Is the Supply of Charitable Donations Fixed? Evidence from Deadly Tornadoes*

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Abstract

Do natural disasters increase charitable giving or simply reallocate a fixed supply of donations? We study this question using IRS data in the context of deadly tornadoes. We find that, among ZIP Codes located in the same state but more than 20 miles away from a tornado's path, donations by households increase by about $2 million per tornado fatality. We find no negative effects of tornado fatalities on donations to charities located in these ZIP Codes. The results imply that giving in response to new needs need not come at the expense of other causes.

JEL codes: D64, Q54, L31

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1 Introduction

Charitable donations are an important source of funding for public goods and redistribution. Overall, U.S. charitable giving makes up about 2 percent of GDP (List, 2011). But it is not well-understood whether an exogenous shock to human need, such as a natural disaster, increases total giving or simply displaces donations that would have gone to other causes. Many laboratory experiments find that incentives or opportunities to donate to one charity reduces giving to the others.[1] However, the laboratory setting may not be reflective of typical giving. Outside of the laboratory, credible causal estimates of displacement effects between causes are rare and generally encompass a small share of charities or of total donations.

We estimate whether deadly tornadoes increase the total amount of charitable giving. We measure charitable giving using an annual panel of ZIP-Code-level individual income tax data from the Internal Revenue Service (IRS), which report all income tax deductions claimed for donations to any registered charity in 2002–2017. Only about 30 percent of households itemize deductions, and itemized donations are disproportionately concentrated among high-income households (Internal Revenue Service, 2020). However, about 84 percent of donations by individuals are itemized, and giving by individuals comprised about 70 percent of all giving in 2017 (Giving USA Foundation, 2018).

We combine the IRS data with geospatial information on the incidence of tornadoes. We focus our attention on lethal tornadoes, which allows us to identify events that affected populated areas and caused tens of millions of dollars' worth of damage, on average. Tornadoes offer a useful natural experiment because they vary over both space and time but are generally limited in their geographic scope. Because tornadoes are short-lived and unpredictable, scientists have not been able to capture most tornadoes' physical properties, such as wind speed. Instead, the National Oceanic and Atmospheric Admin-

[1] See, for example, Reinstein (2012); Cairns and Slonim (2011); Reinstein (2011); Corazzini, Cotton and Valbonesi (2015); Ek (2017); Filiz-Ozbay and Uler (2017); Deck and Murphy (2019); Harwell, Zindler and Eckel. (2020); Schmitz (2019).

istration (NOAA) maintains a database capturing tornado-related fatalities, injuries, and property damage—which are functions of both the tornado's physical properties and the characteristics of the area in which it touches down—of each reported tornado since 1950. Our identifying assumption is that, conditional on a host of fixed effects and controls, tornado fatalities are unrelated to any unobservable determinants of charitable giving.

We find that lethal tornadoes significantly increase total charitable donations by individuals living nearby but outside of the directly affected area. Specifically, a tornado fatality increases total donations by individuals living at least 20 miles away from a tornado's path but in the same state by about $2 million. Because total giving increases, we can rule out perfect substitution between charitable causes and conclude that the supply of donations is not fixed.

We then estimate fatal tornadoes' effects on the receipts of charities using data from information returns that charities file annually with the IRS. The charitable response to a severe tornado typically involves providing victims with basic necessities such as food, clothing, and shelter; tools for clean-up, such as gloves and shovels; and health services, including for mental health.[2] This work is done both by large organizations like the American Red Cross and by local organizations. We show that contributions received by charities within 20 miles of a tornado's path increase by more than $1 million per fatality. We also test whether there is a negative displacement effect on charities in locations more than 20 miles away but in the same state—locations from which total giving increased. Our estimate of the effect on donations to charities in these locations is positive and not statistically significant, suggesting that donations to these charities do not decrease because of increased giving in response to fatal tornadoes.

Charitable giving for natural disasters is common, with a nationally representative survey indicating that about 30 percent of U.S. households made such donations in each of 2017 and 2018 (Bergdoll et al., 2019). Motivations for disaster giving vary, as demon-

[2] See, for example, `https://www.redcross.org/about-us/our-work/disaster-relief/tornado-relief.html`.

strated by two experimental papers studying giving to victims of Hurricane Katrina. Eckel, Grossman and Milano (2007) find that facts about the aftermath and language emphasizing a charity's involvement in the relief effort has a positive effect in a distant location (Minnesota) but a negative effect in a location closer to the hurricane (Texas). Fong and Luttmer (2009) find that showing victims of subjects' own race has a positive or negative effect on giving depending on whether the subjects report feeling close to their racial or ethnic group. Factors external to the donor many also influence the post-disaster giving response: Brown and Minty (2008) find a correlation between media coverage and internet giving for the devastating 2004 Asian tsunami.[3] To our knowledge, our paper is the first to quantify the charitable response to natural disasters using administrative data.[4] With these data we observe donations to the full spectrum of causes, allowing us to estimate effects on total giving.

Our paper studies whether disaster giving displaces other giving. Nearly 80 percent of U.S. households reported that their disaster giving did not affect their giving to other causes (Bergdoll et al., 2019), but people may be reluctant to admit that they reduced charitable giving to other causes. Consistent with the survey evidence and ours, however, Scharf, Smith and Wilhelm (2017) find that donors to international disasters do not decrease their giving to other causes. Using time-series variation, they study donations by individuals in the UK in the weeks following each of six appeals for major international disasters occurring between June 2009 and July 2014. By contrast, we are able to define treatment and control groups in each year and estimate relative changes among the treated.

The extent to which individuals substitute donations to one charity for donations to

[3] A related literature focuses on the determinants of domestic or foreign disaster aid (e.g. Besley and Burgess, 2002; Garrett and Sobel, 2003; Drury, Olson and Van Belle, 2005; Eisensee and Strömberg, 2007; Strömberg, 2007; Healy and Malhotra, 2009; Cole, Healy and Werker, 2012; Deryugina and Kirwan, 2018).

[4] Our use of individual income tax data follows the literature on the tax-price elasticity of charitable giving (Randolph, 1995; Auten, Sieg and Clotfelter, 2002; Bakija, Gale and Slemrod, 2003; Bakija and Heim, 2011). Our use of the information returns that nonprofit organizations file with the government follows studies estimating the effects of government grants on charities' fundraising efforts (Andreoni and Payne, 2003, 2011).

another appears to vary across settings. In theory, increases in the number of charities or in the number of people served by a charity have ambiguously signed effects on donations (Rose-Ackerman, 1982, 1987). The supply of donations may be completely fixed if giving exhibits "mental accounting" (Tversky and Kahneman, 1981; Kahneman and Tversky, 1984; Thaler, 1985, 1999). Descriptively, the ratio of charitable donations to income has been fairly constant over time (Andreoni and Payne, 2013) and across income categories (Meer and Priday, 2020). Field-study findings differ regarding whether intertemporal displacement does or does not occur (Meier, 2007; Landry et al., 2010; Bekkers, 2015)) and whether displacement between causes does or does not occur (Lacetera, Macis and Slonim, 2012; Meer, 2017; Chatterjee et al., 2020; Petrova et al., 2020; Adena and Hager, 2020). In a review of this literature, Gee and Meer (2019) conclude that "the evidence is decidedly mixed on whether the altruism budget is fixed or flexible." Our paper is the first to employ data that contain the majority of dollars donated across the U.S. and the first to identify effects using a natural experiment with both geographic and temporal variation.

The rest of the paper is organized as follows. In Section 2 we describe our data. In Section 3 we lay out our empirical strategy for estimating the effects of tornado fatalities on charitable giving. In Section 4 we report our results. We conclude in Section 5.

2 Data

2.1 Charitable donations to all causes

Annual data on charitable donations come from the IRS (IRS, 1998–2017). The data are based on individual income tax returns, including all Forms 1040, 1040A, and 1040EZ. They report deductions claimed for charitable donations in 2002 and in 2004–2017. We also make use of the number of tax returns that include such deductions, the total number of returns, and total Adjusted Gross Income (AGI). In real terms, charitable deductions over this period ranged from $173 billion in 2009 to $226 billion in 2017 (2017 dollars). Donations were relatively low in 2008–2013, during and after the Great Recession (see Appendix Figure A.1).

Returns are compiled by filing year, providing totals based mostly on the preceding tax year but also including some late returns for the previous tax year. Data are aggregated by the ZIP Code listed on the return, which is usually the ZIP Code of the taxpayer's home address but could alternatively be the address of a lawyer, accountant, or place of business. We focus on ZIP Codes located in the contiguous United States.

The IRS data provide an unbalanced panel of 37,274 ZIP Codes on which we impose a few additional restrictions. The IRS has taken varying steps to avoid disclosure of information about individual taxpayers. ZIP Codes with fewer than a threshold number of returns are excluded from the dataset, and charitable donations below an undisclosed threshold are coded as zeroes. We restrict our sample to ZIP Code-year observations with at least 250 returns (the most stringent threshold). This restriction omits 8,406 small ZIP Codes that comprise about 0.3 percent and 0.2 percent of total observed AGI and charitable giving, respectively. Because IRS disclosure rules prevent us from distinguishing true zeroes in the data from censored values, we also restrict the sample to ZIP Codes for which charitable contributions are always reported to be strictly positive. This restriction omits an additional 1,467 ZIP Codes that comprise about 0.2 and 0.03 percent of total AGI and charitable giving, respectively. Finally, we drop 458 ZIP Codes that only appear in the data once.

To match ZIP Codes to their geographic location, we use the U.S. Census Bureau's ZIP Code Tabulation Areas (ZCTAs), which are spatial representations of the mailing areas covered by ZIP Codes (U.S. Census Bureau, 2010).[5] To account for changes in the coverage of ZIP Codes over time, we use data from the U.S. Postal Service (USPS, 2001–

[5]For details, see https://www.census.gov/programs-surveys/geography/guidance/geo-areas/zctas.html.

2020).[6] The most common changes are creations of new ZIP Codes for part of an area previously covered by another ZIP Code and elimination of ZIP Codes when a post office is closed. Each change reports two ZIP Codes, which we combine with each other and with all other ZIP Codes to which they are connected through one or more changes to create a set of time-invariant "super-ZIPs." We aggregate our data to the super-ZIP level by summing all IRS variables over the ZIP Codes included in a super-ZIP. Hereafter, we simply refer to these super-ZIPs as ZIP Codes.

Figure 1 maps the 26,940 ZIP Codes in our final sample (red areas). Areas that are dropped because of the aforementioned sample restrictions are in light grey. Not all parts of the U.S. are part of a ZCTA; these areas are displayed in white. Our coverage is sparsest in the Mountain States—especially Utah and Nevada—as well as the Dakotas. Because the omitted areas comprise a very small share of charitable giving and experience few or no tornado fatalities during our sample period, our results are unlikely to be affected by their exclusion.

About 30 percent of households itemized their deductions in the years of our sample (Internal Revenue Service, 2020). Income tax data are therefore likely to underestimate the total change in individual donations in response to tornadoes.[7] Moreover, itemization is increasing in income: in 2014, households with AGI below $50,000 made up 29 percent of itemizers but 69 percent of filers. Our estimates will therefore not capture the charitable giving response of the average *household*, but they are more representative of the average *dollar* of donations. This is because higher-income households donate more money on average, and an estimated 84 percent of donations is itemized (Indiana University Lilly Family School of Philanthropy, 2017; Giving USA Foundation, 2018).

[6] Each month, the USPS produces a Postal Bulletin that includes a table of changes to ZIP Code delivery areas.

[7] Alternatively, we might overestimate the total charitable response by individuals if tornadoes cause individuals who have given but not claimed deductions to start claiming deductions. Appendix Table A.3 shows, however, that the number of returns claiming charitable deductions is not significantly affected by tornado fatalities.

2.2 Tornadoes

Tornadoes are rotating columns of air that form during strong thunderstorms. Winds can reach up to 300 miles per hour, causing catastrophic damage to structures with which such a tornado comes in contact. Our data on tornadoes come from NOAA's Tornado Database, which reports the date and location of every known tornado since 1950, as well as the amount of property damage, fatalities, and injuries it caused (NOAA, 1950–2017).[8]

Tornadoes are common in the U.S. In 2002–2017, the period spanned by our IRS data, 14,533 tornadoes were reported, and every state in the contiguous U.S. experienced at least one. However, almost half of these tornadoes (6,928) caused no known property damage, fatalities, or injuries and are thus highly unlikely to have triggered a response by a charity. Even among the thousands of tornadoes that involved fatalities, injuries, or property damage, the median number of each of these is zero (see Panel A of Appendix Table A.1). We therefore restrict attention to tornadoes that are most likely to have prompted a response by charitable organizations: those that caused at least one fatality. Such tornadoes are fairly rare—there were 327 of them during our sample period—and are substantially more devastating than average.[9] On average, a fatal tornado kills four people, causes about 35 injures, and destroys over $50 million worth of property (see Panel B of Appendix Table A.1). Using data for tornado-related disasters in the years 2004–2017, we calculate that the mean amount of federal disaster aid per tornado fatality was $13.3 million and the median was $2.98 million (2008 dollars)[10]

An additional advantage of using fatalities to measure severity is that they are more likely to be reported accurately than property damage or injuries. For example, NOAA

[8]Unfortunately, because tornadoes form and dissipate quickly and have wind speeds that are much higher than that of a hurricane, scientists have not been able to reliably measure most tornadoes' wind speed (Di Justo, 2013). Instead, tornadoes are rated using the "Enhanced Fujita" (EF) scale, which is based on the observed *ex post* damage (National Oceanic and Atmospheric Administration, 2020).

[9]For reference, there were 117 landfalling hurricanes and tropical storms in 2002–2017, and only 24 of them made landfall with hurricane-strength winds.

[10]These data were obtained from `https://www.fema.gov/disasters`. We calculate the average and median amounts of federal disaster aid by dividing the total state-year disaster aid for tornado-related disasters by the corresponding number of fatalities.

records uncertain damage as zero damage, and there is no way to distinguish unknown values from true zeroes. While injuries may also indicate severity, they are also likely to be reported with greater error than fatalities. Furthermore, no distinction is made between minor and major injuries, making them less comparable to each other than fatalities.

Nonetheless, tornado fatalities, injuries, and damage are highly correlated. Among fatal tornadoes in 2002–2017, the correlation between fatalities and damage is 0.88 and the correlation between fatalities and injuries is 0.86.[11] Each additional tornado fatality is associated with 8.2 additional injuries and additional property damage of $18.5 million. Given the high degree of correlation between these variables, we use fatalities as a single severity measure, and our estimates should be interpreted as reflecting the charitable response to a bundle of tornado characteristics.

Figure 1 displays the paths of the 327 tornadoes that formed in 2002–2017 and caused at least one fatality. These tornadoes affected 1,301 ZIP Codes in 34 states. Three key patterns emerge. First, fatal tornado strikes are concentrated in the Midwest and the South, an area known as "Tornado Alley". Second, deadly tornadoes have struck across a wide range of most of the states in which they have occurred. Third, tornadoes are local events, with even the largest rarely passing through more than a handful of ZIP Codes.

We calculate the distance between ZIP Codes and tornadoes using latitude and longitude. These coordinates are available for the start and end points of each tornado. We calculate the latitude and longitude of 2010 ZIP Code centroids using data from Esri (2014). We then calculate the shortest distance between each ZIP Code centroid and the line segment connecting the start and end points of the tornado.

Fatalities are reported at the tornado level. Because we do not know the locations of fatalities along the tornado path, we sum all fatalities caused by tornadoes that passed within a distance band of interest from a given ZIP Code centroid.[12] This process will cre-

[11] Among all tornadoes that cause any damage, fatalities, or injuries, the correlation between fatalities and damage is 0.84 and the correlation between fatalities and injuries is 0.86.

[12] If a tornado affects multiple states, we divide fatalities equally among the affected states (usually two).

ate some degree of mismeasurement, but our design does not depend on finely measured distances.

2.3 Contributions received by charities

Income tax returns report the total amount of charitable donations made but not the organizations to which the money was given. Thus, the income tax data cannot be used to assess how tornadoes affect giving to particular organizations or causes. To do so, we use data on contributions received by charities themselves. These data have been collected by the IRS using Form 990, the annual information return that most charities are required to file (Urban Institute, 1998–2016).[13] Data are available for the years 1998–2016, but we drop years prior to 2002 for comparability with the individual income tax data. Our main variable of interest is contributions, which is the sum of donations and grants.

Data are reported by year and Employer Identification Number (EIN). Because fiscal cycles do not always overlap with calendar years, we match the tornado data to each charity's fiscal cycle by month and then aggregate to the annual level using the year in which the fiscal year ends. When EIN-year duplicates appear in the files provided by the IRS, we keep the observation from the earliest data file. To address likely reporting errors, we drop observations with non-positive contributions or expenses. We also address location discrepancies that are likely to be errors. If a charity's ZIP Code in year $t-1$ matches that in year $t+1$ but not in year t, we replace the ZIP Code in year t so that it is consistent over time. We then replace the ZIP Code with our time-invariant "super-ZIP". Finally, we replace the reported state with the state to which the super-ZIP belongs according to the 2010 Esri ZIP Code centroids file.

[13] Religious congregations are not required to file Form 990.

3 Empirical strategy

3.1 Estimation approach

We estimate how fatal tornadoes affect total charitable giving. Our primary specification uses the inverse hyperbolic sine (IHS) of fatalities as a proxy for overall severity. We focus on areas that are near tornadoes but not directly affected by them because charitable-giving responses in directly affected areas are more difficult to interpret. For example, tornadoes may have negative income effects in areas where they strike or generate a large in-kind giving response, which we cannot measure with our data. Our identification assumption is that, conditional on location and time fixed effects, the number of fatalities caused by tornadoes is unrelated to other determinants of charitable giving. To that end, we estimate:

$$
\begin{aligned}
IHS(d_{it}) = \beta_1 * IHS(fatalities_{it}^{0-20}) + \beta_2 * IHS(fatalities_{it}^{20+}) \\
+\alpha_i + \alpha_{vt} + \boldsymbol{X}_{it} + \varepsilon_{it},
\end{aligned}
\tag{1}
$$

where the outcome $IHS(d_{it})$ is the IHS of charitable donations in ZIP Code i in year t. The key parameter of interest is β_2, which is the coefficient on the variable $IHS(fatalities_{it}^{20+})$, the IHS of tornado fatalities that occurred within the same state but more than 20 miles away from i. We control for any direct impacts with $IHS(fatalities_{it}^{0-20})$, the IHS of fatalities within 20 miles of ZIP Code i. In alternative specifications, we vary the functional forms and measures of tornado severity. The variables α_i control for unit fixed effects. Additionally, we control for year fixed effects interacted with ventiles of AGI (α_{vt}).[14] Standard errors are clustered by state.

The timing of tornado strikes is unpredictable (Simon, 2019), making the occurrence of a tornado plausibly exogenous, conditional on location fixed effects. Whether a tornado

[14] We use AGI in the observed year closest to 2010, the midpoint of our sample, using the later year in cases of ties.

causes fatalities, however, is a function of both the physical features of the tornado (e.g. wind speed, size, and duration of existence) and the characteristics of the area in which it touches down (e.g. population density, building types). Thus, one potential threat to the validity of our estimates is unobservable changes in area characteristics that are correlated with the timing of both tornado fatalities and charitable giving. For example, while our design is not a pre-post difference-in-differences, estimates could still be biased if severe tornadoes became more common in states that happen to have economies that were growing more quickly. To allow for differential trends and to improve the precision of our estimates, we include time-varying controls $\boldsymbol{X}_{it}$ in equation (1). These include 3-digit-ZIP linear time trends and cubic functions of the number of tax returns and total AGI, both of which we show to be unaffected by tornadoes (Appendix Table A.3).

Another concern with equation (1) is that the same-year specification may not capture the full response of charitable giving to severe tornadoes. Scharf, Smith and Wilhelm (2017) find that natural disasters have short-run time-shifting effects on donations to other charities but find no net effect over a 20-week period. Appendix Figure A.2 shows that tornado casualties occur throughout the year but are most prevalent in April and May, therefore allowing enough time for the full net effects to be captured in our annual data.

We also estimate variants of equation (1) using the Form 990 data from charitable organizations. In these equations, the unit of observation is an EIN, and the outcome is contributions received. The time-varying controls are linear trends for the 3-digit ZIP Code in which a charity is first observed.

3.2 Summary statistics

Table 1 summarizes the IRS income tax data for ZIP Codes that do and do not experience a nearby fatal tornado during our sample period, either within 20 miles of their centroid (columns (1) and (2)) or within the same state but more than 20 miles away (columns (3) and (4)). Panel A displays averages and standard deviations of baseline (2002) AGI, charitable deductions per return, the total number of returns, and the share of returns that have any contributions reported. Panel B shows 2002–2017 trends in both the levels and the IHS of these variables.[15]

Of the 26,943 ZIP Codes in our sample, 4,882 have a fatal tornado pass within 20 miles of their centroids, and 22,061 do not. These two sets of ZIP Codes are very similar to each other (columns (1) and (2)), with no statistically significant differences in the four variables of interest at baseline. Trends in these variables are also very similar, except for the IHS of total contributions, which is growing in affected ZIP Codes but falling in unaffected ZIP Codes.

Columns (3) and (4) show summary statistics for ZIP Codes that do and do not, respectively, have an in-state fatal tornado more than 20 miles away at some point in the sample. Because fatal tornadoes affect many states during our sample period, the former group is correspondingly larger: 20,288 ZIP Codes have an in-state fatal tornado more than 20 miles away at some point. These ZIP Codes have significantly lower average AGI (about $40,000 versus $52,000), a lower number of returns (4,200 versus 6,000), and a smaller share of returns with charitable contributions (24 percent versus 33 percent). However, the average contribution amounts are similar ($4,800 versus $4,900). Trends also differ significantly for a few variables, with ZIP Codes in states with deadly tornadoes exhibiting relatively slow growth in AGI and in the IHS number of tax returns filed but relatively rapid growth in the average donations per return, suggesting that the relative growth in returns in these states is among those with less income and donations.

These differences in levels and trends highlight the usefulness of the control variables in equation (1). We also note that our identification comes from locations' *changes* in outcomes in years with deadly tornadoes relative to years without them. Our controls are therefore not only the areas that experience no fatal tornadoes but also treated areas in years in which there are no in-state tornado fatalities.

[15]Whether a return claims any charitable deductions was not reported in 2008. Analogous summary statistics for Form 990 data are available in Appendix Table A.2.

4 Results

4.1 Donations made to all causes

Table 2 shows that fatal tornadoes significantly increase donations to all causes in ZIP Codes located in the same state but more than 20 miles away. The first column shows the IHS-fatalities specification in equation (1), in which coefficients can be interpreted as approximate elasticities.[16] Thus, a one percent increase in same-state fatalities more than 20 miles away increases donations by about 0.0028 percent. Such small elasticities are reasonable because our estimates reflect changes in giving to all types of organizations, most of which do not serve tornado victims.

To convert this elasticity into additional dollars donated per tornado fatality, we predict the change in contributions if each of the fatal tornadoes in the sample had caused one additional fatality. This approach accounts for the fact that deadly tornadoes are not evenly distributed across the country and that ZIP Code exposure may be correlated with its annual charitable donations. We average the effects of these counterfactual tornadoes and find that each fatality increases donations by \$2.21 million dollars, with a standard error of \$1.09 million (calculated by the delta method).

The remainder of Table 2 shows results using alternative functional forms and severity measures. Column (2) employs indicator variables for fatal tornadoes rather than the IHS function and obtains positive estimates that are slightly less precise. Column (3) adds the number of tornado fatalities to this specification. These estimates suggest a large positive effect of the first fatality and a smaller positive effect of additional fatalities, consistent with the IHS form in column (1). The remaining columns employ the other available severity measures. Estimates for injuries (columns (4)–(5)) and for property damage (columns (6)–(7)) are qualitatively similar, with estimates based on damage showing precision comparable to those based on fatalities. These patterns are consistent

[16]Elasticities evaluated at mean values would be somewhat smaller than the estimates because the regressor has a smaller mean than the regressand (Bellemare and Wichman, forthcoming).

with the idea that it is not tornado fatalities that matter per se but that fatalities are a proxy for the overall devastation caused by a severe tornado.

The response to fatal tornadoes could be a function of distance rather than whether they struck within the same state. Table 3 presents estimates for fatal tornadoes that did or did not strike within the state and varies the distance bands. For in-state tornadoes, effects are largest for the 20–100 mile band but are quantitatively similar for distances of 20–200 and 20–500 miles. For out-of-state tornadoes, effects outside of the 0–20 mile radius are generally not statistically significant. These results suggest that state of occurrence matters more than distance, possibly due to differential media coverage or greater affinity for others living in one's own state.

Appendix tables present robustness tests that address potential threats to our identifying assumption. Appendix Table A.4 accounts for the threat of serial correlation and shows that our estimates are essentially unaffected by controlling for leads and/or lags of IHS tornado fatalities. Appendix Table A.5 shows that our results are not substantially affected by removing the linear trends and time-varying controls (columns (2) and (3)), by excluding states that never experience deadly tornadoes during our sample period (column (4)), or by restricting the sample to a balanced panel (column (5)). As an additional robustness check, column (6) shows that spatial clustering with a 200-mile bandwidth produces smaller standard errors than state-level clustering. Finally, Appendix Table A.6 shows that our conclusions are robust to varying the 20-mile distance threshold.

If individuals merely shifted money between charities in response to natural disasters, then we would find no effects on the total amount donated. Thus, we conclude that deadly tornadoes increase total giving—at least among households that itemize charitable donations—and do not merely divert it from other causes.

4.2 Contributions received by charities

Next, we use Form 990 data from charities to estimate effects by location and type of recipient organization (Table 4). We find significant positive effects on contributions received by charities located within 20 miles of a deadly tornado. Using the same counterfactual calculation that we performed with the income tax data, the estimate in column (1) implies that each additional tornado fatality increases donations to local charities by $740 thousand (standard error $423 thousand), on average. The magnitude of this effect is comparable to what we find in the individual income tax data. We would not necessarily expect the two effects to be the same because the sets of donors and charities is not perfectly overlapping. For example, the income tax estimates likely include donations to the American Red Cross and other organizations whose headquarters are far from fatality locations, and the estimates for charity receipts may include receipts from other locations, as well as grants from foundations, corporations, or governments. For these reasons, the charity data provide a rough estimate of the portion of the charitable response that is directed towards organizations located in affected communities.

In column (3) of Table 4, we ask what types of organizations assist tornado victims or raise money for them. To do so, we interact IHS fatalities with indicators for the most common categories (by share of observations): "Arts, culture, humanities" (10.7 percent), "Education" (16.9 percent), "Health" (8.0 percent), and "Human services" (13.5 percent).[17] We also isolate the most apparently relevant category, "Public safety and natural disaster" (1.7 percent of observations), which shows one of the largest increases in contributions. We find statistically significant effects for "Education", but standard errors for most of the six categories are large enough that we cannot rule out the average effect size found in column (1). We conclude that a variety of organizations respond to disasters.

[17] Categories are from the National Taxonomy of Exempt Organizations, which we hold constant within charity by using the first observation.

The specifications in columns (2) and (3) of Table 4 also include the IHS of fatalities caused by in-state tornadoes that struck more than 20 miles away. Their inclusion allows us to estimate one form of substitution between causes, by testing for a decrease in the receipts of charities located in the same areas as the donors who increased their giving in response to fatal tornadoes. The estimated effect on such organizations is positive and not significantly different from zero. While we cannot estimate effects on donations to out-of-state organizations or test for substitution across organizations local to the donor, this result indicates that, on aggregate, donors' local charities do not suffer as a result of increased giving to tornado victims.

Appendix Table A.7 shows that the results are strengthened when dropping larger charities that are more likely to serve individuals far from the charity's own location. Appendix Table A.8 show that our results are similar when we drop observations from 2003, for which charitable giving is not reported in the income tax data. Similarly, our individual income tax results are robust to restricting the sample to years prior to 2017, for which we have data from charitable organizations (Appendix Table A.9).

5 Conclusion

The social value of charitable giving and the optimal subsidies to donors and charitable organizations depend on whether increases in giving to one cause come at the expense of other causes. We use comprehensive annual tax return data to estimate whether fatal tornadoes—which are particularly destructive and rare events—increase *total* charitable giving. We find that each tornado fatality increases total donations of individuals living nearby by about $2 million. Therefore, we can rule out that individuals choose a set amount to donate to charity and then apportion this between charities. Using annual tax return data from charities, we additionally find that there are no significant negative effects on charities in the locations from which increased donations to fatal tornadoes originate.

There is an active debate in research regarding the extent of donor substitution between charitable causes. Our paper is the first in this literature to employ a natural experiment with both geographic and temporal variation and the first to employ datasets that contain the majority of dollars donated across the U.S. Our finding that deadly tornadoes increase charitable giving and do not simply redirect donations from other causes seems likely to generalize to other natural disasters and similar exogenous shocks to human need. It remains to be seen whether displacement arises for other causes and modes of giving. Furthermore, while our data cover the majority of dollars donated, they may not be representative of lower-income households for whom the charitable budget may be more fixed. These questions would benefit from further research.

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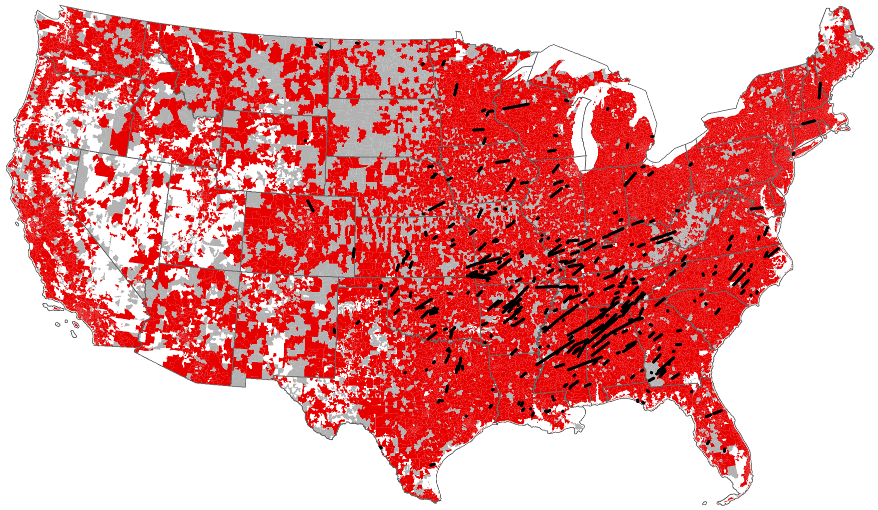
Figures and Tables

Figure 1: Data coverage and fatal tornadoes in the United States, 2002–2017



Notes: Sources are the National Oceanic and Atmospheric Administration's Tornado Database; the Internal Revenue Service; and the US Census. Black markers represent tornadoes that occurred in 2002–2017 and caused at least one fatality. Light grey areas are those that have been dropped due to sample restrictions. White areas are those not assigned to a ZIP Code Tabulation Area.

Table 1: Summary statistics

	(1) Tornado within 20 miles	(2) No tornado within 20 miles	(3) In-state tornado > 20 miles away	(4) No in-state tornado > 20 miles away
Panel A: Levels				
Average adjusted gross income (AGI)	40,854	43,208	39,843	51,950
	(32,223)	(27,875)	(20,069)	(45,136)
Average contribution amount	5,098	4,763	4,795	4,915
	(7,796)	(8,149)	(7,078)	(10,639)
Total number of returns	4,778	4,577	4,174	5,990
	(6,251)	(6,022)	(5,518)	(7,354)
Share of returns with contributions	0.25	0.27	0.24	0.33
	(0.13)	(0.13)	(0.12)	(0.13)
Panel B: Trends				
Average adjusted gross income (AGI)	-111.2	1,523	-576.4	1,947
Average contribution amount	18.08	42.64	32.90	20.69
Total number of returns	4.5540	59.28	-48.18	97.41
Share of returns with contributions	0.0004	-0.0039	0.0007	-0.0043
Average AGI (IHS)	-0.0001	0.0266	0.0010	0.0258
Total contribution amount (IHS)	0.0043	-0.0028	0.0045	-0.0055
Total number of returns (IHS)	0.0000	0.0052	-0.0043	0.0086
Number of ZIP Codes	4882	22061	20288	6655

Notes: Sources are the National Oceanic and Atmospheric Administration's Tornado Database and the Internal Revenue Service. The unit of observation in panel A is a ZIP Code. The unit of observation in panel B is ZIP-Code-year. Dollar values are inflation-adjusted to 2017 dollars. Panel A is based on the year 2002. Standard errors are in parentheses. Panel B includes years 2002 and 2004–2017. Test statistics are based on standard errors that are clustered by state.

Table 2: Effect of fatal tornadoes on charitable donations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Severity metric:		In-state fatalities		In-state injuries		In-state damage	
0–20 miles, IHS	0.0010			0.0012		0.0016	
	(0.0023)			(0.00092)		(0.00082)	
20+ miles, IHS	0.0028			0.0013		0.0014	
	(0.0014)			(0.00081)		(0.00086)	
0–20 miles, any		0.00078	-0.0011		0.0010		0.00056
		(0.0042)	(0.0050)		(0.0050)		(0.0034)
0–20 miles, num.			0.00052		0.000029		0.000016
			(0.00044)		(0.000028)		(8.2e-06)
20+ miles, any		0.0046	0.0027		0.0041		0.0048
		(0.0027)	(0.0030)		(0.0031)		(0.0027)
20+ miles, num.			0.00042		0.000013		6.4e-06
			(0.00031)		(0.000014)		(0.000015)
Observations	368,120	368,120	368,120	368,120	368,120	368,120	368,120
Adj. R-squared	0.99	0.99	0.99	0.99	0.99	0.99	0.99

Notes: The table reports estimates of equation (1). The dependent variable is the inverse hyperbolic sine of donations reported on individual tax returns. The unit of observation is a ZIP-Code-year. The measure of tornado severity is in-state fatalities (columns (1)–(3)), in-state injuries (columns (4)–(5)), or in-state property damage, in millions of dollars (columns (6)–(7)). All regressions include ZIP Code fixed effects; year fixed effects that vary by AGI ventile; 3-digit-ZIP linear time trends; and cubic functions of the number of tax returns and total AGI. Standard errors (in parentheses) are clustered by state.

Table 3: Effect of fatal tornadoes on charitable donations, in-state and out-of-state

	(1)	(2)	(3)	(4)
In-state fatalities, 0–20 miles (IHS)	0.0032	0.0028	0.0028	0.0028
	(0.0025)	(0.0025)	(0.0025)	(0.0025)
Out-of-state fatalities, 0–20 miles (IHS)	-0.011	-0.011	-0.011	-0.011
	(0.0049)	(0.0050)	(0.0051)	(0.0051)
In-state fatalities, 20–X miles (IHS)	0.0020	0.0032	0.0029	0.0028
	(0.0018)	(0.0017)	(0.0016)	(0.0014)
Out-of-state fatalities, 20–X miles (IHS)	0.0020	-0.00014	-0.00034	0.0012
	(0.0031)	(0.0015)	(0.00095)	(0.00096)
X	50	100	200	500
Observations	368,120	368,120	368,120	368,120
Adj. R-squared	0.99	0.99	0.99	0.99

Notes: The table reports estimates of a version of equation (1) that distinguishes between in-state and out-of-state tornadoes and varies the distance over which tornado fatalities are aggregated. The dependent variable is the inverse hyperbolic sine of donations reported on individual tax returns. The unit of observation is a ZIP-Code-year. X denotes the upper bound of the distance (in miles) over which tornado fatalities are aggregated. All regressions include ZIP Code fixed effects; year fixed effects that vary by AGI ventile; 3-digit-ZIP linear time trends; and cubic functions of the number of tax returns and total AGI. Standard errors (in parentheses) are clustered by state.

Table 4: Effect of fatal tornadoes on contributions collected by charities

	(1)	(2)	(3)
In-state fatalities 0–20 miles away, IHS	0.0062	0.0061	
	(0.0037)	(0.0036)	
In-state fatalities 20+ miles away, IHS		0.00046	0.00046
		(0.0015)	(0.0015)
Safety and disaster * IHS(in-state fat. 0–20 miles)			0.019
			(0.027)
Arts * IHS(in-state fat. 0–20 miles)			-0.00016
			(0.0091)
Education * IHS(in-state fat. 0–20 miles)			0.023
			(0.0072)
Health * IHS(in-state fat. 0–20 miles)			0.00018
			(0.015)
Human services * IHS(in-state fat. 0–20 miles)			-0.0039
			(0.0089)
Other * IHS(in-state fat. 0–20 miles)			0.0057
			(0.0044)
Observations	3,219,489	3,219,489	3,219,489
Adj. R-squared	0.82	0.82	0.82

Notes: The table reports estimates of equation (1). The dependent variable is the inverse hyperbolic sine of annual contributions collected by a charity. All regressions include EIN and year fixed effects, as well as 3-digit-ZIP linear time trends. Standard errors (in parentheses) are clustered by state.