Supplemental Appendix for 'Tropical cyclone exposures and risks of emergency Medicare hospital admission for cardiorespiratory diseases in 175 urban United States counties, 1999–2010'

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closest approach.

Table S4: Dispersion diagnostic results.

Details about county-level tropical cyclone exposure assessment

Wind-based exposure. As our main metric of tropical cyclone (TC) exposure, we modeled peak sustained winds associated with each storm in each county and classified a county as exposed or unexposed to the storm based on whether this modeled wind speed exceeded a certain threshold. For each TC, we first used a double exponential windspeed model (Willoughby et al. 2006) to model ground-level peak sustained winds. We started with inputs from the National Hurricane Center's revised Atlantic hurricane database (HURDAT2; Landsea and Franklin 2013) on the storm's position and maximum 10-meter, 1-minute sustained wind speed. From this data, we also determined the storm's direction of movement and forward speed, and then interpolated all measurements from the recorded six-hour intervals to 15-minute intervals using natural cubic splines with number of knots based on the number of available position measurements for that storm (Anderson et al. 2017a). From these inputs and the location of the county's population mean center (as determined by the US Census Bureau, based on 2010 Census results; https://www.census.gov/geographies/reference-files/2010/geo/2010-centers-population.html), we used the model to estimate maximum wind speeds in each study county associated with the storm as the storm moves near or through the county. We have made the code for this TC wind speed model available as an open-source R software package (Anderson et al. 2017b).

This modeling resulted in a time series of wind speeds for each study county over the course of each storm, with a separate wind speed modeled every 15 minutes at each county's center during the storm's transit for as long as the storm was tracked. From this collection of modeled wind speeds, we determined the highest wind speeds over the course of the storm for each county. We then classified each study county as either exposed or unexposed to the storm, based on whether this peak sustained windspeed exceeded a certain threshold. For our primary analysis, we used a threshold of 21 m/s; for secondary analysis, we considered thresholds of 12, 15, and 18 m/s.

Rain-based exposure. To determine TC exposure based on the rainfall experienced in each study county, we used precipitation data from the North American Land Data Assimilation System, phase 2 (NLDAS-2; Rui et al. 2014), aggregated from its original 1/8th degree grid to the county level (Al-Hamdan et al. 2014). This re-analysis dataset applies a land-surface model that integrates data from surface observations and satellites, generating a time series of hourly precipitation across the continental United States (US) (Rui et al. 2014), which was then summed to measure daily precipitation values (Al-Hamdan et al. 2014).

We then matched this precipitation data spatially and temporally with storm tracks. For each storm, we interpolated the storm track to a 15-minute interval, from the original six-hour position measurements given in HURDAT2, using a cubic spline (Anderson et al. 2017a). We then measured, for each county in the study counties, the distance between the county's population-mean center and the storm track. We used the date on which this distance was smallest as the date of the storm's closest approach to the county (Figure S3). A three-day window was crafted separately for each study county, centered on the day that the storm was closest to that county. Figure S1 gives a demonstration of this process for Hurricane Floyd in 1999, showing the evolution of the exact dates used to calculate cumulative rainfall in specific counties as the storm moved up the coast. Cumulative rainfall was measured as the sum of daily precipitation values across the three-day window for each county.

We selected a three-day window based on evidence from the atmospheric science literature on the typical size of tropical cyclone rainfields and tropical cyclone translational speeds. Rainfields for hurricanes hitting the US typically extend about 250 km from the storm's center (Matyas 2010), and peak rainfall rates tend to be within about 40 km of the storm's center (Lonfat, Marks, and Chen 2004). Storms that bring the most precipitation to an area tend to be slower-moving (in terms of translational speed), in part because these slower storms keep a location within the rainfield for a longer period (Hall and Kossin 2019; Matyas 2010). In recent years, the mean coastal North Atlantic tropical cyclone translational speed has been about 15.5 km/h, with a 5th percentile of approximately 5 km/h (Hall and Kossin 2019). A storm moving at a very slow speed of 5 km/h would travel 360 km (217 miles) over a three-day period, while a storm moving at 15.5 km/h would travel over 1,000 km (620 miles) in a three-day period. One study investigated residence times of North Atlantic tropical cyclones—how long the storms spend within a 200 km radius of a location (Hall and Kossin 2019)—and found that, for the 1,110 Atlantic-basin tropical storms between 1944 and 2017, over 90% of storms never lingered more than 48 hours within a 200 km radius of any coastal region between the Yucatan and Maine (Hall and Kossin 2019). Even for most slow-moving storms, therefore, a three-day window will encompass most or all of the period when the storm is close enough that the location falls within the storm's rainfield.

Once we calculated the cumulative rainfall for each study county for each tropical cyclone, we considered a county exposed under the rain-based TC exposure metrics if (1) cumulative rainfall for the three-day window surrounding the storm's closest approach to the county surpassed a certain threshold and (2) the storm track came within 500 kilometers (km) of the county (to exclude cases where study counties far from a storm experienced high precipitation from another weather event concurrent to the storm passing elsewhere in the country). We considered four thresholds for exposure classification: 50, 75, 100, and 125 millimeters (mm).

Flood- and tornado-based exposure. We determined county level exposure to storm-induced floods and tornadoes using data from the National Oceanic and Atmospheric Administration (NOAA)'s Storm Events database (National Oceanic and Atmospheric Administration 2018). For each TC, this Storm Event database was queried for all study counties for which the storm came within 500 km of the county at closest approach. For each of these study counties, we identified all flood and tornado events with a start date within a five-day window of the date of the storm's closest approach to the county.

For TC flood exposures, three counties (Oneida and Broome Counties, NY, and Lackawanna County, PA) were exposed to two storms (Hurricane Gaston and Tropical Storm Hermine) on the same day (August 31, 2004). Since our modeling approach cannot distinguish the effects of two storms on the same day, we modeled the two storm events as a single exposure for these counties.

Distance-based exposure. Finally, we assessed exposure based on distance of the storm's closest approach to the county. For each storm, we interpolated the storm track to a 15-minute interval, from the original six-hour position measurements given in HURDAT2, using a cubic spline (Anderson et al. 2017a). We then measured, for each county in the study counties, the distance between the county's population-mean center and the storm track. We used the minimum value of this distance to measure the storm's closest approach to the county. We investigated four thresholds of distance: 25, 50, 75, and 100 km.

We conducted all TC exposure assessment using the R package "*hurricaneexposure*" (Anderson et al. 2017a), which we created to make this county-level hurricane exposure assessment data available publicly to other researchers.

Statistical models and supplemental results for the associations between the ten most severe TC wind exposures and Medicare emergency hospital admissions

To investigate if the overall estimated associations between TC exposures and hospital admissions were driven by the few most severe TC exposures, we also estimated the storm-specific associations for the ten most severe TC wind exposures, as well as the average associations between hospitalizations and all other TC exposures when excluding these ten most severe wind exposures. To ensure adequate statistical power in this subgroup analysis, we limited this analysis to study counties with >50,000 Medicare beneficiaries.

For each of the top ten TC wind exposures, we estimated the RR on the day of storm's closest approach to the county. To do so, we created a matched dataset as described in the main text and then applied the following overdispersed Poisson model to the matched single-county, single-storm data:

$$Y_t \sim \text{Quasipoisson}(\lambda_t, \phi\lambda_t)$$
$$\log(\lambda_t) = \log(\mathrm{n_t}) + \alpha + \beta_t \mathrm{x_t} + \eta \mathrm{b_t} + \boldsymbol{\kappa}'\mathbf{d_t} \tag{S1}$$

where:

- Y_t is the hospital admission count on day t;
- λ_t is the expected count of hospital admissions for day t;
- ϕ is an overdispersion parameter;
- n_t is the total number of unhospitalized Medicare beneficiaries in the county on day t;
- x_t is an indicator variable denoting whether day t is a storm-exposed day or matched unexposed day;
- b_t is included as a linear variable to adjust for the long-term linear trend in hospital admissions over time, with η as the coefficient for year;
- $\boldsymbol{d_t}$ is vector of categorical variables of day of week and $\boldsymbol{\kappa}$ is a vector of coefficients for day of week.

The value of $\widehat{\beta_t}$ estimated from eq. S1 was used to calculate the RR for the single-storm exposure in the affected county on the day of storm's closest approach to the county.

To estimate the storm-period RRs for the most severe TC wind effects on hospital admissions, we first calculated the total count of hospital admission for the ten-day storm exposure period (two days before to seven days after the storm's closest approach to the county), as well as for the same period surrounding each matched unexposed day. To this data we applied the following overdispersed Poisson model, fitting it separately for each of the ten most severe TC wind exposures:

$$Y_T \sim \text{Quasipoisson}(\lambda_T, \phi\lambda_T)$$
$$\log(\lambda_T) = \log(\mathrm{n_T}) + \alpha + \beta_T \mathrm{x_T} + \eta \mathrm{b_T} \tag{S2}$$

where:

- Y_T is the total count of hospital admissions for the storm period;
- λ_T is the expected count of hospital admissions for the storm period;
- ϕ is an overdispersion parameter;
- n_T is the average of daily number of unhospitalized Medicare beneficiaries in the county over the ten-day storm period;
- x_T is an indicator variable of storm exposure, with $x_T = 1$ denoting storm-exposed period and $x_T = 0$ the matched unexposed period, with β_T the coefficient of storm exposure during the period;
- b_T is a linear term for year to adjust for the long-term linear trend in hospital admission over time, with η as the coefficient for year.

Finally, we investigated the influence of the ten most severe TC wind exposures on the overall estimated associations between TCs and hospital admissions for all the storms and across all the exposed counties. We conducted this analysis based on the TC exposure definition of storm-associated peak sustained winds $\geq$21 m/s in the county. We fit the equation in the main text to all other identified TC exposures (excluding the ten most severe wind exposures) across all study counties with Medicare beneficiaries > 50,000. For this analysis, we excluded days within the ten most severe wind exposures from the pool of candidate unexposed matching days. We compared these estimates to the estimated associations when all storm exposures were included in the analysis.

Sensitivity analysis

Sensitivity analysis to exclusion criteria for selecting matched unexposed days. Unexposed days were typically not close in time to other storm exposures in the county. For example, when storm exposure was defined as local peak sustained wind speed ≥21 m/s, there were 123 TC exposures (Table 1 in the main text). For each TC exposed day, ten unexposed days were randomly selected for matching, resulting a total of 1,230 unexposed days included in analysis. For 805 out of the 1,230 matched unexposed days, there were no TC exposures in that county in the calendar year of the matched unexposed day. For the rest of 425 matched unexposed days, the median distance (days) from the unexposed day to the nearest TC-exposed day was 21 days, ranging from 3 to 114 days.

However, to ensure that our results were robust to a wider exclusion period, we also conducted a sensitivity analysis. In the sensitivity analysis, we used a stricter matching criterion, extending the exclusion period to a two-week (fourteen day) window. The primary statistical model was re-run on this new version of matched data. Results are shown in Figure S8. Our primary results were very robust to this study design choice, as indicated by the similarity in point estimates and confidence intervals when comparing estimates from the original analysis versus the analysis with a wider criterion for excluding days as candidates for matched unexposed days based on proximity to another storm in the county.

Sensitivity analysis to statistical modeling choices. We conducted sensitivity analyses related to several of the modeling choices in our primary statistical model. These sensitivity analyses focused on investigating potential problems with the following assumptions in our primary model: (1) use of Poisson distribution, rather than a distribution that would allow for overdispersion; (2) use of a common coefficient across all study counties to control for potential confounding from long-term trends; and (3) assumption that the county-level intercepts are normally distributed, as assumed through the use of a random effect in the primary model.

We tested seven alternative statistical models to explore for sensitivity and problems with these assumptions in the primary model. The statistical notation used for all models is given in Text Box 1 of this Supplemental Appendix. The model equations for the primary model used for the results presented in the main text, as well as each of the alternative models tested, are given in Text Box 2 of this Supplemental Appendix. Text Box 2 also provides more details of how each alternative model tested for sensitivity from specific modeling choices made in the primary model. Results from re-fitting the study data with each of these models are shown in Figure S9. Estimates were extremely robust to all these changes, with very similar values for both point estimates and confidence intervals regardless of the statistical model used.

We also investigated for problematic overdispersion in the main results by estimating dispersion factors for the primary statistical modeling. Results are shown in Table S3 and indicate little overdispersion, as all estimated dispersion factors were close to 1. By contrast, dispersion factors larger than 1.4 would indicate the potential for problematic overdispersion in the primary analysis (Korner-Nievergelt et al. 2015). In additional to calculating the dispersion factors (Table S3), we also fit an alternative model (Alternative Model 6) with an observation-level random factor added to check for overdispersion (Korner-Nievergelt et al. 2015). When using the primary exposure metric of wind ≥21 m/s, the variance estimates for the random factor were very close to 0 (0.02 and 0.01 for cardiovascular and respiratory hospitalizations, respectively), indicating little overdispersion.

Sensitivity analysis using a negative control exposure. It is plausible that there are long-term trends in the probabilities of both the exposure and outcome in this study, and so there is the potential for confounding by these long-term patterns. In terms of exposure, there are documented long-term patterns in Atlantic-basin tropical cyclones' activity resulting from several large-scale climate phenomena, including the El Niño–Southern Oscillation (ENSO) (Smith et al. 2007; Klotzbach 2011; Klotzbach and Landsea 2015) and the Atlantic Multi-decadal Oscillation (AMO)(Goldenberg et al. 2011). For Medicare hospitalization rates, trends have been documented for several of the outcomes we investigate here, either nationally or locally in the US, over periods similar to our study period, including for heart failure, chronic obstructive pulmonary disease, and acute myocardial infarction (Chen et al. 2011; Holt et al. 2011; Yeh et al. 2010). These trends may be related to changes in population demographics, risk factors (e.g., smoking, high blood pressure, low-density lipoprotein cholesterol, occupational exposures), underlying health status, use of management medication (e.g., beta blockers), and probability of recommending hospitalization versus outpatient care for a condition (Chen et al. 2011; Holt et al. 2011; Yeh et al. 2010).

While we have included control in the model for long-term trends, through a fixed effect categorical variable for year in the primary statistical model, it is possible that residual confounding persists if this control is not adequately flexible or if patterns differ substantially across study counties. To examine potential unmeasured confounding from long-term temporal trends in our main analysis, we conducted a negative control exposure analysis, substituting days that were not truly exposed to storms but in the same year and time of year as the true storm-exposed days in the analysis. We conducted this analysis based on the TC exposure definition of storm-associated peak sustained winds $\geq$21 m/s in the county.

For this analysis, we specified negative control exposure days as the set of days that were two weeks (14 days) before each of the true storm dates identified in the main exposure assessment. These negative control exposure days were therefore in the same year as the true storm days, and so would capture similar phases in any long-term trends across the study years that could introduce confounding in the main results. However, these negative control exposure days were early enough before the true storm days (two weeks) that they would not be affected by the storms' weather systems or by preparations for the storms.

With this set of negative control exposure days, we conducted the same matching process and statistical analysis conducted to obtain our main results, using the generalized linear mixed-effect model described in equation 1 in the main text. If our main results are the result of confounding from long-term trends, we would expect this negative control exposure analysis to generate effect estimates that are similar in size and direction to our main results. Conversely, without long-term confounding, we would expect the negative control exposure estimates to be mostly non-significant and near a relative risk of 1 (i.e., no association between negative exposure control exposure and hospitalizations). Based on this analysis, we found little evidence of residual long-term confounding in our primary estimates (Figure S10).

Text box 1: Model notation

This text box provides the definition of all parameters used in the primary statistical model or one of the alternative models considered for sensitivity analysis. Some terms are used in all models considered, while some terms are only used in some models.

Indices

c	County
l	Days of lag from storm date or control date matched to storm
t	Day
Observed outcome	
$Y_{t,c}$	Number of hospitalizations observed among Medicare population on day t in county c
$Y_{\cdot,c}$	Total number of hospitalizations observed among Medicare population across all days included in the model for county c (for models in conditional Poisson family)
Other observed data	
a_t	Vector of categorical variables for year of day t (used in different models than b_t; allows estimation of a different intercept for each study year)
b_t	Continuous variable for year of day t (used in different models than a_t; allows estimation of a linear trend in baseline hospitalization rate by year)
d_t	Vector of categorical variables for day of week of day t
$n_{t,c}$	Number of people among the Medicare population who could be hospitalized on day t in county c (captures the enrolled, unhospitalized study population size)
$x_{t+l,c}$	Binary indicator of storm exposure at lag l from day t in community c
Parameters	
α	Overall model intercept
α_c	Random-effect coefficient capturing variation from overall intercept for county c
β_l	Coefficient of association of storm exposure and hospitalization rate at lag l
γ_c	Fixed-effect coefficient capturing variation from overall intercept for county c
$\boldsymbol{\delta}$	Vector of coefficients for year measured as a categorical variable (a_t)
η	Coefficient for overall linear yearly trend
η_c	Random-effect coefficient capturing variation in linear yearly trend for county c
θ_c	Fixed-effect coefficient capturing variation in linear yearly trend for county c
$\boldsymbol{\kappa}$	Vector of coefficients for day of week
$\lambda_{t,c}$	Expected number of hospitalizations among the Medicare population on day t in county c
$\xi_{t,c}$	Random-effect coefficient capturing variation from overall intercept for for observation on day t in county c
σ^2_α	Variance in county-level random-effect intercepts
σ^2_η	Variance in county-level random-effect for yearly linear trend
σ^2_ξ	Variance in observation-level random-effect intercepts
ϕ	Overdispersion parameter

Text box 2: Statistical models used for primary and sensitivity analysis

This text box provides the model equations for the primary statistical model as well as all models tested through sensitivity analysis. For all alternative models, explanations are included of differences from the primary model. All terms are defined in Text Box 1.

Primary model

The primary model used a normal Poisson distribution, with a random intercept for each study county (α_c) and categorical variables for year (a_t) and day of week (d_t). The association between storm exposure at different lags l from the storm day and risk of hospitalization are modeled through an unconstrained distributed lag term ($\sum_{l=-2}^{7} \beta_l x_{t+l,c}$). The daily study population in the county that could be hospitalized on day t (i.e., enrolled and currently unhospitalized) is included through a model offset, $log(n_{t,c})$.

$$
\begin{aligned}
Y_{t,c} &\sim Poisson(\lambda_{t,c}) \\
log(\lambda_{t,c}) &= log(n_{t,c}) + \alpha + \alpha_c + \sum_{l=-2}^{7} \beta_l x_{t+l,c} + \boldsymbol{\delta}' a_t + \boldsymbol{\kappa}' d_t \\
\alpha_c &\sim Normal(0, \sigma_\alpha^2)
\end{aligned}
\tag{1}
$$

Alternative models tested for sensitivity analysis

Alternative Model 1

This model, compared to the primary model, replaces the random intercept for each study county (α_c in Model 1) with a fixed effect for each study county (γ_c). This change removes the assumption that the county-level intercepts are normally distributed, helping to test for sensitivity to that assumption in the primary model. Otherwise, this model is identical to the primary model (Model 1).

$$
\begin{aligned}
Y_{t,c} &\sim Poisson(\lambda_{t,c}) \\
log(\lambda_{t,c}) &= log(n_{t,c}) + \alpha + \gamma_c + \sum_{l=-2}^{7} \beta_l x_{t+l,c} + \boldsymbol{\delta}' a_t + \boldsymbol{\kappa}' d_t
\end{aligned}
\tag{Model A1}
$$

Alternative Model 2

This model replaces the random intercept for each study county (α_c in Model 1) with a fixed effect (γ_c), as in Alternative Model 1. In addition, it alters the adjustment for long-term temporal trends by including year as a continuous variable (b_t), with a fixed-effect, county-specific linear term (θ_c), allowing for unconstrained variation in this trend by county. This model helps to test sensitivity to the assumption in the primary model that long-term trends in hospitalization rates follow a similar pattern across study counties.

$$
\begin{aligned}
Y_{t,c} &\sim Poisson(\lambda_{t,c}) \\
log(\lambda_{t,c}) &= log(n_{t,c}) + \alpha + \gamma_c + \sum_{l=-2}^{7} \beta_l x_{t+l,c} + \theta_c b_t + \boldsymbol{\kappa}' d_t
\end{aligned}
\tag{Model A2}
$$

Alternative Model 3

This model uses a random intercept for each county (α_c), as in the primary model (Model 1). However, it allows for more flexibility between counties in controlling for long-term trends by including an overall linear trend for year (η) and a county-specific random-effect for year (η_c) to model variations within each county from the overall yearly trend, while constraining these county-level variations to follow a normal distribution. As with Alternative Model 2, this model helps to test sensitivity to the assumption in the primary model that long-term trends in hospitalization rates follow a similar pattern across study counties, although this model adds the constraint that county-level deviations from the overall trend are normally distributed through use of a random rather than fixed effect.

$$\begin{aligned} Y_{t,c} &\sim Poisson(\lambda_{t,c}) \\ log(\lambda_{t,c}) &= log(n_{t,c}) + \alpha + \alpha_c + \sum_{l=-2}^{7} \beta_l x_{t+l,c} + \eta b_t + \eta_c b_t + \boldsymbol{\kappa}' d_t \\ \alpha_c &\sim Normal(0, \sigma_\alpha^2) \\ \eta_c &\sim Normal(0, \sigma_\eta^2) \end{aligned} \qquad \text{(Model A3)}$$

Alternative Model 4

This model uses the same adjustments for year and study county as the primary model (Model 1). However, it uses a conditional Poisson distribution, conditioning on the sum of daily hospitalizations across all included data for a given county, $Y_{.,c}$ (Armstrong, Gasparrini, and Tobias 2014). The model is actually multinomial (Armstrong, Gasparrini, and Tobias 2014), but is presented here using the given notation to ease presentation and draw parallels with other models. Since this model is conditioned on the total number of hospitalizations in included data for the county, it does not require a model intercept. As with Alternative Model 1, this model removes the assumption that the county-level intercepts are normally distributed, helping to test for sensitivity to that assumption in the primary model.

$$\begin{aligned} Y_{t,c}|Y_{.,c} &\sim ConditionalPoisson(\lambda_{t,c}|Y_{.,c}) \\ log(\lambda_{t,c}) &= log(n_{t,c}) + \sum_{l=-2}^{7} \beta_l x_{t+l,c} + \boldsymbol{\delta}' a_t + \boldsymbol{\kappa}' d_t \end{aligned} \qquad \text{(Model A4)}$$

Alternative Model 5

This model has the same specification as Alternative Model 4 except that it uses a quasi-Poisson distribution rather than a Poisson distribution, allowing for overdispersion through estimation of an overdispersion parameter (ϕ_c) (Armstrong, Gasparrini, and Tobias 2014). As with Alternative Models 1 and 4, this model removes the assumption that the county-level intercepts are normally distributed, helping to test for sensitivity to that assumption in the primary model. Further, this model helps in assessing for evidence of problematic overdispersion in the primary model.

$$\begin{aligned} Y_{t,c}|Y_{.,c} &\sim ConditionalQuasipoisson(\lambda_{t,c}, \phi_c \lambda_{t,c}|Y_{.,c}) \\ log(\lambda_{t,c}) &= log(n_{t,c}) + \sum_{l=-2}^{7} \beta_l x_{t+l,c} + \boldsymbol{\delta}' a_t + \boldsymbol{\kappa}' d_t \end{aligned} \qquad \text{(Model A5)}$$

Alternative Model 6

This model is a generalized linear mixed-effect model with Poisson distribution, including the same adjustments for temporal trends and locations as the primary model. This model also includes a random-effect intercept for every observation ($\xi_{t,c}$) to check for notable overdispersion (Korner-Nievergelt et al. 2015). As with Alternative Model 5, this model helps in assessing for evidence of problematic overdispersion in the primary model.

$$
\begin{aligned}
Y_{t,c} &\sim Poisson(\lambda_{t,c}) \\
log(\lambda_{t,c}) &= log(n_{t,c}) + \alpha + \alpha_c + \xi_{t,c} + \sum_{l=-2}^{7} \beta_l x_{t+l,^c} + \boldsymbol{\delta}' a_t + \boldsymbol{\kappa}' d_t \\
\alpha_c &\sim Normal(0, \sigma_\alpha^2) \\
\xi_{t,c} &\sim Normal(0, \sigma_\xi^2)
\end{aligned} \tag{Model A6}
$$

Alternative Model 7
This model is identical to the primary model, with the exception that it uses a quasi-Poisson distribution rather than the Poisson distribution used in the primary model. This model is fit using Penalized Quasi-Likelihood (PQL) (Venables and Ripley 2002). As with Alternative Models 5 and 6, this model helps in assessing for evidence of problematic overdispersion in the primary model.

$$
\begin{aligned}
Y_t^c &\sim Quasipoisson(\lambda_{t,c}, \phi\lambda_{t,c}) \\
log(\lambda_{t,c}) &= log(n_{t,c}) + \alpha + \gamma_c + \sum_{l=-2}^{7} \beta_l x_{t+l,c} + \boldsymbol{\delta}' a_t + \boldsymbol{\kappa}' d_t \\
\gamma_c &\sim Normal(0, \sigma_{\gamma,c}^2)
\end{aligned} \tag{Model A7}
$$

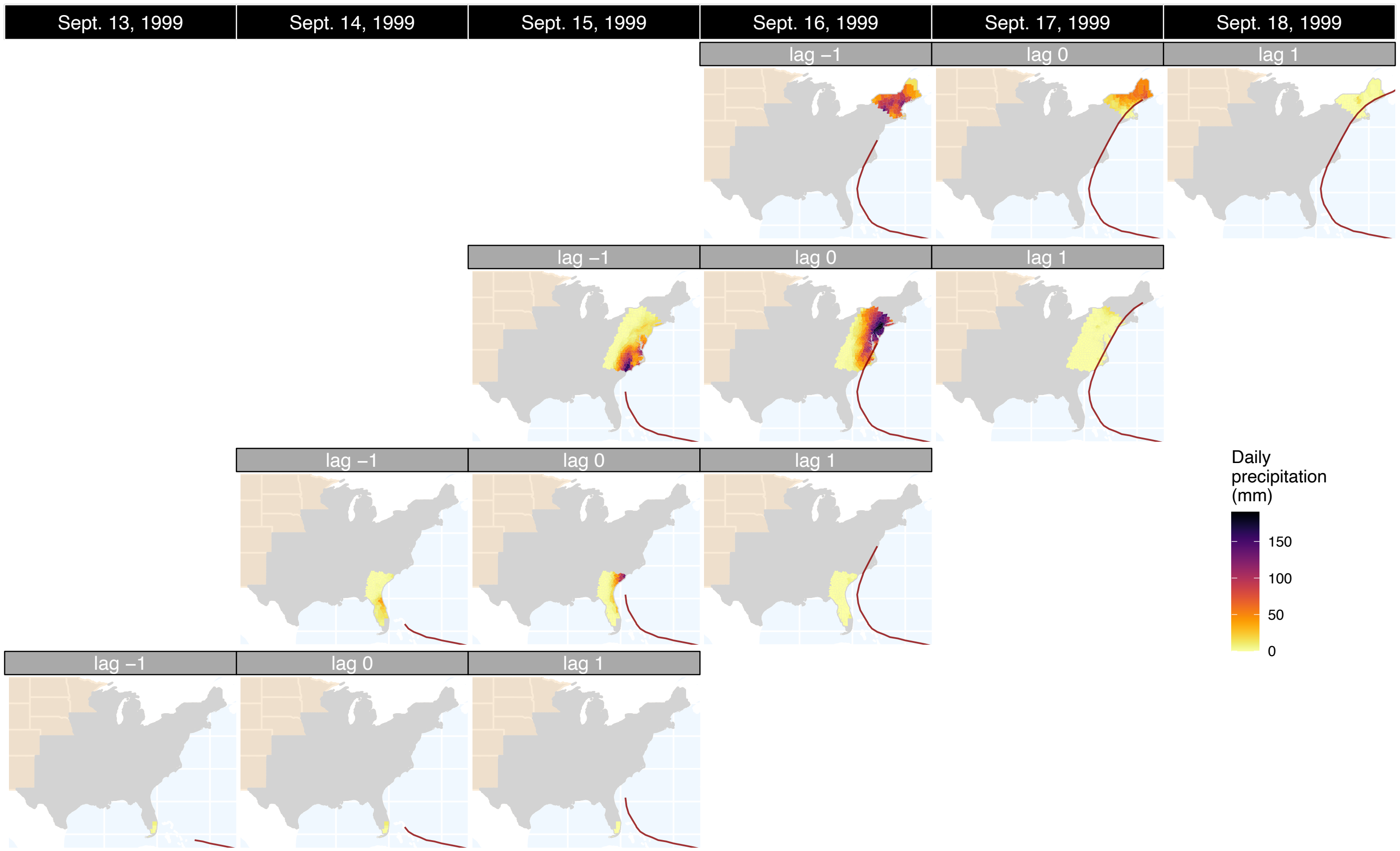

Figure S1: Example of measuring county-specific cumulative precipitation for Hurricane Floyd in 1999. Each column represents a date between September 13, 1999, and September 18, 1999. Each row provides information for a set of US counties—the counties within 500 km of the storm's track for which the storm came closest on a specific date (Figure S3). For example, the bottom row represents counties in southern Florida, which the storm came closest to on September 14. For each of these rows, maps are included for the three-day window surrounding that date of closest approach. Each map panel is labeled with the lag for those counties compared to this closest approach date (lag -1 is the day before the closest approach, etc.). The red line shows the track of the storm as it approaches and passes each area over those days. All other counties (i.e., either beyond 500 km of the storm's track or with a different date of closest approach) are colored gray, while the shade of the colored counties represented by the row show the amount of precipitation on that particular date.

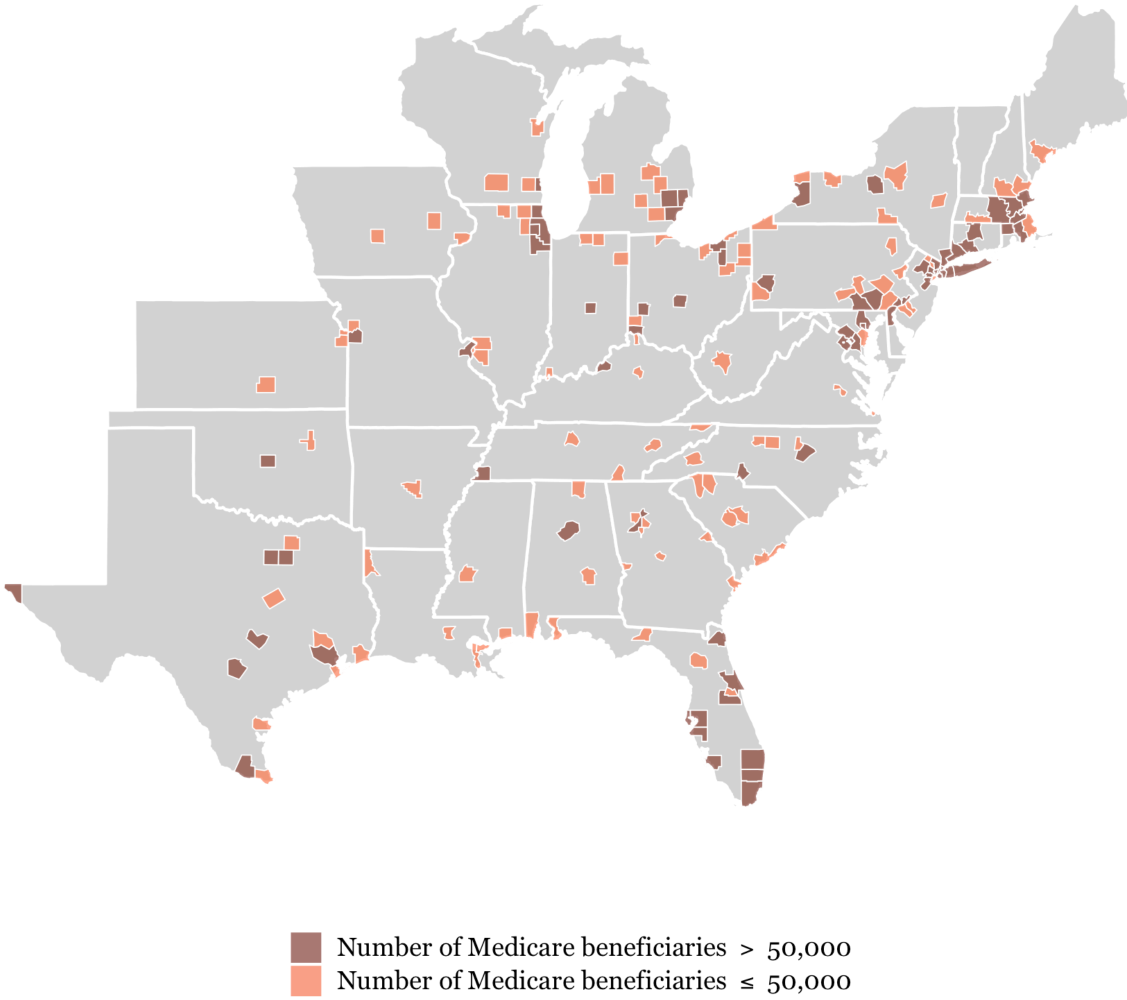

Figure S2: Study counties (n=180), including which covered >50,000 Medicare beneficiaries (n = 77) during the study period. This subset of study counties, shown in darker brown, was used for some sensitivity analysis to prevent problems with model convergence in single-storm analyses.

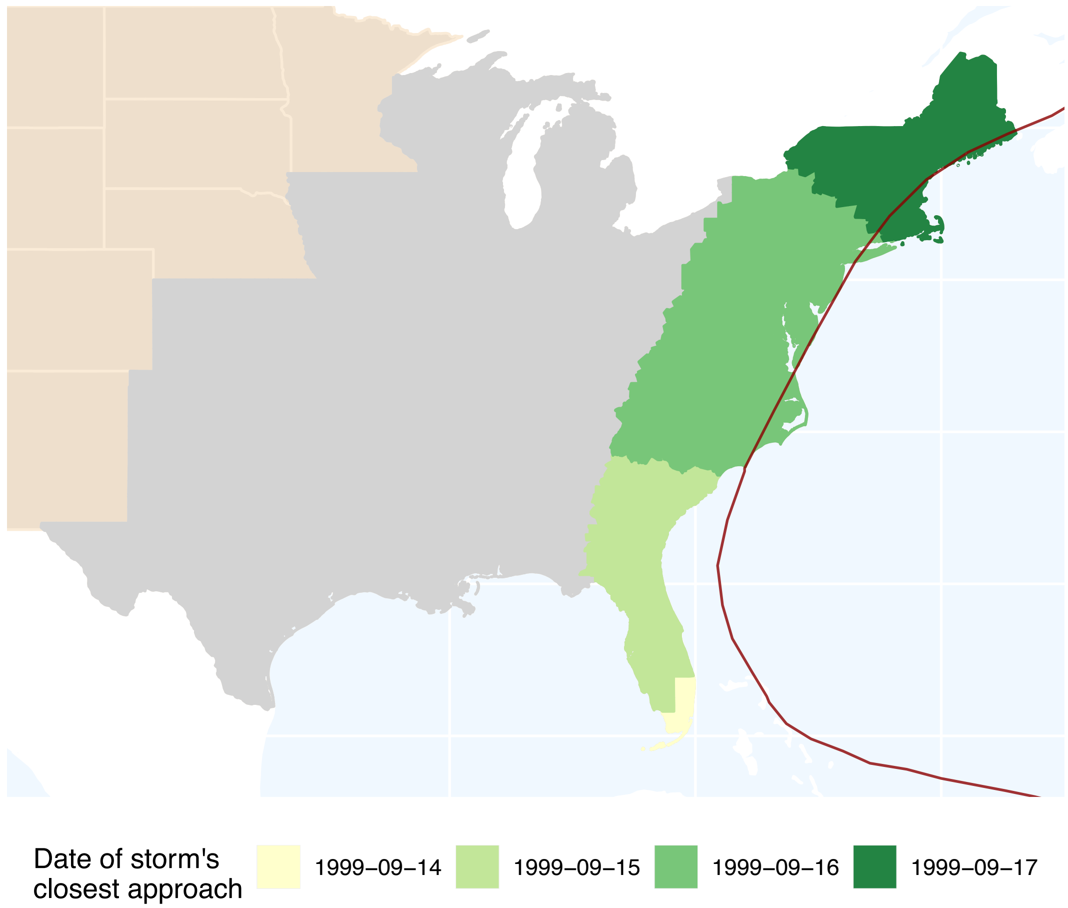

Figure S3: Example of the assignment of the date of the storm's closest approach for each county and storm. The example storm shown is Hurricane Floyd in 1999. Counties within 500 km of the storm's central track are shown in shades of yellow to green, with the shade corresponding to the date that the storm was closest to that county. The storm track was interpolated from 6-hour observations of central location to 15-minute intervals using a cubic spline. The time of the storm's closest approach was converted from UTC to the county's local time zone before determining the date of closest approach, since health data were recorded by date based on local time.

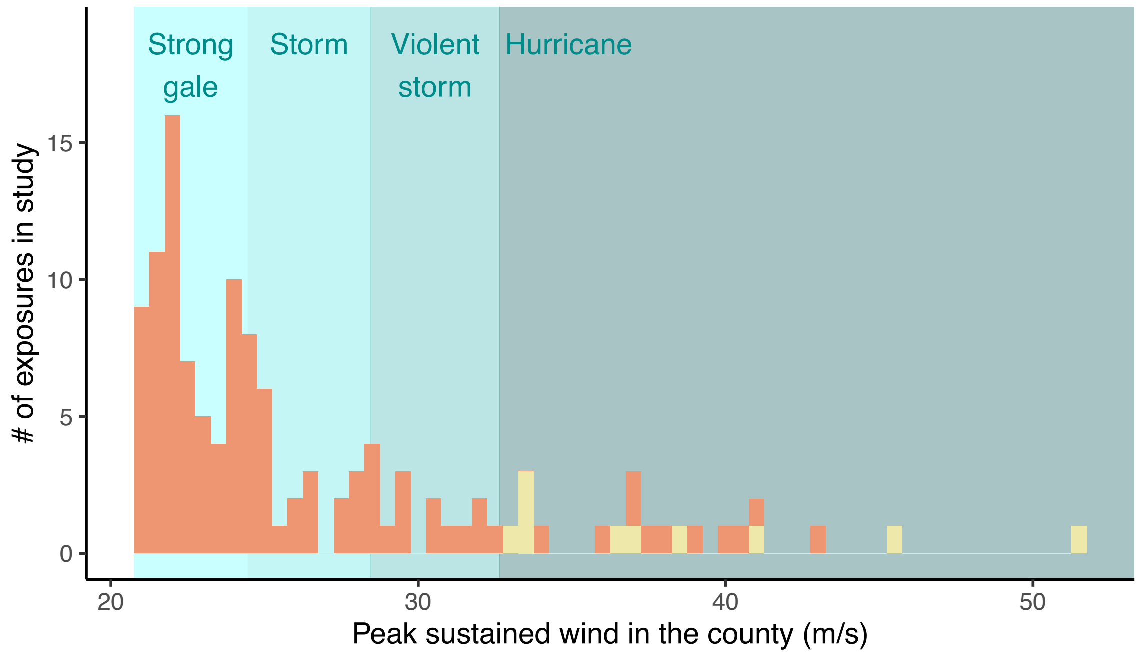

Figure S4: The distribution of local peak sustained winds for county-level tropical cyclone (TC) exposures under the primary exposure assessment (local peak sustained wind in the county of 21 m/s or higher). The height of each bar shows the number of storm exposures that fell within a given range of local peak sustained wind. This plot shows the total 123 storm exposures, within 54 study counties, under this primary exposure assessment (Table 1 of the main text). Shading in the background highlights where each TC exposure fell within the Beaufort wind scale. The color within the bars is used to highlight which storms belong to the group of the 10 most severe storms in counties with 50,000 or more Medicare beneficiaries, whose hospitalization patterns were assessed separately and presented in Table 3 of the main text.

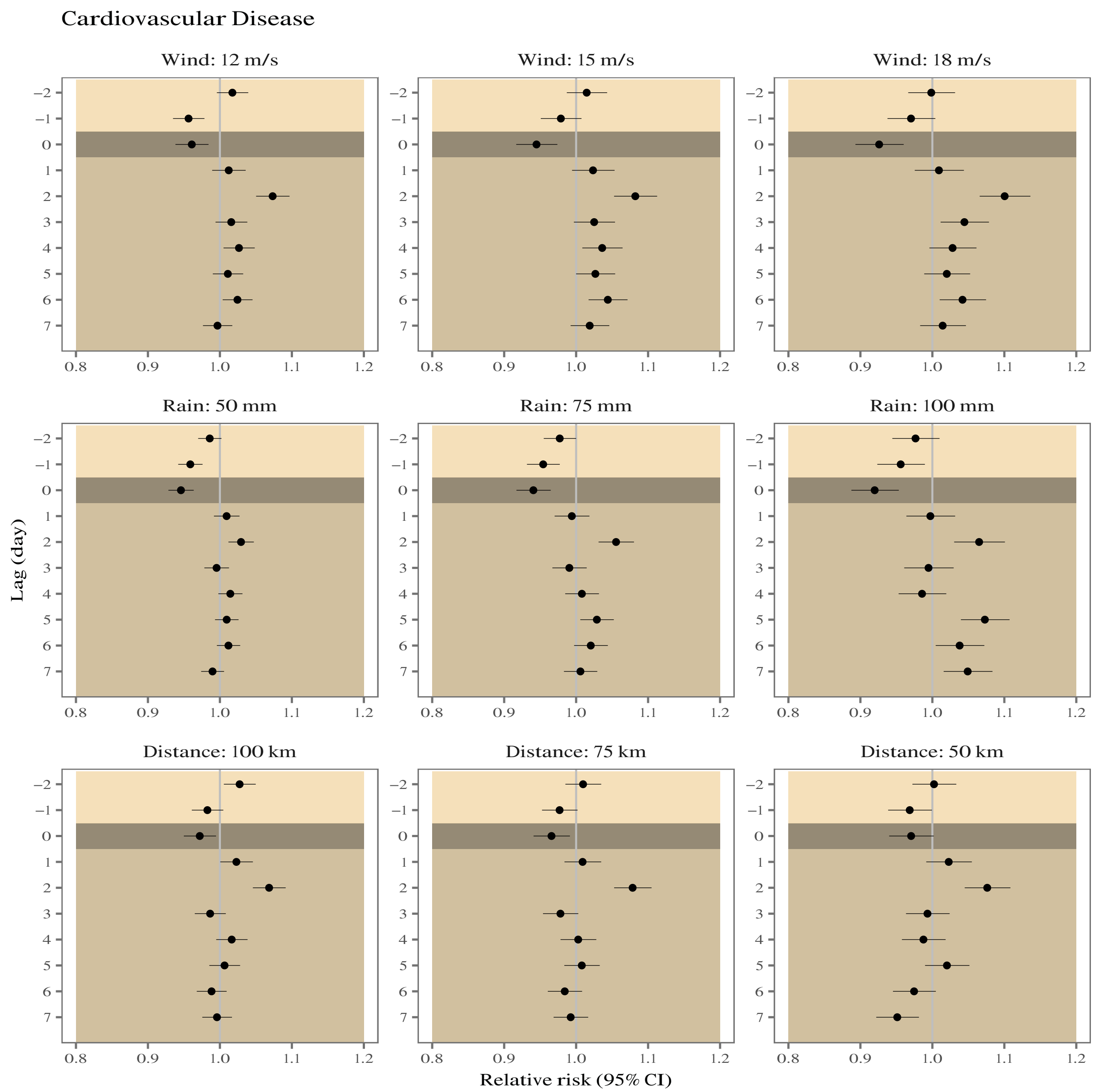

Figure S5: Estimates of distributed relative risks for cardiovascular disease hospitalizations for all TCs and across all the exposed counties, under the thresholds of wind-, rain-, and distance-based exposure metrics not shown in Figure 2 of the main text (labeled above each panel). Circles show point estimates and horizontal lines show 95% confidence intervals. The gray vertical line shows as a reference a relative risk of 1 (i.e., no observed association between TC exposure and hospitalization risk). Shading divides the lag period among pre-storm days (lightest shade), the day of the storm's closest approach (darkest shade), and post-storm days (intermediate shade).

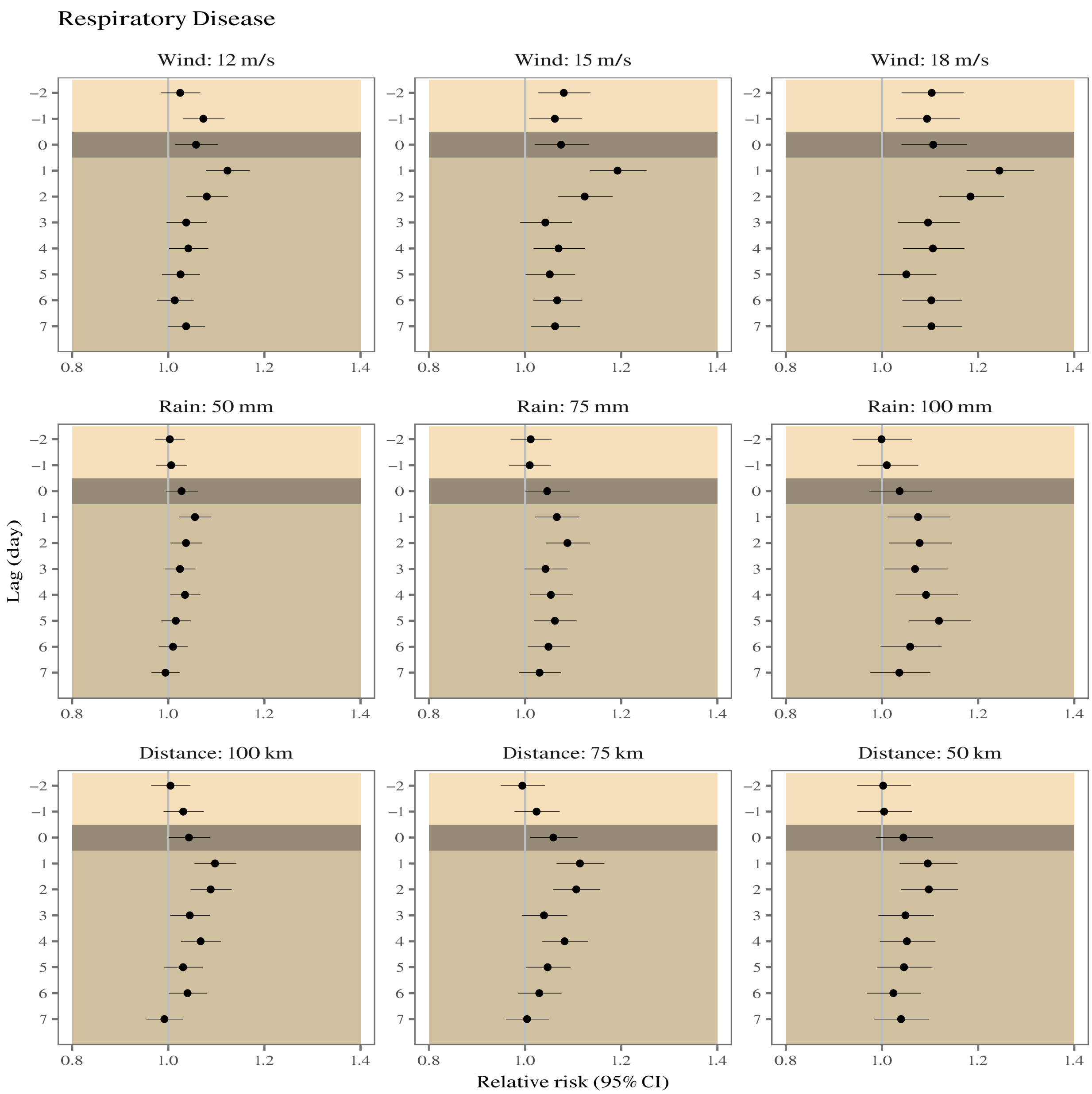

Figure S6: Estimates of distributed relative risks for respiratory disease hospitalizations for all TCs and across all the exposed counties, under the thresholds of wind-, rain-, and distance-based exposure metrics not shown in Figure 2 of the main text (labeled above each panel). Circles show point estimates and horizontal lines show 95% confidence intervals. The gray vertical line shows as a reference a relative risk of 1 (i.e., no observed association between TC exposure and hospitalization risk). Shading divides the lag period among pre-storm days (lightest shade), the day of the storm's closest approach (darkest shade), and post-storm days (intermediate shade).

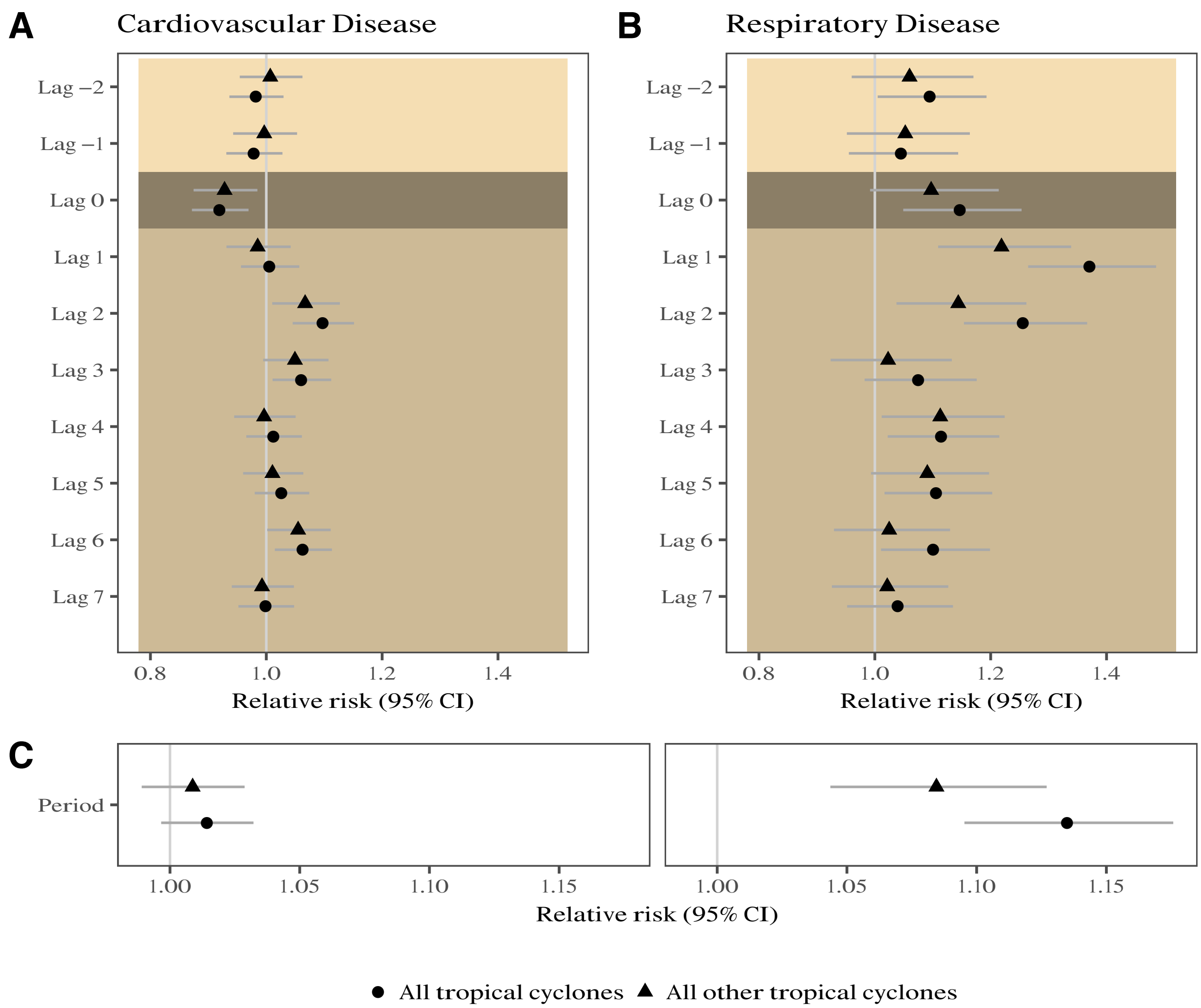

Figure S7: Estimates of relative risks (RR) of hospitalizations for all TCs (shown with triangle) and for TCs excluding the ten most severe wind-based ones (shown with circle). Dots show point estimates and horizontal lines show 95% confidence intervals. The gray vertical line shows as a reference a relative risk of 1. Estimates are shown for lag-specific relative risks for cardiovascular disease hospitalizations (A) and respiratory disease hospitalizations (B), as well as storm-period relative risks for cardiovascular and respiratory hospitalizations (C).

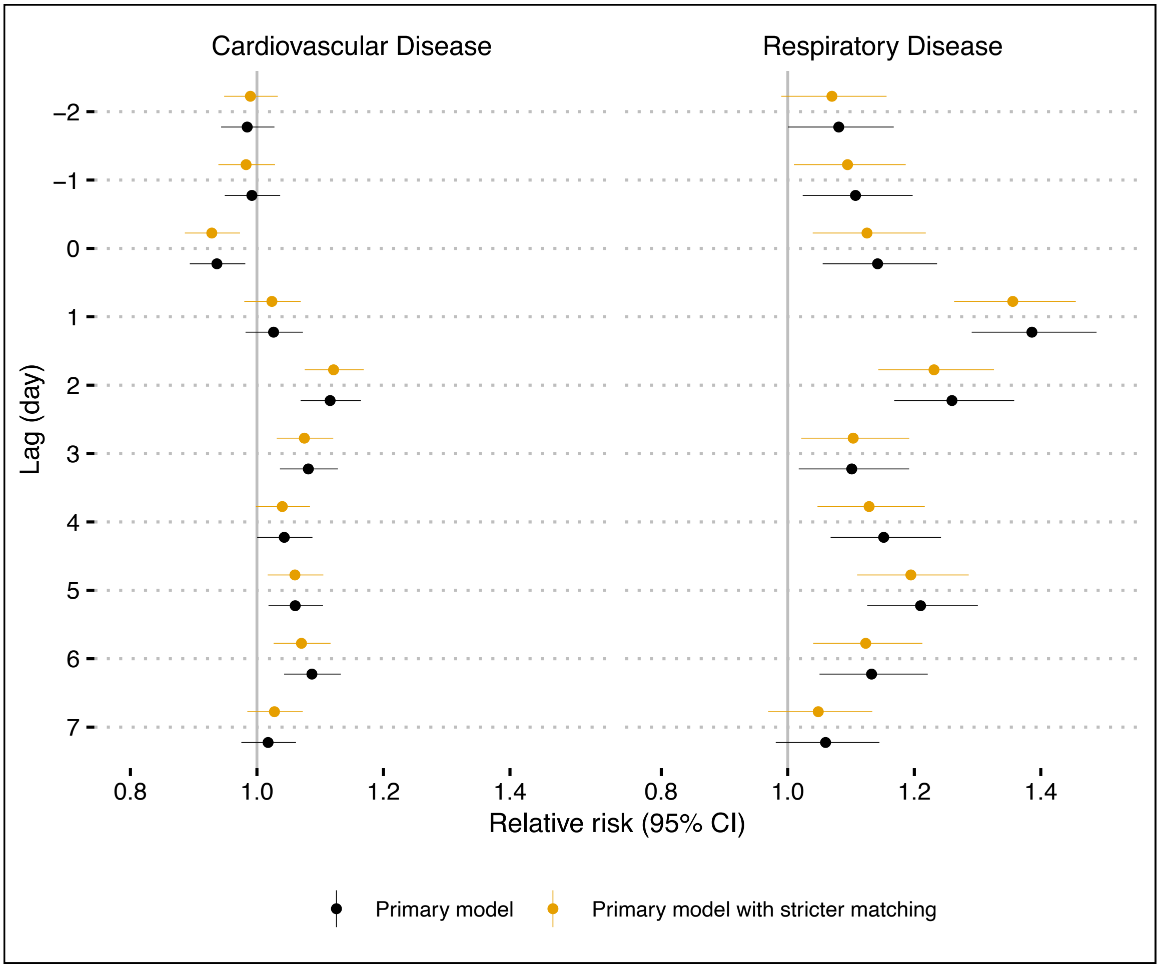

Figure S8: Sensitivity of results when unexposed days were selected through stricter criteria to exclude potential delayed impacts of other TC exposures. Estimates are shown for lag-specific relative risks of hospitalization for cardiovascular disease (left) and respiratory disease (right) when storm exposure was defined as local peak sustained wind speed 21 m/s or higher. Under the stricter matching criteria tested here, all candidates for matched unexposed days had to be outside a fourteen-day window of any other storm-exposed days for the county.

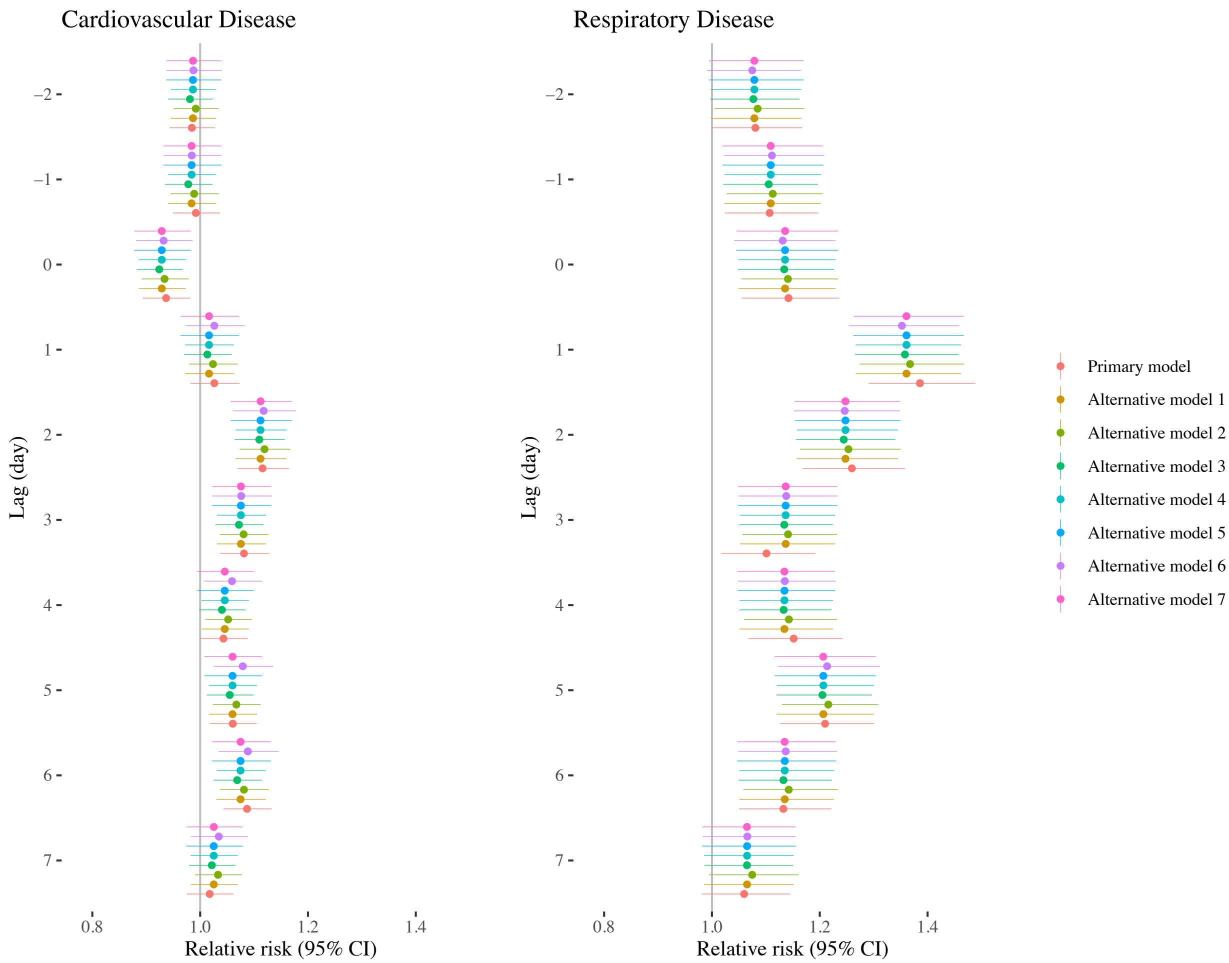

Figure S9: Sensitivity of results to alternative statistical models. Color is used to show estimates from different models, which are defined and explained in Text Box 2, with all notation defined in Text Box 1. Estimates are shown for lag-specific relative risks of hospitalization for cardiovascular disease (left) and respiratory disease (right) when storm exposure was defined as wind speed 21 m/s or higher. Dots show point estimates and horizontal lines show 95% confidence intervals. The vertical gray line shows as a reference a relative risk of 1.

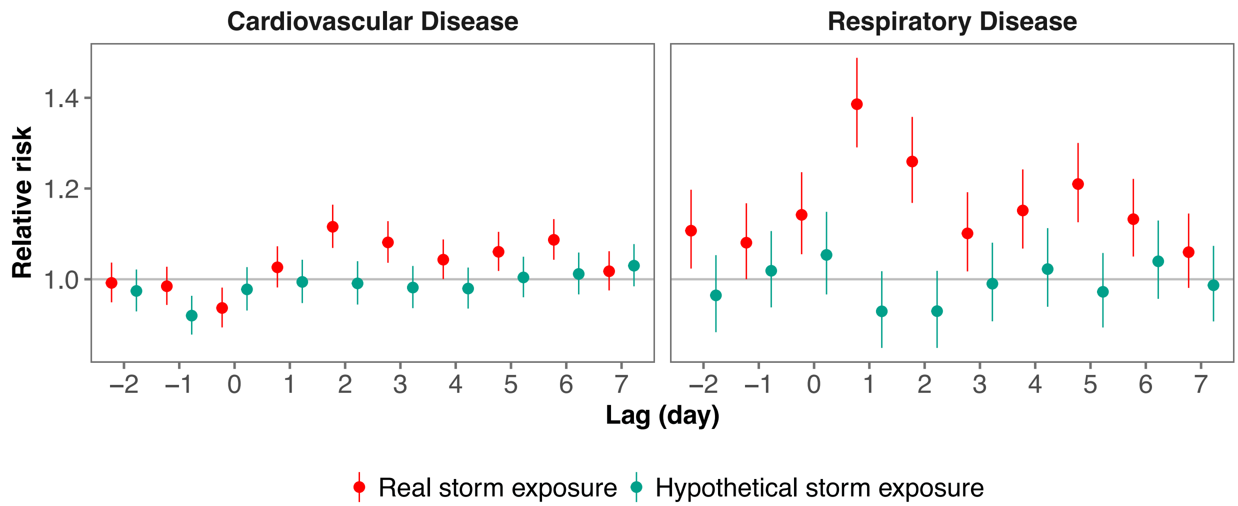

Figure S10: Results of the negative control analysis to determine evidence of confounding results from long-term trends. Estimates are shown for lag-specific relative risks of hospitalization for the real storm exposures (red) and the negative control exposure days (the days two weeks before the real storm exposures) (green). Dots show point estimates and vertical lines show 95% confidence intervals. The gray horizontal line shows as a reference a relative risk of 1.

Table S1: Comparison of population sizes of counties included in this study compared to other counties in the 34 eastern US states/districts shown in Figure 1 of the main text. Population sizes are given for both the overall population and for specific subpopulations by race, ethnicity, and age. Population sizes are summed across all counties in the given group of counties. Values are based on the 2000 and 2010 US Decennial Censuses.

	2000 Census			2010 Census		
	Study counties (N = 180)	Other counties in study states* (N = 2216)	Total in counties in study states	Study counties (N = 180)	Other counties in study states (N = 2216)	Total in counties in study states
Overall						
Total population	111,186,366	99,009,822	210,196,822	118,928,957	109,253,991	228,182,948
By race						
White	77,257,977	83,732,447	160,990,424	78,997,933	89,365,332	168,363,265
Black/African-American	21,116,405	10,216,028	31,332,433	23,272,925	11,858,130	35,131,055
Other	12,811,984	5,061,347	17,873,331	16,658,099	8,030,529	24,688,628
By ethnicity						
Hispanic or Latino	14,913,825	4,794,994	19,708,819	21,139,602	8,288,304	29,427,906
Not Hispanic or Latino	96,272,541	94,214,828	190,487,369	97,789,355	100,965,687	198,755,042
By age						
Under 65 years	97,610,381	85,545,253	183,155,634	104,152,658	93,452,994	197,605,652
65 years an over	13,575,985	13,464,569	27,040,554	14,776,299	15,800,997	30,577,296

*The states/districts covered in this study are shown in Figure 1 of the main text.

Table S2: Comparison of some demographic characteristics of counties included in this study compared to other counties in the 34 eastern US states/districts shown in Figure 1 of the main text. Each table cell gives the median value of the county-level estimates of that demographic characteristic across all counties in the given group of counties, while shown in parentheses are the interquartile range in the county-level measurements of the characteristic across the group of counties. Values are based on the 5-year American Community Survey centered on 2010.

Characteristic	Study counties (N = 180)*	Other counties in study states† (N = 2,216)*
Age		
Percent 65 years and over	12.7 (11.2, 14.3)	15.8 (13.7, 18.1)
Race, ethnicity, and language		
Percent White alone	74.8 (62.9, 84.8)	90.8 (77.4, 96.0)
Percent Black / African American alone	13.6 (7.2, 25.6)	3.3 (0.8, 14.3)
Percent Hispanic or Latino	7.4 (4.4, 15.5)	2.7 (1.4, 6.2)
Percent language other than English spoken at home	12.3 (7.9, 21.0)	4.3 (2.5, 8.1)
Income and poverty		
Percent below poverty level	15.0 (11.0, 17.8)	16.4 (12.4, 20.8)
Percent 65 years and over below poverty level	8.4 (6.8, 10.5)	10.0 (7.7, 13.7)
Percent of households receiving public assistance incomes of food stamps / SNAP	12.4 (9.9, 14.7)	13.9 (10.2, 18.2)
Disability, all ages		
Percent with disability	11.6 (9.9, 13.5)	15.8 (13.1, 18.9)
Percent with independent living difficulty	5.5 (4.7, 6.5)	6.9 (5.5, 8.8)
Percent with ambulatory difficulty	6.6 (5.6, 7.8)	9.3 (7.3, 11.6)
Percent with self-care difficulty	2.4 (2.1, 2.9)	3.1 (2.5, 4.1)
Disability, 65 years and over		
Percent 65 years and over with disability	36.0 (33.2, 38.7)	40.3 (35.4, 45.6)
Percent 65 years and over with independent living difficulty	16.2 (14.7, 18.1)	16.0 (13.3, 19.6)
Percent 65 years and over with ambulatory difficulty	23.7 (20.9, 25.7)	25.9 (21.8, 30.8)
Percent 65 years and over with self-care difficulty	8.4 (7.4, 9.7)	8.6 (6.8, 11.1)

*Median values of each characteristic are given, with the interquartile range across the counties given in parentheses.
†The states/districts covered in this study are shown in Figure 1 of the main text.

Table S3: Estimates of relative risk of hospitalizations for cardiovascular and respiratory diseases, as well as associated excess admission estimates, of ten most severe TC wind exposures across the study storms, among counties with total number of Medicare beneficiaries greater than 50,000 on the day of storm's closest approach. Estimates are included for both the period from two days before to seven days after the storm's closest approach ('Storm period estimates') and for the day of the storm's closest approach to the community ('Storm day estimates').

			Cardiovascular hospitalizations		Respiratory hospitalizations	
Storm (Year)	County	Wind (m/s)[a]	Relative risk	Attributable number[b]	Relative risk	Attributable number[b]
Storm period estimates[c]						
Wilma (2005)	Palm Beach County, FL	51.5	1.03 (0.89, 1.20)	14 (-50, 68)	1.42 (1.04, 1.93)	38 (5, 63)
Charley (2004)	Lee County, FL	45.3	1.10 (0.94, 1.28)	15 (-11, 37)	1.23 (0.91, 1.65)	11 (-6, 23)
Charley (2004)	Orange County, FL	41.2	1.24 (1.07, 1.43)	36 (13, 56)	1.44 (1.09, 1.91)	18 (5, 28)
Ike (2008)	Harris County, TX	38.7	0.94 (0.78, 1.13)	-33 (-142, 56)	1.45 (1.26, 1.66)	37 (25, 48)
Charley (2004)	Volusia County, FL	37.0	1.26 (0.99, 1.61)	22 (-1, 40)	1.11 (0.86, 1.43)	3 (-6, 10)
Wilma (2005)	Broward County, FL	36.7	1.02 (0.87, 1.21)	9 (-59, 66)	1.75 (1.45, 2.10)	43 (31, 53)
Katrina (2005)	Broward County, FL	33.5	1.13 (1.05, 1.21)	38 (16, 58)	1.36 (1.22, 1.51)	22 (15, 28)
Frances (2004)	Palm Beach County, FL	33.3	1.06 (0.91, 1.24)	21 (-35, 69)	1.38 (1.15, 1.66)	24 (11, 34)
Irene (1999)	Broward County, FL	33.3	0.90 (0.74, 1.09)	-41 (-125, 29)	1.10 (0.93, 1.31)	10 (-8, 25)
Irene (1999)	Palm Beach County, FL	33.2	0.84 (0.68, 1.04)	-79 (-197, 17)	1.43 (1.03, 1.98)	28 (3, 46)
Storm day estimates[d]						
Wilma (2005)	Palm Beach County, FL	51.5	0.45 (0.34, 0.58)	-27 (-42, -16)	0.55 (0.15, 2.02)	-4 (-28, 3)
Charley (2004)	Lee County, FL	45.3	1.11 (0.68, 1.82)	1 (-6, 6)	0.37 (0.03, 5.59)	-13 (-310, 7)
Charley (2004)	Orange County, FL	41.2	1.30 (0.77, 2.19)	5 (-7, 13)	1.15 (0.27, 5.02)	1 (-25, 7)
Ike (2008)	Harris County, TX	38.7	0.45 (0.15, 1.36)	-44 (-204, 9)	1.19 (0.52, 2.74)	2 (-14, 10)
Charley (2004)	Volusia County, FL	37.0	0.71 (0.21, 2.42)	-6 (-58, 9)	1.50 (0.57, 3.93)	1 (-2, 2)
Wilma (2005)	Broward County, FL	36.7	0.61 (0.54, 0.69)	-16 (-21, -11)	2.41 (1.76, 3.31)	8 (6, 9)
Katrina (2005)	Broward County, FL	33.5	1.15 (0.53, 2.51)	2 (-15, 10)	1.23 (0.35, 4.33)	1 (-13, 5)
Frances (2004)	Palm Beach County, FL	33.3	1.12 (0.75, 1.67)	4 (-14, 16)	1.21 (0.69, 2.15)	1 (-3, 4)
Irene (1999)	Broward County, FL	33.3	0.66 (0.34, 1.28)	-18 (-67, 7)	0.58 (0.39, 0.87)	-11 (-23, -2)
Irene (1999)	Palm Beach County, FL	33.2	1.30 (0.48, 3.51)	5 (-23, 16)	3.08 (1.04, 9.14)	3 (0, 4)

[a] Peak sustained winds modeled at the study county's population mean center over the storm period.
[b] Number of excess Medicare hospitalizations during the storm exposure in the study county, based on both the estimated relative risk associated with the storm exposure and the baseline number of hospitalizations in the study county. Negative numbers indicate fewer hospitalizations during the storm exposure compared to matched unexposed days. Details on the calculation of the attributable number are given in the Supplementary Appendix.
[c] Estimates for the entire storm period, from 2 days before to 7 days after the storm's closest approach.
[d] Estimates on the single day of the storm's closest approach to the study county.

Table S4: Dispersion diagnostic results. Table shows values of the dispersion factors for mixed-effect model with Poisson distribution. Numbers are calculated using the *dispersion_glmer* function from *blmeco* package for R (Korner-Nievergelt et al. 2015).

Exposure	Cardiovascular disease	Respiratory disease
Peak sustained wind		
12 m/s	1.18	1.08
15 m/s	1.18	1.08
18 m/s	1.19	1.06
21 m/s	1.20	1.08
Cumulative rainfall		
50 mm	1.17	1.07
75 mm	1.18	1.08
100 mm	1.18	1.08
125 mm	1.17	1.06
Distance to storm track		
100 km	1.17	1.07
75 km	1.18	1.07
50 km	1.18	1.07
25 km	1.17	1.07
Flood event(s)		
	1.17	1.07
Tornado event(s)		
	1.17	1.07

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