

# Do Causes Crowd Each Other Out? Evidence From Tornado Strikes

Tatyana Deryugina\* and Benjamin Marx†

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## Abstract

Does charitable giving respond to new demands, and if so, does the response come at the expense of other charitable causes? To answer these questions we exploit exogenous variation in need arising from the random event of a nearby tornado. We use location fixed effects estimators and examine changes in charitable donations claimed for tax deductions in IRS data on individual income taxes by geographic area. We find that having a tornado causing at least ten injuries in one's state raises charitable contributions by about 2 percent in the year of the tornado and two years afterwards. We test for heterogeneous responses by tornado severity, which gives measures of local need, finding that higher fatality and injury levels lead to more donations.

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\*University of Illinois, Urbana-Champaign and National Bureau of Economic Research. E-mail: deryugina@illinois.edu.

†University of Illinois, Urbana-Champaign. E-mail: benmarx@illinois.edu.

# 1 Introduction

In 2005, Hurricane Katrina struck New Orleans, killing nearly 2,000 people, destroying thousands of homes, and causing billions of dollars in damage. It was one of the worst natural disasters to hit the United States. Billions of dollars of aid were given in response, including an estimated \$4.2 billion dollars in charitable donations (Diamant, August 29, 2006). However, overall donations in 2005 look unremarkable when compared to the years before and after (Giving USA Foundation (2015), also see Figure 1). One possibility is that even this unprecedented response is too small to be detectable at the annual level. Another is that the donations to Hurricane Katrina victims came at the expense of other causes. Whether or not competition for charitable donations is a zero sum game (or close to it) has important implications for the welfare effects of various fundraising techniques.

We test the hypothesis that an increase in donations to one cause is offset by decreases in other donations by examining whether total annual charitable giving is higher in the aftermath of tornadoes. Tornadoes are a fairly common event in the United States and it is very difficult to predict where and when they will form. Unlike hurricanes, which can span hundreds of miles, tornadoes are very localized, rarely spanning more than a few hundred feet or traveling more than ten miles. While the majority of tornadoes cause little to no damage, a direct hit by a strong tornado can be devastating to a building and its occupants. Such tornadoes are typically publicized in the news, making it plausible that they would generate donations.

We find that strong tornadoes significantly increase total charitable gifts. Annual charitable deductions increase by about 2 percent when a state is affected by a tornado causing at least ten injuries, and the effect persists for two years after the year of the tornado. This result is not being driven by ZIP codes affected by the tornado directly, which do not show the same increase in charitable giving as the other ZIP Codes in the state. Because total giving increases, we can rule out total crowd-out of charitable donation across causes, at least in the context of tornadoes. Moreover, we see no evidence of intertemporal crowd-out; donations in states affected by tornadoes are also higher in the following two years and are not statistically different from zero the year after that.

Our results are fairly robust to different fatality and injury thresholds.

There is a large literature examining the determinants of charitable giving. Those studies examining the total amount of a taxpayer's donations (e.g. Randolph, 1995; Auten, Sieg and Clotfelter, 2002; Bakija, Gale and Slemrod, 2003; Bakija and Heim, 2011) have primarily focused on the tax-price elasticity of giving. Recent experimental studies have established a wide variety of factors that influence donations in a particular charitable fundraiser, including price (Karlan and List, 2007), gifts for potential donors (Falk, 2007; Garbarino, Slonim and Wang, 2013), economic mechanisms such as lotteries and noneconomic mechanisms (Landry et al., 2006; Landry et al., 2010), information about the contributions of others (List and Lucking-Reiley, 2002; Karlan and List, 2007; Huck and Rasul, 2011; Huck, Rasul and Shephard, 2015), and social pressure (DellaVigna, List and Malmendier, 2012). However, the important question of whether these treatments increase total contributions or crowd out charitable giving to other causes remains open.

The theoretical work in Rose-Ackerman (1982) and Rose-Ackerman (1987) shows the central importance of the question of whether charitable giving is a zero-sum game. In a model with free entry by nonprofits, fundraising simply redirects giving from one recipient organization to another. In contrast, a model with a fixed set of nonprofits predicts that fundraising connects donors with causes that more closely match their preferences and therefore increase total giving. Government grants are more beneficial in the first model because they increase nonprofit provision and improve matching with donors, whereas in the second model government grants crowd out fundraising and giving. Andreoni and Payne (2003) and Andreoni and Payne (2011) provide evidence for the latter prediction, with exogenous shocks to government grant aid reducing charities' fundraising and hence contributions received. This evidence is therefore consistent with our finding that charitable giving is not a zero-sum game, an encouraging result for the growing literature that explores determinants of donations to a particular cause or campaign.

We also contribute to the growing empirical literature on natural disasters. The majority of the relevant literature focuses on the determinants of government disaster aid or foreign aid (see Strömberg, 2007, for a review).

The rest of the paper is organized as follows. Section 2 describes our data. Section 3 outlines our empirical strategy. We discuss the results in Section 4 and conclude in Section 5.

## 2 Data

**Charitable donations** Data on charitable donations come from Internal Revenue Service. The data are based on individual income tax returns, including all Forms 1040, 1040A, and 1040EZ. They are available on an annual basis for years from 2004 to 2013. Returns are compiled by the year of filing, providing totals based mostly on the preceding tax year but 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 alternatively could have been the address of a lawyer, accountant, or place of business.

From year to year the IRS has taken varying steps to avoid disclosure of information about individual taxpayers. ZIP Codes with fewer than a threshold number of returns (ten returns in most years) were excluded. Individual returns were excluded from variables for which the return accounted for a large percentage of the total, though the threshold percentage was not disclosed. Data are provided separately within ZIP Code for ranges of Adjusted Gross Income, but only in cases when there were a sufficient number of returns within the AGI range in the ZIP Code. We restrict our attention to the ZIP Code totals and do not use the AGI-range breakouts.

We have restricted the sample to a set of ZIP Codes with stable definitions over time. We downloaded all monthly Postal Bulletin spreadsheets from the web site of the U.S. Postal Service. These spreadsheets list all changes to the use of any particular ZIP Code, such as extension to use in a broader geographic area or split into multiple ZIP Codes. We have excluded all ZIP Codes with usage that changed during the sample period.

The main variables of interest are the number of returns listing charitable contributions for itemized deductions and the total amount of these contributions. The absence of small values of these variables indicates that such values have been changed to zero, presumably as another mea-

sure to avoid disclosure of information about individual taxpayers, though the data documentation do not explain what procedure was used. Because we cannot distinguish which values of zero are true zeroes we restrict attention to the balanced panel of ZIP Codes for which charitable contributions are always strictly positive. Our main outcome is the log of charitable contributions per return.

Table 1 shows summary statistics for the IRS data at the ZIP Code-year level. We observe a little over 4,000 returns in each ZIP Code in each year, adding up to \$240 million in Adjustable Gross Income. Over a quarter of the returns have some charitable contribution deductions, which average almost \$5 million per ZIP Code-year or \$926 per return.<sup>1</sup>

**Tornadoes** Tornadoes are rotating columns of air with extremely fast winds that form during strong thunderstorms. The winds can reach up to 300 miles per hour, causing catastrophic damage to structures the tornado comes in contact with. Fortunately, most tornadoes are short-lived, have much weaker winds, and do not affect people or buildings. While the majority of tornadoes affect regions of the South and Midwest known as “Tornado Alley”, tornadoes have been observed in every U.S. state. The majority of tornadoes in the United States occur between March and June, although in more northern parts of the United States tornadoes peak in mid-summer.

Data on tornadoes come from the National Oceanic and Atmospheric Administration’s Tornado Database, which tracks the path of every known tornado since 1950.<sup>2</sup> In addition to providing the starting and ending coordinates of each tornado along with the date and time when it occurred, the database contains the number of reported injuries and fatalities for each tornado. We use the latter information to identify tornadoes that are likely to generate a charitable giving response.<sup>3</sup>

To demonstrate some general patterns associated with tornadoes, we map those occurring in 2010 in Figure 2. Tornadoes causing at least ten injuries are highlighted with thick red lines. Three key patterns emerge. First, most of the tornadoes are very localized, showing up as mere dots on

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<sup>1</sup>Whether a return has any charitable contribution deductions was not reported in 2008.

<sup>2</sup>Available from <http://www.spc.noaa.gov/wcm/#data>.

<sup>3</sup>The database also provides estimates of damages, but these are very imprecise and are likely to be much noisier measures of severity than injuries and fatalities.

our map. Second, the vast majority of tornadoes do not cause any injuries. Finally, tornado strikes are concentrated in the Midwest and the South.

More formally, 13,809 tornadoes were reported in the United States between 2004 and 2014, the years for which we have charitable donations information. Across all these tornadoes, the average number of injuries was 0.94, with over 90 percent of tornadoes causing no injuries. The average number of fatalities was 0.08, with over 95 percent of tornadoes causing no fatalities. Close to half of the tornadoes do not cause any damage and the mean amount of reported damage is \$1.7 million, in nominal dollars. Thus, we do not expect the typical tornado to have an effect on charitable donations.

Of all the reported tornadoes between 2004–2014, only 208 caused at least ten injuries. Among these tornadoes, the average number of fatalities is 4.3, the average number of injuries is 52, and reported losses average \$81 million. Only 29 of these tornadoes are not reported to have caused any damage. We use tornadoes that caused at least ten injuries in our baseline estimation and probe the robustness of our results to different fatality and injury thresholds.

Because our analysis will be considering whether the state as a whole is affected by a tornado causing at least ten injuries, it is helpful to consider state-level statistics, shown in Table 2. Panel A shows tornado-related summary statistics for our preferred sample, which restricts the tornadoes of interest to those causing at least ten injuries. On average, 23 percent of states have one or more such tornado in any given year. These tornadoes affect about 8 ZIP Codes, kill almost 5 people, injure 65, and cause \$86 million dollars in damages.

Panel B shows the same summary statistics for *all* tornadoes. Each state in our sample was affected by at least one tornado in each year, which underscores their ubiquity. Within each state, about 83 ZIP Codes were affected by tornadoes each year. However, because the marginal tornadoes in this panel are weaker, the state totals for injuries, fatalities and damages are not much higher than in Panel A.

Finally, Panel C shows the distribution of state-level tornado hits with various fatality and injury thresholds. In the average year during our sample period, almost half the states are affected by at

least one tornado that causes at least one injury. 30 percent are affected by at least one tornado that causes five or more injuries, 16 percent are affected by at least one tornado with twenty or more injuries and 12 percent are affected by at least one tornado causing thirty or more injuries. Lethal tornadoes are much rarer: 23 percent of states have at least one lethal tornado in a typical year, only 14 percent have one or more tornadoes that kill two or more people, and only 6 percent have tornadoes that kill five or more people. Our preferred threshold of ten is meant to identify tornadoes that are strong enough to plausibly generate charitable donations yet frequent enough to enable statistical analysis.

### 3 Empirical Strategy

Our identification assumption is that, conditional on location fixed effects, the occurrence of a tornado is unrelated to other determinants of charitable giving. The plausibility of this assumption is supported by the fact that tornadoes are very unpredictable.

To estimate the relationship between the occurrence of tornadoes and charitable giving, we estimate the following equation:

$$\ln(cont_{zt}) = \sum_{\tau=0}^L \beta_{\tau} StateTornado_{z,t-\tau} + \sum_{\tau=0}^L \gamma_{\tau} OwnTornado_{z,t-\tau} + \alpha_z + \alpha_t + \varepsilon_{zt} \quad (1)$$

where  $z$  is the ZIP Code and  $t$  is the year. The main outcome of interest is  $\ln(cont_{zt})$ , the natural log of charitable contributions in the ZIP Code that year. The variable  $StateTornado_{z,t-\tau}$  is equal to 1 if in year  $t - \tau$  a tornado affected the state in which ZIP Code  $z$  is located. The variable  $OwnTornado_{z,t-\tau}$  is equal to 1 if the ZIP Code itself was affected by a tornado in year  $t - \tau$ . We control for year and ZIP Code fixed effects with  $\alpha_z$  and  $\alpha_t$ , respectively. Standard errors are clustered by state.

Tornadoes may crowd out other charity not just within a year but over time as well. Alternatively, giving more in one year may prompt people to give more the next year. For these reasons,

we also include  $L$  lags of the tornado variables in our estimation. We vary  $L$  to probe the robustness of our results.

## 4 Results

**Main Results** Table 3 shows our key estimates of the effect of tornadoes on charitable giving. The first column shows the specification corresponding to equation 1 with no lags ( $L=0$ ). The results indicate that having a tornado that causes at least ten injuries in the same state raises total charitable donations that year by a marginally-significant 1.5 percent. At the same time, charitable donations in the affected ZIP Code fall by 1.5 percent relative to others in the state, meaning that there is zero effect in the ZIP Codes hit by the tornado. There are many possible explanations for the latter effect, including negative wealth effects, changes in beliefs about risk, and in-kind charitable giving that we cannot measure in our data.

Columns (2)-(4) show changes in charitable giving in the years *following* the tornado. In general, the contemporaneous effects become stronger because they are no longer compared to years following the tornado, in which effects are also significant. We see persistently higher giving in affected states (among the ZIP Codes that are not themselves affected by the tornado). The fact that giving is elevated for three straight years could be due to habit formation/persistence of charitable giving. There are no detectable effects on giving beyond two years after the tornado, either in the affected ZIP Codes or in the state as a whole.

**Robustness** To check the robustness of our estimates, we vary the sample of tornadoes we consider. Specifically, we lower the threshold to five injuries or increase it to twenty and thirty injuries. We also use a fatality threshold, considering tornadoes that cause 1 or more fatalities or 2 or more fatalities. Figure 3 shows the resulting sum of coefficients on  $StateTornado_{z,t-\tau}$  for  $\tau = 0$  to 2. In general, our estimated effects are similar across the specifications, with the exception of tornadoes that cause one or more fatalities, for which the estimated effect is insignificant. This suggests that tornadoes with only 1 fatality are not severe enough to generate charitable donations.

The results in Figure 3 suggest that tornado intensity matters. In Table 4, we test this explicitly. Specifically, we begin with the sample of tornadoes causing at least one fatality. We then construct a measure of intensity at the state level as either the total number of injuries, fatalities, reported damages or total crop losses. To minimize the probability that our results are driven by outliers, we take the log of the intensity measure, adding one to avoid missing values. We then interact this measure with the *StateTornado* indicator.

The results in Table 4 show that charitable giving in a state is higher when state-level injuries or fatalities caused by tornadoes are higher. Specifically, for every 1 percent increase in injuries, contemporaneous charitable giving per return increases by a small but significant 0.009%. For fatalities, the response is larger (about 0.014% per 1 percent increase in state-level fatalities). Similar to earlier estimates, the effects persist for at least two years. Conversely, we see no response to higher levels of total damages or crop losses. Whether this is because loss measures are imprecise, less publicized or simply do not cause people to give more is part of our future research agenda.

Our results are similar if we use the log of total rather than per return contributions as the outcome variable. We also find that the share of returns with charitable contributions is higher. This is consistent with either an extensive margin response (more people giving positive amounts to charity) or an intensive margin response that causes some people to become itemizers. Finally, a caveat about our analysis is that charitable contributions are observed only for those who itemize. This should not affect our conclusions unless those who do not itemize respond to tornadoes differently from those who do itemize.

## 5 Conclusion

Charitable organizations are continuously developing new fundraising techniques to increase donations. An unresolved question is whether the increased donations to one charity come at the expense of donations to other causes. We tackle this question by estimating whether tornadoes increase *total* charitable giving, which would imply less than full crowd out. Indeed, we find that

charitable donations in a state affected by a tornado causing ten or more injuries increase by 1.7-2 percent in the year of the tornado and by 1.9-2 percent in the two years after. The results provide evidence that new sources of need increase charitable giving and do not simply redirect donations from other causes.

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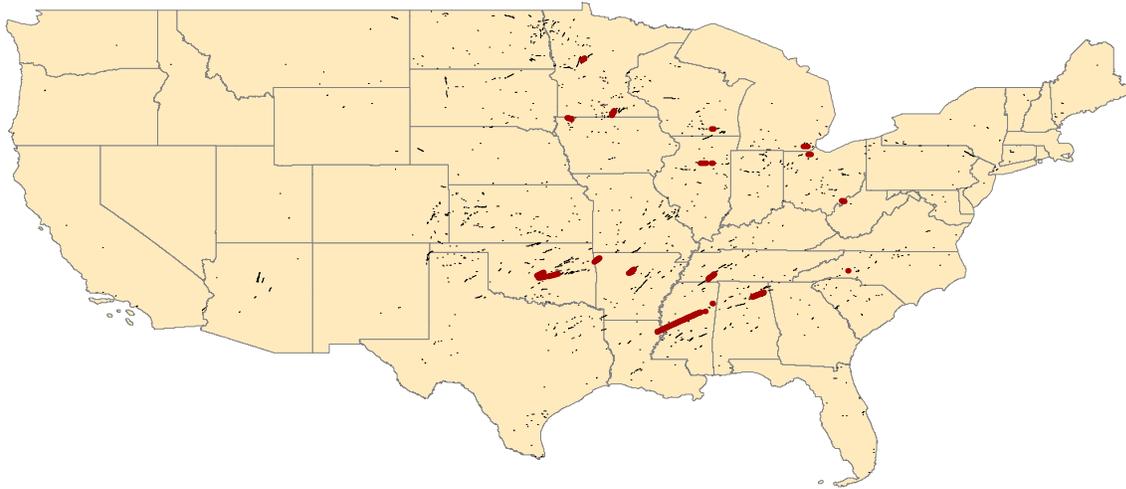
# Figures

Figure 1: Total charitable giving in the United States



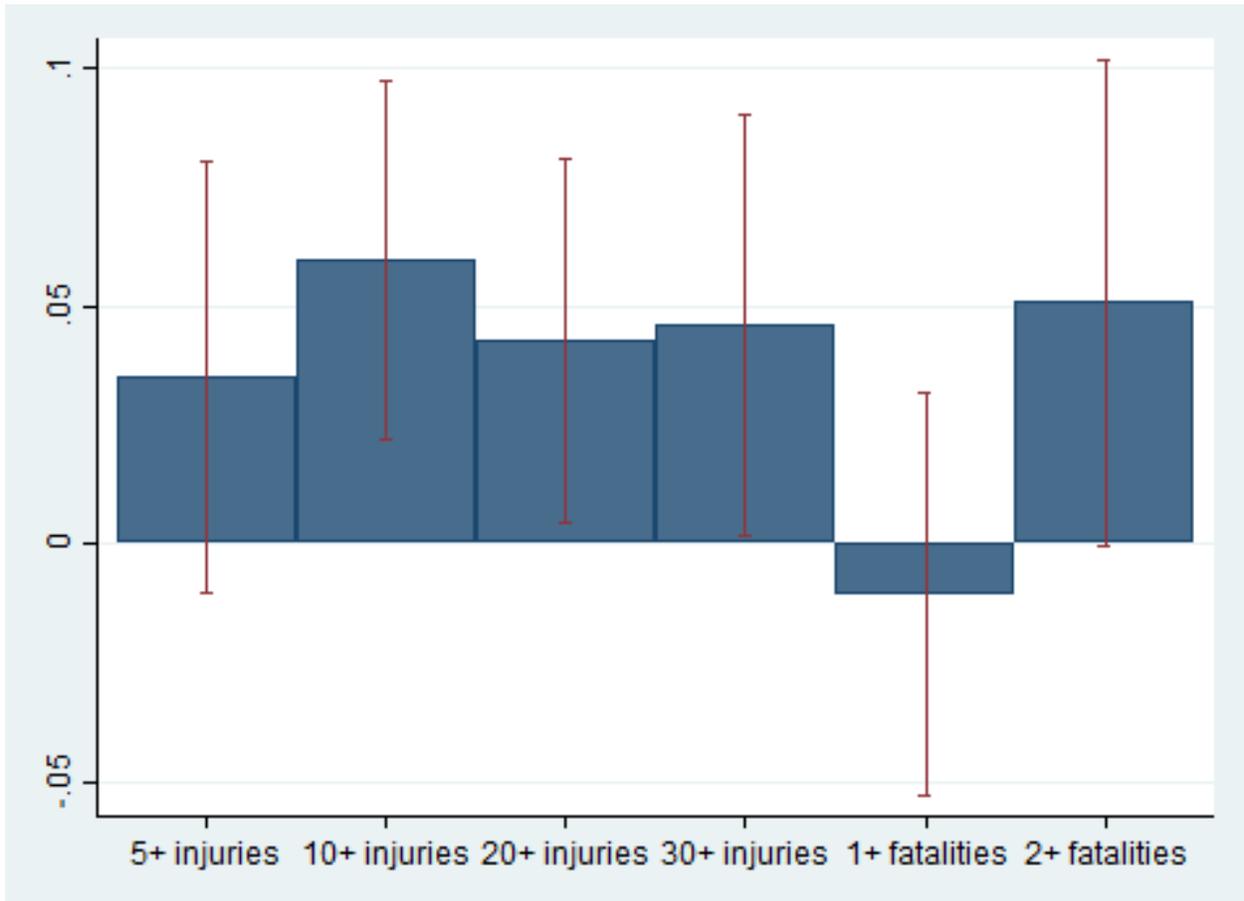
Source: Giving USA Foundation (2015). Donations in current dollars. The red line corresponds to the year in which Hurricane Katrina struck the United States.

Figure 2: Tornadoes in the United States, 2010



Source: NOAA. Black lines represent reported tornadoes in 2010. Red lines correspond to tornadoes that caused at least ten injuries.

Figure 3: Robustness of estimates to different fatality and injury thresholds



Total three-year (contemporaneous and two lags) effect on charitable giving in unaffected ZIP Codes in the state shown. Spikes correspond to 95 percent confidence intervals.

## Tables

Table 1: Summary statistics for IRS data

	(1)	(2)	(3)	(4)	(5)
	Mean	Std. Dev.	Min	Max	Obs
Number of returns	4,190	6,028	10	98,117	328,391
Total Adjusted Gross Income, thousands	237,664	433,258	-47,556	10,930,729	328,391
Number of returns with charitable contributions	1,181	2,002	0	20,335	296,129
Total charitable contributions, thousands	4,926	11,962	0	790,224	328,391
Charitable contributions per return	926	4,474	0	1,763,353	328,391

Source: Internal Revenue Service. Unit of observation is ZIP Code-year.

Table 2: Tornado summary statistics

	(1)	(2)	(3)	(4)	(5)
	Mean	Std. Dev.	Min	Max	Obs
Panel A: tornadoes causing 10+ injuries					
Number of affected zip codes	7.19	23.10	0	297	1,040
Number of fatalities	4.67	34.49	0	866.43	1,040
Number of injuries	64.51	372.87	0	9,707.74	1,040
Total losses, millions of dollars	86	784	0	20,412	1,040
Panel B: all tornadoes					
Number of affected zip codes	83.27	109.57	0	726	1,040
Number of fatalities	5.53	39.37	0	1,036.02	1,040
Number of injuries	74.12	386.35	0	10,034.56	1,040
Total losses, millions of dollars	113	839	0	21,685	1,040
At least one tornado	1	0	1	1	1,040
At least one tornado with 1+ injuries	0.48	0.50	0	1	1,040
At least one tornado with 5+ injuries	0.32	0.47	0	1	1,040
At least one tornado with 10+ injuries	0.23	0.42	0	1	1,040
At least one tornado with 20+ injuries	0.16	0.36	0	1	1,040
At least one tornado with 30+ injuries	0.12	0.32	0	1	1,040
At least one tornado with 1+ fatalities	0.23	0.42	0	1	1,040
At least one tornado with 2+ fatalities	0.14	0.35	0	1	1,040
At least one tornado with 5+ fatalities	0.06	0.24	0	1	1,040

Source: National Oceanic and Atmospheric Administration's Tornado Database. Unit of observation is state-year.

Table 3: The effect of tornadoes on charitable donations

	(1)	(2)	(3)	(4)
Tornado in same state, time T	0.015* (0.009)	0.017* (0.009)	0.021** (0.009)	0.021** (0.009)
Tornado in same state, time T-1		0.017** (0.007)	0.020*** (0.007)	0.021*** (0.007)
Tornado in same state, time T-2			0.019** (0.007)	0.019** (0.008)
Tornado in same state, time T-3				0.004 (0.007)
Tornado in zip code, time T	-0.015 (0.009)	-0.018* (0.010)	-0.021** (0.010)	-0.022** (0.010)
Tornado in zip code, time T-1		-0.018** (0.008)	-0.022** (0.008)	-0.022** (0.009)
Tornado in zip code, time T-2			-0.017* (0.009)	-0.017* (0.009)
Tornado in zip code, time T-3				-0.000 (0.010)
Observations	264,713	264,713	264,713	264,713
R-squared	0.100	0.101	0.102	0.102

Significance levels: \* 10 percent, \*\* 5 percent, \*\*\* 1 percent. Standard errors (in parentheses) clustered by state. Outcome variable is charitable contributions per return, in logs. Controls include year and zip code fixed effects.

Table 4: The responsiveness of charitable giving to tornado intensity

	(1) Injuries	(2) Fatalities	(3) Total losses	(4) Crop losses
Tornado in state, time T	-0.034** (0.016)	-0.034** (0.017)	-0.006 (0.028)	-0.002 (0.009)
Tornado in state x intensity, time T	0.009** (0.003)	0.014*** (0.005)	0.000 (0.002)	0.002* (0.001)
Tornado in state, time T-1	-0.037*** (0.010)	-0.034** (0.013)	-0.002 (0.022)	-0.009 (0.008)
Tornado in state x intensity, time T-1	0.009*** (0.002)	0.014*** (0.005)	-0.000 (0.001)	0.002* (0.001)
Tornado in state, time T-2	-0.030** (0.013)	-0.027* (0.016)	0.000 (0.030)	-0.010 (0.010)
Tornado in state x intensity, time T-2	0.007** (0.003)	0.010* (0.005)	-0.000 (0.002)	0.003* (0.002)
Tornado in zip code, time T	-0.029** (0.014)	-0.031** (0.014)	-0.020 (0.015)	-0.022 (0.015)
Tornado in zip code, time T-1	-0.020** (0.010)	-0.020* (0.010)	-0.010 (0.011)	-0.015 (0.010)
Tornado in zip code, time T-2	-0.025** (0.010)	-0.024** (0.009)	-0.019** (0.010)	-0.025*** (0.009)
Observations	264,713	264,713	264,713	264,713
R-squared	0.103	0.102	0.099	0.101

Significance levels: \* 10 percent, \*\* 5 percent, \*\*\* 1 percent. Standard errors (in parentheses) clustered by state. Outcome variable is charitable contributions per return, in logs. Controls include year and zip code fixed effects. Intensity measures (shown at the top of the column) are constructed by adding 1 to the intensity measure and taking the log.