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Daily Variation in Natural Disaster Casualties: Information Flows, Safety, and Opportunity Costs in Tornado Versus Hurricane Strikes

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Casualties from natural disasters may depend on the day of the week they strike. With data from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), daily variation in hurricane and tornado casualties from 5,043 tornado and 2,455 hurricane time/place events is analyzed. Hurricane forecasts provide at-risk populations with considerable lead time. Such lead time allows strategic behavior in choosing protective measures under hurricane threat; opportunity costs in terms of lost income are higher during weekdays than during weekends. On the other hand, the lead time provided by tornadoes is near zero; hence tornados generate no opportunity costs. Tornado casualties are related to risk information flows, which are higher during workdays than during leisure periods, and are related to sheltering-in-place opportunities, which are better in permanent buildings like businesses and schools. Consistent with theoretical expectations, random effects negative binomial regression results indicate that tornado events occurring on the workdays of Monday through Thursday are significantly less lethal than tornados that occur on weekends. In direct contrast, and also consistent with theory, the expected count of hurricane casualties increases significantly with weekday occurrences. The policy implications of observed daily variation in tornado and hurricane events are considered.

KEY WORDS: Daily variation; forecasting; mortality and morbidity risk; natural disasters; opportunity costs

1. INTRODUCTION

Hurricane Andrew made landfall near Homestead, Florida, on August 24, 1992. As the second most destructive hurricane in U.S. history, Andrew caused an estimated $26.5 billion in property loss ($40.4 billion, in 2010 U.S. dollars), left 1.4 million residents in southern Florida without electricity, and rendered more than 180,000 persons homeless.[(1–4)] Perhaps the most striking feature of Hurricane Andrew was the relatively low count of deaths and injuries. Andrew caused only 15 casualties in afflicted counties of Dade, Monroe, Broward, and Collier, Florida. In contrast, on September 22, 1989, the counties of Dorchester, Orangeburg, Lee, Richland, and Berkeley, South Carolina were visited by Hurricane Hugo. Hugo caused about one-sixth the damage of Andrew, exposed about one-sixth the number of people to mortality and morbidity risks, yet resulted in six times the number of human casualties.[(5)]

In this article, we advance a simple partial explanation to the Andrew versus Hugo damage-casualty

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count paradox. Previous research on casualties from natural disasters has emphasized the demography of at-risk populations, the efficacy of governmental and nongovernmental emergency response agencies, the effectiveness of warning systems, and the quality of housing stock.[6–10] In this article, we pursue a more quotidian yet potentially illuminating economic logic. Perhaps death and injury counts from hurricanes and tornados are partially explainable by the *day of the week* they strike.

Prior literature provides at least three reasons to pursue the question of daily variation in casualties from hurricane and tornado events. First, studies of evacuation behavior find that *inconveniences and potential losses* due to evacuation may cause at-risk populations to stay rather than evacuate at-risk areas.[33] These inconveniences and losses are particularly costly under Type II error scenarios (false alarm), where individuals and households assume the costs of protective action against a threatening event that does not materialize.[5,39] For hurricane events, it is reasonable to assume that the size of nonrecoverable costs are higher during weekdays than on weekends, given that remunerated work and work-related activities occur primarily on weekdays, and that there is more time available to assume efforts of protective action on weekends. Second, formal models of both household protective action[35] and compliance with emergency recommendations[36] predict higher evacuation rates in weekend timing of evacuation notices given the added time on weekends that households enjoy to arrange their affairs.[36] Third, there is an intriguing technical literature on the temporal dimension of risk assessment, from questions on lead-time optimization of warning systems[38] to time-of-day variation in the size of at-risk populations.[39,40] Assuming that a hazard event is equally likely to occur at any time of day, studies show that failure to account for the diurnal flow of population can lead to orders of magnitude error in the estimation of at-risk population.[39] The same *ex ante* analytic error, we hold, can occur if risk analysts insufficiently account for the weekly and monthly rhythms of work and leisure routines in estimation of at-risk population for hurricane and tornado events.

In this article, we argue that daily variation in the opportunity costs of adopting protective measures (sheltering or evacuating) and/or accessing crucial information may give rise to a daily variation in causality counts from hurricane and tornado events. Our main argument is that the lead time provided by hurricane forecasts may induce individuals to act strategically about the choice of adopting protective measures.[44] To highlight the determinants of the opportunity cost of protection, we lay out a simple expected utility framework in which individuals value income, wealth, and health status, building on the work of Whitehead.[11] To anchor our intuition and provide a useful baseline for quantitative analyses, we begin our theory section with the case of tornado risk. Unlike hurricane events, tornadoes are more rapid in onset. This rapidity of onset has important implications for sheltering behavior, the provision of risk information, and opportunity cost reasoning in representative agents.

To test our intuition on daily variation in hurricane and tornado casualties, 5,043 tornado and 2,455 hurricane time/place events are analyzed, exploiting a unique data set inventorying the deaths, injuries, and dollar damage from disaster events in the United States from 1989 to 2005. Following the description of our intuition, we describe elements of research design, including variable operations, data sources, unit and period of analysis, and empirical strategy to test our hypothesis of daily variation in casualties from natural disasters. After that, we present statistical results, beginning with descriptive information, and ending with random-effects negative binomial regression models of both tornado and hurricane casualties. We conclude the investigation with discussion of the possible policy implications of our theory and empirics.

2. INTUITION

2.1. Benchmarking Hurricane Risk with Tornado Risk

Differently from hurricanes, tornadoes are more frequent, provide near zero hours of lead time, and are less destructive of property/crops, but are at least two times more lethal. In most cases, people aware of an impending tornado event have little time to secure their valuables and evacuate. In the event of a tornado, the most common protective measure is to shelter-in-place.[9] Provided that a residential or commercial building is structurally sound, sheltering oneself is generally sufficient to avoid the risk of death.[12] If a building is structurally unsound, fleeing in a motor vehicle may minimize the risk of death.[13]

Consider the following very stylized setting. Agents, indexed by $i = 1, \ldots, N$, value material assets, namely, income y_i and wealth w_i, and personal health status, h_i.[3] Personal health can only assume two values: 0, denoting bad health, like death or injury, and 1, denoting good health. We assume the following Cobb-Douglas functional form for agent $i's$ utility:

$$u\,(h_i, y_i, w_i) = h_i w_i^{\alpha} y_i^{1-\alpha}, \quad \alpha \in [0, 1], \qquad (1)$$

displaying nonincreasing marginal utility in both income and wealth. A person in bad health ($h_i = 0$) is not able to derive any utility from her material assets, which can be justified considering the seriousness of the health threat associated with natural disasters.

In the event of a natural disaster, people living in affected areas suffer both income and wealth losses. Wealth losses typically involve damage to residential or commercial property, whereas income losses involve lost wages, profits, dividends, and rents in consequence of the disaster. We specify income and wealth losses for individual i as fractions of her lifetime income and wealth. To simplify, we assume that the fractions of lost income and wealth are described by a single parameter $0 < c_i^T < 1$. Hence, the utility of an individual remaining in good health after a tornado event is $(1 - c_i^T)w_i^{\alpha} y_i^{1-\alpha}$, while the utility of an injured person is zero. Consider also the probability that a person finds herself in bad health whether or not a natural disaster occurs. Denote this individual-specific probability by $d_i \in (0, 1)$.

A tornado hits with probability $p^T \in (0, 1)$. When the tornado hits, a person suffers income and wealth losses, but suffers the bad health outcome with conditional probability $q_i^T \in [0, 1]$. This parameter describes the probability of the event {Bad health|Tornado occurs}, and can be interpreted as a combination of an objective measure of tornado intensity and a subjective measure of the likelihood of bad health conditional on a tornado occurrence. Using basic probability theory, the intersection event {Bad health $\cap$ Tornado occurs} occurs with probability $p^T q_i^T$, while conditional on the tornado strike an individual remains in good health with probability $p^T(1 - q_i^T)$.

The short lead time under tornado risk makes it unlikely that all individuals gather relevant information about a tornado threat, particularly if they are not in a work or institutional setting with centralized information provision. Because of the absence of perfect information processing, people know the probability of a tornado strike only up to a degree $1 - z_i$, where $0 \leq z_i \leq 1$ represents the individual-specific percentage of information lost, depending on individual characteristics such as geographic location during the tornado (e.g., indoor vs. outdoor; work vs. home), and a person's income or wealth.[29,31] Because an unsafe setting also harms agents' welfare, we also account for the extent of the loss of safety, denoted by $0 \leq l_i \leq 1$. Loss of information and safety is what matters to an individual.

If information loss is complete ($z_i = 1$), only the extent to which building safety influences the probability of bad health matters (the relevant parameter is now $p^T(1 - l_i)$), while when there is no safety loss only information matters (the relevant parameter becomes $p^T(1 - z_i)$).

Conversely, an individual protecting herself in the face of a tornado threat avoids the risk of bad health associated with the tornado. In the absence of information loss, individuals will always choose to adopt protective measures. On the other hand, significant loss of information can alter an individual's cost-benefit calculations, and may ultimately lead to casualties due to lack of protection.

We maintain that the risk of information/safety loss may be particularly relevant during weekends or holiday periods given the structure of work and leisure routines in the United States. Data from the American Time Use Survey from the Bureau of Labor Statistics indicate that leisure-work routines in the United States have a pronounced weekly rhythm.[29] Table I shows how civilian populations in the United States allocate time across activities by weekdays and weekends. Data show that U.S. citizens spend considerably more time on weekends engaging in leisure activities, and spend less time engaging in work and work-related activities in more organized settings.

During weekdays, security divisions at workplaces process and provide information about possible hazards, and work buildings are safer than private homes.[30,31] Even with the short lead time provided by tornado events, security personnel send alerts to employees, and recommend appropriate protective measures. Institutions in areas with known tornado risk such as schools and companies routinely drill students and workers in sheltering measures. On weekends, such centralized information flows, as well as private individuals, sheltering facilities, are not as effective: on the one hand, people spending weekend days outdoors, for instance, may not acquire the necessary information to shelter from bad health

[3]The model is a simple and static one, so we have to think about w_i, y_i as individual valuations of *lifetime* material assets.

Table I. Time Spent in Primary Activities, Averages per Day on Weekdays and Weekends, 2005 Annual Averages

	Weekdays (Average Hours/Day)	Weekend (Average Hours/Day)	Weekdays (Average Hours/ Day) Persons Engaged in Activity	Weekend (Average Hours / Day) Persons Engaged in Activity
Working and work-related activities	4.71	1.29	8.35	5.87
Educational activities	0.54	0.19	5.64	3.32
Leisure and sports	4.59	6.42	4.79	6.59

Note: Reported statistics drawn from the Bureau of Labor Statistics, American Time-Use Survey Data Table A-2. Averages reported in columns 1 and 2 are calculated across all respondents, whether or not they reported engaging in the measured activity. Averages in columns 3 and 4 are calculated across individuals who report engaging in the measured activity.

risk. On the other hand, even when accurate information is acquired, poor safety features/quality of individual shelters can result in failure to protect oneself. Fatalities and injuries caused by tornado events that strike on weekends or holiday periods may therefore be partially explained by the difficulty of acquiring information in decentralized environments like being outdoors,[14] as well as by low quality of decentralized sheltering environments.

These considerations are supported by the available studies on building safety. In addition to the risk of information loss, data from the National Weather Service (NWS) show that the least vulnerable places to be during a tornado event are, in fact, schools and businesses. According to NWS data, from 1996 to 2010, 918 tornado-caused fatalities occurred. Of these, only nine occurred in a school setting, and 13 occurred in a workplace setting, constituting less than 1% and 1.5% of all tornado fatalities, respectively.[29] Permanent buildings such as schools and businesses are substantially safer in minimizing risk of death of injury from tornado events.[32] Because work and school activities occur primarily during weekdays, we expect to observe statistical variation in tornado casualties by day of the week.

In empirical analyses that follow, we test whether injury and death counts from tornado events vary nonrandomly by the day of the week they strike. Given the above logic, we anticipate significantly higher casualty counts on weekend days as compared to weekdays. We also test whether daily variation in tornado casualties behaves differently over summer months of June, July, and August as compared to nonsummer months. Because work and leisure routines change measurably in summer months, with the discrete distinction between work (weekday) and nonworkdays (weekend) dissolving for substantial fractions of population employed in the public sector or following the academic calendar, we logically anticipate no significant daily variation in casualty counts from tornado events over leisure months.

2.2. Hurricane Risk and Opportunity Cost

The lead time provided by hurricane forecasts makes hurricane events fundamentally different than tornado events. With improvements in intensity and track forecasting, at-risk regions and populations have 72 hours of preparation time before landfall.[44] Such lead time, we maintain, induces people to behave strategically in relation to the choice of adopting protective measures like evacuation so as to avoid the *inconveniences and potential losses* associated with Type II error (false alarm). A person alerted to a hurricane threat with considerable lead time evaluates the seriousness of the risk, and weighs the expected costs and benefits associated with adopting protective measures.[15,34]

A hurricane hits with probability $p^H \in (0, 1)$.[4] Because of the ample lead time provided by hurricane alerts, we assume that no information is lost: $z_i = 0$ for all i. The assumption of complete or near complete information about hurricane risk is supported by numerous empirical studies showing near zero ignorance by households of an impending storm, though the number of informed hours before landfall varies by population subgroups. For example, Peacock *et al*. report that 95% of citizens in Miami-Dade felt they received adequate information to undertake preparations for Hurricane Andrew, with

[4]Hurricanes are less frequent than tornadoes, hence one can impose $p^H < p^T$. However, this restriction is irrelevant for the argument.

preparations occurring on average between 31 hours and 41 hours before landfall (depending on the demographic stratum examined).[(2)] Observe that imposing no information loss implies that the lack of safety is also not relevant in the event of a hurricane. The intuition is that ample lead time will induce agents to find appropriate shelter.

Conditional on the hurricane hit, an individual suffers the bad health outcome with probability $q_i^H \in (0,1)$, which is a combination of an objective measure of storm intensity and a subjective measure of the likelihood of bad health. As before, the intersection event {Bad health ∩ Hurricane occurs} occurs with probability $p^H q_i^H$, while conditional to a hurricane strike an individual remains in good health with probability $p^H(1 - q_i^H)$. Considering the nonhazard-related risk of bad health d_i as before, the expected utility function of an individual who does not enact protective measures under hurricane threat is:

$$EU_i^{H,N} = w_i^{\alpha} y_i^{1-\alpha}\big[p^H(1 - q_i^H)(1 - c_i^H) + (1 - p^H)(1 - d_i)\big].$$

Conversely, an individual who evacuates in the face of a hurricane is able to eliminate the conditional risk of bad health $q_i^H = 0$ for himself.[5] But evacuation is successful only if it occurs significantly before the arrival of the hurricane, and therefore entails an opportunity cost. This opportunity cost, which we denote by m, is measured in units of lost income only,[6] and adds up to the fraction c_i^H of lifetime income/wealth lost because of the hurricane. The income loss surrendered by a person choosing to evacuate in the event of a hurricane is $c_i^H(1+m)y_i$. The expected utility of a hurricane evacuee is then:

$$EU_i^{H,P} = w_i^{\alpha} y_i^{1-\alpha}\big[p^H(1 - c_i^H)^{\alpha}\left(1 - c_i^H(1+m)\right)^{1-\alpha} + (1 - p^H)(1 - d_i)\big].$$

An individual will choose to evacuate over not to evacuate if $EU_i^{H,P} \geq EU_i^{H,N}$, that is, if:

$$\left(1 - c_i^H\right)^{\alpha}\left(1 - c_i^H(1+m)\right)^{1-\alpha} \geq \left(1 - q_i^H\right)\left(1 - c_i^H\right),$$

which can be solved for the opportunity cost parameter m, yielding:

$$m \leq \bar{m}_i \equiv \frac{1 - c_i^H}{c_i^H}\left[1 - \left(1 - q_i^H\right)^{\frac{1}{1-\alpha}}\right]. \qquad (2)$$

Evacuation will be chosen if the opportunity cost m does not exceed the individual-specific threshold $\bar{m}_i$. This threshold parameter only depends on the probability of bad health because of the hurricane q_i^H, the elasticity parameter in the utility function α, and the individual fraction of lost income/wealth c_i^H. Also, note that if $m = 0$ (no opportunity cost associated with protecting oneself), a person will always choose protective measures, exactly like in the tornado case with full information.

Conversely, when $m > 0$, everything else equal, a higher value q_i^H, associated, for instance, with a high objective measure of storm intensity or a high individual probability of bad health in the event of a hurricane, increases the threshold parameter $\bar{m}_i$ making it more likely that the inequality appearing in Equation (2) is fulfilled, hence making it more likely that a person will choose evacuation. Under extreme situations where the risk of death or injury is intolerably high, the decision to evacuate is made mandatory by officials and emergency response agencies. We will refer to these scenarios as *risk effects* on the choice of evacuation.

Similarly, a higher elasticity of the utility function with respect to income, as measured by $1 - \alpha$, lowers the threshold parameter, making it less likely that an individual will evacuate. This is also intuitive, as an individual valuing income more will more carefully consider the income loss and inconveniences caused by evacuation. We will refer to this implication as the *income-elasticity effect* on the choice of evacuation. Thus, the *risk effect* functions to increase the individual threshold parameter, making evacuation more likely, while the *income-elasticity effect* works in the opposite direction.

We anticipate daily variation in casualty counts from hurricane events arising from the income-elasticity effect. The expected loss on income and inconveniences are structured by the work routine, with losses less severe on nonworkdays that typically occur on weekends. For persons at the lower

[5]In the short run, individuals may experience a bad health outcome by criminal victimization following from evacuation to unsafe areas (as observed in New Orleans following Hurricane Katrina) or, in the longer run, by disease outbreak or untreated medical condition (as observed in Haiti following the catastrophic earthquake in 2010).

[6]It can be shown that the conclusions of this analysis are unchanged if we assume that the opportunity cost also affects individual wealth. Hurricane evacuees can and do apply wealth to protecting property, gathering emergency supplies and foodstuffs, transporting selves and family to safe areas, and securing places to stay.

end of income distribution, daily income losses are likely crucial in determining whether or not to adopt protective measures in the face of hurricane risk. Moreover, given that time budgets, on average (see Table I on work and work-related activities), are ventilated on weekends, persons can engage in preparation activities to minimize loss of property. These thoughts and empirical facts cause us to anticipate higher numbers of casualties by hurricanes making landfall on weekdays.

In the next section, we describe a research design to test our intuition in terms of casualty frequencies across days of the week, although current data do not allow for direct evaluation of the noted behavioral parameters.

3. RESEARCH DESIGN

3.1. Variable Measurement

Two dependent variables are analyzed: *hurricane casualties* and *tornado casualties*. Both variables are measured as the count of death and injuries caused by a hazard event at the county scale (see Table II for summary of variable measures and descriptive statistics by hazard type). Data on hurricane and tornado casualties are from Spatial Hazard Events and Losses Database for the United States (SHELDUS). SHELDUS data on hazard event outcomes are compiled from many public sources, including the National Climatic Data Center's monthly publications. Hazard event records from SHELDUS include a start and end date, estimated property damage and crop loss, and the number of human injuries and deaths caused by the hazard event for 18 natural hazard types, including hurricanes and tornadoes.

Predictors of casualty counts from SHELDUS records include: total *disaster damage; recency bias;* and the *day of the week* the hazard event occurred. *Disaster damage* is measured as the total property damage plus crop loss caused by a disaster event in a county area in 2000 U.S. dollars. The most damaging hurricane event in the period examined was Hurricane Andrew, exacting tens of billions of dollars of damage from a series of counties in Florida and Louisiana from August 24, 1992 to August 26, 1992. The costliest tornado event over the study period occurred in Jefferson County, Alabama, causing about $213 million in property damage. Dollar damage estimates from SHELDUS are used to characterize event intensity.[7] Scholars claim that the severity of an impending disaster appears to affect the rapidity of household protective action.[38]

Recency bias is a binary variable measuring whether or not a county was visited by a hazard event causing $1 billion of damage 12 months prior. In 4.2% of hurricane place/events examined, a county experienced a billion dollar loss event in the last year. Literature in behavioral economics and disaster studies shows that recent events, and in particular, recent extreme events are more readily available in human memory and appear to inform subjective risk assessments of the future.[16–19,37] In our case, we hypothesize that locales visited by a catastrophic hazard event 12 months prior or less are more likely to take necessary protective measures to minimize (psychologically elevated) bad health expectations from an impending hazard event.[20] The *day of the week* a hurricane or tornado event strikes a county are measured as binary variables. *Sunday* is the reference category in empirical models. We expect death and injury outcomes to vary by the day of the week a hazard event occurs, with significantly lower hurricane casualties on weekends given the lower opportunity costs of taking protective measures, and significantly lower tornado event casualties during weekdays given potentially lower information loss and higher likelihood of being in workplace or school setting where the risk of death is substantially lower.[30]

In addition to features of the hazard event itself, empirical models include a series of control variables that plausibly account for variation in casualty counts. *Population size* is measured as total population in a county divided by 100,000. Mechanically, areas with more persons at risk of death and injury will increase the observed count of casualties from a hazard event. *Per capita income* is the combined income earned (from all sources) by all persons, divided by the population size (in $1,000s, year 2000 inflation-adjusted units). As detailed in our wealth/income effect logic above, we expect lower counts of hazard

[7]Hurricane event intensity can also be classified on the basis of wind speed using the Saffir-Simpson Hurricane Scale. The classification scheme is intended for measuring the "potential damage" a hurricane will cause upon landfall. Our measure of intensity makes use of recorded (not potential) damage imposed on communities. Similarly, tornados can be classified by the Fugita Scale. Estimated wind speeds for F-scale categories are: $F0$ 40–72 mph, $F1$ 73–112 mph, $F2$ 113–157 mph, $F3$ 158–206 mph, $F4$ 207–260 mph, and $F5$ 261–318 mph. By relying on wind speed and not measured damages, counterintuitive results obtain, like the injury per building risk being higher under $F3$ than $F4$ and $F5$.[33]

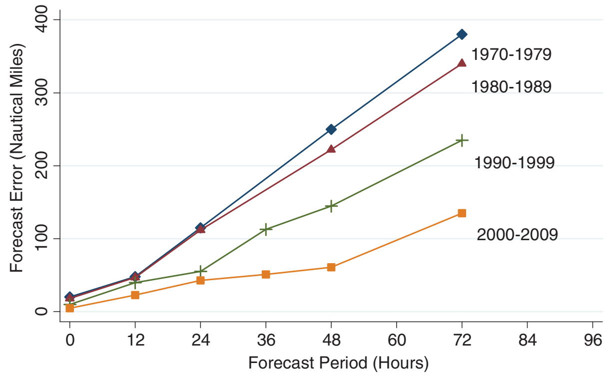
Table II. Variable Operations and Descriptive Statistics

		Hurricane Data Set			Tornado Data Set		
Variable Label	Variable Definition	Mean (*SD*)	Min	Max	Mean (*SD*)	Min	Max
Daily variables							
Sunday (Reference)	1 = disaster event occurred in county; 0 = did not occur.	0.148 (0.355)	0	1	0.147 (0.354)	0	1
Monday	1 = disaster event occurred in county; 0 = did not occur.	0.174 (0.379)	0	1	0.155 (0.362)	0	1
Tuesday	1 = disaster event occurred in county; 0 = did not occur.	0.088 (0.283)	0	1	0.135 (0.342)	0	1
Wednesday	1 = disaster event occurred in county; 0 = did not occur.	0.216 (0.412)	0	1	0.119 (0.323)	0	1
Thursday	1 = disaster event occurred in county; 0 = did not occur.	0.134 (0.341)	0	1	0.150 (0.357)	0	1
Friday	1 = disaster event occurred in county; 0 = did not occur.	0.114 (0.318)	0	1	0.151 (0.357)	0	1
Saturday	1 = disaster event occurred in county; 0 = did not occur.	0.126 (0.332)	0	1	0.145 (0.352)	0	1
Control variables							
Event damage	Sum of property damage and crop loss caused by the disaster event (in $1 million units, year 2000 US$).	39.207 (158.804)	0	2,207.45	0.910 (7.179)	0	212.448
Recency bias	$1 billion event occurred in county 12 months prior (2000 US$).	0.0419 (.201)	0	1			
Income per capita	Total annual county income divided by mid-year population size (in $1,000 units, year 2000 US$).	21.868 (7.730)	5.839	57.129	21.188 (7.623)	4.779	62.312
Population	Total mid-year population in a county divided by 100,000.	1.484 (3.432)	0.019	37.628	1.788 (4.289)	0	37.628
Nonprofit assets	Total BOY assets (minus liabilities) of all nonprofit organizations of tax-exempt status required to file Form 990 with the IRS in a county (in $100,000 units, year 2000 US$).	3, 007.06 (12, 841.3)	0	189,914.4	4, 001.371 (16, 423.46)	0	192,921.9
Response variables							
Hurricane casualties	The sum of deaths and injuries caused by hurricane event in a county.	0.758 (10.032)	0	329			
Tornado casualties	The sum of deaths and injuries caused by a tornado event in a county.				2.119 (12.436)	0	484

event casualties in counties with higher per capita income. Both population size and income per capita data are from the Bureau of Economic Analysis. Finally, with data from the National Center of Charitable Statistics, we estimate the level of nonprofit organization activity in a county. Nonprofit organizations provide crucial support before, during, and after hazard events that substantially reduce the risk of human death and injury.[21–25] Our *nonprofit net assets* variable is measured as the sum of end-of-year assets minus the sum of end-of-year liabilities for all nonprofits in a county.

3.2. Unit and Period of Analysis

The decision to examine casualty counts at the county scale is motivated by three reasons. First, the finest spatial resolution for hazard casualties in SHELDUS is the county scale. Compressed mortality data from the CDC are also organized at



Note: Data are from the National Hurricane Center Forecast Verification System.

Fig. 1. National Hurricane Center average track errors, Atlantic Basin tropical storms and hurricanes.

the county scale (with considerable suppression to protect victim identity) but Centers for Disease Control (CDC) data are only summarized at the annual time-step (not daily, as demanded by our study). Second, data for critical predictors in our empirical model—*income per capita*, *event damage*, *recency bias*, *nonprofit net assets*—are available only at the county scale, and for the time period analyzed. Third, counties are more empirically appropriate because they are large enough to capture the spatial extent of typical hurricane or tornado events.

We fix the period of analysis from 1989 to 2005 for two reasons, related to the quality of information provided to at-risk populations before a hurricane strikes. First, prior to 1989, National Hurricane Center average 72-hour track forecast error for Atlantic Basin tropical storms and hurricanes ranged from 300 to 400 nautical miles (see Fig. 1). Only regional dynamical models of the period had sufficient resolution to make more accurate track forecasts. With more empirical data, improved computational power, and increased understanding of hurricane physics, average 72-hour track forecast errors have improved significantly. Second, in the early 1990s, we observed the introduction of Statistical Hurricane Intensity Forecasting, the Statistical Hurricane Intensity Prediction Scheme, and the Geophysical Fluid Dynamics Laboratory model. These tools improved the accuracy of *intensity forecasts*. These forecasting capabilities provide households greater certainty with regard to the expected intensity of the storm/hurricane on landfall. With improved track *and* intensity forecasts, the opportunity cost logic described above more plausibly operates.

Table III. Summary Statistics of (A) Hurricane and (B) Tornado Casualties and Damage by Day of the Week, 1989–2005

Day of Week	At-Risk Population	Injuries	Fatalities	Casualties	Injuries (per 1,000,000)	Fatalities (per 1,000,000)	Casualties (per 1,000,000)	Property Damage ($1 Million)	Crop Damage ($1 Million)	Total Damage ($1 Million)
(A) Hurricane Casualties										
Sunday	46,683,770	45	18	63	0.964	0.386	1.350	22,350	129	22,479
Monday	79,551,463	34	53	87	0.427	0.666	1.093	21,370	2,102	23,472
Tuesday	28,578,087	2	41	43	0.070	1.439	1.509	8,013	452	8,465
Wednesday	66,717,689	111	28	139	1.665	0.422	2.087	6,709	1,692	8,401
Thursday	44,178,656	74	25	99	1.666	0.574	2.240	5,324	1,620	6,944
Friday	44,521,248	1,374	37	1,411	30.865	0.832	31.696	13,820	1,845	15,665
Saturday	50,385,520	10	8	18	0.198	0.157	0.357	8,437	221	8,658
Total	360,616,433	1,650	211	1,861	4.575	0.584	5.159	86,023	8,061	94,084
(B) Tornado Casualties										
Sunday	101,000,000	2,195	139	2,334	21.732	1.376	23.109	1,023	11	1,034
Monday	198,900,000	1,084	82	1,166	5.450	0.412	5.862	774	3	777
Tuesday	119,200,000	824	52	876	6.913	0.436	7.349	488	9	497
Wednesday	121,900,000	1,291	89	1,380	10.591	0.730	11.321	655	6	661
Thursday	124,700,000	1,542	73	1,615	12.366	0.585	12.951	681	68	749
Friday	114,700,000	1,297	111	1,408	11.308	0.967	12.275	510	5	515
Saturday	121,500,000	2,029	99	2,128	16.700	0.815	17.514	449	4	453
Total	901,900,000	10,262	645	10,907	11.378	0.715	12.093	4,579	105	4,684

Table IV. Random-Effects Negative Binomial Regression Models Predicting the Count of Tornado Event Casualties

	State Random Effects		County Random Effects	
	IRR	95% CI	IRR	95% CI
Day of Week (Sunday Reference)				
Monday	0.670** (0.070)	0.546–0.824	0.639** (0.069)	0.518–0.790
Tuesday	0.723** (0.080)	0.583–0.897	0.681** (0.076)	0.548–0.847
Wednesday	0.671** (0.079)	0.534–0.844	0.642** (0.076)	0.509–0.811
Thursday	0.802* (0.082)	0.657–0.978	0.777* (0.080)	0.635–0.951
Friday	0.945 (0.091)	0.782–1.142	0.884 (0.087)	0.782–1.142
Saturday	0.892 (0.089)	0.733–1.085	0.870 (0.088)	0.713–1.062
Control Variables				
Event damage ($1,000,000)	1.021** (0.001)	1.018–1.023	1.025** (0.002)	1.021–1.028
Population (100,000)	1.037** (0.012)	1.013–1.061	1.015 (0.015)	0.987–1.044
Income per capita ($1,000)	0.932** (0.004)	0.923–0.941	0.927** (0.005)	0.917–0.936
Nonprofit assets ($100,000)	0.999 (0.000)	0.999–1.000	1.000 (0.000)	0.999–1.000
Wald χ^2	627.23		527.09	
Log likelihood	−5,757.19		−5,715.06	
N	5,043		5,043	

Note: Standard errors in parentheses. $^{**}p < 0.01$, $^{*}p < 0.05$.

3.3. Empirical Strategy

Our response variables are measured as the number of deaths and injuries caused by a hazard event. Poisson regression is a commonly used procedure for count variables that are discrete and result from an underlying stochastic process. As reported in Table II, tornado and hurricane casualty counts are overdispersed, violating the Poisson assumption that the variance of a response variable is equal to its mean.(26) The negative binomial regression relaxes this assumption, allowing the variance of the response variable to differ from the mean. To account for temporal and spatial heterogeneity across locales, we use a random-intercept model (with county and/or state effects) to analyze the count of casualties caused by hazard events.

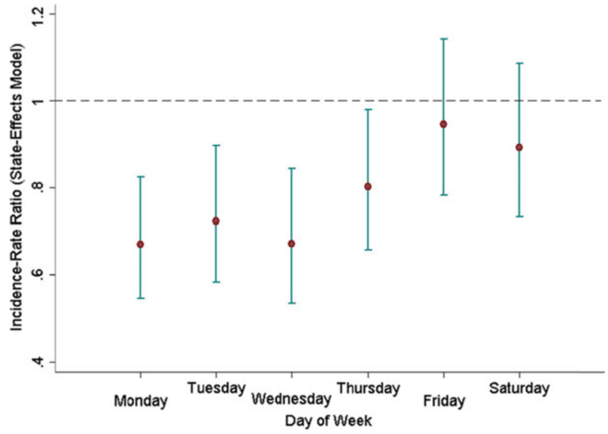
4. RESULTS

Table III present summary statistics on hurricane and tornado casualty and damage outcomes by day of the week. Over the study period of 1989–2005, a total of 1,861 hurricane casualties occurred. The crude casualty rate is 5.2 per 1 million persons. Consistent with theoretical expectations, the least risky days in terms of the rate of death and injury are Saturday (0.36 per 1 million), Monday (1.1 per 1 million), and Sunday (1.4 per 1 million), where, given the structure of the work week, opportunity costs in terms of lost income of adopting protective measures are likely lower, and preparation time is higher. In terms of daily variation, about 75% of all hurricane casualties occurred on a Friday, at a rate of 31.7 persons per 1 million at risk. The days with the next highest risk of death and injury are Wednesday and Thursday. A *hurricane damage-casualty paradox* is evident in Table III, as the most destructive days in terms of property damage and crop loss, Sunday and Monday, are among the safest days in terms of the casualty rate.

By contrast, over the same period, 10,907 persons were killed or injured by tornado events. Whereas Saturday and Sunday are among the safest days to be visited by a hurricane event in terms of human casualty risk, they are the most lethal days in the case of the rapid onset hazard of tornados. Sunday tornados, for example, have a crude casualty rate of 23.1 per 1 million persons at risk, a figure roughly twice the size of the day-nonspecific rate of 12.1 per 1 million persons at risk. This result is consistent with expectations, as the acquisition of risk information is more difficult on nonworkdays, and the likelihood of being in a less durable, high-wind-resistant building is higher.

Table IV reports random-effects negative binomial regression models predicting the count of tornado event casualties. Both state and county random-effects models are presented. For ease of interpretation, incidence rate ratios are reported with intervals of confidence. The incidence rate ratio (or relative risk ratio) is the exponentiation of model log odds. Sunday is the reference category. We concentrate interpretation on the state random-effects model. Everything else equal, and consistent with expectations, we find that tornado events that occur on the workdays of Monday through Thursday are significantly less lethal than tornadoes that occur on Sunday. The casualty rate ratio for Monday tornadoes, for example, is lower by a multiplicative factor of 0.670 (95% CI 0.546–0.824). Casualty rate ratios for Friday and Saturday tornadoes are statistically indistinguishable from Sunday events. In terms of control variables, the expected count of tornado deaths and injuries increases with event intensity (or damage) and the size of the at-risk population. Also, an income effect is observed, with risk of death and injury decreasing by about 6–8% for every $1,000 of per capita income added. Fig. 2 plots incidence rate ratios from the state random-effects model reported in Table IV, illustrating how daily variation in the excepted count of tornado casualties mirrors the labor-leisure routine of the work week.

To corroborate our logic that the labor-leisure routine structures death and injury counts from tornado events, we subdivide fully observed 5,043 place/time events into summer and non-summer months. With the exception of farm laborers, the summer months of June, July, and August are peak leisure periods for American workers. Insofar as our logic on how the labor-leisure routine structures tornado casualty outcomes is correct, daily variation in tornado casualty counts observed in Table IV ought to dissipate in leisure months of June, July, and August. Consistent with expectations, Table V shows that the risk of death and injury is statistically equal across days of the week for tornado events that occur in the leisure months of June, July, and August. Interestingly, effect sizes of event damage (IRR = 1.07), population size (IRR = 1.08), and income per capita (IRR = 0.913) amplify in statistical relevance in leisure summer months as compared to nonleisure summer months.



Note: Sunday is the reference category. Incidence rate ratios are adjusted by population size, tornado damage, income levels, and nonprofit assets, and derived from the state-effects negative binomial model.

Fig. 2. Incidence rate ratios (with 95% confidence intervals) predicting tornado event casualties by day of week.

With casualty models from our baseline, rapid onset hazard of tornadoes in mind, we turn attention to daily variation in hurricane casualties. Table VI reports random-effects negative binomial regression models predicting the count of hurricane event casualties, with both state and county random effects. Again, incidence rate ratios with intervals of confidence are reported, with Sunday as the reference category day. Consistent with theory, results show that the expected count of hurricane casualties increases significantly with hurricane events occurring on weekdays of Tuesday, Wednesday, Thursday, and Friday. The state random-effects model shows that Friday hurricanes are two to four times more lethal than hurricanes that strike on Sunday. Other things held constant, Monday and Saturday hurricane events are statistically indistinguishable from Sunday events in terms of death and injury count. Given the 72 hours of lead time provided to at-risk communities, what Saturday, Monday, and Sunday share is weekend time for preparation.[8] Given the

[8]In the Appendix, we report random-effects negative binomial regression models predicting the count of hurricane event casualties with large casualty count simulated Sunday events. These simulated Sunday events are designed to test the sensitivity of model results reported in Table V. Model results are unmoved by both 500 and 1,000 casualty events on Sunday.

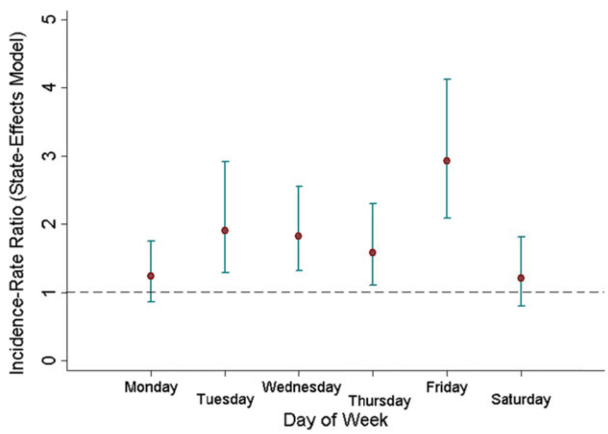
Table V. Random-Effects Negative Binomial Regression Models Predicting the Count of Tornado Event Casualties, Contrasting Summer (June, July, August) Versus Nonsummer Months

	State Random Effects		County Random Effects	
	Summer IRR	Not Summer IRR	Summer IRR	Not Summer IRR
Day of Week (Sunday Reference)				
Monday	1.121	0.647**	1.155	0.603**
	(0.350)	(0.073)	(0.407)	(0.070)
Tuesday	0.965	0.709**	0.866	0.663**
	(0.325)	(0.083)	(0.325)	(0.079)
Wednesday	0.691	0.676**	0.817	0.637**
	(0.246)	(0.085)	(0.317)	(0.081)
Thursday	0.915	0.778*	0.741	0.752**
	(0.307)	(0.083)	(0.287)	(0.082)
Friday	0.944	0.944	1.073	0.870
	(0.310)	(0.096)	(0.402)	(0.090)
Saturday	0.721	0.888	0.656	0.869
	(0.286)	(0.092)	(0.290)	(0.092)
Control Variables				
Event damage ($1,000,000)	1.068**	1.020**	1.113**	1.024**
	(0.010)	(0.001)	(0.023)	(0.002)
Population (100,000)	1.083*	1.037**	1.096	1.014
	(0.037)	(0.013)	(0.055)	(0.016)
Income per capita ($1,000)	0.915**	0.936**	0.898**	0.930**
	(0.014)	(0.005)	(0.015)	(0.005)
Nonprofit assets ($100,000)	0.999	0.999	0.999	1.000
	(0.000)	(0.000)	(0.000)	(0.000)
Wald χ^2	75.81	522.78	62.41	442.60
Log likelihood	−631.24	−5, 090.40	−618.30	−5, 060.07
N	891	4,152	891	4,152

Note: Standard errors in parentheses. $^{**}p < 0.01$, $^{*}p < 0.05$.

structure of the work week, the weekend days of Saturday and Sunday impose lower opportunity costs in terms of lost income and greater time budget flexibility, increasing the likelihood of protection measures being adopted. Also worth noting, and consistent with literature in behavioral economics and cognitive science on availability bias, results indicate that the expected count of hurricane casualties is lower by a factor of 0.365 (95% CI 0.191–0.697) in areas that experienced a massive hurricane event up to 12 months prior. Fig. 3 plots incidence rate ratios from the state random-effects model reported in Table VI, displaying daily variation in the excepted count of hurricane casualties, and corroborating the theoretical expectation of how the risk of death and injuries from hurricanes are meaningfully structured by work week.

Given that Friday events cause the majority of hurricane casualty outcomes, we conduct a series of model sensitivity tests to address potential outlier



Note: Sunday is the reference category. Incidence rate ratios are adjusted by population size, hurricane damage, income levels, nonprofit assets, and recent hurricane activity, and derived from the negative binomial model.

Fig. 3. Incidence rate ratios (with 95% confidence intervals) predicting hurricane event casualties by day of week.

Table VI. Random-Effects Negative Binomial Regression Models Predicting the Count of Hurricane Event Casualties

	State Random Effects		County Random Effects	
	IRR	95% CI	IRR	95% CI
Day of Week (Sunday Reference)				
Monday	1.235	0.866–1.762	1.260	0.850–1.868
	(0.224)		(0.253)	
Tuesday	1.914**	1.256–2.916	2.111**	1.356–3.288
	(0.411)		(0.477)	
Wednesday	1.832**	1.317–2.547	2.363**	1.653–3.777
	(0.308)		(0.431)	
Thursday	1.590*	1.103–2.293	2.080*	1.390–3.113
	(0.340)		(0.428)	
Friday	2.928**	2.078–4.126	4.560**	3.129–6.644
	(0.512)		(0.876)	
Saturday	1.211	0.804–1.823	1.715*	1.093–2.692
	(0.253)		(0.394)	
Control Variables				
Event damage ($1,000,000)	1.002**	1.001–1.002	1.003**	1.002–1.003
	(0.000)		(0.000)	
Recency bias	0.365**	0.191–0.697	0.165**	0.074–0.371
	(0.121)		(0.068)	
Income per capita ($1,000)	0.969**	0.956–0.981	0.935**	0.921–0.949
	(0.009)		(0.011)	
Population (100,000)	1.029	0.996–1.063	1.027	0.981–1.074
	(0.018)		(0.023)	
Nonprofit assets ($100,000)	0.999	0.999–1.000	0.999	0.999–1.000
	(0.000)		(0.000)	
Wald χ^2	169.89		247.03	
Log likelihood	−1529.86		−1422.93	
N	2,455		2,455	

Note: Standard errors in parentheses. $^{**}p < 0.01$, $^{*}p < 0.05$.

distortion. First, we drop the top six time/place events and recapitulate analyses in Table VI. The six most lethal hurricane events (all occurring on a Friday), account for about 60% of the total count of persons killed or injured over the study period. In Table VII, results from our outlier elimination exercise are reported. We find that incidence rate ratios for days of the week behave similarly, with casualty counts statistically significantly higher on weekdays of Tuesday through Friday as compared to our reference day of Sunday. Given that Friday events account for about 75% of all hurricane-related deaths and injuries (see Table III), Table VII also reports results from a robustness check where all Friday events are eliminated. Note that *N* declines from 2,455 time/place events to 2,175. Again, we find that the casualty risk on weekday events on Tuesday through Thursday is statistically distinguishable from Sunday. In fact, incidence rate ration (IRR) corresponding to weekdays appear to strengthen in the counterfactual scenario of Friday eliminated events.

5. DISCUSSION/CONCLUSION

In this article, we examined daily variation in tornado and hurricane casualty outcomes. We theorized that event variation in hurricane and tornado mortality and morbidity outcomes would be structured by weekly and monthly rhythms of work and leisure routines in the United States. In support of the weekly rhythm claim, in Table I we report data from the American Time Use Survey showing that U.S. populations do, in fact, allocate time differently across work and leisure activities by weekdays and weekends. We described a simple but plausible microanalytic logic involving risk information and the opportunity costs of adopting protective measures (sheltering-in-place or evacuation). In statistical analyses, we tested whether variation in casualties by natural disasters are partially explained by the day of the week a disaster strikes, accounting for more commonly analyzed covariates like the destruction caused by a disaster event and the count of at-risk population.

Table VII. Random-Effects Negative Binomial Regression Models Predicting the Count of Hurricane Event Casualties with Outlier and Friday Event Adjustments

	Outlier Eliminated State Random Effects		Friday Events Eliminated State Random Effects	
	IRR	95% CI	IRR	95% CI
Day of Week (Sunday Reference)				
Monday	1.417	0.967–2.076	1.324	0.894–1.959
	(0.276)		(0.265)	
Tuesday	1.993**	1.287–3.085	2.194**	1.400–3.439
	(0.444)		(0.503)	
Wednesday	2.244**	1.576–3.194	2.551**	1.771–3.673
	(0.404)		(0.475)	
Thursday	1.771**	1.191–2.633	2.790**	1.826–4.263
	(0.359)		(0.604)	
Friday	3.128**	2.163–4.522		
	(0.588)			
Saturday	1.413	0.907–2.200	1.292	0.816–2.046
	(0.319)		(0.303)	
Control Variables				
Event damage ($1,000,000)	1.002**	1.001–1.002	1.002**	1.001–1.002
	(0.000)		(0.000)	
Recency bias	0.530*	0.280–0.999	0.574	0.297–1.107
	(0.173)		(0.193)	
Income per capita ($1,000)	0.963**	0.949–0.977	0.969**	0.953–0.986
	(0.007)		(0.008)	
Population (100,000)	1.063	1.028–1.100	1.077	1.041–1.115
	(0.018)		(0.019)	
Nonprofit assets ($100,000)	0.999	0.999–1.000	0.999	0.999–1.000
	(0.000)		(0.000)	
Wald χ^2	165.11		143.05	
Log likelihood	−1310.09		−1010.51	
N	2,449		2,175	

Note: Standard errors in parentheses. $^{**}p < 0.01$, $^{*}p < 0.05$.

In analyses of tornado events we highlighted the human toll of limited information windows and sheltering-in-place opportunities, showing how casualty rates are significantly higher during information-constrained weekends, and where U.S. populations are significantly less likely to be in school and business settings where the fatality risk is near zero.[31,32] More specifically, adjusting for the size of at-risk population, the amount of destruction caused by a tornado event, the income per capita of the afflicted locality, and the size of the local nonprofit sector, we found that the expected count of casualties involving tornados striking on Monday through Thursday is 20–33% lower than tornados striking on Sunday. Taken against the event damage coefficient reported Table III, showing a 2% increase in the odds of death or injury for an additional $1 million dollars of damage, in effect, populations visited by a tornado during weekdays can absorb an order of magnitude more damage before the casualty risk equalizes the risk observed for weekend tornado events. In modal leisure months of June, July, and August, daily variation in the expected count of human casualties logically dissipates as daily variation in risk information loss likely increases, and populations are less likely to be in tornado-resistant buildings like businesses and schools.

A practical implication that we drew from our tornado event results is that risk communication efforts are likely to be especially valuable, in terms of human health costs averted, on weekends and summer months where the acquisition of information may occur in a more uncoordinated and decentralized fashion. Field-tested automated emergency notification systems are known to be effective in communicating risk information and preparedness instructions like sheltering-in-place strategies.[29] The spread of cellular phone use in the United States makes automated emergency notification systems technically possible. According to the semiannual

U.S. Wireless Industry Survey, as of 2011, the estimated number of mobile phone subscriber connections in the United States is about 323 million.[27] As cell phone usage in the United States increases in time, to buttress existing media of risk communication, policymakers and telecommunication companies can feed location-specific weather or tornado alert systems to cell phone users. A default "opt-out" setting could be enacted, preserving individual choice, but requiring individuals to explicitly request to be excluded from the alert system. If such a proposal is politically untenable, to provide individual incentive to join an opt-in system, insurance companies could be encouraged to grade and risk rate individual and/or household insurance policies on the basis of involvement in the cellular risk communication system.

In our analysis of hurricane events, we highlighted the fact that at-risk populations enjoy the lead time of forecasts, advancing the theoretical suppositions that at-risk populations make evacuation decisions based on particular combinations of health risk and income (and implied time) considerations. In our stylized model of household protective action under hurricane threat, building on the formative work of Whitehead,[11] we supposed an opportunity cost premium on weekday hurricane strikes. We therefore hypothesized that hurricane events unfolding on weekdays would be significantly more lethal than weekend events because of less preparation time and greater expected income losses from evacuation, what Zhai and Ikeda call *inconveniences and potential losses*.[33] Statistical results on event morbidity and mortality outcomes are consistent with these intuitions. Other things equal, we find that hurricanes occurring on Tuesday through Friday are between 1.6 and 2.9 times more lethal than Sunday-occurring events. Sensitivity analyses showed that results on daily variation in hurricane casualties cannot be explained away by outlier distortion. In light of these statistical results, the Hurricane Andrew versus Hurricane Hugo puzzle we describe in the first paragraph of this article can be partially explained: Hurricane Andrew hit Florida on the weekend, and Hurricane Hugo struck South Carolina on a Friday.

Moreover, because of the opportunity cost premium attached to weekday hurricane events, our theory and results also imply that at-risk populations will likely wait till the last moment before evacuating to rationally limit inconveniences and Type II error losses. Such waiting behavior implied by our model can create evacuation bottleneck problems that may exacerbate health risks. Emergency management agencies must therefore be especially vigilant for hurricanes that strike on weekdays. As a practical implication of results on daily variation in hurricane casualties, and insofar as the household opportunity cost calculus described earlier is plausible, it is useful to consider policy options that directly alter the noted incentive structure at work in the decision to adopt protective measures. If lives, property, and other resources are put at risk by a rational response to clear information about an approaching natural disaster, it may be worth overcoming the benefit of non- or stalled evacuation with incentive to evacuate, provided that such a policy can in fact on net save lives that may otherwise require postimpact compensation. Exposed insurance companies and/or state/federal government may have the most to lose in such situations, and may be willing to offset likely losses springing from deaths, injuries, and lost productivity[28] with some form of benefit to those evacuating—or at least reduce the costs, both direct (i.e., lodging) and opportunity (i.e., lost wages), for those evacuating a target area. Given the theorized importance of household benefit-cost calculus in the critical evacuation decision, further work on the economics and psychology of risk perception in the face of such natural disasters would be invaluable in evaluating optimal pre- or postimpact compensation policies.

The plausibility of daily variation in human mortality and morbidity outcomes from disaster events is supported by existing literature on daily variation in vital events. For instance, researchers find that the count of birth events falls dramatically on Saturdays and Sundays,[9] and that the risk of neonatal mortality increases significantly on weekends.[41] Research also shows that the risk of death (for all causes of mortality) declines measurably on Saturdays among Jewish populations in Israel.[42] In the United States,

[9] At first glance this result may seem peculiar, as there is no obvious physiological reason to expect fewer births on weekends. Perhaps the statistical pattern is an aberration specific to the Arkansas live birth cohort, 1974–1975. We obtained data on U.S. births from the National Vital Statistics System for the year 2000. Data show that average number of live births during weekdays is 458,553 and 332,259 for weekends, constituting a 27.5% shortfall on Saturdays and Sundays, fully consistent with the Arkansas live birth cohort, 1974–1975. However, adjusting for the risk of birth induction, the striking weekday versus weekend pattern in live births substantially dissipates, suggesting that obstetricians and gynecologists may plan deliveries to minimize disruptions to weekend leisure.

both traffic accidents and fatalities have a persistent daily structure, with the risk of death about 30% higher on weekends.(43) Of course, there is nothing intrinsically meaningful about, say, a Tuesday or a Saturday; instead, these statistical regularities emerge from the deep structure of the social and economic organization of human work and leisure. Anson and Anson(42,p.152) state it more elegantly: "human mortality is, in some sense, patterned by the institutionalization of daily life, and that the timing of death is not just a physiological phenomenon, but is also a social event, patterned, at least in part, by the social organization of collective events."

Although our study may usefully extend existing risk analytic literature(11,33,36,38–40) by emphasizing the weekly rhythm of labor and leisure routines, it is not without limitations. Our analysis is of casualties summarized over time/place events. As an ecological study, we do not directly observe the behavior of individuals or households. Important household demographic and economic variables may be camouflaged by aggregation. Prospective studies of evacuation and sheltering behaviors of at-risk populations have the benefit of household data detail, but are usually limited to single events.(42) In our study, what is lost analytically in data granularity is perhaps partially mitigated by the analytic value of studying thousands of place/time events. Future research may benefit from a meta-analytic strategy, assembling many prospective studies of household protective action. In our study we show that such meta-analytic efforts can benefit from paying attention to the subtle, but powerful, structure and rhythm of daily life.

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APPENDIX: RANDOM-EFFECTS NEGATIVE BINOMIAL REGRESSION MODELS PREDICTING THE COUNT OF HURRICANE EVENT CASUALTIES WITH LARGE COUNT SIMULATED SUNDAY EVENTS

	500 Hurricane Casualty Sunday		1,000 Hurricane Casualty Sunday	
	IRR	95% CI	IRR	95% CI
Day of Week (Sunday Reference)				
Monday	1.217	0.859–1.725	1.222	0.865–1.727
	(0.217)		(0.216)	
Tuesday	1.861**	1.226–2.827	1.861**	1.227–2.822
	(0.397)		(0.395)	
Wednesday	1.736**	1.254–2.404	1.709**	1.236–2.362
	(0.288)		(0.282)	
Thursday	1.615**	1.125–2.319	1.657**	1.156–2.376
	(0.298)		(0.305)	
Friday	2.740**	1.953–3.843	2.687**	1.917–3.765
	(0.473)		(0.462)	
Saturday	1.180	0.788–1.769	1.180	0.789–1.766
	(0.244)		(0.243)	
Control Variables				
Event damage ($1,000,000)	1.002**	1.001–1.002	1.002**	1.001–1.002
	(0.000)		(0.000)	
Recency bias	0.406**	0.214–0.772	0.428**	0.225–0.811
	(0.133)		(0.140)	
Population (100,000)	1.026**	0.994–1.060	1.025**	0.993–1.058
	(0.017)		(0.017)	
Income per capita ($1,000)	0.966**	0.954–0.978	0.966**	0.954–0.978
	(0.006)		(0.006)	
Nonprofit assets ($100,000)	0.999	0.999–1.000	0.999	0.999–1.000
	(0.000)		(0.000)	
Wald χ^2	145.92		139.37	
Log likelihood	–1,573.83		–1,597.43	
N	2,456		2,456	

Note: Standard errors in parentheses. $^{**}p < 0.01$, $^{*}p < 0.05$.

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