Disparities 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 use a heterogeneity-robust difference-in-differences estimator and focus on deadly tornadoes, which are local and unpredictable. Donations decrease with time and distance and increase with tornado 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 it suggests a role for coordinated redistribution. However, 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 disparity in donations to the ARC.

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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., Lubbock Avalanche-Journal, 2011; United Policyholders, nd; 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). Another potentially important source of informal insurance is charitable giving: 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) and Begley et al. (2023) have documented disparities in insurance coverage and government disaster aid. 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 connects donors with intended recipients for a large number of disasters, 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 heterogeneous donation responses to deadly tornadoes, a local and unpredictable natural disaster. We use transaction-level data from the American Red Cross (ARC) that include the date and ZIP Code for 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, demographics and income in both donor areas 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 significant effects within 200 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 increasing in the income of the donor area, a novel finding that high-income places are relatively responsive to disasters not only in levels but in proportion. The proportional response also increases in the income of the affected area, perhaps due to differences in media coverage.

Natural disasters in the U.S. are one setting in which the dollar value of donations is comparable to the value of government aid. Such decentralization can lead to disparities if there is in-group bias, which we test with respect to income and the share of white residents. To do so for each characteristic, we examine the interaction of the value of the characteristic for a donor areas 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 areas' relatively large response when a tornado affects low-income areas provides suggestive evidence of distributional preferences, and because high-income areas provide the majority of donations, we might therefore expect to find that donations are decreasing in the income of affected areas.

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 causes average of donations of $600,000 from donors within 100 miles and $2 million from within 200 miles, and both estimates are larger by more than $1 million for tornadoes that strike areas in the top tercile of income. 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. The areas surrounding high-income affected areas contain larger populations, higher incomes, and higher baseline giving than the areas surrounding lower-income affected areas. This unexpected form of agglomeration effects results in a distribution of giving that, based on the proportional responses, appears less supportive of low-income areas than donors themselves intended.

We then test whether the disparity in donations is offset by government aid. We measure progressivity of the government response 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 offsets no more than a small fraction of the disparity in private donations.

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. Charities' reallocation of donations is limited by a legal requirement to adhere to donor intent, and while a former head of the ARC described the requirement as a "straitjacket" for ARC and other large charities, the organization has been accused of reallocating funds in many instances.[1] We cannot measure

[1]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

the degree to which ARC reallocates funds, but our estimates inform the degree to which it or the government should do so. We also note that our estimates are likely a substantial underestimate of disparities in total support because they are driven by spatial sorting and therefore likely to also apply for smaller, local organizations that would not redistribute across disasters. Donations to local organizations are comparable in magnitude to ARC and FEMA support (Deryugina and Marx, 2021).

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 so much as an increase in total giving.[2]

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

president of the ARC at that time (https://edition.cnn.com/2001/US/11/06/rec.charity.hearing/index.html).

[2]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.

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.

2 Data

2.1 Tornadoes and affected-area characteristics

Tornadoes are rotating columns of air that form over land, typically during thunderstorms. Tornadoes 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.[3] 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

[3]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.

tornadoes are most common in the spring, the timing of a tornado strike is overall 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.[4] Over 90% of the 33,550 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 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.[5] 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

[4]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 only for about 45 fatal tornadoes in our sample.

[5]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.

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 2020 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 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 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 blood transfusions, food, shelter, emotional support, and other assistance.[6]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 2020 dollars. To calculate the physical distance between donors and tornado-affected areas, we

[6]https://www.redcross.org/donations/how-the-red-cross-spends-your-donations.html?srsltid=AfmBOoqcNrPLkfX3l7uB_uyQSX05qXbP-DSILnvKBNqsw5f6QS8CdsV7

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.[7] 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 occurring around the same time. We define outlier days as those on which total national donations exceed the maximum of all December 31st donations. There are 28 weeks that include such days, and they fall within 5 continuous spans of time.[8] 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.

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 U.S. Postal Bulletins.

[7] 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.

[8] The 5 spans follow Sept 11, 2001, the Indian Ocean Tsunami in 2004, Hurricane Katrina in 2005, the Haiti earthquake in 2010, and the northeast snowstorm in 2012. We make one span continuous by dropping 2 weeks within it in which donations did not exceed the cutoff threshold.

2.3 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.[9] 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.[10]

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 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,

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

[10] 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.

and 38% of affected counties received some Public Assistance.

2.4 Descriptive statistics

After determining donor and affected-area characteristics, we aggregate our data to the 4-digit-ZIP-by-week level to ease computational burdens. There are 4,051 4-digit ZIP Codes in our data. For simplicity, we refer to 4-digit ZIP Codes as simply "ZIP Codes" in the remainder of the paper.

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 (2020 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 ar-

eas 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).[11] 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 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

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

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 4-digit 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 2-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 4-digit ZIP Code that is not preceded by a fatal tornado within radius R of any ZIP within the relevant 2-digit ZIP Code in the previous $p+K+1$ weeks. The restriction depends on the 2-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.[12]

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) 4-digit 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 2-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.

This estimator yields similar average effects to the two-way fixed effects estimation of

[12]For example, suppose a fatal tornado occurs within R miles of a given 2-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.

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.[13] 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 $\widehat{ln(d^0_{zet})} = max(0, ln(d^1_{zet})) - \widehat{\beta_{zet}}$, and then exponentiating both sides of the equation yields

[13] 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.

$\widehat{d^0_{zt}} = exp(max(0, ln(d^1_{zet}) - \widehat{\beta_{zet}})$. 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 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.[14] 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.[15]

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

[14] 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.

[15] 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.

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

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.

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.

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%.[16],[17] 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 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.

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 2020 dollars (panel (b)).[18] 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.[19] 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.[20]

[16] 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.

[17] 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.

[18] 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.

[19] 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.

[20] 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.

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 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 5 shows total donations as a more flexible function of affected-area incomes using a finer partition of its distribution. [21] Panel

[21] After calculating the total dollars donated by donors living within 100 miles in response to each tornado,

B of Table 5 shows that the difference in absolute donations between the low-income and 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. Figures 6 and 7 show 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 8

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.

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 FEMA aid

Figure 9 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 9 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 9, 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 10 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 9.[22]

5 Conclusion

Charitable giving plays a vital role in funding disaster relief efforts across the United States. We use detailed donation data 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 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. Furthermore, because of spatial autocorrelation in income and population, tornado-affected areas with higher incomes end up attracting a larger amount of post-disaster giving than the relative responses alone would imply. This finding demonstrates that disparities along a particular dimension do not require donors to have explicit preferences

[22] 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.

for one group but can arise indirectly due to other forces that shape social and geographic proximity.

Patterns of giving may not map one-to-one to the relative amount of aid victims ultimately receive. Charities have some latitude in allocating donations across causes, unless a specific event is used to fundraise. But because the relationship between donors and charities is a repeated one, charitable organizations risk alienating future donations if they reallocate funds in ways that contradict donor intent. Additionally, patterns of giving are informative about underlying preferences, and the tendency to give more when victims live closer to the donor may also arise for gifts to small organizations that would not redistribute them.

References

Alesina, A., R. Baqir, and W. Easterly (1999). Public goods and ethnic divisions. *The Quarterly Journal of Economics 114*(4), 1243–1284.

Alesina, A. and E. La Ferrara (2000). Participation in heterogeneous communities. *The Quarterly Journal of Economics 115*(3), 847–904.

Andreoni, J. (1989). Giving with impure altruism: Applications to charity and ricardian equivalence. *The Journal of Political Economy 97*(6), 1447–1458.

Begley, T. A., U. G. Gurun, A. Purnanandam, and D. Weagley (2023). Disaster lending:'fair'prices, but'unfair'access. *Georgia Tech Scheller College of Business Research Paper* (18-6).

Bergdoll, J., C. Clark, A. D. Kalugyer, X. C. Kou, and U. Osili (2019). U.s. household disaster giving in 2017 and 2018. Technical report, Indiana University Lilly School of Philanthropy, Candid, and Center for Disaster Philanthropy.

Billings, S. B., E. A. Gallagher, and L. Ricketts (2022). Let the rich be flooded: the distribution of financial aid and distress after hurricane harvey. *Journal of Financial Economics 146*(2), 797–819.

Borusyak, K., X. Jaravel, and J. Spiess (2024). Revisiting event-study designs: Robust and efficient estimation. *The Review of Economic Studies 91*(6), 3253–3285.

Charness, G. and Y. Chen (2020). Social identity, group behavior, and teams. *Annual Review of Economics 12*, 691–713.

Chen, J. and J. Roth (2024). Logs with zeros? some problems and solutions. *The Quarterly Journal of Economics 139*(2), 891–936.

Cookson, A., E. Gallagher, and P. Mulder (2024). Coverage neglect in homeowners insurance. *Available at SSRN 5057551*.

Cookson, J. A., E. Gallagher, and P. Mulder (2023). Money to burn: Wildfire insurance via social networks. *Available at SSRN 4535190*.

Cornelissen, S., D. Heller, and M. DeLong (2024). Exposed: A report on 1.6 trillion dollars of uninsured american homes. Technical report, The Consumer Federation of America.

Deryugina, T. (2017). The fiscal cost of hurricanes: Disaster aid versus social insurance. *American Economic Journal: Economic Policy 9*(3), 168–198.

Deryugina, T. and B. M. Marx (2021). Is the supply of charitable donations fixed? evidence from deadly tornadoes. *American Economic Review: Insights 3*(3), 383–98.

Enke, B., R. Rodríguez-Padilla, and F. Zimmermann (2023). Moral universalism and the structure of ideology. *The Review of economic studies 90*(4), 1934–1962.

Fong, C. M. and E. F. Luttmer (2009). What determines giving to hurricane katrina victims? experimental evidence on racial group loyalty. *American Economic Journal: Applied Economics 1*(2), 64–87.

Fong, C. M. and E. F. P. Luttmer (2011). Do fairness and race matter in generosity? evidence from a nationally representative charity experiment. *Journal of Public Economics 95*, 372–394.

Intergovernmental Panel on Climate Change (2021). Summary for policymakers. In P. Z. A. P. S. L. C. C. P. S. B. N. C. Y. C. L. G. M. I. G. M. H. K. L. E. L. J. M. T. K. M. T. W. O. Y. R. Y. Masson-Delmotte, V. and B. Zhou (Eds.), *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*.

Jayaraman, R., M. Kaiser, and M. Teirlinck (2023). Charitable donations to natural disasters: Evidence from an online platform. *Oxford Economic Papers 75*(4), 902–922.

Kalin, M. and N. Sambanis (2018). How to think about social identity. *Annual Review of Political Science 21*, 239–257.

Kousky, C. (2013). Facts about fema household disaster aid: examining the 2008 floods and tornadoes in missouri. *Weather, Climate, and Society 5*(4), 332–344.

Lubbock Avalanche-Journal (2011). Data shows tornado victims often uninsured.

Meer, J. (2017). Does fundraising create new giving? *Journal of Public Economics 145*, 82–93.

Ottoni-Wilhelm, M., L. Vesterlund, and H. Xie (2017). Why do people give? testing pure and impure altruism. *American Economic Review 107*(11), 3617–3633.

Roth, J., P. H. Sant'Anna, A. Bilinski, and J. Poe (2023). What's trending in difference-in-differences? a synthesis of the recent econometrics literature. *Journal of Econometrics*.

Scharf, K., S. Smith, and M. Ottoni-Wilhelm (2022). Lift and shift: The effect of fundraising interventions in charity space and time. *American Economic Journal: Economic Policy 14*(3), 296–321.

Shayo, M. (2020). Social identity and economic policy. *Annual Review of Economics 12*, 355–389.

Tajfel, H., M. G. Billig, R. P. Bundy, and C. Flament (1971). Social categorization and intergroup behaviour. *European journal of social psychology 1*(2), 149–178.

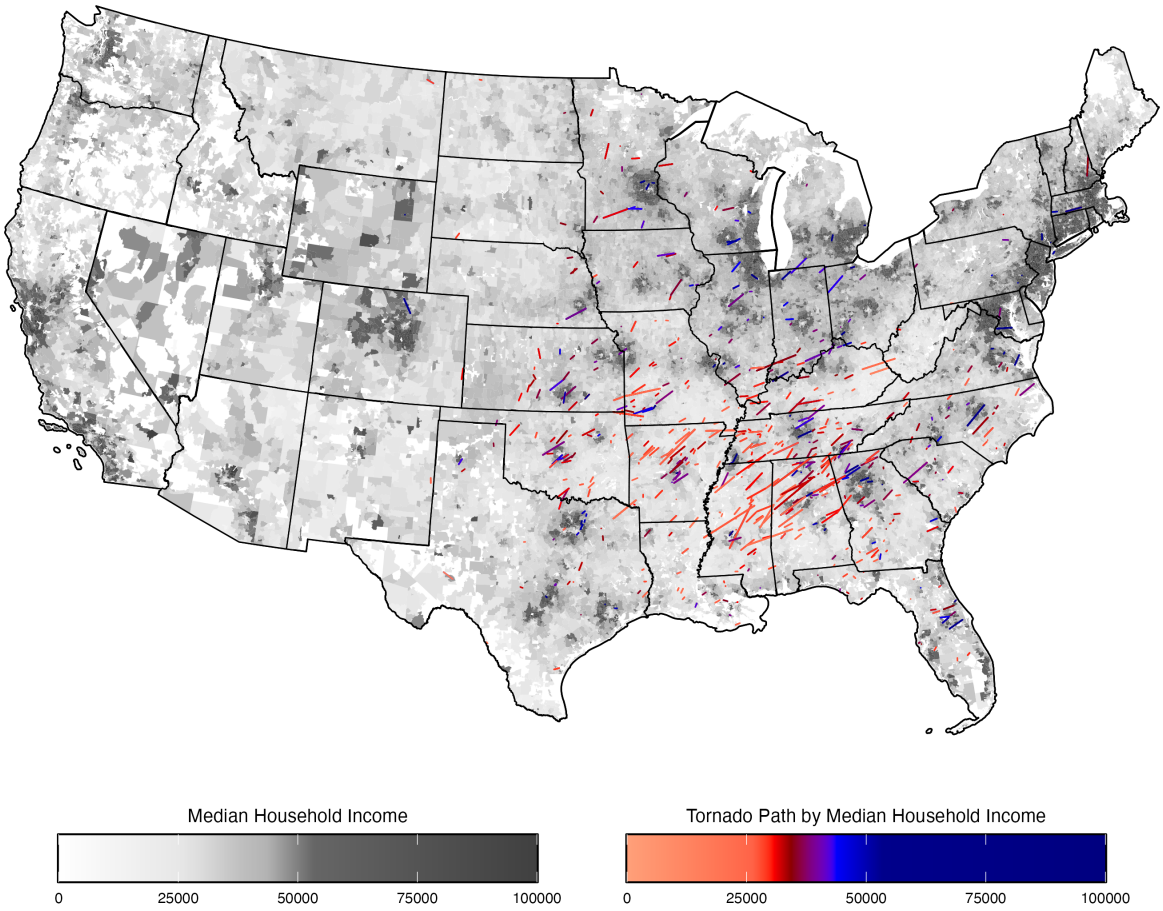
United Policyholders (n.d.). A guide to underinsurance.

Vigdor, J. L. (2004). Community composition and collective action: Analyzing initial mail response to the 2000 census. *The Review of Economics and Statistics 86*(1), 303–312.

Yildirim, P., A. Simonov, M. Petrova, and R. Perez-Truglia (2020). Are political and charitable giving substitutes? evidence from the united states. Technical report, National Bureau of Economic Research.

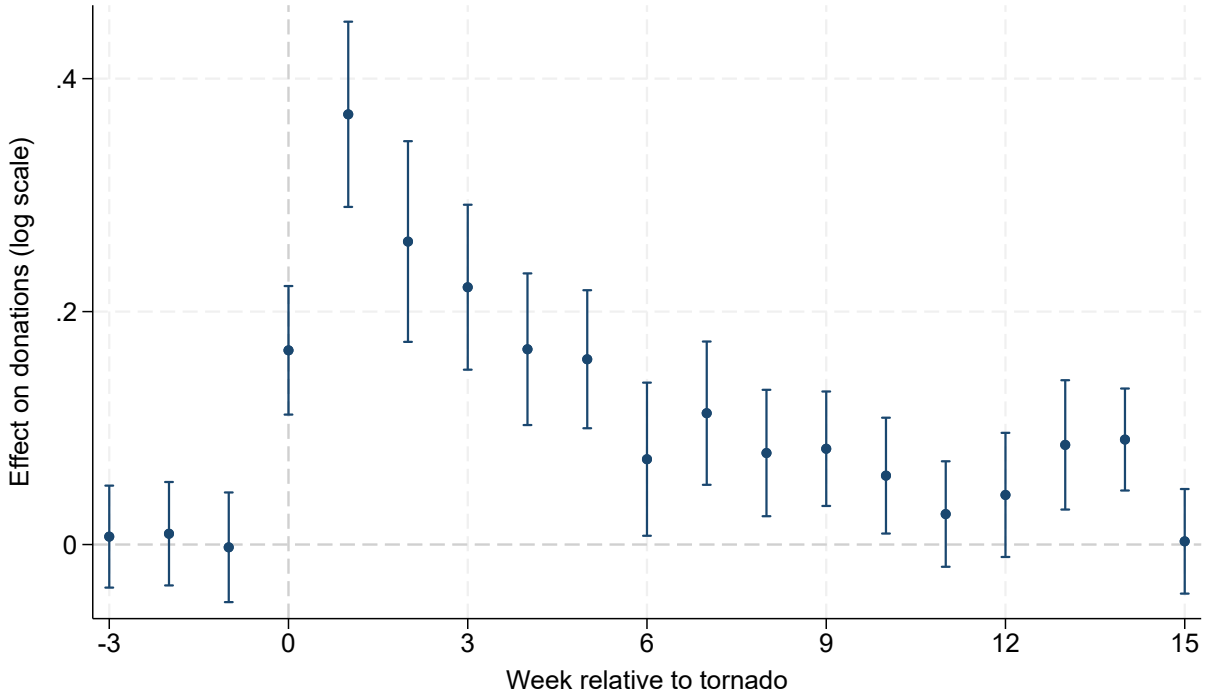
Figures

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.

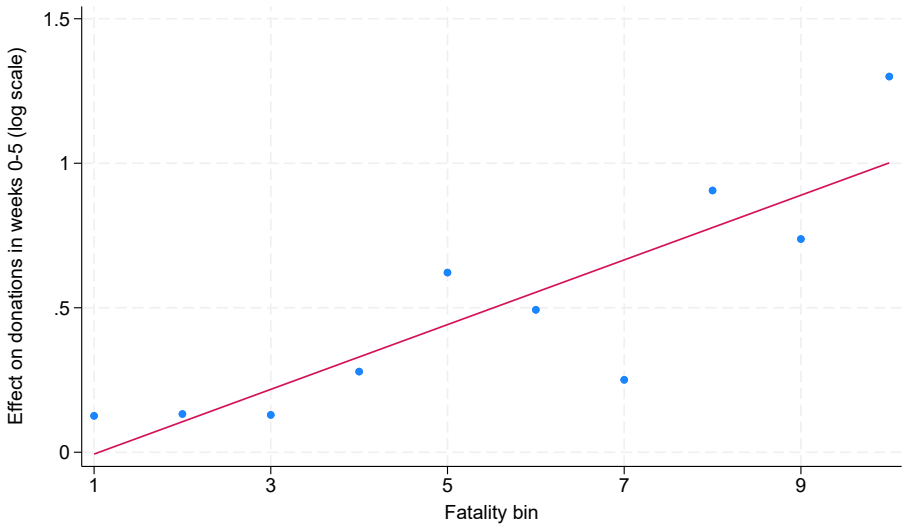
Figure 2: Temporal response of donations



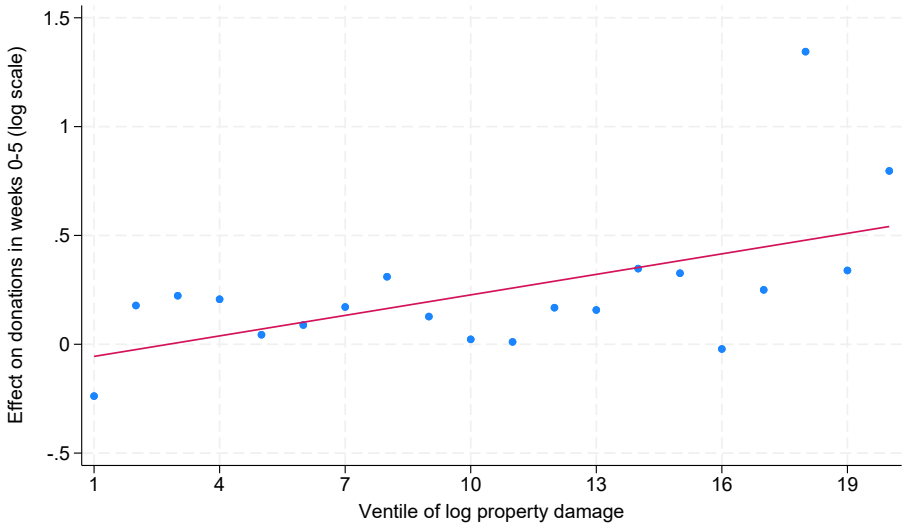
Notes: This figure shows point estimates and 95 percent confidence intervals for the giving response over time. Treatment is defined as being within 100 miles of a fatal tornado. Standard errors are clustered by 2-digit ZIP Code.

Figure 3: Response of donations by tornado severity

(a) Fatalities

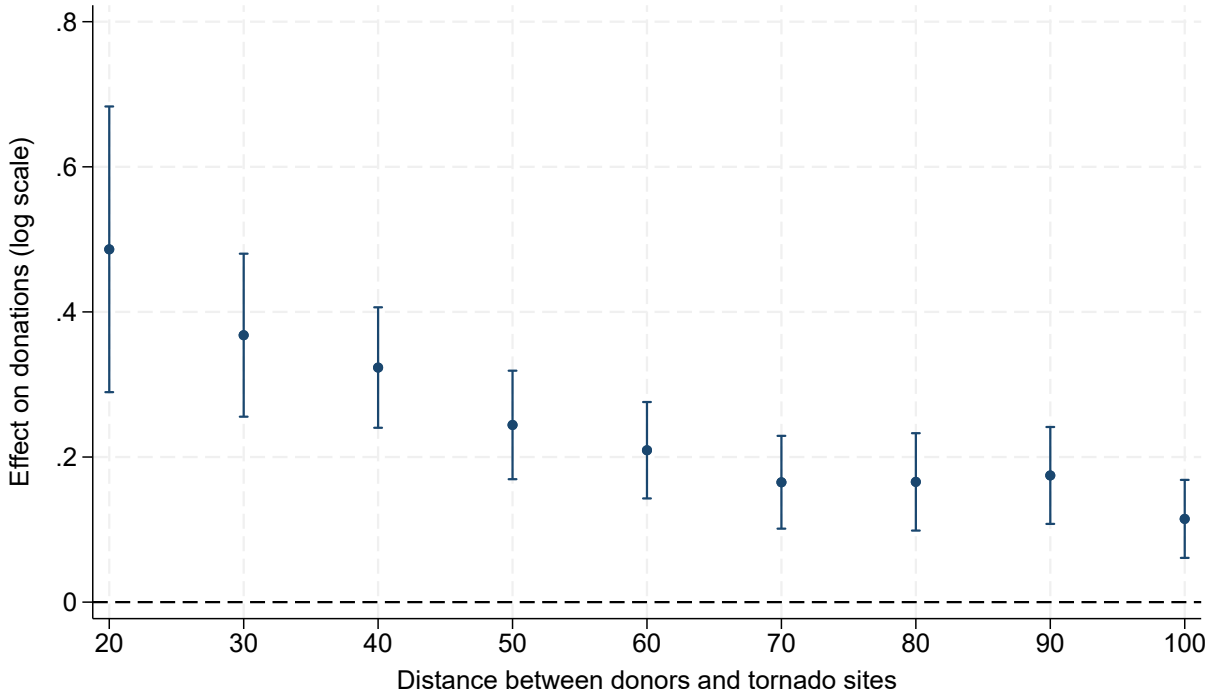


(b) Damage



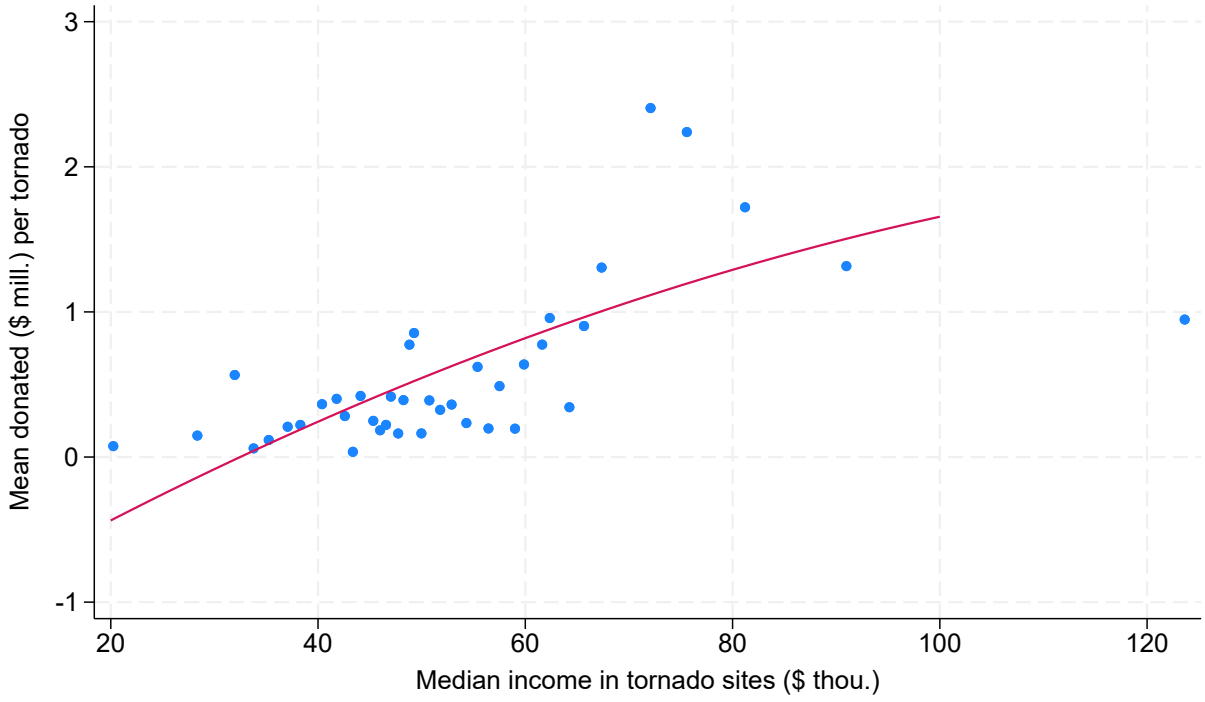
Notes: This figure shows estimates of the relative giving response within 100 miles and 15 weeks of a fatal tornado by binned tornado severity, as measured by (a) the natural log of fatalities or (b) the natural log of damage. We utilize 11 bins for fatalities and 20 bins for property damage.

Figure 4: Donation response by distance



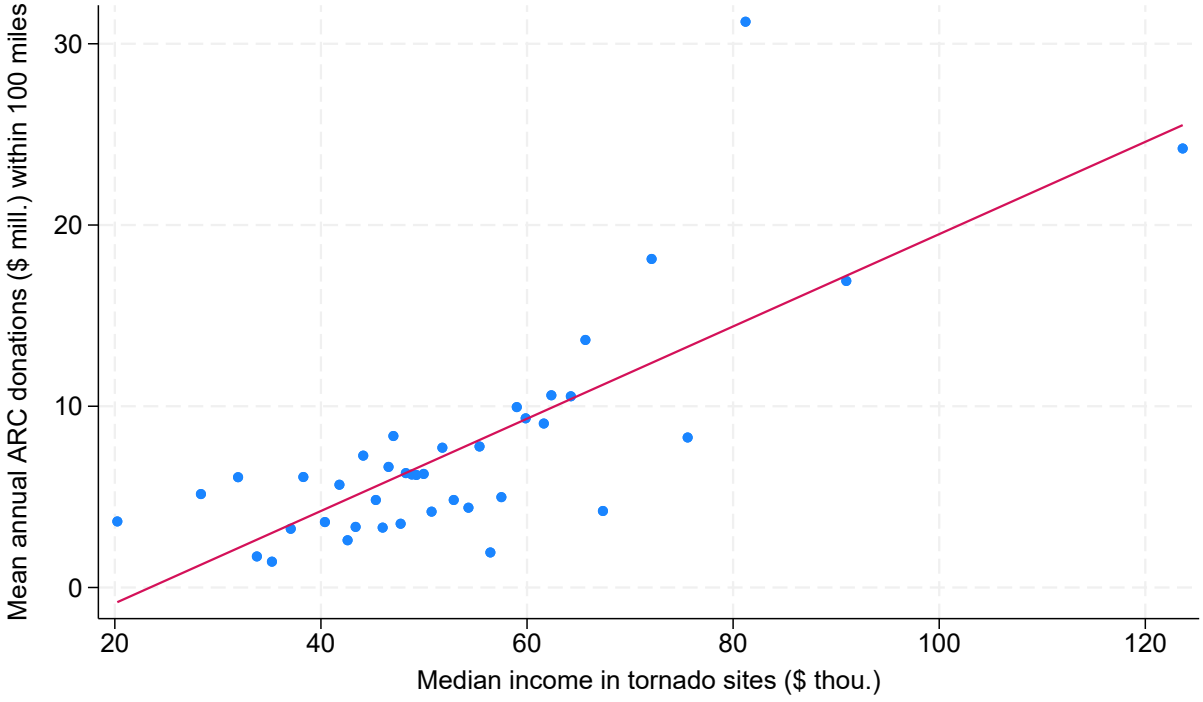
Notes: This figure shows estimated coefficients, averaged over all observations within 10-mile bins of distance between donors and affected areas.

Figure 5: Dollars donated by income in tornado sites



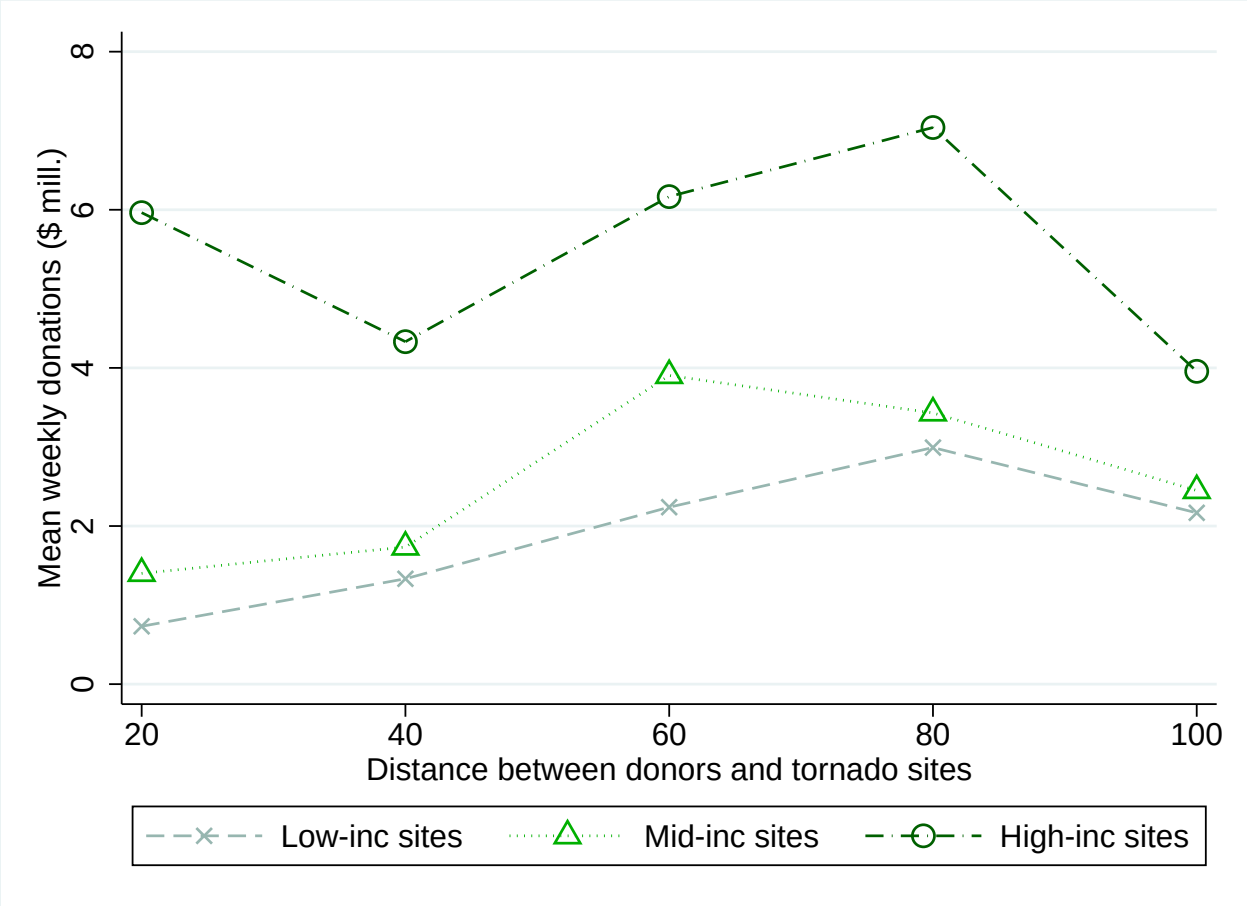
Notes: This figure shows estimates of dollars donated, which are calculated from coefficients as described in the text. Each mark represents the sum within a bin for a quantile of income in affected areas.

Figure 6: Year-round donations by income in tornado sites



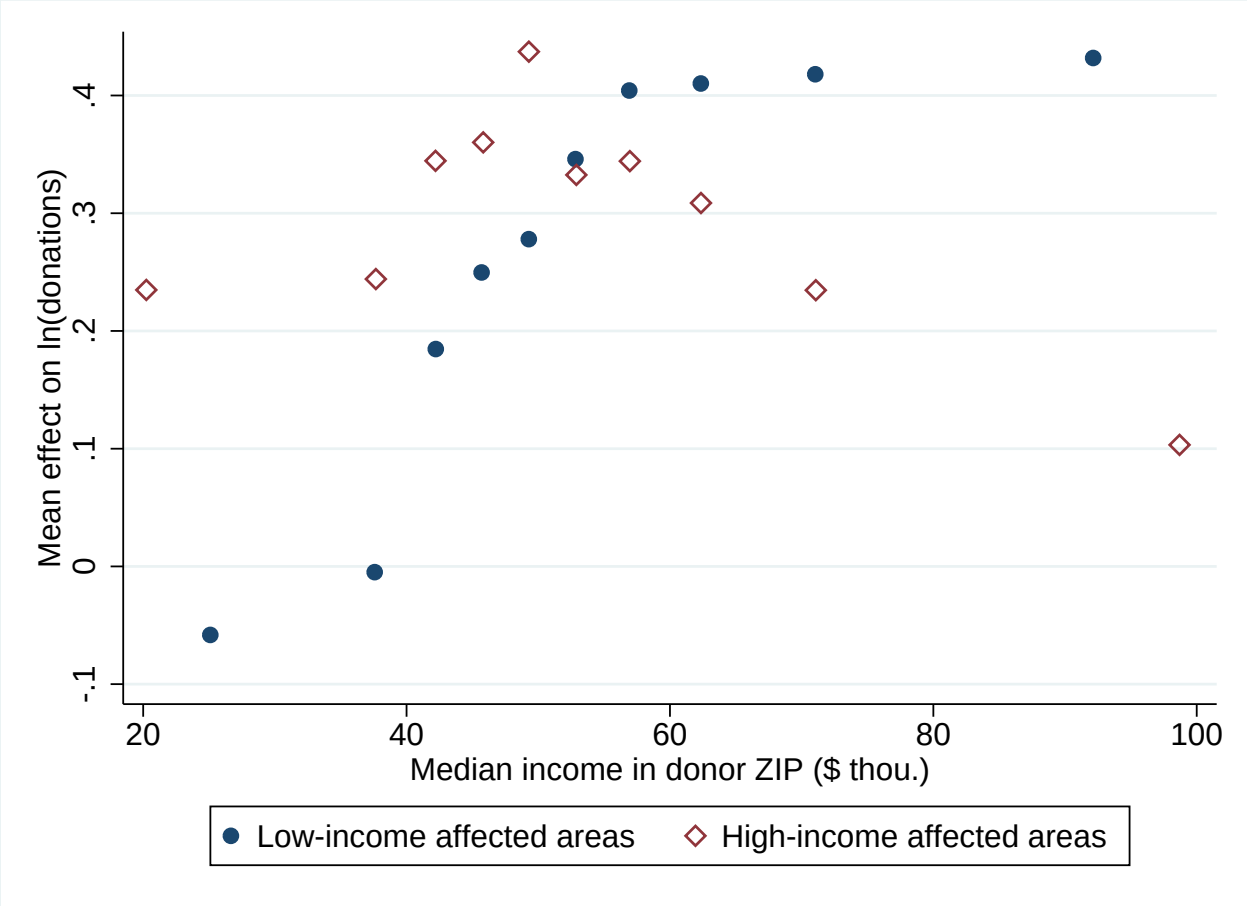
Notes: This figure shows average annual dollars donated by ZIP Codes within 100 miles of areas ever struck by a fatal tornado. Each mark represents the sum within a bin for a quantile of income in affected areas.

Figure 7: Year-round donations by distance from tornado sites



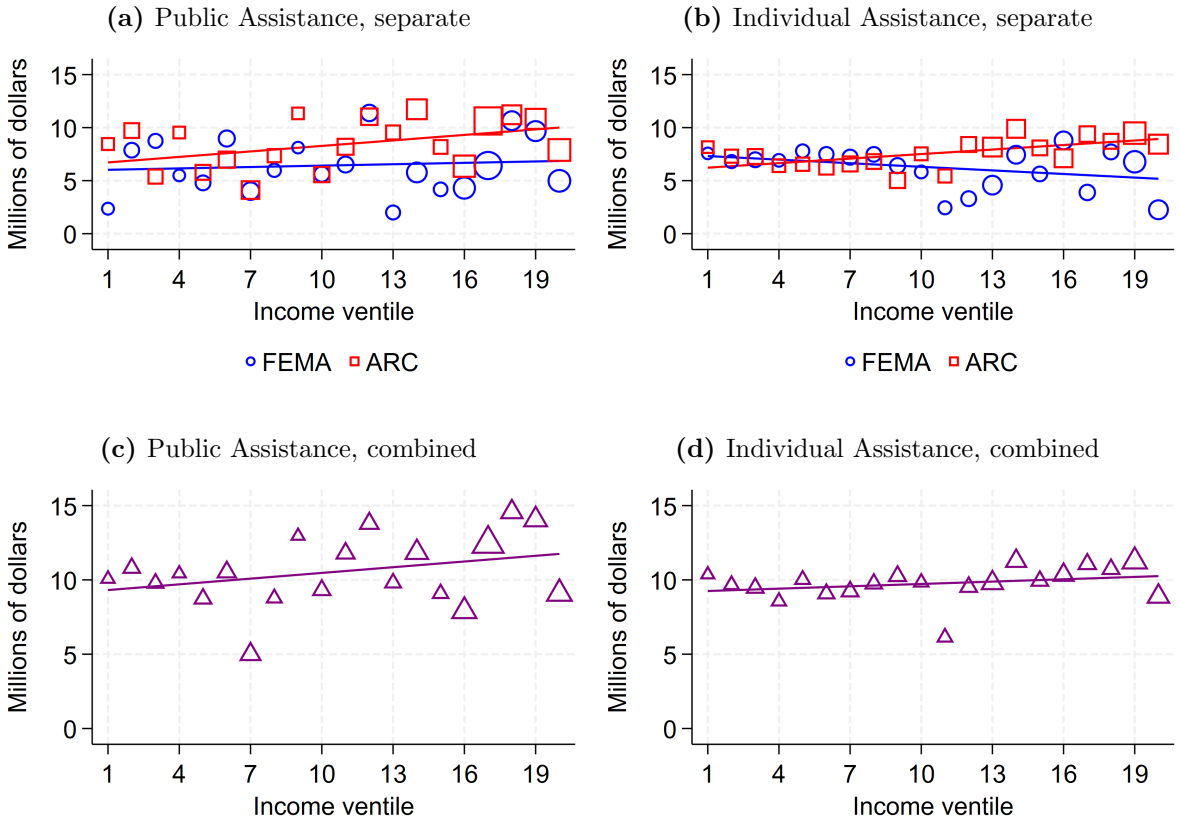
Notes: This figure shows annual dollars donated, averaged within 10-mile bins of distance between donors and affected areas for each tercile of the overall distribution of income in affected areas.

Figure 8: 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 9: 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)
Sq. mi. affected	45.01	59.76	2.52	24.57	105.08	568
Num. blocks affected	8.54	11.04	1	5	18	568
Fatalities	4	9	1	1	7	568
Injuries	34	97	0	10	73	568
Losses (millions USD)	48.29	232.40	0	2.96	72.84	568
Affected population	3,622	8,012	64	1,053	8,671	568
Percent white	83.37	20.16	54.54	92.29	99.13	561
Percent black	11.44	18.86	0	1.80	39.92	561
Median income	52,769	17,164	35,364	49,415	72,549	566

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

Table 2: Predictors of tornado damage, affected area

	(1)	(2)	(3)	(4)	(5)	(6)
	Fatalities		Injuries		Losses (millions USD)	
Population (1000s)	0.39***	0.22	6.5**	4.4*	15***	12**
	(0.13)	(0.15)	(2.6)	(2.7)	(5)	(4.9)
Median inc. (1000s)	-0.015	-0.019	-0.31	-0.25	-0.28	-0.13
	(0.012)	(0.014)	(0.25)	(0.22)	(0.44)	(0.43)
Urban	0.36	-0.55	12	13	8.9	15
	(1.3)	(1)	(15)	(13)	(32)	(31)
Pct. black	-0.022*	-0.014	-0.055	0.081	-0.48	-0.27
	(0.013)	(0.0096)	(0.12)	(0.087)	(0.30)	(0.25)
Injuries (log)		1.2***				-3.8
		(0.30)				(5.7)
Losses (log)		0.97**		3.4		
		(0.45)		(2.6)		
Fatalities (log)				45***		86**
				(9.9)		(34)
Dep. var. mean	3.6	3.6	34	34	49	49
N	560	560	560	560	560	560

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	(2) Injuries	(3) Losses (millions USD)	(4) Distance (miles)
Population (1000s)	0.00088	-0.0019	0.053**	-0.0071**
	(0.00070)	(0.0071)	(0.021)	(0.0033)
Median inc. (1000s)	-0.012***	-0.19***	-0.20***	-0.067***
	(0.0018)	(0.018)	(0.049)	(0.0095)
Urban	0.0087	-0.63	-3.0	0.58
	(0.099)	(0.94)	(2.8)	(0.38)
Pct. black	0.0015	-0.10***	-0.43***	0.024**
	(0.0025)	(0.022)	(0.059)	(0.011)
Dep. var. mean	3.5	30	47	64
N	31,625	31,625	31,625	31,625

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)
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.

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: 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 10: 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.

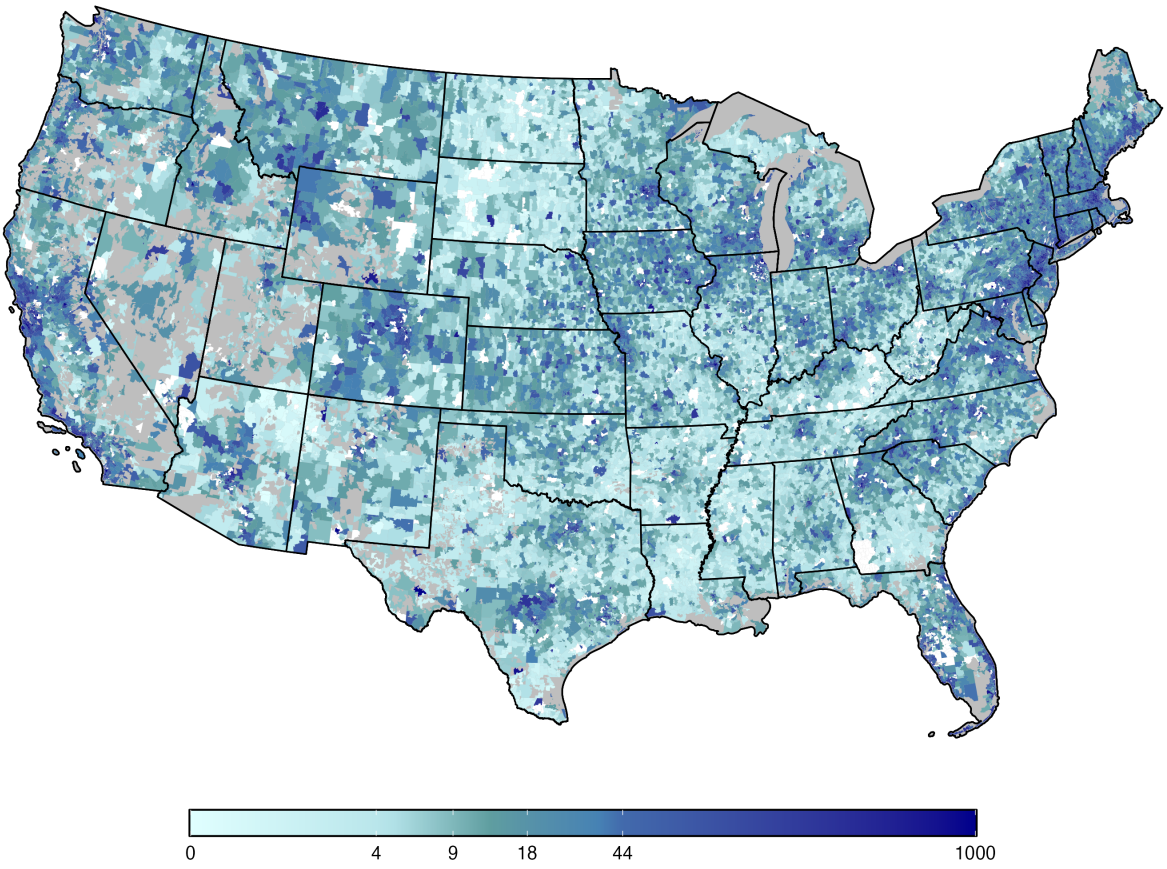
Online Appendix

Disparities in Aid for Natural Disasters

Tatyana Deryugina and Benjamin M. Marx

A Appendix Figures

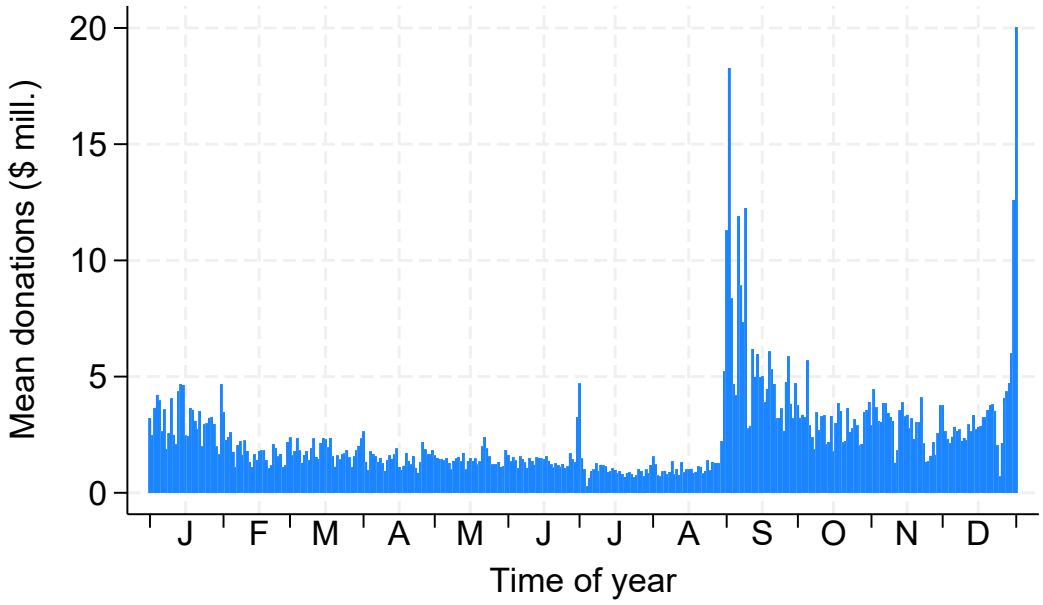
Figure A.1: Spatial distribution of per-capita donations to the ARC



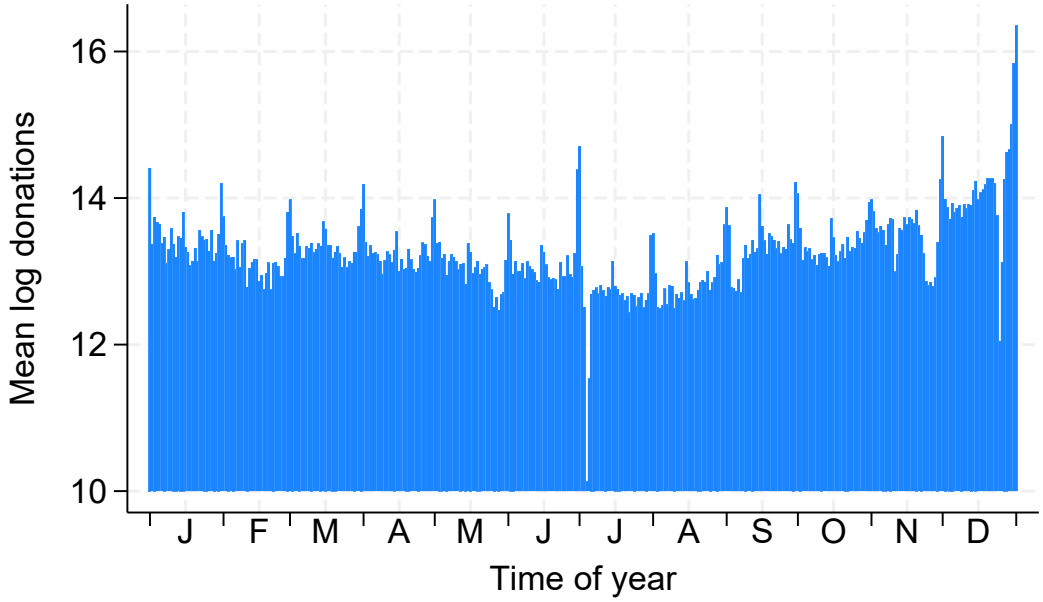
Notes: This map shows total per-capita donations to the American Red Cross over the time period 1989-2017 by ZCTA. White areas have zero donations per capita. Grey areas are not assigned a ZCTA.

Figure A.2: Mean donations by day of year

(a) Levels

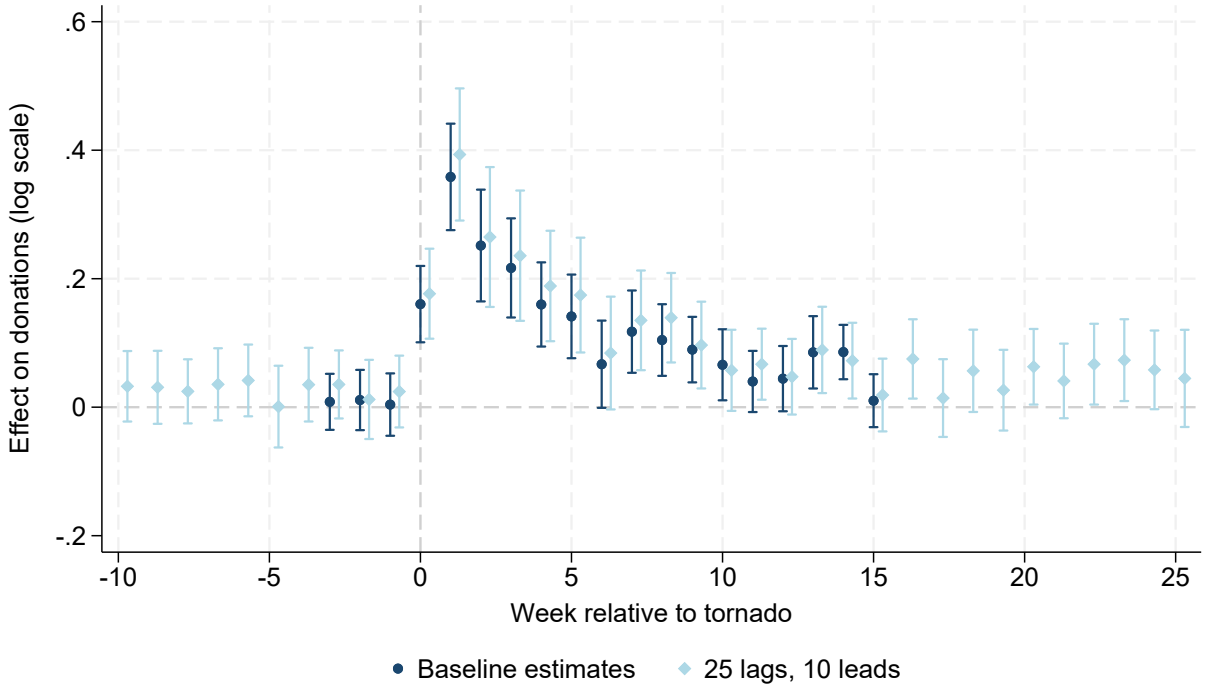


(b) Logs



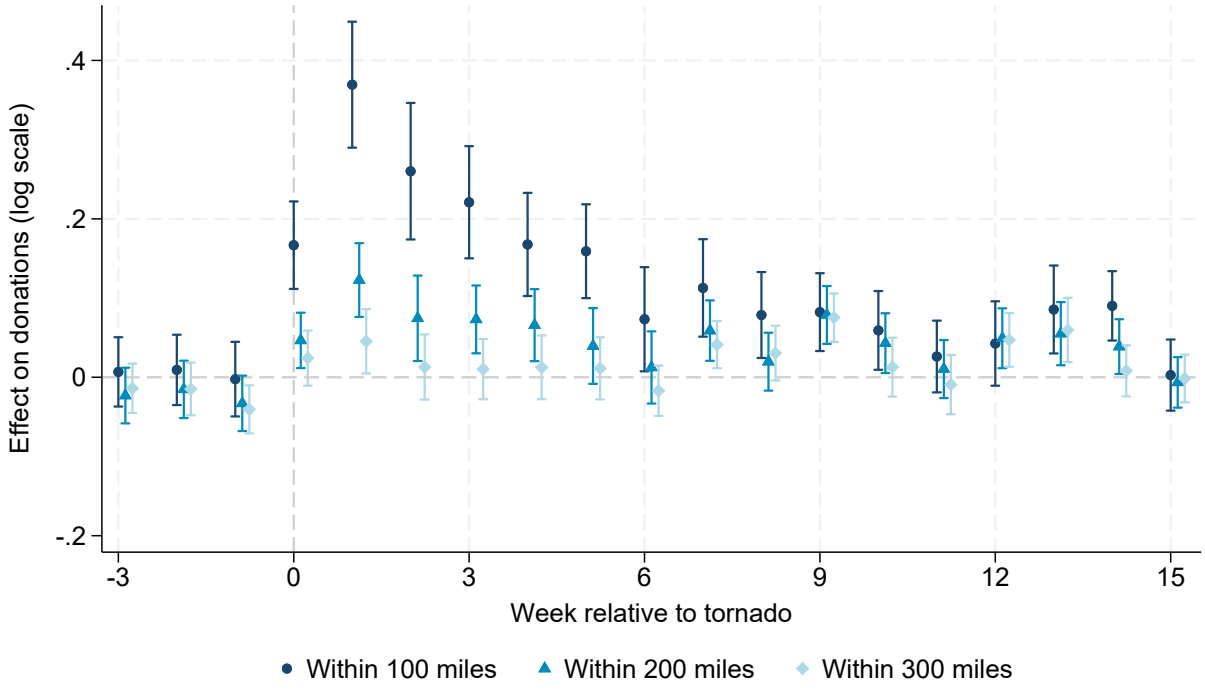
Notes: This figure shows mean daily donations by day of year. The means are obtained by first calculating daily donations across all ZIP Codes in the US, then either averaging across years (panel (a)) or taking the natural log followed by averaging across years (panel (b)).

Figure A.3: Temporal response of donations: robustness



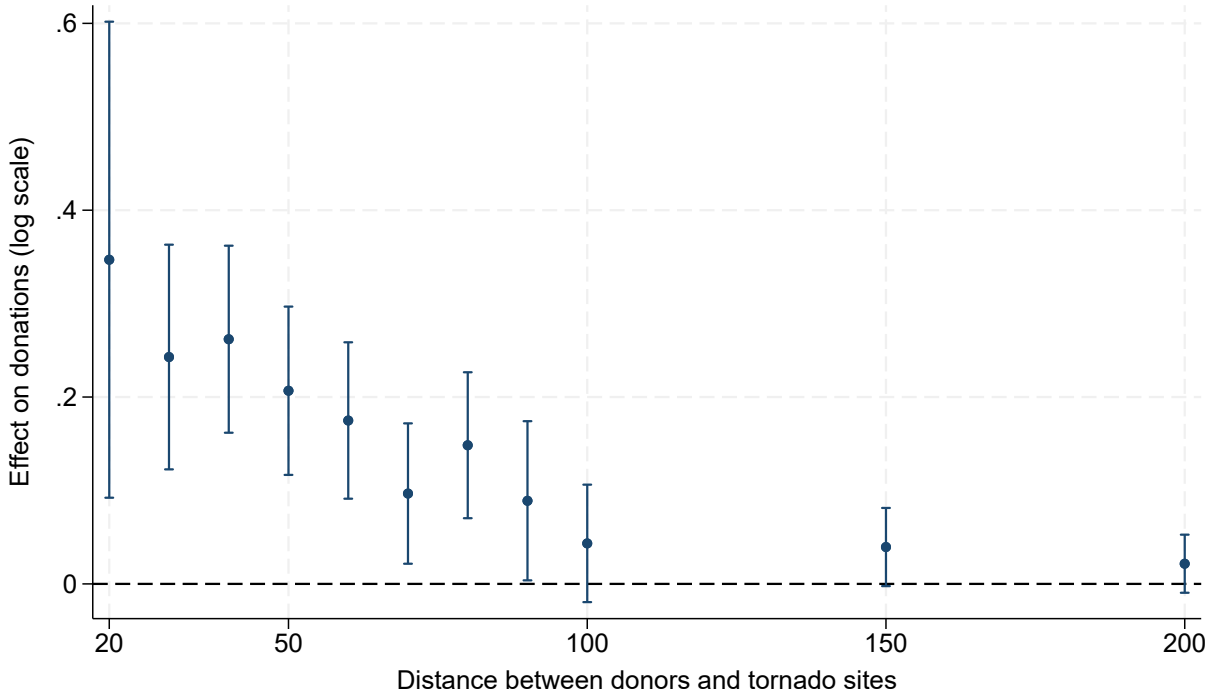
Notes: This figure shows point estimates and 95 percent confidence intervals for the giving response over time with more included leads and lags. Treatment is defined as being within 100 miles of a fatal tornado. Standard errors are clustered by the 2-digit ZIP Code.

Figure A.4: Temporal response of donations by distance



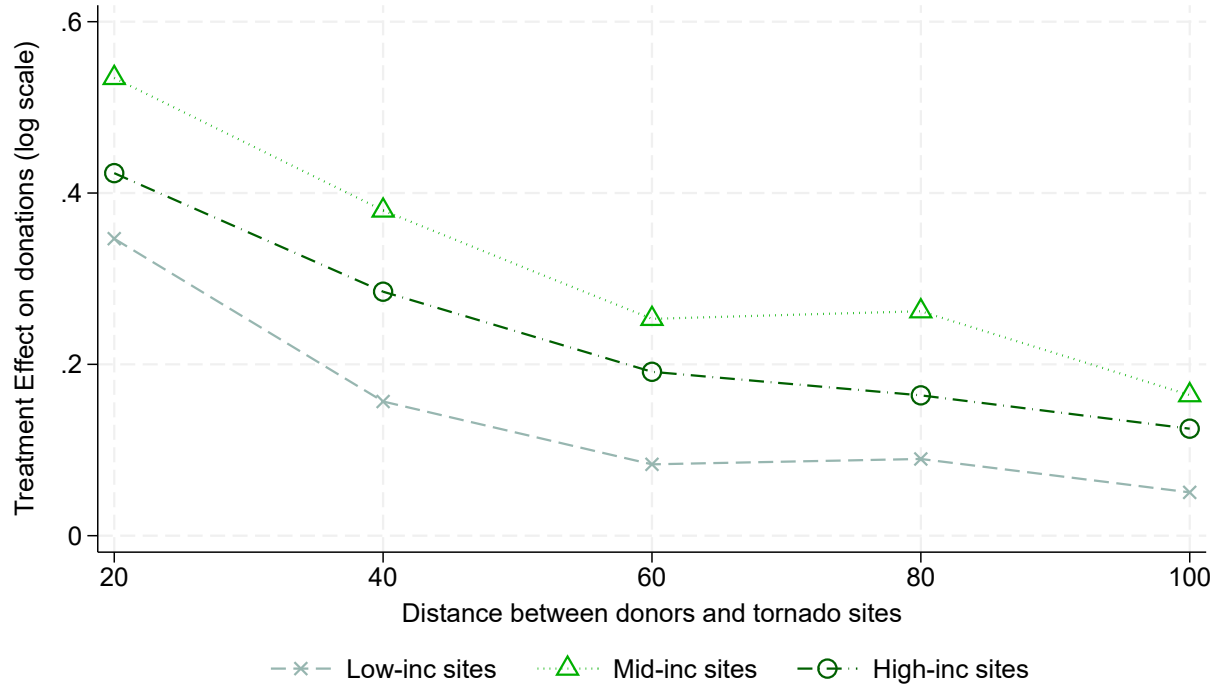
Notes: This figure shows estimates and 95 percent confidence intervals for three sets of estimates, each defining treatment using tornadoes within a different distance. Standard errors are clustered by 2-digit ZIP Code.

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



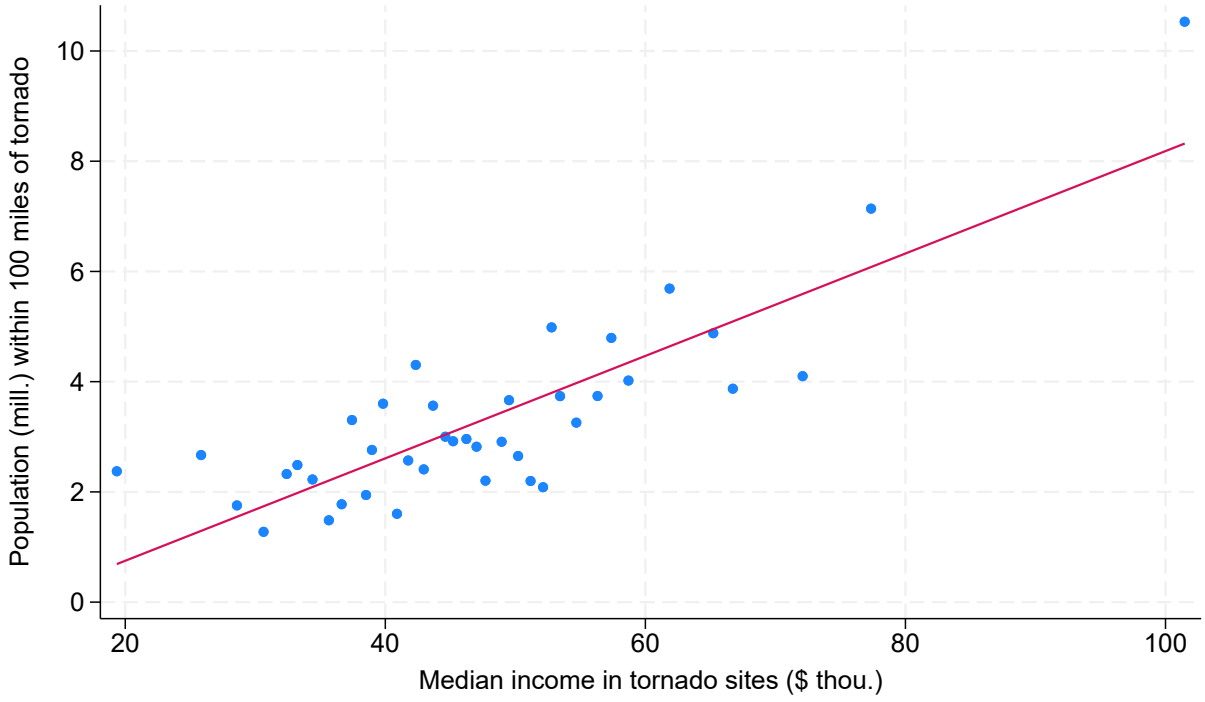
Notes: This figure shows estimated effects on giving 0-5 weeks following a fatal tornado, averaged over all observations within bins of distance between donors and affected areas. Bin width is 10 miles for distances less than 100 and is 50 for longer distances.

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



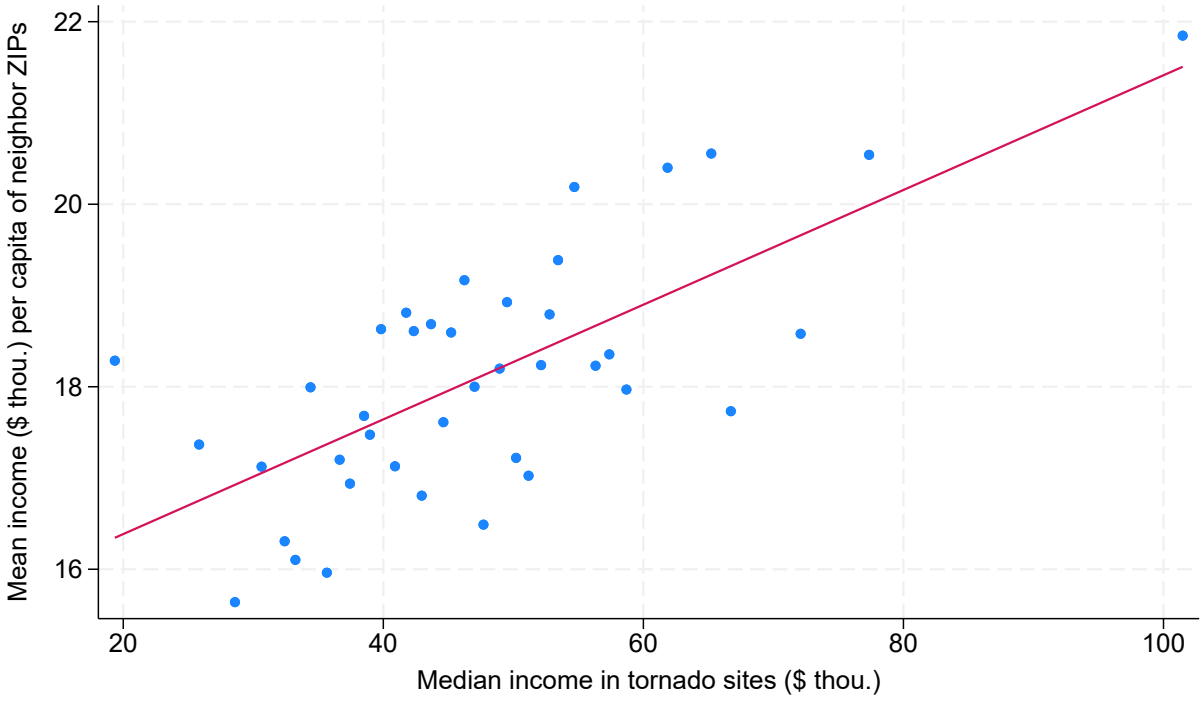
Notes: This figure shows estimated coefficients for tornadoes within 100 miles, averaged within 10-mile bins of distance between donors and affected areas for each tercile of the overall distribution of income in affected areas.

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



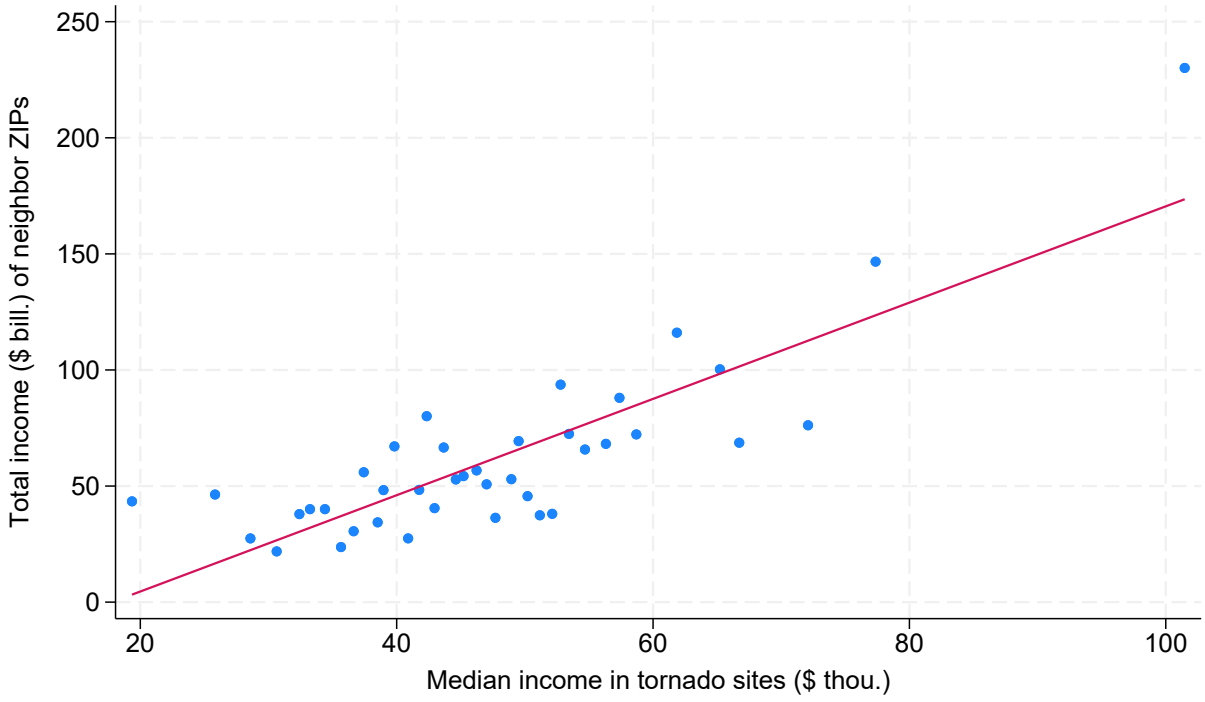
Notes: This figure shows the sum of population within 100 miles of affected areas. Each mark represents the mean within a bin for a quantile of income in affected areas.

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



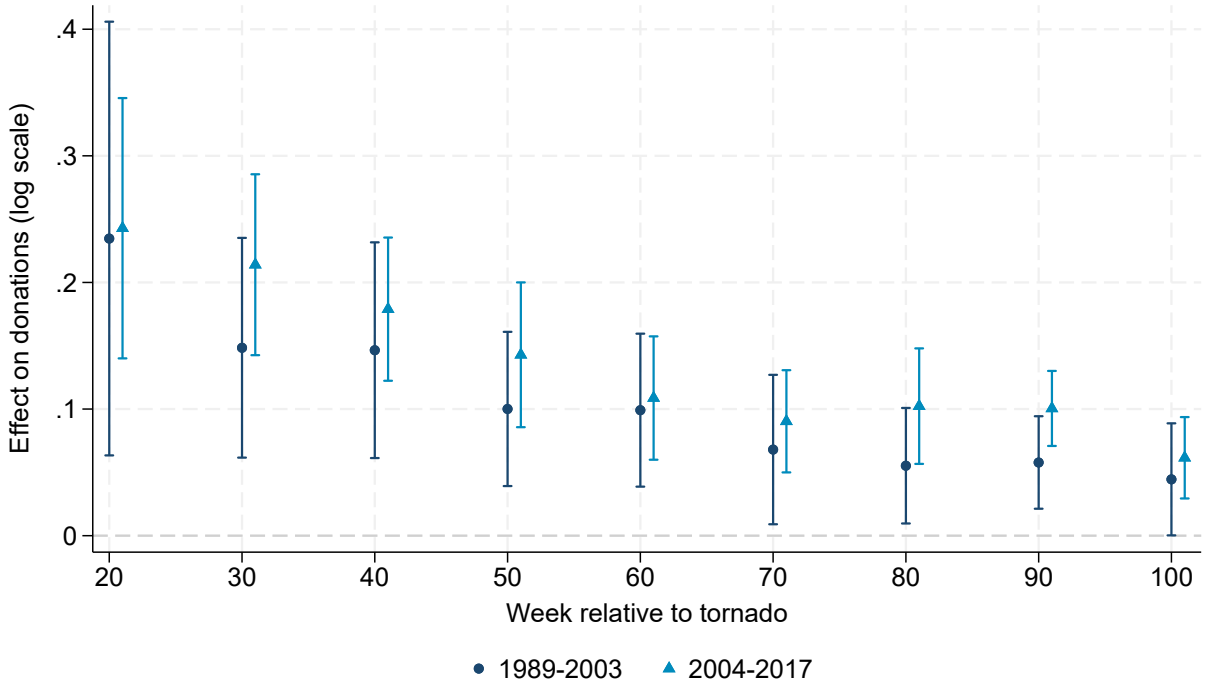
Notes: This figure shows mean income in ZIP Codes within 100 miles of affected areas. Each mark represents the mean within a bin for a quantile of income in affected areas.

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	(2) Injuries	(3) Losses (millions USD)	(4) Distance (miles)
Population (1000s)	-0.00043	0.00060	0.012	-0.0083*
	(0.00039)	(0.0044)	(0.012)	(0.0046)
Median inc. (1000s)	-0.013***	-0.24***	-0.29***	-0.21***
	(0.0010)	(0.011)	(0.031)	(0.012)
Urban	0.17***	0.75	-3.3*	-0.56
	(0.064)	(0.66)	(2)	(0.53)
Pct. black	0.010***	-0.086***	-0.58***	-0.15***
	(0.0018)	(0.017)	(0.038)	(0.017)
Dep. var. mean	3.4	30	47	129
N	59,514	59,514	59,514	59,514

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

Table A.2: Income summary statistics

	Tornado-affected area				Donor area	
Tercile	Mean (1)	Std. dev (2)	10th pctile (3)	Median (4)	90th pctile (5)	Obs. (6)
All	58,637	22,070	5,301,017	54,573	20,813	4,750,435
1	36,654	7,340	1,195,199	32,293	11,639	1,086,719
2	50,584	3,249	1,685,020	47,584	3,015	1,446,426
3	75,096	21,864	2,420,798	70,052	18,466	2,217,290

Table shows average incomes of donors and tornado-affected areas, overall and by income tercile. Sources: 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.