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Double danger in the double wide: Dimensions of poverty, housing quality and tornado impacts[☆]

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ABSTRACT

Tornadoes are the most frequent of the natural hazards in the United States, causing significant yearly human and economic losses. Given the potential destructive power of tornado events and their largely unpredictable nature, it is important to identify the major determinants of vulnerability. To date, only a limited number of studies have empirically investigated the determinants of tornado-induced deaths. Based on a conceptual framework where risk is considered to be a function of physically defined natural hazards and socially constructed vulnerability, we extend previous empirical studies by examining a wider range of potential socio-economic, governmental, and housing factors that determine tornado-induced fatalities. Using detailed county-level data for years 1980–2014, we find that counties with higher per capita income and per capita government spending on public safety and welfare have fewer deaths, whereas counties with greater income disparity are more vulnerable to tornadoes. We explore which aspects of poverty seem most associated with fatalities. Housing quality (measured by mobile homes as a proportion of housing units) is a critical factor in explaining tornado-induced fatalities.

1. Introduction

Natural disasters such as tornadoes result in the significant loss of human life, as well as substantial economic damages. For example, in 2011 there were a record breaking 1701 tornadoes in the United States resulting in 551 deaths (the most in the 62-year period for which we have records) and estimated total economic damages of over 28 billion U.S. dollars.[1] Given the recent demonstrations of the destructive power of tornado events and their largely unpredictable nature, improving our understanding of the factors that determine tornado-induced fatalities will help identify ways to potentially reduce losses. Surprisingly, to date there are relatively few studies that have empirically investigated the determinants of tornado impacts. This paper adds to this literature in several ways. First, we consider a broader array of socio-economic factors that influence vulnerability. In particular, we consider a range of alternative measures of poverty, including housing quality. We also consider factors such as family structure as well as local government spending on emergency services. As a prelude to full analysis, we find that counties with higher per capita income and per capita government spending on public safety and welfare have fewer deaths, whereas counties with greater income disparity and more female-headed households are more vulnerable to tornadoes. Perhaps of most importance, housing quality as measured by mobile homes as a proportion of housing units is a critical factor in explaining tornado-induced fatalities. It might seem that tornado fatalities are simply a function of location – living in an area with a high risk of tornadoes increases the chances that one would die from a tornado. While this is certainly true, other factors are also at play. Blaikie et al. (1994) argue that *Disaster = Risk + Vulnerability*, where vulnerability depends on community and socio-economic variables in addition to location. Similarly, Cutter et al. (2003) discuss the interaction between social and biophysical vulnerabilities that determine overall place vulnerability. Overall, numerous scholars assert that underlying socio-economic factors such as poverty, access to social protection and security, as well inequalities with regard to gender, economic position, age, or race play an important role in determining disaster vulnerability (Aptekar and Boore 1990; Albala-Bertrand, 1993; Cannon, 1994; Blaikie et al., 1994; Cutter, 1996; Enarson and Morrow, 1998; Peacock et al., 1997; Morrow, 1999).

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[1] NOAA National Climatic Data Center, State of the Climate: Tornadoes for Annual 2011, published online December 2011, retrieved on January 6, 2015 from http://www.ncdc.noaa.gov/sotc/tornadoes/2011/13.

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A number of empirical studies of disasters sought to identify the major determinants of direct disaster impacts, where several focus on the role economic development plays in reducing disaster impacts using multinational disaster data obtained from EM-DAT (Kahn, 2005; Toya and Skidmore, 2007; Strömberg, 2007; Raschky, 2008; Gaiha et al., 2013). Some of the above mentioned studies evaluate the role of governmental conditions and structure, inequality, and education in determining disaster impacts. We build upon a study by Simmons and Sutter (2013), which uses U.S. county level tornado data from 1984–2007 to evaluate factors that determine vulnerability. They find that tornado characteristics such as timing, magnitude, and length are the major drivers of tornado-induced fatalities, but also find that economic and demographic factors such as education, race, community and housing type are important. As discussed in detail below, we expand on Simmons and Sutter (2013) by using data from a longer period of time as well as considering a broader array of potential factors and, importantly, account for potential interactions between tornado severity and the socio-economic factors that determine vulnerability.

Based on a conceptual framework where risk is considered to be a function of physical natural hazard characteristics as well as socially constructed factors, the present study uncovers a number of the socio-economic variables that make people and places more vulnerable to tornadoes. Our examination uses panel structured tornado data with observations at the sub-national level −3107 U.S. counties[2] - over the 1980–2014 period. The detailed data on tornado events in U.S. counties are collected from NOAA, while socio-economic, housing, and local government fiscal data are obtained from U.S. Bureau of the Census. Taking into consideration that tornadoes are localized events as opposed to other more geographically dispersed disasters such as hurricanes, or earthquakes, our county level data (as opposed to aggregated national level data) allow us to more accurately identify and thus better understand the determinants of disaster vulnerability.

By identifying the factors influencing tornado-induced fatalities, with particular focus on which dimensions of poverty seem to contribute most, this study provides insight that will help policy makers to better prepare for future devastating events and reduce societal vulnerability to disasters. The following section offers a review of the empirical literature regarding the determinants of the impacts of natural disasters. Section III discusses tornado risks in the United States, and section IV describes the underlying theoretical foundation for our analysis and introduces our primary hypotheses. Sections V and VI present the empirical framework of our analysis and empirical results, respectively.

2. Empirical studies on the determinants of disaster impacts

While many sociologists, geographers and other social scientists have studied how social, economic, and political factors potentially affect a society's vulnerability to natural disasters (Aptekar and Boore, 1990; Albala-Bertrand, 1993; Cannon, 1994; Blaikie et al., 1994; Cutter, 1996; Enarson and Morrow, 1998; Peacock et al., 1997; Morrow, 1999), most of these studies are qualitative in nature in that they use subjective identification rather than quantitative methods to suggest statistical evidence.

In addition, economists have studied the economic impacts of natural disasters, estimating the economic consequences of significant disaster events. However, there are relatively few quantitative empirical studies that investigate the underlying determinants of disaster impacts. In this section, we focus on this last category – research that empirically examines the major factors associated with the disaster-induced losses.

Many of these studies focus on the relationship between income/wealth and disaster impacts. The overall argument is that economic development plays an important role in mitigating the disaster vulnerability of a society. One of the first studies to identify this relationship (Burton et al., 1993) compares the post-disaster responses of high-income and low-income countries and finds that the consequences of natural disasters such as drought, floods and tropical cyclones differ across countries not only by hazard, but also by income. Horwich (2000) draws a similar conclusion, arguing that the critical underlying factor in any economy's response to disaster is its level of wealth. He explains that a rise in income will provide not only general safety but also improved protection from natural disasters.

Many of the more recent empirical studies that examine the determinants of disaster vulnerability have been cross-national and use disaster data obtained from EM-DAT.[3] For instance, Kahn (2005) uses this data source to examine the relationship between disaster-induced death and explanatory factors such as income, geography, and national institutions in the context of multiple types of natural disasters in 73 nations from 1980 to 2002. He finds that while a nation's level of development is not correlated with the number of natural disaster events it experiences, higher levels of development reduce disaster-induced deaths. Kahn estimates that an increase in per capita GDP from $2000 to $14,000 results in a reduction in natural disaster deaths from 9.44 to 1.80 per million people per year. He also finds that democracies and nations with less income inequality suffer fewer deaths from disasters.

Toya and Skidmore (2007) expand on Kahn's (2005) investigation of the disaster-safety-development relationship by including other socio-economic measures. Specifically, they use disaster impact data from EM-DAT and several other sources for 151 countries over 44 years (1960–2003). Their study confirms that economic development as measured by per capita GDP is inversely correlated with both disaster deaths and damages. However, they also find that higher levels of educational attainment, greater openness and a stronger financial sector are also associated with fewer deaths and less damage.

Other studies corroborate and expand on the cross-country link between economic development and disaster outcomes. For instance, Anbarci et al. (2005) in their study of earthquakes show that greater income inequality increases earthquake fatalities. Raschky (2008) also shows that economic development reduces disaster fatalities and losses, but this relationship is nonlinear. Economic development decreases disaster losses but with a diminishing rate. Kellenberg and Mobarak (2008) find a similar relationship between economic development and disaster vulnerability with losses increasing at first and then declining as GDP rises. Raschky also incorporates a national government stability measure and finds that more stability is associated with fewer losses. Similarly, Stromberg (2007) finds that greater wealth and government effectiveness are associated with fewer disaster fatalities. Finally, Gahia et al. (2013) find that poorer and larger countries suffered more disaster related fatalities, but that experience from past disasters and more resources targeted to disaster prevention and mitigation can dramatically reduce deaths.

One cross-country study that does not find a significant link between GDP/income inequality and disaster vulnerability is Brooks et al. (2005). In an effort to develop national-level indicators of vulnerability and present a set of socio-economic, political and environmental variables that correlate with mortality from disasters, they include many additional socio-economic factors beyond GDP into their analysis. They find that including factors such as sanitation, life expectancy, government effectiveness, and literacy are significant predictors of disaster fatalities, whereas GDP and income inequality are not. However, their significant factors may serve as proxies for GDP.

As noted earlier, most of the research discussed above incorporates multiple types of natural disasters across multiple countries and relies

[2] Alaska and Puerto Rico are excluded.

[3] Emergency Events Database EM-DAT that has been maintained by the Centre for Research on the Epidemiology of Disasters (CRED) contains essential core data on the occurrence and effects of mass disasters in the world from 1900 to present.

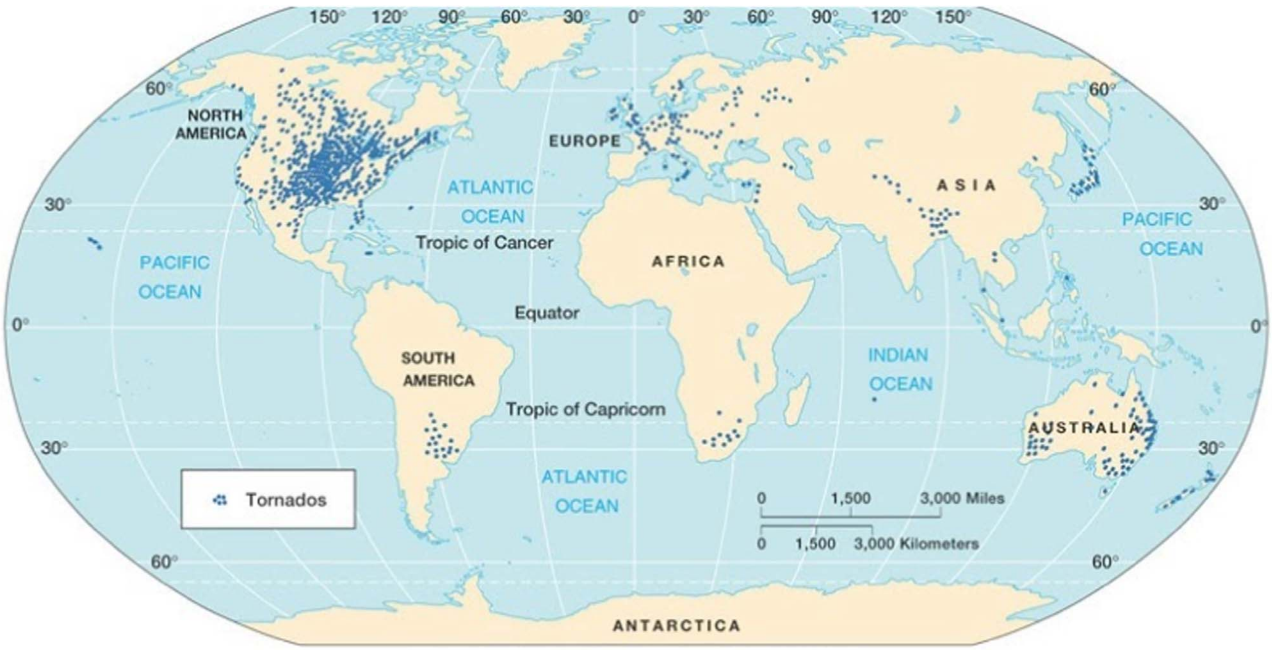

Fig. 1. Global tornado activity. Copyright © 2005 Pearson Prentice Hall, Inc.

primarily on the multi-national EM-DAT data set as their source of information on disasters and their impacts. In contrast, our study focuses on a specific disaster type within a single country. As previously noted, the study most closely related to ours is that by Simmons and Sutter (2013); they employ detailed U.S. county level tornado data from National Oceanic and Atmospheric Administration (NOAA) over the period 1984–2007 to examine the societal impacts of tornadoes. In this book, the authors examine the patterns in tornado casualties over time, by state and Fujita Scale rating, and provide a regression analysis on the potential determinants of tornado casualties. Using a Poisson estimation method, they show that not only do the elements of tornado hazards (timing, magnitudes, and length of incidence) determine tornado impacts, but that economic and demographic factors such as level of education, percentage of non-white and rural population, and percentage of mobile homes contribute to tornado vulnerability. However, the authors offered little evidence that income, poverty and income distribution were important determinants of disaster impacts. In the present study, we extend this line of research by examining a wider range of potential socio-economic factors using U.S. county level data over the 1980–2014 period.

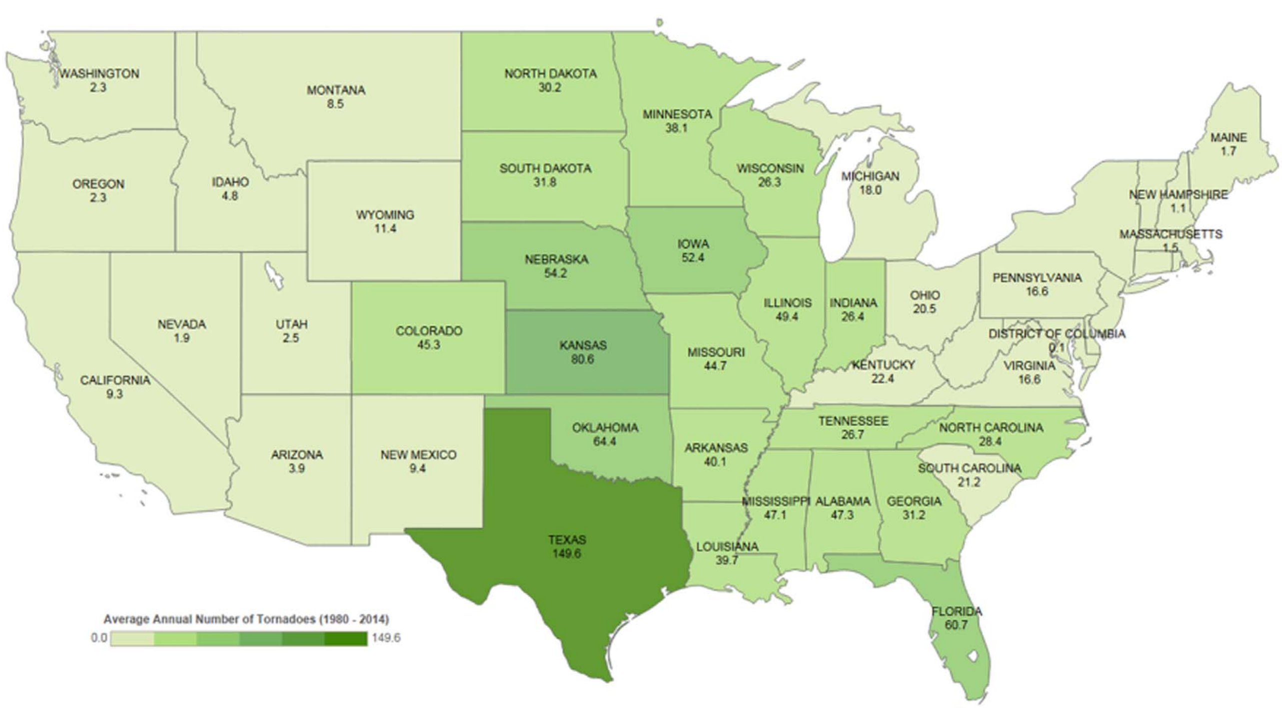

Fig. 2. Average annual number of tornadoes during 1980–2014. Data from NOAA; map generated by authors.

3. Tornado risk in the United States

3.1. Tornado frequency and intensity

As shown in Fig. 1, the United States is the most tornado-prone country worldwide, with an average of 1200 recorded tornado events each year. Canada is a distant second with around 100 tornadoes per year.[4]

Focusing on the United States, the darker green areas shown in Fig. 2 spanning from Texas to South Dakota are called "Tornado Alley" because of the disproportionately high frequency of tornadoes. Specifically, Tornado Alley[5] includes the states of Texas, Oklahoma, Kansas, Colorado, Nebraska, South Dakota, Iowa, Illinois, Missouri, and Arkansas. The average annual number of tornadoes (all intensities) by state for years 1980–2014 is presented in Fig. 2. Meteorologically, Tornado Alley is ideally situated for the formation of the 'supercell' thunderstorms that often produce tornadoes.[6]

In addition to tornado frequency, the magnitude and intensity of tornadoes are also important in determining impacts. According to National Climatic Data Center (NOAA), over the 1950 to 2010 time period the vast majority of tornadoes (about 77%) in the United States were categorized as weak (i.e., Fujita Scale F0 or F1).[7] Thus, nearly a quarter of tornadoes are classified as significant or strong/violent (F2 and above), with only 0.1% achieving F5 status (winds over 200 mph, resulting in near complete destruction of everything in its path). Given that on average close to 1200 tornadoes occur in the United States each year, about 276 will be classified as strong/violent, with perhaps one being F5. These strong/violent tornadoes account for the vast majority of tornado-induced fatalities and damage. For example, in May of 2013, a severe tornado produced catastrophic damage in Moore, Oklahoma and adjacent areas. This F5 rated tornado was the most deadly and devastating tornado of the year, claiming 24 lives and injuring 377 people. The tornado destroyed approximately 1150 homes, and caused more than $2 billion in damage (Insurance Journal, 2013). Another recent example is the tornado outbreak that occurred during April 25–28, 2011. This 4-day period included hundreds of tornadoes that struck communities across the southern plains and southeastern United States and was the largest and the deadliest tornado outbreak since formal record keeping began in 1950. In total, the National Weather Service (NWS) confirmed 351 tornadoes of which four were rated F5. In the four-day period 316 people died, more than 2400 were injured, and economic damages totaled over $4.2 billion.[8]

3.2. Population exposure to tornadoes

Exposure to tornadoes is not random but dependent on the spatial distribution of the population. Table 1 presents average population exposure to strong tornadoes in metropolitan, micropolitan, and non-core counties. Average exposure measures weighted by total population, as well as by persons in poverty are presented. The highest average population exposure to tornadoes were recorded during 1974–1985 nationwide. Overall, average population exposure measures in each county status indicate that people in metropolitan counties have been exposed to a decennial average of .794 strong tornado events, .778 in micropolitan counties, and .666 in non-core counties during the 40 year between 1974 and 2014. In most periods, except for the last decennial period (2005–14), more urbanized counties have experienced relatively frequent strong tornadoes compared to non-core counties.

On the other hand, Table 1 shows that average exposure measures weighted by people in poverty tend to be greater than those weighted by total population regardless of county status or years of comparison. This implies that poor people tend to cluster in high tornado risk areas, which reveals clear evidence of existing environmental disparity in the United States where lower-income people are disproportionately exposed to weather extremes. The gaps between the two measures with different weights are greatest in non-core counties, which reflects a stronger tendency of asymmetric concentration of poor people in at risk regions across non-core counties.

Table 1
Population exposure to strong tornadoes by county status, 1974–2014.

Decennial Average Exposure to Strong Tornadoes[a] (Weighted)						
Status[b]	Weights	1974–1985	1984-1895	1995–2004	2005–2014	Total
Metropolitan (N=1156)	w=Total Population	1.283	0.743	0.618	0.646	0.794
	w=Persons in Poverty	1.292	0.761	0.622	0.698	0.807
	Difference	0.010	0.018	0.005	0.052	0.014
Micropolitan (N=639)	w=Total Population	0.926	0.749	0.700	0.751	0.778
	w=Persons in Poverty	0.999	0.717	0.712	0.790	0.798
	Difference	0.072	−0.032	0.012	0.039	0.020
Non-Core counties (N=1309)	w=Total Population	0.790	0.541	0.563	0.767	0.666
	w=Persons in Poverty	0.881	0.527	0.600	0.877	0.723
	Difference	0.091	−0.014	0.037	0.110	0.058

[a] Total counts of strong tornadoes of F-scale 2 or higher that occurred during each decennial time block are used to calculate the weighted average of population exposure to strong tornadoes.
[b] We use the *Statistical Area classification* used by the Office of Management and Budget in 2013: "The Office of Management and Budget designates counties as Metropolitan, Micropolitan, or Neither. A Metro area contains a core urban area of 50,000 or more population, and a Micro area contains an urban core of at least 10,000 (but less than 50,000) population." Non-core counties are the areas not classified as either Metro or Micro.

4. Determinants of tornado vulnerability

While it is clear that some places are simply more prone to tornadoes due to climactic reasons, this does not fully explain the differences in fatalities across the regions. For example, Figs. 3 and 4 show the differences between tornado frequencies and fatalities. The map in Fig. 3 presents the total number of F2 or higher rated tornadoes (strong/violent) over the period 1980–2014 by state, whereas the map in Fig. 4 shows total fatalities from these tornadoes over the same period. As is clear, the areas with relatively high tornado fatalities do not necessarily match up with the areas with the highest tornado intensities. For example, though tornado activity is relatively modest in Missouri, this state experienced a relatively high number of fatalities

[4] NOAA National Climatic Data Center, U.S. Tornado Climatology, retrieved on November 6, 2014 from http://www.ncdc.noaa.gov/climate-information/extreme-events/us-tornado-climatology
[5] Although the boundaries of "Tornado Alley" are not clearly defined, for our analysis we define the states of Texas, Oklahoma, Kansas, Colorado, Nebraska, South Dakota, Iowa, Illinois, Missouri, and Arkansas as the "Tornado Alley".
[6] NOAA National Climatic Data Center, U.S. Tornado Climatology: Tornado Alley, retrieved on January 12, 2015 from http://www.ncdc.noaa.gov/climate-information/extreme-events/us-tornado-climatology/tornado-alley
[7] Note that in 2007–2008 NOAA introduced and began using the Enhanced Fujita scale for measuring tornado intensity. We use the term Fujita scale throughout the paper since the majority of the data falls under this category.
[8] National Oceanic and Atmospheric Administration. Service assessment: the historic tornadoes of April 2011. Silver Spring, MD: US Department of Commerce, National Oceanic and Atmospheric Administration; 2011. Available at http://www.nws.noaa.gov/om/assessments/pdfs/historic_tornadoes.pdf Accessed November 15, 2014.

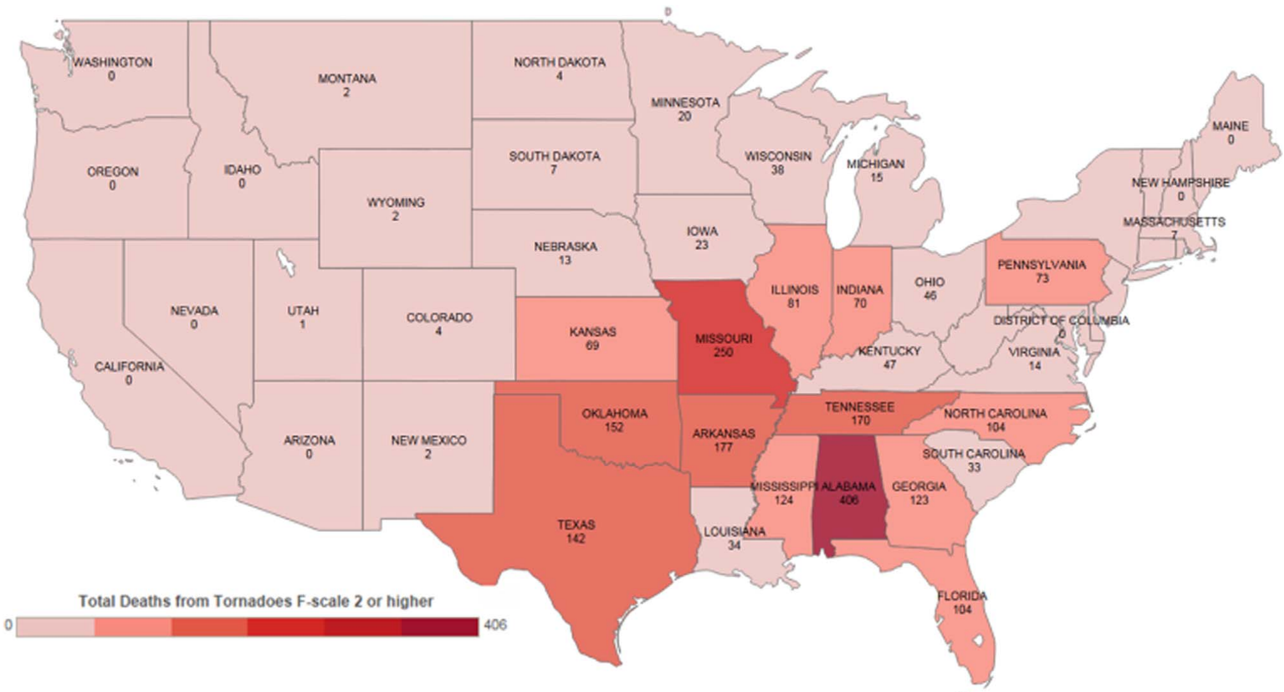

Fig. 3. Total number of strong/violent tornadoes (F2-F5), 1980–2014.

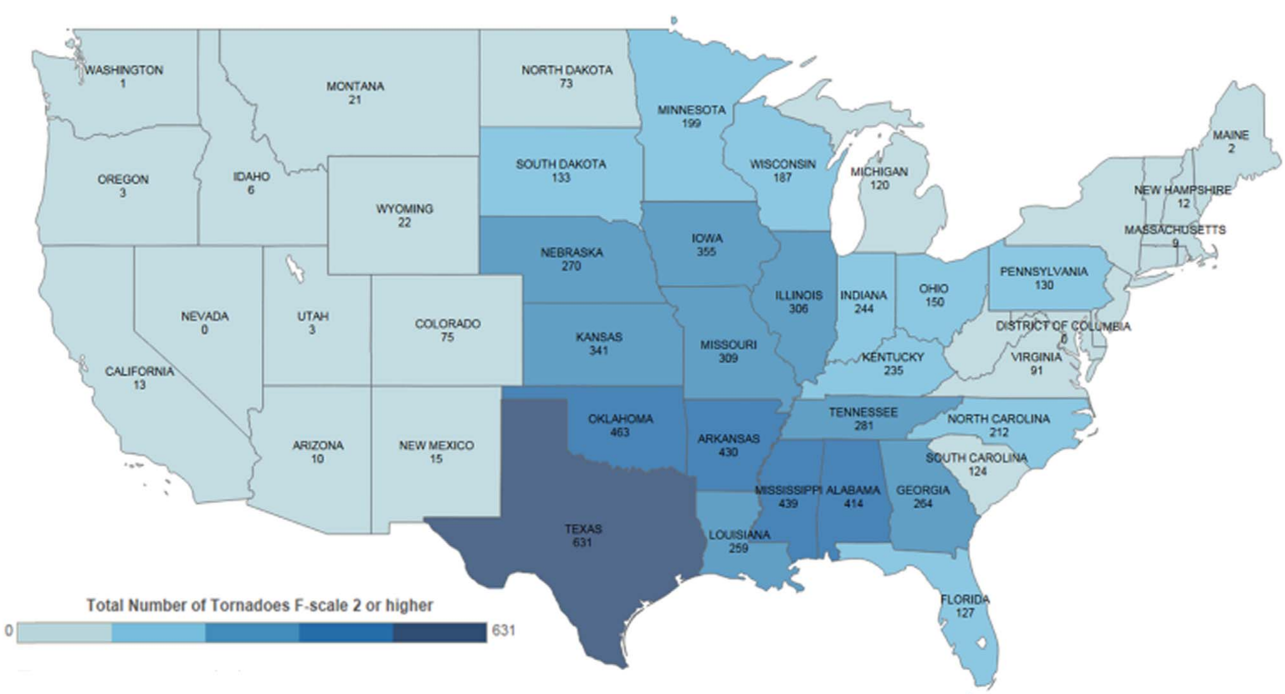

Fig. 4. Fatalities from strong/violent tornadoes (F2-F5), 1980–2014.

per year.[9] The present research is in part motivated by this observation. Note that these differences could be driven by many things including that there may have been a higher ratio of violent (F4 and F5) events in Missouri relative to say Texas. Our analysis below takes this into account and yet we still find significant evidence that specific socio-economic factors appear to be, at least in part, driving these differences.

[9] We present these maps at the state level for ease of exposition, but county-level maps reveal a similar divergence.

As highlighted earlier, Cutter et al. (2003) discuss the possible interactions between social and biophysical vulnerabilities that determine overall place vulnerability. They explain that the hazard potential is either moderated or enhanced via a combination of geographic factors and the social fabric of the place. This social fabric can include a community's experience with hazards, and its ability to respond to, cope with, recover from, and adapt to hazards, which in turn are influenced by socio-economic status, demographics, and housing characteristics. In their model, disaster fatalities are largely determined by socio-economic factors that shape a community's vulnerability to disasters and in turn determine the impacts of disasters.

Similarly, Blaikie et al. (1994) note that vulnerability, in the disaster context, is a person's or group's "capacity to anticipate, cope with, resist, and recover from the impact of a natural hazard" (p. 9). The group's disaster risk is determined purely exogenously by nature; however, a group's vulnerability against natural hazard is shaped by human components (O'Keefe et al., 1976; Hewitt, 1983). In the same vein, Cannon (1994) asserts that economic systems and class structures allocate income and access to resources, and this affects people's ability to cope with and recover from hazards. In general, it has been argued by many scholars that structural factors such as poverty, access to social protection and security, and inequalities with regard to gender, economic position, age, or race, cause or exacerbate vulnerability (Cannon, 1994; Aptekar and Boore, 1990; Albala-Bertrand, 1993, Enarson and Morrow, 1998; Peacock et al., 1997; Morrow, 1999). Fothergill and Peek (2008) point out that disaster researchers increasingly use a "socio-political ecology of disasters" as a theoretical framework of their disaster research, conducting analyses of minority, gender, and inequality issues in the context of disasters.

Based on a conceptual framework where risk is considered to be a function of physically defined natural hazards and socially constructed vulnerability, we seek to identify key elements of tornado fatalities through empirical analysis using detailed data on tornado events and socio-economic data for 3107 U.S. counties from 1980 through 2014. In addition to controlling for primary factors such as county population, lagged tornado frequency, and tornado magnitude (Fujita scale), we hypothesize that there are a number of demographic, socio-economic, housing, and governmental factors that may also play significant roles in determining tornado-induced deaths.

4.1. Income/wealth and income distribution

First, as one of the well-known determinants of disaster impacts, we test the robustness of the hypothesis that the level of community's income/wealth plays significant role in vulnerability of disasters. Researchers such as Wildavsky (1988) contend that greater income and wealth translates to a safer society. Safety can be viewed as a natural product of a growing market economy since higher income places have a higher demand for safety and more resources to invest in risk reduction measures, which in turn leads to reduced vulnerability to disasters. The income/wealth hypothesis has been supported by many empirical studies (Kahn, 2005; Toya and Skidmore, 2007; Strömberg, 2007; Raschky, 2008; Gaiha et al., 2013). Note that these studies use cross-country data where GDP is used as a measure of income/wealth, whereas in our study, we use U.S. county per capita income.

In addition to per capita income, we also include the county top ten percentile income level and county poverty rates in our analysis as measures of income distribution. If income distributions are similar across all counties and over time, the top ten percentile income level measure should be closely correlated with per capita income. However, since income disparity in the United States has increased over our sample period and more so in some counties than others, we speculate that controlling for per capita income the top ten percentile income variable will capture the role income disparity play in determining disaster vulnerability. Similarly, we hypothesize that societies with a higher concentration of poverty might encounter higher tornado-induced human losses. According to Fothergill and Peek (2008), the poor in the United States are more vulnerable to natural disasters due to such factors as place and type of residence, building construction, access to information, low quality infrastructure, and social exclusion. Furthermore, Moore (1958) highlighted the relationship between socio-economic status and warning response, reporting that lower income groups were less likely to take the warnings of impending natural disasters seriously. Gladwin and Peacock (1997) reported in their study of warnings and evacuation for Hurricane Andrew that lower income people were less able and thus less likely to evacuate, mostly due to constraints placed by a lack of transportation and affordable refuge options. Similarly, an empirical study of natural disasters in Fiji, (Lal et al., 2009) finds evidence that the level of poverty (measured by the HDI) negatively affects disaster outcomes. The authors argue that those living in poverty are more sensitive to disasters because they have lower economic and social conditions; that is, they are unable to invest in adequate preparedness and risk reduction measures.

4.1.1. Gender and female-headed households

We also hypothesize that female-headed households are likely to be among the most vulnerable. According to the 2012 Census, families headed by a single adult are more likely to be headed by women, and these female-headed families are at greater risk of poverty and deep poverty; 30.2% of families with a female householder where no husband is present were poor and 16.9% were living in deep poverty. In addition, a study by Neumayer and Plumper (2007) suggests that the socially constructed gender-specific vulnerability of females – which is built into everyday socio-economic patterns – leads to relatively higher female disaster mortality rates as compared to men.

While this study attempts to shed light on the direct impacts of disasters on female-headed households, the vulnerability of female-headed households during and in the wake of disaster events is highlighted in the literature. Researchers focusing on post-disaster outcomes indicate the degree of disaster impacts vary by gender not only in terms of direct physical loss, but also during the periods of emergency response, recovery, and reconstruction. For example, Blaikie et al. (1994) argue that women have a more difficult time during the recovery period than men, often due to sector-specific employment, lower wages, and family care responsibilities. Similarly, two years after Hurricane Andrew, thousands of poor families headed by minority women were still living in substandard temporary housing (Morrow and Enarson, 1996).

4.1.2. Human capital

Our third hypothesis is that human capital – as measured by percentage of population aged 25 and over holding a Bachelor's degree – is one of the major characteristics defining social vulnerability. Several cross-country studies found significant correlations between level of educational attainment and reduced fatalities (see Skidmore et al. (2007)). Educational attainment is linked to the emergency decision-making process; education influences one's ability to understand warning information and perform evacuation or other necessary actions. Cutter et al. (2003) explain that while education is clearly linked to socio-economic status (higher educational attainment resulting in greater lifetime earnings), lower education may also constrain the ability to understand warning information and access to recovery information. Additionally, they argue that those with higher levels of education are more likely to choose safer locations and homes constructed with more durable materials, thus resulting in fewer fatalities.

In a recent study, Muttarak and Lutz (2014) argue that education can directly influence risk perceptions, skills and knowledge and indirectly reduce poverty, as well as promote access to information and resources. These factors contribute to higher adaptive capacity and vulnerability reduction. The authors collect empirical evidence from a series of studies contained in a special issue aimed at investigating the role of education in vulnerability reduction; the authors provide consistent and robust findings on the positive impact of formal education in reducing vulnerability.

4.1.3. Housing choice

The fourth hypothesis is that communities with a higher proportion of households living in mobile homes or trailers will suffer increased levels of tornado casualties. Aptekar (1991) argues that it is more likely that disasters adversely affect those with lower socio-economic status largely because of the types of housing they occupy. Logically, people living in mobile homes are more vulnerable to natural events such as tornadoes because mobile homes typically have no foundation or basement and can more be easily destroyed. From 1996 to 2000, about half of tornado-induced deaths in the United States were in mobile homes,[10] even though mobile homes accounted for less than 8% of the nation's housing during the same period, according to the National Oceanic and Atmospheric Administration and the U.S. Census Bureau. Historical data on tornado fatalities (1975–2000) tell us that the rate of death from tornadoes in mobile homes is about 20 times higher than that in site-built homes[7].

As shown in Table 2, the proportion of households living in mobile homes increased significantly since 1950. While the quality of these homes is probably higher than in the past, they still lack structural characteristics (e.g. foundations and basements) that make other types of construction more resistant to tornadoes. Importantly, mobile home living is very high in many rural counties across the United States. As shown in Fig. 5, in 2010 many rural counties had more than a third of households living in mobile homes. The increase in the U.S. population living in mobile homes is likely to have important policy implications for disaster management in the context of tornadoes and other high wind events (Brooks, 2001; Merrell et al., 2005; Kusenbach et al., 2010; Fothergill and Peek, 2008; Schmidlin et al., 2009).

Table 2
Mobile Homes in the United States. *Source: U.S. Census Bureau, Housing and Household Economic Statistics Division.*

Year	Mobile Homes (%) in U.S. housing units	Total Mobile Homes in U.S. housing units	Total U.S. housing units
1950	0.7%	315,218	45,983,398
1960	1.3%	766,565	58,326,357
1970	3.1%	2,072,887	68,679,030
1980	5.1%	4,401,056	88,411,263
1990	7.2%	7,399,855	102,263,678
2000	7.6%	8,779,228	115,904,641
2010[a]	6.7%	8,684,414	130,038,080

[a] 2010 data are estimates produced by American Community Survey while data for years 1950–2000 are from Decennial Census.

4.1.4. *Local government investment*

Our last hypothesis is that communities where local governments invest more resources in safety, protection and welfare will experience fewer fatalities. To capture this effect, we construct a measure of government spending on public safety, protection, and welfare by aggregating local government expenditures on fire/police protection and protective inspections/regulations and housing/community development, and public welfare. Local government resources devoted to public safety services such as fire/police protection and protective inspection and regulation should lead to better preparedness and faster responses to disaster events, which, in turn, may play critical roles in reducing fatalities. It is also possible that allocating more resources to public welfare may reduce community vulnerability. In the context of local government, welfare services are not direct cash assistant (this comes from state government), but are for services like children's homes or payments to vendors for substance abuse treatment and the like.

5. Empirical analysis

The county level panel data in the analysis consists of: (1) data on tornadoes from NOAA (1980–2014) used to develop detailed information on tornado locations, magnitudes and deaths, (2) data from U.S. Decennial census of population for the major socio-economic and housing factors in 3107 counties from 1980 to 2010, and (3) local government fiscal data from the U.S. Census of Governments (1982 to 2012). Note that the Census of Population data are only available every ten years, whereas local government fiscal data are reported every five years (years ending in 2 or 7). Also, since, at the county level, the tornado data has many zero observations we organize our panel data such that it contains county level tornado observations across seven time blocks between 1980 and 2014 (in five year intervals): '80–84, '85–'89, '90–'94, '95–'99, '00–'04, '05–'09, '10–'14. The detailed tornado data are aggregated and rearranged to form county level observations and the tornado variables are averaged over each time block and are assigned middle years of each time block, 1982, 1987,... 2012. Decennial census data for demographic and housing variables are interpolated to obtain data in 1982, 1987,., 2012. Lastly, averaged tornado data and the interpolated census data are merged with the local government fiscal data. Overall, we construct seven time-blocks for each of the 3107 counties.[11]

When we average tornado data across time blocks, we include only strong/violent tornadoes rated F2 or greater for our main analysis or, for our additional analysis F3 or greater. Accordingly, our dependent variable is the average number of deaths[12] caused by tornadoes rated F2-F5 (or F3-F5 in additional analysis). As noted earlier and shown in Table 3, most tornadoes are classified as F0 or F1 and those tornadoes commonly lead to very few deaths or do not claim lives at all. Since these types of tornadoes are effectively non-disasters we do not include them. As a result, county level panel data for our empirical estimation contains 2120 counties that have experienced tornadoes of F2+ at least once over the study period. Table 3 presents the total number of tornadoes and resulting fatalities and injuries by F-scale over the years 1980–2014.

The dependent variable in this analysis is the average number of fatalities per tornado and thus, non-negative value. We employ a Poisson model which properly treats the non-negative variables within the county level panel data framework (Wooldridge, 1991).[13] Also, considering the large portion of zeros in the dependent variable, we repeat the analysis using a Negative Binomial model as a robustness check. In this study, many of the county socio-economic characteristics do not change much over time. Thus, there is little within-county variation for many of our explanatory variables. Given this, the fixed effects model is not necessarily preferred to random effects model.[14] In his multi-national disaster study, Kahn (2005) points out the presence of sluggish adjustment and long latency in economic development, which makes the inclusion of country fixed effects problematic. Taking the same stance as Kahn, we estimate our model using both random and fixed effects Poisson, but mainly discuss the random effects estimates.[15]

[10] Brooks and Doswell III (2001). A brief history of deaths from tornadoes in the United States. *Weather and Forecasting*, 1–9. http://www.nssl.noaa.gov/users/brooks/public_html/deathtrivia/

[11] Given that county level socio-economic variables are only available every ten years, we use averaged tornado data in time intervals to avoid using interpolated data for all the socio-economic variables for all years except for years ending in 0, and interpolated government fiscal data for most time periods as well. By having a county as a unit of observation in this study, we are able to retain and explore a long-term variation in county socio-economic and government fiscal factors more accurately whose role in disaster events is the main interest of our study.

[12] For example, a county A experienced two tornadoes each rated F2 and F0, having fatalities of 3 and 0 respectively, in a time block B, then county A in year B is assigned 3 for its average fatalities per tornadoes F2 or higher. We exclude and do not count F0 andF1 tornadoes when we generate *Avg Fatalities_F2-F5* or *Avg.Fscale_F2-F5* variables.

[13] Our dependent variable is an average value and can be non-integer. However, the Poisson (quasi-MLE) model is robust to distributional assumptions; it can be applied to any nonnegative outcome, either continuous or integer valued (Wooldridge, 1991).

[14] Wooldridge (2010) also discusses that when the key explanatory variables do not vary much over time, fixed effects methods can lead to imprecise estimates.

[15] The result of Fixed Effects Poisson is presented in Appendix.

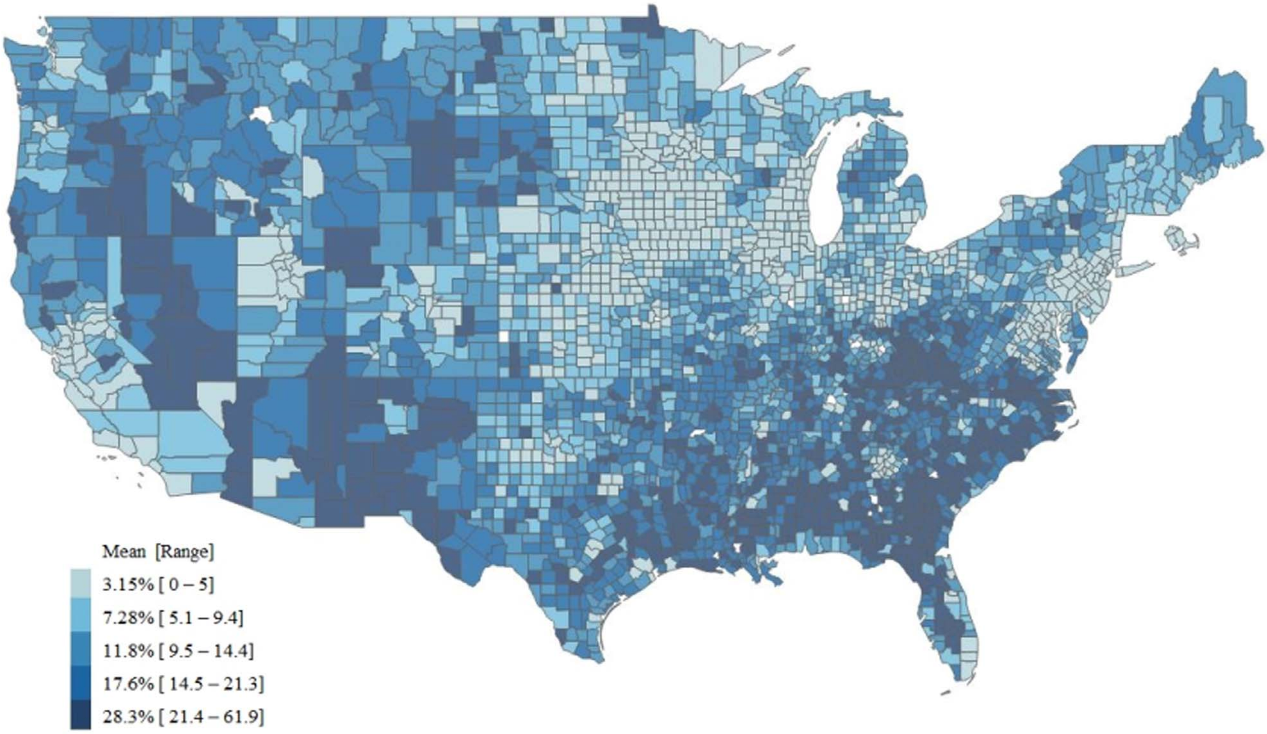

Fig. 5. Proportion of households living in Mobile Homes, 2010.

Table 3
Tornadoes and resulting impacts by Fujita-scale (1980–2014)[a].

	Tornado		Fatalities		Injuries	
F-scale	Obs.	%	Total	Avg.	Total	Avg.
F0	22,028	51.31	12	0.001	536	0.024
F1	11,977	27.90	128	0.011	3945	0.329
F2	**3907**	**9.10**	**330**	**0.084**	**8427**	**2.157**
F3	**1193**	**2.78**	**880**	**0.738**	**13,586**	**11.388**
F4	**301**	**0.70**	**869**	**2.887**	**13,055**	**43.372**
F5	**27**	**0.06**	**639**	**23.667**	**4567**	**169.148**
Total	42,934	100	2447	0.057	39,877	0.929

[a] Only F2-F5 tornadoes are examined in this study.

The regression analysis is characterized by the following equation:

$$E[Y_{jt}] = \exp(\beta X_{jt} + \rho G_{jt} + \gamma_1 Z_{1jt} + \gamma_2 Z_{2jt-1} + Z_{1jt}{*}Z_{2jt} + \delta D_j + \theta D_T + \alpha_j + \varepsilon_{jt})$$

where Y_{jt} is the average deaths per tornado in county j during time block t, $\boldsymbol{X_{jt}}$ is a vector of socio-economic and housing variables affecting deaths in county j at time t, G_{jt} is local government spending on public/safety, D_j is the dummy variable for Tornado Alley, Z_{1jt} is the average F-scale occurred in a county j at time t, Z_{2jt-1} is the number of strong tornadoes in county j at time $t-1$, $Z_{1jt}{*}Z_{2jt}$ is an interaction term between the magnitude and the number of tornadoes, D_T represents a series of time indicator variables, α_j is a time-invariant effect for county j, and ε_{jt} is the unobservable error term. The detailed explanation for the variables in the model is provided in Table 4, and Table 5 provides summary statistics for these variables.

Table 6 shows that over the 35 years from 1980 to 2014, a total of 5428 tornadoes of F2 or greater occurred and caused 2718 deaths and 39,635 injuries; 4733 of these tornado events resulted in zero fatalities.

Table 4
List of dependent and explanatory variables in the model.

Dependent Variable		
Avg. Deaths from tornadoes		Y_{jt}
Explanatory Variables		
Demographic	Population size (in million)	X_{ijt}
	Percent of urban population	
	Percent of population over 65	
	Percent of population under 18	
	Percent of people holding Bachelor's degree (aged 25 and over)	
	Percent of female-headed households	
Economic	Log (Per capita Income)	
	Log (Top 10 percentile income level)	
	Poverty rate	
Housing	Percent of mobile homes in total housing units	
Government	Log (Local government expenditures on public safety/welfare)	G_{it}
Tornado	Magnitude of tornadoes	Z_{ijt}
	Lagged tornado frequency of F2+	
	F-scale*Tornado Frequency	$Z_{1jt}{*}Z_{2jt}$
	Tornado alley	D_j
Time Dummy	1987, 1992, 1997, 2002, 2007, 2012	D_T

We aggregate tornado data into the aforementioned five-year intervals and form a panel structure. The county level panel data for our study contains 15,046 county-year observations[16] of which 4831 observations had strong/violent tornado(es) rated F2 or higher and 1016 observations had fatalities from those events. Using these data, we estimate equation (1) using Poisson and Negative Binomial estimation procedures.

[16] Counties without any experience of tornadoes of F2+ over the whole periods are excluded; 2150 counties are examined.

Table 5
County summary statistics.

	Mean	Standard Deviation	Min	Max	Number of Obs.
Dependent Variables					
Avg. Tornado Deaths (F2-F5)	0.29	1.34	0	52.67	4828
Independent Variables					
Avg. Fscale (F2-F5)	2.40	0.58	2	5	4828
Fscale[a]Torando Freq.(F2-F5)	1.14	2.18	0	38.44	15,071
Lagged Tornado Frequency (F2-F5)	0.46	0.84	0	9	15,071
Tornado Alley Dummy	0.40	0.49	0	1	15,071
Persons Total (mil.)	0.09	0.35	0.00	9.88	15,071
Pct Urban Population	39.15	29.31	0	100	15,071
Pct Over 65	14.04	3.95	2.31	43.64	15,071
Pct Under 18	25.93	3.42	7.72	46.77	15,071
Log (Per Capita Gov Expenditure on Public Safety & Welfare)	−1.52	0.75	−5.90	1.12	15,071
Log (Per Capita Income)	9.80	0.26	8.57	10.98	15,071
Log (Top 10% Income)	11.53	0.29	10.64	12.08	15,071
Poverty Rate	15.79	6.95	0	60.94	15,071
Pct BA Degree	15.07	7.32	2.01	72.79	15,071
Pct Mobile Home	12.51	8.26	0	59.50	15,071
Pct Female-Headed Household	10.38	4.17	0.88	38.34	15,071

[a] Tornado statistics (Avg. Tornado Deaths and Avg. Fscale) are from only observations with F2-5 tornadoes, whereas all other demographic and socio-economic statistics are from our general data set.

Table 6
Fatalities induced by strong tornadoes (F2-F5), 1980–2014[a].

Fatalities	Freq.	Percent
0	4733	87.20
1–5	577	10.63
6–15	86	1.58
16–30	26	0.48
31–158	6	0.11
Total	5428	100.00

[a] For this information, yearly tornado data from NOAA is used. However, this study exploits a panel data with county-year observations.

Eight specifications are estimated to test our hypotheses. Our dependent variable is the average number of deaths per tornado (of Fujita Scale 2–5) in each county in a particular time block. Some of the socio-economic determinants are highly correlated with each other, which may result in multicollinearity. To address this possibility, we conduct preliminary analyses using more parsimonious model specifications as shown in columns (1) to (6) of Table 7. Each hypothesized potential determinant of tornado impacts – for example, poverty rate, education level, female-headed household, and mobile homes – are examined separately but with a consistent set of control variables. Given that many prior studies found income level to be one of the most important factors, per capita income is included in every specification. Government spending on public safety and welfare also appears in every specification because this is the only variable that represents the role of government, although government spending might be weakly related to the economic variables discussed above. The last specification includes all the poverty-related potential determinants, testing them in a single specification. In all specifications, we include the following variables as controls: average tornado magnitude, population size, land area, percent of urban population, percent of population over age 65 and under 18, lagged tornado frequency, an interaction term between magnitude and frequency, and a categorical variable for counties located in the Tornado Alley region.

The EM-DAT data used in most of the prior studies discussed do not contain information on disaster magnitude for many of the recorded disaster events, so most studies using those data are unable to control for disaster magnitude. The tornado data from NOAA, however, does provide a magnitude measure for each tornado (F-scale), and thus we can more readily distinguish impacts on fatality due to disaster magnitude versus other explanatory variables we wish to explore. Specifically, we use the average magnitude of all tornadoes of F2-F5 that occurred in a particular county in a given period because our unit of observation of this study is counties, not individual tornado events.

Also, considering that Tornado Alley regions are more highly prone to tornadoes than other regions, we introduce a dummy variable in the model. (D_j=1, if the county j is in this geographic region and D_j=0, otherwise) along with lagged tornado frequency of F2-F5 (or F3-F5 in additional analysis on severe tornadoes). These variables allow us to test whether greater familiarity with this type of emergency makes the area more able to cope (e.g., building codes, population behavior during the event). An interaction term between magnitude and frequency is included to see if areas with a greater number of larger tornadoes experience greater fatalities.

6. Results

Table 7[17] presents the results of our regressions using F2 or higher tornado observations recorded in counties over 1980–2014 and a set of demographic, socio-economic, housing, and government fiscal factors as presented in Table 5. We focus our discussion on Random Effects Poisson and Negative Binomial specifications here; however, the Fixed Effects specification estimates outcomes are provided in the Appendix for the interested reader.

Before discussing our primary findings as they relate to our hypotheses, consider the estimated effects of the control variables. The F-scale variable which is an indicator of the average magnitude of tornadoes within a given time period, has a strong association with the number of deaths in all specifications. As expected, our analysis confirms the magnitude of the tornado is a critical physical determinant of the tornado fatalities. The estimated coefficient on the average F-scale in column (7) in Table 7 implies that an increase in F-scale to the next level increases expected tornado fatalities by a factor of 4.78. The positive estimates of *Fscale*Tornado_F2+* imply that tornado magnitude and the fatalities are associated non-linearly; counties with more severe tornadoes suffer greater human losses. Both lagged tornado frequency and tornado alley variables are estimated to be negatively correlated with fatalities in all specifications. Counties in the tornado alley region suffering tornadoes relatively often are estimated to experience 28% lower fatalities than counties outside of the tornado-prone area, all other conditions being equal. This result supports the idea that there might be some kind of learning effects from past tornado experiences, where counties that suffered more tornado outbreaks tend to put more efforts to reduce their vulnerability and be better prepared for disasters and in turn better able to mitigate the societal impacts. McEntire (2001) asserts that beliefs and activities play

[17] We discuss both Poisson and Neg. Binomial regressions results here, however, the likelihood ratio test of α (dispersion parameter) = 0 rejects the null hypothesis that the errors do not exhibit overdispersion. Thus, the Poisson regression model is rejected in favor of its generalized version, the Neg. Binomial regression model. The results of Poisson model are very similar to the results of Negative Binomial and thus presented in Table A1 in the Appendix. When explaining the estimated effects of explanatory variables in the result section, we refer to the estimation results of Neg. Binomial model in Table 7.

Table 7
Socio-economic characteristics and disaster impacts— negative binomial random effect regressions results.

Dependent variable: *Average Deaths from F2-F5 tornadoes*							
Independent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fscale_F2+	1.543***	1.544***	1.546***	1.540***	1.567***	1.539***	1.565***
	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)
Fscale*Tornado_F2+	0.085***	0.087***	0.085***	0.086***	0.087***	0.084***	0.088***
	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Lag Tornado Freq_F2+	−0.011	−0.014	−0.014	−0.009	−0.016	−0.015	−0.022
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)
Tornado Alley	−0.506***	−0.504***	−0.478***	−0.487***	−0.381***	−0.397***	−0.327***
	(0.098)	(0.098)	(0.099)	(0.099)	(0.097)	(0.104)	(0.104)
Persons Total (in mil.)	0.332**	0.339**	0.286*	0.342**	0.345**	0.271*	0.312**
	(0.144)	(0.145)	(0.147)	(0.144)	(0.141)	(0.147)	(0.144)
Pct Over 65	−0.060***	−0.046***	−0.059***	−0.066***	−0.025	−0.051***	−0.013
	(0.016)	(0.017)	(0.016)	(0.016)	(0.015)	(0.016)	(0.018)
Pct Under 18	−0.047***	−0.052***	−0.048***	−0.052***	−0.019	−0.056***	−0.027
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.019)
Pct Urban Population	0.003	0.003	0.002	0.004*	0.009***	0.001	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Log(Gov Exp on Public Safety & Welfare)	−0.236***	−0.245***	−0.239***	−0.234***	−0.182**	−0.273***	−0.207***
	(0.074)	(0.075)	(0.074)	(0.074)	(0.074)	(0.076)	(0.076)
Log (Per Capita Income)	−0.816***	−1.660***	−0.146	−0.563*	0.008	−0.191	−0.294
	(0.263)	(0.484)	(0.451)	(0.311)	(0.283)	(0.341)	(0.715)
Log (Top 10% Income)		1.171**					0.943*
		(0.564)					(0.558)
Poverty Rate			0.020*				0.005
			(0.011)				(0.014)
Pct BA Degree				−0.015			0.001
				(0.010)			(0.011)
Pct Mobile Home					0.050***		0.048***
					(0.007)		(0.007)
Pct Female-Headed						0.043***	0.018
						(0.015)	(0.017)
Dummy 1987	0.257*	0.173	0.182	0.237	0.082	0.138	−0.046
	(0.150)	(0.155)	(0.155)	(0.151)	(0.150)	(0.156)	(0.163)
Dummy 1992	−0.008	−0.114	−0.162	−0.040	−0.394**	−0.231	−0.593***
	(0.156)	(0.164)	(0.177)	(0.157)	(0.162)	(0.174)	(0.195)
Dummy 1997	0.462***	0.311*	0.241	0.413**	−0.050	0.144	−0.335
	(0.166)	(0.182)	(0.205)	(0.169)	(0.177)	(0.200)	(0.236)
Dummy 2002	0.683***	0.448**	0.425*	0.633***	0.093	0.303	−0.291
	(0.179)	(0.213)	(0.228)	(0.182)	(0.192)	(0.222)	(0.273)
Dummy 2007	0.838***	0.489**	0.544**	0.803***	0.235	0.411*	−0.267
	(0.176)	(0.244)	(0.239)	(0.177)	(0.191)	(0.231)	(0.307)
Dummy 2012	0.703***	0.216	0.377	0.677***	0.108	0.257	−0.521
	(0.176)	(0.294)	(0.251)	(0.177)	(0.191)	(0.235)	(0.353)
Constant	5.251*	0.150	−1.399	3.191	−4.536	−0.989	−12.358**
	(2.720)	(3.678)	(4.543)	(3.036)	(2.989)	(3.468)	(5.942)
No. of Observations	15,054	15,054	15,047	15,054	15,054	15,054	15,047
No. of Counties	2151	2151	2150	2151	2151	2151	2150

Robust standard errors in parentheses,
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

a major role in the creation of vulnerabilities and past disaster lessons reduce future consequences.

We also include county population, the share of population in urbanized areas in a county, and the proportions of the population over the age of 65 and under 18. With these variables, we see that counties with greater populations experience more deaths when tornadoes strike – an unsurprising result. The positive coefficients on the percent urban population variable indicate that more urbanized counties experience more tornado fatalities. However, in all estimates we see that counties with greater proportions of seniors and young people experience fewer fatalities. In our initial assessment, we thought that these population groups would be more vulnerable rather than less. One possible explanation is the older people and families with children may be more risk averse and heed tornado warnings, thus reducing exposure. It could also be caused by higher proportions of these individuals being in environments (schools, retirement communities) where warnings are more easily distributed.

We now turn to our primary interest in the role that the various dimensions of poverty, and social vulnerability play in determining tornado impacts. We begin this portion of the discussion by considering the factors that align with our first hypothesis regarding the role of income/wealth in determining vulnerability.

6.1. Richer counties experience fewer tornado-induced deaths

Consistent with most other empirical studies, we find that per capita income is a key determinant of tornado impacts. The negative relationship between income and tornado fatalities is robust in both the Poisson and Negative Binomial analysis, indicating that higher county per capita income results in fewer tornado-induced fatalities, whereas greater poverty rates appear to aggravate the vulnerability of a community, intensifying disaster impacts. As Anbarci et al. (2005) and Kahn (2005) argued in their studies, we also find that income distribution (as measured by the top ten percentile income level) is a significant factor. Holding other factors constant including per capita income and the poverty rate, a higher top ten percentile income level means a larger lower-middle income group, which indicates wider income disparity in the community. Our estimates suggest that greater income inequality tends to exacerbate the impacts of disasters.

6.2. Human capital plays an important role in reducing tornado vulnerability

Our findings indicate that human capital, as measured by the proportion of the population aged 25 and over with a Bachelor (or higher) degree, is negatively linked to community vulnerability to tornadoes. Educational attainment may be linked to emergency decision-making processes such as the ability to quickly comprehend warning information and perform evacuation or other necessary actions or to having more workers located inside buildings with more solid construction (e.g., office building versus pole barn). Thus, those with lower education attainment may be more vulnerable to disaster shocks. The estimated results are consistent with previous studies (e.g., Skidmore et al., 2007; Muttarak and Lutz, 2014). However, again, education and other explanatory variables such as income levels and poverty measures are highly correlated; thus, the insignificance of education in column (7) is likely the result of multicollinearity.

6.3. Mobile home residents experience more tornado fatalities

The fourth hypothesis is that mobile home living results in more tornado fatalities. The regression estimates in specifications (6) and (8) show that the percent of mobile homes in a county is positively related to tornado fatalities, and the estimates are robust. These estimates confirm that more mobile homes in a county results in greater vulnerability to tornadoes. The estimated coefficient implies that a one percentage point increase in the proportion of mobile homes to total housing units increases tornado-related deaths by 5 percent. Further, as noted earlier, more households are choosing this type of housing arrangement over time and thus vulnerability may be increasing. This finding may have important policy implications in the context of developing approaches to reduce tornado vulnerability. For example, mobile home parks could potentially provide common tornado shelter areas to be used in the event of a tornado watch or warning.

6.4. Female-headed households are more vulnerable to tornadoes

The fifth hypothesis is that female-headed households are more vulnerable to tornadoes. This hypothesis is explicitly examined in specifications (6) and (7). These regressions show that female-headed households and tornado-induced fatalities are positively correlated, though it only achieves statistical significance in specification (6). These results suggest that all else equal, places with more female-headed households are more vulnerable, perhaps because female-headed households have limited access to resources during high risk events. The result is consistent with the previous arguments by sociologists (Enarson and Morrow, 1998; Enarson et al., 2006). While our findings shed light on the direct impacts of disasters on female-headed households, the vulnerability of female-headed households in a longer-run framework is highlighted in the literature. Researchers focusing on post-disaster outcomes indicate the degree of disaster impacts vary by gender not only in terms of direct physical loss, but also during the periods of emergency response, recovery, and reconstruction. For example, Blaikie et al. (1994) argue that women have a more difficult time during the recovery period than men, often due to sector-specific employment, lower wages, and family care responsibilities. Similarly, two years after Hurricane Andrew, thousands of poor families headed by minority women were still living in substandard temporary housing (Morrow and Enarson, 1996). Our analysis weakly supplements these research, revealing which types of households are more vulnerable when disasters occur.

6.5. Government spending in public safety and welfare mitigates losses from tornadoes

Finally, we test the degree to which local government plays a role in reducing potential tornado fatalities. We find a significant and negative relationship between tornado fatalities and per capita government spending on public safety/welfare in all specifications of the Poisson and Negative Binomial models.[18] Our empirical analysis suggests that such local government expenditures appear to improve overall safety/welfare of a community, thus playing a role in mitigating citizens' vulnerability. However, further research is needed to better target which set of public services provided by local governments most effectively mitigates the degree to which their citizens are vulnerable to tornadoes.

7. Conclusion

While tornado activity is exogenously determined by natural forces, it is also true that socio-economic factors are critical in determining vulnerability. In this article, we seek to uncover these underlying factors. To this end, we investigate the relationship between tornado fatalities and the potential determinants of tornado impacts within U.S. counties over the period from 1980 to 2014. Findings of our study enable us to identify which societal characteristics exacerbate or mitigate vulnerability to hazards, which in turn allow us to suggest

[18] As in prior studies (e.g. Garcia-Mila and McGuire (1992) and Cullen and Levitt (1999)), we also estimate our model using lagged government expenditure variable to address potential endogeneity. The results of these estimation do not alter any of our conclusions and are available upon request.

policies that may help mitigate human losses from such events.

Our empirical analysis consistently demonstrates that income level is a crucial determinant of tornado fatalities; this finding is consistent with an array of previous studies, but we offer more detail on how the various expressions of poverty may contribute to deaths. In addition, we offer evidence that per capita government spending on public safety and welfare is also negatively related to death tolls. This suggests that increased government spending in critical areas such as safety, protection and welfare, reduce overall vulnerability within a community. In this regard, further research is needed to investigate which particular public service provided by local government mitigates the degree to which their citizens are affected by tornadoes.

Our analysis also suggests that income inequality is a significant factor that may exacerbate the impacts of disasters. Furthermore, counties with a higher poverty rate and more female-headed households tend to be more vulnerable, whereas the higher the county's education level, the lower is vulnerability. In general, households most affected by disasters are those with weaker economic and social bases. The information presented here may help to target the most vulnerable households and provide improved access to safety resources.

Another key finding is that the number of mobile homes in a county is critical factor in explaining tornado fatalities. This finding implies that housing quality is perhaps the most important factor in determining tornado vulnerability. Importantly, the proportion of households living in mobile homes has increased nearly three-fold since the 1970s, with much of this increase occurring between 1970 and 1980 (prior to the period of analysis). Though mobile homes offer a relatively inexpensive but comfortable housing alternative, it appears that this trend has made the United States more vulnerable to tornadoes over time. Given this trend and our findings, it is critical that federal, state and local policy makers consider alternatives to reduce vulnerability for those living in this type of housing arrangement.

Policies aimed at strengthening the ability of mobile homes to withstand high winds and flying objects and more systematically required communal mobile home park tornado shelters may be effective at reducing tornado fatalities. In particular, mobile homes are commonly classified and taxed as personal property, placing lower tax burden to home owners. This tax advantage makes mobile home living economically more attractive, but at the same time the tax policy is in fact encouraging more people to live in housing that is more vulnerable to tornados. The external cost of being exposed to greater tornado risks may be ignored when households choose to live in mobile homes due to affordability. One potential policy scheme that would internalize this social cost would be to: i) require communal shelters in mobile home parks and communities,[19] ii) impose a higher tax rate on mobile homes where tornado shelter/safe room are unavailable, and iii) direct the tax revenue raised from item ii) towards additional government funds for the local communities' safety/protection. In this way, local governments could broaden their tax base and target the revenue from that source to further mitigate human losses from future tornado events.

Overall, this study reveals which types of households tend to have more difficult time when disaster occurs, thus informing policies targeted at reducing tornado fatalities. More generally, addressing the root of the issue by improving the conditions of those with lower socio-economic status reduce vulnerability over time. The future median annual impact of tornadoes is predicted to rise threefold over the next few decades due to the twin forces of increased climate variability and growth in the human-built environment (Strader et al., 2017). The importance of natural disasters and their societal impacts are increasingly being emphasized due to the disproportionate impact on socially vulnerable populations. This has widened social concerns regarding environmental justice and disparities beyond such issues as the siting polluting facilities near low income communities to the exposure to climate shocks and resulting impacts of such events on such communities. In this context, it is critical to identify what kind of socioeconomic conditions characterize the most vulnerable households and how and to what extent they are disproportionally affected by natural disasters. We expect that our findings will increase our understanding of the socio-economic nature of tornado impacts and better inform future policies and regulatory actions designed to mitigate disaster impacts and further, reduce environmental disparities.

Appendix A

See Table A1.

Though we do not offer a detailed discussion of the fixed effects estimates presented in Appendix Table A2, in general the statistical significance of the socio-economic variables is greatly reduced. Few of the variables are significant, but this is not too surprising given that within county changes over the 1980–2014 period are typically small for most of these variables. However, note that in Table A2 we observe a reversal of sign on several socio-economic variables such as poverty rate, female-headed household, education variable, where coefficient estimates are neither robust nor consistent with previous findings. As noted by Kahn (2005) the fixed effects approach be problematic, given the presence of sluggish adjustment and long latency in economic development. Nevertheless, we present these estimates for the interested reader.

[19] There are communities that already require all mobile home parks to provide storm shelters for their residents, including the State of Minnesota, and some individual counties (e.g. Sedgwick County and Butler County in KS, St. Joseph County, MO, etc.)

Table A1
Socio-economic characteristics and disaster impacts—Poisson random effect regressions results.

Dependent variable: *Average Deaths from F2-F5 tornadoes*

Independent variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fscale_F2+	1.651***	1.648***	1.653***	1.648***	1.669***	1.652***	1.667***
	(0.044)	(0.044)	(0.044)	(0.044)	(0.045)	(0.045)	(0.045)
Fscale*Tornado_F2+	0.084***	0.087***	0.085***	0.085***	0.086***	0.083***	0.088***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Lag Tornado Freq_F2+	−0.003	−0.005	−0.004	−0.001	−0.004	−0.008	−0.008
	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)
Tornado Alley	−0.624***	−0.620***	−0.598***	−0.603***	−0.478***	−0.521***	−0.435***
	(0.114)	(0.112)	(0.115)	(0.115)	(0.108)	(0.118)	(0.114)
Persons Total (in mil.)	0.337**	0.342**	0.294**	0.346**	0.355**	0.282**	0.325**
	(0.136)	(0.138)	(0.135)	(0.139)	(0.140)	(0.132)	(0.141)
Pct Over 65	−0.069***	−0.054**	−0.069***	−0.075***	−0.036*	−0.061***	−0.023
	(0.021)	(0.023)	(0.021)	(0.022)	(0.020)	(0.021)	(0.023)
Pct Under 18	−0.052**	−0.055***	−0.054***	−0.057***	−0.025	−0.059***	−0.032
	(0.021)	(0.021)	(0.020)	(0.021)	(0.021)	(0.022)	(0.023)
Pct Urban Population	0.004	0.004	0.003	0.005*	0.010***	0.002	0.009***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Log(Gov Exp on Public Safety & Welfare)	−0.260***	−0.265***	−0.264***	−0.258***	−0.210**	−0.289***	−0.229**
	(0.087)	(0.088)	(0.087)	(0.088)	(0.087)	(0.090)	(0.091)
Log (Per Capita Income)	−0.868***	−1.757***	−0.207	−0.600*	−0.009	−0.322	−0.367
	(0.298)	(0.540)	(0.498)	(0.346)	(0.328)	(0.407)	(0.820)
Log (Top 10% Income)		1.242**					1.072*
		(0.630)					(0.620)
Poverty Rate			0.020*				0.008
			(0.012)				(0.017)
Pct BA Degree				−0.016			0.000
				(0.010)			(0.013)
Pct Mobile Home					0.052***		0.050***
					(0.008)		(0.008)
Pct Female-Headed						0.039**	0.012
						(0.016)	(0.019)
Dummy 1987	0.377*	0.286	0.296	0.359*	0.175	0.283	0.039
	(0.198)	(0.201)	(0.199)	(0.198)	(0.196)	(0.211)	(0.201)
Dummy 1992	0.100	−0.014	−0.051	0.066	−0.314*	−0.092	−0.522**
	(0.176)	(0.183)	(0.204)	(0.177)	(0.185)	(0.202)	(0.226)
Dummy 1997	0.545***	0.376*	0.327	0.495**	0.011	0.271	−0.293
	(0.196)	(0.209)	(0.244)	(0.201)	(0.211)	(0.243)	(0.284)
Dummy 2002	0.794***	0.538**	0.535**	0.741***	0.169	0.461*	−0.239
	(0.205)	(0.236)	(0.258)	(0.207)	(0.221)	(0.264)	(0.308)
Dummy 2007	0.907***	0.531*	0.617**	0.870***	0.281	0.540*	−0.255
	(0.219)	(0.275)	(0.291)	(0.221)	(0.239)	(0.295)	(0.361)
Dummy 2012	0.814***	0.296	0.491*	0.789***	0.194	0.422	−0.488
	(0.215)	(0.326)	(0.293)	(0.217)	(0.230)	(0.291)	(0.397)
Constant	3.131	−2.376	−3.389	0.956	−6.948**	−2.320	−15.703**
	(3.023)	(4.179)	(4.979)	(3.326)	(3.418)	(4.014)	(6.699)
No. of Observations	15,054	15,054	15,047	15,054	15,054	15,054	15,047
No. of Counties	2151	2151	2150	2151	2151	2151	2150

The standard errors are adjusted for within-county clustering.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table A2
Socio-economic characteristics and disaster impacts—Poisson fixed effect regressions results.

Dependent variable	*Avg. Deaths from F2+*	*Avg. Deaths from F3+*
Fscale_F2+	1.910***	
	(0.071)	
Fscale*Tornado_F2+	0.098***	
	(0.017)	
Fscale_F3+		2.007***
		(0.102)
Fscale*Tornado_F3+		0.066***
		(0.024)
Lag Freq. of Strong Tornadoes	0.015	0.032
	(0.074)	(0.072)
Persons Total (in mil.)	0.274	0.016
	(1.377)	(1.974)
Pct Over 65	−0.023	−0.138
	(0.080)	(0.103)
Pct Under 18	0.013	0.000
	(0.069)	(0.087)
Pct Urban Population	0.004	−0.022
	(0.013)	(0.019)
Log(Gov Exp on Public Safety & Welfare)	−0.152	−0.209
	(0.203)	(0.275)
Log (Per Capita Income)	−3.918*	−4.202
	(2.035)	(2.780)
Log (Top 10% Income)	3.001***	2.099
	(1.066)	(1.422)
Poverty Rate	−0.072*	−0.067
	(0.040)	(0.054)
Pct BA Degree	0.083	0.183*
	(0.061)	(0.097)
Pct Mobile Home	0.013	0.018
	(0.027)	(0.034)
Pct Female-Headed	−0.150*	−0.170
	(0.088)	(0.122)
Dummy 1987	0.502	0.468
	(0.313)	(0.411)
Dummy 1992	0.372	0.170
	(0.461)	(0.533)
Dummy 1997	0.423	0.310
	(0.681)	(0.774)
Dummy 2002	0.656	0.731
	(0.787)	(0.839)
Dummy 2007	0.373	0.640
	(0.875)	(0.971)
Dummy 2012	0.216	0.257
	(0.994)	(1.170)
No. of Observations	5492	4193
No. of Counties	785	599

Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

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