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Severe Tornadoes and Infant Birth Weight in the United States

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ABSTRACT Increasing evidence links exposure to extreme weather events in utero with adverse health outcomes at birth, including lower birth weight. This research, however, often faces data limitations because natural disasters may be localized, often affecting some neighborhoods but not others, whereas outcome data are often available only at higher geographic levels, such as counties. In this article, we introduce a novel strategy for estimating the effects of geographically bounded disasters when localized outcome data are unavailable. We employ this strategy to estimate the effect of exposure to severe tornadoes on infant birth weight in the United States from 1991 to 2017. We merge county-month data on singleton births with block-group-level monthly data on the paths of severe tornadoes and block-group data on the distribution of the population at risk of a birth. We then estimate difference-in-differences models in which the treatment variable is equal to the percentage of the population at risk of a birth affected by the tornado. This strategy results in an estimand that is both more interpretable and more policy-relevant than estimands from traditional models. Our findings demonstrate that exposure to a tornado during pregnancy reduced birth weight for Black mothers.

KEYWORDS Disasters • Tornadoes • Infant health • Statistical methods

Introduction

Communities are increasingly exposed to severe weather and natural disasters as climate change influences global weather patterns. Demographers have amassed a body of evidence on the consequences of environmental stressors and extreme weather hazards for core population outcomes, including mortality, fertility, natality, and migration (Frankenberg et al. 2014). One influential line of inquiry in this literature examines the effects of acute extreme weather events, such as heat waves, earthquakes, and tropical cyclones, on health at birth (Barreca and Schaller 2020; Deschênes et al. 2009; Torche 2011). Research on extreme weather and infant health is particularly important because health at the start of life matters for child development and later life outcomes (Conley et al. 2003). Improving estimates of the effects of extreme weather events in utero for health at birth can inform scholarly understanding of inter- and intragenerational disparities in well-being and equip policymakers with data to intervene and promote health equity from a life course

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perspective, as recent birth cohorts age and as newer cohorts are increasingly exposed to more extreme severe weather (Thiery et al. 2021).

Some of the most acute and devastating extreme weather events are severe tornadoes, yet relative to other hazards, very few studies have examined their consequences for infant health outcomes, and none have examined how they influence marginalized or vulnerable populations specifically. A 2010 systematic review of research on weather disasters and perinatal health found no studies that had examined tornadoes (Harville et al. 2010). Since then, we are aware of only two published articles on tornadoes and birth outcomes. First, Christopher et al. (2019) examined birth outcomes using the case of the 2011 tornado outbreak in Missouri and Alabama and found no differences between the health of newborns born in counties that experienced or did not experience a tornado. Second, Cotet-Grecu (2016) used county-month data on the number of severe tornadoes from 1990–2007 and similarly documented little evidence of effects on birth weight. Notably, this study restricted the sample of tornadoes to those that occurred within 100 kilometers of the population centroid of the county. Although this strategy improves upon approaches that ignore within-county population distributions, it risks oversimplifying exposure, particularly in counties with multiple population centers. By representing population distribution as a single centroid, it may exclude tornadoes that affect secondary population centers or overestimate exposure near sparsely populated areas between population hubs. Neither study examined differences in the infant health effects of tornadoes by maternal race, leaving unanswered questions about demographic group vulnerability. Because tornadoes and other extreme weather events occur at smaller spatial scales than counties, and because vulnerability to health adversity may vary across demographic groups, including along racial lines, there is a critical need for research that uses more fine-grained data to improve effect estimates and to examine disparities across groups. For infant health and other demographic processes of interest, such as mortality, internal migration, and union formation, these data are often not available, leading to a gap in our understanding of the demography of disasters.

In this article, we make a methodological and substantive contribution to the literature on the demography of disasters. First, we illustrate a novel strategy for estimating the demographic effects of localized natural disasters when localized outcome data are unavailable. Traditional estimation of treatment effects in such scenarios applies a binary indicator to the smallest level at which localized outcome data are available (Christopher et al. 2019), identifying an average treatment effect on the treated area (ToTA). Our new strategy relies on using a treatment variable that accounts for the share of the local population affected by the disaster. This treatment variable can be created by combining more localized data on the path of the disaster with the distribution of the population in the treated area, and it can be extended to population subgroups of interest based on their geographic distribution along the path of the disaster. Because the treatment variable is scaled by the fraction that was potentially treated, the method permits estimation (under certain assumptions) of what we call the approximated treatment effect on the treated individual (aToTI). This estimand is both more interpretable and more policy-relevant than the ToTA and allows for a more precise estimation of treatment effects that vary by the extent of exposure, rather than relying on coarse binary indicators. This strategy can be particularly valuable in understanding the heterogeneous impacts of disasters on different subgroups, such as elderly individuals or socially disadvantaged populations, whose geographic distribution may intersect with disaster paths in distinct ways.

Second, we apply this strategy to severe tornadoes and birth outcomes. We construct a county-month dataset of infant birth weight using population-level natality data from 1991–2017 linked to (1) monthly data on the paths of severe tornadoes through census block groups and (2) the populations (and subpopulations) of block groups within affected counties. We then use heterogeneity-robust difference-in-differences methods to estimate the effects of tornadoes on infant birth weight (Callaway and Sant'Anna 2021; Cengiz et al. 2019; de Chaisemartin and D'Haultfœuille 2020; Goodman-Bacon, 2021). We find that exposure to a tornado significantly reduces birth weight among births to Black mothers, suggesting that natural disasters may exacerbate existing racial health disparities. These effects are particularly pronounced for births exposed to tornadoes that cause more material and human damage. Furthermore, we find that the timing of exposure matters: the most substantial reductions in birth weight are observed among infants exposed during the first trimester of pregnancy, a critical period for fetal development.

Our methodological innovations can inform future studies of environmental hazards and demographic outcomes, such as migration, mortality, and other health morbidities, which are often available to researchers at aggregated levels but for which the exposure occurs at a smaller scale and operates across theorized dimensions, such as intensity or the degree to which people are affected.

Tornadoes and Birth Outcomes

Relative to other natural hazards that cause disasters, severe tornadoes are more acute, and they are more difficult to anticipate, making exposure highly unexpected. There is often very little time between a tornado watch (a public notice of atmospheric conditions conducive to tornado formation), a tornado warning (a public notice that a tornado has formed on radar), and touchdown in a community, and the unpredictability renders the most marginalized people vulnerable to exposure (Raker 2020; Zhang et al. 2018). These factors mean that local residents are unable to take many preparatory actions, unlike in cases of forecasted heat waves, or to evacuate out of harms way, unlike in cases of hurricanes. Tornadoes are also comparatively more spatially defined than other hazards, such as floods, reducing the risk of bias posed by spillover effects in estimating their effects. Hence, tornadoes' acuteness, unpredictability, and destructive properties make them analytically useful for examining the mechanisms theorized to link extreme weather and infant health.

The most commonly posited mechanism linking disaster exposure to infant health outcomes in the United States is prenatal parental stress (Currie and Rossin-Slater 2013; Torche 2011). Persons who are pregnant and are exposed to a disaster, such as a severe tornado, may experience financial strain from property damage or wage loss, disruption of stable housing, or heightened anxiety about their safety, among other distressful experiences. An extensive literature shows that the intrauterine period is highly sensitive to stress and that adverse exposures during pregnancy may be transmitted from the person who is pregnant to the fetus (Entringer et al. 2015). Physiologically, an elevated cortisol level is one of the most important biological pathways through which acute or chronic stress may alter the development of the fetus. Cortisol can affect the placenta's function by altering blood flow, nutrient transport, and hormone production, which may lead to reduced nutrient and oxygen delivery to the developing fetus, and these changes can result in intrauterine growth restriction and low birth weight (Buss et al. 2012). Elevated cortisol levels can also contribute to preterm birth by promoting inflammation and increasing the risk of infections, which can initiate preterm labor (Coussons-Read et al. 2012).

The negative effects of elevated stress-induced cortisol levels during pregnancy can also cross the placental barrier and lead to changes in fetal programming and have long-term consequences on offspring health (Aizer et al. 2016). Stress and elevated cortisol levels during pregnancy have been associated with altered cognitive and emotional development of children, which in turn are proximate causes of attention and learning difficulties, as well as risk for behavioral and emotional problems in childhood (Bergman et al. 2010). Later in life, stress during pregnancy has been linked with offsprings' higher risk for metabolic and cardiovascular disorders (O'Donnell et al. 2009).

A second mechanism by which tornadoes can affect birth outcomes is by altering access to healthcare services during pregnancy. Tornadoes and other disasters often cause significant damage to physical infrastructure, which in turn may reduce access to basic services, including healthcare, by destroying hospital or clinic facilities or by impeding regular healthcare delivery (Radcliff et al. 2021). Some studies have suggested that in postdisaster contexts, women's healthcare services (e.g., provision of contraception) are neglected in favor of emergency response priorities (Kusuda et al. 1995). As a result, persons who are pregnant may face difficulties in obtaining the essential prenatal care that is crucial for ensuring healthy pregnancies and preventing adverse birth outcomes.

The consequences of disrupted healthcare access during natural disasters have been documented in various contexts (Martinelli et al. 2014). Although we are unaware of any study that has looked at effects on access to prenatal or maternal healthcare services in the aftermath of tornadoes in general, the 2011 Joplin, Missouri, tornadoes were associated with a reduction in healthcare service utilization, especially among women with mental health problems (Houston et al. 2015). Additionally, several studies have documented widespread damage to the healthcare infrastructure in New Orleans after Hurricane Katrina (Berggren and Curiel 2006; Rudowitz et al. 2006). Importantly, these two mechanisms—parental stress and healthcare access—are not necessarily mutually exclusive but can compound one another. Indeed, some research has provided mixed evidence regarding an independent effect of disasters on the frequency of prenatal visits (Currie and Rossin-Slater 2013) or other behavior-related proximate factors (La Greca et al. 2022). This evidence suggests that reduced access to health services may exacerbate the infant health consequences of maternal stress, even without an independent effect, especially in developed country contexts.

Social science theories of disaster vulnerability point to the unequal distribution of resources in the production of disparate outcomes across race (Bolin and Kurtz 2018). Both of the theorized mechanisms—stress response and healthcare disruption—may also be implicated in racial differences in disaster effects on birth weight. Processes of historical and contemporary marginalization have led to accelerated biological aging, or "weathering," among Black women, potentially making them more susceptible to stress-induced adverse birth outcomes (Geronimus 2023). Additionally, disaster-induced disruptions to healthcare likely disproportionately affect underserved populations, including rural populations and people of color (Davis et al. 2010). The effects of Hurricane Katrina on healthcare access, for example, were particularly pronounced among the low-income, Black population of New Orleans, who are also more likely to have preexisting comorbid risks, suggesting that effects of disasters may be especially large for disadvantaged groups (Brodie et al. 2006; Hurricane Katrina Community Advisory Group and Kessler 2007; Schneider and Rousseau 2013; Stehling-Ariza et al. 2012).

In sum, studies have documented an effect of disasters on adverse infant health outcomes, yet few have considered severe tornadoes despite their empirical advantages. Given prior tests of the mechanisms of parental stress and healthcare access, we expect that the most damaging tornadoes, measured using either the Fujita Scales or a measure of storm loss on casualties and damage, will yield greater effects on infant health than relatively less severe or intense tornadoes. We further hypothesize that, because of racial differences in social and health-related vulnerabilities, we will detect greater deleterious effects of tornadoes on births to Black mothers relative to White mothers. In light of the common data limitations of scale mismatch between exposure and observed outcomes, the empirical estimands developed in the following will help improve scholarly efforts to quantify the consequences of disasters on social and demographic outcomes, including infant birth weight.

Data

Births

We use restricted birth certificate data from the National Center for Health Statistics that include all singleton[1] births in the period 1991–2017 to women aged 15–45 who were residing in the United States when they gave birth. We drop counties that had never experienced a tornado during that period, leaving 1,467 counties in the sample. We focus on birth weight as the outcome. Observations are at the county-month level, so they represent the average birth weight in that county and month. There are 467,233 county-month observations in the sample, covering 28,104,579 births to White mothers and 8,926,807 births to Black mothers.

Populations

Block-group demographic data are sourced from the U.S. Census (1990, 2000) and the American Community Survey (2006–2010, 2015–2019). Block-group boundaries are fixed using their 2010 delineations. For tornadoes occurring in years without available census or ACS data, we linearly interpolate between years with available data.

[1] Multiple births are much more likely to have lower birth weight and are therefore excluded.

Tornadoes

GIS information on the paths, widths, and damage attributes of severe tornadoes comes from the Storm Prediction Center Severe Weather GIS (SVRGIS) database housed by the National Oceanic and Atmospheric Administration (NOAA). Our data on tornadoes include those from 1992[2] to 2017, during which 808 tornadoes touched down in the United States with an (E)F-3, (E)F-4, or (E)F-5 rating on the Fujita (F) or Enhanced Fujita (EF) Scale (the latter scale has been used since 2007). For simplicity, we refer to these as the Fujita scale throughout the analysis, though specific post-2007 events are described using the EF scale when relevant.

In our analysis, we use two measures for the intensity and severity of tornado exposure. The first measure uses the aforementioned Fujita Scales, which we understand as the "estimated intensity." Relying on a series of 28 poststorm damage indicators, the Fujita Scale estimates wind speed and assigns tornadoes a rating on a scale from 0 to 5, with an F-5 tornado as the most intense with 3-second wind gusts exceeding 200 mph. This measure captures a tornado's destructive potential and is widely used in academic papers and is also understood by individuals on the ground (Christopher et al. 2019; Cotet-Grecu 2016; Raker 2020). However, this measure only approximates a tornado's actual toll on the population that causes maternal stress or healthcare disruption, which are theorized as the proximal mechanisms linking tornado effects on infant health. That is, just because a tornado reaches wind speeds capable of stress-causing destruction does not necessarily reflect the level of damage, as the actual impact depends on factors such as the quality of infrastructure and the level of community preparedness.

Consequently, we construct a second measure, which we call "damage severity," that is based on the realized human and economic impacts. This tornado-level measure combines and reduces the data dimensionality of four variables: the number of injuries, the number of fatalities, the amount of property damage (in inflation-adjusted dollars), and the amount of crop damage (in inflation-adjusted dollars).[3] Specifically, we perform a principal component analysis on these four variables to create an index that captures the overall severity of tornado impacts. This analysis yields four components, with the first component (Component 1) explaining 79.1% of the total variance.[4] The loadings of each variable on Component 1 are similar in magnitude, with injuries (.48), fatalities (.49), property damage (.52), and crop damage (.51) all contributing positively to the component. This balanced combination indicates that Component 1 represents a comprehensive measure of tornado impacts, integrating both human and material loss dimensions.

To facilitate interpretation and analysis, we divide Component 1 into tertiles to construct a three-part categorical variable indicating low-, middle-, and high-severity tornadoes. This categorical variable allows us to better approximate the disaster's potential impact on infant health through the theorized mechanisms of stress and

[2] We include counties from 1992 on to ensure that we have a valid pretreatment period for births.

[3] Prior to 1994, only property damage was used owing to data availability.

[4] Component 1 had an eigenvalue of 3.16, accounting for 79.1% of the total variance. Component 2 contributed an additional 13.6% of the variance. Components 3 and 4 explained only 5.9% and 1.4% of the variance, respectively.

healthcare disruption. By distinguishing tornadoes not just by their physical intensity but also by their realized human and economic consequences, this measure captures aspects of disaster severity that are not directly correlated with physical intensity alone. The correlation between the principal-component-derived measure of severity and the intensity indicator for whether the tornado was an F-4 or F-5 versus F-3 is only .26, suggesting that although related, these two measures capture substantially different dimensions of tornado impacts. Figure 1 shows the distribution of tornadoes by year and intensity/severity in the entire sample.

Among the tornadoes in our sample, 652 (80.6%) were F-3, and 156 (19.4%) were F-4 or F-5 on the Fujita Scale. In terms of casualties, approximately one third of tornadoes resulted in at least one fatality (mean = 1.8, standard deviation (SD) = 7.2), and approximately two thirds of tornadoes caused at least one injury (mean = 20.8, SD = 61.3). In terms of material loss, the tornadoes on average caused 36.9 million (2021-adjusted) dollars in property damage (SD = 187.5) and 29.0 million dollars in crop damage (SD = 206).[5] By almost all the measures of human and material loss, the worst tornado across the period was an EF-5 tornado that occurred in the May 2011 outbreak across four counties in Missouri, mainly affecting Joplin, which injured nearly 1,150 people and killed 158. Figure 2 shows the paths of all severe tornadoes included in the analysis, color-coded by the Fujita Scale in panel a and the level of severity in panel b. Note that tornadoes frequently affect multiple counties; in our sample, more than 75% of tornadoes affected two or more counties.

Analytic Sample Construction

The monthly data covering births and tornadoes in U.S. counties are matched to create "treatment" and "control" groups of counties for each month in which at least one tornado occurred. We match monthly observations of counties that experienced a tornado with observations from the same months for counties that did not experience a tornado then but did experience a tornado at some other time point. We restricted the sample to counties that experienced at least one tornado because tornadoes are geographically concentrated and excluding counties at very low risk of experiencing a tornado improves the comparability of our treatment and control groups. Within these counties, it is plausible that the timing of the tornado is quasi-random. Only county-month observations for the two years before and the nine months after each tornado are included. For example, for a tornado occurring in the month of June 2015, the sample period would extend from June 2013 (two years prior) through March 2016 (nine months after). The treatment group consists of counties that experienced a tornado in June 2015. The control group consists of counties that experienced a tornado at some point from 1991 to 2017 other than in the June 2013–March 2016 period. If a county experienced multiple tornadoes in one nine-month period, that county was dropped from the data until nine months after the last tornado.

[5] Data on property damage and crop damage in millions of dollars were available for tornadoes only after 1996 (N=688).

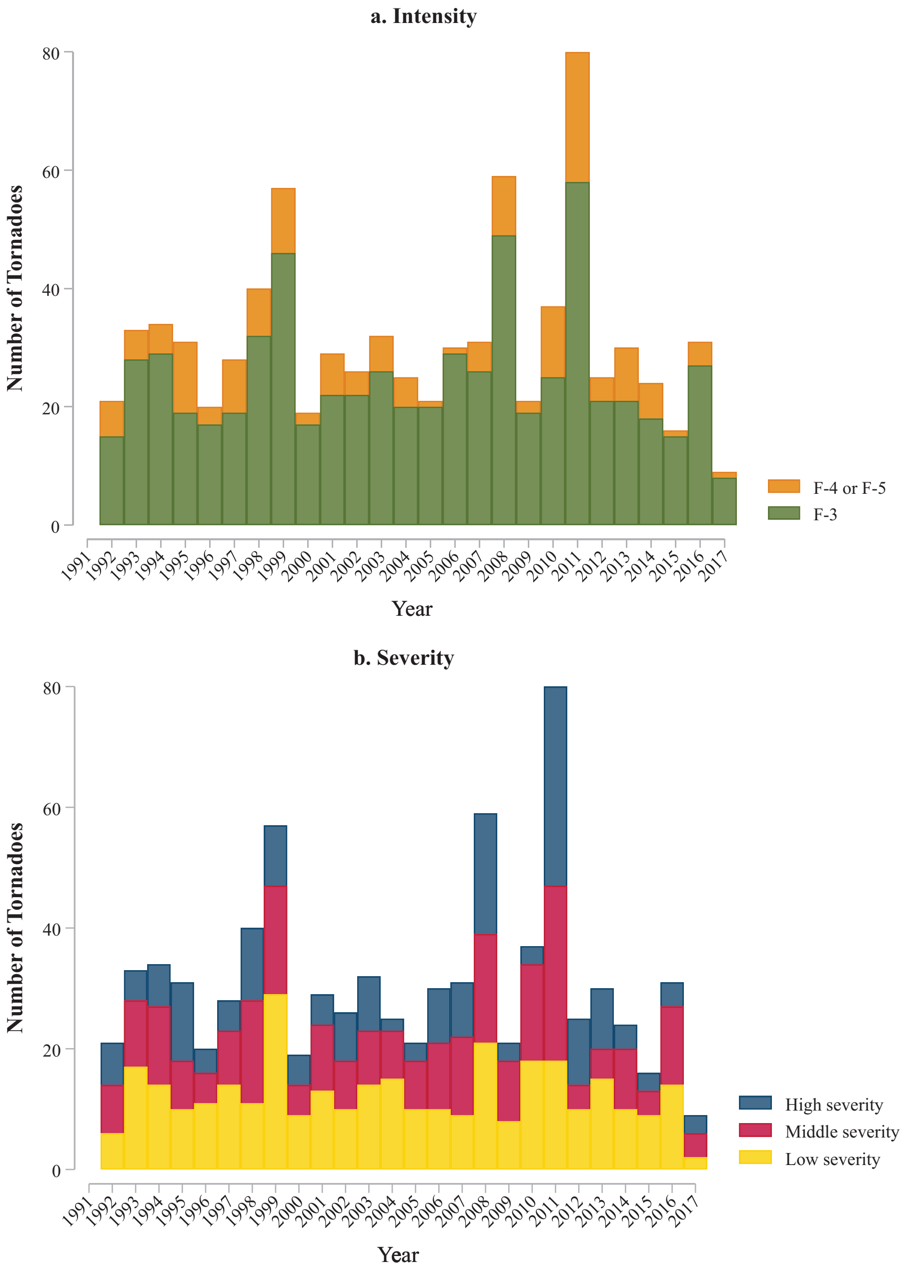

Fig. 1 Frequency of tornadoes by year, 1992–2017, according to (a) intensity and (b) severity. Data are from the Storm Prediction Center Severe Weather GIS database housed by the National Oceanic and Atmospheric Administration. Intensity is measured on the (Enhanced) Fujita Scale. Severity tertiles are constructed from the first principal component of the number of injuries, number of fatalities, amount of property damage (in inflation-adjusted dollars), and amount of crop damage (in inflation-adjusted dollars) caused by the tornado. See text for details.

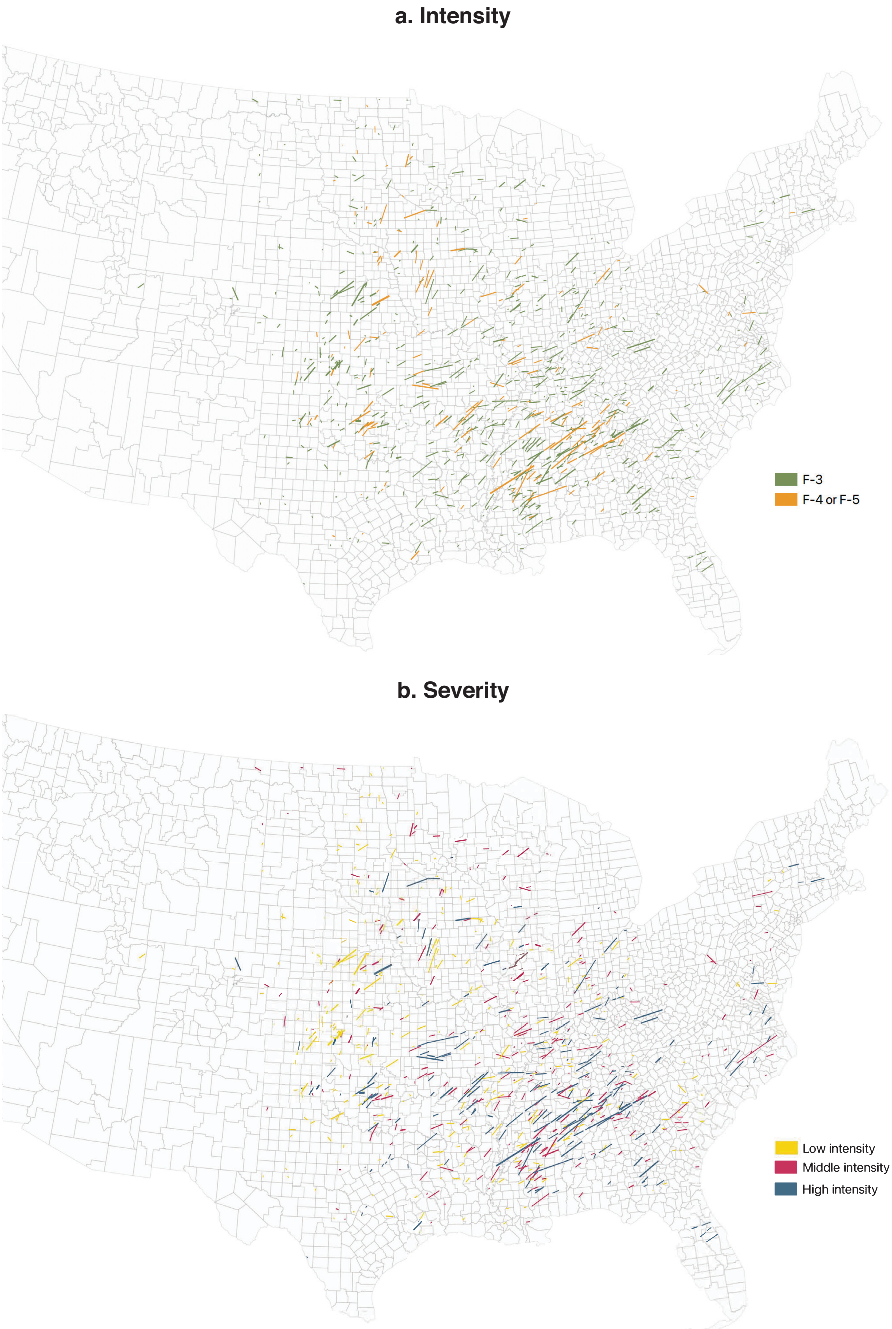

Fig. 2 Spatial distribution of severe tornadoes in the United States, 1992–2017, according to (a) intensity and (b) severity. Data are from the Storm Prediction Center Severe Weather GIS database housed by NOAA. Intensity is measured on the (Enhanced) Fujita Scale. Severity tertiles are constructed from the first principal component of the number of injuries, number of fatalities, amount of property damage (in inflation-adjusted dollars), and amount of crop damage (in inflation-adjusted dollars) caused by the tornado. See text for details.

Table 1 Descriptive statistics for county-months

Variable	Tornado Counties 24 Months Before (pretreatment)	Tornado Counties 9 Months After (posttreatment)	Tornado Counties Other Months (control)	Nontornado Counties (excluded)
Average Birth Weight				
All births	3,279	3,273	3,292	3,305
White	3,319	3,313	3,331	3,335
Black	3,065	3,059	3,077	3,012
Average Number of Births				
All births	89	91	98	116
White	56	56	56	63
Black	17	17	18	14
N	35,000	13,966	338,238	614,061

Notes: Data on timing of tornadoes in 1992–2017 are from the Storm Prediction Center Severe Weather GIS database housed by the National Oceanic and Atmospheric Administration. Data on births in 1991–2017 are from National Center for Health Statistics restricted natality files.

Table 1 shows the descriptive statistics for all counties in the sample. On average, counties that experienced tornadoes had slightly more than 90 births per month, of which just under 60 were to White mothers and just under 20 were to Black mothers. Within these counties, average birth weights were about 6 grams lower in the post-tornado period, with similar pre-post differences across racial groups. The control counties, which experienced tornadoes but at different times, looked fairly similar to the tornado counties, with slightly more births and slightly higher birth weights. The excluded counties were substantially different, with higher birth weights than the tornado counties and far fewer births to Black mothers. These differences likely reflect the geographic concentration of tornadoes in the U.S. Southeast.

Each of the treatment–control pre-post comparisons for a given tornado can be conceived of as a separate sample, which can then be analyzed in a difference-in-differences framework, a well-developed method for estimating causal effects from observational data (Angrist and Pischke 2009). The individual difference-in-differences samples are "stacked" so that aggregate effects can be estimated from a single model. This method, developed by Cengiz et al. (2019), avoids bias induced by heterogeneity in treatment timing and treatment effects (Callaway and Sant'Anna 2021; de Chaisemartin and D'Haultfœuille 2020; Goodman-Bacon 2021).

Methods

We develop a novel strategy for estimating the effects of tornadoes that uses granular information on their trajectories to make inferences about their effects when outcome data are available only at higher levels of aggregation (e.g., counties). This strategy relies on using a treatment variable that accounts for the share of the local population affected by the disaster. The variable can be created by combining more localized data on the path of the disaster with the distribution of the population in the treated area.

The first set of analyses we present come from Model 1 below, where the outcome Y_{cmd} is measured at the county level c for each month m for each sample d. The key independent variable is an indicator for whether a tornado occurred in the past 10 months, T_{cmd}, which varies by month m, county c, and sample d. We also include sample-specific county fixed effects to account for time-invariant characteristics of the county ($\boldsymbol{\theta}_{cd}$) and month fixed effects to account for time-varying factors that influence all counties equally ($\boldsymbol{\psi}_{md}$). Thus, the coefficient α_1 refers to the difference in differences in the outcome between treatment and control groups in the nontornado and immediate posttornado periods, net of time trends:

$$Y_{cmd} = \alpha_1 T_{cmd} + \boldsymbol{\theta}_{cd} + \boldsymbol{\psi}_{md} + \epsilon_{cmd}. \tag{1}$$

Models like (1) are commonly used to estimate average effects on an entire treated area unit, an estimand we will refer to as the effect of the treatment on the treated area, or ToTA. The ToTA is not necessarily informative when the area unit is an aggregate of individual outcomes and the treatment does not affect all individuals equally, as is often the case with localized disasters. In such cases, responses to disaster may be better targeted if responders know the effect on *individuals* who are actually impacted. In the case of tornadoes and birth outcomes, it is highly unlikely that all persons who are pregnant in the county would have been affected by the tornado. Some pregnant individuals were likely to have been greatly affected, for example, if the tornado passed very close to them or their home. Others, such as those who lived far from the tornado's path, would be less likely to be affected. In sparsely populated rural counties, distances between affected and unaffected areas within the same county could be large. By averaging effects across all people in the county, the ToTA does not relate to the effect of the tornado on individual affected people and is thus difficult to interpret in an actionable way.

A potentially more informative estimand would be the effect of the treatment on the treated individual (ToTI). The ToTI is greater than or equal to the ToTA because it is identified only from affected individuals; only if all individuals in an area were affected would the ToTI and ToTA be equal. Estimating the ToTI is possible when data on the treatment and outcome are available at the individual level. In the context of localized disasters, however, such data are often not available, forcing researchers to rely on the less informative ToTA.

In the following, we describe a strategy for estimating an *approximated* ToTI, or aToTI, even without individual-level data. We do so by leveraging more granular data on the distribution of the population within a larger geographic unit to create a continuous treatment variable that is equal to the percentage of the population affected by the treatment. This variable is analogous to a "dosage" effect, where the dosage is the fraction of the population in an affected area.

In our application to tornadoes' impact on birth outcomes, we conceptualize the dosage as the probability that a given pregnancy in a county was affected by a tornado. Thus, if a tornado's path touched all parts of a county, 100% of pregnancies would have been exposed to the tornado. If, on the other extreme, the tornado affected only one minimally populated part of the county, then a very low percentage of pregnancies would have been affected.

We create a continuous measure of the percentage of the county's population affected by the tornado by combining two sources of more localized data: (1) the

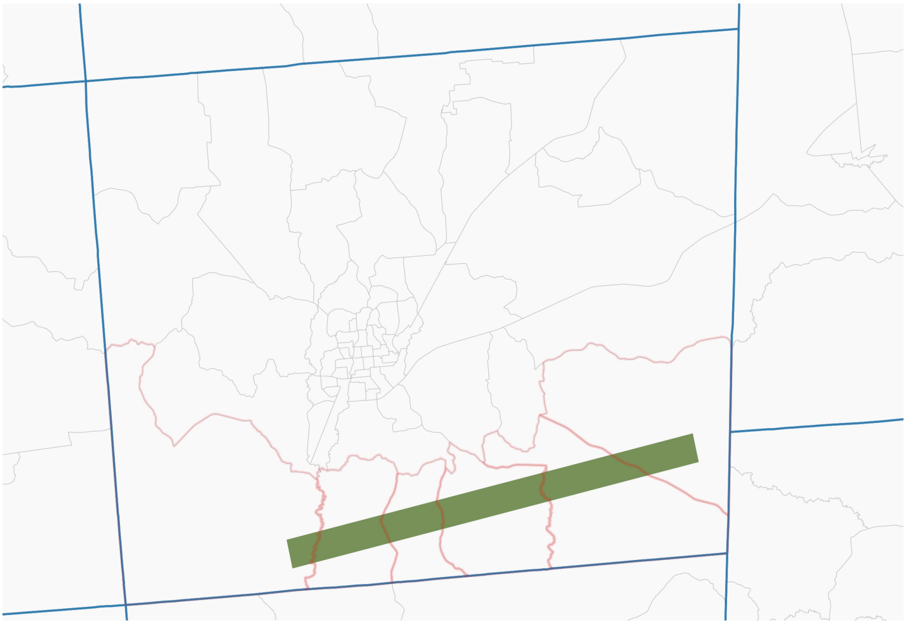

Fig. 3 Map of Lauderdale County, Mississippi. The green bar represents the path of an F-3 tornado that passed through six census block groups (outlined in red) on March 10th, 1992. Data are from the Storm Prediction Center Severe Weather GIS database housed by NOAA.

latitude and longitude of tornadoes' paths and (2) census-block-group populations of women aged 15–45. By merging these two data sources, we can estimate the percentage of a county's population at risk of a pregnancy that was in a census block group affected by a tornado, $\frac{P_{cmd}^{T_t=1}}{P_{cmd}}$, where $P_{cmd}^{T_t=1}$ is the number of female residents of reproductive age in all block groups affected by a tornado in county c in month m and P_{cmd} is the total population of female residents of reproductive age in county c affected by a tornado in month m. This measure is illustrated in Figure 3, which displays a map of Lauderdale County, Mississippi, subdivided by its 73 census block groups. The path of an F-3 tornado that passed through the southern part of the county on March 10th, 1992, is indicated by the green bar. This tornado path went through six census block groups (outlined in red), which made up ~9% of the county's population, so the continuous measure is .09.

Inserting this continuous measure in place of the binary treatment variable in Eq. (1) gives us Eq. (2):

$$Y_{cmd} = \beta_0 + \beta_1 \frac{P_{cmd}^{T_t=1}}{P_{cmd}} + \boldsymbol{\theta}_{cd} + \boldsymbol{\psi}_{md} + \epsilon_{cmd}. \tag{2}$$

Note that the interpretations of α_1 and β_1 are different, with α_1 from Eq. (1) referring to the ToTA under standard difference-in-differences assumptions, whereas β_1 from Eq. (2) refers to the aToTI under three additional assumptions: (1) that the distribution of pregnancies is analogous to the distribution of women of childbearing age,

(2) that the effects on pregnancies in one block group can be linearly extrapolated to others in a county, and (3) that the percentage of the population in block groups affected by a tornado is not correlated with the average effect of the tornado. We discuss these assumptions, and their plausibility, in more detail in the following section.

In a further contribution to the literature, this extension allows us to more accurately estimate subgroup effects. We estimate effects on births to Black women by replacing the outcome Y_{cmd} with the outcome specific to Black women, $Y_{cmd}^{B=1}$, and replacing $\frac{P_{cmd}^{T_t=1}}{P_{cmd}}$ with a variable specific to the populations of Black women ($B=1$) in the census block group and county, $\frac{P_{cmd}^{T_t=1,B=1}}{P_{cmd}^{B=1}}$. Likewise for White women.

Equation (2) can be modified to estimate impacts by the trimester of the pregnancy during which the tornado occurred by specifying a vector of trimester variables $\boldsymbol{\alpha}_{cmd}$ in lieu of a single treatment variable, as in Eq. (3):

$$Y_{cmd} = \beta_0 + \boldsymbol{\alpha}\frac{P_{cmd}^{T_t\,=\,1}}{P_{cmd}} + \boldsymbol{\theta}_{cd} + \boldsymbol{\psi}_{md} + \epsilon_{cmd}. \tag{3}$$

We estimate Eqs. (1), (2), and (3) for all births, for births to White mothers, and for births to Black mothers. We weight county-month observations by the number of births, and cluster standard errors at the county level. In further analyses, we report results stratified in two ways: (1) by the level of the tornado intensity as measured by the Fujita scale (F-3 vs. F-4/5) and (2) by tertile of human and material loss.

Assumptions

In this section, we describe the assumptions necessary for identifying causal effects using the methodology outlined above and test their plausibility in our context.

The first assumption necessary to identify causal effects in our framework is that trends in the treatment and control counties are parallel in the pretreatment period and would have remained parallel in the posttreatment if the treatment had not occurred. The plausibility of this assumption, foundational to difference-in-differences analysis, is typically examined by estimating trends in pretreatment differences (i.e., "pretrends"). Figure 4 shows these differences using the continuous exposure measure,[6] illustrating monthly differences in birth weight between the treatment and control counties relative to differences in the month before the tornado. Monthly coefficients and 95% confidence intervals are plotted in gray. The line of best fit through the preperiod coefficients and upper and lower bounds of the confidence interval are in black. Monthly estimates are quite noisy, but the parallel trends assumption is very plausible; differences are fairly constant over time in the pretornado period.

One potential threat to the parallel trends assumption in our case is differential mobility in response to a tornado. If persons who are pregnant with higher (lower)

[6] Alternative graphs using the binary exposure measure are provided in the online appendix.

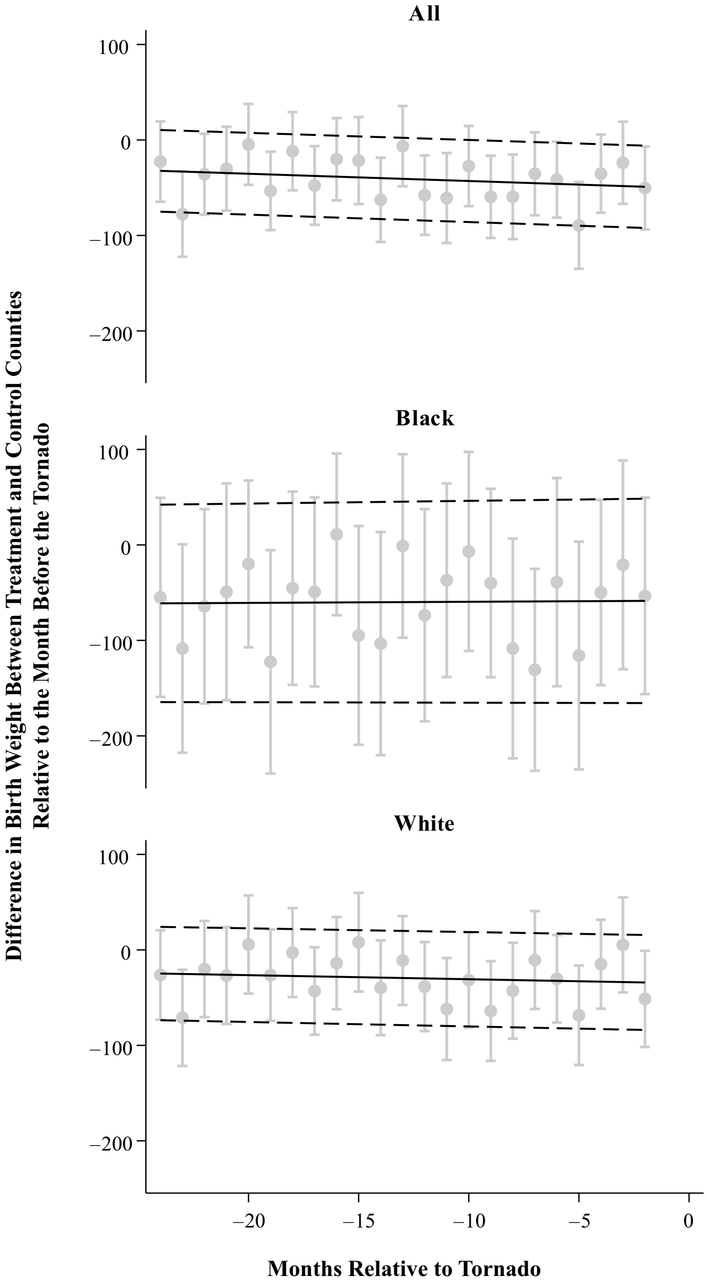

Fig. 4 Test of parallel trends assumption plausibility: Pretreatment trends. Monthly coefficients and 95% confidence intervals are plotted in gray. The line of best fit through the preperiod coefficients (solid lines) and the upper and lower bounds of the confidence intervals (dashed lines) are in black. Data on the timing of tornadoes in 1992–2017 are from the Storm Prediction Center Severe Weather GIS database housed by NOAA. Data on births in 1991–2017 are from National Center for Health Statistics restricted natality files.

expected birth weights are more likely to be displaced from a county in response to a tornado, that would bias estimates downward (upward). In the only recent paper estimating migration rates in response to tornadoes, DeWaard et al. (2023) found some slight evidence of migration following the Joplin disaster, but not for a less severe tornado, and they were unable to test for selectivity of migrants. Given that the Joplin tornado was an outlier in terms of its impacts, it is unlikely that migration results in a large-scale violation of the parallel trends assumption, though we are unable to rule it out.

The second assumption is that the distribution of the population used to estimate the continuous treatment measure is analogous to the distribution of risk of the outcome. For birth outcomes, only those at risk of a birth should be included in the creation of the continuous treatment measure. We take two steps to preserve the plausibility of this assumption. First, we use the population of women of reproductive age (15–45) to create our treatment measure. Second, within that age group, we can test the difference between treated and untreated block groups in the same county in more incremental age breakdowns. Because the age structure of fertility is fairly regular, rising from the teens through the late 20s and falling from the late 30s through the 40s, similar age structures in treated and untreated block groups would suggest that the continuous measure accurately captures the distribution of those at risk.

The third assumption is that potential treatment effects are independent of treatment assignment. If people in the areas affected by tornadoes have particularly large (or small) potential treatment effects, our estimates would be biased upward (downward). This assumption can be evaluated by comparing observable characteristics of populations in the affected and unaffected areas of the county. If populations are similar across observable characteristics, the risk of bias due to heterogeneity in potential treatment effects is theoretically limited.

Figure 5 presents results assessing the second and third assumptions in a coefficient plot. Each coefficient represents the within-county difference in female age groups (15–19, 20–24, 25–29, 30–34, and 35–39) and educational attainment levels (less than high school, high school only, some college, and college or more) between block groups inside and outside tornado trajectories, with data again derived from the decennial census and interpolation between census years. These estimates come from block-group-level regressions of age and educational attainment categories (in percentage points) on a tornado trajectory indicator and county and year fixed effects. The coefficient on the trajectory indicator reflects how the age structure and educational attainment of block groups within the tornado's trajectory differ from other block groups in the county. We measure age structure and educational attainment for all females (panel a), for White females (panel b), and for Black females (panel c), reporting results by these categories. We find minimal differences in the age structure of block groups inside and outside tornado trajectories. The differences in age structure are below 1 percentage point for all age categories and racial groups, and most 95% confidence intervals include zero. For educational attainment, we also find minimal and mostly statistically nonsignificant differences for Black females. However, block groups inside tornado trajectories have a slightly higher share of White females with lower levels of educational attainment—specifically, those without a high school diploma, with only a high school diploma, or with some college but no degree. On average, and relative to other block groups in the same county, block

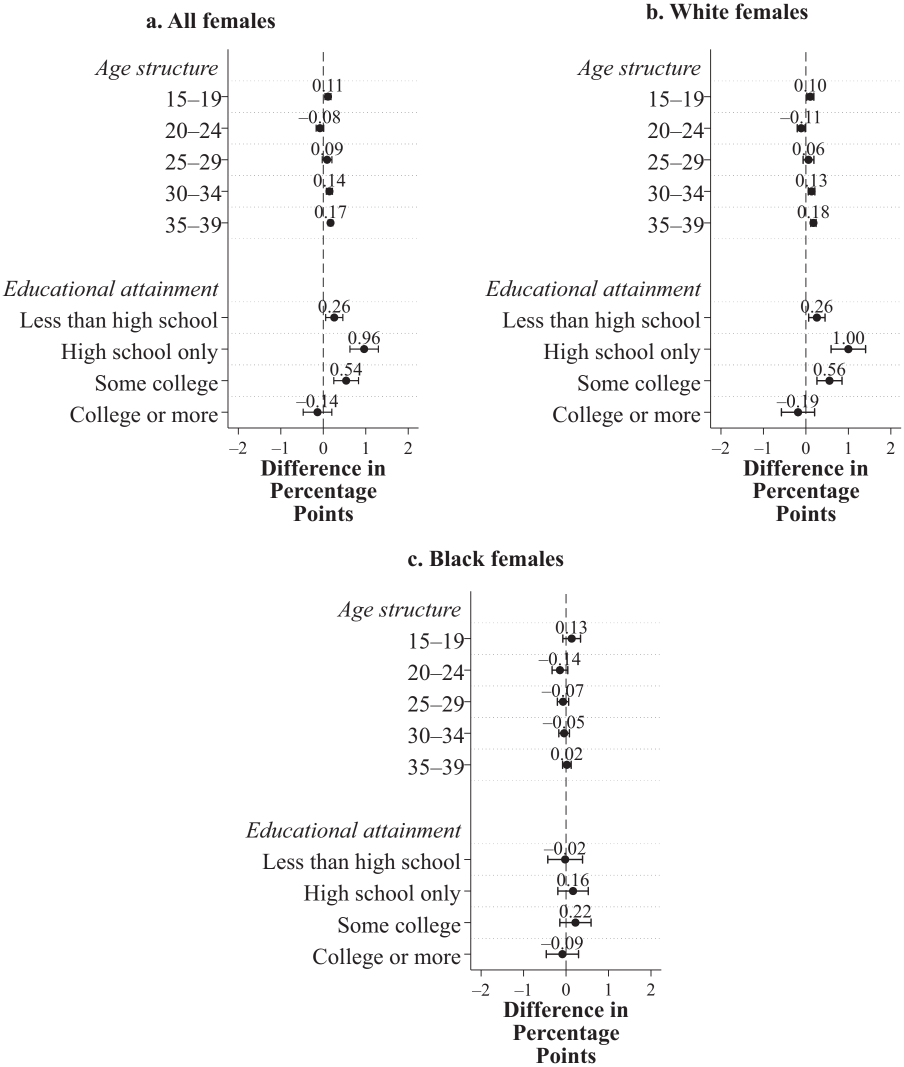

Fig. 5 Within-county differences in age structure and educational attainment in block groups affected versus unaffected by tornadoes. The bars around the point estimates represent 95% confidence intervals. Block-group demographic data are sourced from the U.S. Census (1990, 2000) and the American Community Survey (2006–2010, 2015–2019). Block-group boundaries are fixed using their 2010 delineations. For tornadoes occurring in years without available census or ACS data, we linearly interpolate between years with available data.

groups within tornado trajectories have a 1-percentage-point-higher share of White females with only a high school diploma and a 0.56-percentage-point-higher share of White females with some college but no degree. These imbalances in the educational composition of White females result in similar imbalances when considering all females collectively (panel a). This is expected, given that White females constitute the majority of the U.S. female population.

Table 2 Association between intensity or severity and fraction of population affected by tornado, 1992–2017

	All Births	White	Black
Damage Severity	–0.199	0.0112	0.0385
(human and material loss)	(0.140)	(0.139)	(0.112)
N	1,575	1,575	1,575
Estimated Intensity	.0725	.0773	.0425
(Fujita Scale)	(0.0641)	(0.0636)	(0.0521)
N	1,575	1,575	1,575

Notes: Coefficients are from ordinary least-squares regression of the severity (continuous first principal component) or intensity (indicator of F4/5 vs. F3) of the tornado on the fraction of a county's population affected by the tornado. GIS information on the paths, widths, and damages comes from the Storm Prediction Center Severe Weather GIS database housed by NOAA. See text for description of severity and intensity measures. Block-group demographic data are sourced from the U.S. Census (1990, 2000) and the American Community Survey (2006–2010, 2015–2019). Block-group boundaries are fixed on the basis of their 2010 delineations. For tornadoes occurring in years without available census or ACS data, we linearly interpolate between years with available data.

The patterns shown in Figure 5 inform our identification assumptions in several ways. First, the minimal differences in age structure across treatment groups suggest that age-related predictors of fertility and birth outcomes are unlikely to introduce significant bias. This is critical because age is a key determinant of the probability of both birth and birth outcomes. Second, although there are small imbalances in the educational composition of White females, these differences are modest and unlikely to meaningfully influence the overall validity of our approach. Educational attainment is an important predictor of health outcomes, but the observed differences are sufficiently small and specific to a subset of the population that their impact on the results is likely limited.

A final assumption is that the individual-level treatment effects for a given tornado are not correlated with the fraction of the population receiving treatment. If these two were positively (negatively) correlated, then the treatment effects estimated from our models would be biased upward (downward). For example, if the more severe tornadoes had systematically hit more populous census block groups, then these tornadoes would receive outsize weights. While it is impossible to test this assumption directly because the true individual-level treatment effects are unobservable, we can test it more theoretically. Table 2 shows the results of a regression of the intensity or severity of the tornado on the fraction of a county's population affected. The intensity measure is an indicator for whether the tornado was a 4 or 5 (coded 1), as opposed to a 3 (coded 0), on the Fujita scale. The severity measure is the first principal component described earlier (combining measures of injuries, fatalities, and financial loss). We find no evidence of a connection between intense tornadoes or tornadoes with more severe impacts and the fractions of county populations they affected.

Results

Our results show deleterious causal effects of tornadoes on birth outcomes for Black mothers. We identify no impact of tornadoes overall or for White mothers. The Figure 6

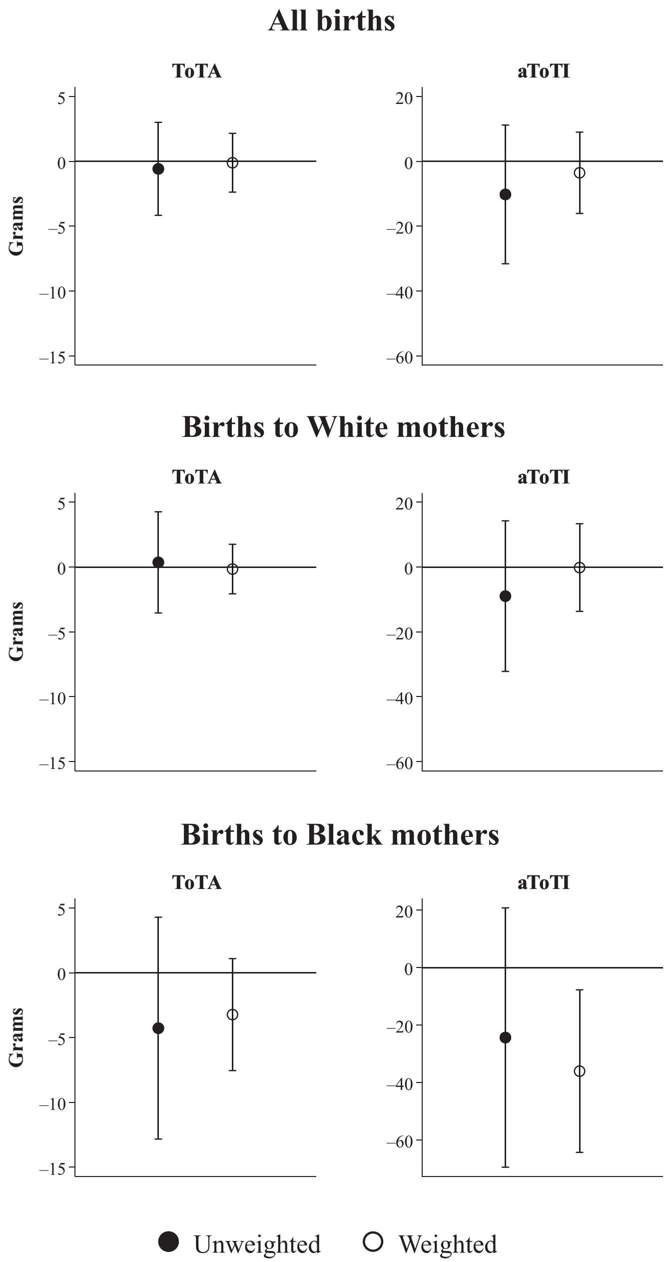

Fig. 6 Estimated treatment effect on the treated area (ToTA) and approximated treatment effect on the treated individual (aToTI) of exposure to a severe tornado. The bars around the point estimates represent 95% confidence intervals. GIS information on the paths, widths, and damages comes from the Storm Prediction Center Severe Weather GIS database housed by NOAA. Infant health data are from restricted birth certificate files provided by the National Vital Statistics System. Block-group demographic data are sourced from the U.S. Census (1990, 2000) and the American Community Survey (2006–2010, 2015–2019). Block-group boundaries are fixed using their 2010 delineations. For tornadoes occurring in years without available census or ACS data, we linearly interpolate between years with available data.

results are consistent in direction for Black mothers: counties that experienced a tornado had worse birth outcomes than comparison counties in the nine months following the occurrence of a tornado, relative to the difference in pretornado periods. The ToTA, at –3.23 grams (95% confidence interval (CI) = –7.54, 1.09), was approximately one tenth of the aToTI, at –36.04 grams (95% CI = –64.34, –7.74), in the model weighted by the number of births in the county-month. The average tornado affected census block groups that were home to about 10% of the Black population of a county, so the relationship between these two estimated effects is consistent.

Previous research on the effects of stress on fetal health has shown that impacts are largest in the first trimester (Torche 2011). That is indeed what we find for Black mothers, the only group for which any estimate is statistically significant. The estimated aToTI of the tornado was –49.31 grams (95% CI = –91.50, –7.12) in the first trimester, –34.40 grams (95% CI = –80.40, 11.61) in the second trimester, and –23.76 grams (95% CI = –80.86, 33.34) in the third trimester (Figure 7). The impacts in the first trimester are comparable to those found by Torche (2011) for the 2005 Tarapaca earthquake in Chile. That earthquake had few spillover effects or substantial impacts on infrastructure, and thus impacts were not observed for later trimesters. In our case, the tornadoes could have caused lasting damage and disruption, leading to lingering effects through mechanisms other than stress. We find limited evidence that this is the case; impacts in other trimesters were not statistically significant, though the point estimate for the second trimester is substantively large.

To examine mechanisms, albeit indirectly given the lack of direct data on maternal stress or healthcare disruption, we examine whether the effects of tornado exposure vary by tornado intensity and severity. Tornado intensity reflects the physical force and potential destructiveness of the tornado, while damage severity measures the realization of this destruction and loss. Our approach allows us to infer whether greater destruction and disruption—likely associated with both more intense and severe tornadoes—exacerbates adverse birth outcomes. If these mechanisms are relevant, we expect larger effects for both more intense and more severe events. Of course, both mechanisms are likely to operate simultaneously, and their effects may compound one another. For example, heightened stress due to displacement or loss may coincide with reduced access to prenatal care if healthcare facilities are damaged or overwhelmed.

Panel a of Figure 8 shows the aToTI results of models stratified by the intensity of the tornado. Again focusing on births to Black mothers, we find much larger effects for intense tornadoes (F-4 and F-5) than for less severe tornadoes (F-3), for which estimates were not significantly different from zero. We estimate that the aToTI from an intense tornado on babies born to Black mothers is –85.08 grams (95% CI = –152.19, –17.96).

Results for the measure of severity are shown in panel b of Figure 8. Recall that we divide the severity index into tertiles to classify tornadoes as low severity, middle severity, and high severity. We run models assessing effects of each of these three types of tornadoes. In line with the previous models that classified tornadoes using the Fujita scale, we find that, in population-weighted models, tornadoes in the high-severity (–41.88 grams, 95% CI = –85.82, 2.06) and middle-severity categories (–37.52 grams, 95% CI = –92.46, 17.43) produce the largest coefficients on birth weight among Black mothers, although neither is statistically significant at the 95%

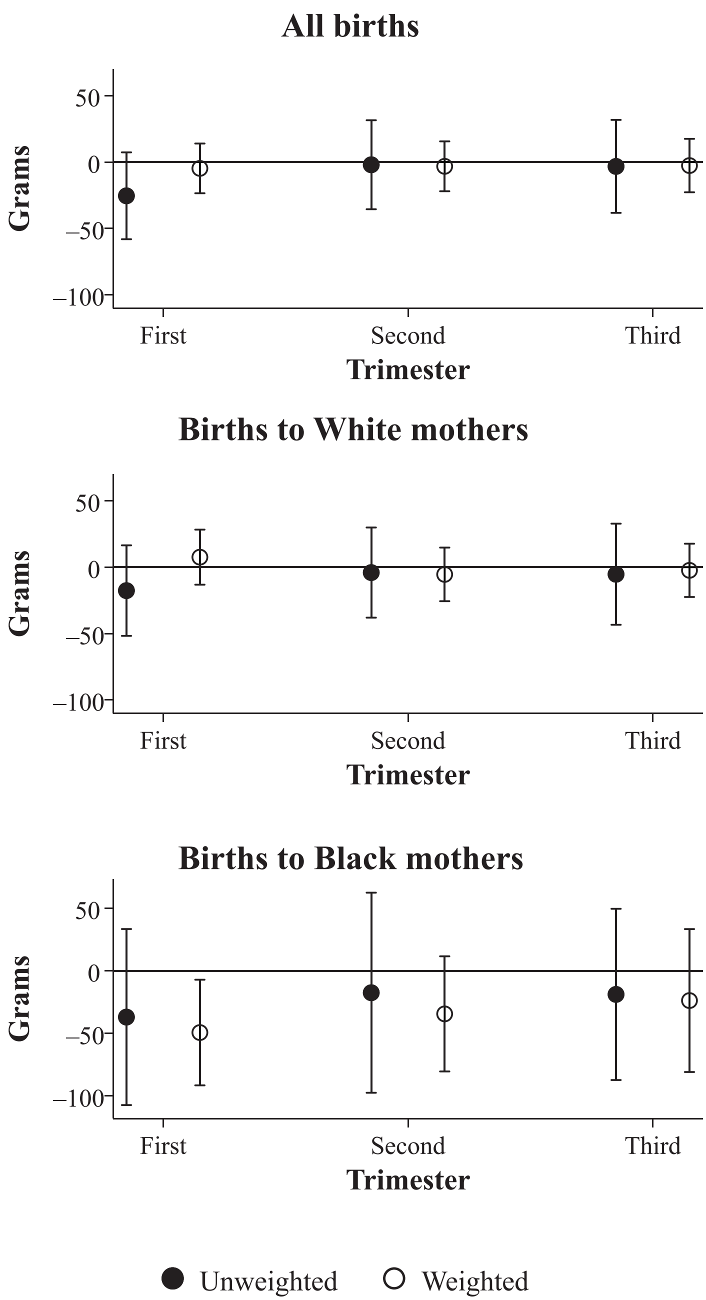

Fig. 7 Estimated aToTI effects by trimester. The bars around the point estimates represent 95% confidence intervals. GIS information on the paths, widths, and damages comes from the Storm Prediction Center Severe Weather GIS database housed by NOAA. Infant health data are from restricted birth certificate files provided by the National Vital Statistics System. Block-group demographic data are sourced from the U.S. Census (1990, 2000) and the American Community Survey (2006–2010, 2015–2019). Block-group boundaries are fixed using their 2010 delineations. For tornadoes occurring in years without available census or ACS data, we linearly interpolate between years with available data.

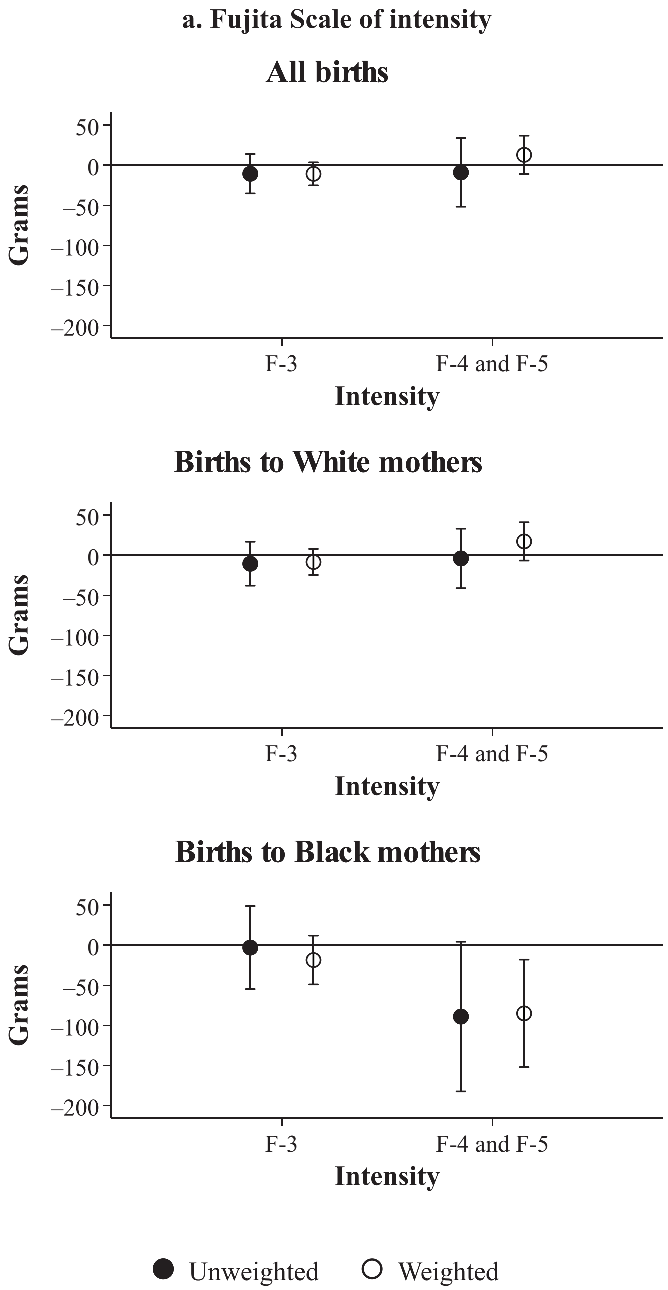

Fig. 8 Estimated aToTI effects by measure of intensity or severity. The bars around the point estimates represent 95% confidence intervals. See text for description of severity and intensity measures. GIS information on the paths, widths, and damages comes from the Storm Prediction Center Severe Weather GIS database housed by NOAA. Infant health data are from restricted birth certificate files provided by the National Vital Statistics System. Block-group demographic data are sourced from the U.S. Census (1990, 2000) and the American Community Survey (2006–2010, 2015–2019). Block-group boundaries are fixed using their 2010 delineations. For tornadoes occurring in years without available census or ACS data, we linearly interpolate between years with available data.

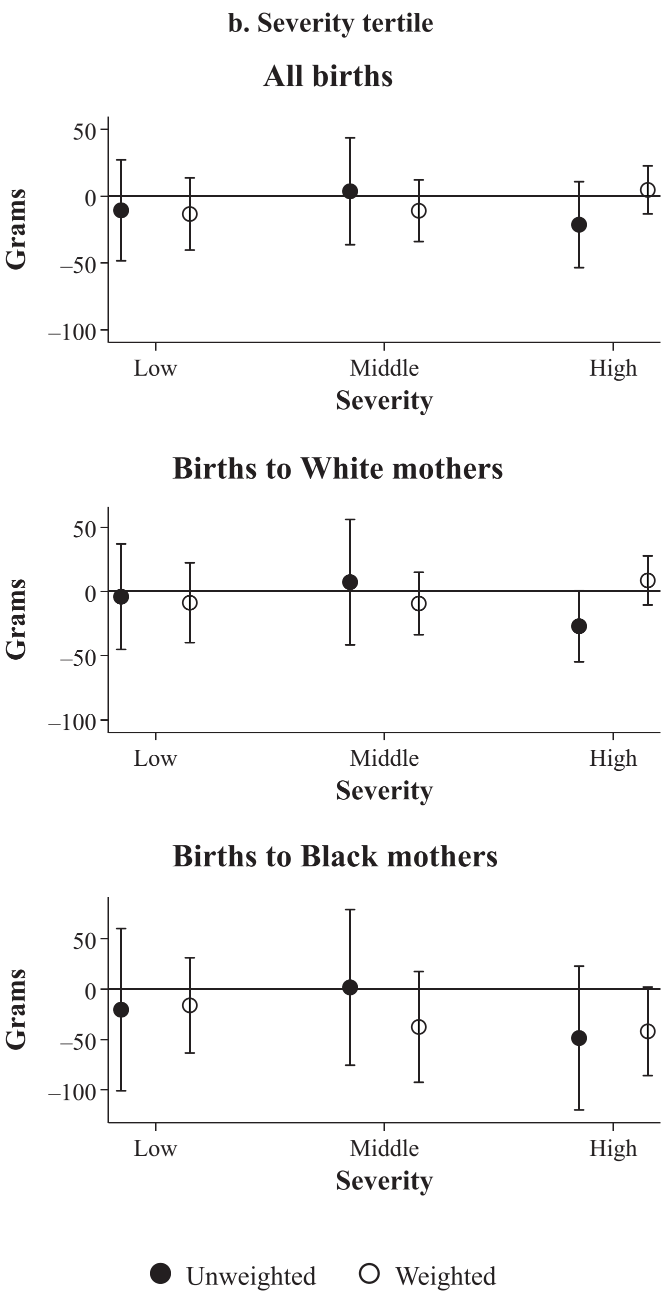

Fig. 8 (continued)

level. Low-severity tornadoes had no impact on any group. This result, which further approximates the stress and disruption mechanisms linked to tornadoes that cause a significant amount of human and economic damage, reinforces evidence that the infant health effects of tornadoes likely operate through some combination of the stress and healthcare disruption linked to greater realized damage severity. Moreover, the consistent findings of greater deleterious health effects on infants born to Black women bolster evidence of the unequal consequences of natural disasters, reflecting the cumulative disadvantage and heightened vulnerability experienced by marginalized groups.

Discussion

As extreme weather events become more common, social scientists and policymakers are becoming increasingly interested in their impact on individuals and communities (Boustan et al. 2017; Elliott and Pais 2010; Raker 2020; Schultz and Elliott 2013). In this study, we build on a growing literature on exposure to environmental stressors and birth outcomes by focusing on birth weight (Brown 2020; Duncan et al. 2017; Mulder et al. 2002; Segerstrom and Miller 2004; Torche 2011; Wadhwa et al. 2001) and examine the acute impact on the health of live singleton births to mothers who were pregnant when a tornado affected their county of residence. Like many other types of natural hazards, the destruction and disruption that severe tornadoes inflict on communities are likely to induce high levels of stress in persons who are pregnant and potentially alter important access to forms of prenatal healthcare.

Using birth data from the National Center for Health Statistics and tornado activity data from the NOAA Severe Weather GIS database, we leveraged the quasi-random timing and trajectory of 808 severe tornadoes that hit the United States between 1992 and 2017 to estimate the effects of tornadoes on birth weight. To do so we develop a novel weighting scheme, which we apply with the help of localized population data and heterogeneity-robust difference-in-differences methods. We find that severe tornadoes led to sizable and meaningful reductions in birth weight for Black mothers' infants, particularly those affected early in pregnancy by the most severe tornadoes.

Using two measures of tornado severity or intensity, we document consistent evidence that more extreme tornadoes had greater deleterious effects on infant birth weight when exposure occurred in the first trimester, particularly for infants born to Black women. Our findings are consistent with other research documenting a need for accounts of climate vulnerabilities and impacts that emphasize heterogeneity in contrast to one-size-fits-all approaches (Arcaya et al. 2020). Our results on effect timing aligns with prior research that fetal health is most sensitive to adverse events in the first trimester (Glynn et al. 2001; Torche 2011). Because the Fujita Scale estimates intensity on the basis of wind speed and structural damage, it may not fully capture the material and human tolls that drive the mechanisms of parental stress and healthcare disruption. Our principal-component-analysis-derived indicator of severity, which integrated information on casualties and economic losses, better reflects potential sources of stress and provides additional evidence of the greatest effect from the most devastating tornado occurrences, aligning with the prediction that a combination of acute stressors, such as fear, trauma exposure, community disruption, housing loss, or financial problems, plays a key role (Torche 2011; Wadhwa et al. 1993). Moreover, tornado-induced healthcare infrastructure damage may reduce access to prenatal care. Both processes likely disproportionately affect marginalized populations because of preexisting barriers to healthcare and unequal vulnerability to stress. The dual mechanisms—maternal stress and healthcare disruption—may operate interactively, amplifying impacts on birth outcomes. Future research could further disentangle these mechanisms by exploring granular healthcare utilization data and biomarkers of maternal stress before and after tornado exposure.

This article adds to a growing literature in demography that points to environmental hazards as drivers of inequality and stratification. This evidence is of particular relevance given the growing concern for the increasing intensity and frequency of natural hazards in the United States (Field et al. 2012). Our twofold contribution—providing the first empirical causal estimates of tornadoes on birth outcomes and offering a methodological toolkit for examining effect heterogeneity and improving estimates—has broad implications for scholars interested in the demography of disasters.

Despite the empirical improvements made with our novel use of localized data with aggregated outcomes, analysts should still be attentive to important limitations of this approach. Effects are still estimated as averages over areas, thereby combining the experienced effects of both exposed and nonexposed mothers within those geographic boundaries. While the population-weighting procedure improves on traditional binary treatment variables, the averaging process inherently dilutes the more pronounced effects likely experienced by directly exposed mothers by incorporating the outcomes of those who are not exposed. Furthermore, while our approach addresses some limitations in traditional treatment effect estimation, it assumes that treatment intensity can be accurately captured by geographic proximity and exposure, which may oversimplify the complexities of how disasters impact communities.

Our study not only advances understanding of the demographic and health impacts of severe weather events but also underscores the importance of integrating fine-grained spatial and demographic data to uncover disparities in disaster vulnerability. Our strategy has the potential to be generalized to other settings where localized outcome data are unavailable but where fine-grained information about treatment intensity and population distribution is accessible. Examples include assessing the demographic effects of localized economic shocks or other natural disasters such as wildfires. ■

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