

Lives Saved vs Time Lost: Direct Societal Benefits of Probabilistic Tornado Warnings

Alexander Ugarov,^a

^a *University of Oklahoma, CIMMS*

Current Affiliation: HiveReview. The author appreciates support and comments from other University of Oklahoma CIMMS researchers, but most of all Kimberley Klockow and Harold Brooks.

Corresponding author: Alexander Ugarov, alugarov@gmail.com

9 ABSTRACT: National Weather Service is planning to implement the system of probabilistic
10 tornado warnings. In this paper, we estimate and compare full societal costs of tornadoes with
11 existing deterministic and potential probabilistic warnings. These full costs include the value of
12 statistical lives lost as well as the value of the time spent sheltering. We find that probabilistic
13 tornado warnings would decrease total expected fatalities. The improvement in decision-making
14 would also decrease the total opportunity cost of time spent sheltering even though the total
15 sheltering time is likely to increase. In total, probabilistic warnings should lower societal costs of
16 tornadoes relative to deterministic warnings by approximately 75-150 million USD per year with
17 a large portion of this improvement coming from lower casualties.

18 SIGNIFICANCE STATEMENT: We measure societal benefits of probabilistic and deterministic
19 tornado warnings in the US by evaluating their effects on expected casualties and sheltering
20 costs. We find that probabilistic warnings deliver almost twice as much net societal benefits as
21 deterministic ones. These gains happen due to less casualties and due to making protective behavior
22 more responsive to risks and sheltering costs. This paper provides additional evidence of the need
23 to implement probabilistic extreme weather warnings.

24 1. Introduction

25 Most people are aware about grim costs of tornados killing dozens of people per year¹, but less
26 know about warnings killing hundreds thousand of hours of sheltering time. Sheltering is costly
27 because it forces people to reduce time spent on work and leisure. These losses can be plausibly
28 measured in monetary terms: Simmons and Sutter (2013) estimate that tornados impose roughly 3
29 to 4 billion USD of annual implicit costs on the US society, and the opportunity costs of sheltering
30 is one of its largest cost components amounting to 1.3-2.6 billion USD.

31 One proposed way to reduce societal costs of tornados is to provide information on the probability
32 of a tornado to happen in a location instead of providing deterministic yes/no prediction (Rothfusz
33 et al. 2018). In theory, probabilistic extreme weather warnings give more detailed information
34 to users and enable them to make better decisions (Murphy 1993; Papastavrou and Lehto 1996).
35 Potential users in the US also demonstrate preference for receiving probabilistic versus deterministic
36 weather forecasts (Morss, Demuth,, and Lazo 2008; Morss, Lazo,, and Demuth 2010). At the same
37 time, probabilistic warnings might reduce the decisions quality for some users, and hence it is
38 not clear apriori whether their potential societal benefits would outweigh the additional cost of
39 development and delivery of more sophisticated forecasts.

40 This paper uses population responses to calculate societal benefits of deterministic and proba-
41 bilistic tornado warnings. Our calculation of societal benefits accounts for their effects on fatalities,
42 injuries and on sheltering time. We assign monetary measures to fatalities and injuries by using
43 the value of statistical life approach and price the inconveniences of sheltering time based on the
44 concept of opportunity costs of time.

45 This work involves three steps. First, we conduct a household survey to learn the population's
46 protective responses both to current deterministic tornado warnings and to prospective probabilistic

¹National Weather Service, <https://www.weather.gov/media/pah/Skywarn/TORNADOsafety.pdf>

ones. These responses account both for probability levels and for housing types. However, extreme weather alerts do not help if protective responses are inefficient. So, on the second step, we evaluate the efficiency of protective responses conditional on housing type by using the data on historic variation in weather information quality and tornado casualties. Finally, we use the current joint distribution of deterministic forecasts and tornado events to estimate the frequency of probabilistic alerts for each probability level. This last step is important, because it allows us to change the forecasting format while keeping the quality of forecasting technology constant.

The survey collects the data on hypothetical protective responses from the population mostly living in tornado-prone areas. To achieve better representation of diverse populations, it recruits respondents both through mail invitations sent to random addresses in the US Postal Service database and through the Qualtrics Internet-panel. The mail sample includes 718 households with the majority (514) coming from the twenty states with the highest incidence of significant tornadoes. The Internet sample includes 403 responses with 247 responses from English speakers and 156 responses from Spanish speakers with limited English. All the Internet survey responses come from the residents of 20 states with the highest rate of significant tornadoes which are located mostly in Midwest and South of the continental U.S.

We calculate that probabilistic tornado warnings should create net annual benefits between 78 to 138 million USD depending on the calculation method used. The lower estimate assumes that the population has identical opportunity costs of time, while the larger estimate assumes that these costs vary across individuals. Varying opportunity costs imply that individuals sheltering always do it because of facing lower costs of sheltering relative to costs of life or injury. The benefit of probabilistic warnings is relative to deterministic ones, which on their own already create 100-145 million USD per year of net societal value. This is a rather conservative estimate, because it accounts for imperfect awareness and compliance with warnings and for imperfect protection technology.

Most respondents demonstrate good understanding of probabilistic warnings and good calibration of responses to threat levels. Reported protective responses tend to increase with tornado probabilities. More interestingly, opportunity costs of time implied by their protective responses are consistent with previous estimates of opportunity costs of time in the literature. It supports the idea that potential users correctly deduce their personal risk levels from probabilistic warnings.

77 In response to probabilistic alerts, more people report willing to monitor the threat as compared to
78 deterministic warnings, but expect to shelter when the danger becomes imminent. Many individuals
79 expect to respond to probabilistic warnings even when the tornado probability in a 10-mile radius
80 circle is as low as 10-15% which we estimate to be below the average implied probability for
81 a deterministic tornado warning. It leads to more people reacting to probabilistic warnings and
82 eventually more people taking shelter. As a result, probabilistic warnings reduce total casualties.
83 At the same time, probabilistic warnings increase the total time spent sheltering or monitoring the
84 weather. This increase does not necessarily convert to higher societal costs. If we account for
85 optimal response to predicted tornado probabilities and deduce opportunity costs from reported
86 protective responses, then the societal value or opportunity cost of sheltering/monitoring time goes
87 down due to more graduated reaction to probabilistic warnings. Probabilistic warnings deliver this
88 positive effect by enabling users with higher opportunity costs to shelter only if tornado threats are
89 sufficiently high.

90 We contribute to the literature by directly measuring net benefits of both deterministic and
91 probabilistic tornado warnings. Similar to our study, Howard et al. (2021) measure economic
92 benefits of probabilistic warnings for businesses and find that they allow firms to save extra 1.3-5.6
93 billion USD per year. With respect to general population, Simmons and Sutter (2013) calculate that
94 contemporary societal costs of tornados are roughly 6 billion USD lower than the hypothetical costs
95 with tornado lethality at the 1925 US level and with no warnings. However, this change cannot
96 be completely attributed to the effect of deterministic tornado warnings, because other safety
97 improvements happen simultaneously during this period. This paper takes a more conservative
98 approach to estimate the benefits of both deterministic and probabilistic warnings by accounting for
99 imperfect compliance with warnings and by calculating their efficiency directly from the variation
100 in casualties between warned and non-warned populations.

101 In contrast to our approach, multiple other studies of economic value of weather information
102 (Lazo and Chestnut 2002; Lazo et al. 2009; Lazo and Waldman 2011; Wehde et al. 2021) use the
103 contingent valuation method in which potential users directly report their willingness-to-pay for the
104 service. Most relevant for our study, Wehde et al. (2021) find that the US population is willing to pay
105 on average \$7.5 per person for an app providing probabilistic graphical tornado alerts. This price
106 translates to one-time aggregate benefit between 900 million to 1.56 billion USD depending on

107 aggregation assumptions used. While contingent valuation studies can potentially reflect additional
108 benefits of information such as peace of mind or increased safety of others, they suffer from the
109 hypothetical bias emerging due to respondents deliberately overstating their willingness-to-pay
110 (Blumenschein et al. 2008; Johnston et al. 2017). As a result, contingent valuation studies often
111 provide excessively high and varying estimates of economic benefits. Hence a direct approach we
112 use provides an important and more reliable lower bound of the new system's value.

113 Our study supports the conclusion that the US population can interpret and use probabilistic
114 warnings. Multiple previous studies (Ash et al. 2014; Lindell et al. 2016; Miran et al. 2017) test
115 perception and hypothetical responses to graphical representation of probabilistic severe weather
116 alerts. In general, they find that people increase protection in response to increasing threat
117 probabilities, even though presentation formats have strong influence both on average response
118 levels and on sensitivity of response to presented probabilities. Additionally, LeClerc and Joslyn
119 (2015) find that probabilistic information improves decision-making and reduces the "cry-wolf"
120 effect, while Krocak et al. (2022) find that probabilistic information allows for better decision-
121 making compared to categorical verbal descriptions of uncertainty. We do not only find that
122 protective responses are sensitive to projected probabilities, but also that response levels are well-
123 calibrated to threat levels and consistent with choices made in other domains (such as speeding
124 (Wolff 2014)).

125 **2. Survey Design and Implementation**

126 *a. Data Collection*

127 We collect the data from two samples. The mail survey recruited respondents across the whole
128 US but with the emphasis on tornado-prone regions (see Table ?? in the Appendix). Respondents
129 could choose to respond by mail by using an enclosed envelope or to fill the survey online.
130 The Internet-survey recruited subjects from the tornado-prone regions only. The use of different
131 sampling methods intended to get a wider representation of different demographic groups. Mail
132 survey reached more older respondents living in rural communities, while the Internet-survey
133 helped to get answers from younger respondents. We received 718 responses from the mail survey

134 and 403 responses from the Internet survey. Questionnaires were practically identical except for
 135 small changes needed to screen respondents in the Internet survey.

TABLE 1: Mail Survey Sample

	Tornado-prone states			Other states		
	Sample		Population	Sample		Population
	N	(%)	(%)	N	(%)	(%)
Male	227	43	49	31	39	48
<35	43	8	30	7	9	30
35-59	231	45	41	38	49	41
60+	240	47	29	33	42	29
No school	5	1	2	1	1	1
Grades 1-12, no HS diploma	9	2	8	2	2	9
HS diploma	65	12	29	10	12	33
Some college	111	21	25	13	16	26
Associate or bachelor's degree	200	37	22	25	31	20
Advanced degree	148	28	14	29	36	11

136 The mail survey uses stratified probabilistic sampling to get a more representative sample which
 137 allows us to use statistical tests. Our initial frame comes from the USPS delivery route database. We
 138 stratify the sampling frame by state of residence and by housing type and sample 10600 addresses
 139 with more addresses from tornado-prone states. We consider the state to be tornado-prone if it
 140 belongs to 20 states with the highest average incidence of significant tornadoes (EF2 and above)
 141 per square mile within the last 20 years. The selected states include 45% of the US population, but
 142 88% of tornado fatalities. This paper uses only the sample obtained from the tornado-prone states.

143 The questionnaire was pretested, first, by using qualitative personal interviews conducted either
 144 in person or over Google Meets and Skype. These interviews helped us to clarify the question's
 145 wording and make sure that their interpretation by subjects matches our expectations. On the
 146 second stage, we conducted quantitative pilots both for the Internet-sample and for the mail survey.

147 We pretest our surveys by using, first, qualitative face-to-face² interviews and, second, through
 148 quantitative pilot studies. The qualitative interviews help to clarify the understanding of questions
 149 and refine the lists of response options. The interview followed think-aloud protocols (Dillman
 150 et al. 2008) in which respondents read all the questions aloud and vocalize their thinking process.
 151 Quantitative pilots followed the same procedure we intended to use for the main study but with

²Due to COVID-19 pandemic, we conducted most of the qualitative interviews online either through Zoom, Skype or Google Meets.

152 smaller samples. We conducted two pilots for the Internet-sample and two pilots (400 and then
153 200 letters) for the mail survey. Our pilots helped to adjust our sampling strategies and redesign a
154 few questions which turned to be ambiguous to the subjects.

155 *b. Representativeness and Selection Bias*

156 Despite our effort to use different recruiting efforts, both samples had disproportionally more
157 females and more people with college education and above (see Table 1 above and Table A2 for
158 the Internet-sample in the Appendix A). Additionally, the mail survey recruited more older white
159 respondents. Hence in order to translate our findings to the US population we re-weight our results
160 to match the US population structure by age and gender.³

161 **3. Use of Standard and Extended Tornado Alerts**

162 First, we study how extended tornado warnings would affect protective responses. We ask our
163 respondents to imagine being at home with their family at 7 PM when a tornado warning is issued.
164 Next, we elicit their protective responses conditional on lead times and on probabilities of a tornado
165 to happen within a given time interval. The Internet-survey asks the same set of questions for the
166 nighttime warnings (2 AM).⁴ While these questions cannot describe the multitude of scenarios for
167 different times and for different circumstances (such as staying outside or being separated from
168 the family), we still believe that they cover the most common scenario. Most respondents choose
169 to respond to a standard tornado warning by taking a shelter at home or near. The proportion
170 of respondents choosing this action (55%) is surprisingly stable across samples and across times
171 in the same sample (Figure 1). Roughly one-third of responds expects to seek more information
172 without taking shelter. About 10% of respondents in the Internet sample choose to drive to another
173 house or structure or to drive out of the potential tornado path. This proportion is slightly higher
174 for the Internet sample (Figure ??).

175 Increasing lead time to 40 minutes on its own have practically no effect on the total proportion
176 of people taking any protective action, as more than 90% of individuals do it anyway. However,
177 increasing lead time decreases the likelihood of sheltering at home in favor of seeking more

³We use the data from the American Community Survey 2018, downloaded from IPUMS (Ruggles et al. (2021)).

⁴Mail survey conducted after the Internet-survey had to drop these questions in effort to shorten the questionnaire.

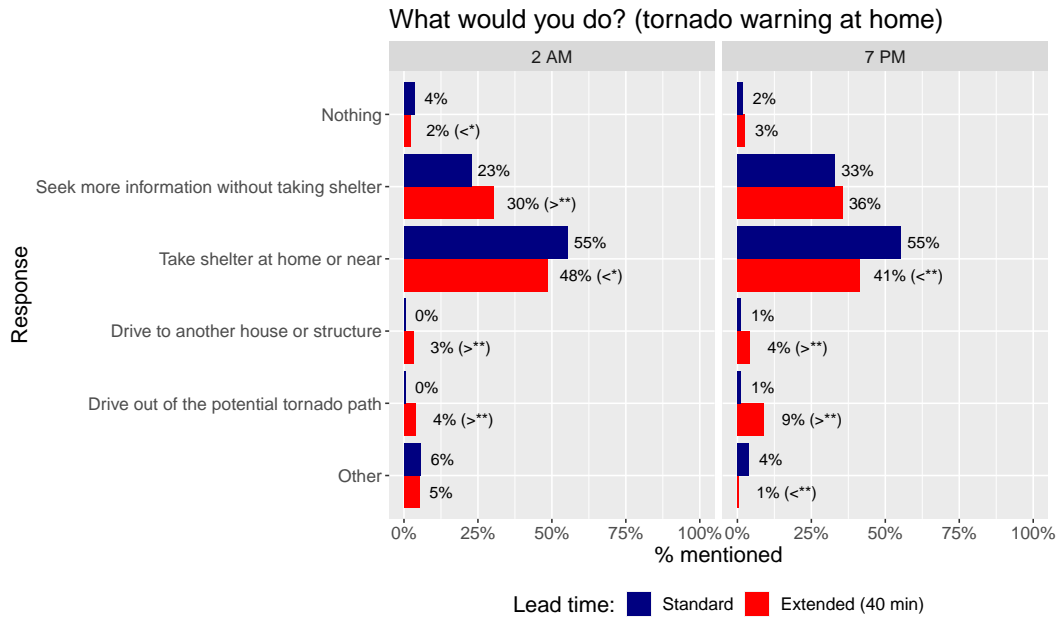


FIG. 1: Protective Response by Lead Time

information and evacuating. It is clear that extended lead time improves safety of people in vulnerable housing conditions, such as mobile houses. But the safety of people living in more robust homes depends on their ability to interpret additional information they receive while not sheltering and properly responding to it.

Providing probabilistic information is the most crucial aspect of prospective tornado alerts system, but their usefulness relies on the users' ability to understand and react to probabilistic forecasts. The survey indicates that most individuals respond rationally to probabilistic warnings. The proportion of respondents choosing to protect increases with the forecasted probability. Almost 100% of respondents expect to take some protective action if they learn that a tornado would happen with probability 100% in the next 40 minutes in a 10 mile radius from their location. Less than 5% of respondents make non-monotonic choices meaning that 95% of respondents protect for all the probabilities which are higher than their threshold probability.

Most individuals expect to take protective actions when the probability gets to 20%. The range between 0 and 20% probability is also the range of highest sensitivity to risk in which the largest share of respondents switches from no protection to protection as can be seen from the slope of the line in Figure 2. Interestingly, this is the probability most consistent with implied probabilities of existing deterministic tornado warnings, which also prompt the majority of users to protect.

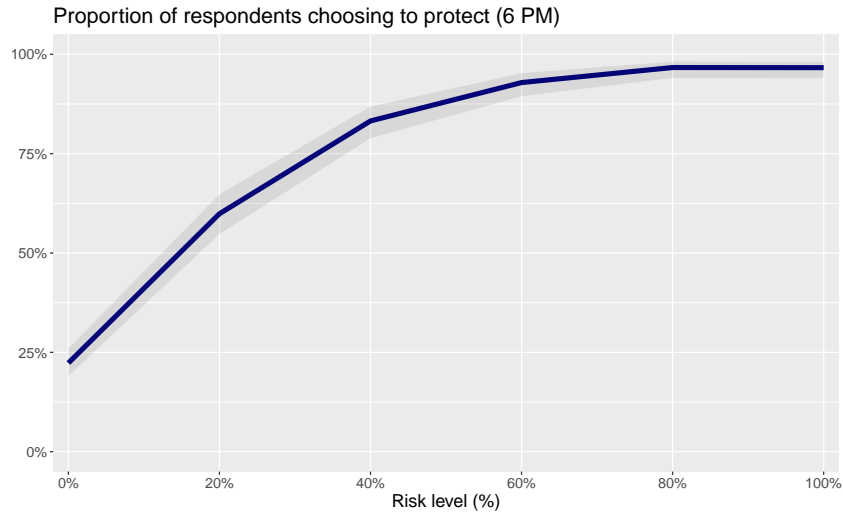


FIG. 2: Protective Response by Probability of a Tornado

195 The reaction threshold is higher for nighttime warnings (see Figure B2 in Appendix B). This is
 196 consistent with higher costs of nighttime protective actions for most respondents as they potentially
 197 require interrupting sleep and driving with poor visibility.

198 4. Computation of Direct Societal Benefits

199 a. Overview of the Approach

We estimate direct economic benefits of extended tornado warnings as the difference in direct societal costs between standard and extended warnings. Direct societal costs in our calculation include the cost of tornado deaths and injuries and the cost of time spent sheltering (Sheltering Costs). This approach is similar to the approach used by Simmons and Sutter (2013). We convert each of the cost components to the monetary scale. Value of statistical life and value of statistical injury metrics translate predicted numbers of deaths and injuries into equally undesirable monetary costs. We use the Value of Time to price the time spent sheltering under both standard and extended tornado alerts. Direct costs of tornadoes is:

$$\text{Direct Costs} = \text{VSL Lost} + \text{Value of Injuries} + \text{Sheltering Costs}$$

Value of statistical life (VSL) assigns a monetary value to life based on observed trade-offs between money and small chances of death. Based on literature review for wage differentials for risky occupations, Viscusi and Aldy (2003) suggest the range from \$7 million to \$12.4 million per statistical life. We use VSL of \$11.13 million which is equal to the value recommended by Kniesner and Viscusi (2019) and adjusted for inflation from 2019 to 2020. For comparison, Simmons and Sutter (2013) use the value of \$7.6 million per statistical life in prices of 2007, which corresponds to \$9.5 million in 2020 prices. The US Environmental Protection Agency recently used the value of \$10.9 million in its Emission Guidelines for Greenhouse Gas Emissions from Existing Electric Utility Generating Units (2018)⁵, which also translates to \$11.2 million in 2020 prices.

We assign monetary value to injuries in a similar fashion. Most tornado injuries are minor, and so following the approach in (Simmons, and Sutter 2006, 2013), the monetary value of injury is 1/100 of the value of statistical life which is \$86,000 per injury.

The following formula calculates expected injuries and fatalities⁶ under deterministic warnings as the product of the affected population (P_A), baseline injury/fatality rate (r) in the affected population and the mitigation factor due to protective responses (M):

$$F_D = P_A \times r \times M$$

Affected Population (P_A) is the expected annual population in tornado strike zones. It is equal to the product of the average annual number of tornado warnings N_w , average tornado strike area A and population density d corrected for the false alarm rate (FAR) and probability of detection (POD):

$$P_A = N_w \times A \times d \times (1 - FAR) / POD$$

The US issues $N_w = 2063$ warnings per year on average (Howard et al. (2021)). The population density in 20 states with the highest frequency of significant tornadoes is $d = 119$ people per square mile. Simmons and Sutter (2013) estimate that the average tornado strike area A is approximately 0.3 square miles. We also use estimates of $POD = 0.7$ and $FAR = 0.7$. Based on this calculation, Affected Population P_A includes 31.8 thousand people per year.

⁵<https://www.epa.gov/stationary-sources-air-pollution/electric-utility-generating-units-emission-guidelines-greenhouse>

⁶To save on notation, we use the same variable names to denote both expected injuries and expected fatalities. The formulas are identical.

217 The baseline fatality (injury) rate per person in a strike area r is the probability that a person
 218 in a tornado strike zone is killed (injured) in a tornado if they do not protect. The protective
 219 mitigation factor m measures the proportional decrease in risk of injury/death from the expected
 220 protective response. It depends both on the expected behavior and on the efficiency of this behavior
 221 in reducing the risk. These two variables strongly depend on housing conditions, so we condition
 222 our calculation on living in permanent vs. mobile houses and weight by corresponding population
 223 proportions. We explain the calculation of the baseline fatality and injury rates and the protective
 224 response mitigation factors in the next subsection.

We use a similar approach to forecast casualties under probabilistic forecasts, but now we account for different responses for each tornado probability. We also need to make sure that probabilistic forecasts do not under-predict or over-predict tornadoes. For this purpose, the affected population P_A stays constant between different forecasting approaches. As a result, the probability of a tornado to happen enters the casualty calculation only indirectly through the population's protective response. The expected number of casualties for each predicted probability $F(p)$ is the product of the population affected P_A , baseline risk r and probability-specific mitigation factor $M(p)$:

$$C(p) = P_A \times r \times M(p)$$

The total expected number of casualties for the probabilistic forecast F_P is the sum of casualties for each predicted probability $C(p_i)$ weighted by frequency of forecasting each probability $f(i)$:

$$F_P = \sum_i f(i)C(p_i) = \sum_i f(i) \times r \times M(p_i)$$

225 The survey describes protective responses to both existing deterministic and prospective proba-
 226 bilistic alerts. For the protective response, we assume that people who report needing to collect
 227 more information will eventually shelter before a tornado. Hammer and Schmidlin (2002) and
 228 Klockow (2011) show that most people in a tornado strike zone take shelter, but fewer people
 229 do it in a tornado warning zone (Liu, Quenemoen, Malilay, Noji, Sinks,, and Mendlein 1996;
 230 Sherman-Morris 2010).

231 *b. Protective Response Efficiency*

232 Protective response mitigation factor M measures the proportional effect of protective actions
 233 on tornado fatalities and injuries. Because we are not aware of any generalized estimates of
 234 protective response efficiency in the literature, we estimate it indirectly from casualty effects of
 235 tornado warnings and other historical data. This estimation assumes that households protect only
 236 in response to warned tornadoes, and that the protection response is not universal. We also assume
 237 that the protective response has the same proportional effect on reducing both fatalities and injuries.

238 Simmons and Sutter (2009) find that the warned tornadoes on average have 30-40% less injuries
 239 controlling for tornado strength, strike area, geography, and time. Similarly, Simmons and Sutter
 240 (2005) find that when a Weather Forecast Office (WFO) in the US installs a WSR-88 weather radar,
 241 tornado injuries in covered counties go down by approximately 40%. Based on this evidence,
 242 we make a relatively conservative assumption that warnings reduce injuries by 35%. While the
 243 paper does not observe the effect of warnings on fatalities, this is likely the result of a much
 244 smaller number of fatalities in the sample. Consistent with these observations, we also assume that
 245 warnings reduce fatalities by 35%.

246 The following more technical calculation then infers protective response efficiency. The calcula-
 247 tion accounts for housing type t (permanent, mobile) to reflect much higher vulnerability of people
 248 living in mobile homes. The effect of protective response depends both on the probability of a
 249 response and on its efficiency in reducing casualties. Let r_t^0 denote the baseline probability of death
 250 for an unprotected person in home of type t in a tornado strike zone and r_t^w is the probability of
 251 death for a protected person. Additionally, R_t is the probability of protective response to a warning
 252 and m_t is the mitigation efficiency (for example, an action with $m = 0.6$ reduces casualties by 40%
 253 relative to the baseline). Then the casualty rates are described by the following expressions for
 254 each type of housing t with P_t denoting the corresponding population share:

$$r_t^w = r_t^0(R_t m_t + (1 - R_t)), t = \text{mobile, permanent} \quad (1)$$

255 Next, we assume that warnings reduce casualties by 35%:

$$\sum_t P_t(r_t^0 - r_t^w) = 0.35 \sum_t P_t r_t^0, t = \text{mobile, permanent} \quad (2)$$

Finally, the average fatality rate $r_t^a v$ is the weighted average for warned and unwarned fatality rates accounting for the probability of detection (POD):

$$r_t^a v = POD r_t^w + (1 - POD) r_t^0, t = mobile, permanent \quad (3)$$

Next, we solve the system of equations above to find both baseline hazard rates r_t and mitigation efficiency parameters m_t . As a first step, we consider the population living in mobile homes. Simmons and Sutter (2013) estimate the average probability of death of mobile home resident r_{mob}^{av} to be 0.8472% if located in a tornado strike zone. The best and practically the only protection response for a mobile house resident is to evacuate to a sturdier building, shelter or travel out of the tornado path (Schmidlin et al. 2009). We assume for simplicity that evacuation eliminates the tornado risk for this group ($m_{mob} = 0$). However, Schmidlin et al. (2009) find that only around 30% of mobile house residents currently evacuate if they receive a tornado warning. Using equations (1) and (3), we obtain that the baseline rate of fatalities for mobile house residents is 110% of the average or 1.01% and the warned rate is 0.751%.

Next, we estimate the baseline risk and the mitigation efficiency for residents of permanent homes. We do it by substituting the risks of mobile home residents into the equation (2) and solving the resulting system of (1-3) for r_{perm}^0 and r_{perm}^w . The estimate for the average risk of fatalities in permanent homes comes again from Simmons and Sutter (2013), who calculate that 0.0882% of residents in permanent homes die in the average tornado strike zone. We calculate that the baseline risk of death for residents of permanent homes r_{perm}^0 is 0.126% and the risk for warned residents of permanent homes r_{perm}^w is 0.0743%. Thus, warnings reduce fatalities in permanent homes by roughly 40%.

To calculate the mitigation efficiency factor m_{perm} for residents of permanent homes, we need to account for imperfect compliance with issued warnings. Previous studies indicate that while the response rate to warnings R_{perm} is close to around 30% for warned counties (Liu et al, 1996; Schmidlin et al, 2009), the response rate reaches 70-90% for population directly in a tornado path and for stronger tornadoes (Klockow 2011; Paul, Stimers,, and Caldas 2015). As only the response of individuals in a path matters for casualties, we assume that 60% of permanent homes residents in a tornado path take some protective action ($R_{perm} = 0.6$). It follows that taking protective actions mitigates the baseline risk for permanent homes by approximately 65% ($m_{perm} = 0.361$).

284 Event studies support our finding of high mitigation efficiency for permanent homes. For
285 example, Niederkrotenthaler et al. (2013) finds that sheltering in a basement reduced injuries by
286 roughly 80% during April 2011 Alabama tornadoes, while Daley et al. (2005) find no severe
287 injuries and deaths among people doing it during the Oklahoma-city 1999 tornado. The same
288 applies for the 2011 Joplyn tornado (Paul, Stimers,, and Caldas 2015). The evidence for using
289 interior rooms as a shelter is more mixed. Niederkrotenthaler et al. (2013) find that sheltering in an
290 interior room had reduced the risk of injury by about 60%, but Daley et al. (2005) find just 20-30%
291 reduction in severe injuries and Hammer and Schmidlin (2002) find no effect of using an interior
292 room vs any other room in a permanent house.

293 We apply the same approach to the calculation of injury risks. The calculation assumes the
294 average risk of injury at 0.025 for mobile homes in the strike area and the risk of 0.0224 for
295 permanent homes in the strike area (based on Simmons and Sutter, 2013 calculation). The baseline
296 risk of injury for permanent homes equals 0.0306 and the baseline risk for mobile homes equals
297 0.0316. While the predicted injury risk is very similar for both home types, it seems that permanent
298 homes give a better protection against death, but little protection against non-fatal injuries.

299 *c. Distribution of Probabilistic Forecasts*

300 Population's protective responses depend on perceived probabilities. Hence we need to know
301 how often each probability is forecasted in order to estimate the costs of probabilistic warnings.
302 This task is non-trivial, because for any probability of a tornado, one can issue different unbiased
303 probabilistic forecasts. For example, one completely unbiased but also completely useless forecast
304 is the forecast which is always equal to the baseline (environmental) probability of a tornado to
305 happen. On the opposite end of the precision spectrum, forecasters can predict a probability of 1 if a
306 tornado is going to happen and zero otherwise. In practice, dynamic properties of weather systems
307 and imperfect information impose constraints on the maximum precision of tornado forecasts.

308 We are going to use signal detection theory to infer the distribution of probabilistic forecasts
309 from the joint distribution of tornado warnings and tornado events.⁷ The signal detection approach
310 assumes that probabilistic forecasts use the same information as existing standard warnings. If it is

⁷Howard et al. (2021) use a simpler approach by assuming equal forecasting frequency for each probability. However, this approach can easily over-estimate the precision of probabilistic forecasts and their value, because it implies a much higher average confidence of forecaster than allowed by the existing technology.

indeed true, all the information can be aggregated to one signal equal to the posterior probability of a tornado to happen. In the simplest case which we use here, this signal has a normal distribution with dispersion 1⁸ and a mean depending on actual state of the world. If the state of the world is indeed the state in which a tornado forms, the signal has a higher mean. The difference between signal means in tornadic and non-tornadic state D' measures the forecaster's ability to discriminate between two states of the world.

Brooks (2004) demonstrates how to use the historic performance of tornado warnings to estimate the difference in means D' between the latent signal distribution in tornado and non-tornado states. Brooks and Correia (2018) use the same approach and estimate that in recent years, the performance is consistent with $1 < D' < 1.4$ if the baseline probability of a tornado conditional on a storm is 10%. We use $D' = 1.35$ on the upper end of this range to reflect improvements in warnings performance in early 2000's and potential improvements due to better satellite data and dual polarization radars in more recent years.

The projected distribution of probabilistic forecasts then comes from Monte-Carlo analysis. We draw $N = 100,000$ binary events ω from the set $\{0, 1\}$ in which 1 is a tornado state emerging with probability $p_0 = 0.1$ and then draw N random signals from the corresponding normal distributions ($N(0, 1), N(D', 1)$). Then we calculate the posterior probability f by using the Bayes formula:

$$f = \frac{p_0 \phi(S; D')}{(p_0 \phi(S; D') + (1 - p_0) \phi(S; 0))}$$

Here $\phi(S; x)$ is a normal distribution density with mean x and $\sigma = 1$ which is calculated when the signal equals S . The formula would never produce certain forecasts, but it can get very close to certain forecasts if the signal's value S is very high.

The resulting distribution of forecast probabilities (3) is concentrated around low-probability events, which follows from both low baseline probability of a tornado and our relatively modest ability to forecast tornados.⁹ Only 2.5% of forecasts predict probabilities above 50%. However, 30% of forecasts predict that chances are above the baseline 10% and 14.5% predict that chances of a tornado are above 20%.

⁸One can always rescale the signal without the loss of generality to get the dispersion to equal one.

⁹It is arguably much harder to forecast a tornado 10 minutes in advance than to forecast rain one hour in advance.

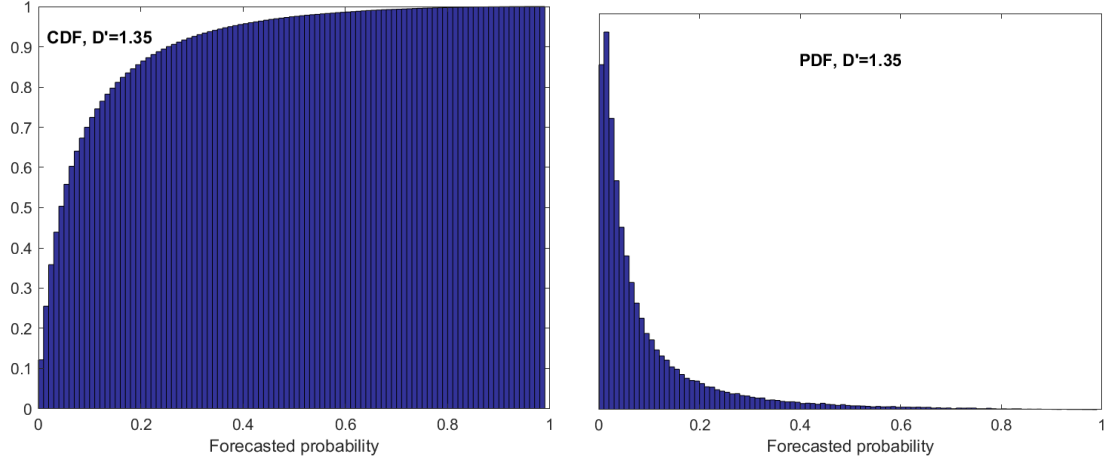


FIG. 3: Projected Distribution of Probabilistic Tornado Forecasts

d. Sheltering Costs

Opportunity costs of sheltering reflect the disutility of sheltering instead of continuing normal activities. It is equal to the product of value of time per total annual number of hours spent sheltering in each scenario. Obviously, value of time depends on activities interrupted and their utility versus the utility of sheltering which can drastically differ both by individual and by time of the day. For example, a person sleeping in their basement do not have to interrupt this activity for sheltering and hence has exactly zero value of time for sheltering. In contrast, a person working at home in an unsafe location might need to stop working which either reduces their earnings roughly by wage rate per hour or reduces their remaining leisure time.

The total number of hours spent sheltering equals the number of people warned during a typical year P_w multiplied by the average duration of warnings. We use the following formula to calculate the expected annual population warned P_w for deterministic warnings:¹⁰

$$P_w = N_w \times A_w \times d$$

We again follow Howard et al. (2021) in using the average warning area $A_w = 275$ sq. miles and the average number of $N_w = 2063$ warnings per year. The population warned for probabilistic warnings is adjusted proportional to the ratio of current probability of event in deterministic forecasts to their average probability of event properly adjusted for area. Our survey describes a positive event as a

¹⁰We count one person multiple times if he/she receives multiple warnings during the year.

345 tornado within 10 miles of the house or closer which corresponds to a slightly larger area (314 sq.
346 miles) than the average area of deterministic impact-based warning, so the adjustment increases
347 the population warned in probabilistic forecasts by a factor of $1.14=314/275$ even before adjusting
348 for probabilities.

349 Because paid work is one of the main activities conducted by working adults, the wage rate
350 provides a natural benchmark for the value of time. However, multiple studies find that even for
351 working adults the value of time is significantly lower than their wage rate. For example, Larson
352 et al. (2004) find that the value of time varies from 0.5 for adults with fixed week to 0.8 for adults
353 with flexible workweek. Wolff (2014) put the value of time as 50% of the wage rate based on the
354 analysis of speeding tickets and gasoline consumption. Given the large proportion of individuals
355 out of labor force in our sample, we use 1/3 of the average wage rate to value the sheltering time.
356 The average civilian non-farm wage was equal to \$29.35 in 2020. It corresponds to our opportunity
357 cost of sheltering time of \$9.8 per hour.

358 Most value for probabilistic warnings comes from heterogeneity of their users in terms of costs
359 of sheltering versus safety concerns. Probabilistic warnings allow rational sheltering decisions
360 based on individual cost-benefit analysis with respect to predicted probabilities. For example, a
361 person in a well-protected house might decide against sheltering if the probability is 20%, but will
362 shelter when the probability increases to 60%.

Our alternative calculation of direct costs of tornado warnings accounts for heterogeneous opportunity costs of sheltering. We infer heterogeneous opportunity costs from protective responses reported in the survey similarly to the approach used for firms in Howard et al. (2021). Subjects report their protective response for each probability of a tornado p which allows us to infer their opportunity costs in the following way. First, for each probability level p , not sheltering imposes a certain increase in fatality risk $c(p)$ which we value similarly by using the value of statistical life approach. We calculate the cost of fatality risk $c(p)$ as the product of tornado probability p , baseline fatality risk r , the efficiency of mitigation measures $(1 - m)$, and the value of statistical life VSL :

$$c(p) = p \cdot r \cdot (1 - m) \cdot VSL$$

363 Next, we assume that individuals switching from not sheltering to sheltering at probability p do
364 so because their opportunity costs of sheltering start to exceed the fatality costs of not sheltering

$c(p)$. In other words, we assume that individuals behave consistently with cost-benefit analysis and successfully evaluate their fatality risks. If an individual does not shelter in response to the forecast with the probability p_1 and associated costs $c(p_1)$, but does so when the probability increases to the level $p_2 > p_1$, then the individual's latent opportunity costs of time c_o should be in between these two costs: $c(p_1) \leq c_o \leq c(p_2)$. This gives a range of plausible opportunity costs for each group of subjects with identical probabilistic thresholds. The upper estimate comes from the assumption that individuals switching when probability increases from p_1 to p_2 have opportunity costs based on higher probability p_2 . The lower bound estimate uses the lower probability p_1 to calculate sheltering costs and does so for each probability range. The true value of sheltering costs for each group has to lie somewhere in between higher and lower bounds. Using the largest value of the range of plausible opportunity costs produces more conservative estimates of tornado warnings' value. It also eliminates the need of inferring zero opportunity costs for subjects protecting for the lowest possible probability of 20%. However, we also show calculation of opportunity costs under the lower bound approach. We assign the probability 0.0463 as the risk for the lowest group which corresponds to the average tornado probability conditional on having a storm and on the probabilistic forecast being below 20%.

TABLE 2: Distribution of Opportunity Costs

Housing	Population share (%)	Value of Time (USD per hour)	
		Lower est.	Upper est.
Permanent	58.43	0.78	3.35
	21.09	3.35	6.71
	11.06	6.71	10.06
	3.69	10.06	13.41
	0.45	10.06	16.76
	5.31	16.76	>16.76
Mobile	17.69	8.87	38.31
	9.61	38.31	76.62
	9.22	76.62	114.93
	5.00	114.93	153.24
	10.95	114.93	191.55
	47.5	191.55	>191.55

381 The calculated sheltering costs (see Table 2) are comparable to the uniform sheltering costs
382 which we took at 1/3 of the median wage rate or 9.8 USD per hour. Note that the calculation of
383 heterogeneous sheltering costs uses only reported decision and not wage rates. It demonstrates
384 that most individuals neither overreact nor underreact to predicted tornado risks with protection
385 decisions being highly consistent with other domains used to estimate the Value of Statistical Life.
386 The lowest opportunity cost of sheltering for permanent home residents is just 3.35 USD per hour if
387 using the upper bound approach and 0.8 USD if using the lower bound approach. The second group
388 of permanent homes residents which switches to protection when the risk goes from 20% to 40%
389 has sheltering costs between 3.35-6.71 USD range. The average sheltering costs is between 3.2 to
390 5.9 USD for permanent home residents and between 126 to 144 USD for mobile home residents.¹¹
391 Higher sheltering costs for mobile home residents reflect both limited protection options and their
392 higher efficiency: the only realistic protection plan involves moving to a closest sturdy shelter or
393 out of the tornado path.

394 We assume that everyone taking a shelter or evacuating stops their normal activities exactly for
395 the duration of tornado warning. The average warning duration has been decreasing since early
396 2000's. For this reason, we use the latest number available from Brooks and Correia (2018). The
397 latest year they cover is 2015 with the corresponding average duration of 37.5 minutes. We also
398 assume that people choosing to collect more information without sheltering do not bear any time
399 costs. Checking information sources most frequently mentioned in the survey (cell phone apps,
400 Internet) requires relatively little time or can be done without interrupting normal activities. While
401 we assume that these individuals would eventually shelter if they happen to be in a strike zone, the
402 average strike zone area is negligible relative to the average warning area.

403 5. Results

404 While our calculation does not aim to provide accurate forecasts of total tornado fatalities and
405 injuries in the US, it is important to match the scale of potential casualties to receive an unbiased
406 estimate of total cost savings and we do it reasonably well. Our predicted tornado casualties with
407 deterministic warnings (around 50 fatalities per year) are similar to historic rates. For comparison,

¹¹Some individuals do not expect to shelter for any projected risk. The calculation of average sheltering costs when assumes that their opportunity costs correspond to 100% probability of a tornado. As this group never protects, their presence has no effect on total sheltering costs for any type of warning.

408 on average tornadoes were killing 78 people in the US per year in 1980 - 2019, and this number
409 included people killed outside of their residencies.

410 The calculation presented at Table 3 indicates that deterministic warnings save roughly 15-20
411 lives per year, not accounting for victims outside and in places of work. We expect that probabilistic
412 warnings would on average save additional seven lives per year. This effect comes from many people
413 starting to react to warnings when the forecast probability is still below the threshold required to
414 issue deterministic warnings. The reduction in injuries is proportional to the reduction in fatalities
415 as consistent with our assumptions.

416 The decrease in fatalities and injuries translates into significant monetary gains from both standard
417 and probabilistic warnings if we use the statistical value of life or injury to value casualties. The
418 total casualty cost of tornadoes without warnings is \$871 million per year. Deterministic warnings
419 reduce costs of casualties by more than \$200 million. Probabilistic warnings additionally reduce
420 costs of casualties by almost \$90 million per year.

421 Accounting for the opportunity costs of sheltering time obviously decreases the net societal value
422 of deterministic warnings, but it is still fairly large. The net benefit of deterministic warnings is
423 approximately \$78 million per year under the assumption of uniform opportunity costs and \$143
424 million per year under the assumption of heterogeneous opportunity costs. The assumption of
425 heterogeneity of opportunity costs matters because it implies that only users with lower opportunity
426 costs take shelter in response to warnings if their costs are lower than the average risk implied
427 by the deterministic warning. We find that even for the deterministic warnings the benefit of
428 reduced casualties outweighs additional opportunity costs of sheltering. This observation is true
429 both for uniform and heterogeneous opportunity costs. However, their net effect on societal costs is
430 relatively modest. In contrast, Simmons and Sutter (2013) find that the societal costs of tornadoes
431 calculated for the constant population and constant value of statistical life and injury go down by
432 around 6 billion USD between 1925 and 2000. Their approach is very similar to ours as they also
433 account for value of statistical lives lost and opportunity costs of time. However, the enormous
434 change in tornado casualties which stands behind this large change in societal costs, does not
435 necessarily comes from tornado warnings. The calculation also seems to use an inflated baseline
436 due to the most deadly and extremely strong Tri-State tornado event happening at the beginning

TABLE 3: Societal Costs by Tornado Warning Approach

Uniform opportunity costs			
	No warning	Deterministic	Probabilistic
Expected fatalities	68.5	49.6	42.2
Expected injuries	976	607	569
Cost of fatalities (mln USD)	763	552	469
Cost of injuries (mln USD)	109	67.6	63.3
Opport. cost of time (mln USD)	0	156.5	164.8
Total costs (mln USD)	871	776	697.6
Heterogeneous opportunity costs (upper est.)			
	No warning	Deterministic	Probabilistic
Expected fatalities	68.5	49.6	42.2
Expected injuries	976	606.98	569
Cost of fatalities (mln USD)	763	551.94	469
Cost of injuries (mln USD)	109	67.6	63
Opport. cost of time (mln USD)	0	112	60
Total costs (mln USD)	871	728	590
Heterogeneous opportunity costs (lower est.)			
	No warning	Deterministic	Probabilistic
Expected fatalities	68.5	49.6	42.2
Expected injuries	976	606.98	569
Cost of fatalities (mln USD)	763	551.94	469
Cost of injuries (mln USD)	109	67.6	63
Opport. cost of time (mln USD)	0	28.4	19.7
Total costs (mln USD)	871	648	552.5

437 of this period. This period also saw improvements in building quality, better healthcare and more
 438 awareness of tornado protective strategies.

439 Probabilistic warnings further reduce societal costs of tornadoes. Most of this effect comes
 440 from reducing tornado fatalities and casualties. This safety increase has a downside as more
 441 people start sheltering, but as long as decisions to shelter respond rationally to actual opportunity
 442 costs, probabilistic warnings would also reduce the societal costs of sheltering. We estimate that
 443 probabilistic warnings would provide net benefit¹² of \$70 million per year if assuming uniform

¹²Not accounting for technological costs: research and development and additional training of meteorologists.

444 opportunity costs of time and \$138 million if accounting for costs heterogeneity.¹³ The large
445 discrepancy between value calculated for uniform and heterogeneous costs shows that most value
446 of probabilistic warnings comes from more nuanced sheltering decisions. When forecasters predict
447 a very high chance of a tornado, most individuals expect to take shelter, but when the predicted
448 chance is low, only people with easy access to shelter or no important competing activities do.

449 **6. Conclusion**

450 We evaluate the benefits of deterministic and probabilistic tornado warnings by asking potential
451 users about their behavioral responses. Based on individual responses, we predict lives saved and
452 hours of sheltering time and convert them into monetary terms. This work requires evaluating the
453 effectiveness of protective responses and the effectiveness of future probabilistic forecasts.

454 We find that both deterministic and projected probabilistic tornado warnings deliver significant
455 positive net benefits for the US. Deterministic tornado warnings save around 20 lives per year
456 and create around 80-140 million USD of net societal benefit. Probabilistic warnings additionally
457 increase this benefit by another 70-140 million USD per year. We estimate that most probabilistic
458 forecasts will involve low tornado probabilities. Hence the benefit of probabilistic forecasts emerges
459 mostly because warnings issued for probabilities below deterministic threshold save additional lives.
460 In addition, probabilistic warning also reduce sheltering of individuals with high sheltering costs
461 when projected probabilities are low which reduces the total cost of time spent sheltering.

462 Our calculation of societal benefits of tornado alerts does not account for other potential psy-
463 chological benefits of tornado warnings. For example, the laboratory experiment conducted by
464 Eliaz and Schotter (2010) demonstrates that people are willing to pay for information not used
465 in decision-making if this information helps to evaluate previously made decisions. In a similar
466 vein, the model of Golman et al. (2021) postulates that people want to get information to fill their
467 information gaps. In addition, many people derive value from public goods only due to their use
468 to others ("non-use value"). For these reasons, our estimate of societal benefits should be treated
469 as a lower bound, while the real value might be significantly higher. But it is important that even

¹³We use the upper bound estimate of sheltering costs to get a more conservative estimate of net societal benefits.

470 the calculated benefits seems large enough to justify the costs of developing and implementing
471 probabilistic tornado warnings.

472 High calculated benefits of probabilistic warnings points to the need for further research work on
473 their optimal design. While this is already an active research area, it still might benefit from more
474 experimental studies using their actual implementations instead of hypotheticals. Using actual
475 technologies would allow to elicit unbiased users' preferences between different systems as well as
476 track their usage over time, geography and weather events. This amazing research becomes much
477 easier due to proliferation of mobile devices and increasing mobile connection speeds.

478 *Acknowledgments.* This work was supported by NOAA/Office of Oceanic and Atmospheric Re-
479 search under NOAA–University of Oklahoma Cooperative Agreement NA16OAR4320115, U.S.
480 Department of Commerce.

481 *Data availability statement.* The anonymized survey data is and the code used to process it is
482 available at https://github.com/AlUgarov/Benefits_ProbWarnings.

Additional Tables

TABLE A1: Tornado-prone States (Sampling Frame Structure)

N	State	Incidence rate, F2- F5 tornadoes per 100 sq. miles	Injuries	Fatalities	Population
1	Oklahoma	1.41	6,173	469	3,943,079
2	Mississippi	1.35	8,163	658	2,986,530
3	Alabama	1.25	8,782	777	4,887,871
4	Indiana	1.24	4,827	303	6,691,878
5	Arkansas	1.18	5,515	405	3,013,825
6	Iowa	1.11	2,197	85	3,156,145
7	Illinois	1.01	4,519	217	12,741,080
8	Louisiana	0.93	3,148	210	4,659,978
9	Tennessee	0.90	4,089	349	6,770,010
10	Kansas	0.88	3,095	275	2,911,505
11	Kentucky	0.79	3,998	224	4,468,402
12	Missouri	0.76	4,766	419	6,126,452
13	Georgia	0.70	3,950	223	10,519,475
14	Ohio	0.67	5,064	259	11,689,442
15	Delaware	0.63	24	2	967,171
16	Florida	0.63	2,743	154	21,299,325
17	Wisconsin	0.62	1,363	100	5,813,568
18	South Carolina	0.62	1,762	70	5,084,127
19	Texas	0.60	10,438	614	28,701,845
20	Nebraska	0.59	1,173	59	1,929,268
Total:		0.85	85,789	5,872	148,360,976
<i>US total:</i>		<i>0.34</i>	<i>100,178</i>	<i>6,652</i>	<i>327,167,434</i>
<i>Percentage (of the US)</i>		<i>248.7%</i>	<i>85.6%</i>	<i>88.3%</i>	<i>45.3%</i>

TABLE A2: Internet Survey Sample

	Good English			Lim. English Hispanics		
	Sample		Popul.	Sample		Popul.
	N	%	%	N	%	%
Male	97	39	49	48	31	47
<35	52	21	30	55	35	21
35-59	97	39	41	87	56	54
60+	98	40	29	14	9	25
No school	0	0	1	6	4	9
Grades 1-12, no HS diploma	11	4	8	21	13	46
HS diploma	54	22	34	48	31	29
Some college	56	23	26	21	13	7
Associate or bachelor's degree	76	31	20	50	32	6
Advanced degree	50	20	11	10	6	2
White	197	80	77	88	56	74
Black	28	11	16	6	4	1
Asian	6	2	3	1	1	0
Native American	2	1	1	2	1	1
Other	6	2	2	56	36	23
Mixed	8	3	2	3	2	1

Additional Graphs (Internet Sample)

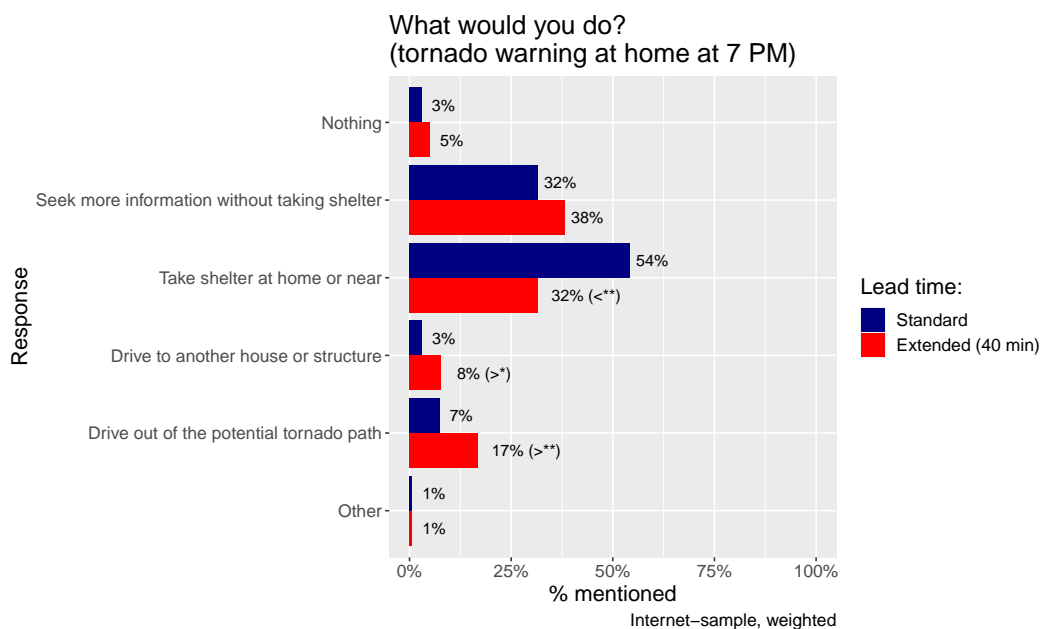


FIG. B1: Protective Response by Lead Time (Internet-sample)

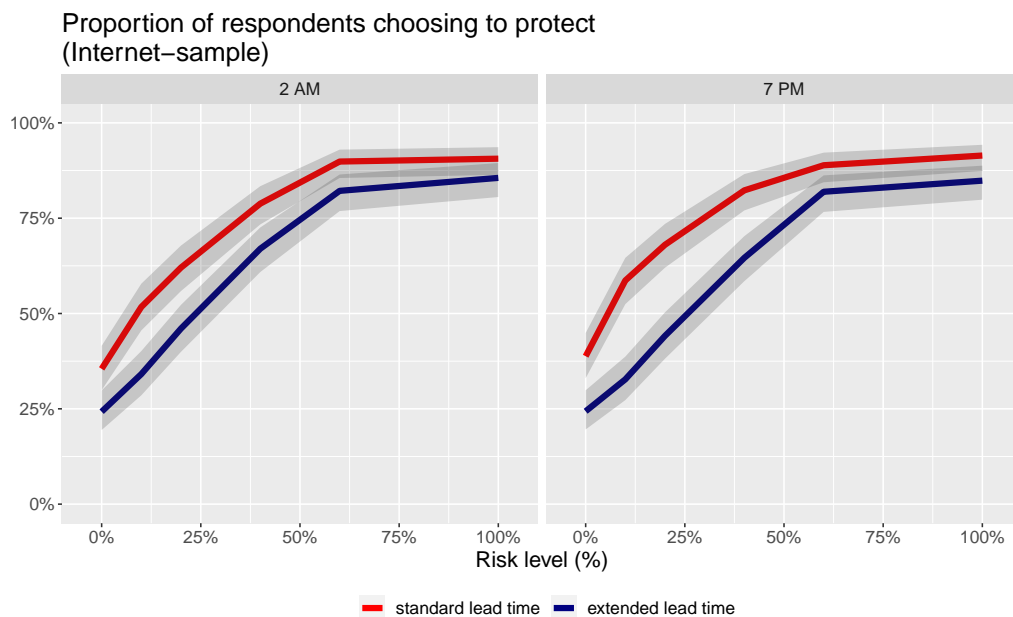


FIG. B2: Protective Response by Probability of a Tornado (Internet sample)

References

- Ash, K. D., R. L. Schumann, and G. C. Bowser, 2014: Tornado Warning Trade-Offs: Evaluating Choices for Visually Communicating Risk. *Weather, Climate, and Society*, **6** (1), 104–118, <https://doi.org/10.1175/WCAS-D-13-00021.1>, URL https://journals.ametsoc.org/view/journals/wcas/6/1/wcas-d-13-00021_1.xml, publisher: American Meteorological Society Section: Weather, Climate, and Society.
- Blumenschein, K., G. C. Blomquist, M. Johannesson, N. Horn, and P. Freeman, 2008: Eliciting Willingness to Pay Without Bias: Evidence from a Field Experiment. *The Economic Journal*, **118** (525), 114–137, <https://doi.org/10.1111/j.1468-0297.2007.02106.x>, URL <https://doi.org/10.1111/j.1468-0297.2007.02106.x>.
- Brooks, H. E., 2004: TORNADO-WARNING PERFORMANCE IN THE PAST AND FUTURE: A Perspective from Signal Detection Theory. *Bulletin of the American Meteorological Society*, **85** (6), 837–844, <https://doi.org/10.1175/BAMS-85-6-837>, URL <https://journals.ametsoc.org/view/journals/bams/85/6/bams-85-6-837.xml>, publisher: American Meteorological Society Section: Bulletin of the American Meteorological Society.
- Brooks, H. E., and J. Correia, 2018: Long-Term Performance Metrics for National Weather Service Tornado Warnings. *Weather and Forecasting*, **33** (6), 1501–1511, <https://doi.org/10.1175/WAF-D-18-0120.1>, URL https://journals.ametsoc.org/view/journals/wefo/33/6/waf-d-18-0120_1.xml, publisher: American Meteorological Society Section: Weather and Forecasting.
- Daley, W. R., S. Brown, P. Archer, E. Kruger, F. Jordan, D. Batts, and S. Mallonee, 2005: Risk of Tornado-related Death and Injury in Oklahoma, May 3, 1999. *American Journal of Epidemiology*, **161** (12), 1144–1150, <https://doi.org/10.1093/aje/kwi142>, URL <https://doi.org/10.1093/aje/kwi142>.
- Dillman, D. A., J. D. Smyth, and L. M. Christian, 2008: *Internet, Mail, and Mixed-Mode Surveys: The Tailored Design Method*. 3rd ed., Wiley, Hoboken, N.J.
- Eliasz, K., and A. Schotter, 2010: Paying for confidence: An experimental study of the demand for non-instrumental information. *Games and Economic Behavior*, **70** (2), 304–324,

515 <https://doi.org/10.1016/j.geb.2010.01.006>, URL <https://www.sciencedirect.com/science/article/pii/S0899825610000229>.

517 Golman, R., G. Loewenstein, A. Molnar, and S. Saccardo, 2021: The Demand for, and Avoid-
518 ance of, Information. SSRN Scholarly Paper ID 2149362, Social Science Research Network,
519 Rochester, NY. <https://doi.org/10.2139/ssrn.2149362>, URL [https://papers.ssrn.com/abstract=](https://papers.ssrn.com/abstract=2149362)
520 2149362.

521 Hammer, B., and T. W. Schmidlin, 2002: Response to Warnings during the 3 May
522 1999 Oklahoma City Tornado: Reasons and Relative Injury Rates. *Weather and Fore-*
523 *casting*, **17** (3), 577–581, [https://doi.org/10.1175/1520-0434\(2002\)017<0577:RTWDTM>2.0.](https://doi.org/10.1175/1520-0434(2002)017<0577:RTWDTM>2.0.CO;2)
524 CO;2, URL [https://journals.ametsoc.org/view/journals/wefo/17/3/1520-0434_2002_017_0577_](https://journals.ametsoc.org/view/journals/wefo/17/3/1520-0434_2002_017_0577_rtwdtm_2_0_co_2.xml)
525 [rtwdtm_2_0_co_2.xml](https://journals.ametsoc.org/view/journals/wefo/17/3/1520-0434_2002_017_0577_rtwdtm_2_0_co_2.xml), publisher: American Meteorological Society Section: Weather and Fore-
526 casting.

527 Howard, S. P., K. E. Klockow-McClain, A. P. Boehmer, and K. M. Simmons, 2021:
528 Firm Behavior in the Face of Severe Weather: Economic Analysis between Prob-
529 abilistic and Deterministic Warnings. *Weather and Forecasting*, **36** (3), 757–767,
530 <https://doi.org/10.1175/WAF-D-20-0107.1>, URL [https://journals.ametsoc.org/view/journals/](https://journals.ametsoc.org/view/journals/wefo/aop/WAF-D-20-0107.1/WAF-D-20-0107.1.xml)
531 [wefo/aop/WAF-D-20-0107.1/WAF-D-20-0107.1.xml](https://journals.ametsoc.org/view/journals/wefo/aop/WAF-D-20-0107.1/WAF-D-20-0107.1.xml), publisher: American Meteorological So-
532 ciety Section: Weather and Forecasting.

533 Johnston, R. J., and Coauthors, 2017: Contemporary Guidance for Stated Preference Stud-
534 ies. *Journal of the Association of Environmental and Resource Economists*, **4** (2), 319–
535 405, <https://doi.org/10.1086/691697>, URL [https://www.journals.uchicago.edu/doi/abs/10.1086/](https://www.journals.uchicago.edu/doi/abs/10.1086/691697)
536 691697, publisher: The University of Chicago Press.

537 Klockow, K., 2011: *Investigation of individual spatial awareness relating to response during the*
538 *April 27, 2011 tornado outbreak*. Natural Hazards Center.

539 Kniesner, T. J., and W. K. Viscusi, 2019: The Value of a Statistical Life. SSRN Scholarly Paper
540 ID 3379967, Social Science Research Network, Rochester, NY. [https://doi.org/10.2139/ssrn.](https://doi.org/10.2139/ssrn.3379967)
541 3379967, URL <https://papers.ssrn.com/abstract=3379967>.

- Krocak, M. J., J. T. Ripberger, S. Ernst, C. L. Silva, and H. C. Jenkins-Smith, 2022: Exploring the Differences in SPC Convective Outlook Interpretation Using Categorical and Numeric Information. *Weather and Forecasting*, **37** (2), 303–311, <https://doi.org/10.1175/WAF-D-21-0123.1>, URL <https://journals.ametsoc.org/view/journals/wefo/37/2/WAF-D-21-0123.1.xml>, publisher: American Meteorological Society Section: Weather and Forecasting.
- Larson, D. M., S. L. Shaikh, and D. F. Layton, 2004: Revealing Preferences for Leisure Time from Stated Preference Data. *American Journal of Agricultural Economics*, **86** (2), 307–320, <https://doi.org/10.1111/j.0092-5853.2004.00580.x>, URL <http://onlinelibrary.wiley.com/doi/abs/10.1111/j.0092-5853.2004.00580.x>, eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.0092-5853.2004.00580.x>.
- Lazo, J., and D. Waldman, 2011: Valuing improved hurricane forecasts. *Economics Letters*, **111**, 43–46, <https://doi.org/10.1016/j.econlet.2010.12.012>.
- Lazo, J. K., and L. G. Chestnut, 2002: Economic Value of Current and Improved Weather Forecasts in the U.S. Household Sector. Tech. rep., Office of Policy and Strategic Planning. URL <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.170.7648&rep=rep1&type=pdf>.
- Lazo, J. K., R. E. Morss, and J. L. Demuth, 2009: 300 BILLION SERVED: Sources, Perceptions, Uses, and Values of Weather Forecasts. *Bulletin of the American Meteorological Society*, **90** (6), 785–798, URL <https://www.jstor.org/stable/26220993>, publisher: American Meteorological Society.
- LeClerc, J., and S. Joslyn, 2015: The Cry Wolf Effect and Weather-Related Decision Making. *Risk Analysis*, **35** (3), 385–395, <https://doi.org/10.1111/risa.12336>, URL <https://onlinelibrary.wiley.com/doi/abs/10.1111/risa.12336>, eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1111/risa.12336>.
- Lindell, M. K., S.-K. Huang, H.-L. Wei, and C. D. Samuelson, 2016: Perceptions and expected immediate reactions to tornado warning polygons. *Natural Hazards*, **80** (1), 683–707, <https://doi.org/10.1007/s11069-015-1990-5>, URL <https://doi.org/10.1007/s11069-015-1990-5>.
- Liu, S., L. E. Quenemoen, J. Malilay, E. Noji, T. Sinks, and J. Mendlein, 1996: Assessment of a severe-weather warning system and disaster preparedness, Calhoun County, Alabama, 1994.

570 *American Journal of Public Health*, **86** (1), 87–89, URL [https://www.ncbi.nlm.nih.gov/pmc/](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC1380369/)
571 [articles/PMC1380369/](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC1380369/).

572 Miran, S. M., C. Ling, J. J. James, A. Gerard, and L. Rothfusz, 2017: User perception and
573 interpretation of tornado probabilistic hazard information: Comparison of four graphical designs.
574 *Applied Ergonomics*, **65**, 277–285, <https://doi.org/10.1016/j.apergo.2017.06.016>, URL <https://www.sciencedirect.com/science/article/pii/S0003687017301497>.
575

576 Morss, R. E., J. L. Demuth, and J. K. Lazo, 2008: Communicating Uncertainty in Weather
577 Forecasts: A Survey of the U.S. Public. *Weather and Forecasting*, **23** (5), 974–991,
578 <https://doi.org/10.1175/2008WAF2007088.1>, URL [https://journals.ametsoc.org/view/journals/](https://journals.ametsoc.org/view/journals/wefo/23/5/2008waf2007088_1.xml)
579 [wefo/23/5/2008waf2007088_1.xml](https://journals.ametsoc.org/view/journals/wefo/23/5/2008waf2007088_1.xml), publisher: American Meteorological Society Section:
580 Weather and Forecasting.

581 Morss, R. E., J. K. Lazo, and J. L. Demuth, 2010: Examining the use of weather fore-
582 casts in decision scenarios: results from a US survey with implications for uncertainty
583 communication. *Meteorological Applications*, **17** (2), 149–162, [https://doi.org/https://doi.org/](https://doi.org/https://doi.org/10.1002/met.196)
584 [10.1002/met.196](https://doi.org/https://doi.org/10.1002/met.196), URL <https://rmets.onlinelibrary.wiley.com/doi/abs/10.1002/met.196>, eprint:
585 <https://rmets.onlinelibrary.wiley.com/doi/pdf/10.1002/met.196>.

586 Murphy, A. H., 1993: What Is a Good Forecast? An Essay on the Nature of Good-
587 ness in Weather Forecasting. *Weather and Forecasting*, **8** (2), 281–293, [https://doi.org/10.](https://doi.org/10.1175/1520-0434(1993)008<0281:WIAGFA>2.0.CO;2)
588 [1175/1520-0434\(1993\)008<0281:WIAGFA>2.0.CO;2](https://doi.org/10.1175/1520-0434(1993)008<0281:WIAGFA>2.0.CO;2), URL [https://journals.ametsoc.org/view/](https://journals.ametsoc.org/view/journals/wefo/8/2/1520-0434_1993_008_0281_wiagfa_2_0_co_2.xml)
589 [journals/wefo/8/2/1520-0434_1993_008_0281_wiagfa_2_0_co_2.xml](https://journals.ametsoc.org/view/journals/wefo/8/2/1520-0434_1993_008_0281_wiagfa_2_0_co_2.xml), publisher: American Me-
590 teorological Society Section: Weather and Forecasting.

591 Niederkrötenhaler, T., and Coauthors, 2013: Injuries and Post-Traumatic Stress following His-
592 toric Tornadoes: Alabama, April 2011. *PLOS ONE*, **8** (12), e83 038, [https://doi.org/10.1371/](https://doi.org/10.1371/journal.pone.0083038)
593 [journal.pone.0083038](https://doi.org/10.1371/journal.pone.0083038), URL [https://journals.plos.org/plosone/article?id=10.1371/journal.pone.](https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0083038)
594 [0083038](https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0083038), publisher: Public Library of Science.

595 Papastavrou, J. D., and M. R. Lehto, 1996: Improving the effectiveness of warnings by increasing
596 the appropriateness of their information content: some hypotheses about human compliance.
597 *Safety Science*, **21** (3), 175–189, [https://doi.org/10.1016/0925-7535\(95\)00060-7](https://doi.org/10.1016/0925-7535(95)00060-7), URL <https://www.sciencedirect.com/science/article/pii/0925753595000607>.
598

599 Paul, B. K., M. Stimers, and M. Caldas, 2015: Predictors of compliance with tornado
600 warnings issued in Joplin, Missouri, in 2011. *Disasters*, **39** (1), 108–124, [https://doi.org/](https://doi.org/10.1111/disa.12087)
601 10.1111/disa.12087, URL <http://onlinelibrary.wiley.com/doi/abs/10.1111/disa.12087>, _eprint:
602 <https://onlinelibrary.wiley.com/doi/pdf/10.1111/disa.12087>.

603 Rothfusz, L. P., R. Schneider, D. Novak, K. Klockow-McClain, A. E. Gerard, C. Karstens,
604 G. J. Stumpf, and T. M. Smith, 2018: FACETs: A Proposed Next-Generation Paradigm for
605 High-Impact Weather Forecasting. *Bulletin of the American Meteorological Society*, **99** (10),
606 2025–2043, <https://doi.org/10.1175/BAMS-D-16-0100.1>, URL [https://journals.ametsoc.org/](https://journals.ametsoc.org/view/journals/bams/99/10/bams-d-16-0100.1.xml)
607 [view/journals/bams/99/10/bams-d-16-0100.1.xml](https://journals/bams/99/10/bams-d-16-0100.1.xml), publisher: American Meteorological Soci-
608 ety Section: Bulletin of the American Meteorological Society.

609 Ruggles, S., S. Flood, S. Foster, R. Goeken, J. Pacas, M. Schouweiler, and M. Sobek, 2021: IPUMS
610 USA. Minneapolis, MN: IPUMS, URL <https://usa.ipums.org/usa/>.

611 Schmidlin, T., B. Hammer, Y. Ono, and P. King, 2009: Tornado shelter-seeking behavior and
612 tornado shelter options among mobile home residents in the United States. *Natural Hazards:*
613 *Journal of the International Society for the Prevention and Mitigation of Natural Hazards*,
614 **48** (2), 191–201, URL [https://econpapers.repec.org/article/sprnathaz/v_3a48_3ay_3a2009_3ai_](https://econpapers.repec.org/article/sprnathaz/v_3a48_3ay_3a2009_3ai_3a2_3ap_3a191-201.htm)
615 [3a2_3ap_3a191-201.htm](https://econpapers.repec.org/article/sprnathaz/v_3a48_3ay_3a2009_3ai_3a2_3ap_3a191-201.htm), publisher: Springer.

616 Sherman-Morris, K., 2010: Tornado warning dissemination and response at a university campus.
617 *Natural Hazards*, **52** (3), 623–638, <https://doi.org/10.1007/s11069-009-9405-0>, URL <https://doi.org/10.1007/s11069-009-9405-0>.

619 Simmons, K., and D. Sutter, 2013: *Economic and Societal Impacts of Tornadoes*. Springer Science
620 & Business Media, google-Books-ID: Icg_AAAAQBAJ.

621 Simmons, K. M., and D. Sutter, 2005: WSR-88D Radar, Tornado Warnings, and
622 Tornado Casualties. *Weather and Forecasting*, **20** (3), 301–310, [https://doi.org/](https://doi.org/10.1175/WAF857.1)
623 10.1175/WAF857.1, URL [https://journals.ametsoc.org/waf/article/20/3/301/38735/](https://journals.ametsoc.org/waf/article/20/3/301/38735/WSR-88D-Radar-Tornado-Warnings-and-Tornado)
624 WSR-88D-Radar-Tornado-Warnings-and-Tornado, publisher: American Meteorological
625 Society.

626 Simmons, K. M., and D. Sutter, 2006: Direct Estimation of the Cost Effectiveness of
 627 Tornado Shelters. *Risk Analysis*, **26** (4), 945–954, [https://doi.org/10.1111/j.1539-6924.](https://doi.org/10.1111/j.1539-6924.2006.00790.x)
 628 2006.00790.x, URL <http://onlinelibrary.wiley.com/doi/abs/10.1111/j.1539-6924.2006.00790.x>,
 629 _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1539-6924.2006.00790.x>.

630 Simmons, K. M., and D. Sutter, 2009: False Alarms, Tornado Warnings, and Tor-
 631 nado Casualties. *Weather, Climate, and Society*, **1** (1), 38–53, [https://doi.org/](https://doi.org/10.1175/2009WCAS1005.1)
 632 10.1175/2009WCAS1005.1, URL [https://journals.ametsoc.org/wcas/article/1/1/38/750/](https://journals.ametsoc.org/wcas/article/1/1/38/750/False-Alarms-Tornado-Warnings-and-Tornado)
 633 False-Alarms-Tornado-Warnings-and-Tornado, publisher: American Meteorological Society.

634 Viscusi, W. K., and J. E. Aldy, 2003: The Value of a Statistical Life: A Critical Review of Market
 635 Estimates Throughout the World. *Journal of Risk and Uncertainty*, **27** (1), 5–76, [https://doi.org/](https://doi.org/10.1023/A:1025598106257)
 636 10.1023/A:1025598106257, URL <https://doi.org/10.1023/A:1025598106257>.

637 Wehde, W., J. T. Ripberger, H. Jenkins-Smith, B. A. Jones, J. N. Allan, and C. L. Silva, 2021:
 638 Public Willingness to Pay for Continuous and Probabilistic Hazard Information. *Natural Haz-*
 639 *ards Review*, **22** (2), 04021 004, [https://doi.org/10.1061/\(ASCE\)NH.1527-6996.0000444](https://doi.org/10.1061/(ASCE)NH.1527-6996.0000444), URL
 640 <https://ascelibrary.org/doi/10.1061/%28ASCE%29NH.1527-6996.0000444>, publisher: Ameri-
 641 can Society of Civil Engineers.

642 Wolff, H., 2014: Value of time: Speeding behavior and gasoline prices. *Journal of Environmental*
 643 *Economics and Management*, **67** (1), 71–88, <https://doi.org/10.1016/j.jeem.2013.11.002>, URL
 644 <https://www.sciencedirect.com/science/article/pii/S009506961300106X>.