Discounting under Severe Weather Threat

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ABSTRACT: The human and economic costs of severe weather damage can be mitigated by appropriate preparation. Despite the benefits, researchers have only begun to examine if known decision-making frameworks apply to severe weather–related decisions. Using experiments, we found that a hyperbolic discounting function accurately described participant decisions to prepare for, and respond to, severe weather, although only delays of 1 month or longer significantly changed decisions to evacuate, suggesting that severe weather that is not imminent does not affect evacuation decisions. In contrast, the probability that a storm would impact the participant influenced evacuation and resource allocation decisions. To influence people's evacuation decisions, weather forecasters and community planners should focus on disseminating probabilistic information when focusing on short-term weather threats (e.g., hurricanes); delay information appears to affect people's evacuation decision only for longer-term threats, which may hold promise for climate change warnings.

KEYWORDS: Atmosphere; Ocean; Social Science; Flood events; Hurricanes/typhoons; Storm surges; Uncertainty; Risk assessment

1. Introduction

People in the United States experienced record numbers of droughts, floods, freezes, wildfires, severe storms, and tropical cyclones during 2017 (National Oceanic and Atmospheric Administration 2019). Among events that cost greater than $1 billion, these weather-related disasters accrued an estimated $91 billion in 2018 and $1.6 trillion in economic cost since 1980 (National Oceanic and Atmospheric Administration 2019), which do not include the 247 people that were killed during these events in 2018. Researchers, meteorologists, and governmental officials actively work toward solutions to reduce the cost of weather-related disasters. One potentially fruitful avenue is to help improve disaster-related choice. However, before we can improve the choices people make to mitigate the human and economic costs of severe weather, we must first understand how people make short- and long-term decisions relevant to threats from severe weather and climate change, respectively. In the present work, we examine severe weather decisions from a robust-choice framework adapted from psychology and behavioral economics—*discounting*—in which people make binary choices about relevant behaviors (e.g., evacuation, levee investment) across a broad array of temporal horizons (delay discounting) and likelihoods of occurrence (probability discounting). This is the first such investigation to examine delay and probability discounting of severe weather based on wind speeds using hypothetical hurricanes.

Past judgment and decision-making researchers have broadly approached environment-related judgments and decisions (e.g., Böhm and Pfister 2005; Gattig and Hendrickx 2007; Hendrickx and Nicolaij 2004; Svenson and Karlsson 1989) focusing less on specific environmental situations such as threat of severe weather (Gladwin et al. 2009). Much of this research has focused on how communication about impending threats can improve weather-related decisions (e.g., Joslyn and LeClerc 2012; Joslyn and Nichols 2009; Roulston et al. 2006). Typically, these studies observe how participants choose between response options based on a limited range of probabilities that a weather event will occur (e.g., whether to salt a road based on the probability freezing temperatures will occur; Joslyn and Grounds 2015; Grounds and Josyln 2018; Joslyn and LeClerc 2012). Although these studies document the choices people make when faced with decisions about severe weather, researchers have yet to explore how existing models of choice empirically account for such decisions.

The present work uses controlled experiments where participants are randomly assigned to conditions because doing so maximizes *internal validity*—the extent to which one can assume a causal relationship between the variables of interest, uncontaminated by other variables (e.g., other potential causal explanations). One drawback of controlled experiments, however, is that they often lack *external validity*—the extent to which one can generalize the findings to other situations (e.g., real hurricanes or other weather-related disasters) or other populations beyond the sample (e.g., nonstudent samples outside the southeastern United States).

There is an inherent trade-off between internal and external validity. Controlled experiments often have high internal—but only modest external—validity. In contrast, field data collection settings (e.g., interviewing people fleeing from a hurricane, harvesting online secondary or archival data about actual weather conditions and evaluation rates) often have modest internal—but rather high external—validity. In short, experimental methods can tell us about causal processes, whereas field methods can tell us how people actually behave, but any causal links may be difficult

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to establish. Because discounting methods are typically used in controlled experimental (vs field) settings, both of our experiments use contrived but highly controlled conditions to maximize causal inference, but in so doing, limit the generalizability of the findings to our hypothetical hurricanes and our southeastern U.S. student-based sample.

Below, we describe the discounting framework, how discounting is measured, and why a discounting framework is advantageous for understanding severe weather decisions. We then describe two studies that examine different decisions under severe weather threat and how well discounting accounts for the data.

a. *Discounting*

Discounting refers to a reduction in the value of a commodity, outcome, or event as a function of changes to some quality or characteristic of that outcome or event. For example, one might be willing to pay \$2 for a liter of one's favorite soda. But, if the soda is open and no longer carbonated, one would be less likely to pay \$2, if any money at all, for the soda. Here, the value of the soda differs depending on its quality. That is, the value of uncarbonated soda is discounted relative to the value of carbonated soda. Quality affects value.

Many commodity characteristics can reduce its value (i.e., lead to discounting). For example, the value of a commodity can be influenced by the effort needed to obtain it (effort discounting; e.g., Białaszek et al. 2017b; Nishiyama 2014), if a family member or a complete stranger will get the commodity (social discounting; e.g., Locey et al. 2013; Osińskia et al. 2015), how much time passes before obtaining the commodity (delay discounting; e.g., Critchfield and Kollins 2001; Odum 2011), and the probability you actually receive the commodity (probability discounting; e.g., McKerchar and Renda 2012; Shead and Hodgins 2009).

There are two models commonly used for discounting: exponential and hyperbolic (see the appendix for more details). The exponential discounting model, which draws from economic theory (Samuelson 1937), proposes that the value of a commodity reduces by an equivalent proportion with each time step. Thus, discounting can occur exponentially:

$$V = Ae^{-\gamma\beta}. \tag{1}$$

Here, V is the current value of a commodity, A is the objective amount of the commodity, β is the independent variable under study (e.g., delay for delay discounting; odds against for probability discounting), and γ is a free parameter reflecting rate of discounting. In contrast, the hyperbolic model reflects an alternative way to describe discounting (Mazur 1987):

$$V = \frac{A}{(1 + \gamma\beta)}. \tag{2}$$

In Eq. (2), V, A, γ, and β are the same as in Eq. (1). We examine both exponential and hyperbolic discounting models in the present work because most research in the discounting literature presents results from both models.

b. *Discounting severe weather*

Severe weather varies along many dimensions. As relevant to delay and probability discounting, severe weather varies in how long it will be until a storm impacts a geographical area and how likely it is a storm will impact an area. Importantly, both the delay and the probability that a storm will impact an area can change dynamically as storms move geographically. Applying discounting to weather-related decisions means asking whether discounting accounts for different weather-related decisions people make and how those decisions change with the dynamically changing delays and probabilities for storms.

The purpose of the present experiments was to determine if people make decisions about severe weather in a manner consistent with a discounting framework. Experiment 1 examined how the probability or delay to a hurricane influences a decision to evacuate. Experiment 2 further examined how longer delays to a hurricane influence a decision to evacuate and how the probability of severe weather influences the amount of money people are willing to spend to prepare the local community. Thus, experiments 1 and 2 respectively focus on short- and longer-term delays relevant to acute weather threats (a landfalling hurricane) or more chronic climate change challenges (increased hurricane frequencies; levee maintenance costs). Participants also completed several other common measures of discounting to determine how discounting severe weather relates to more common monetary discounting tasks. Last, the hyperbolic and exponential models of discounting were fit to the data obtained in both experiments.

2. Experiment 1

Weather-related decisions generally involve choosing between protecting oneself at a cost or risking greater harm from exposure to severe weather (Grounds and Joslyn 2018). But exactly what protecting oneself and risking greater harm look like may vary. For example, people may mitigate physical harm by using resources to evacuate from the geographical location where the storm may occur (i.e., choosing to stay or flee).

Experiment 1 had two purposes: testing whether people discount hurricane severity based on (i) the delay until the storm makes landfall and (ii) the probability that the storm makes landfall. We expected that the wind speed at which people would evacuate would systematically decrease as a function of decreasing delay and increasing probability.

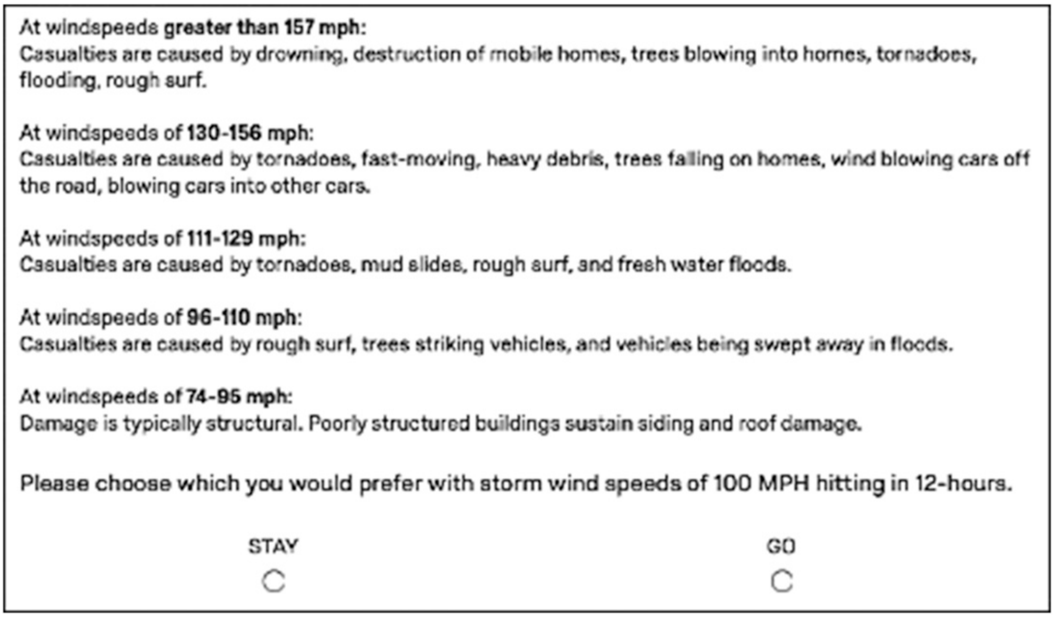
a. *Method*

1) Participants

We recruited 304 participants from the general psychology participant pool over a two-semester period at the University of Florida, a large public university in the southeastern United States. The average participant age was 19.3 years (range 18–24). The percentage of participants that self-identified as female was 58.7%. The percentage of participants that self-identified as Caucasian, African American, Hispanic/Latino, and Other were 60.5%, 12.0%, 11.4%, and 16.2%, respectively.

2) Weather discounting tasks

We used an adjusting-amount procedure similar to traditional discounting research (e.g., Du et al. 2002). All


At windspeeds **greater than 157 mph:**
Casualties are caused by drowning, destruction of mobile homes, trees blowing into homes, tornadoes, flooding, rough surf.

At windspeeds of **130-156 mph:**
Casualties are caused by tornadoes, fast-moving, heavy debris, trees falling on homes, wind blowing cars off the road, blowing cars into other cars.

At windspeeds of **111-129 mph:**
Casualties are caused by tornadoes, mud slides, rough surf, and fresh water floods.

At windspeeds of **96-110 mph:**
Casualties are caused by rough surf, trees striking vehicles, and vehicles being swept away in floods.

At windspeeds of **74-95 mph:**
Damage is typically structural. Poorly structured buildings sustain siding and roof damage.

Please choose which you would prefer with storm wind speeds of 100 MPH hitting in 12-hours.

STAY GO

FIG. 1. Example question for participants randomly assigned to complete the delayed severe discounting task in experiment 1.

participants were randomly assigned to complete either delayed ($n = 171$) or probabilistic ($n = 133$) weather discounting tasks.

The adjusting-amount delay discounting tasks began by presenting a brief description of the damage likely to occur at category-1, category-2 category-3 category-4, and category-5 hurricane wind speeds (Fig. 1). Below the description was a sentence asking participants whether they would stay or go if wind speeds of $100\,\mathrm{mi\,h^{-1}}$ (hereinafter mph; 1 mph $\approx 0.45\,\mathrm{m\,s^{-1}}$) would hit in some specified delay (e.g., in 12 h). If the participant chose to stay, then the wind speed increased by 50 mph and the participant was again asked if they would stay or go if 150-mph winds would hit in the specified delay. If the participant chose to go, then the wind speed decreased by 50 mph and the participant was asked if they would stay or go if 50-mph winds would hit in the specified delay. The magnitude of the wind speed continued to increase or decrease after each choice to stay or go. Wind speeds adjusted following the second, third, fourth, and fifth choice by 25, 12.5, 6.25, and 3.125 mph, respectively, and rounded to the nearest mile per hour for ease of presentation. The wind speed following the final choice was considered to be the participant's indifference point for a storm landing at the specified delay. Each participant repeated this process for seven delays (12 h, 1 day, 1.5 days, 2 days, 3 days, 4 days, and 5 days) with the order of delays randomly determined (35 total choices with delayed weather).

The adjusting-amount probability discounting task was identical to the delay task above. The only difference was that each trial asked each participant if they would stay or go if there was a specified probability that a storm with the adjusting wind speeds would hit their location (e.g., "100% chance a storm with 100-mph winds will hit your location"). All adjustments to the wind speed occurred identically to the delay group, and the adjusted wind speed following the fifth trial was considered to be the indifference point for that participant at the specified probability. Each participant repeated this process for six probabilities (100%, 70%, 40%, 10%, 5%, and 1%) with the order of probabilities randomly determined (30 total choices with probabilistic weather).

3) MONETARY DISCOUNTING TASKS

We used 5-trial adjusting-delay (Koffarnus and Bickel 2014) and 5-trial adjusting-probability tasks (Cox and Dallery 2016) to measure discounting of monetary outcomes. These tasks were used because they provide similar measures of discounting as the longer, adjusting-amount tasks for delay and probability discounting, and for gains and losses (Cox and Dallery 2016; Koffarnus and Bickel 2014). In 5-trial adjusting-delay tasks, the participant initially chooses between "getting \$500 immediately" and "getting \$1,000 in 3 weeks."[1] Depending on the participant's choice, the delay to the larger amount either increases or decreases for five trials with a minimum of 1 h or a maximum of 25 years. The adjustment following choice

[1] If these amounts seem arbitrary, it is because they are. In discounting, the amounts themselves do not matter so much as their relation to one another in terms of their relative expected value. Thus, we could have instead used hypothetical taxes of \$50 and \$100 or \$5 and \$10 or even \$5,000 and \$10,000 so long as the intervals in the 5-trial adjusting delay were the same relative to the maximum amount. Psychological studies reliably show that people often attend more closely to relative amounts of money than absolute amounts (e.g., Garland and Newport 1991).

TABLE 1. Study 1: descriptive statistics for delay discounting task.

	12 h	1 day	1.5 days	2 days	3 days	4 days	5 days
Max	197	197	197	197	197	197	197
90%	159	153	153	153	141	141	153
75%	128	121.5	124.75	121.5	115	115	121.5
50%	109	103	103	97	97	97	97
Mean	111.44	107.33	105.76	106.44	102.35	103.38	104.53
Std dev	37.49	32.46	33.34	32.20	33.57	34.35	37.25
25%	91	91	91	91	91	91	91
10%	72	72	72	72	72	72	59
Min	28	0	3	28	3	3	3

on the fifth trial was the delay at which the value of $1,000 reduces by one-half to $500 (i.e., effective decay 50% or ED_{50}). Five-trial adjusting-probability tasks were conducted in an identical manner as delay but using choice options of 100% chance of $500 and $p < 100\%$ for $1,000. The final adjusted probability provided a measure of EP_{50}. ED_{50} and EP_{50} provide estimates of discounting similar to fitting Eq. (2) to a full set of indifference points (Cox and Dallery 2016; Koffarnus and Bickel 2014). The 5-trial adjusting-delay or adjusting-probability tasks for monetary losses were identical to the monetary gain tasks, with the exception that the adjustment to the delay or probability was in the opposite direction of the adjustments in the gain tasks.

Participants completed two 5-trial adjusting-delay or adjusting-probability tasks. If participants made choices involving delayed weather, then they completed one 5-trial adjusting-delay task for gaining money and one for losing money. If participants made choices involving probabilistic weather, then they completed one 5-trial adjusting-probability task for gaining money and one for losing money.

4) PROCEDURE

Participants came to a laboratory on the university campus. Following completion of an informed consent document, participants were randomly assigned to complete delayed outcome tasks or probabilistic outcome tasks programmed in Qualtrics. The adjusting-amount weather tasks were completed before the monetary discounting tasks with the order of delays or probabilities randomly determined. Following the weather discounting tasks, participants completed the gain and loss discounting tasks; the order was randomly determined for each participant.

5) DATA ANALYSIS

Typically, the objective amount of a commodity at a zero delay or 100% chance of occurring is known (e.g., $100, or $10 worth of cocaine) and is used for A when fitting Eq. (1) or (2). Sometimes the commodity under investigation, however, has an unknown value at a zero delay or 100% chance of occurring; examples include health outcomes (Friedel et al. 2016) and sexual experiences (Johnson and Bruner 2012). In these situations, indifference points are typically transformed and normalized using the indifference point obtained at the shortest delay or highest probability (i.e., A is set to 1.0).

The decision of how to transform the data is difficult for severe weather. Reference points refer to values, states, expectations, or standards used as a comparison for decision-making (e.g., Koop and Johnson 2010). For example, receiving $100 for work completed would be an improvement for the person who typically receives $10 for the same work but would be worse for the person who typically receives $1,000. Each person has a history with an amount of money earned for work (i.e., a reference point) that influences whether earning $100 for work completed is a gain or a loss (e.g., Kahneman and Tversky 1979).

Reference points can influence human choice (e.g., Koop and Johnson 2010), and for our purposes, they could be low or high wind speeds. If people make decisions to evacuate in reference to the worst possible storm they could experience (200 mph in experiment 1; Fig. 1), then the normalized indifference points should be transformed as the difference from 200 mph. However, if people make decisions to evacuate based on the nominal magnitude of the wind (i.e., technically relative to 0 mph), then the indifference points should only be normalized relative to the wind speed they chose to evacuate when there was the shortest delay (12 h) or the highest probability (100%). We fit the discounting equations to both types of transformations.

Discounting parameters γ for the weather discounting tasks were estimated using the Solver Add-In for Microsoft Excel. Discounting parameters for the monetary discounting tasks were estimated by dividing 1 by ED_{50} or 1 by EP_{50} (Yoon and Higgins 2008). All parameters were logarithmically transformed before

TABLE 2. Study 1: descriptive statistics for probability discounting task.

	0.00 odds against	0.43 odds against	1.50 odds against	9.00 odds against	19.00 odds against	99.00 odds against
Max	197	197	197	197	197	197
90%	141	152.4	191	197	197	197
75%	115	122.75	144	191	197	197
50%	97	97	115	147	153	191
Mean	104.12	107.45	122.49	143.80	152.05	165.65
Std dev	31.65	34.46	38.18	46.34	41.37	41.34
25%	91	91	97	109	115	134
10%	72	72	79	91	103	97
Min	21	15	41	15	21	34

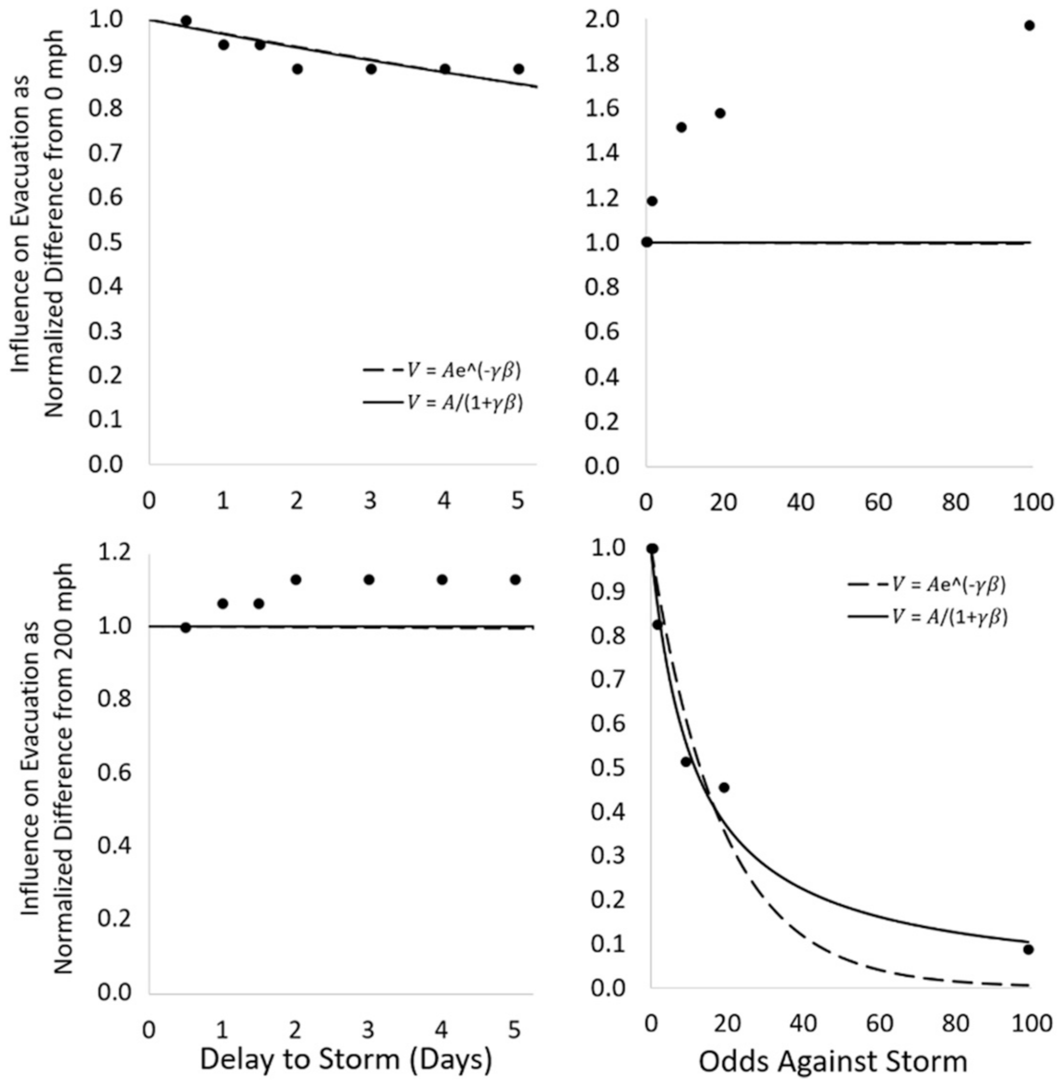


FIG. 2. Group median indifference points (black circles) for each severe weather discounting task in experiment 1. (left) Evacuation wind speeds for participants randomly allocated to the delayed severe weather task. (right) Evacuation wind speeds for participants randomly allocated to the probabilistic severe weather task. Dashed lines are the fits for Eq. (1), and solid lines are the fits for Eq. (2).

statistical analyses to normalize their distributions. Descriptive statistics for the delay and probability discounting tasks appear in Tables 1 and 2, respectively.

b. Results and discussion

Figure 2 shows the normalized evacuation points for participants that completed the weather delay discounting task (left panels) or the weather probability discounting task (right panels). The top and bottom panels are the data plotted assuming decisions were made using 0- or 200-mph wind speeds as a reference point, respectively.

Participants in the delayed severe weather group showed little-to-no change in evacuation point based on the delay to the severe storm. For this group, values of 1.0 equate to choosing to evacuate at 109 mph. Although there was a slight decrease in evacuation point when decision to evacuate was plotted as a function of a 0-mph reference point, and a slight increase in evacuation point when the decision to evacuate was plotted as a function of 200 mph, neither trend was significant. These data suggest that people did not discount severe weather as a function of delay to the storm. In other words, people's evacuation choices were unaffected by an approaching hurricane's time horizon within a 5-day landfall window.

The right panels in Fig. 2 show the results for participants that completed the weather probability discounting task. For this group, values of 1.0 equate to choosing to evacuate at 97 mph. Although there was no systematic effect using 0 mph as a reference point (upper-right panel), using a 200-mph reference point (lower-right panel) showed discounting.

Here, the wind speed at which people chose to evacuate changed systematically as a function of the probability of the severe storm. If the probability the storm would occur were high (e.g., 100% chance, 75% chance; odds against of 0.00, 0.43), participants would evacuate at wind speeds near 100 mph. If, however, the probability a storm would occur were low (e.g., 1% chance; odds against of 99), participants would only evacuate if the windspeeds were near 200 mph. These data suggest that participants discounted severe weather based on the probability they would experience the storm.

All four plots in Fig. 2 show the fit of Eq. (1) (dashed lines) and Eq. (2) (solid line) to the group median indifference points. Consistent with descriptions above, neither equation described the data well for delayed severe weather with 0 mph as a reference point [correlation coefficient squared $R^2 = 0.55$ and 0.59 for Eqs. (1) and (2), respectively] or with 200 mph as a reference point (values increased with delay so discounting equations were not meaningful). In contrast, both equations described the data better for participants in the probability weather group with 200 mph as a reference point [$R^2 = 0.66$ and 0.80 for Eqs. (1) and (2), respectively, with the latter fitting the data better than the former: $z = 2.84$, $p = 0.005$], but not with 0 mph as a reference point. Similar to discounting with other commodities, the hyperbolic equation described participant choice with severe weather better than the exponential equation (e.g., McKerchar et al. 2009).

Most research on discounting has studied choice with hypothetical monetary outcomes (for a review, see Odum 2011). Thus, participants in experiment 1 also completed discounting tasks using hypothetical monetary outcomes to compare with discounting weather. There was a weak correlation between the estimated γ parameters from Eq. (2) for (i) delay discounting of severe weather and (ii) for money gained ($r = 0.20$, $p = 0.02$) and money lost ($r = 0.28$, $p < 0.001$). In contrast, there was no significant correlation between the estimated γ parameters from Eq. (2) for (i) probability discounting of severe weather and (ii) money gained ($r = -0.15$, $p = 0.07$) or money lost ($r = -0.16$, $p = 0.07$). Consistent with prior research (e.g., Johnson et al. 2016), we found no statistically significant correlation between estimated γ parameters for delay discounting of monetary gains and losses ($r = -0.06$, $p = 0.27$) or for probability discounting of monetary gains and losses ($r = 0.01$, $p = 0.80$).

The data in experiment 1 fit warily with previous research on delay discounting. Participants did not discount severe weather based on delays of up to 5 days. Instead, there was an approximate wind speed at which participants chose to evacuate regardless of the delay. The absence of delay discounting in severe weather may have been the result of the restricted range of delays examined. We chose delays ranging from 12 h to 5 days because they are similar to timeframes typical of hurricane warnings and the limits of forecasting accuracy. Most research on delay discounting with people, however, uses delays of weeks, months, and years (Odum 2011). It is possible that people *do* discount severe weather as a function of delay to the storm, but that our methods failed to capture the effect. This possibility is supported by the weak correlation between delay discounting severe weather and money, which is similar to the relationship between discounting money and other nonconsumable commodities (e.g., Sze et al. 2017; Weatherly et al. 2010). Another, perhaps simpler possibility is that most people simply do not show systematic temporal discounting for an approaching hurricane; instead, they focus on its intensity, its probability of striking them, or a combination of both, regardless of its arrival time within 5 days of landfall.

The data from experiment 1 fit well with previous research on probability discounting. The speed at which people chose to evacuate systematically changed as a function of the odds against the storm when 200 mph was used as a reference point. In addition, rate of discounting was described better by a hyperbolic function than the exponential function. Further, discount rate of probabilistic severe weather did not correlate significantly with the rate of probability discounting monetary outcomes. Thus, the rate that one outcome is discounted probabilistically (e.g., money) may not be predictive of how they discount other probabilistic outcomes (e.g., food, leisure, severe weather).

In summary, experiment 1 suggests that the decision to evacuate in a severe weather event is influenced systematically by the probability that the severe weather event will occur but not by delays of up to 5 days. These data suggest that the probability that a person will experience a hurricane will influence evacuation preparation decisions more than the delay of a hurricane.

3. Experiment 2

Previous research on delay discounting with people typically asks about delays of years to decades (see Odum 2011 for review). A large range of delays is typical because the value of different commodities rarely changes significantly over delays of days to weeks (e.g., Odum 2011). The absence of delay discounting severe weather in experiment 1 may have been the result of the narrow duration of delays examined. In other words, experiment 1 used discounting delays of a few days, whereas most discounting tasks use delays of months, years, or decades. Indeed, restriction of range in independent variables such as the discounting delay can severely undercut one's statistical power to detect significant effects in data (McClelland 1997).

Expanding the delay discounting range to the scale of months and years may be important because the hyperbolic function of delay discounting can predict preference reversals. For severe weather, a preference reversal might occur when a person chooses to stay home when a hurricane is 5–7 days out but changes their mind and tries to evacuate when the hurricane is 1 day out. Knowing if—and when—preference reversals may occur for decisions to evacuate an area could be essential information for community planners. And although evacuation *decisions* for any *specific* hurricane are indeed made within only hours or days of landfall, people's thresholds for evacuation *intentions* for hurricanes *in general* can be assessed for longer time intervals and are similarly based on perceptions of

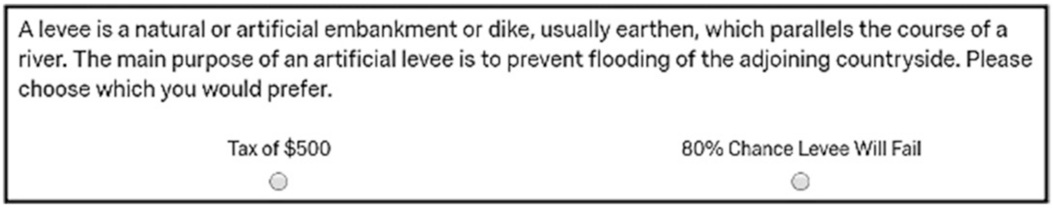


FIG. 3. Example question for participants randomly assigned to complete the probability weather preparation discounting task in experiment 2.

storm intensity or wind speed. For example, residents of hurricane-prone areas such as Florida, coastal Louisiana, and coastal North Carolina might expect to directly experience the effects of a tropical storm every year, a hurricane every five years, and a major hurricane every 10 years. With the ongoing challenges presented by climate change, understanding how people's decisions unfold over longer time horizons is essential. Specifically, rising sea levels and warmer ocean surface temperatures will contribute to higher storm surges and stronger hurricanes in the coming years and decades. Thus, asking people about their evacuation intensions for hypothetical hurricanes of various intensities (wind speeds) is meaningful at longer discounting delays, especially given that people often think in terms of once-in-a-decade hurricanes or "storms of the century."

In addition, prior delay discounting research has typically asked participants to choose between a small amount of a tangible commodity now versus a large amount of a tangible commodity at some delay [e.g., beer, cigarette, cocaine, heroin, or money; see Odum (2011) for a review]. Decisions about accessing tangible outcomes typically involve a single outcome. For example, one obtains $20 (or not), pulls a cigarette from the pack and smokes (or not), or eats a salad (or not). Each of these decisions has a single known outcome. But decisions about severe weather are less straightforward because they involve uncertainty (Tversky and Kahneman 1974). People may board up the windows on their homes to prevent potential damage from flying debris, but this is unlikely to reduce damage from storm surges that accompany coastal areas impacted by hurricanes. Similarly, people may invest in an electric generator to power their homes during a power outage that results from severe weather. But the generator helps little if severe weather causes a tree to crash through one's roof. This suggests that there are multiple ways people can allocate resources to prepare for a severe weather event.

The purpose of experiment 2 was twofold. Experiment 1 suggested that the decision to evacuate a severe weather event is influenced systematically by the probability that the severe weather event will occur, but not delays of up to 5 days. Given the ubiquity of delay discounting when longer delays are used, experiment 2 examined delays to severe weather with delays more common to traditional delay discounting research (months, years). Whereas experiment 1's discounting delay range focused on evacuation decisions in the immediate future (≤5 days), experiment 2's discounting delay range focuses on evacuation intentions over the course of a decade—a time frame in which the sample we studied, which lives within 60 miles of the coast, will likely experience at least one hurricane. In addition, different decisions can be made in allocating resources to prepare for severe weather. Experiment 2 examined probability discounting for a different severe weather-related decision—investing resources to protect the local community. This longer time frame and economic approach more closely reflect some of the climate change challenges faced by coastal residence. In other words, experiment 2 concerns people's willingness to act or make economic sacrifices in the present for threatening events that may—or may not—happen in the distant future. Thus, whereas experiment 1 focused solely on short-term weather threats, experiment 2 focuses on long-term climate change threats.

a. Method

1) PARTICIPANTS

We recruited 169 participants from the general psychology participant pool at the University of Florida. The average participant age was 19.8 year (range 18–54). The percentage of participants that self-identified as female was 82%. The percentages of people that self-identified as Caucasian, African American, Hispanic/Latino, and Other were 49.7%, 7.7%, 21.1%, and 4.7% respectively.

2) WEATHER DISCOUNTING TASKS

All participants were randomly assigned to complete either delayed (n = 85) or probabilistic (n = 84) weather discounting tasks. Participants in the delay group completed an identical set of discounting tasks as experiment 1. The difference was that we used delays to severe weather of 1 day, 1 week, 1 month, 1 year, 5 years, and 10 years. Participants also completed the same two delay discounting tasks of gaining and losing monetary outcomes as in experiment 1.

The adjusting-amount severe weather probability discounting task asked about participants' willingness to pay a tax to repair a levee. We chose to use a flat tax for ease of experimental manipulation and to maintain methodological similarity to previous discounting research. Similar to experiment 1, each choice trial presented a description of a levee and its function (Fig. 3). The initial question asked participants to choose between a "tax of $500" and a "$P$% chance levee will fail" (e.g., "80% chance"). If the participant chose to pay the tax, then the amount of the tax increased by $250. If the participant chose to risk levee failure, then the amount of the tax decreased by $250. Participants then chose between the adjusted tax amount and the probabilistic levee failure on the second trial. The tax amount adjusted by $125, $62.50, $31.25, and $15.62 following the second through fifth trials, respectively, and was rounded to the nearest dollar amount. The adjustment after the fifth trial was considered to be the point at which the participant was indifferent between spending the preparatory tax and the specific probability that the levee would fail. Participants repeated the adjusting–tax amount procedure 7 times, once at each probability of 100%, 80%, 50%, 25%, 10%, 5%, and 1%. Last, participants allocated to the probability group also completed the same two probability discounting tasks of gaining and losing monetary outcomes as in experiment 1.

3) Procedure

Participants came to a laboratory on campus. Following completion of an informed consent document, participants were randomly assigned to complete either delayed or probabilistic outcome tasks programmed in Qualtrics. The adjusting-amount weather tasks were completed before the monetary discounting tasks with the order of delays or probabilities randomly determined. Following the weather discounting tasks, participants completed the gain and loss discounting tasks with the order randomly determined.

4) Data analysis

Similar to experiment 1, we transformed weather indifference points relative to the evacuation wind speed (delay group) at the shortest delay. In addition, we analyzed the data for the delayed weather group relative to the same two reference points from experiment 1 (0 and 200 mph). We analyzed probability group data only relative to the max amount of tax they were willing to spend if the levee failure was certain (i.e., $p = 1.0$) because participants were not provided with any reference points for high or low tax amounts.

Discounting parameters γ for the weather discounting tasks were estimated using the Solver Add-In for Microsoft Excel. Discounting parameters for the monetary discounting tasks were estimated in the same manner as experiment 1 and all parameters were log transformed before statistical analysis. Descriptive statistics for the delay and probability discounting tasks appear in Tables 3 and 4, respectively.

b. *Results and discussion*

Figure 4 shows the results from experiment 2. The left panel shows the normalized median evacuation points for the delayed severe weather group relative to a reference point of 200 mph. The right panel shows the normalized tax that participants were willing to pay as a function of the odds against levee failure.

In contrast to experiment 1, the delay to a severe storm influenced decisions to evacuate (left panel of Fig. 4; y axis value of 1.0 = 107 mph). Specifically, the wind speed participants chose to evacuate systematically changed as the delay to the storm increased and assuming a reference point of 200 mph.[2]

TABLE 3. Study 2: descriptive statistics for delay discounting task.

	1 day	7 days	30 days	1 yr	5 yr	10 yr
Max	196	196	196	196	196	196
90%	175	196	196	196	196	196
75%	133	133	167	196	196	184
50%	108	116	120	129	142	129
Mean	117.23	120.50	129.88	139.62	141.71	137.71
Std dev	36.73	39.14	45.63	46.78	48.80	46.65
25%	94	96	96	104	108	96
10%	71	79	79	91	94	90
Min	46	16	20	4	4	4

Nevertheless, the median evacuation wind speed was 107 and 116 mph at 1 and 7 days, respectively. This pattern replicates the results from experiment 1 that short delays do not impact decisions to evacuate for severe storms. Large differences in normalized evacuation points were observed at 30 days and longer. In sum, although participants discounted delayed severe storms, the delays at which decisions were impacted may be outside typical storm warning durations or forecasts (i.e., from minutes up to weeks). Thus, people may temporally discount severe weather threats, but only on longer time scales more consistent with climate change or perhaps multiyear cyclical effects (e.g., El Niño and La Niña).

The right panel in Fig. 4 shows the group median data from participants in the probability discounting group. Here, a value of 1.0 equates to willingness to pay a tax of $984. The amount of taxes that participants were willing to pay systematically decreased as a function of the odds against the levee failing. These findings extend the results of experiment 1 to decisions about weather preparations. The amount of resources that people will spend to prepare for severe weather decreases based as the probability of experiencing severe weather diminishes.

We also fit the discounting equations to participant data in experiment 2. Similar to experiment 1, neither Eq. (1) (dashed line) nor Eq. (2) (solid line) described discounting delayed weather well (R^2s of 0.67 and 0.70, respectively). This result questions the practical utility of using delay discounting to understand people's short-term weather-related decisions, but it may speak to how people approach longer-term decisions related to severe weather stemming from climate change that may unfold over years or decades (e.g., greater likelihood of coastal flooding, more frequent and intense hurricanes). In contrast, Eqs. (1) and (2) described data from the probabilistic weather tasks well (R^2s of 0.98 and 0.99, respectively). Residual analysis of the fitted models suggests that the hyperbolic model describes the pattern of choices made at low probabilities (high odds against) better than the exponential model. As with experiment 1, the high amount of variance accounted for suggests a probability discounting framework could be useful for understanding and predicting people's weather preparatory decisions.

Last, we compared rates of weather discounting with rates of monetary discounting using Eq. (2). We observed a correlation between weather delay discounting and monetary gain delay discounting ($r = 0.31$, $p = 0.004$), but no such relationship for loss discounting ($r = 0.18$, $p = 0.10$), which was significantly positive in experiment 1. For the probability

[2] The data from the 0-mph reference point are not shown because they are the inverse of the data in the left panel in Fig. 4. That is, normalized values would increase, which would not be meaningful in analyzing choice from a discounting framework.

TABLE 4. Study 2: descriptive statistics for probability discounting task.

	0.00 odds against	0.25 odds against	1.00 odds against	3.00 odds against	9.00 odds against	19.00 odds against	99.00 odds against
Max	984	984	984	984	984	984	922
90%	984	984	984	984	984	756	391
75%	984	984	984	844	523	266	180
50%	984	984	813	453	203	109	47
Mean	926.34	844.12	731.40	507.07	326.64	230.28	138.02
Std dev	142.27	236.48	298.23	350.19	336.29	294.58	202.42
25%	953	766	539	195	47	47	16
10%	775	419	266	78	16	16	16
Min	203	16	16	16	16	16	16

discounting group, we did not observe a correlation between weather probability discounting and monetary gain probability discounting ($r = -0.03$, $p = 0.78$). But we did find a weak correlation between weather probability discounting and monetary loss discounting ($r = 0.23$, $p = 0.04$). This makes sense considering that the weather discounting task asked about paying taxes, which may be considered as similar to losing money. That we detected a significant correlation is noteworthy given the restricted range of weather discounting because restricted ranges often decrease statistical power to detect effects (see McClelland 2000).

The findings from experiment 2 add to the growing literature on the diversity of commodities and events examined using a discounting framework. Originally described with monetary outcomes (e.g., Rachlin et al. 1991), discounting has also been observed with decisions involving food items (e.g., Estle et al. 2007), illicit drugs (e.g., Kirby et al. 1999), licit drugs (e.g., Odum and Rainaud 2003), leisure activities (e.g., Hirst and DiGennaro-Reed 2016), physical activity (e.g., Sofis 2015), tornado shelter-seeking (Gelino and Reed 2019), and other commodities or events. Experiment 2's finding suggests that decisions to evacuate from severe weather may be influenced by its delay, but only on time scales that exceed weather forecasting models and government-issued warnings. In contrast, decisions to prepare for weather are clearly influenced by the probability of the weather event occurring; both probability discounting equations described people's willingness to pay taxes to avoid levee failure especially well. Together, these findings suggest that discounting to severe weather can influence evacuation and preparation behavior, but particularly for *probability* discounting, and only for *delay* discounting involving longer time horizons more consistent with climate change challenges that acute weather threats. Thus, there is likely more that goes into such decisions than can be captured by currently accepted delay discounting models of human choice.

4. General discussion

We examined whether a discounting framework would describe decisions related to severe weather. In experiment 1, we

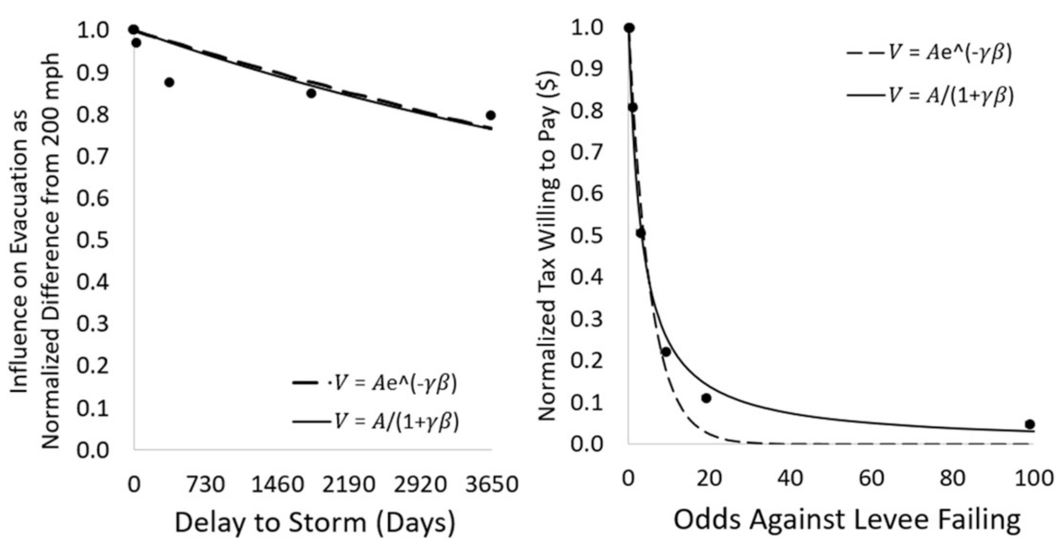


FIG. 4. Group median indifference points (black circles) for each severe weather discounting task in experiment 2. (left) Normalized evacuation points for participants randomly allocated to the delayed severe weather task. (right) Normalized tax amounts participants were willing to pay in the probabilistic levee failure task. Dashed lines are the fits for Eq. (1), and solid lines are the fits for Eq. (2).

found that probability—but not delays of up to 5 days—influenced people's decisions to evacuate. In experiment 2, we found that people's decisions to evacuate were only influenced by delays of long time horizons and people's decisions to prepare for weather damage were influenced by the probability to the weather event. In short, people discount severe weather, but only for probability judgments, not shorter temporal delays.

The present findings have multiple practical implications for public policy. For example, most people may have advance notice of severe weather on the order of minutes (e.g., flash floods or tornadoes; Gelino and Reed 2019) to a week (hurricanes). In both experiments, decisions to evacuate for severe weather were unaffected by this brief time frame; delay discounting only occurred for delays 1 month or longer. This is not unusual for people in delay discounting tasks. But it does suggest a delay discounting framework may not be the most practical approach to understanding and influencing people's decisions to evacuate for hurricanes. Instead, both experiments suggested that people were primarily influenced by storm severity and probability (e.g., Gelino and Reed 2019; Losee et al. 2017; Whitehead et al. 2000). Thus, public officials who write and issue severe weather warnings should focus on influencing people's evacuation decisions by communicating accurate strike probabilities with them. Although communicating arrival time is necessary and essential, it appears to have little effect on people's decisions to evacuate in the time frames that warnings are issued and effective (i.e., minutes, hours, or days but not months or years). Future research should examine the variables that influence people's perception of storm severity, and the processes that lead to individual differences in evacuation thresholds.

Severe storm probability emerged as a highly relevant feature of people's decisions, including evacuation and preparation to mitigate damage. In both situations, the probability that severe weather would occur systematically influenced people's decisions and was well described by the hyperbolic discounting equation. Together, the data on probability discounting severe weather add to a growing literature on the important influence of probability discounting relative to delay discounting (Cox and Dallery 2016, 2018; Vanderveldt et al. 2015; Weatherly et al. 2015) and suggest more research is needed on the best ways to communicate storm probability to the general public (e.g., Gelino and Reed 2019; Joslyn and Nichols 2009; Joslyn and Savelli 2010; Losee and Joslyn 2018). From a public policy perspective, people may indeed agree to pay higher taxes for levee repairs to protect their property and livelihood, but this may require clear and accurate communication of the risk or threat probability involved (e.g., the chances of levee failure).

Determining whether people make decisions about severe weather from a discounting framework poses multiple advantages. First, there are known variables that can change each person's rate of discounting (e.g., amount effect, framing effects, commodity type). For example, a person may discount \$100 worth of damage to her home as a function of the probability that the storm will hit her house by a rate of 4.2 [i.e., $\gamma = 4.2$ in Eqs. (1) and (2)]. This means the amount of preparatory behavior will decrease by a factor of 4.2 with every 1% change in the probability the storm will cause damage. Past research on discounting suggests that the rate of discounting (and the associated amount of preparatory behavior) will change if (i) the amount of damage increases to \$1,000 (magnitude effect), (ii) an emergency manager or weather forecaster describes the probability of damage in abstract ways (framing effect), or (iii) preparatory decisions are considered relative to protecting one's family and friends versus money lost (commodity type). Stated succinctly, past research on discounting provides methods for increasing or decreasing preparatory behavior for severe storms.

A second advantage of describing decisions about severe weather from a discounting framework is that different discounting rates have been correlated with group variables (e.g., socioeconomic status, clinical populations). Research in these areas of discounting may provide information to city and state planners about the likelihood and timing of preference reversals related to severe weather by the citizens in their community (e.g., if and when most citizens are likely to evacuate, or how much in preparatory taxes they may support)—sometimes referred to by municipal planners as ''understanding and describing the community'' (Center for Community Health and Development 2018). Thus, policy makers may be able to harness discounting research not only to better communicate warnings to their constituents, but also as a tool for better understanding the needs and risk preferences of their constituents.

Both experiments had limitations. For example, although our experiments focused mainly on discounting decisions, other factors are certainly important in relation to people's hurricane preparation and evacuation decisions, such as the peer pressure they may experience from their in-person social networks (Losee et al. 2021). In addition, the delay and probability that a storm will make landfall often vary together in nonlaboratory settings. This was a novel first attempt to apply the discounting framework to decision contexts with severe weather. Thus, we began with a simple situation to see whether the discounting models applied at all. Future research will want to examine more relevant, real-world decision contexts. And as stated earlier, we chose controlled experiments (vs field studies) (i) because discounting experiments demand controlled hypothetical situations and (ii) because experiments maximize internal validity (and hence allow for casual inference) while limiting external validity (i.e., generalizability to other situations and samples). Consequently, our findings are limited in their generalizability to university students in the southeastern United States—especially Florida—making decisions about hypothetical hurricanes and fictitious taxes.

First, we recruited participants from an undergraduate university. The amount of available resources, financial investment in home and property, ability to evacuate, and other relevant variables are likely to differ in this population when compared with others varying in age and socioeconomic status. Although U.S. university students are poorer—or at least in greater debt—than most adults, their families are likely to be wealthier than average, and so most students—especially those working to support themselves—have a keen understanding of their economic situation. And although most students rent (vs own) their dorms, homes, or attached dwellings, more than one-third of all residents in the state where these experiments were conducted—Florida—are also nonhomeowners (U.S. Census Bureau 2019). Further, although homeowners (vs renters) may seem to have more to lose in floods and hurricanes, insurance tends to equalize the two groups, and surely both groups are equally interested in protecting their personal property, regardless of who owns the surrounding structure or the land beneath it. But because our experiments were limited to mostly female samples of university students from the southeastern United States, the extent to which our findings might generalize to older, more diverse populations, especially those outside the United States, remains a topic for further study (see Henrich et al. 2010; Simons et al. 2017).

Second, questions in this study involved hypothetical outcomes. Previous research has demonstrated that discounting with real and hypothetical outcomes produces similar results (e.g., Johnson and Bickel 2002; Madden et al. 2003; Robertson and Rasmussen 2018), but this research has not been conducted with weather-related decisions. The extent to which these results would generalize to real severe storm situations remains unclear.

Third, participants have different past experiences with severe weather, and these differences can influence people's threat perceptions (Agdas et al. 2012, 2017; Webster et al. 2013) and decisions to evacuate and prepare. We did not control for prior severe weather experience in either experiment. Nevertheless, these experiments were conducted at a university where most students grew up within an hour's drive of the Atlantic or Gulf Coasts (or both); consequently, most students had likely experienced at least one—and likely more than one—landfalling hurricane near their home during their lifetimes. Indeed, prior research recruiting participants from the University of Florida showed that they had experienced just over five tropical storms on average (Agdas et al. 2012; Webster et al. 2013). Thus, even though we used hypothetical hurricanes, most students likely had prior experience preparing for and fleeing from real hurricanes. Further still, our controlled experimental design allows us to make causal inferences linking individual differences in discounting to behavioral decisions and intentions, something that more realistic field studies simply cannot do.

Both experiments had several important strengths. First, discounting is a well-studied description of choice behavior. As of this writing, a Google Scholar search of delay and probability discounting resulted in about 375 000 hits. The methods used to examine discounting in this work are similar to those used in many other studies of discounting, which suggests that the data obtained in this work likely accurately reflect choice about severe weather change as a function of the storm's delay or the probability that it will occur. Thus, the present experiments contribute to the translational research literature by showing that the same processes responsible for other choices involving delayed and uncertain outcomes also occur with weather-related decisions. Second, these data were collected in Florida, a location with an annual active hurricane season. Thus, most participants were likely familiar with hurricanes (from prior experiences) and the damage that they can cause. Past familiarity with hurricanes increases the likelihood that the responses provided are accurate reflections of what people have done, or might do, to prepare for an impending severe storm.

Risk communicators—community planners, weather forecasters, and government agencies—can leverage research on discounting when communicating impending weather alerts and warnings to encourage people to engage in safe preparatory behavior (e.g., Rung and Madden 2018). Our findings suggest that effectively communicating severe weather probability information—but not necessarily storm delay information—may be vital to influencing people's evacuation decisions. That delay discounting of storm severity information was found only for longer delays (months, years, and decades) suggests that this approach may hold promise for how people perceive more chronic long-term threats such as those affected by climate change (e.g., rising sea levels or stronger and more-frequent hurricanes). For officials needing to raise taxes or sell bonds to raise funds for vital protective infrastructure such as levees or seawalls, communicating the probability of relevant weather or climate threats may prove more influential to constituents than focusing on distant temporal horizons. Future research that targets how weather severity communication can alter risky weather-related behavior could significantly impact public safety, including reducing loss of life. Future research should also strive to examine how people actually behave when confronted by real approaching hurricanes of varying intensity and certainty (about their projected paths). The present research highlights discounting as a novel tool that can help researchers and policy makers better understand how people make both short- and long-term decisions about severe weather and climate change.

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APPENDIX

Details on Discounting and Discounting Models

a. Discounting

Most discounting research focuses on delay and probability discounting [see McKerchar and Renda (2012) and Odum (2011) for reviews] for two reasons. First, delay and probability discounting possess face validity with many everyday choices. For example, people select their routes to work based on what gets them there sooner. People plan the time and distance of their runs based on the likelihood it will rain. Uncertainty about whether a new message is available leads people to check their email, social media, and text messages at a frequency resembling a rat depressing a lever in an operant chamber.

The second reason that research focuses on delay and probability discounting is predictive validity. For example, how much delay and probability influence value differentiates clinical from nonclinical populations. Research consistently shows that delay decreases value less for control groups relative to smokers (e.g., Białaszek et al. 2017a,b; Johnson et al. 2007), heroin users (e.g., Kirby et al. 1999; Scherbaum et al. 2017), alcoholics (e.g., Bailey et al. 2018; MacKillop et al. 2010), sedentary people (e.g., Bickel et al. 2018; Dassen et al. 2018), and pathological gamblers (e.g., Cooper 2007; Dixon et al. 2003). Similarly, many of these groups show increased preference for the uncertain, clinically relevant option in probability discounting tasks when compared with control groups. For example, pathological gamblers show greater preference for risky monetary gains, and people with chronic illness adhere to medication regimens based on the risks of side effects and medication efficacy (e.g., Bruce et al. 2018; Madden et al. 2009).

Researchers have discovered several consistent variables that lead people to choose more self-controlled and less risky options. First, amount matters (e.g., Green et al. 1997; Myerson et al. 2011). People wait longer to get more of something (i.e., delay decreases value less with larger amounts of the commodity), and people are less willing to take risks when getting more of something is on the table (i.e., probability decreases value more with larger amounts of the commodity). Second, gaining something is different than losing something (e.g., Green et al. 2014; Myerson et al. 2017). People generally prefer to get things as soon as possible but to lose things at a later date in time. Similarly, people are willing to gamble more to avoid a loss but are more likely to choose the safe gain (e.g., Cox and Dallery 2016; Mitchell and Wilson 2010). Third, commodity matters (e.g., Estle et al. 2007; Odum and Rainaud 2003). Value decreases less quickly for commodities with higher liquidity and lower perishability (e.g., money). But value decreases rapidly for commodities with low liquidity and high perishability (e.g., food and cigarettes).

b. *The discounting model*

Researchers measure delay and probability discounting in people in multiple ways [see Madden and Johnson (2010) for a review]. One common method involves presenting a series of trials where people choose between one of two outcomes. One is a smaller outcome occurring immediately (delay discounting) or with certainty (probability discounting). The second outcome is a larger-delayed or more-uncertain outcome. For example, a person may choose between

(i) $50 immediately or
(ii) $100 in 6 months.

After the participant chooses, the amount of the immediate or certain option (option i) increases or decreases, and the participant then makes another choice between the two options (e.g., Du et al. 2002). This adjustment following participant choice occurs for approximately 5 trials until an indifference point is obtained. The indifference point is the amount at which the participant's preference switches from the larger-delayed or more-uncertain alternative to the smaller-immediate, or less-uncertain alternative. This adjusting-amount method repeats across a range of delays (or probabilities) until 5–7 indifference points are obtained for each participant. These indifference points are then used to model how delay (or probability) influences commodity value.

Several mathematical models have been used to describe delay and probability discounting (for review, see McKerchar et al. 2009). One of the earliest models describing discounting came from economic theory (Samuelson 1937). This model proposes that the value of a commodity reduces by an equivalent proportion with each time step. Mathematically, this means discounting occurs exponentially and can be written as

$$V = Ae^{-\gamma\beta}. \tag{A1}$$

Here, V is the current value of a commodity, A is the objective amount of the commodity, β is the independent variable under study (e.g., delay for delay discounting; odds against for probability discounting), and γ is a free parameter reflecting rate of discounting. Importantly, this exponential model predicts that preference for one alternative will remain unchanged over time. If a smaller/sooner option is preferred now, then the smaller/sooner option will be preferred in 6 months, 1 year, and 10 years.

A common alternative model for describing discounting is a hyperbolic model. Described by Mazur (1987), the hyperbolic form of discounting can be written as

$$V = \frac{A}{(1+\gamma\beta)}. \tag{A2}$$

In this equation V, A, γ, and β are the same as in Eq. (A1). In contrast to the exponential model, the hyperbolic model proposes that the value of a commodity reduces more with changes across shorter delays and less with changes across longer delays. The benefit of the hyperbolic model is that it accounts for time-inconsistent patterns of preference (e.g., preference reversal), whereas the exponential model does not (McKerchar et al. 2009). We examine both exponential and hyperbolic discounting models in the present work simply because most research in the discounting literature presents results from both models. [Note that Eqs. (A1) and (A2) are identical to Eqs. (1) and (2) in the main text].

A preference reversal occurs when the larger, more-delayed option is initially chosen when the smaller, sooner option is also at some delay. As time moves closer to both alternatives, however, preference reverses and the smaller, sooner option is chosen. For example, many people have signed up for a gym membership or committed to a rigorous workout the day before one is to go to the gym. In this moment of choice, the larger-delayed gains of physical fitness are worth more than the rest gained from sleeping longer in the morning. As time draws nearer the moment of choice between sleeping in and working out, however, the smaller/immediate gain of additional sleep may become more valuable than the larger/delayed gain of physical fitness. People are thus likely to remain in bed and skip the workout. Preference reversed from favoring the larger/delayed gain of physical fitness to favoring the smaller/immediate gains of sleeping in as time to both drew closer. Preference reversals are also common to uncertain outcomes in which preference commonly favors the smaller/certain option when both choices have high probabilities; but preference commonly favors the larger/uncertain option when both choices have low probabilities (e.g., Allais paradox; Allais 1953). Importantly, rate of discounting, and the timing of preference reversals, differ between individuals.

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