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Public Willingness to Pay for Continuous and Probabilistic Hazard Information

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Abstract: Investments in new weather forecasting technologies and communication products can be costly and serve the ultimate purpose of protecting life and property. The Forecasting a Continuum of Environmental Threats (FACETs) paradigm attempts to improve technology and communication through the provision of probabilistic hazard information (PHI). The research and technology necessary to produce this information requires a substantial resource investment, but the societal value of the information may outweigh the costs. This study provides an initial estimate of this value by exploring public willingness to pay (WTP) for an app that provides continuously updated, geographically situated PHI that could be utilized during a tornado event. Findings indicate that the mean WTP, in a one-time payment, for this precise hazard information product is \$7.53 per person. Aggregated to the US population, the estimated value is between \$901 million and \$1.56 billion. These findings indicate that federal agencies and private companies are likely to generate a substantial surplus by developing these products and will contribute to improving informed decision-making and protecting lives and property. **DOI: 10.1061/(ASCE)NH.1527-6996.0000444.**

Introduction

Since the mid-2000s, the National Weather Service (NWS) has dedicated significant resources to developing better methods for incorporating and communicating uncertainty into their weather and climate forecasts and products. Under the Forecasting a Continuum of Environmental Threats (FACETs) paradigm, the National Severe Storms Laboratory (NSSL) and NWS have developed forecast products that incorporate probabilistic hazard information (PHI) into the current deterministic, binary system for severe weather warnings. Along with the development of these products, the National Research Council recommended investments in social, behavioral, and economic research that would examine how the public interprets probabilistic information and how to improve communication thereof (NRC 2006, 2012). Under these initiatives, scholars have examined some of the ways that probabilistic information is understood and used by the American public.

An important goal of the FACETs paradigm, according to Rothfusz et al. (2018, p. 2027), "is to determine and compare the value and merits of new and legacy forecast methodologies." Previous research has estimated a value of approximately \$31.5 billion for the current services such as forecasting, collecting, and publishing climate and weather data provided by the NWS, for a net benefit of \$26.4 billion a year (Lazo et al. 2009). Other research has estimated household willingness to pay (WTP) for improvements to current forecasting systems generally (Lazo and Chestnut 2002) and hurricane forecasts specifically (Lazo and Waldman 2011). However, research has yet to examine the value the public attaches to specific probabilistic hazard information products. Understanding this value is vital to assessing if the public considers these probabilistic products to be an improvement over the current deterministic system.

Following from these initiatives, this paper has two objectives. First, the study heeds the call of the NWS and the FACETs paradigm to provide an estimate of the value to society for the provision of PHI during severe weather. Second, the paper assesses a specific methodological approach—contingent valuation—for valuing specific programmatic initiatives by public agencies to provide applied PHI to US residents. The authors use a nationally representative survey and a contingent valuation (CV) experiment to estimate average individual WTP for a weather app that provides continuously updated, geographically situated information about hazard or threat levels for a tornado event. The study finds a mean WTP of \$7.53 per average US person, which, when aggregated across relevant US populations, is between \$901 million and \$1.56 billion.

Background

The National Weather Service and the broader meteorological community have committed significant resources to the development and understanding of probabilistic information. Discussions regarding the utility of estimating probabilities for various forecasts and then communicating them with the public have been ongoing

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within the meteorological community for decades (Murphy 1991; Doswell 2004; NRC 2012). Under the current system, probabilistic forecasts seem to have been most thoroughly incorporated into the products of the National Hurricane Center (NHC). The NHC has been using strike probability grid systems for more than three decades (Sheets 1985) and probability-derived surge maps for more than half a decade (Morrow et al. 2015). Various local weather forecasting offices across the country, the Storm Prediction Center (SPC), and even broadcast media have been testing similar probability-based products for various other threats including thunderstorms, snow, and lightning (Sobash et al. 2011; Novak et al. 2014; Frederick and Amburn 2015). The FACETs paradigm seeks to integrate these various efforts into an overall framework for forecasting that incorporates PHI that is continuously updated over time and geography with the current system of intermittent, deterministic products.

Previous research has demonstrated that the goals of the FACETs paradigm to produce and disseminate probabilistic information may be preferred over deterministic information. Regarding temperature forecasts, Morss et al. (2008) found that not only do end users (the public) prefer forecasts that incorporate uncertainty, they also implicitly incorporate uncertainty into deterministic forecasts. Joslyn and Savelli (2010) also found that respondents infer uncertainty in deterministic forecasts across a variety of weather phenomenon. They argue that explicit probabilistic information may help overcome the biased interpretations of the deterministic forecasts that were apparent in their analyses. In other contexts, scholars found that individuals prefer to receive precise, numerical estimates of probability rather than verbal, descriptive estimates, even when the numerical and verbal estimates have been determined to be equivalent (Erev and Cohen 1990; Olson and Budescu 1997; Lenhardt et al. 2020).

Regarding forecasts, scholars have examined the effect of including probabilistic information on decision quality (Joslyn and LeClerc 2012, 2013; Grounds and Joslyn 2018). These studies found that providing individuals with probabilistic information improves decision quality by reducing expected value losses (Grounds and Joslyn 2018). Probabilistic information improves decision quality regardless of numeracy and level of education, and across both samples of undergraduates and the general population (Grounds and Joslyn 2018; Grounds et al. 2018). The effect of probabilistic information on decision quality is independent of and more important than the inclusion of categorical guidance or advice regarding the decision (Joslyn and LeClerc 2012). The format of this information matters: Joslyn and Nichols (2009) found that a probability format, as opposed to an equivalent frequency format, leads to more confidence in forecast understanding and improved decision-making for wind advisories. Joslyn and LeClerc (2013) found that numerical and verbal descriptions of probability improve understanding and decision-making while the graphical portrayals they tested were misunderstood by most respondents.

Finally, in a series of projects directly examining PHI under the FACETs paradigm, Miran et al. (2017) compared four different formats of probabilistic hazard information for tornadoes. They first documented that respondents preferred and most quickly understood probabilistic hazard information for a tornado that was portrayed using the familiar four-color spectral design on a map. The grayscale format performed better when combined with radar image; they also found some evidence that color coding is better than numeric probability information in a contour graphic. Miran et al. (2018) then documented how PHI increases protective action for respondents who are closer to the tornado threat. They found that this relationship is stronger for individuals who received PHI as opposed to the traditional deterministic warning and was especially relevant for lead times less than 20 min.

In sum, research on risk communication provides substantial evidence that the public can, in the context of weather, understand and utilize probabilistic information. We therefore turn to the question of estimating the explicit social value of this information.

Social Valuation and Applications to Weather-Related Risk Information

While the information may be implicitly valued for how it increases protective action decisions, providing a direct monetary estimate of its value will be beneficial to policy makers and others when deciding where to invest resources within the National Oceanic and Atmospheric Administration (NOAA) and the NWS. Additionally, knowing this value may be of use to private companies who are also important providers of weather information in the United States. These private companies typically repackage and sometimes enhance NWS data and products; these can be delivered through apps or websites such as RadarScope and AccuWeather. A potentially more familiar private weather information provider is the Weather Channel with its cable news channel, apps, website, and more.

Program investments, such as the development of probabilistic hazard information, could be valued using a variety of different methods. These include assessments of market prices, hedonic analysis, and stated preference approaches such as CV. In a 2015 report, the World Meteorological Organization evaluated the advantages and disadvantages of these various methods for estimating the value of meteorological and hydrological services (Anderson et al. 2015). In the context of weather information, a market price analysis would consider the most similar good sold on the market to assess the social value of a good if it were publicly provided (Boardman et al. 2017). Thus, a market analysis of weather information and forecasts could examine the price that companies such as AccuWeather and the Weather Channel set for their weather apps. Analysts can combine this price information with information about the quantities sold to potentially estimate a demand curve for the good. While relatively conceptually straightforward, using market analyses for publicly or quasi-publicly provided goods has a number of shortcomings. First, it relies on data, such as sales numbers or cost estimates from private companies, that may not be readily available to analysts seeking to estimate the social value of public programs. Second, it requires assumptions about the similarities of the good or product sold in the market to the publicly provided good. In some cases, such as that of public housing, there are clear market alternatives that can be used to help establish the value of publicly provided social goods (Boardman et al. 2017). While weather apps may provide a decent analogous good, they may differ in important ways from the public programs that seek to create and disseminate new types of information in innovative ways. Additionally, in fact, many private market applications rely on repackaging publicly provided weather information, further complicating the use of this method to value weather information. Finally, this method also fails to consider the positive externalities associated with public goods and would likely undervalue the social net benefit of improved weather information.

Another potential valuation method for forecasts and weather information is hedonic pricing analysis, which implicitly estimates prices for a good based on changes in the attributes of another good. This method relies on an observed price for a good, say, housing, that may differ based on a variety of attributes (Boardman et al. 2017). The analyst must determine all possible attributes that are associated with that price aside from the one being valued;

remaining differences in price are then credited to differences in the valued attribute. The World Meteorological Organization report by Anderson et al. (2015) provides an example of when hedonic pricing could be used to measure the value of a forecast. In their example, they state the value could be found by comparing the prices of newspapers that do and do not include a forecast. As with all valuation approaches, this method is also subject to a number of limitations. First, it relies on the assumption that all attributes related to a good's value are known, that people are able to consider them, and that they are measurable (Boardman et al. 2017). Additionally, there must be a wide variety of the good; ideally, there would be multiple options for all possible combinations of attributes. However, this is unlikely because many attributes are correlated with each other. Finally, this method assumes prices respond quickly to differences and changes in these attributes. More succinctly, the method assumes that a good's price captures the good's value (Anderson et al. 2015). This method commonly works for goods that have strong, competitive markets such that the goods have a wide variety of measurable attributes. Common examples of this method rely on differences in property values to measure the value of goods (e.g., air pollution, noise pollution, scenic views, or other environmental goods).

Finally, a third common approach that could be used to value probabilistic information or forecasts is the stated preference method. This method typically relies on surveys that ask respondents to value a change in the quality or quantity of a particular good or policy change. Designs of these surveys can vary in complexity from direct elicitation of value or willingness to pay to more complex experimental designs such as single-bound dichotomous choice, double-bound dichotomous choice, and even conjoint experiments (Anderson et al. 2015). Stated preference methods have some disadvantages over the previous methods. Specifically, they rely on descriptions of both a hypothetical good and a particular payment vehicle. The hypothetical nature of the good requires the researcher to devote a certain amount of detail to the description of the good being valued (Boardman et al. 2017). This can be problematic, however. If the good is described in too much detail it can lead to overload of the survey respondent; if the good is not described in enough detail, the respondents may not be able to respond accurately (Morrison and Brown 2009). Assuming analysts are able to describe the good in appropriate detail, they must then choose a payment vehicle for the good. This payment vehicle must be a plausible way to pay for the good being valued. In the case of most public goods or government programs, the payment vehicle is an increase in taxes. For other goods the payment vehicle must simply be a realistic choice. The challenge is that contingent valuation studies commonly suffer from hypotheticality bias, where respondents upwardly bias reported WTP because the situation is unrealistic and they do not actually have to pay (Champ and Bishop 2001).

While contingent valuation methods, and stated preference methods more broadly, are subject to the kinds of limitations described, they also have important strengths. First, the hypothetical nature of the good is a strength when a similar good does not exist in the real world. We can learn what people are willing to pay for a much wider variety of goods that are not market goods (Boardman et al. 2017). For public goods more generally, CV methods are particularly useful because markets generally fail to provide appropriate analogs, and therefore market pricing or hedonic methods are unavailable (Anaman and Lellyet 1996). For real-world policy decisions, once a decision to provide a good is made it is difficult, if not impossible, to estimate the value of the alternative options that were not chosen. The CV technique can allow analysts to value a wide variety of possible policy decisions without the expense of implementing them or even running pilot programs. Contingent valuation and choice experiments are also preferred to these other methods because they can capture both use and nonuse values. Given the benefits of CV methods, in particular their usefulness for assessing willingness to pay for public or quasi-public goods that come from government programs, it is unsurprising that many scholars have used this method to value weather information in the past.

Previous Valuations of Forecasts and Weather Information

A handful of studies have provided estimates of the monetary value of improved general forecasts, improved hazard-specific forecasts, and other natural hazard–related phenomena in the US (Lazo and Chestnut 2002; Lazo et al. 2009; Lazo and Waldman 2011; Mozumder et al. 2014). Most of this work uses contingent valuation, through discrete-choice survey experiments, to inform cost-benefit analysis (Carson and Czajkowski 2014). Generally, these studies use survey experiments to estimate median or mean household WTP and aggregate economic value to society. For example, in 2002, Lazo and Chestnut calculated that the current forecast system in the US has an aggregate economic value of $11.4 billion with a median household WTP of $109 per year. They also valued improvements to the forecast system through increasing the frequency of updates per day, refined area specificity, and increased accuracy of 1-day and multiday forecasts. Maximizing each of these attributes resulted in an estimated median household WTP of $16, or a total national value of $1.73 billion. To produce these estimates, Lazo and Chestnut (2002) relied on a sample of 381 respondents drawn from nine cities from the nine regional climates as defined by the National Centers for Environmental Information (NCEI). The authors note concern with "embeddedness" in their design, meaning that respondents provide WTP estimates that include more goods than just the one being valued.

More recent work by Lazo et al. (2009) estimated a higher economic value of forecasts at $31.5 billion, compared to an estimate of $11.4 billion in Lazo and Chestnut (2002). Consistent with prior studies, the authors used a tax payment vehicle for the valuation exercise after informing respondents that the NWS is the primary provider of weather forecast information. For the valuation question, bids ranged between $2 and $240; however, notably, more than 50% of respondents who were shown the maximum value of $240 per year indicated that they would willingly pay that price. Thus, they extrapolated a median WTP of $286, or $46 over their maximum bid amount. This method has been applied outside of the US as well. Using an open-ended WTP solicitation and a telephone survey of 524 Sydney residents, Anaman and Lellyet (1996) found a mean WTP of $24 ($19 US) for the public weather service in Australia.

Valuing Specific Forecast Types

Other work has examined the value of other more specific types of forecasts such as hurricane forecasts. Lazo and Waldman (2011) found a mean household WTP of approximately $13 for improvements to hurricane forecasts in the US from a survey of 80 respondents who live within approximately 48 km (30 mi) of the Miami coast. Using a choice experiment, the authors estimate WTP for specific types of forecast improvements. For example, the authors found a mean WTP of $4.36 per household for improvements in landfall time forecasts, but willingness to pay only $1.30 for improvements in wind-speed forecasts. Other more specific forecasts that have been valued include climate forecasts in Benin (Amegnaglo et al. 2017), improvements in tropical cyclone forecasts in Vietnam (Nguyen and Robinson 2015), and improvements in forecasts for agricultural producers in Italy (Predicatori et al. 2008). Nguyen and Robinson (2015) relied on a national sample of 863 Vietnamese residents and a choice experiment attempting to value various aspects of cyclone forecasts including accuracy, number of updates, and mobile phone messages. They found that WTP varies as a function of individual characteristics, with the highest WTP for maximum improvements equaling approximately 194 thousand Vietnamese dong (equivalent to about $8) in a one-time payment on their electricity bill. Amegnaglo et al. (2017) found, using a survey with iterative bidding of 354 farmers in Benin, a value of approximately $19 per farmer for improved cyclone forecasts.

Limitations of Previous Research

While valuable, these studies have a few limitations. First, as Lazo and Chestnut (2002) note, the problem of embeddedness may cause respondents to overstate their willingness to pay for the good they are being asked to value. This may also be due to the vague nature of the improvements defined in the surveys. What does a 1-day forecast that is accurate 85% of the time really mean? What is an improvement in the accuracy of tropical cyclone forecasts? Vague and general language will likely lead to overstatements of value because respondents will, of course, value something that they are told is an improvement. Finally, most of these studies rely on a hypothetical tax or bill increase as the payment vehicle (Anaman and Lellyet 1996; Lazo and Chestnut 2002; Lazo et al. 2009; Nguyen and Robinson 2015). The hypothetical nature of the payments may be leading respondents to overstate their WTP. While taxes represent a well-understood and plausible payment vehicle for a pure public good, policy change, or government program, they may not be the best payment vehicle for a good like weather information that is publicly provided but then packaged in various ways by private actors including weather companies and broadcasters. Anaman and Lellyet (1996) note this difficulty when they discuss valuing weather information or the weather service as a consumption good.

While previous studies have valued various hypothetical improvements to the forecast system, the current study focuses on a forecast product that is currently being tested by the NWS and its forecasters. The survey question emphasized the investments already being made in this technology; we believe including this information may help address concerns about consequentiality (Carson and Groves 2007). Because respondents know the technology is already being researched and invested in, they may believe their responses are more likely to be considered when making decisions about increasing, decreasing, or even ending investments in this technology. This paper improves on previous attempts to value weather information by reducing the hypothetical nature of the good and therefore the associated bias of the improvement being valued. In so doing, we ultimately estimate the WTP for the app itself, which includes many different dimensions and characteristics including PHI, continuous updates, and geographic precision. To accomplish this, as described in the next section, respondents watched a video that represented the type of information that is being valued. Additionally, the use of a charge for a cell phone app as the payment vehicle further reduces the hypothetical upward bias by bringing the good into a familiar and more realistic setting than a tax or other payment vehicle. However, using the cell phone app as a payment vehicle may also induce upward bias because the responses reflect WTP for the PHI as well as app characteristics (e.g., app notifications). Given the more realistic portrayal of the good, coupled with the use of a more plausible payment vehicle, we can have greater confidence that our estimate reflects societal value for this type of information.

Valuation for Informing Policy Decisions and Program Investments

The weather app and video respondents watched is a realistic depiction of the possibilities from investments in current NOAA and NWS programs under the FACETs paradigm. Specifically, the good to be valued is an app that would provide continuously updated, geographically oriented PHI in the context of tornado forecasts. Probabilistic hazard information is central to the FACETs paradigm of the NSSL and NWS as is the goal of the FACETs paradigm to compare the value of innovative PHI forecast methodologies to legacy ones (Rothfusz et al. 2018). Compared to the current deterministic warning system, probabilistic hazard information provides a more nuanced assessment of a developing threat or hazard situation. Estimating a value for an app that provides this information will be of interest to policy makers and administrators within NOAA and the NWS who are considering implementing the FACETs paradigm across an array of weather hazards and employing innovative means to deploy the products. To value an app that provides these types of information, a technique that considers the unique nature of the underlying weather information, as a publicly provided consumption good, must be used. The following section of the paper describes, in more detail, the phone app and the contingent valuation technique used to estimate its value.

Survey Design and Data

The data for this project come from the Severe Weather and Society Survey, fielded by the Center for Risk and Crisis Management at the University of Oklahoma in June 2017 (Silva et al. 2017). The data were collected using an online survey of individuals from Survey Sampling International (SSI) with quotas for gender, age group, race, ethnicity, and NWS region. The resulting sample is intended to be nationally representative of the US adult (age 18+) population based on geographic location (region) and demographic categories. For reference, Table 1 lists the demographic characteristics of the sample ($n = 2{,}008$ respondents) in comparison to US Census estimates from 2017. Previous research has shown that surveys conducted on the internet produce results that are consistent with other technologies of survey delivery including face-to-face interviews, mail, and telephone (Berrens et al. 2003; Li et al. 2004; Lindhjem and Navrud 2011).

Table 2 presents summary statistics for respondent experiential and attitudinal variables, as well as demographics not included in Table 1. Survey question wording and measurement details are provided in the Appendix. A few aspects of the sample deserve note for their relevance to the study. Approximately 71% of respondents have never experienced a tornado before. Only 24% of respondents report having ever paid for a phone app, while approximately 10% have paid for a phone app that provides weather information. Finally, the average respondent reports being somewhat reliant on automated text notifications for severe weather information. These statistics are important because they relate to the payment vehicle we use to elicit WTP in the valuation experiment.

In the valuation portion of the survey, respondents were presented with a hypothetical weather product that incorporates continuously updated, high-resolution probabilistic information. This product was developed by scientists at the National Severe Storms

Table 1. Demographic representativeness of Severe Weather and Society Survey respondents

Demographic categories	US adult population[a] (%)	Respondents (%)
Gender		
Female	51.3	51.3
Male	48.7	48.7
Age		
18–34	30.2	30.5
35–54	33.4	31.6
55+	36.4	37.9
Ethnicity		
Hispanic	15.8	16.5
Non-Hispanic	84.2	83.5
Income		
Less than \$50,000	43.7	38.2
Between \$50,000 and \$100,000	30.0	33.6
Between \$100,000 and \$150,000	14.0	18.4
Greater than \$150,000	12.3	9.80
Race		
White	78.5	74.7
Black or African American	12.8	13.5
American Indian or Alaska Native	1.1	1.8
Asian	5.6	6.3
Native Hawaiian or Pacific Islander	0.2	0.5
Two or more races	1.8	3.2
NWS region		
Eastern	31.8	32.6
Southern	26.9	27.3
Central	20.8	20.7
Western	20.5	19.4

Source: Adapted from Silva et al. (2017).
[a]Population estimates were obtained from the US Census Bureau (2019a).

Laboratory to represent information that *could* be provided using technology that is in development under the FACETs paradigm. To explain the product, respondents were given text which stated:

> Currently, tornado WARNINGS from the National Weather Service are binary (the warning is either "on" or "off"). If you are in a tornado WARNING, a tornado is close to or occurring in the warning area during the time of the warning. If you are not in a tornado WARNING, a tornado is *not* close to or occurring in the warning area during the time of the warning. In some cases, the tornado WARNING can be relatively large and span 30 min or more.
>
> Scientists are working on a new tornado WARNING technology that may allow you to access more specific information, such as the probability that a tornado will occur at your exact location at a specific point in time. Research and development of this technology is ongoing, but the new WARNING might look something like this (see video).
>
> *In the video, the red shapes represent current (binary) tornado warnings; the small colorful pixels show more specific information about the tornado threat at the location identified by the small box.*

A short video also demonstrated the product (Karstens and Murnan 2016; Video S1). Due to the nature of the payment vehicle, our estimates will capture the WTP for the application and the sum of its characteristics, which will likely result in higher WTP than if we were able to estimate the WTP_{PHI} alone. This is represented below in Eq. (1), where WTP for the application (WTP_{app}) is a function of the probabilistic hazard information (WTP_{PHI}), the continuous updates ($WTP_{continuous}$), the geographic precision ($WTP_{geographic}$), and all app characteristics ($WTP_{characteristics}$) including the color and sound choices. While each of the WTPs are of theoretical interest, our current framework only allows us to directly estimate WTP_{app}. We, however, believe WTP_{app} in this case may be of most interest to policy makers because it reflects the WTP for the overall product and potential innovations from investment in PHI and the FACETs paradigm

$$WTP_{app} = f(WTP_{PHI}, WTP_{continuous}, WTP_{geographic}, WTP_{characteristics}) \tag{1}$$

To estimate WTP, respondents were asked, "If this technology were available as a free application (mobile app) for a smart phone (such as an Android or iPhone), would you download it?" Respondents could choose between yes, no, and not sure. Those who replied yes were then asked their WTP for the technology displayed in the video as provided through a phone. Those who replied no to the free download question were excluded from further analysis. Specifically, respondents replying yes to the question were then asked, "Would you download this application (mobile app) for a one-time cost of \$[0.99:49.99]?" where the dollar amount seen by the respondent was randomly drawn from a discrete uniform distribution ranging between \$0.99 and \$49.99. The bid range was chosen based on an informal survey of applications available on commonly used app stores at the time of survey administration. Though continuous distributions can lead to improved precision of WTP estimates (Lewbel et al. 2011), this study relies on a discrete-bid estimate because phone apps are typically priced in dollar increments ending in 0.99. Thus, the prices presented to respondents reflect this norm of mobile app pricing. Possible responses to this question were yes, no, or not sure. Finally, respondents who responded yes to the valuation question were then asked, "On a scale from 0 to 10, where 0 means not at all certain and 10 means completely certain, how certain are you that you would download this smart phone application (mobile app) for a one-time cost of \$[0.99:49.99]?" This certainty question was asked to address potential hypothetical bias in the survey (Champ et al. 2009); results from these analyses can be found in the Appendix.

Table 2. Summary statistics

Variable	*N*	Mean	SD	Minimum	Maximum
Education, 1 = less than high school and 8 = Ph.D./MD/JD	2,007	4.1	2.0	1	8
Risk perceptions of tornadoes, 1 = no risk to 5 = extreme risk	2,008	2.7	1.2	1	5
Probability of injury or fatality when tornado warning issued (verbatim)	2,008	37.2	30.5	0	100
Reliance on automated text notifications for severe weather, 1 = not much to 5 = a great deal	2,008	3.4	1.3	1	5
Ever paid for mobile app	1,996	0.24	0.43	0	1
Ever paid for weather mobile app	2,001	0.097	0.30	0	1
Never experienced tornado	2,007	0.71	0.46	0	1
Number of tornado days in county warning area, standardized (mean = 0, SD = 1)	2,002	−0.027	0.94	−1.4	2.5

Table 3. Responses to willingness-to-download (at no cost) and willingness-to-pay questions, n (%)

Question	Yes	No	Not sure
If this technology were available as a free application (mobile app) for a smart phone (such as an Android or iPhone), would you download it?	1,276 (63.7)	252 (12.6)	475 (23.7)
Would you download this application (mobile app) for a one-time cost of $[0.99:49.99]?	200 (15.7)	759 (59.8)	311 (24.5)

Table 3 breaks down the responses to the no-cost and the valuation questions. Approximately 85% of responses to the WTP question are no or not sure. This is consistent with similar research that finds approximately 63%–74% of respondents answer no or not Sure (Anaman and Lellyet 1996; Mozumder et al. 2014; Jones et al. 2018). While we have a slightly higher proportion of no responses, this is likely due to the payment vehicle of an app as opposed to taxes as in these studies. Only 24% of our sample has ever paid for a phone app and less than 10% have paid for a phone app that provides weather information, suggesting that revealed prior economic behavior largely mirrors reported behavior in our study. Additionally, app cost amounts were drawn from a uniform distribution, meaning a respondent was as likely to see a reasonable app cost of $0.99 as they were to see a potentially unreasonable cost of $49.99. Fig. 1 demonstrates how responses to the valuation question vary by randomly assigned bid amounts. Economic theory suggests that as the price of the app increases, the likelihood of observing a yes response to the WTP question should go down. Fig. 1 demonstrates this trade-off for our respondents; predicted probabilities of responding yes to the WTP question decrease as the price of the app increases. The probability of a yes response at the lowest app price, $0.99, is approximately 0.38, while the probability of a yes response at the highest app price, $49.99, is just under 0.06. The downward slope of this curve, through the range of price amounts, conforms to economic theory and provides an initial validity check of the WTP estimates they imply. In the next section, we describe our estimation strategy.

Contingent Valuation Method

Estimating WTP works by estimating the underlying household or individual WTP function. This value is not directly observable, so first the probability to accept the bid or price for the good (in this case a phone app) is observed. Assuming a log-logistic distribution of the error term, because WTP cannot be negative in this case, this probability of acceptance (P^y) at bid t is calculated using Eq. (2) from Bishop and Heberlein (1979)

$$P^y(t) = \frac{1}{\exp(-\alpha + \beta \ln(t))} \tag{2}$$

Following Aizaki et al. (2014) who follow Carson and Hanemann (2005) and Hanemann and Kanninen (1999), the values for α, the intercept, and β, the coefficient on the bid amount, can be estimated using a logit model and the following log-likelihood function:

$$\ln L = \sum_{n=1}^{N} \left[d_n \ln\left\{\frac{1}{\exp(-\alpha + \beta t_n)}\right\} + (1 - d_n) \ln\left\{\frac{1}{\exp(-\alpha + \beta t_n)}\right\} \right] \tag{3}$$

where d_n = indicator variable that is equal to 1 if respondent n answers yes to bid t_n and 0 if they answer no. To account for how individual characteristics of the respondent n, such as demographics or other relevant attitudes, are related to utility changes for the respondent, α is specified as

$$\alpha = \gamma + \sum_{k=1}^{K-1} \gamma_k X_k \tag{4}$$

where X_k, $k = 1, \ldots, K-1$, are the individual's characteristics; γ_k = corresponding parameters that measure the effect of these characteristics on utility changes; and γ = constant term. In the current study, X_k first includes covariates for basic demographics such as age, sex, race, ethnicity, income, and education. In order to validate these models and their estimates of WTP, we conducted further analyses that included variables representing tornado experience,

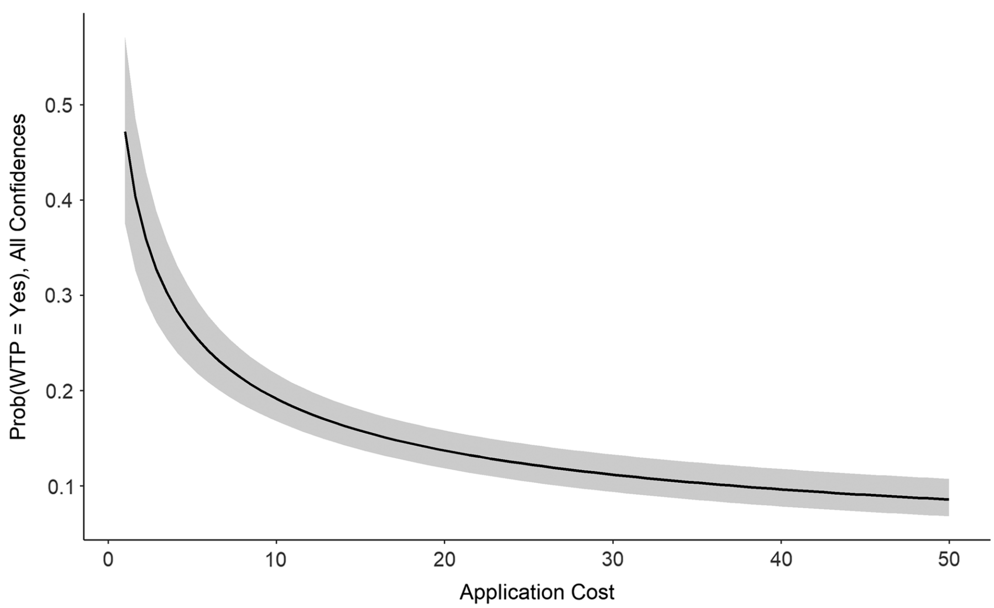

Fig. 1. Predicted probabilities (95% confidence interval) of yes response to WTP question across range of app costs.

Table 4. Marginal effect at the mean from logit models estimated using Eq. (1)

Variable	Model 1	Model 2
Logged bid value	−0.07*** (0.01)	−0.07*** (0.01)
Age	—	0.0002 (0.001)
Male	—	0.04* (0.02)
Income	—	−0.02* (0.01)
Hispanic	—	−0.04* (0.02)
White	—	−0.02 (0.02)
Education	—	0.01** (0.006)
Constant	−0.02 (0.03)	−0.03 (0.04)
N	1,238	1,238
AIC	1,011.4	1,010.1

Note: Standard errors in parentheses; AIC = Akaike information criterion; $*p < 0.1$; $**p < 0.05$; and $***p < 0.01$.

risk perceptions of tornadoes, usage of weather information from phone apps, and measures of whether respondents have ever paid for any app or paid for a weather app specifically. The study also includes a measure of exposure to tornadoes, which is calculated as the average number of tornado days in a year in the respondent's county warning area (standardized to have a mean of 0 and a standard deviation of 1). Theory suggests that tornado experience, objective exposure, and risk perceptions will impact the respondent's likelihood of replying yes to the WTP question. In addition, theory suggests that respondents who have used, downloaded, or paid for a weather app are more likely to respond yes to the valuation question than respondents who have not. From these equations, the mean WTP values can be calculated and validated. We use mean WTP because of its intuitive interpretation as the WTP for the good for the average individual in our data. Using the estimates from Eqs. (3) and (4), the proper, normalized truncated mean WTP from Boyle et al. (1988) is calculated using the following equation:

$$\text{MeanWTP} = \int_0^{t_{\max}} \left[\frac{1 - F(t)}{F(t_{\max})}\right] dt \tag{5}$$

where $F(t)$ = cumulative log-logistic distribution function of the WTP; and $t_{\max}$ = highest bid in the survey. For the purposes of this analysis, a conservative approach was taken and all individuals who reported either no or not sure to the CV question were categorized as no responses (Johnston et al. 2017). A certainty question, as well as the realistic delivery device of an app, as described previously, was used to account for potential hypothetical bias (Little and Berrens 2004; Morrison and Brown 2009). As described previously, results from certainty-recoded valuations are reported in the Appendix.

Parameter Estimates

Table 4 presents the parameter estimates from the basic logit regression models and provides insight into the demographic factors that relate to respondent WTP. The results indicate some heterogeneity in who is willing to pay for a mobile app that provides continuously updated, geographically oriented probabilistic hazard information.

Table 4 also confirms the negative relationship between bid amount and the likelihood a respondent reports yes to the WTP question across both specifications, in line with economic theory. Demographic variables including gender, ethnicity (Hispanic), income, and education are related to the probability of responding yes to the WTP question. Race (White) and age are not associated with the probability a respondent answers yes to the WTP question. Males and individuals with more education were more likely to respond yes, while income and ethnicity (Hispanic) are associated with a lower probability of responding yes to the WTP question. In the next section, we expand our models to include variables about respondent experiences and usage of weather information as validity checks.

Table 5. Marginal effect at the mean from estimated logit model for validity checks using Eq. (1)

Variable	Model 3
Logged bid value	−0.07*** (0.01)
Age	0.001*** (0.001)
Male	0.03 (0.02)
Income	−0.03** (0.01)
Hispanic	−0.04* (0.02)
White	−0.02 (0.02)
Education	0.01* (0.006)
Probability of injury or fatality if warning issued	0.001* (0.000)
No tornado experience	−0.05** (0.02)
Reliance on automated phone apps for weather information	0.003 (0.01)
Ever paid for mobile app	0.05** (0.02)
Ever paid for weather app	0.14*** (0.04)
Standardized average number of tornado days	−0.01 (0.01)
Constant	−0.07 (0.05)
N	1,238
AIC	972.69

Note: Standard errors in parentheses; AIC = Akaike information criterion; $*p < 0.1$; $**p < 0.05$; and $***p < 0.01$.

Validity Checks

To check the validity of our estimates, a model that included a variety of relevant experiential characteristics that go beyond demographics was estimated. The results from this model are given in Table 5.

Examination of covariates that are more specific to the good in question suggests that experiences and perceptions of tornadoes and weather information are strongly related to WTP for an app that provides probabilistic hazard information. The higher a respondent reported the probability of an injury or fatality occurring when a tornado warning is issued, the more likely they are to respond yes; the 5-point scale of risk perceptions of tornadoes, however, was unrelated to responses. Individuals who report never having experienced a tornado were, as one would expect, much less likely to respond yes to the valuation question. However, the standardized average number of tornado days by county warning area had no relationship with responses to the valuation question. Additionally, both those who had downloaded a weather app and those who had paid for a weather app were more likely to respond yes. The effect of having paid for a weather app previously has the largest marginal effect estimate of all covariates, suggesting a particularly strong relationship with the likelihood of responding yes to the valuation question. General reliance on automated phone notifications for severe weather information was not significantly related to a respondent's probability of WTP. In general, these relationships confirm our expectations that experience and familiarity with tornadoes and weather information are associated with a respondent's likelihood of responding yes to the valuation question. More importantly, they indicate that respondents were carefully thinking about their circumstances when deciding whether they would purchase the app. This lends credibility to the experimental results and the WTP estimates provided subsequently. We also checked the

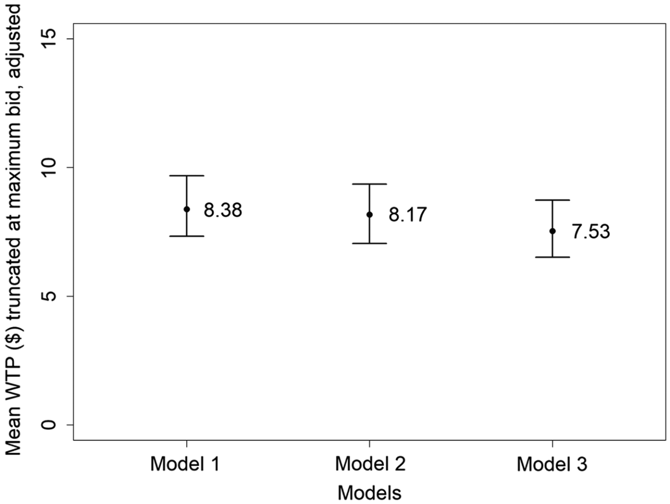

Fig. 2. Estimated mean WTP with 95% confidence intervals across models.

validity by comparing those who reported yes to high app costs, $29.99 and above, to the average overall respondent because those who respond yes to these high values drive a portion of the mean WTP we estimated. We found no statistical differences for demographic factors; however, those willing to pay high values ($29.99 and greater) are more likely to have purchased an app, purchased a weather app, and be reliant on automated phone apps for weather information, and less likely to have no experience with tornadoes than the average respondent.

WTP Estimates

Using Eq. (4) and the results from Tables 4 and 5, the truncated (at the maximum bid) mean WTP, adjusted using the method in Boyle et al. (1988) described previously, for all yes responses with no certainty recoding with confidence intervals calculated using the method suggested by Krinsky and Robb (1990) was estimated and is presented in Fig. 2.

Fig. 2 demonstrates the difference in truncated, adjusted mean WTP when moving from a model with no covariates, other than the bid amount, to a model including demographic covariates, to a model including variables related to experiential and informational characteristics. Including these covariates in the model results in slightly lower and slightly more precise mean WTP. These estimates suggest the mean WTP among respondents is between $7.53 and $8.38 for a one-time payment for an app that provides continuously updated, geographically oriented probabilistic hazard information.

One potential way to address the upward bias in the estimation of WTP for CV exercises is to create nonparametric estimates of WTP. In particular, the Kaplan-Meier-Turnbull estimation strategy is considered the most conservative, when no covariates are accounted for, because it relies on a step function between point estimates from a survival function (Aizaki et al. 2014). The nonparametric estimate of mean WTP using this technique is $7.39, which is very similar to the estimate from Model 3 (in Table 5, which includes experiential characteristics as a validity check). This estimate helps establish the reasonable bounds around individual estimates of WTP for continuously updated, probabilistic hazard information.

Aggregating WTP: Societal Value of Probabilistic Hazard Information

For this delivery method, there are several different populations relevant for aggregation. One population of interest to policy makers is the total number of households in the US. However, given the delivery device used in the study, another relevant population may be the total number of mobile phone users in the US, and particularly the total number of smartphone users (because apps can only be downloaded on these devices). Using a more conservative mean WTP value ($7.53) and assuming each household would only purchase the app once results in an aggregate value of approximately $901 million by multiplying the mean WTP value of $7.53 by the average number of US households between 2014 and 2018, which is 119,730,128 (US Census Bureau 2019b). Another population of interest may be the more than 206 million smartphone owners, because our payment vehicle and WTP are for a smartphone app. This results in an aggregate value of approximately $1.56 billion when multiplying the mean WTP of $7.53 by the more than 206 million adults who owned a smartphone in the US in 2018 (Pew Research Center 2019). Future research ought to further examine the relatively high prevalence of respondents who are unwilling to pay and their motivations. Studies that use other research designs common to the contingent valuation literature may be better able to estimate the value, if any, these individuals attach to this sort of app and information. One important limitation to this value is, as Shogren and Crocker (1991) note, our WTP estimate likely includes WTP for the app as well as utility from the potential risk reduction it might provide. To differentiate between this value expression and the risk reduction of the app is beyond the scope of this article. We simply note that this may upwardly bias our aggregate value of the app by also including the value of the potential risk reduction.

While the current study focuses on probabilistic hazard information, among other characteristics, for a tornado threat, the FACETs paradigm from the NWS applies to all types of weather-related threats, including hurricanes. This study provides an initial estimate of the value of one product that represents the FACETs paradigm including but not limited to PHI. Our study suggests that efforts to develop new more precise severe weather information such as that valued in this article for a variety of hazards may produce significant economic value for households in the United States. Future research may consider methodological approaches such as variation in the WTP stimuli that will allow for researchers to value PHI separately from the other attributes valued here. Work such as this will help researchers and policy makers better understand which specific information characteristics provide the most value and deserve the most investment of public resources. However, only 15% of our sample were willing to purchase the app at any cost, compared to almost 64% who would have downloaded the app if it were free. This suggests respondents may view this type of information as a public good that should be provided freely. While the value of the app is high, only a small proportion of the population would reap these benefits, using this payment vehicle. It is possible a tax payment vehicle might be more appropriate if it is the case that respondents view this type of information as a public good or if we are capturing a norm around not paying for apps; future work could investigate this possibility. However, the current study suggests that the FACETs paradigm represents an area of significant value for NWS investment.

Conclusions

This paper provides estimates of mean WTP for a continuously updated, geographic, probabilistic hazard information product, like

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those currently being developed by the NWS. Most respondents, more than 63%, reported a desire for this type of information when it was freely provided. Mean WTP for an app providing this information was estimated to be $7.53 per household (as a one-time payment) or approximately $901 million for all US households. These estimates are generally lower than those found by previous research in this domain. However, this may be due to the specificity of the type of information and type of delivery being valued. For example, Lazo and Chestnut (2002) valued all current weather services at $109 per year per household, while maximizing all improvements to the system were valued at $16 per year per household. Similarly, Lazo and Waldman (2011) estimated that improving hurricane forecasts is valued at $13 per household per year among a small sample of Miami–Dade County respondents. These findings are similar to Mozumder et al. (2014), who found an annual household value of approximately $7 for residents of Florida for a hurricane mitigation fund. One reason these studies may find higher WTP for improvements to forecasting and mitigation is that they focus on populations

Table 6. Measurement of independent variables

Variable	Survey question	Measurement
Age	How old are you?	Self-report in years
Male	Are you male or female?	0 = Female 1 = Male
Income	What was the estimated annual income for your household in 2016?	1 = Less than $50,000 2 = At least $50,000 but less than $100,000 3 = At least $100,000 but less than $150,000 4 = $150,000 or more
Hispanic	Do you consider yourself to be Hispanic, Latino, or Spanish or to have Hispanic, Latino, or Spanish origins?	0 = No 1 = Yes
White	Which of the following best describes your race?	1 = White 2 = Black or African American 3 = American Indian or Alaska Native 4 = Asian 5 = Native Hawaiian or Pacific Islander 6 = Two or more races 7 = Some other race (please specify) Recoded to 0 = All else 1 = White
Education	What is the highest level of education you have completed?	1 = Less than high school 2 = High school/GED 3 = Vocational or technical training 4 = Some college; NO degree 5 = 2-year college/associate's degree 6 = Bachelor's degree 7 = Master's degree 8 = Ph.D./JD/MD
Probability of injury or fatality if warning issued	If the National Weather Service issues a tornado WARNING for your area, what is the probability that someone in the warning area will be injured or killed? Please indicate the probability as a percent that ranges from 0 to 100, where 0 means there is no chance of an injury or fatality and 100 means that an injury or fatality is certain.	Self-reported probability between 0 and 100
No tornado experience	Have you or members of your family, neighbors, friends, or associates ever experienced property damage, personal injury, or loss of life from a TORNADO? Please select all that apply.	No Yes, for you personally Yes, for family Yes, for neighbors Yes, for close friends or associates Only use No responses, coded as 1
Reliance on automated phone apps for weather information	Warnings and information about severe weather are available from multiple sources. How much do you, *personally*, rely on each of the following sources of information about severe weather? For automated text or phone notifications.	1 = Not much 2 = Little 3 = Somewhat 4 = Much 5 = A great deal
Ever paid for mobile app	Have you ever paid for an application (mobile app) of *any kind* for a smart phone (such as an Android or iPhone)?	0 = No 1 = Yes
Ever paid for weather app	Have you ever paid for an application (mobile app) that *provides information about the weather* for a smart phone (such as an Android or iPhone)?	0 = No 1 = Yes
Standardized average number of tornado days	Collected from NCEI.	Average number of tornado days for respondent county warning area, standardized to mean 0, standard deviation 1, such that positive numbers are above average tornado days and negative numbers are below average tornado days.

for whom the good is particularly relevant while the current study surveyed a national sample, many of whom have never experienced a tornado. Additionally, hurricanes are considerably more damaging than tornadoes, costing on average almost 10 times as much each year according to the Storm Prediction Center (2018). Other reasons for the higher WTP in previous studies include differences in method, small sample sizes, and higher hypothetical biases.

The estimates of WTP in this study are generally in line with previous contingent valuation research in weather; however, they may underestimate the value of this type of information. First, the payment vehicle, a phone app, was chosen in order to prevent the upward bias often associated with tax payment vehicles. Under the current prompt, respondents are likely only considering their personal need for such an app and the associated information; thus, we are not able to assess a broader existence value of this information. Additionally, we do not know how the app characteristics are associated with WTP. For example, would the mean WTP be substantially different if we had used a different aesthetics such as different graphic styles or color schemes? In this regard, we also do not know which characteristic of the app is driving WTP. Is it the probabilistic nature, the continuous updates, or the geographic precision? Future research should examine the WTP for precise severe weather information under these varying conditions.

Additionally, the provision of continuously updated PHI will also create other benefits, not measured in this study, such as its retransmission through personal networks and other platforms. This characteristic of the information may be why income is negatively associated with WTP; higher-income individuals may believe they could get this type of information elsewhere. Additionally, individuals with higher incomes may perceive themselves as better insulated from the effects of natural hazards than individuals with lower incomes. These higher-income individuals may not see a need to acquire more information about weather threats. Finally, provision of probabilistic information such as that examined here often improves decision-making and protective action during natural hazards (Ash et al. 2014; Grounds and Joslyn 2018). Therefore, the estimated value of the information to individuals' WTP may be exceeded by the social value from the protection of life and property that results from individuals using (and sharing) the warning information.

In sum, this study concludes that members of the US public are willing to pay a substantial amount to receive probabilistic hazard information. Probabilistic hazard information will thus be likely to contribute to societal welfare generally. In addition, the study demonstrates the utility of a robust methodology for estimating values that can inform policy decision and public agency programs about the provision of probabilistic hazard information. Contingent valuations, as demonstrated in this study, can provide reliable estimates of the value of different types of forecast information such as probabilistic hazard information. Carefully designed contingent valuation studies, relying on a realistic payment vehicle and national sampling frame, can provide lower-bound estimates of value that may be particularly useful for informing programmatic investments.

Appendix. Survey Measurement and Hypothetical Bias Analyses

Table 6 provides details about the survey questions and measurement used in our analyses. Fig. 3 depicts the appropriate mean WTP from the demographic-only model (Model 2 in Table 4) following Mozumder et al. (2014). This figure demonstrates the effects of another method from Champ and Bishop (2001) commonly used to address hypothetical bias where yes responses are recoded as no at different levels of certainty.

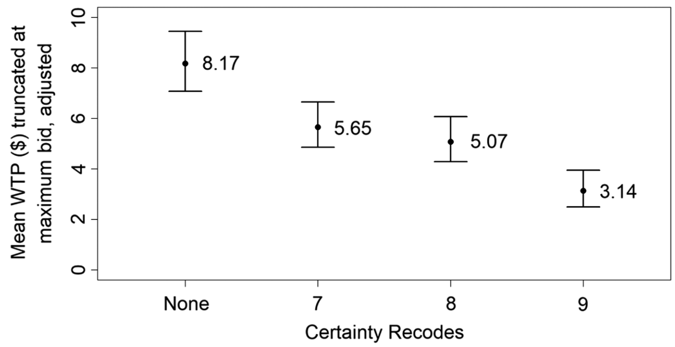

Fig. 3. Truncated, adjusted mean WTP with 95% confidence intervals across certainty recodes.

Data Availability Statement

The authors will make all data and code available upon reasonable request.

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Supplemental Materials

Video S1 is available online in the ASCE Library (www.ascelibrary.org).

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