance" use ZIP-level individual aid information. We take the maximum of ln() and 0 for each quantity and then calculate a weighted average for each income ventile, weighted by the affected area's population. In panels (c) and (d), we first sum FEMA aid and ARC donations, then take the maximum of ln() and 0 and calculate a weighted average.

Tables

Table 1: Tornado-level summary statistics

	Mean	Std. dev	10th pctile	Median	90th pctile	Obs.
	(1)	(2)	(3)	(4)	(5)	(6)
Tornado length (miles)	17.63	19.70	2.00	11.09	40.00	504
Num. blocks affected	119.53	183.94	4.00	50.00	320.00	504
Fatalities	3.00	9.00	1.00	1.00	7.00	504
Injuries	31.00	78.00	0.00	10.00	73.00	504
Losses (millions USD)	44.49	211.95	0.00	2.87	66.88	504
Affected population	3,348.00	7,179.00	62.00	975.00	8,258.00	504
Urban	0.25	0.43	0.00	0.00	1.00	498
Median income	52,840.00	17,503.00	34,899.00	49,760.00	72,960.00	501

Table shows tornado-level summary statistics. Sources: NOAA, US Census.

Table 2: Predictors of tornado damage, affected area

	(1) Fatalities (log)	(2) Injuries (log)	(3) Losses (log)
Population (1000s)	0.039***	0.078***	0.12***
	(0.0097)	(0.013)	(0.029)
Median inc. (1000s)	-0.0013	-0.0030	0.017
	(0.0018)	(0.0043)	(0.013)
Urban	-0.029	0.58***	0.16
	(0.11)	(0.19)	(0.64)
Dep. var. mean	0.64	2.2	13
N	497	497	497

Notes: Robust standard errors are reported in parentheses. *** p< 0.01 ** p< 0.05 * p< 0.1.

Table 3: Correlations between tornado damage and donor-area characteristics

	(1) Fatalities (log)	(2) Injuries (log)	(3) Losses (log)	(4) Distance (miles)
Population (1000s)	0.00014	-0.00026	-0.00075	-0.0044
	(0.000093)	(0.00018)	(0.00062)	(0.0030)
Median inc. (1000s)	-0.0025***	-0.0065***	-0.0099***	-0.053***
	(0.00020)	(0.00043)	(0.0015)	(0.0070)
Urban	0.014	0.026	0.21***	0.80**
	(0.012)	(0.022)	(0.069)	(0.36)
Dep. var. mean	0.70	2.3	14	64
N	35,576	35,576	35,576	35,576

Notes: Robust standard errors are reported in parentheses. *** p< 0.01 ** p< 0.05 * p< 0.1.

Table 4: Relative changes in donations within 100 miles, by income in tornado sites

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
dist	100	100	100	100	100	100	100
2nd tercile, affected area	0.31***	0.26***	0.21***	0.21***	0.20***	0.17***	0.17***
	(0.051)	(0.072)	(0.063)	(0.061)	(0.059)	(0.058)	(0.057)
3rd tercile, affected area	0.28***	0.24***	0.15***	0.16***	0.096*	0.079	0.088*
	(0.048)	(0.063)	(0.052)	(0.053)	(0.050)	(0.051)	(0.053)
p-value for 2nd=3rd	0.69	0.66	0.31	0.31	0.085	0.16	0.19
Distance controls		yes	yes	yes	yes	yes	yes
Fatality controls			yes	yes	yes	yes	yes
Injury controls				yes	yes	yes	yes
Loss controls					yes	yes	yes
Urban controls						yes	yes
Same TV market controls						yes	yes
In same state controls						yes	yes
Population controls							yes

Notes: Standard errors, clustered by 2-digit ZIP Code, are reported in parentheses. *** p< 0.01 ** p< 0.05 * p< 0.1. Sample includes 7015872 observations and 410 tornadoes.

Table 5: Donations within 100 and 200 miles by income in tornado sites

Income in affected areas:	(1) All areas	(2) Tercile 1	(3) Tercile 2	(4) Tercile 3
Panel A: 100 miles				
Donations (thou. USD) per tornado	1,192***	610***	807***	2,162***
	(76)	(70)	(70)	(235)
Difference from previous tercile			198**	1,354***
			(94)	(232)
Panel B: 200 miles				
Donations (thou. USD) per tornado	2,804***	2,341***	2,375***	3,698***
	(172)	(255)	(309)	(219)
Difference from previous tercile			35	1,323***
			(396)	(367)

Notes: Standard errors, clustered by 2-digit ZIP Code, are reported in parentheses. *** p< 0.01 ** p< 0.05 * p< 0.1. Panel A includes 6,929,972 observations and 405 tornadoes. Panel B includes 6,929,972 observations and 354 tornadoes.

Table 6: Relative changes in donations within 100 miles by donor income

	(1)	(2)	(3)	(4)	(5)	(6)
2nd tercile, donor area	0.32***	0.30***	0.29***	0.27***	0.24***	0.24***
	(0.037)	(0.059)	(0.060)	(0.060)	(0.056)	(0.057)
3rd tercile, donor area	0.30***	0.28***	0.31***	0.28***	0.25***	0.26***
	(0.044)	(0.059)	(0.065)	(0.066)	(0.061)	(0.061)
p-value for 2nd=3rd	0.64	0.66	0.64	0.85	0.76	0.63
Distance controls		yes	yes	yes	yes	yes
Fatality controls			yes	yes	yes	yes
Injury controls			yes	yes	yes	yes
Loss controls				yes	yes	yes
Urban controls					yes	yes
Same TV market controls					yes	yes
In same state controls					yes	yes
Population controls						yes

Notes: Standard errors, clustered by 2-digit ZIP Code, are reported in parentheses. *** p< 0.01 ** p< 0.05 * p< 0.1.

Table 7: Donations within 100 and 200 miles by donor income

Income in donor areas:	(1) All areas	(2) Tercile 1	(3) Tercile 2	(4) Tercile 3
Panel A: 100 miles				
Donations (thou. USD) per tornado	1,192***	477***	1,076***	2,246***
	(76)	(114)	(183)	(149)
Difference from previous tercile			599***	1,170***
			(198)	(226)
Panel B: 200 miles				
Donations (thou. USD) per tornado	2,804***	1,511***	1,948***	4,982***
	(172)	(336)	(204)	(247)
Difference from previous tercile			437	3,034***
			(435)	(274)

Notes: Standard errors, clustered by 2-digit ZIP Code, are reported in parentheses. *** p< 0.01 ** p< 0.05 * p< 0.1. Panel A includes 6,929,972 observations and 405 tornadoes. Panel B includes 6,929,972 observations and 354 tornadoes.

Table 8: Relative changes in donations within 100 miles by donor- and affected-area incomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Low site inc.	0.072	-0.16***	-0.077	-0.13**	-0.098	-0.17***	-0.11**
	(0.044)	(0.059)	(0.051)	(0.057)	(0.060)	(0.066)	(0.054)
High donor inc.	0.26***	0.045	0.088*	0.059	0.089	0.030	0.077
	(0.051)	(0.049)	(0.050)	(0.052)	(0.055)	(0.053)	(0.053)
Interaction	-0.011	0.26***	0.22***	0.25***	0.16*	0.20**	0.22***
	(0.077)	(0.091)	(0.081)	(0.079)	(0.091)	(0.093)	(0.080)
Tornado length, area		yes	yes	yes			yes
Fatality controls			yes	yes			yes
Damage and injuries				yes			yes
Distance controls					yes	yes	yes
In-state and in-TV-market						yes	yes

Notes: Standard errors, clustered by 2-digit ZIP Code, are reported in parentheses. *** p< 0.01 ** p< 0.05 * p< 0.1.

Table 9: Donations to charities within 20 miles of tornado

	(1)	(2)	(3)	(4)	(5)	(6)
Log fatalities, tercile 1	0.0098	0.014	0.013	0.0091	0.010	0.0081
	(0.014)	(0.012)	(0.014)	(0.014)	(0.014)	(0.015)
Log fatalities, tercile 2	0.0060	0.0047	0.0046	0.0069	0.0075	0.0073
	(0.0081)	(0.0079)	(0.0082)	(0.0081)	(0.0082)	(0.010)
Log fatalities, tercile 3	0.026***	0.024***	0.028***	0.026***	0.020***	0.017***
	(0.0056)	(0.0052)	(0.0056)	(0.0057)	(0.0057)	(0.0061)
Tornado, tercile 1	–0.016	–0.011	–0.012	–0.016	–0.013	0.0011
	(0.013)	(0.012)	(0.013)	(0.013)	(0.014)	(0.014)
Tornado, tercile 2	–0.0077	–0.0054	–0.0034	–0.0070	–0.0096	–0.018
	(0.014)	(0.013)	(0.015)	(0.014)	(0.014)	(0.015)
Tornado, tercile 3	–	–	–	–	–	–0.0060
	0.017***	0.014**	0.020***	0.016**	0.015**	
	(0.0063)	(0.0057)	(0.0062)	(0.0063)	(0.0065)	(0.0071)
p-val, coeff. 1 = coeff. 2	0.81	0.51	0.59	0.89	0.87	0.96
p-val, coeff. 1 = coeff. 3	0.28	0.46	0.33	0.24	0.53	0.56
p-val, coeff. 2 = coeff. 3	0.046	0.041	0.021	0.049	0.23	0.38
$ mill. per tornado, tercile 1	0.63	0.92	0.84	0.59	0.66	0.52
	(0.88)	(0.80)	(0.89)	(0.89)	(0.89)	(0.94)
$ mill. per tornado, tercile 2	0.65	0.51	0.50	0.75	0.82	0.79
	(0.89)	(0.86)	(0.89)	(0.88)	(0.90)	(1.1)
$ mill. per tornado, tercile 3	11***	10***	12***	11***	8.2***	7.2***
	(2.4)	(2.2)	(2.4)	(2.4)	(2.4)	(2.6)
p-val, dollar-val 1 = dollar-val 2	0.98	0.72	0.78	0.90	0.90	0.84
p-val, dollar-val 1 = dollar-val 3	0.000049	0.000058	0.000018	0.000033	0.0027	0.012
p-val, dollar-val 2 = dollar-val 3	0.000058	0.000041	0.000011	0.000049	0.0037	0.017
Organization FE	X	X	X	X	X	X
Year FE	X					
Drop large orgs		X				
Org-size-by-year FE			X			
Org-mission-by-year FE				X		
1-digit-ZIP-by-year FE					X	
State-by-year FE						X

Notes: Standard errors (in parentheses) calculated by Delta Method. ***p < 0.01, **p < 0.05, *p < 0.10.

Table 10: Correlation between FEMA Public Assistance and victim characteristics

	(1)	(2)	(3)	(4)	(5)
Percent black	0.00071				0.00097
	(0.016)				(0.029)
Percent white		0.0023			0.020
		(0.015)			(0.025)
Population			0.77**		0.86**
			(0.21)		(0.22)
Median income (1000s of dollars)				-0.0026	-0.021
				(0.020)	(0.021)
Observations	518	518	518	516	516
R-squared	0.28	0.28	0.30	0.28	0.31

Notes: Table shows the results of equation 3. Clustered standard errors (county-level) in parentheses. The dependent variable is the maximum of 0 and the natural log of public assistance from FEMA. Controls include fatality and year fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Correlation between FEMA Individual Assistance and victim characteristics

	(1)	(2)	(3)	(4)	(5)
Percent black	0.012				-0.034
	(0.0094)				(0.031)
Percent white		-0.018			-0.032
		(0.0097)			(0.030)
Population			0.90**		0.91**
			(0.11)		(0.11)
Median income (1000s of dollars)				-0.022	-0.033**
				(0.012)	(0.012)
Observations	1,153	1,153	1,153	1,177	1,151
R-squared	0.32	0.32	0.38	0.32	0.39

Notes: Table shows the results of equation 3. Clustered standard errors (3-digit ZIP Code level) in parentheses. The dependent variable is the maximum of zero and the natural log of individual assistance from FEMA. Controls include fatality and year fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

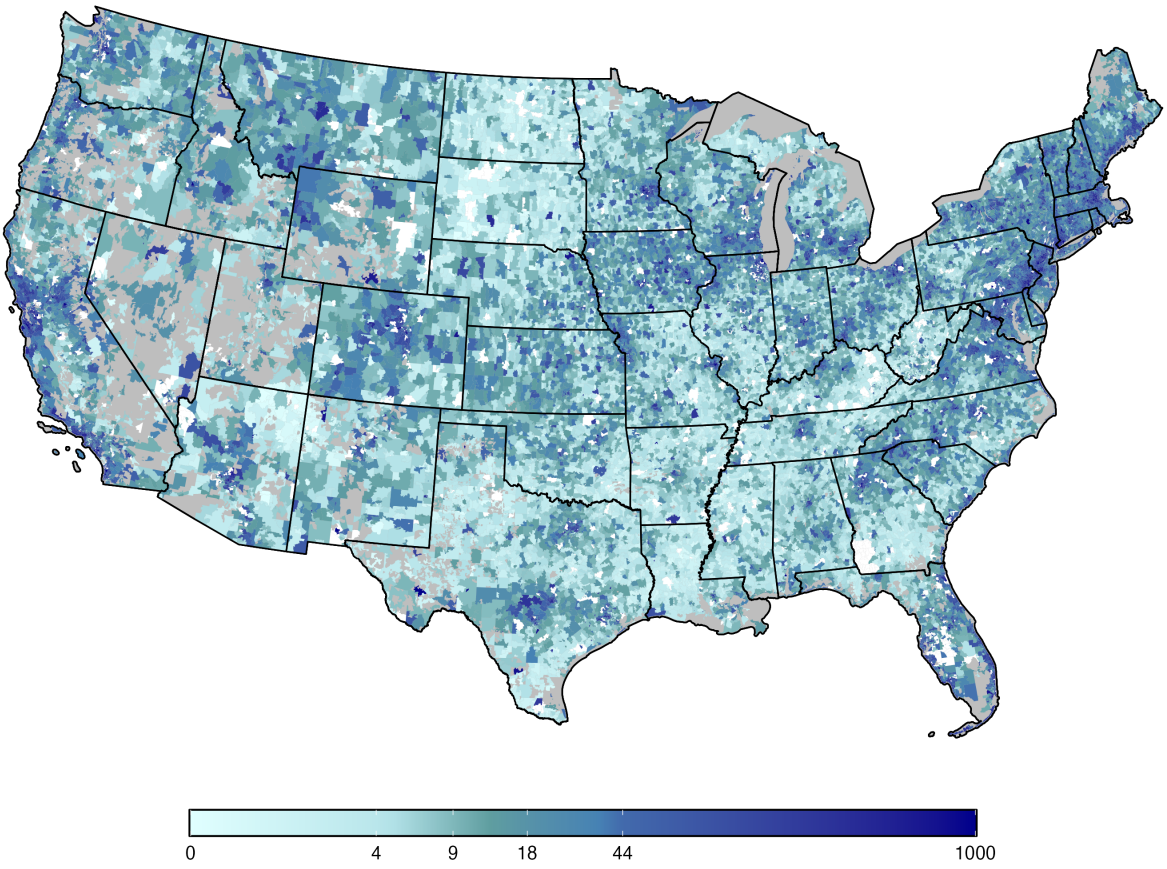
Online Appendix

Disparities in Aid for Natural Disasters

Tatyana Deryugina and Benjamin M. Marx

A Appendix Figures

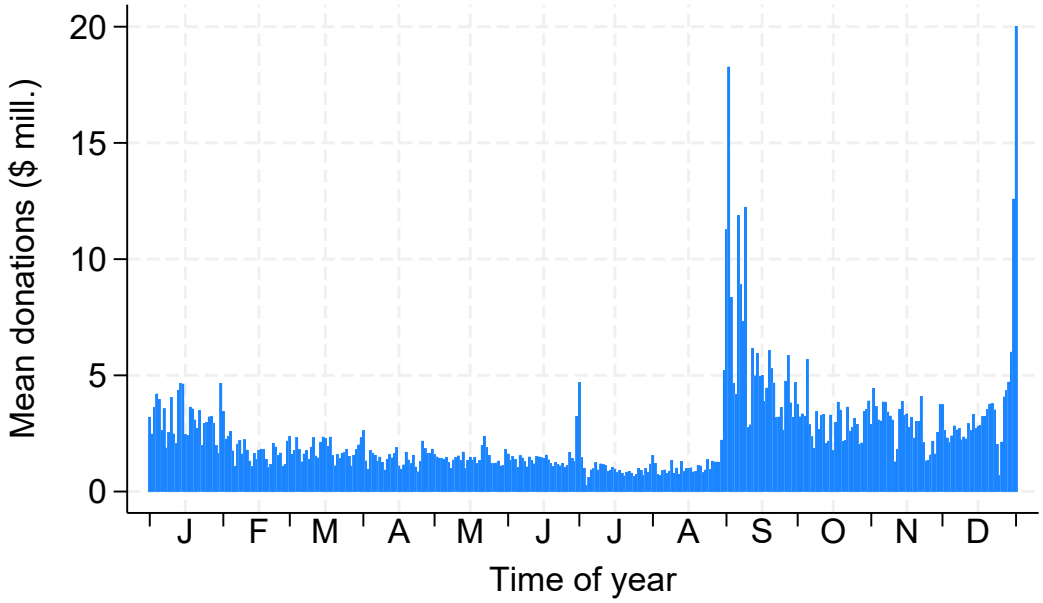
Figure A.1: Spatial distribution of per-capita donations to the ARC



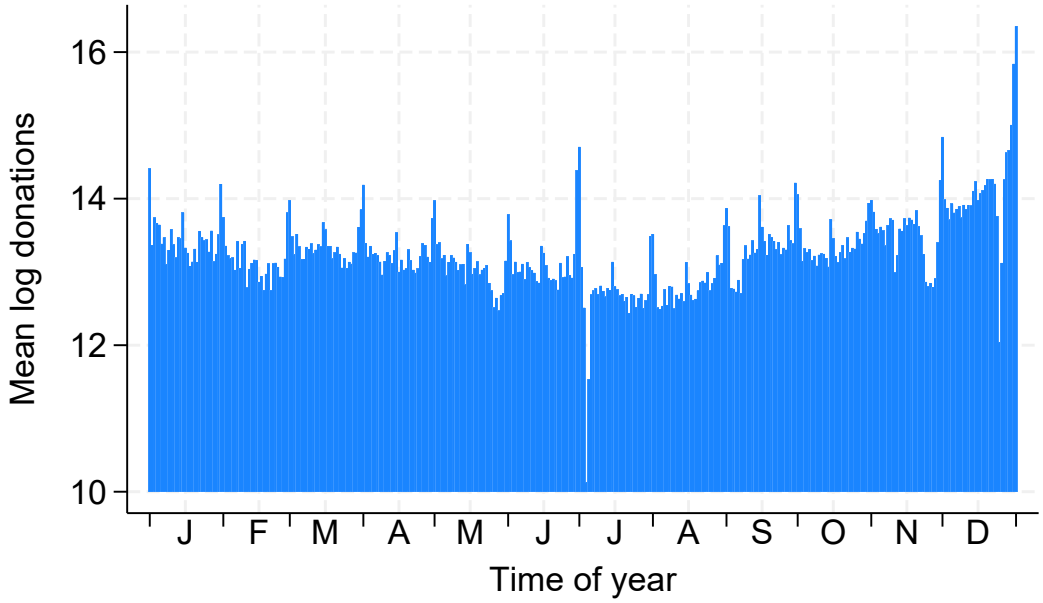
Notes: This map shows total per-capita donations to the American Red Cross over the time period 1989-2017 by ZCTA. White areas have zero donations per capita. Grey areas are not assigned a ZCTA.

Figure A.2: Mean donations by day of year

(a) Levels

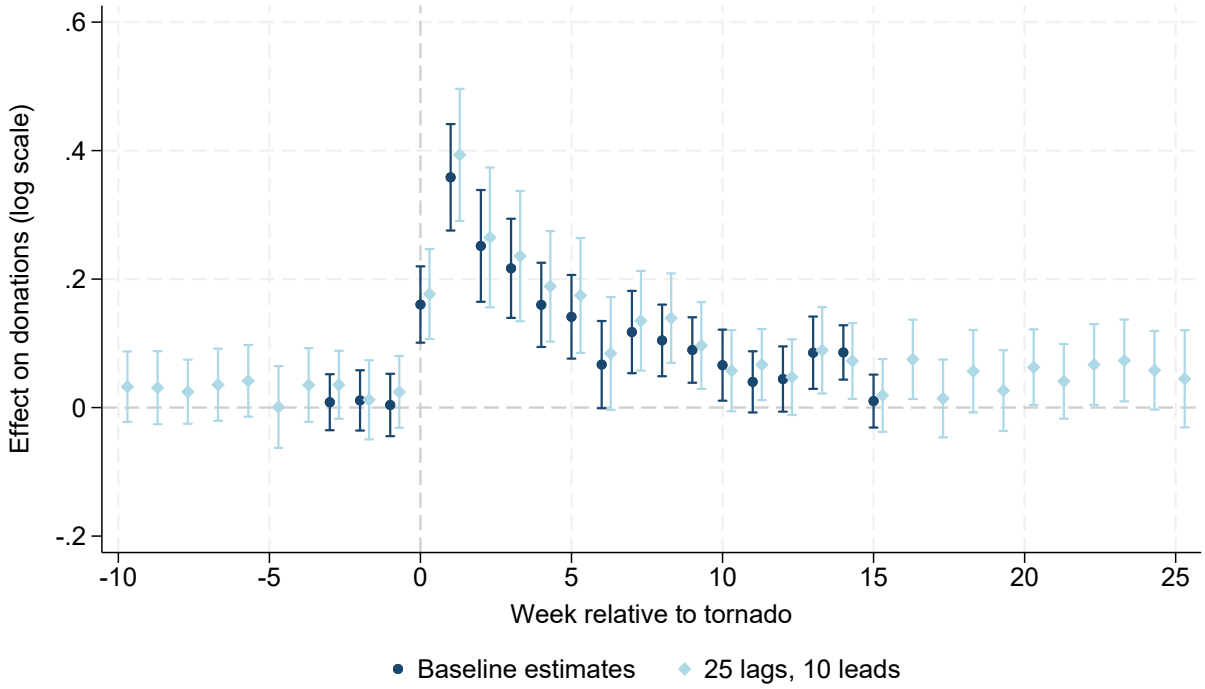


(b) Logs



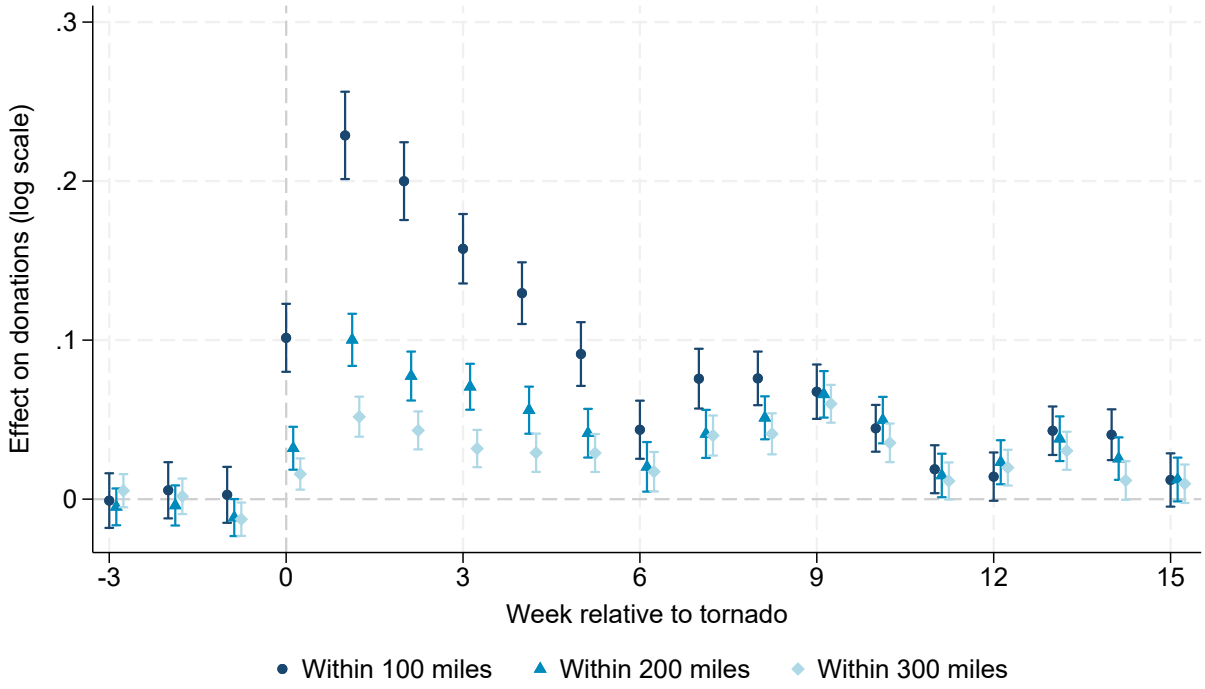
Notes: This figure shows mean daily donations by day of year. The means are obtained by first calculating daily donations across all ZIP Codes in the US, then either averaging across years (panel (a)) or taking the natural log followed by averaging across years (panel (b)).

Figure A.3: Temporal response of donations: robustness



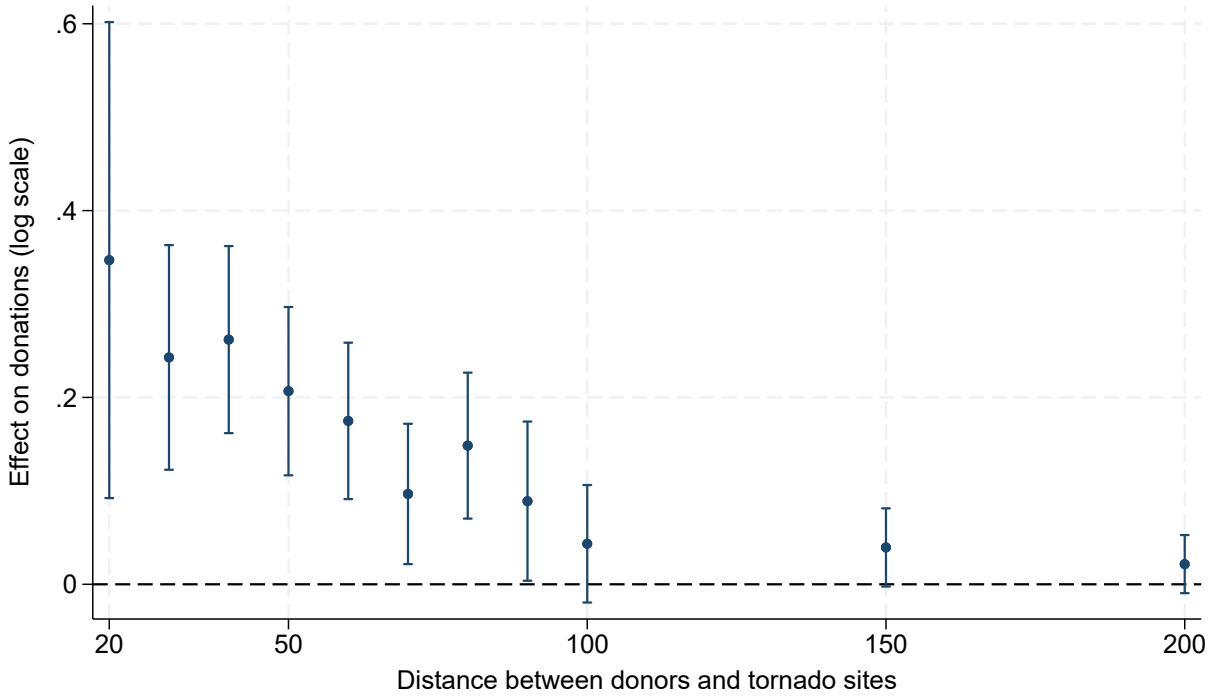
Notes: This figure shows point estimates and 95 percent confidence intervals for the giving response over time with more included leads and lags. Treatment is defined as being within 100 miles of a fatal tornado. Standard errors are clustered by the 3-digit ZIP Code.

Figure A.4: Temporal response of donations by distance



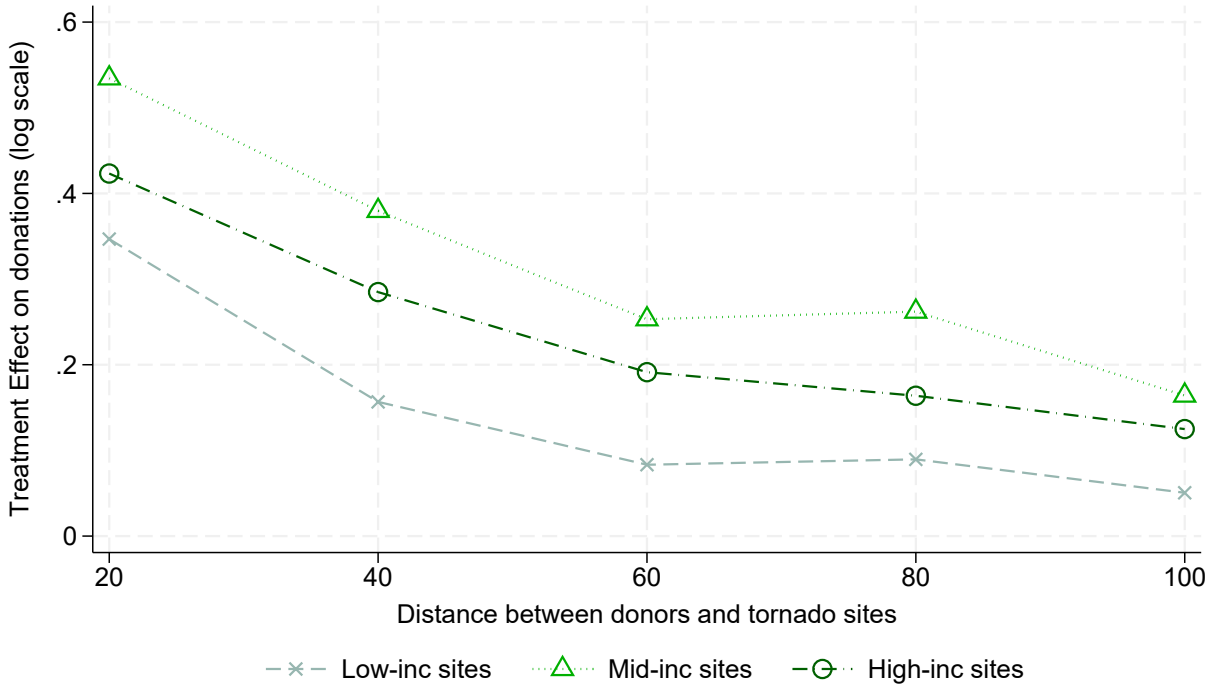
Notes: This figure shows estimates and 95 percent confidence intervals for three sets of estimates, each defining treatment using tornadoes within a different distance. Standard errors are clustered by 3-digit ZIP Code.

Figure A.5: Response of donations by distance up to 200 miles



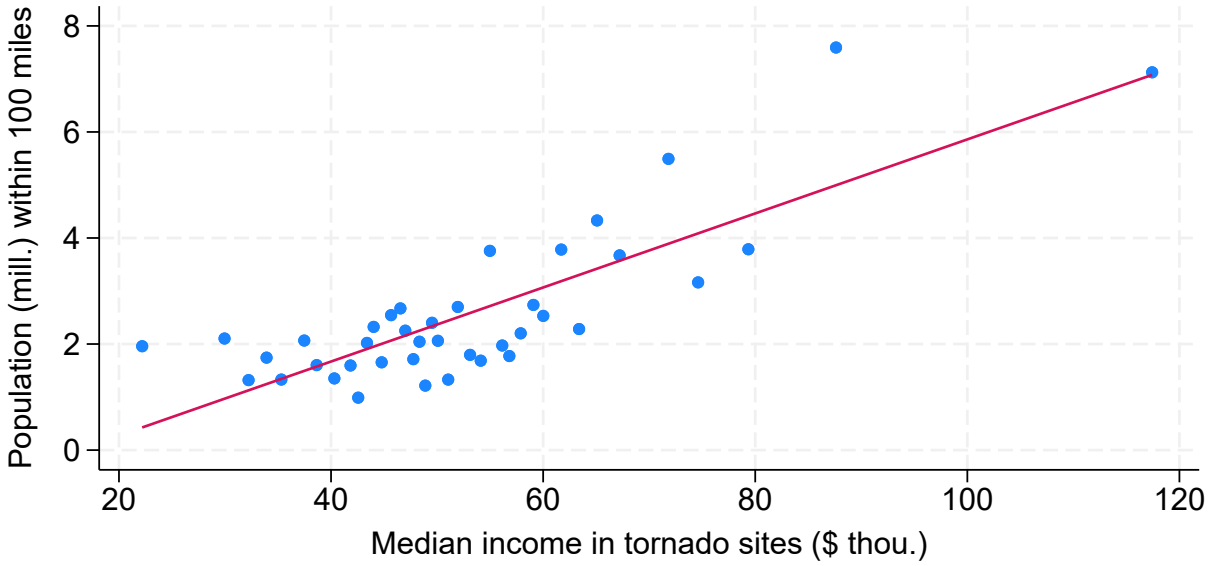
Notes: This figure shows estimated effects on giving 0-5 weeks following a fatal tornado, averaged over all observations within bins of distance between donors and affected areas. Bin width is 10 miles for distances less than 100 and is 50 for longer distances.

Figure A.6: Donation response by distance and income in tornado sites



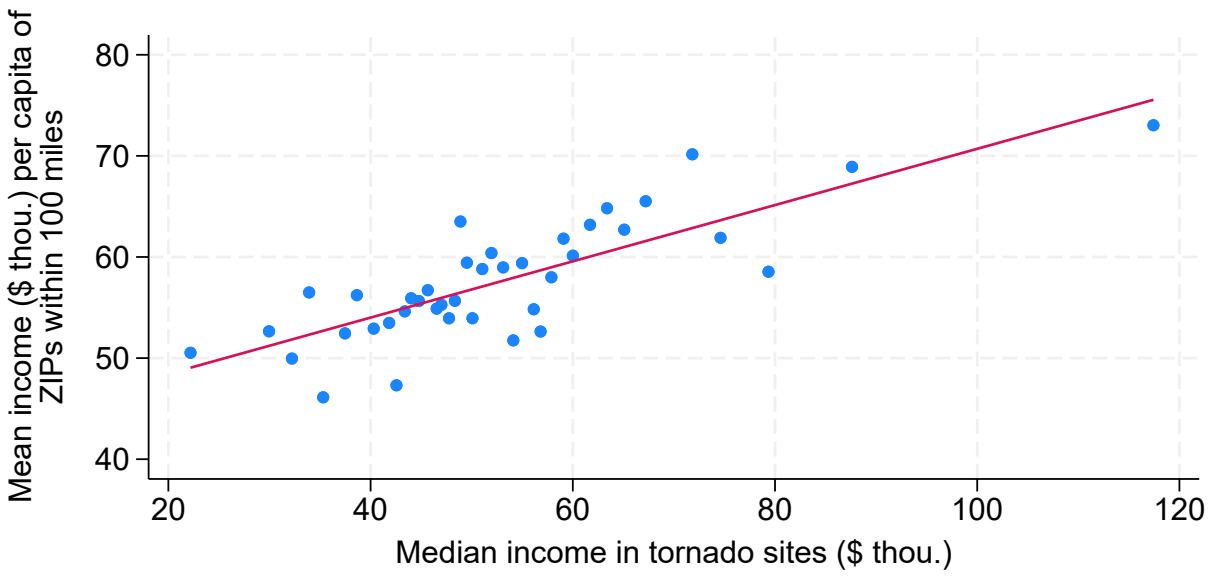
Notes: This figure shows estimated coefficients for tornadoes within 100 miles, averaged within 10-mile bins of distance between donors and affected areas for each tercile of the overall distribution of income in affected areas.

Figure A.7: Nearby population by income in tornado sites



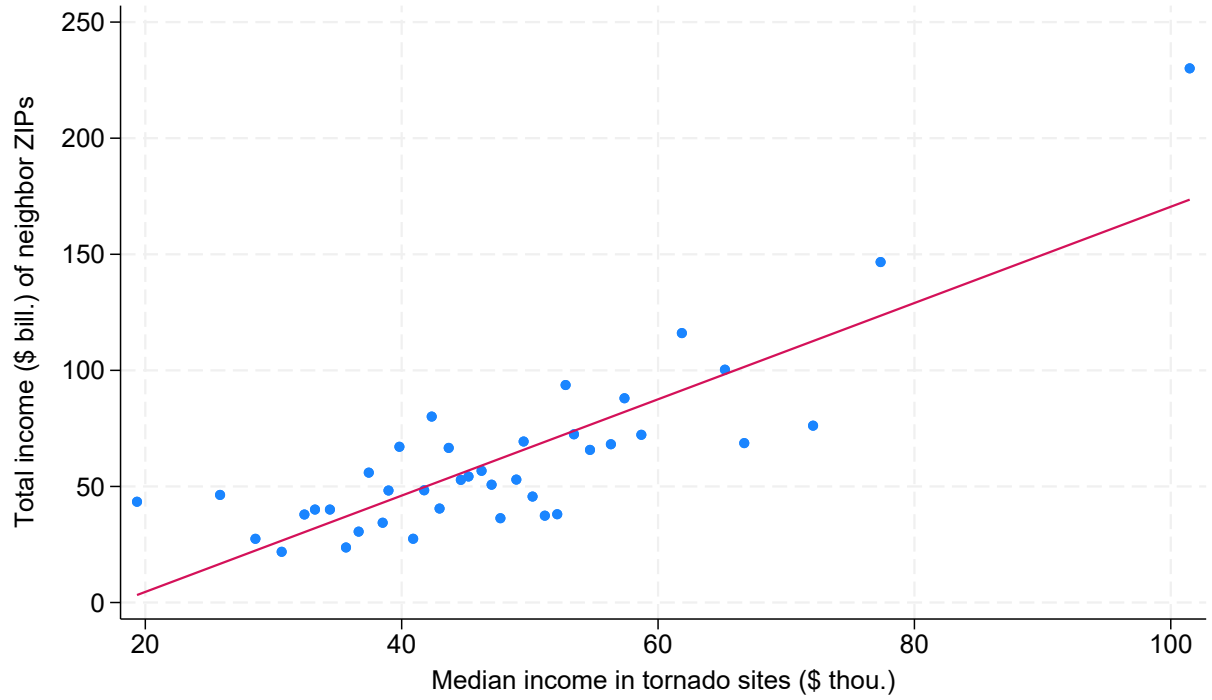
Notes: This figure shows the sum of population within 100 miles of affected areas. Each mark represents the mean within a bin for a quantile of income in affected areas.

Figure A.8: Nearby mean income by income in tornado sites



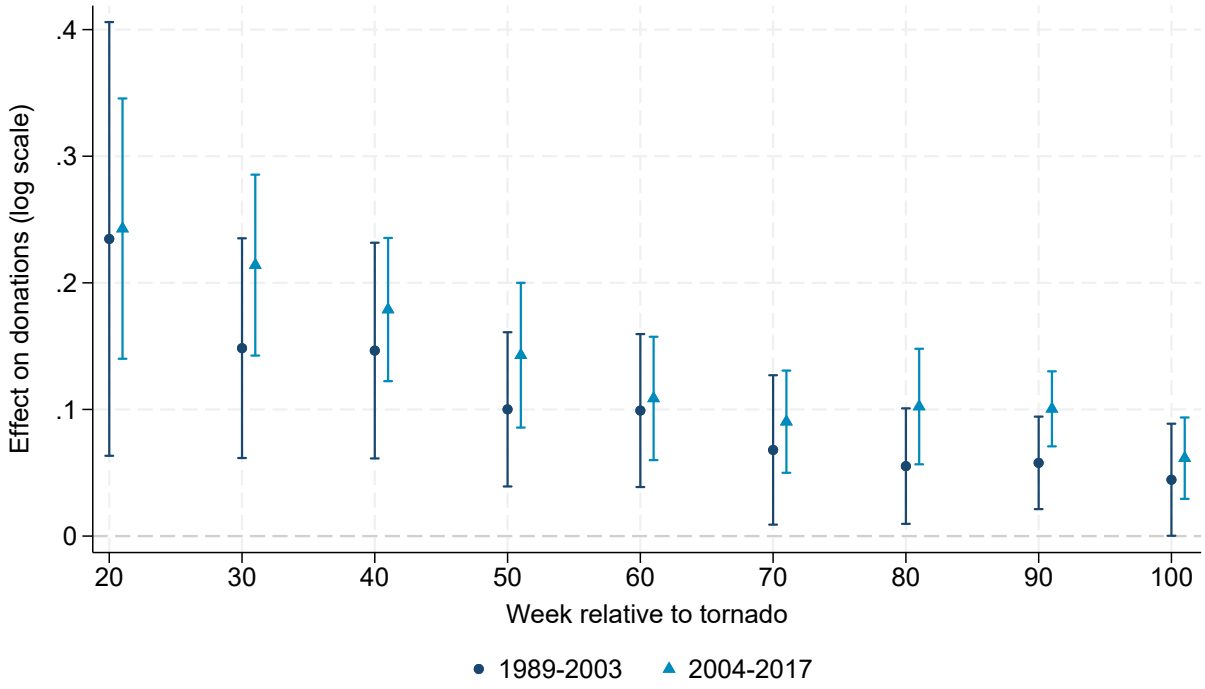
Notes: This figure shows mean income in ZIP Codes within 100 miles of affected areas. Each mark represents the mean within a bin for a quantile of income in affected areas.

Figure A.9: Nearby total income by income in tornado sites



Notes: This figure shows total income, calculated by multiplying per capita income by population, within 100 miles of affected areas. Each mark represents the mean within a bin for a quantile of income in affected areas.

Figure A.10: Giving response by distance and time period



Notes: This figure shows point estimates and confidence intervals of the giving response 0-5 weeks following a fatal tornado by distance and time period.

B Appendix Tables

Table A.1: Correlations between tornado damage and donor-area characteristics, 200 miles

	(1) Fatalities (log)	(2) Injuries (log)	(3) Losses (log)	(4) Distance (miles)
Population (1000s)	-0.000015	-0.00044***	-0.00033	-0.020***
	(0.000056)	(0.00012)	(0.00039)	(0.0039)
Median inc. (1000s)	-0.0021***	-0.0069***	-0.0097***	-0.18***
	(0.00013)	(0.00030)	(0.00095)	(0.0091)
Urban	0.045***	0.040***	0.10**	-0.88*
	(0.0078)	(0.015)	(0.046)	(0.48)
Dep. var. mean	0.69	2.2	14	129
N	71,768	71,768	71,768	71,768

Notes: Robust standard errors are reported in parentheses. *** p< 0.01 ** p< 0.05 * p< 0.1.

Table A.2: Income summary statistics

	(1)	(2)	(3)	(4)	(5)	(6)
	Tornado-affected area			Donor area		
Tercile	Mean	Std. dev.	Obs.	Mean	Std. dev.	Obs.
All	52,840	17,503	501	65,889	23,015	35,576
1	37,651	6,408	167	45,618	7,421	11,859
2	50,252	3,077	167	61,618	4,259	11,859
3	70,616	17,763	167	90,434	22,008	11,858

Table shows means and standard deviations of incomes in donor and tornado-affected areas, overall and by income tercile. Sources: NOAA, US Census.

Table A.3: Average effect on other outcomes weeks 0-5 after a fatal tornado

	(1)	(2)	(3)	(4)
	ln(donation)	Any donation	ln(donations)	donations per donor pop (pct)
Average effect weeks 0-5	0.21***	0.022***	0.077***	0.0024***
	(0.031)	(0.0044)	(0.013)	(0.00043)
N	7,037,994	7,037,994	7,037,994	6,261,112

Notes: Standard errors, clustered by 2-digit ZIP Code, are reported in parentheses. *** p< 0.01 ** p< 0.05 * p< 0.1. Outcome variable indicated above each column.

Table A.4: Donations to charities within 10 miles of tornado

	(1)	(2)	(3)	(4)	(5)	(6)
Log fatalities, tercile 1	0.0076	0.016	0.014	0.0053	0.0092	0.0021
	(0.020)	(0.017)	(0.020)	(0.020)	(0.020)	(0.021)
Log fatalities, tercile 2	0.013	0.010	0.013	0.013	0.015	0.021*
	(0.011)	(0.010)	(0.011)	(0.011)	(0.011)	(0.012)
Log fatalities, tercile 3	0.018**	0.017**	0.022***	0.018**	0.014*	0.011
	(0.0082)	(0.0078)	(0.0082)	(0.0082)	(0.0083)	(0.0085)
Tornado, tercile 1	–0.011	–0.017	–0.013	–0.0094	–0.0089	0.0030
	(0.020)	(0.019)	(0.020)	(0.020)	(0.020)	(0.021)
Tornado, tercile 2	–0.020	–0.013	–0.021	–0.018	–0.021	–0.037
	(0.024)	(0.022)	(0.024)	(0.024)	(0.024)	(0.025)
Tornado, tercile 3	–0.0028	–0.0034	–0.0095	–0.0017	–0.0022	0.0092
	(0.0093)	(0.0085)	(0.0091)	(0.0094)	(0.0095)	(0.010)
p-val, coeff. 1 = coeff. 2	0.81	0.76	0.95	0.72	0.81	0.44
p-val, coeff. 1 = coeff. 3	0.64	0.95	0.72	0.55	0.83	0.69
p-val, coeff. 2 = coeff. 3	0.72	0.58	0.49	0.71	0.97	0.52
$ mill. per tornado, tercile 1	0.14	0.30	0.26	0.096	0.17	0.038
	(0.36)	(0.31)	(0.36)	(0.36)	(0.36)	(0.38)
$ mill. per tornado, tercile 2	0.82	0.64	0.79	0.82	0.91	1.3*
	(0.68)	(0.63)	(0.68)	(0.67)	(0.68)	(0.76)
$ mill. per tornado, tercile 3	3.1**	3.0**	3.9***	3.2**	2.5*	2.0
	(1.4)	(1.4)	(1.5)	(1.4)	(1.5)	(1.5)
p-val, dollar-val 1 = dollar-val 2	0.38	0.63	0.49	0.34	0.33	0.14
p-val, dollar-val 1 = dollar-val 3	0.045	0.054	0.016	0.038	0.13	0.21
p-val, dollar-val 2 = dollar-val 3	0.15	0.11	0.055	0.14	0.33	0.68
Organization FE	X	X	X	X	X	X
Year FE	X					
Drop large orgs		X				
Org-size-by-year FE			X			
Org-mission-by-year FE				X		
1-digit-ZIP-by-year FE					X	
State-by-year FE						X

Notes: Standard errors (in parentheses) calculated by Delta Method. ***p $<$ 0.01, **p $<$ 0.05, *p $<$ 0.10.

Table A.5: Donations to charities within 30 miles of tornado

	(1)	(2)	(3)	(4)	(5)
Log fatalities, tercile 1	–0.0080	–0.0014	–0.0058	–0.0086	–0.0063
	(0.010)	(0.0096)	(0.010)	(0.010)	(0.010)
Log fatalities, tercile 2	0.0065	0.0052	0.0045	0.0072	0.0059
	(0.0067)	(0.0066)	(0.0067)	(0.0067)	(0.0068)
Log fatalities, tercile 3	0.020***	0.017***	0.021***	0.020***	0.014***
	(0.0048)	(0.0045)	(0.0048)	(0.0048)	(0.0049)
Tornado, tercile 1	–0.0039	–0.0042	–0.00065	–0.0043	–0.0034
	(0.010)	(0.0095)	(0.010)	(0.010)	(0.011)
Tornado, tercile 2	–0.0058	–0.0035	–0.0010	–0.0052	–0.0061
	(0.010)	(0.0098)	(0.010)	(0.010)	(0.010)
Tornado, tercile 3	–0.0065	–0.0023	–0.0053	–0.0056	–0.0049
	(0.0050)	(0.0046)	(0.0050)	(0.0051)	(0.0052)
p-val, coeff. 1 = coeff. 2	0.23	0.56	0.40	0.20	0.32
p-val, coeff. 1 = coeff. 3	0.015	0.071	0.021	0.011	0.077
p-val, coeff. 2 = coeff. 3	0.10	0.13	0.052	0.11	0.33
$ mill. per tornado, tercile 1	–0.79	–0.14	–0.57	–0.85	–0.62
	(1)	(0.94)	(1)	(1)	(1)
$ mill. per tornado, tercile 2	1.1	0.86	0.75	1.2	0.98
	(1.1)	(1.1)	(1.1)	(1.1)	(1.1)
$ mill. per tornado, tercile 3	13***	11***	13***	13***	9.0***
	(3.1)	(2.9)	(3.1)	(3.1)	(3.1)
p-val, dollar-val 1 = dollar-val 2	0.21	0.48	0.37	0.17	0.29
p-val, dollar-val 1 = dollar-val 3	0.000031	0.00019	0.000021	0.000019	0.0033
p-val, dollar-val 2 = dollar-val 3	0.00037	0.00087	0.00014	0.00030	0.015
Organization FE	X	X	X	X	X
Year FE	X				
Drop large orgs		X			
Org-size-by-year FE			X		
Org-mission-by-year FE				X	
1-digit-ZIP-by-year FE					X
State-by-year FE					

Notes: Standard errors (in parentheses) calculated by Delta Method. ***p < 0.01, **p < 0.05, *p < 0.10.