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

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ABSTRACT: The National Weather Service is planning to implement the system of probabilistic tornado warnings. In this paper, I estimate and compare the full societal costs of tornadoes with existing deterministic and potential probabilistic warnings. These full costs include the value of statistical lives lost as well as the value of the time spent sheltering. I find that probabilistic tornado warnings would decrease total expected fatalities. The improvement in decision-making would also decrease the total opportunity cost of time spent sheltering, even though the total sheltering time is likely to increase. In total, probabilistic warnings should lower the societal costs of tornadoes relative to deterministic warnings by approximately $76–139 million per year, with a large portion of this improvement coming from fewer casualties.

SIGNIFICANCE STATEMENT: I measure societal benefits of probabilistic and deterministic tornado warnings in the United States by evaluating their effects on expected casualties and sheltering costs. I find that probabilistic warnings deliver almost twice as much net societal benefit as deterministic ones. These gains happen as a result of fewer casualties and making protective behavior more responsive to risks and sheltering costs. This paper provides additional evidence of the need to implement probabilistic extreme weather warnings.

KEYWORDS: Social science; Probability forecasts/models/distribution; Economic value; Risk assessment

1. Introduction

Most people are aware of the grim costs of tornadoes killing dozens of people per year,[1] but fewer know about warnings killing hundreds of thousands of hours in sheltering time. Sheltering is costly because it forces people to reduce time spent on work and leisure. These losses can be plausibly measured in monetary terms; Simmons and Sutter (2013) estimate that tornadoes impose roughly $3–4 billion of annual implicit costs[2] on the U.S. society, and the opportunity cost of sheltering is one of the largest cost components, amounting to $1.3–2.6 billion.

One proposed way to reduce the societal costs of tornadoes is to provide information on the probability of a tornado happening in a location instead of providing deterministic yes/no prediction (Rothfusz et al. 2018). In theory, probabilistic extreme weather warnings give more detailed information to users and enable them to make better decisions (Murphy 1993; Papastavrou and Lehto 1996). Potential users in the United States also demonstrate preference for receiving probabilistic versus deterministic weather forecasts (Morss et al. 2008, 2010). At the same time, probabilistic warnings might reduce the decision quality for some users, and hence, it is not clear a priori whether their potential societal benefits outweigh the additional cost of development and delivery of more sophisticated forecasts.

The main question of this study is to evaluate whether providing probabilistic tornado warnings instead of deterministic ones would benefit U.S. households. It involves measuring the total societal costs of tornadoes, both with deterministic and probabilistic warnings. If probabilistic warnings indeed significantly reduce the societal costs of tornadoes, then their development and implementation should be supported by the government. The second question of this study is to explore the responses to probabilistic warnings, which can help to improve the design of both deterministic and probabilistic warnings.

This paper uses population surveys to calculate the societal benefits of deterministic and probabilistic tornado warnings. The calculation of societal benefits accounts for their effects on fatalities, injuries, and sheltering time. I assign monetary measures to fatalities and injuries by using the value of statistical life (VSL) approach and price the inconveniences of sheltering time based on the concept of opportunity costs of time.

This work involves three steps. First, I conduct a household survey to learn the population's protective responses both to current deterministic tornado warnings and to prospective probabilistic ones. These responses account both for probability levels and for housing types. However, extreme weather alerts do not help if protective responses are ineffective in the sense that they have weak effects on casualty rates. So, in the

[1] https://www.weather.gov/media/pah/Skywarn/TORNADOsafety.pdf.

[2] By implicit costs, I mean those costs that are not paid directly. For example, plumbers stuck in a traffic jam bear implicit costs because they could have earned more if they had worked instead.

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second step, I evaluate the effectiveness 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 the forecasting format to change while keeping the quality of forecasting technology constant.

I calculate that probabilistic tornado warnings should create net annual benefits between $76 and $139 million 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 shelter if and only if their costs of sheltering are below their perceived costs of life or injury. The benefit of probabilistic warnings is calculated relative to deterministic ones, which on their own already create $96–140 million per year of net societal value. This estimate already 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. This supports the idea that potential users correctly deduce their personal risk levels from probabilistic warnings.

In response to probabilistic alerts, more people report being willing to monitor the threat as compared with deterministic warnings, but they expect to shelter when the danger becomes imminent. This leads to more people reacting to probabilistic warnings and eventually more people taking shelter. Hence, probabilistic warnings reduce total casualties, while increasing the total time spent sheltering or monitoring the weather. This increase does not necessarily convert to higher societal costs. If we account for optimal responses to predicted tornado probabilities and deduce opportunity costs from reported protective responses, then the societal value or opportunity cost of sheltering/monitoring time goes down due to a more graduated reaction to probabilistic warnings. Probabilistic warnings deliver this positive effect by enabling users with higher opportunity costs to shelter only if tornado threats are sufficiently high.

This paper contributes to the literature by directly measuring the net benefits of both deterministic and probabilistic tornado warnings for the population. Howard et al. (2021) estimate the value of probabilistic warnings for businesses in the Dallas metropolitan area and find that probabilistic warnings would save an additional $1.3–5.6 billion per year as compared with deterministic warnings. Their calculation does not cover the general population (households), which has very different capabilities to understand and respond to warnings. This paper also significantly improves on their method by using the distribution of probabilistic forecasts, which is more consistent with existing forecasters' skills. Simmons and Sutter (2013) calculate societal costs of tornadoes for the general population but do not study the value of probabilistic warnings. They estimate that the contemporary costs are roughly $6 billion lower than the hypothetical costs with tornado lethality at the 1925 U.S. level, when warnings were nonexistent. However, this reduction in costs cannot be completely attributed to the effect of deterministic tornado warnings due to other safety improvements happening during this period. This paper takes a more conservative approach to estimate the benefits of both deterministic and probabilistic warnings by accounting for imperfect compliance with warnings and by calculating their effectiveness directly from the variation in casualties between warned and nonwarned populations.

In contrast to my approach, multiple other studies evaluate weather information (Lazo and Chestnut 2002; Lazo et al. 2009; Lazo and Waldman 2011; Wehde et al. 2021) with the contingent valuation method, in which potential users directly report their willingness to pay for the service. The only published valuation study of probabilistic tornado warnings for the population, that by Wehde et al. (2021), falls into this category. It finds that the U.S. population is willing to pay on average $7.5 per person for an app providing probabilistic graphical tornado alerts. This price translates to a one-time aggregate benefit between $900 million and $1.56 billion depending on the aggregation assumptions used. While contingent valuation studies can potentially reflect additional benefits of information, such as peace of mind or the increased safety of others, they suffer from a hypothetical bias emerging due to respondents deliberately overstating their willingness to pay (Blumenschein et al. 2008; Johnston et al. 2017). As a result, contingent valuation studies often provide excessively high and varying estimates of economic benefits. Hence, my direct approach gives an important and more reliable lower bound of the new system's value.

My study supports the conclusion that the U.S. population can interpret and use probabilistic warnings. Multiple previous studies (Ash et al. 2014; Lindell et al. 2016; Miran et al. 2017) have tested perception and hypothetical responses to the graphical representation of probabilistic severe weather alerts. In general, they have found that people increase protection in response to increasing threat probabilities, even though presentation formats have a strong influence both on average response levels and on the sensitivity of response to presented probabilities. Additionally, LeClerc and Joslyn (2015) find that probabilistic information improves decision-making and reduces the "cry wolf" effect, whereas Krocak et al. (2022) find that probabilistic information allows for better decision-making when compared with categorical verbal descriptions of uncertainty. I find that protective responses are sensitive to projected probabilities, but also that response levels are well calibrated to threat levels and consistent with choices made in other domains (such as speeding; Wolff 2014).

2. Survey design and implementation

a. Data collection

I collect the data from two samples. The mail survey recruited respondents across the whole United States but with an emphasis on tornado-prone regions (see Table 1, along with Table A1 in appendix A). Respondents could choose to

TABLE 1. Mail survey sample.

	Tornado-prone states			Other states		
	Sample No.	Sample %	Population %	Sample No.	Sample %	Population %
Male	227	43	49	31	39	48
<35 yr old	43	8	30	7	9	30
35–59 yr old	231	45	41	38	49	41
60+ yr old	240	47	29	33	42	29
No school	5	1	2	1	1	1
Grades 1–12, no high school diploma	9	2	8	2	2	9
High school 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

respond by mail by using an enclosed envelope or to fill out the survey online. The internet survey recruited participants from the tornado-prone regions only. The use of different sampling methods allowed for a wider representation of different demographic groups. The mail survey reached more older respondents living in rural communities, while the internet survey helped to get answers from younger respondents. I received 718 responses from the mail survey and 403 responses from the internet survey. Questionnaires were practically identical, except for small changes needed to screen respondents in the internet survey.

The mail survey uses stratified probabilistic sampling to get a more representative sample, which allows the use of statistical tests. My initial frame comes from the U.S. Postal Service delivery route database. I stratify the sampling frame by state of residence and by housing type and sample 10 600 addresses, with more addresses from tornado-prone states. I consider the state to be tornado prone if it belongs to one of 20 states with the highest average incidence of significant tornadoes (EF2 and above) per square mile (1 mi ≈ 1.6 km; 1 mi^2 ≈ 2.6 km^2) within the last 20 years. The selected states include 45% of the U.S. population, but 88% of tornado fatalities. This paper uses only the sample obtained from the tornado-prone states.[3]

The questionnaire was pretested, first, by using qualitative personal interviews conducted either in person or over Google Meets and Skype. These interviews helped to clarify the questions' wording and make sure that their interpretation by participants matched my expectations. In the second stage, I conducted quantitative pilots both for the internet sample and for the mail survey.

I pretest our surveys by using, first, qualitative face-to-face[4] interviews and, second, quantitative pilot studies. The qualitative interviews helped to clarify the understanding of questions and refine the lists of response options. The interview followed think-aloud protocols (Dillman et al. 2008) in which respondents read all the questions aloud and vocalize their thinking process. Quantitative pilot studies followed the same procedure I intended to use for the main study, but with smaller samples. I conducted two pilot studies for the internet survey and two pilot studies for the mail survey. The pilots helped to adjust my sampling strategies and redesign a few questions that had turned out to be ambiguous to the participants.

b. *Representativeness and selection bias*

Despite my effort to use different recruiting efforts, both samples had disproportionately more females and more people with a college education or above (see Table 1 along with Table A2 for the internet sample in appendix A). Additionally, the mail survey recruited more older White respondents. Hence, to translate our findings to the U.S. population, I reweight my results to match the U.S. population structure by age and sex.[5]

3. Use of standard and extended tornado alerts

First, I study how extended tornado warnings would affect protective responses. I ask the respondents to imagine being at home with their family at 7:00 p.m. when a tornado warning is issued. Next, I elicit their protective responses conditional on lead time and on probability of a tornado happening within a given time interval. The internet survey asks the same set of questions for the nighttime warnings (2:00 a.m.).[6] Note that individuals can face tornado threats at other times and locations beyond their homes; due to limitations on the number of questions I can include in the study, I focus only on these two scenarios, which I consider to be the most representative. Most respondents choose to respond to a standard tornado warning by taking shelter at home or nearby. The proportion of respondents choosing this action (55%) is surprisingly stable across samples and across times in the same sample (Fig. 1). About 10% of respondents in the internet

[3] I have 100 responses from the other states but decided not to include them because, as evidenced by their open-response comments, many of these respondents have never considered responding to a tornado emergency/heard a warning and, hence, their reported protection plans are unlikely to correlate well with future behavior.

[4] Because of the COVID-19 pandemic, most of the qualitative interviews were conducted online through Zoom, Skype, or Google Meets.

[5] I use the data from the American Community Survey 2018, downloaded from IPUMS (Ruggles et al. 2021).

[6] The mail survey conducted after the internet survey had to drop these questions in an effort to shorten the questionnaire.

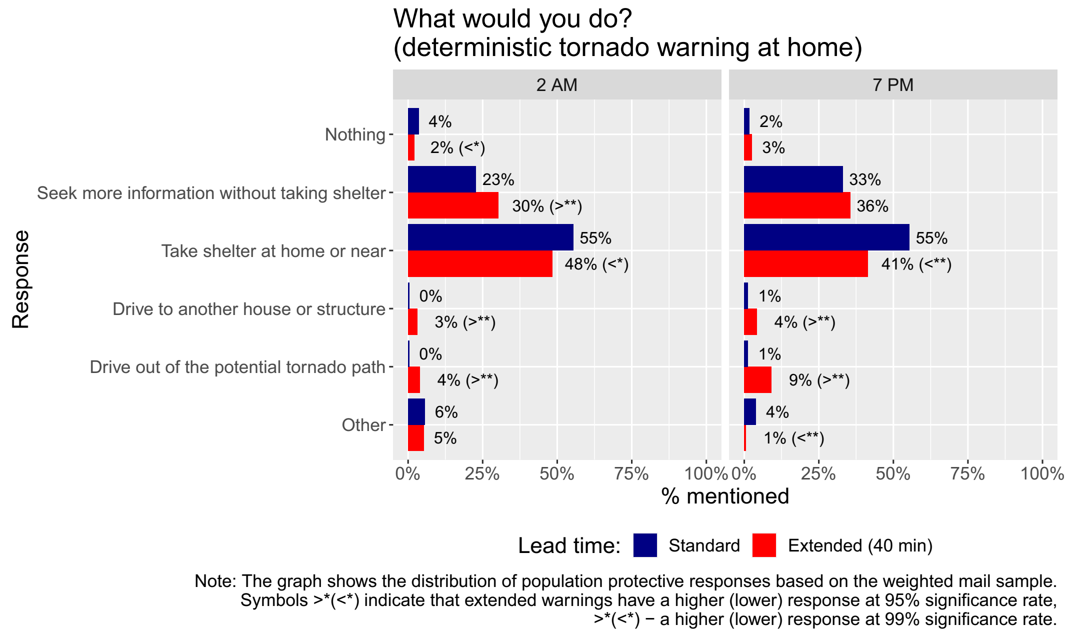

FIG. 1. Protective response by lead time.

sample choose to drive to another house or structure or to drive out of the potential tornado path. This proportion is slightly higher for the internet sample (Fig. B1 in appendix B).

Roughly one-third of respondents expect to seek more information without taking shelter. Here, and in the calculation of effectiveness of probabilistic warnings, I consider seeking more information as one of the protective actions, because previous studies have shown that most people take shelter when they know that the danger is imminent. Hammer and Schmidlin (2002) and Klockow (2011) show that most people in a tornado strike zone take shelter, but fewer people do it in a tornado warning zone (Liu et al. 1996; Sherman-Morris 2010). Because tornado strike zones or paths are much smaller than typical warning areas, residents often prefer to collect information before taking protective actions. For example, Hammer and Schmidlin (2002) surveyed residents in the Oklahoma City, Oklahoma, tornado strike zone and found that 55% received tornado warnings from more than one source, and almost 90% of residents eventually either evacuated or took shelter in interior rooms during the tornado. A household survey in the area of the 2011 Alabama tornado outbreak (Klockow 2011) also found that most people monitored media and that many looked at the sky but started sheltering only when a tornado was 1–2 min away from them.

Increasing lead time to 40 min on its own has practically no effect on the total proportion of people taking any protective action (which includes seeking more information without taking shelter), as more than 90% of individuals do it anyway. However, increasing lead time decreases the likelihood of sheltering at home in favor of seeking more information and evacuating. It is very plausible that extended lead time improves the safety of people in vulnerable housing conditions, such as mobile homes, when evacuation is practically the only effective protection option (Schmidlin et al. 2009). However, 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 alert systems, but its usefulness relies on 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 take protective actions increases with the forecast probability. Almost 100% of respondents expect to take some protective action if they learn that a tornado will happen with 100% probability in the next 40 min in a 10-mi radius from their location. Fewer than 5% of respondents make nonmonotonic choices, meaning that 95% of respondents take protective actions for all probabilities that are higher than their threshold probability.

Most individuals expect to take protective actions when the probability gets to 20%. In the internet survey, 59% of individuals respond when the probability of a tornado within a 10-mi-radius circle is just 10%. In the mail sample, 60% of respondents take protective actions when the probability is 20% (it was the lowest probability in the mail sample). For comparison, my calculations show that the comparable implied probability for the deterministic warning is roughly 35%,[7] so the majority of the population expects to take protective actions for much lower probabilities than the tornado probability

[7] I calculate this number by taking the probability of a tornado conditional on a deterministic warning, which is roughly $1 - \mathrm{FAR} = 0.3$ (Simmons and Sutter 2013), and correcting it upward to reflect a larger area of a 10-mi-radius circle (314.2 mi^2) as compared with the average area of a tornado warning (272 mi^2).

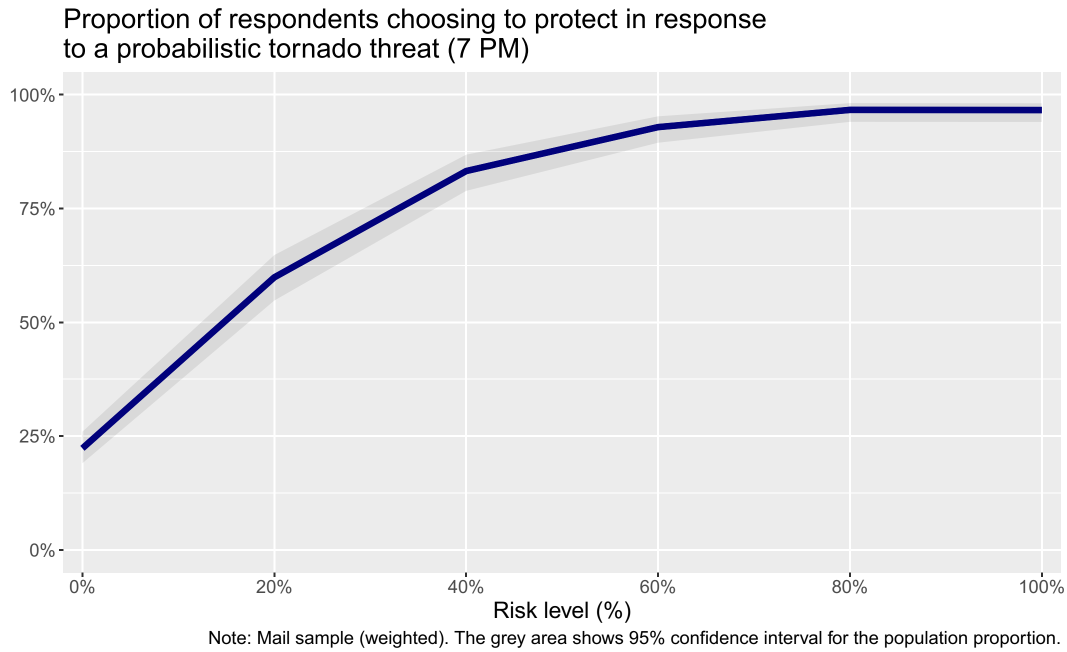

FIG. 2. Protective response by probability of a tornado.

of the deterministic warning. 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 Fig. 2. The reaction threshold is higher for nighttime warnings (see Fig. B2 in appendix B). This is consistent with the higher costs of nighttime protective actions for most respondents, as they potentially require interrupting sleep and driving with poor visibility.

4. Computation of direct societal benefits

a. *Overview of the approach*

I estimate the direct economic benefits of extended tornado warnings as the difference in direct societal costs between standard and extended warnings. Direct societal costs in my calculation include the cost of tornado deaths and injuries and the cost of time spent sheltering (sheltering costs). The calculation uses the surveys to calculate the proportion of the population taking protective actions for each level of the probabilistic forecast. My approach is similar to the approach used by Simmons and Sutter (2013). I convert each of the cost components to a monetary scale. The value of statistical life and the value of statistical injury metrics translate predicted numbers of deaths and injuries into equally undesirable monetary costs. I use the value of time to price the time spent sheltering under both standard and extended tornado alerts. Direct costs of tornadoes are calculated as follows:

$$\text{direct costs} = \text{VSL lost} + \text{value of injuries} + \text{sheltering costs}.$$

The value of statistical life assigns a monetary value to life based on observed tradeoffs between money and small chances of death. Based on a 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. I use a 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 2007 prices, which corresponds to \$9.5 million in 2020 prices. The U.S. 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),[8] which also translates to \$11.2 million in 2020 prices.

I assign monetary value to injuries in a similar fashion. Most tornado injuries are minor, 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 \$111,300 per injury.

The following formula calculates expected injuries and fatalities[9] 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:

$$F_D = P_A r M.$$

[8] https://www.epa.gov/stationary-sources-air-pollution/electric-utility-generating-units-emission-guidelines-greenhouse.

[9] To save on notation, I use the same variable names to denote both expected injuries and expected fatalities. The formulas are identical.

The affected population 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):[10]

$$P_A = N_w A d(1 - \mathrm{FAR})/\mathrm{POD}.$$

The United States issues $N_w = 2063$ warnings per year on average (Howard et al. 2021). The population density in the 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 mi^2. We also use their reported estimates of POD = 0.7 and FAR = 0.7.[11] Based on this calculation, the affected population P_A includes 31 800 people per year.

The baseline fatality or injury rate per person in a strike area r is the probability that a person in a tornado strike zone is respectively killed or injured in a tornado if the person does not take protective actions. The protective mitigation factor M measures the proportional decrease in risk of injury/death from the expected protective response. It depends both on the expected behavior and on the effectiveness of this behavior in reducing the risk. These two variables strongly depend on housing conditions, so I condition my calculation on living in permanent versus mobile homes and weight by corresponding population proportions. I explain the calculation of the baseline fatality and injury rates and the protective response mitigation factors in the next subsection.

I use a similar approach to forecast casualties under probabilistic forecasts, but now I account for different responses to each tornado probability. The total population affected by tornadoes P_A does not change between different forecasting approaches, because the underlying meteorology does not change. However, there are changes in the distribution of forecasts received by the population and hence in their protective actions. I consider probabilistic forecasts with a finite potential number of possible forecasts $i = 1, 2, \ldots, n$. Each forecast i is associated with a forecast probability, denoted by p_i, indicating the likelihood of a tornado occurrence (e.g., $p_i = 0.2$ means a 20% chance of occurrence), and with its frequency f_i. I calculate the expected number of casualties $C(p_i)$ for each predicted probability p_i as the population affected by tornadoes P_A multiplied by the proportion of tornadoes happening within that probabilistic forecast $f_i p_i / \sum_k (f_k p_k)$ and then multiplied also by the baseline risk r and the probability-specific mitigation factor $M(p_i)$:[12]

$$C(p_i) = P_A\left(\frac{f_i p_i}{\sum_k f_k p_k}\right) r M(p_i). \tag{1}$$

The total expected number of casualties C_P for the probabilistic forecast is the sum of casualties $C(p_i)$ for each predicted probability p_i among the possible forecasts:

$$C_P = \sum_{i=1}^{n} C(p_i) = \sum_i \left(\frac{f_i p_i}{\sum_k f_k p_k}\right) P_A r M(p_i). \tag{2}$$

Note that, in the expression above, the denominator $\sum_k (f_k p_k)$ is just a total probability of a tornado conditional on having a forecast. I use the survey's proportion of people taking protective actions for each probability to calculate the probability-specific mitigation factor.[13] As before, for the protective response, I assume that people who report needing to collect more information will eventually shelter before a tornado.

b. *Protective response effectiveness*

Protective response mitigation factor M measures the proportional effect of protective actions on tornado fatalities and injuries. Because I am not aware of any generalized estimates of protective response effectiveness in the literature, I estimate it indirectly from the casualty effects of tornado warnings and other historical data. This estimation assumes that households take protective actions only in response to warned tornadoes and that the protection response is not universal. I also assume that the protective response has the same proportional effect on reducing both fatalities and injuries.

Simmons and Sutter (2009) find that the warned tornadoes on average have 30%–40% fewer injuries, controlling for tornado strength, strike area, geography, and time. Similarly,

[10] The formula is derived in the following way. By definition, POD is equal to the proportion of positive events for which the warning is issued: POD = warned tornadoes/total tornadoes. The number of warned tornadoes is equal to the number of warnings multiplied by the proportion of true warnings: warned tornadoes = $N_w(1 - \mathrm{FAR})$. Hence, total tornadoes = warned tornadoes/POD = $N_w(1 - \mathrm{FAR})/\mathrm{POD}$. Then, I calculate the area affected as the product of the total tornadoes multiplied by the average tornado strike area: area affected = $A \times$ total tornadoes = $AN_w(1 - \mathrm{FAR})/\mathrm{POD}$. Last, I multiply the total area affected by average population density d to get the final formula above. The last step assumes that the tornado strike area is independent of the population density.

[11] Brooks and Correia (2018) find that with storm-based warnings, POD went from 0.7 in 2011 to 0.5 in 2016. Using a POD of 0.5 in my calculation slightly increases my projected benefits of both probabilistic and deterministic warnings. However, as this POD decrease does not reflect a growing frequency of tornadoes or worsening of forecasters' skills (Brooks and Correia 2018), I choose to keep the same POD of 0.7 both in calculations based on historical data and for future projections.

[12] One can obtain this equation by noting, first, that if there are F forecasts in total, then there are $F_i = f_i F$ forecasts predicting probability p_i. If the forecast probability matches the true probability of a tornado conditional on forecast, then there are $X_i = p_i F_i = p_i f_i F$ people affected by tornadoes within that predicted probability bin. As the total number of people affected by tornadoes remains constant at P_A, I know that $\sum_k X_k = \sum_k p_k f_k F = P_A$. Hence, $F = [1/\sum_k (p_k f_k)] P_A$, and consecutively, $X_i = [p_i f_i / \sum_k (p_k f_k)] P_A$ From here, I immediately obtain the formula for the predicted casualties as the product of the affected population X_i corrected for effectiveness of the protective response.

[13] I use only a larger mail sample for calculating protective responses, because responses in the internet sample seem to involve more social desirability bias with more excessive protection. This is evident in a sizable proportion of the population reporting protective actions when the probability of a tornado is zero (see Fig. B2 in appendix B).

Simmons and Sutter (2005) find that when a weather forecast office (WFO) in the United States installs a WSR-88, tornado injuries in covered counties go down by approximately 40%. Based on this evidence, I make a relatively conservative assumption that warnings reduce injuries by 35%. While the paper does not observe an effect of warnings on fatalities, this is likely the result of a much smaller number of fatalities in the sample. Consistent with these observations, I also assume that warnings reduce fatalities by 35%.

The following more technical calculation then infers protective response effectiveness. The calculation accounts for housing type t (permanent, mobile) to reflect the much higher vulnerability of people living in mobile homes. The effect of protective response depends both on the probability of a response and on its effectiveness in reducing casualties. Let r_t^0 denote the baseline probability of death for an unprotected person in a home of type t in a tornado strike zone, and r_t^w is the probability of death for a protected person. Additionally, R_t is the probability of protective response to a warning, and m_t is the mitigation effectiveness (e.g., an action with $m = 0.6$ reduces fatalities by 40% relative to the baseline).[14] Then, the fatality rates are described by the following expressions for each type of housing t, with P_t denoting the corresponding population share:

$$r_t^w = r_t^0[R_t m_t + (1 - R_t)] \equiv r_t^0 M_t, \quad t = \text{mobile, permanent}. \tag{3}$$

Here, $[R_t m_t + (1 - R_t)]$ is the average decrease in casualties due to protective responses, which includes both the population that takes protective actions R_t and the rest of the population that does not change its behavior $(1 - R_t)$. As we assumed before based on existing literature, warnings reduce both fatalities by 35%:

$$\sum_t P_t(r_t^0 - r_t^w) = 0.35 \sum_t P_t r_t^0, \quad t = \text{mobile, permanent}. \tag{4}$$

Last, the average fatality rate r_t^{av} is the weighted average for warned and unwarned fatality rates accounting for the POD:

$$r_t^{\text{av}} = \text{POD} r_t^w + (1 - \text{POD}) r_t^0, \quad t = \text{mobile, permanent}. \tag{5}$$

Next, I solve the system of equations above to find both baseline hazard rates r_t and mitigation effectiveness parameters m_t. As a first step of this calculation, I consider the population living in mobile homes. Simmons and Sutter (2013) estimate the average probability of death of a mobile home resident $r_{\text{mob}}^{\text{av}}$ to be 0.8472% if located in a tornado strike zone. The best and practically the only protection response for a mobile home resident is to evacuate to a sturdier building or shelter or travel out of the tornado path (Schmidlin et al. 2009). I assume for simplicity that evacuation eliminates the tornado risk for this group ($m_{\text{mob}} = 0$). However, Schmidlin et al. (2009) find that only around 30% of mobile home residents currently evacuate if they receive a tornado warning. Using Eqs. (3) and (5), I obtain a baseline rate of fatalities for mobile home residents of 110% of the average, or 1.01%, and the warned rate is 0.751%.

Next, I estimate the baseline risk and the mitigation effectiveness for residents of permanent homes. I do this by substituting the risks of mobile home residents into Eq. (4) 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. I 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 effectiveness factor m_{perm} for residents of permanent homes, I 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 et al. 2015). As only the response of individuals in a path matters for casualties, I assume that 60% of permanent home residents in a tornado path take some protective action ($R_{\text{perm}} = 0.6$). It follows that taking protective actions mitigates the baseline risk for permanent homes by approximately 65% ($m_{\text{perm}} = 0.361$).

Event studies support my finding of high mitigation effectiveness for permanent homes. For example, Niederkrotenthaler et al. (2013) finds that sheltering in a basement reduced injuries by roughly 80% during the April 2011 Alabama tornadoes, while Daley et al. (2005) find no severe injuries or deaths among people doing so during the Oklahoma City 1999 tornado. The same applies for the 2011 Joplin tornado (Paul et al. 2015). The evidence for using interior rooms as shelters is more mixed. Niederkrotenthaler et al. (2013) find that sheltering in an interior room reduced the risk of injury by about 60%, but Daley et al. (2005) find just a 20%–30% reduction in severe injuries, and Hammer and Schmidlin (2002) find no effect of using an interior room versus any other room in a permanent house.

We apply the same approach to the calculation of injury risks. The calculation assumes an average risk of injury of 0.025 for mobile homes in the strike area and a risk of 0.0224 for permanent homes in the strike area [based on the Simmons and Sutter (2013) calculation]. The baseline risk of injury for permanent homes equals 0.0306, and the baseline risk for mobile homes equals 0.0316. While the predicted injury risk is very similar for both home types, it seems that permanent

[14] Note that in contrast to the mitigation factor M, which combines the propensity of protective actions with their effectiveness, m_t measures only the effectiveness of the protective action conditional on acting.

homes give better protection against death, but not much more protection against nonfatal injuries.[15]

c. *Distribution of probabilistic forecasts*

A population's protective responses depend on perceived probabilities. Hence, we need to know how often each probability is forecast to estimate the costs of probabilistic warnings. This task is nontrivial, because for any probability of a tornado, one can issue different unbiased probabilistic forecasts. For example, one completely unbiased but also completely useless forecast is a forecast that is always equal to the baseline (environmental) probability of a tornado occurring. At the opposite end of the precision spectrum, forecasters can predict a probability of 1 if a tornado is going to happen and 0 otherwise. In practice, dynamic properties of weather systems and imperfect information impose constraints on the maximum precision of tornado forecasts.

I am going to use the signal detection theory to infer the distribution of probabilistic forecasts from the joint distribution of tornado warnings and tornado events.[16] The signal detection approach assumes that probabilistic forecasts use the same information as existing standard warnings. If it is indeed true, all the information can be aggregated to one signal equal to the posterior probability of a tornado occurring. In the simplest case, which I use here, this signal has a normal distribution with a dispersion of 1[17] and a mean depending on the 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 nontornadic 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 nontornado 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%.[18] I use $D' = 1.35$ on the upper end of this range to reflect improvements in warning performance in the early 2000s 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 a Monte Carlo analysis. I 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, I calculate the posterior probability f by using the Bayes formula as follows:

$$f = \frac{p_0\phi(S;\, D')}{[p_0\phi(S;\, D') + (1 - p_0)\phi(S;\, 0)]}. \tag{6}$$

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 (Fig. 3) is concentrated around low-probability events, which follows from both a low baseline probability of a tornado and our relatively modest ability to forecast tornadoes.[19] 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%.

d. *Sheltering costs*

The 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 day. For example, people sleeping in their basements do not have to interrupt this activity for sheltering and hence have exactly zero value of time for sheltering. In contrast, people 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.

I calculate the sheltering costs in two ways. First, I use the opportunity costs of time reported in previous studies and in different contexts. Second, I use the protective responses from the survey to infer the distribution of opportunity costs of sheltering across the population. In both approaches, 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. I use the following formula to calculate the expected annual population warned P_w for deterministic warnings:[20]

$$P_w = N_w A_w d.$$

[15] The absence of differences in injury rates between permanent and mobile homes seems counterintuitive and can be a result of measurement issues. Other studies, unfortunately, report varying results due to even smaller sample sizes. For example, Glass et al. (1980) find a much higher injury rate among mobile home residents, but their results are based on just 14 households with mobile homes. Daley et al. (2005) find a higher incidence of severe injuries among mobile home residents than among residents of permanent homes but a lower incidence of minor injuries.

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

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

[18] This probability corresponds to the average forecast probability of a tornado weighted by forecast frequency $\sum_k f_k p_k$ that I introduced previously in Eqs. (1) and (2).

[19] It is arguably much harder to forecast a tornado 10 min in advance than to forecast rain 1 h in advance.

[20] I count one person multiple times if they receive multiple warnings during the year.

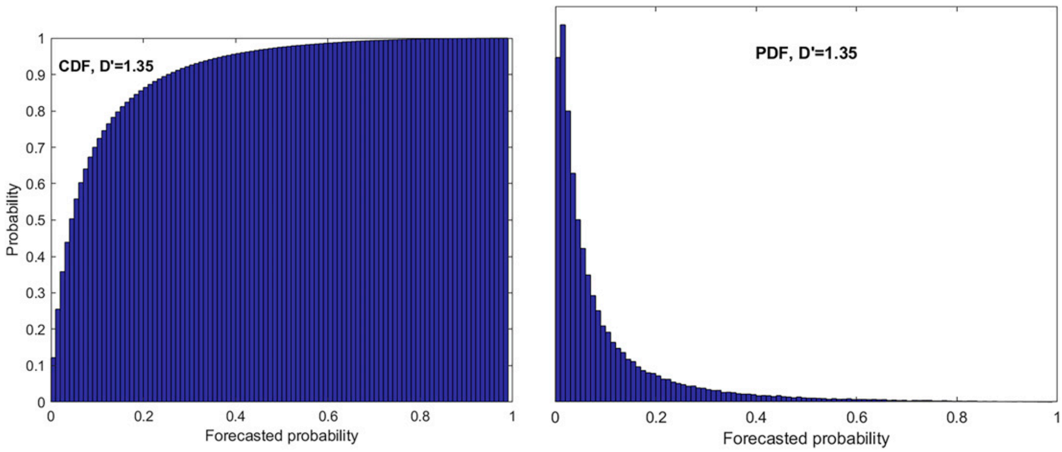

FIG. 3. Projected distribution of probabilistic tornado forecasts.

I again follow Howard et al. (2021) in using the average warning area $A_w = 275$ mi^2 and the average number of $N_w = 2063$ warnings per year. The population warned for probabilistic warnings is adjusted proportionally to the ratio of the current probability of an event in deterministic forecasts to the average probability of event properly adjusted for area. My survey describes a positive event as a tornado within 10 mi of the house or closer, which corresponds to a slightly larger area (314 mi^2) than the average area of deterministic impact-based warnings, so the adjustment increases the population warned in probabilistic forecasts by a factor of 1.14 = 314/275, even before adjusting for probabilities.

The first approach assumes that the opportunity cost of time is uniform across the population and sets this parameter based on previous literature. However, I cannot use the same exact numbers because the costs change with inflation, wages, and sample structure. Instead, I rely on studies calculating opportunity costs as the proportion of wage rate and then translate older results for the contemporary state of the economy. As paid work is one of the main activities conducted by working adults, the wage rate provides a natural benchmark for the value of time in this approach. Multiple studies, however, find that even for working adults, the value of time is significantly lower than their wage rate. For example, Larson et al. (2004) find that the value of time varies from 0.5 for adults with a fixed week to 0.8 for adults with a flexible workweek. Wolff (2014) put the value of time as 50% of the wage rate based on an analysis of speeding tickets and gasoline consumption. Consistent with this literature but corrected for the large proportion of individuals out of the labor force in my sample, I use one-third of the average wage rate to estimate the sheltering time. The average civilian nonfarm wage was equal to \$29.35 in 2020. This translates to an opportunity cost of sheltering time of \$9.80 h^{-1}.

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

My second calculation of the direct costs of tornado warnings accounts for heterogeneous opportunity costs of sheltering. I 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 me 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 I value similarly by using the value of statistical life approach. I calculate the cost of fatality risk $c(p)$ as the product of tornado probability p, baseline fatality risk r, the effectiveness of mitigation measures $(1 - m)$, and the value of statistical life VSL, as follows:

$$c(p) = pr(1 - m) \times \mathrm{VSL}.$$

Next, I assume that individuals switching from not sheltering to sheltering at probability p do so because their fatality costs of not sheltering $c(p)$ start to exceed the opportunity costs of sheltering c_o. In other words, I assume that individuals behave consistently with the 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: $c(p_1) \le c_o \le c(p_2)$. 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 the probability increases from p_1 to p_2 have opportunity costs based on a 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 to infer zero opportunity costs for subjects taking protective actions for the lowest possible probability of 20%. However, I also show the calculation of opportunity costs under the lower-bound approach. I assign the probability of 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%.

The calculated sheltering costs (see Table 2) are comparable to the uniform sheltering costs, which I took as one-third of the median wage rate or \$9.80 h^{-1}. Note that the calculation of heterogeneous sheltering costs uses only reported decision and not wage rates. It demonstrates that most individuals neither overreact nor underreact to predicted tornado risks, with protection decisions being highly consistent with other domains used to estimate the value of statistical life. The lowest opportunity cost of sheltering for permanent home residents is just \$3.35 h^{-1} if using the upper-bound approach and \$0.80 if using the lower-bound approach. The second group of permanent homes residents, which switches to protection when the risk goes from 20% to 40%, has sheltering costs ranging between \$3.35 and \$6.71. The average sheltering cost is between \$3.20 and \$5.90 for permanent home residents and between \$126 and \$144 for mobile home residents.[21] Higher sheltering costs for mobile home residents reflect both limited protection options and their higher effectiveness; the only realistic protection plan involves moving to the closest sturdy shelter or out of the tornado path.

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

5. Results

While my calculation does not aim to provide accurate forecasts of total tornado fatalities and injuries in the United States, it is important to match the scale of potential casualties to receive an unbiased estimate of total cost savings, and I do it reasonably well. My predicted tornado casualties with deterministic warnings (around 50 fatalities per year) are similar to historical rates. For comparison, on average, tornadoes were killing 78 people in the United States per year in 1980–2019,[22] and this number included people killed outside of their residences.

TABLE 2. Distribution of opportunity costs.

Housing	Population share (%)	Value of time (\$ h^{-1}) Lower estimate	Upper estimate
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

The calculation presented in Table 3 indicates that deterministic warnings save roughly 19 lives per year, not accounting for victims outside and in places of work. I expect that probabilistic warnings would on average save an additional seven lives per year. This effect comes from many people starting to react to warnings when the forecast probability is still below the threshold required to issue deterministic warnings. The reduction in injuries is proportional to the reduction in fatalities as consistent with my assumptions.

The decrease in fatalities and injuries translates into significant monetary gains from both standard and probabilistic warnings if using the statistical value of life or injury to value casualties. The total casualty (fatalities + injuries) cost of tornadoes without warnings is \$871.5 million per year. Deterministic warnings reduce the costs of casualties by approximately \$250 (\$252.0) million. Probabilistic warnings additionally reduce the costs of casualties by roughly \$85 million per year.

Accounting for the opportunity costs of sheltering time obviously decreases the net societal value of deterministic warnings, but it is still fairly large. The net benefit of deterministic warnings is \$95.5 million per year under the assumption of uniform opportunity costs and \$139.6 million per year under the assumption of heterogeneous opportunity costs. The assumption of the heterogeneity of opportunity costs matters because it implies that only users with lower opportunity costs take shelter in response to warnings if their costs are lower than the average risk implied by the deterministic warning. I find that even for the deterministic warnings, the benefit of reduced casualties outweighs additional opportunity costs of sheltering. This observation is true both for uniform and heterogeneous opportunity costs. However, their net effect on societal costs is relatively modest. In contrast, Simmons and Sutter (2013) find that the societal costs of tornadoes calculated for the constant population and constant value of statistical life and injury go down by around \$6 billion between 1925 and 2000. Their

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

[22] My calculation based on the Storm Prediction Center database.

TABLE 3. Societal costs by tornado warning approach.

	No warning	Deterministic Total	Deterministic Change (column 2 − column 3)	Probabilistic Total	Probabilistic Change (column 3 − column 5)
Uniform opportunity costs					
Expected fatalities	68.5	49.6	19.0	42.4	7.2
Expected injuries	976.0	607.0	369.0	569.1	37.9
Cost of fatalities, $ million	762.9	551.9	210.9	471.5	80.4
Cost of injuries, $ million	108.6	67.6	41.1	63.3	4.2
Total cost of casualties, $ million	871.5	619.5	252.0	534.9	84.6
Opportunity cost of time, $ million	0.0	156.5	−156.5	165.1	−8.6
Total cost, $ million	871.5	776.0	95.5	700.0	76.0
Heterogeneous opportunity costs (upper estimate)					
Expected fatalities	68.5	49.6	19.0	42.4	7.2
Expected injuries	976.0	607.0	369.0	569.1	37.9
Cost of fatalities, $ million	762.9	551.9	210.9	471.5	80.4
Cost of injuries, $ million	108.6	67.6	41.1	63.3	4.2
Total cost of casualties, $ million	871.5	619.5	252.0	534.9	84.6
Opportunity cost of time, $ million	0.0	112.4	−112.4	57.6	54.8
Total cost, $ million	871.5	731.9	139.6	592.5	139.4
Heterogeneous opportunity costs (lower estimate)					
Expected fatalities	68.5	49.6	19.0	42.4	7.2
Expected injuries	976.0	607.0	369.0	569.1	37.9
Cost of fatalities, $ million	762.9	551.9	210.9	471.5	80.4
Cost of injuries, $ million	108.6	67.6	41.1	63.3	4.2
Total cost of casualties, $ million	871.5	619.5	252.0	534.9	84.6
Opportunity cost of time, $ million	0.0	29.7	−29.7	19.2	10.5
Total cost, $ million	871.5	649.2	222.3	554.1	95.1

approach is very similar to mine, as they also account for the value of statistical lives lost and opportunity costs of time. However, this enormous change in societal costs does not necessarily come from tornado warnings. The calculation also seems to use an inflated fatality baseline due to the most deadly and extremely strong tristate tornado event happening at the beginning of this period. This period also saw improvements in building quality, better health care, and more awareness of tornado protective strategies.

Probabilistic warnings further reduce the societal costs of tornadoes. Most of this effect comes from reducing tornado fatalities and casualties. This safety increase has a downside as more people start sheltering, but as long as decisions to shelter respond rationally to actual opportunity costs, probabilistic warnings would also reduce the societal costs of sheltering. I estimate that probabilistic warnings would provide net benefits[23] of $76 million per year if assuming uniform opportunity costs of time and $139.4 million if accounting for costs heterogeneity ($95.1 million if using a lower-bound estimate of sheltering cots). The large discrepancy between the values calculated for uniform and heterogeneous costs shows that a large, if not the largest, value of probabilistic warnings comes from more nuanced sheltering decisions. When forecasters predict a very high chance of a tornado, most individuals expect to take shelter, but when the predicted chance is low, only people with easy access to shelter or no important competing activities do so.

[23] Not accounting for technological costs: research and development and additional training of meteorologists.

6. Conclusions

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

I find that both deterministic and projected probabilistic tornado warnings deliver significant positive net benefits for the United States. Deterministic tornado warnings save around 20 lives per year and create around $96–140 million of net societal benefit. Probabilistic warnings additionally increase this benefit by another $76–139 million per year. I estimate that most probabilistic forecasts will involve low tornado probabilities. Hence, the benefit of probabilistic forecasts emerges mostly because warnings issued for probabilities below deterministic threshold save additional lives. In addition, probabilistic warnings also reduce sheltering by individuals with high sheltering costs when projected probabilities are low, which reduces the total cost of time spent sheltering.

My calculation of the societal benefits of tornado alerts does not account for other potential psychological benefits of tornado warnings. For example, the laboratory experiment conducted by Eliaz and Schotter (2010) demonstrates that people are willing to pay for information not used in decision-making if this information helps them evaluate previously made decisions. In a similar vein, the model of Golman et al. (2021) postulates that people want to get information to fill their information gaps. In addition, many people derive value from public goods only due to their use to others ("nonuse value"). For these reasons, my estimate of societal benefits should be treated as a lower bound, while the real value might be significantly higher. However, it is important that even the calculated benefits seem large enough to justify the costs of developing and implementing probabilistic tornado warnings.

This research has two significant policy implications. First, even though my estimates are on the lower and more conservative side, the projected annual benefits of $76–139 million are still high enough to more than justify the research and development expenses needed to develop and transition to probabilistic warnings. For comparison, in 2023, NOAA expects to spend just $20.9 million on its Tornado Severe Storm Research/Phased Array Radar,[24] which includes probabilistic warnings as part of the research agenda. Second, it indicates that probabilistic warnings should be issued for much lower probabilities than the currently existing thresholds for deterministic warnings. I observe that around one-half of the population starts taking some protective measures if the tornado probability is as low as 10%. Hence, the distribution of potential forecasts should include warnings even when the probability of a tornado is estimated to be as low as 10% or potentially 5%. Additional information provided to households will still allow them to make better decisions and shelter only if their perceived risks outweigh the costs of sheltering.

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

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Data availability statement. The anonymized survey data and the code used to process them are available online (https://github.com/AlUgarov/Benefits_ProbWarnings).

APPENDIX A

Additional Tables

Table A1 lists tornado-prone states, and Table A2 shows an internet survey sample.

[24] https://www.noaa.gov/sites/default/files/2022-05/508_Compliant_Final_FY23_NOAA_Blue_Book_Budget_Summary.pdf for the Green Book NOAA budget request for 2023.

TABLE A1. Tornado-prone states (sampling frame structure). The incidence rate (column 3) is incidence of F2–F5 tornadoes per 100 square miles.

N	State	Incidence rate	Injuries	Fatalities	Population
1	OK	1.41	6173	469	3 943 079
2	MS	1.35	8163	658	2 986 530
3	AL	1.25	8782	777	4 887 871
4	IN	1.24	4827	303	6 691 878
5	AR	1.18	5515	405	3 013 825
6	IA	1.11	2197	85	3 156 145
7	IL	1.01	4519	217	12 741 080
8	LA	0.93	3148	210	4 659 978
9	TN	0.90	4089	349	6 770 010
10	KS	0.88	3095	275	2 911 505
11	KY	0.79	3998	224	4 468 402
12	MO	0.76	4766	419	6 126 452
13	GA	0.70	3950	223	10 519 475
14	OH	0.67	5064	259	11 689 442
15	DE	0.63	24	2	967 171
16	FL	0.63	2743	154	21 299 325
17	WI	0.62	1363	100	5 813 568
18	SC	0.62	1762	70	5 084 127
19	TX	0.60	10 438	614	28 701 845
20	NE	0.59	1173	59	1 929 268
Total		0.85	85 789	5872	148 360 976
U.S. total		0.34	100 178	6652	327 167 434
Percentage (of the U.S.)		248.7%	85.6%	88.3%	45.3%

TABLE A2. Internet survey sample.

	Good English			Limited-English Hispanics		
	Sample *N*	Sample %	Population %	Sample *N*	Sample %	Population %
Male	97	39	49	48	31	47
<35 yr old	52	21	30	55	35	21
35–59 yr old	97	39	41	87	56	54
60+ yr old	98	40	29	14	9	25
No school	0	0	1	6	4	9
Grades 1–12, no high school diploma	11	4	8	21	13	46
High school 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

APPENDIX B

Additional Graphs (Internet Sample)

Figure B1 shows protective response by lead time, and Fig. B2 shows protective response by probability of a tornado.

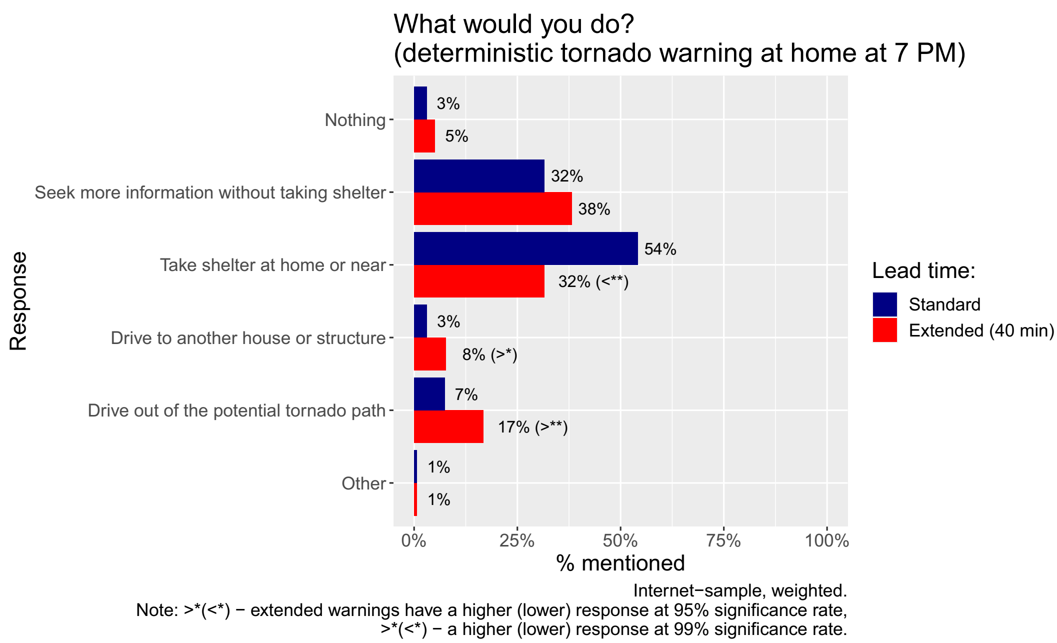

FIG. B1. Protective response by lead time (internet sample).

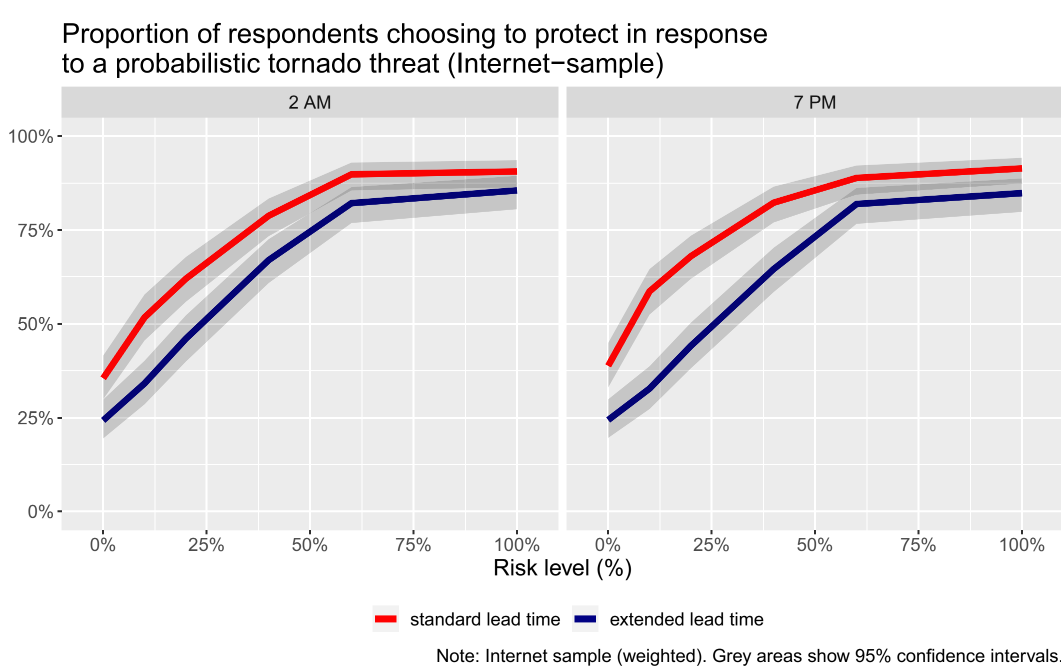

FIG. B2. Protective response by probability of a tornado (internet sample).

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