Communicating Forecast Uncertainty (CoFU) 2:

Replication and Extension of a Survey of the US Public's Sources, Perceptions, Uses, and Values for Weather Information

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Table of Contents

Table of Tables

Table of Figures

Executive Summary

Introduction

In the 2021 AMS White Paper[1] "Weather-Water-Climate Value Chain(s): Giving VOICE to the Characterization of the Economic Benefits of Hydro-Met Services and Products" (Lazo and Mills 2021) present the weather information value chain (see Figure ES-1) and emphasize that "It is within the context of information improving, reinforcing, or changing the decisions of end-users, that economists would argue there is actual or potential economic value to this information" (p. 4). Thus, understanding end-users' sources, perceptions, uses, and values of weather information is critical to the Weather Enterprise's efforts to "to deliver the most accurate, most timely, most relevant weather information to all 330 Million Americans."[2]

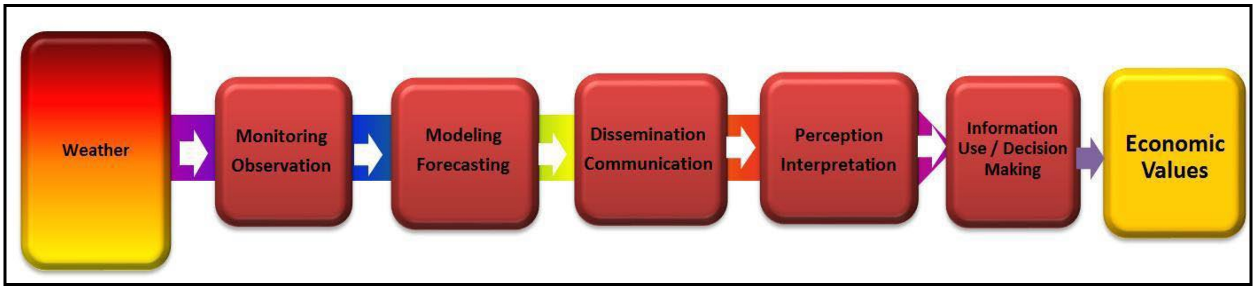

Figure ES-1: Weather Information Value Chain

In 2006 the research team of Julie Demuth, Jeff Lazo, and Rebecca Morss from the National Center for Atmospheric Research (NCAR), and Alan Stewart of The University of Georgia designed and implemented a survey of the general public of the United States to explore a range of issues related to the communication, use, understanding, and value of weather forecasts. This resulted in five published articles including Lazo et al. (2009).

In 2022, with support provided by the Policy Program of the American Meteorological Society[3] (AMS), which is under the direction of Paul Higgins, we reimplemented essentially the same survey. To the maximum extent possible the exact same survey instrument, implementation methods, and target population were replicated. Five additional topics were included at the end of the instrument to begin to assess these related concepts (cultural risk theory, numeracy, perceived vulnerability, political preferences, and risk preferences).

The current report focusses mainly on analysis related to the topics from the Lazo et al. (2009) paper ("300 Billion Served"), which covered questions related to the sources, perceptions, uses, and value of weather information (i.e., not the decision scenarios or

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[1] https://www.ametsoc.org/index.cfm/ams/policy/studies-analysis/weather-water-climate-value-chain-s-giving-voice-to-the-characterization-of-the-economic-benefits-of-hydro-met-services-and-products/

[2] https://www.weather.gov/about/weather-enterprise

[3] https://www.ametsoc.org/index.cfm/ams/policy/

the communication of uncertainty questions included in the survey). In this report we also document our survey design and implementation methods.

Objectives and thoughts on replication

Why did we reimplement the 2006 survey? We felt revisiting this effort would provide a useful "retrospective" and that some of the issues addressed in the 2006 survey had not been adequately built upon and thus deserved to be looked at again. Two of these issues reported in the "300 Billion Served" article (Lazo et al. 2009) include 1) the general public's sources and frequency of use of forecasts across all sources and 2) the general public's value (i.e., Willingness-to-Pay) for current forecast information.

In addition, we feel that, as in all sciences, *replication* is a critical component of scientific research. Stefan Schmidt suggests a functional approach to defining replication:

> "Therefore, I suggest differentiating at a fundamental level between two basic notions of replication: 1. Narrow bounded notion of replication: Repetition of an experimental procedure. Henceforth, this notion will be termed direct replication. 2. Wider notion of replication: Repetition of a test of a hypothesis or a result of earlier research work with different methods. Henceforth, this will be referred to as a conceptual replication." (Schmidt 2009, p. 91)

In our current effort though we feel we are pursuing two objectives that confound the issue of a true replication to test prior hypotheses or findings (i.e., conceptual replication):

1. What has changed since the 2006 survey? One area we expect this to have changed is in the value of current forecasts—at least when not adjusted for inflation and wealth changes.
2. What has stayed the same, and thus can we provide additional support for the finding reported in prior articles? One area this seems feasible is in the analysis of the Weather Saliency concept (see Stewart 2009).

These two questions seem to identify a fundamental conflict in our objectives: for any given result we can argue it is important as it either 1) indicates what has changed or 2) it reconfirms our original findings. Thus, any result can be claimed as highly relevant! This may well be the case with any type of social science research over time. Thus, even though we may not be able to claim to be replicating tests of our 2006 analysis, we feel that we are replicating the 2006 study at least in terms of implementation of essentially the same survey, by the same research team, and using the same research methods (i.e., direct replication). We also feel that replication in the social sciences is fundamentally different than in the physical sciences.

> "…human minds are so complex that building clear, practical, testable theories can be a long process, often well beyond the scope of a single research report. Many social problems are similarly complex: it is prudent to accumulate detailed demonstrations of empirical phenomena in the literature before making confident recommendations about solutions to big problems." ((Burke and Moss-Racusin 2023) p. 536)

The question of the need for replication of social science studies for the weather enterprise should be driven in part by the importance and impact of the use of results of such research. If operational changes are being made that affect the safety or welfare of millions of people, then confirmation of research results would seem prudent.

Survey design and implementation

Morss et al. (2008, 2010) describe the design and implementation of the 2006 survey that the 2022 survey is based on. The original survey questions were retained as implemented in 2006, but five additional topics were included at the end of the instrument to begin to assess these related concepts:

- Cultural risk theory
- Numeracy
- Perceived vulnerability
- Political preferences
- Risk preferences

The current report does not deal with these new topics in depth at this time although we use some aspects of these in our analysis here. Future work will undertake analysis of these new topics. Additional changes include, first, a minor change made to the question assessing individuals' Willingness-to-Pay for current weather information. While the question format was the exact same as 2006, additional price points were added to the randomization to try to cover the higher values not covered in the 2006 analysis. Second, to allow for screening for respondents' sociodemographic characteristics to meet the desired sample distribution, several sociodemographic questions were moved to the beginning of the survey including zip code, gender, age, and race.

The 2022 survey was contracted with Dynata (https://www.dynata.com/) for programming, sampling, and hosting. Dynata used their online panel for the sample to implement the survey through their survey router rather than an email invitation as used by ResearchExec in the 2006 survey. The intended population for this research is the entire population of the United States 18 years old or older. The sociodemographic criteria provided to Dynata included 1) a roughly 50/50 split on gender and 2) as representative of the general U.S. population as possible based on current census data. Overall, we feel that the Dynata process provides a sample that comes from a well-developed panel that meets our population requirements, and removes respondents who are not providing useful information.

The soft launch was implemented on May 3, 2022 and after a quick evaluation of the soft launch data and a minor revision to the price offers on the Willingness-to-Pay question, the complete launch began May 5, 2022. The final response (n = 1,202 including the soft launch) was started May 11, 2022. The final dataset was provided by Dynata on May 12, 2022. As only complete responses were provided and there were 3,930 survey starts of which only 1,202 qualified and completed the survey, one calculation of completion rate is 30.59%.

As in CoFU1, we fitted a value for income for respondents who declined to respond to the income question. The income and the Willingness-to-Pay price points were adjusted from 2005 values (as asked in the survey) to 2021 values using median household income and the Consumer Price Index (CPI) respectively.

Following data cleaning and various adjustments the 2006 and 2022 datasets were joined using SAS® software append stacking with the same number of variables except the new questions added in CoFU2[4]. The compiled dataset has 267 variables and 2,722 observations.

Analysis and results

In this report we present an initial analysis of some aspects of the survey. For the current analysis we note that the margin of error is not specifically discussed with each result but in general is ±3%. In our analysis and reporting we generally use a 10% level as the relevant level of significance. This is a subjective decision and has not accounted for potential multiple related significance tests. We also feel that any results reported here (or in most scientific literature) should be reevaluated and replicated especially if decisions based on those results may affect peoples' safety or welfare as communication of weather information certainly does. We further note that comparing results or drawing inferences for the samples as a whole, basically assumes that the samples were both random and representative. To further explore various results, we undertake regression analysis including sociodemographic explanatory variables mentioned above as well as the "CoFU_Version" indicator variable. We feel that regression analysis where the version indicator is still significant suggests that there is more likely a real difference in behavior, perceptions, or values between 2006 and 2022 than just comparing sample means.

We compared individuals' time to complete the survey between the 2006 and 2022 implementations. We further split this into those who indicated they do and do not use weather forecasts as those who indicated they do not use forecasts answered considerably fewer questions. The mean time is almost identical for those who do use forecasts (28.95 minutes versus 28.97 minutes). Statistical tests showed no significant difference for time to complete the survey between the 2006 and 2022 respondents in those using forecasts.

For CoFU1 we had respondents from all 50 states and the District of Columbia. In CoFU2 we have respondents from all states except Alaska and Delaware.

There is no significant difference (at the 10% level) between samples on several measures including income (adjusted using the median value); gender; education; full-time or part-time employment, retired or student; or the portion of the sample that identifies their race as Black or Native. There is significant difference (at the 10% level) between samples on several measures including years in current residence; age; being a homemaker or unemployed; and the portion of the sample that identifies their race as Asian, Latino, White, or other. We feel that these differences reflect that we have reached a somewhat more representative sample with the 2022 survey including better reaching younger respondents and those from racial groups not as well represented in the 2006 sample.

[4] SAS is a suite of software with a range of statistical processes. SAS and all other SAS Institute Inc. product or service names are registered trademarks or trademarks of SAS Institute Inc. in the USA and other countries. ® indicates USA registration.

In 2006, 8.1% of respondents indicated they were unemployed. Unemployment in November 2006 was 4.3%. For the 2022 survey, 12.1% of respondents indicated they were unemployed. The unemployment rate in June 2022 was only 3.8%. Respondents thus reported a much higher rate of unemployment in both surveys than in the official statistics for the corresponding period.

Throughout most of the analysis reported here (especially regression analysis) we attempted to use a consistent set of explanatory variables including sociodemographics, employment, race, and personal time allocation. Analysis variables include gender, which for the 2022 survey options were (male/female). For analysis here we use a "female" indicator variable. For income we generally use income adjusted to current (2021) values using the median income adjustment. We have a series of indicator variables for employment status and indicator variables for race identifiers that are not necessarily exclusive. Finally, we include a series of self-assessed measures of time allocation including percent of leisure time or work time spent outside and how many hours per week spent travelling to work or being outside at home (which may or may not include leisure time).

1.1. Personal weather impact scale

Not included in the 2009 BAMS analysis, for the current analysis, a "personal weather impact scale" was developed in a preliminary manner based on a series of questions asking respondents if they have experienced personal (or household level) weather-related impacts (weather-related property damage, motor vehicle injury, non-motor vehicle injury, and weather-related medical conditions). Responses to four dichotomous questions (yes/no) used for this preliminary scale were totaled, so a zero meant the respondent answered "no" to all four impacts and a score of 4 means they had experienced all four types of impacts. An ordered probit regression analysis on the total personal weather impact scale found that CoFU2 respondents experienced fewer personal impacts than CoFU1 respondents. Other measures significantly related to experiencing more weather impacts include lower income; older; non-female; larger household; more education; spend more time working outside; spend more leisure time outside; do not get forecasts for their own city; do get forecasts for other states or countries; use forecasts in the early morning; do not use forecasts in the midmorning (8 to 11 am). Those who use forecasts to get to work or who feel NWS information is more important are also more likely to have experienced personal weather impacts. No employment or race variables were significant nor were satisfaction or confidence in forecasts. The relationship between having experienced weather impacts and a large number of variables is complex and worthy of future examination. We note that this scale is preliminary and is mainly used as an explanatory variable in several other regressions in this report. The regression though does indicate that substantial useful information may be revealed by these questions especially when combined with the responses to the follow-up questions on levels or personal impacts.

1.2. Use forecasts

In 2006, 3.62% of respondents indicated they never used forecasts; however, that had changed to 9.15% in 2022. This is a statistically significant difference (chi-square = 36.09; df = 1; Prob < 0.0001) representing a very important and significant change if valid. We thus explored this further in some depth. First, as shown in Table ES-1, we looked at the 95% confidence intervals responses using binomial proportions (using exact confidence limits as calculated in SAS). As would be indicated by the chi-square test noted above, the 95% confidence intervals do not overlap.

Table ES-1: Do You Use Weather Forecasts? 95% Exact Confidence Limits on Percent Yes

	CoFU1	CoFU2	Combined
Lower Bound	95.32	89.08	92.98
Mean	96.38	90.85	93.94
Upper Bound	97.26	92.42	94.81

To explore this issue further we included data from the (Lazo and Chestnut 2002) study. Counting the number of individuals in each survey who do not use forecasts (1, 55, and 110, respectively, for a total of 166) and the total number of respondents (381, 1520, and 1202, respectively, for a total of 3,103) yields 5.35% not using forecasts. For purposes of further analysis and aggregation in this report, we use 5.35% as the baseline value for those not accessing weather information in the U.S. general public. Future research is needed to determine the true proportion of the population not using forecasts. In the current study this was based on a single yes/no question with no follow-up to determine why individuals do or do not use forecasts or how exactly they even interpret the question. It would also be useful to further explore what "not using" forecasts means in terms of not seeking information, not using weather information for decision-making, not hearing anything, or some more precise or nuanced way of characterizing not using weather forecasts.

A probit regression on the "Yes" response to the use forecasts questions indicates that, even after controlling for the included sociodemographic characteristics, significantly fewer people used forecasts in 2022 compared to 2006. Those with higher income are more likely to access weather information. Female, more highly educated, White, Black, Asian, Native, and those who spend more of their leisure time outdoors are more likely to use forecasts.

1.3. Sources

We asked how often respondents obtain forecasts from 10 different information sources. Even though we are aware of technical developments since 2006 we retained the identical question from 2006 to maintain consistency. As shown in Figure ES-2, the more "traditional" sources (local and cable TV stations, commercial or public radio, other web pages, and newspapers) have all decreased in usage at the expense of more "modern" or "social" sources (i.e., NWS web pages, friends, family, coworkers, etc., NOAA Weather Radio (NWR), cell phone, PDA, pager, or other electronic device, and telephone weather information source).[5]

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[5] As noted by a reviewer this may also be a function of "active" seeking of weather information compared to "passively" receiving this information. The decrease in use seems to fall on more "passive" sources and the increase on more "active" sources where individuals are more actively seeking information. This would be another area worth future investigation to determine for different sources how much "active" versus "passive" information seeking is involved. As this reviewer noted "Anecdotally, I use my weather

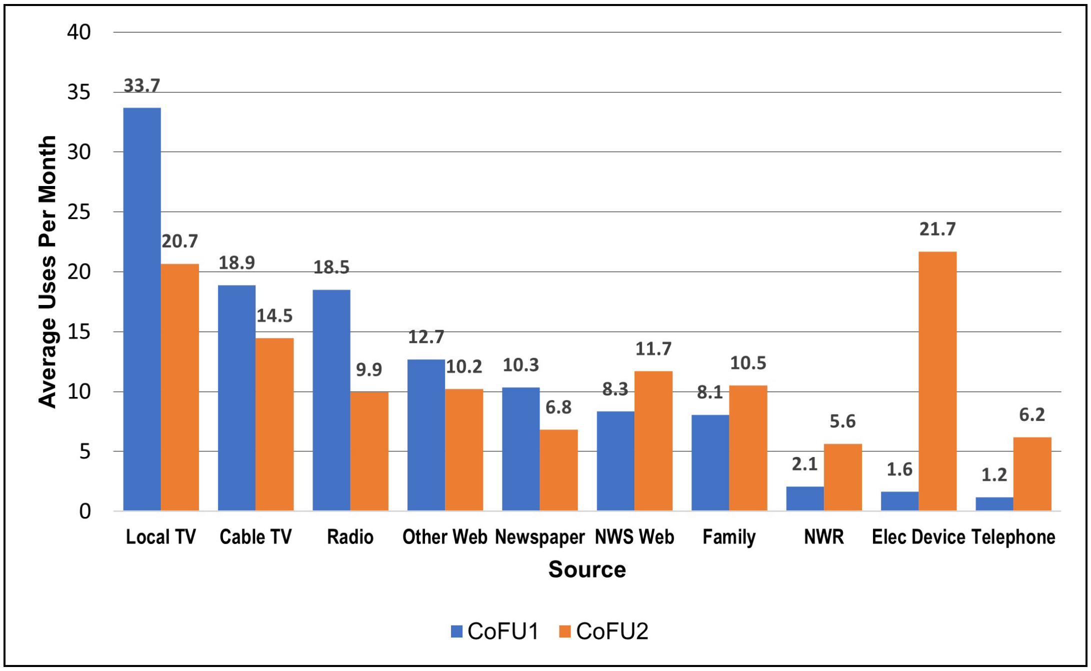

Figure ES-2: Frequency of Use by Source by Survey Version

Notes: The survey question asked "How often do you get weather forecasts from the sources listed below?" Response options ranged from "Rarely or never" to "Two or more times a day" that were conservatively recoded into times per month. (CoFU1 n = 1,465; CoFU2 n = 1,092)

1.3.1. Total annual frequency

For each individual we summed their monthly uses for each of the sources to derive a total monthly frequency. For CoFU1 this was 115.40 and for CoFU2 this was 117.80. A *t* test of the difference between the means indicated no statistical difference [t(2555) = -0.70, p = 0.48]. We note that the monthly use is likely a lower bound because the maximum offered in the frequency question was "twice or more a day" and this is conservatively treated as twice a day. A regression on total frequency of use indicated that the CoFU version is not significant confirming no difference by version. Showing the result in the regression analysis is a somewhat stronger test as it also controls for potential variation in the samples (e.g., age, gender, income, etc.) that may have masked a difference in use. Those individuals who have lived in his/her house longer use more forecasts. Individuals using forecasts more for any of the four geographic levels (see "geographic area of use" below) access more forecasts. Those who spend a larger percentage of their time outside on the job or for leisure access more forecasts. Individuals using forecast information to get dressed, get to work, or for weekend activities all use more forecasts. Those with a higher level of confidence in 1-day precipitation forecasts access more forecasts but those with more confidence in less than 1-day forecasts in general do not. Finally, as may be expected, those who place a higher level of importance on NWS forecast information access more of that information. The

app as needed, which generally means in planning for the day ahead. In the past, you'd get weather info based on when it was available passively through tv/radio and based on when you are watching."

largest standardized coefficient estimate is for "percent of job outside" suggesting that weather forecasts are very important or useful for outside work activities or possibly that those activities also require more frequent updating of weather information.

The title of the Lazo et al. (2009) BAMS paper "300 Billion Served" was based on the calculation of total forecasts accessed by the U.S. public in 2006. Following the same approach as in (Lazo et al. 2009), we calculate a national total based on the 2022 responses and recalculate the 2006 total using the value of 5.35% as the percent of the U.S. population not using weather forecasts. The 2006 estimate is slightly reduced to 295 billion from the 300 billion number due to the use of a different fraction of respondents not using weather forecasts. The 2022 estimate is roughly 317 billion forecasts accessed annually by members of the U.S. public. These results indicate that there has been a 7.26% increase in aggregate use between 2006 and 2022. This is driven partly by the slight increase in "times per month" (a 2.14% increase) and more so by the increase in U.S. population over 18 (a 9.40% increase).

1.3.2. Time of day obtaining forecasts

We asked how often people obtained weather forecasts during different times of the day. As shown in Figure ES-3, there has been a shift toward using forecasts earlier in the day away from evening periods. We conjecture this may be related in part to a shift away from the use of forecasts from TV sources in the evening. We further conjecture this may be related to changes in work habits since COVID.

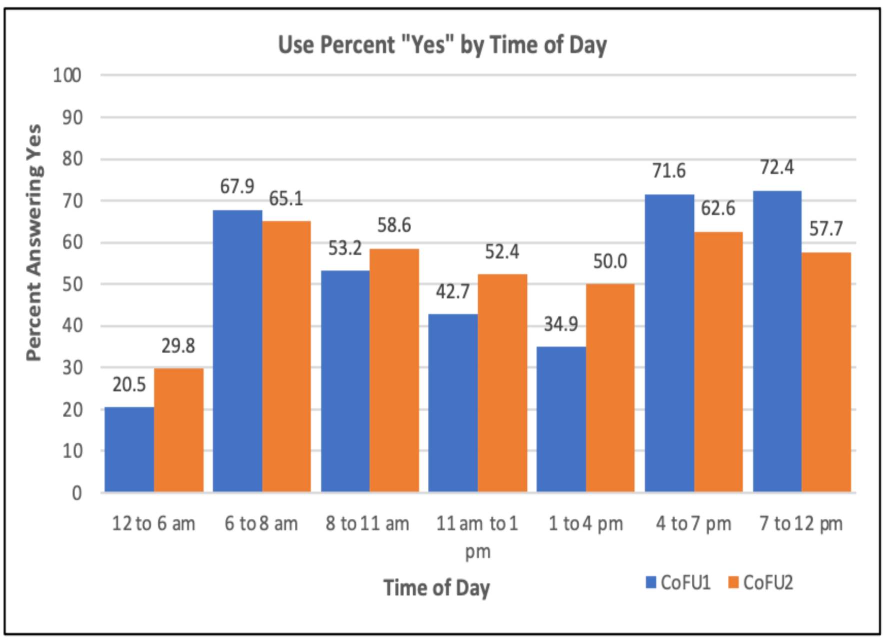

Figure ES-3: Difference in Time of Day for Use of Forecasts between CoFU1 and CoFU2

Notes: The time periods indicated are not of the same temporal length. The survey question asked "Do you normally get weather forecasts during the time periods listed below?" Response options were "yes" and "no." (CoFU1 n = 1,465; CoFU2 n = 1,092)

1.4. Perceptions

1.4.1. Satisfaction with weather forecasts

As stated in Lazo et al. (2009), “We explored respondents’ perceptions by examining their satisfaction with and confidence in the forecasts they currently receive” (p. 790). As seen in Figure ES-4, overall, there is a high level of satisfaction, and this has increased somewhat since the 2006 survey. One a 5-point scale (1 = very dissatisfied to 5 = very satisfied), the mean response in the 2006 survey was 3.791 and in 2022 it was 4.035. This was significantly higher in 2022. A regression model of satisfaction indicated that even controlling for various sociodemographic aspects, confidence in and use and importance of forecasts, the level of satisfaction in 2022 is still significantly greater than 2006. Those with higher education are more satisfied with weather information as are Latinos and those who use forecasts for the city where they live or for cities in other parts of the world. Those who access forecasts simply to know what the weather will be like are more satisfied with forecast information. Conversely, those who spend more time outside while at home or use forecasts for social activities are *less* satisfied with weather forecasts. This seems to suggest that current weather information does not meet expectations or needs for some people.

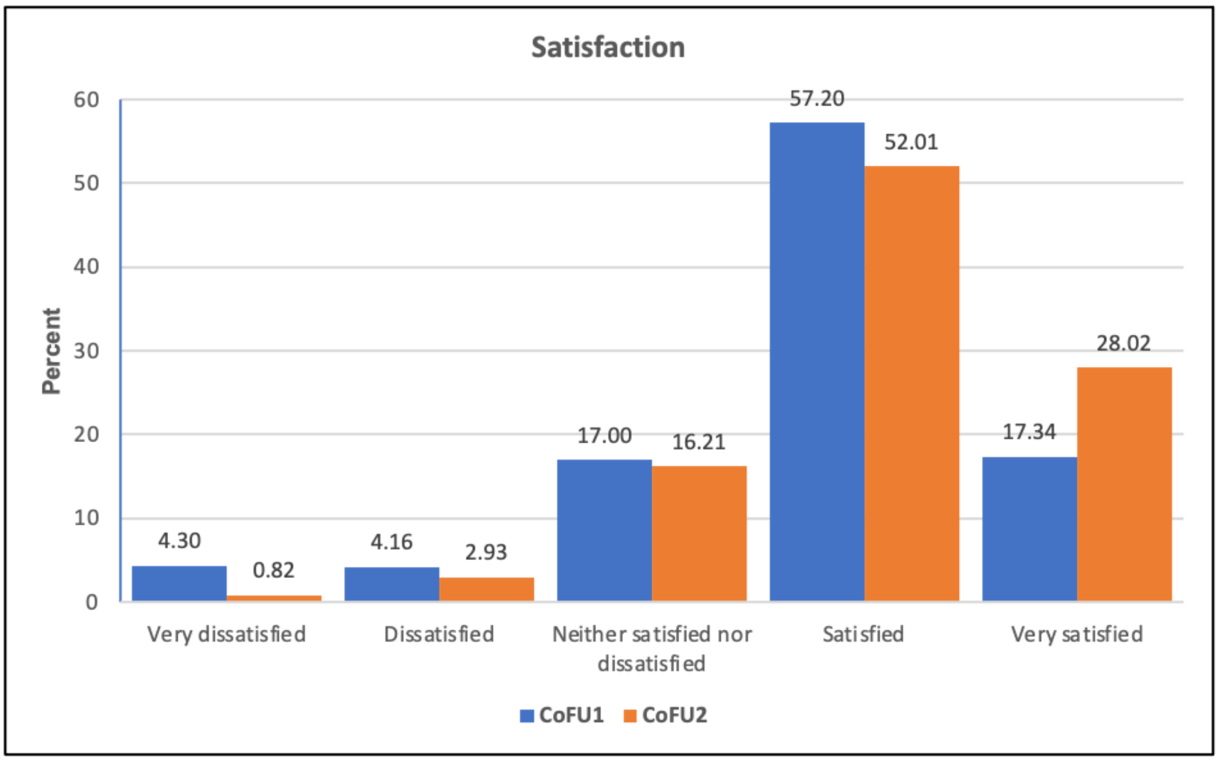

Figure ES-4: Satisfaction with Forecasts by Survey Version

Notes: The survey question asked “Overall, to what extent are you satisfied or dissatisfied with the weather forecast information that you currently receive?” (CoFU1 n = 1,465; CoFU2 n = 1,092)

Using the regression model we “fit” the satisfaction level for the “average” CoFU2 respondent using the means of all sociodemographics and other explanatory variables used in the regression model—except we fit this value for a CoFU1 response versus a

CoFU2 response (i.e., calculating the level of satisfaction by only varying which version of the survey they answered and thus only the parameter estimate on version affected the difference in fitted satisfaction). The average CoFU1 level of satisfaction was calculated as 3.78 and for CoFU2 as 4.03 for a 0.26-point increase in satisfaction on the 5-point scale. Adjusting for the fact that the scale starts at "1" this represents a 9.29% increase in satisfaction with forecasts between 2006 and 2022.

1.4.2. Confidence in weather forecasts

We asked respondents to indicate their confidence in weather forecasts at different lead times with average responses as shown in Figure ES-5. There is a declining trend in forecast confidence for the longer time periods with statistical tests indicating that confidence in shorter-term weather forecasts (1 day or less) appears to have decreased while confidence in 3-day or longer forecasts has increased between 2006 and 2022. Further, when asked about confidence in different forecast attributes (temperature and precipitation chance and amount) at different lead times all of the responses were significantly different between the two survey implementations but not all in the same direction. Confidence in short-term forecasts (1-day) has decreased since 2006 but increased for the 3-day and 7-day forecasts for all attributes. The reasons for these changes cannot be determined from this survey but warrant more explanation. It could be interesting to compare confidence in forecasts to weather verification metrics to see if there is a correlation between these performance metrics and subjective perceptions.

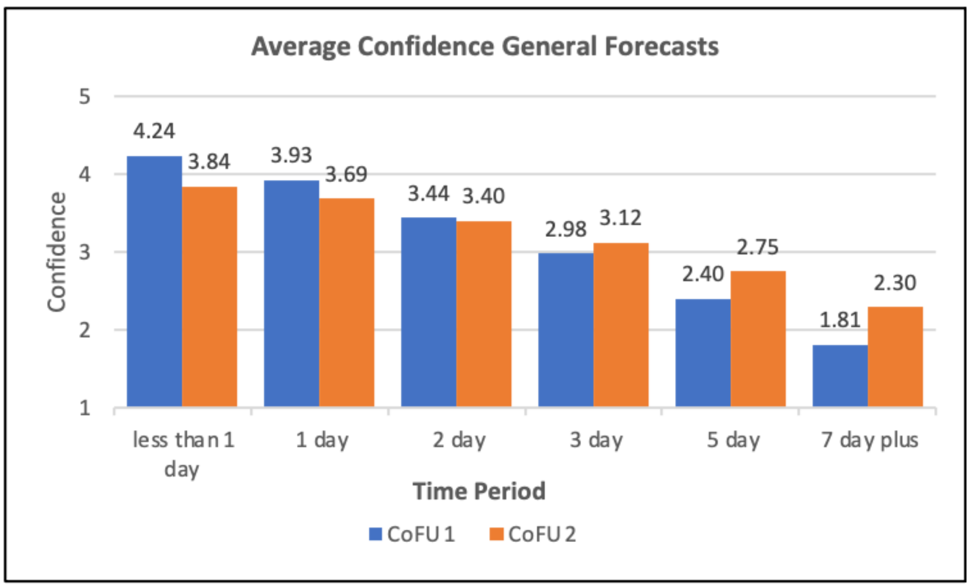

Figure ES-5: Average Confidence in Forecasts by Time Period and Survey Version

Notes: The survey question asked "How much confidence do you have in weather forecasts for the times listed below?" The times were listed as "Less than 1 day from now, "1 day from now," and so on, out to "7 to 14 days from now." (CoFU1 n = 1,465; CoFU2 n = 1,092)

1.5. Uses

1.5.1. Geographic area of forecast use

We asked respondents if they use weather forecasts for different geographic areas (city where the respondent lives, other cities in the state, other cities in other states, cities in other countries). Figure ES-6 show the mean responses by location and survey version. There has been a shift in interest from local areas to broader geographic areas between the two survey implementations.

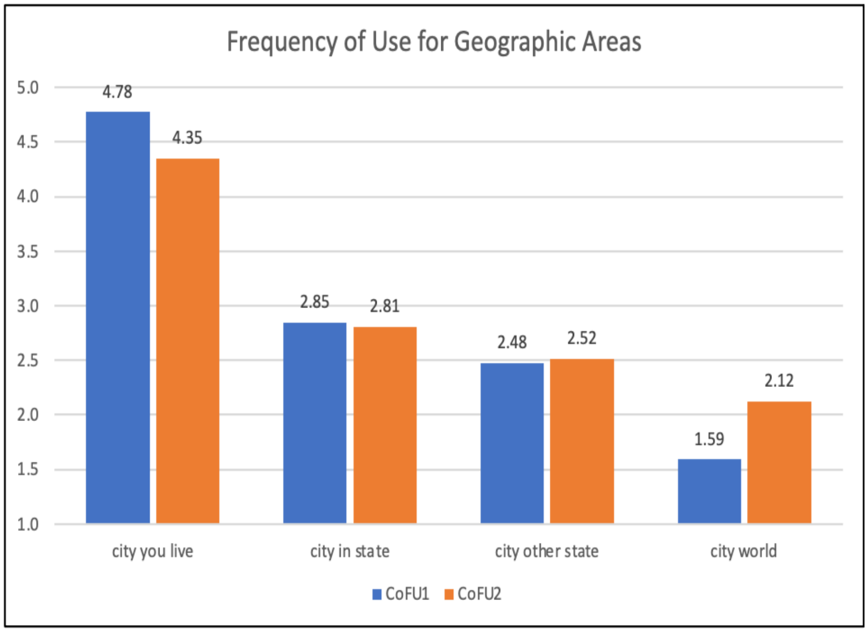

Figure ES-6: Frequency of Use by Geographic Area and Survey Version

Notes: The survey question asked "When you get weather forecasts, how often do you get them for the cities or areas listed below?" (CoFU1 n = 1,465; CoFU2 n = 1,092)

1.5.2. Forecast information attributes

We asked respondents about the importance of different "attributes" of weather forecasts. "High temperature" is considered most important in 2022 compared to when precipitation would occur considered most important by 2006 respondents. Most of the forecast attributes are considered as important or more important to the 2022 respondents (only two attributes decreased in importance—type and location of precipitation). In general, temperature attributes were more important to CoFU2 respondents and precipitation attributes were more important to CoFU1 respondents. It is possible this is related to the time of year during which each survey was implemented (May for CoFU2 and November for CoFU1). Figure ES-7 shows the mean importance ratings by survey version. The attributes are arranged from largest to smallest difference between the CoFU1 and CoFU2 implementations. Note also that the scale is only shown from 1 to 4 (the response scale was 1 to 5). It would be very interesting to determine if changes over time may be related to perceptions of a changing climate.

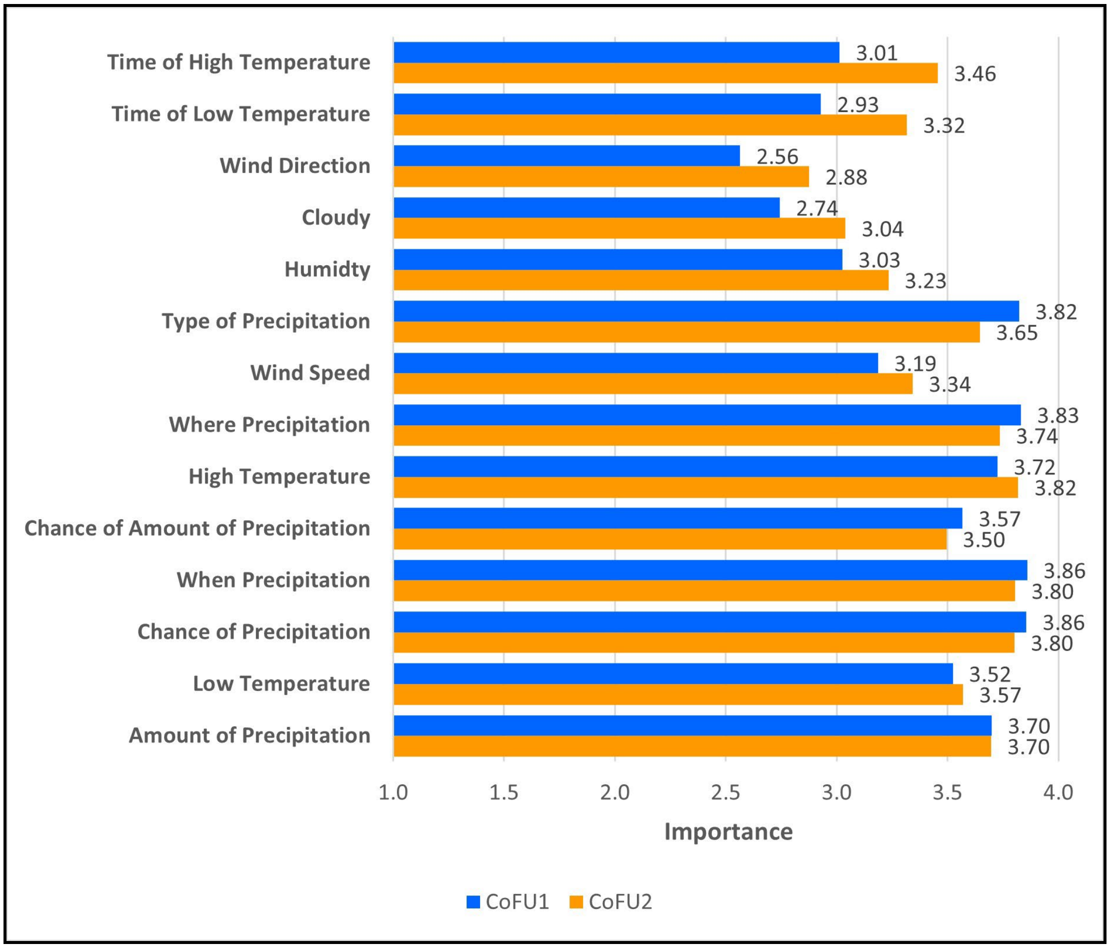

Figure ES-7: Mean Importance of Forecast Attributes Ranked by Difference between Surveys

Notes: The survey question asked "How important is it to you to have the information listed below as part of a weather forecast?" (CoFU1 n = 1,465; CoFU2 n = 1,092)

1.6. Weather forecast–related decisions and activities

We asked how much (from rarely to always) respondents use forecast information for various activities. Figure ES-8 shows average responses by activity and survey from most to least used. Interestingly the activity most prevalent was simply to know what the weather was going to be like. It would be worth future exploration what this means—we hypothesize this may be a matter of "monitoring" weather information in case something important comes up or something changes in the weather that may affect behavior.

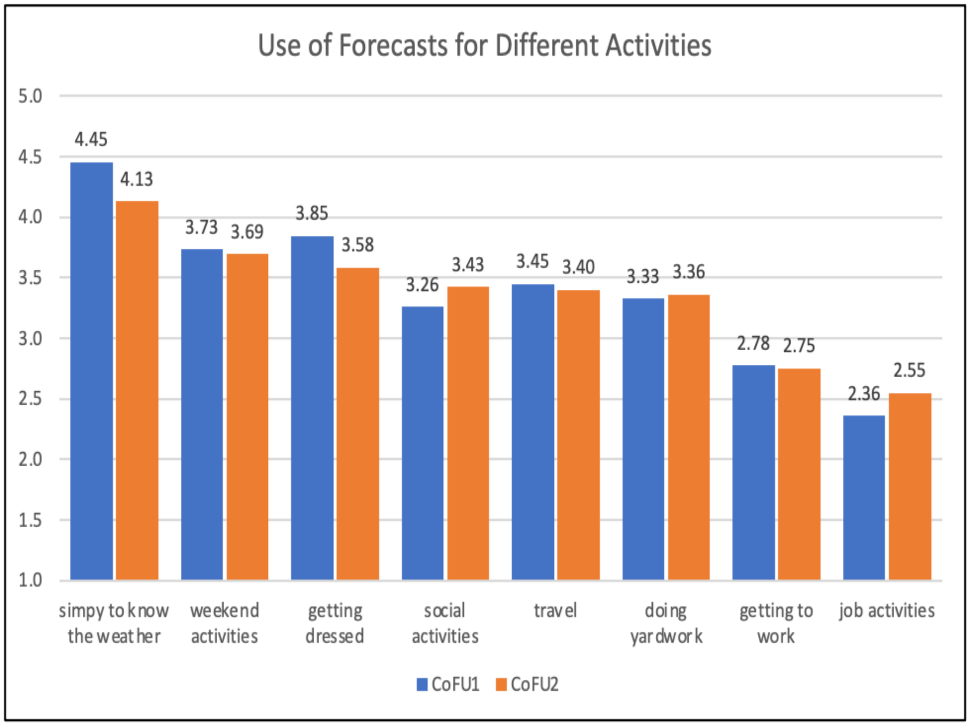

Figure ES-8: Mean Use of Forecasts for Different Activities by Survey Version

Notes: The survey question asked "On average, year round, how often do you use weather forecasts for the activities listed below?" The number in parentheses after each activity indicates the percentage that responded "not applicable to me." (CoFU1 n = 1,465; CoFU2 n = 1,092)

A principal component analysis of these "use" responses yielded two factors we have named "nondiscretionary" and "discretionary." We considered job, school, and travel activities, which loaded on the first factor as "nondiscretionary" as quite often these activities related to specific schedules not determined by the respondents. Simply knowing the weather and weekend, social, or yard work, which loaded on the second factor seem more "discretionary" with respect to timing and participation.

Value of current forecasts

1.7. Elicitation of Willingness-to-Pay for current forecasts

To elicit the respondent's value for current forecast information we implemented a contingent valuation method (CVM) question. We note here that the implementation of this question does not meet many of the standard guidelines for CVM studies. Given the limitations of this implementation we can most likely interpret responses as indications of the strength of preferences for current forecasts rather than a reasonably valid and reliable benefit estimate. That said, at the end of this section we treat the valuation estimate as valid and provide a national aggregate value—subject to the relevant caveats described here. Our implementation is essentially a referendum CVM where individuals are given a set price point and asked to "vote" yes or no on that option as they may in a referendum on a tax policy. We do note that the referendum approach is recommended for CVM analysis as it is considered highly "incentive compatible." Our analysis of values here applies to households instead of individuals because the question was framed in terms of household taxes rather than individual costs.

We first informed respondents that the NWS is the primary U.S. source for all basic data for weather forecasting and information services, including severe weather forecasts, watches, and warnings. The survey was thus designed to elicit household values for all forecast information, including severe weather watches and warnings. We also clarified that all NWS information is disseminated to media and private weather services. The valuation question then presented or "offered" respondents a hypothetical amount that they are currently paying in taxes for all NWS activities and asked if the services they are receiving are worth more than, worth exactly, or worth less than the amount indicated. Each individual was randomly presented a single dollar amounts ranging from $2 a year to $580 a year. By varying the amount that different respondents are told they are paying, we can derive a profile of the percentage of people willing to pay different dollar amounts for weather information.

The 2022 (CoFU2) survey was essentially identical except that we inserted a different set of offer prices. Figure ES-9 shows the question and where in the question different "offer prices" were provided (the offer prices shown in this figure were adjusted following the soft launch).

SELECT AND INSERT 'N' VALUE BASED ON LEAST-FILLED:
2, 5, 10, 30, 60, 90, 120, 150, 180, 210, 240, 286, 320, 360.

22 **All of the activities of the National Weather Service (NWS) are paid for through taxes as a part of the federal government. This money pays for all of the observation equipment (such as satellites and radar), data analysis, and products of the NWS (including all the forecasts, watches, and warnings).**

Suppose you were told that every year about $[INSERT VALUE] of your household's taxes goes toward paying for all of the weather forecasting and information services provided by the NWS. Do you feel that the services you receive from the activities of the NWS are worth more than, exactly, or less than $[INSERT VALUE] a year to your household? *Please select only one option.*

1. Worth more than **$[INSERT VALUE]** a year to my household
2. Worth exactly **$[INSERT VALUE]** a year to my household
3. Worth less than **$[INSERT VALUE]** a year to my household

Figure ES-9: Question on Willingness-to-Pay for Current Forecast Information

With 2022 we included a larger number of price points in an attempt to have the highest price point be above the median WTP level (the point where 50% would answer yes and 50% would answer no to the "are you willing to pay" question). Dynata provided the researchers with data from the first 100 respondents in the soft launch. With the responses to the 2022 soft launch, even at the highest offer price ($360) less than 50% of respondents indicated "No." Thus we increased the highest offer level to $508. For purposes of current analysis, we also adjusted the offer price levels from 2006 to 2022 dollars based on the change in median income. In analyzing the response data, we combined the "worth exactly" and "worth more" into a "worth it" response (we treat this simply as "Yes" response hereafter).

1.8. Regression analysis of household WTP

To evaluate responses to the WTP question we undertake a regression analysis on the response variable "Yes." We use a probit regression as the response variable is a dichotomous variable (No = 0; Yes = 1) where we regress on the "Yes" value so positive parameter estimates indicate more likely to respond Yes.

We ran several models but focused here on the backward selection probit model used in the national aggregation using only the CoFU2 data. In the model "NWS_Cost" is negative and highly significant, which conforms to the economic theory of a downward-sloping demand curve—the higher the price the fewer people are willing to pay for the commodity. This result can also serve as an internal validity check in CVM studies. We also found income to be positive as is generally expected outcome for normal goods where people with higher incomes are generally willing (and able) to pay more for the good.

Age, full-time and homemaker employment, White, use forecasts for social activities, and the factor for importance of temperature extremes are all negative and significant indicating people with higher values on these parameters are less willing to pay for current forecasts. Using forecasts to "simply know weather and "hours at home spent outside" are negative and significant indicating lower Willingness-to-Pay. The greater the "percent of job outside," more frequent use of forecasts, the greater the "importance of NWS information," the more personal weather impacts, the more important information on wind and clouds, and the greater total weather salience are all related to greater Willingness-to-Pay for current forecast information.

While not explained in this report, of the five new factors in the CoFU2 survey (political leanings, cultural risk theory, vulnerability, risk preferences, and numeracy), the individualist factor from cultural risk theory is significant and negative. One explanation of the individualist factor is that "people with more individualist worldviews perceive lower risks arising from the environment" ((Lazo et al. 2015), p. 1880). If so, this may suggest that they feel less threat from the weather and thus less value in knowing what it will be.

1.9. Fitting an average household value

Using average values for all independent variables included in the regression model, we created a synthetic dataset to run in SAS for model predictions as a step in the probit modeling. In this dataset we entered the price offer level for a range of values to determine the price level where 50% would be predicted to respond yes and 50% would be predicted to respond no. The median fitted value using this approach is $898.50 (rounded to the nearest penny). Figure ES-10 extrapolates the 95% confidence intervals to the 50% Yes/No line to derive a confidence interval on the median WTP. First, in Figure ES-10 we have extended a lower and upper limit line to intersect the 0.50 line. We then used the graphics editing program's grid to calculate values on the horizontal axis.

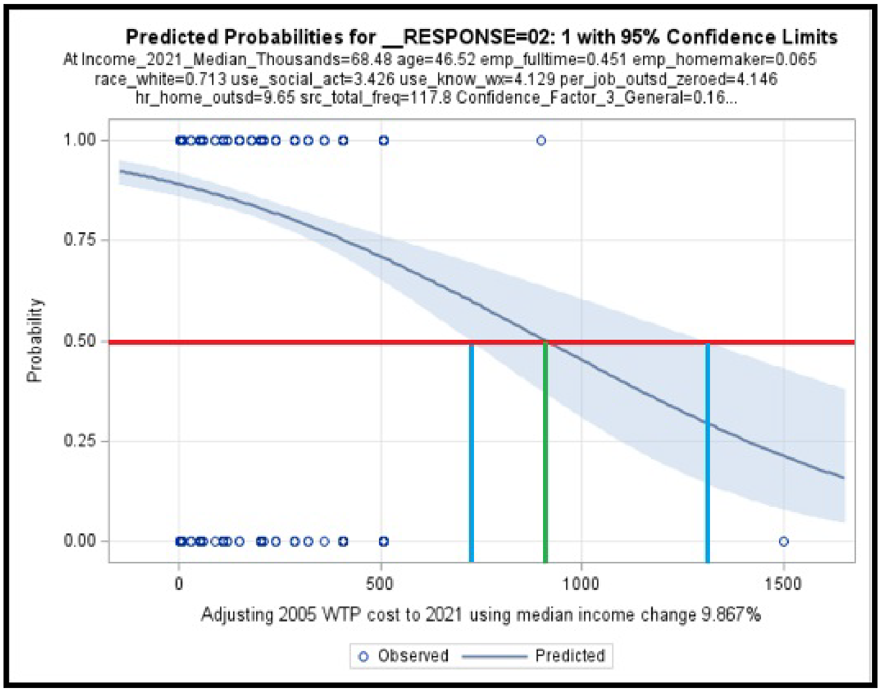

Figure ES-10: Fitted Demand Curve Extrapolated to Median WTP 95% Confidence Interval

Notes: The survey question asked "Do you feel that the services you receive from the activities of the NWS are worth more than, exactly, or less than $N a year to your household?" (CoFU2 data only n = 1,094)

The green vertical line is the median WTP, the blue lines show the lower and upper bound of the 95% CI. These values are shown in Table ES-2. The $898.50 value of the point estimate was taken from the synthetic dataset calculation described above. The WTP confidence interval is based on many assumptions including that the sample is representative of the U.S. population and that the median value reflects the average WTP. We thus take $898.50 as the average U.S. WTP for current forecasts information in 2021 with a $709.98-$1,300.14 95% confidence interval. In order to not overstate the precision of these estimates, we say the point estimate is about $900 and the 95%CI is roughly $700-$1,300.

Table ES-2: 95% Confidence Interval for Median WTP

	Lower Bound	Point Estimate	Upper Bound
Derived WTP 95% CI	$709.98	$898.50	$1,300.14
WTP 95% CI (Rounded)	$700	$900	$1,300

1.10. National aggregation

Table ES-3 shows the aggregation of the WTP values from 2022 survey. As noted above this is based on the assumption that the median value is equal to the average and that this is representative of the general population. This is aggregated assuming that the WTP value derived in the survey is for the household and not the individual. We adjust for population and household size as well as the percent of individuals indicating that they do not use weather information. This estimate of the benefit to the U.S. public of current (2021) weather information is $102.1 billion.

Table ES-3: U.S. National Aggregation of WTP for Current Forecast Information–CoFU2	
Year	2022
Population	332,403,650
Household Size	2.77
Number of Households	120,001,318
Percent Not Using Forecasts	5.35%
Households Using Forecasts	113,581,247
Per HH WTP	$898.50
Total U.S. Value of Current Forecasts (2021 Dollars)	$102,053,204,928.03
Total U.S. Value of Current Forecasts (Billions)	$102.1

We also calculated a 95% confidence interval lower bound of $80.6B ($80,640,346,850.63) and an upper bound of $147.7B ($147,671,902,571.17). Using a value of 5.35% of the population as not using forecasts, this generates an estimate of the value of current forecasts (in 2021) of $102.1 billion dollars with a $80.6-$147.7B 95% confidence interval. We note that while this may seem like a large value, dividing this by the estimate of annual use of forecasts of 317 billion yields a per forecast value of 32.2 cents.

Discussion and future work

This work replicates (at least in implementation) the 2006 survey implemented by Lazo, Morss, Demuth, and Stewart. Key findings related to the Lazo et al. (2009) work include that there has been an understandable shift in sources from more "traditional" sources such as print and TV to more "modern" electronic and social media sources. Aggregating these uses generates an estimate of total annual forecasts accessed by the public. This has increased slightly from roughly 300 billion a year in 2006 to roughly 317 billion a year in 2022 mainly due to the increase in population. With respect to the value of current forecasts and aggregation to a national value, we derive a significantly larger estimate of per household benefit of current forecasts in 2022 ($898) than we did in 2006 ($286). Even while fully recognizing the limitations of the elicitation and analysis it is notable that we generate an estimate of the national value of current forecasts (in 2021) of $102.1 billion with a $81–$148B 95% confidence interval. At roughly 32 cents per forecast, while large in aggregate this seems a viable estimate. Future work in improving this benefit estimate is necessary for the weather enterprise to use such an estimate for funding justification.

There is a plethora of future research that could use the current dataset as well as build on findings discussed here. This includes but is not limited to work on the weather salience concept; examination of the decision scenarios and communication of uncertainty questions included in the survey; building on the climate zone data findings relating weather experiences and perceptions to climatic zones; further use of the “weather impact scale” beyond the simple initial scale used here; full analysis of the five new sets of questions included in the 2022 survey related to cultural risk theory (CRT), vulnerability, numeracy, political leanings, and risk preferences that have only been touched on in the current report; analysis of specific concepts and questions such as measures of confidence and an in-depth analysis of 2022 WTP values using the five new concepts included in the 2022 survey.

1. Introduction

In 2006 the research team of Julie Demuth, Jeff Lazo, and Rebecca Morss from the National Center for Atmospheric Research (NCAR), and Alan Stewart of The University of Georgia designed and implemented a survey of the general public of the United States to explore a range of issues related to the communication, use, understanding, and value of weather forecasts. This effort was funded under the Societal Impacts Program (SIP) of the NCAR. At that time the SIP was supported with funding from the National Oceanic and Atmospheric Administration (NOAA). Table 1 lists the five papers published from analysis of this survey and the objectives identified in each paper using data from the 2006 survey implementation (Demuth et al. 2011; Lazo et al. 2009; Morss et al. 2008; Morss et al. 2010; Stewart et al. 2012).

A compilation of these objectives and our approach is that with a large national sample of the general public, multiple research questions were explored with the 2006 survey analysis:

- Where, when, and how often do people obtain weather forecast information and how do they judge, understand, use, and value that information?
- How do people interpret uncertainty in forecasts (especially probability of precipitation) and what formats do people prefer for receiving forecast uncertainty information?
- Do people infer uncertainty into deterministic forecasts and, if so, how much, and to what extent do they prefer to receive forecasts that are deterministic versus those that express uncertainty?
- Do the weather salience questionnaire (Stewart 2009) items perform in the same manner and relate to the same dimensions of weather salience in a national sample, and what are the relationships of weather salience with the sources, perceptions, and uses of weather information that people reported?

In 2022, with support provided by the Policy Program of the American Meteorological Society[1] (AMS), which is under the direction of Paul Higgins, the same research team reimplemented essentially the same survey. To the maximum extent possible the same survey instrument, implementation methods, and target population were replicated.

The current report is focused on analysis related to the topics from the Lazo et al. (2009) paper ("300 Billion Served") which covered mainly questions related to the sources, perceptions, uses, and value of weather information (i.e., not the decision scenarios included in the survey). In this report we also document as best as possible our survey design and implementation methods. This report can thus serve as "formal" documentation of this aspect of the research to support subsequent publications.

Section 2 (Replication: Concepts and issues) discusses some of the concepts and issues related to replication in the sciences and with respect to the current effort. Section 3 (Survey design) discusses the original 2006 survey design and revisions to this for the 2022 implementation. Section 4 (Survey Implementation) discusses the 2022 implementation. Section 5 (Results) discusses analysis of the combined data mainly

[1] https://www.ametsoc.org/index.cfm/ams/policy/

related to analysis as undertaken in the Lazo et al. (2009) paper. Section 6 (Analysis) presents analysis of the source, perceptions and uses of forecasts. Section 7 (Value of current forecasts) presents analysis of the value of current weather forecasts and the aggregation of this up to an estimate of the annual value of current weather information to the U.S. public. Section 8 (Discussion and future work) briefly indicates potentially useful future analysis including using the new factors included in the 2022 implementation. Section 9 (Acknowledgments) notes in particular the fact that the Policy Program of the American Meteorological Society (AMS) provided support for the 2022 survey implementation. Section 10 (Appendices) provides more specific information on data revisions and the combination of the datasets from the two implementations.

Throughout this report we interchangeably refer to the 2006 survey implementation both by its implementation year (2006) and as CoFU1 as an acronym for Communicating Forecast Uncertainty 1. In a similar manner, we refer to the 2022 implementation as the 2022 survey or as CoFU2.

Table 1: Articles from 2006 Survey and the Objectives Identified in Each Article		
Full Reference	**Article Code**	**Article Objectives (as indicated in each article)**
Morss, R. E., J. L. Demuth, and J. K. Lazo, 2008: Communicating uncertainty in weather forecasts: A survey of the U.S. public. *Wea. Forecasting*, **23**, 974–991, https://doi.org/10.1175/2008WAF2007088.1.	MDL2008	MDL2008 p.975 Five research questions are explored: Do people infer uncertainty into deterministic forecasts and, if so, how much? How much confidence do people have in different types of weather forecasts? How do people interpret a type of uncertainty forecast information already commonly available and familiar: probability of precipitation forecasts? To what extent do people prefer to receive forecasts that are deterministic versus those that express uncertainty? What formats do people prefer for receiving forecast uncertainty information?
Lazo, J. K., R. E. Morss, and J. L. Demuth, 2009: 300 billion served: Sources, perceptions, uses, and values of weather forecasts. *Bull. Amer. Meteor. Soc.*, **90**, 785–798, https://doi.org/10.1175/2008BAMS2604.1.	LMD2009	LMD2009 p.785–786 Specifically, we investigate the following four interdependent concepts: sources: where, when, and how often people obtain weather forecast information; perceptions: how people judge and understand forecasts; uses: how people use forecasts for activities and decision-making; and values: what dollar value households place on currently available forecasts.
Morss, R. E., J. K. Lazo, and J. L. Demuth, 2010: Examining the use of weather forecasts in decision scenarios: Results from a U.S. survey with implications for uncertainty communication. *Meteor. Appl.*, **17**, 149–162, https://doi.org/10.1002/met.196.	MLD2010	MLD2010 p.149 Examines how members of the broad U.S. public interpret and use different types of weather forecasts, including those conveying uncertainty, based on people's responses to decision scenario questions.
Demuth, J. L., J. K. Lazo, and R. E. Morss, 2011: Exploring variations in people's sources, uses, and perceptions of weather forecasts. *Wea. Climate Soc.*, **3**, 177–192, https://doi.org/10.1175/2011WCAS1061.1.	DLM2011	DLM2011 p.177 Patterns in people's sources, uses, and perceptions of everyday weather forecasts; and relationships among people's sources, uses, and perceptions of forecasts, their personal characteristics, and their experiences with weather and weather forecasts.
Stewart, A. E., J. K. Lazo, R. E. Morss, and J. L. Demuth, 2012: The relationship of weather salience with the perceptions and uses of weather information in a nationwide sample of the United States. *Wea. Climate Soc.*, **4**, 172–189, https://doi.org/10.1175/WCAS-D-11-00033.1.	SLMD2012	SLMD2012 p.173 … build upon Stewart's (2009) initial work by examining weather salience in a nationwide sample of the United States population. Do the Weather Salience Questionnaire (WxSQ) items perform in the same manner and relate to the same dimensions of weather salience in a new and broader sample? Examin[e] the relationships of weather salience with the sources, perceptions, and uses of weather information that people reported [to] further the field's understanding of how people think of and interact with available weather products.

2. Replication: Concepts and issues

2.1. Objectives for repeating the 2006 survey

Why did we reimplement the 2006 survey? In part we decided to undertake this work as the original survey was highly successful in terms of research output and in addressing a wide range of questions and issues, and we felt revisiting this effort would provide a useful "retrospective." In part we felt that some of the issues addressed in the 2006 survey had not been built upon and thus deserved looking at again. Two of these issues reported in the "300 Billion Served" article (Lazo et al. 2009) include 1) the general public's sources and frequency of use of forecasts across all sources and 2) the general public's value (i.e., Willingness-to-Pay) for current forecast information. We are unaware of any studies reevaluating or replicating these results, which would seem highly relevant to the weather information community given that between January 2023 and August 2024, the United States has experienced a 47 events that each have resulted in over $1 billion in losses for total losses during this period of $144.5B.[1]

We are pursuing two objectives that confound the issue of a true replication, to test prior hypotheses or findings (i.e., conceptual replication):

1. What has changed since the 2006 survey? Two areas we expect may have changed are (i) the value of current forecasts (at least when not adjusted for inflation and wealth changes) and (ii) sources of weather information given changes in technology and especially the increasing prevalence of electronic devices.
2. What has stayed the same, and thus can we provide additional support for the findings reported in prior articles? One area where this seems feasible is in the analysis of the Weather Saliency (WxSx) concept (in spite of there apparently being a coding error or miscommunication in the data collection for the WxSx scales).

These two questions seem to identify a fundamental conflict in our objectives: for any given result we can argue it is important as it either 1) indicates what has changed or 2) it reconfirms our original findings. Thus, any result can be claimed as highly relevant! This may well be the case with any type of social science research over time.[2]

2.2. Replication of the 2006 survey

During this process the question arises of whether we are conducting a replication of the original study. Recognizing that there are complex conceptual issues in this research area, we may use the words replication, repetition (e.g., repeatable), and reproduction (e.g., reproducible) interchangeably here (Fidler and Wilcox 2021).

A fundamental tenet of "science's claim to objective truth" is "the idea that the same experiments always get the same results, no matter who performs them." ((Economist

[1] NOAA Billion Dollar Disasters (CPI-Adjusted) https://www.ncei.noaa.gov/access/billions/time-series

[2] "It would be interesting in future work to test if replicability differ for older versus newer studies or depends on the time that has elapsed between the original study and the replication." Camerer et al. (2018, p. 15).

2013), p. 96). Fidler and Wilcox (2021) note “the terms ‘reproducibility crisis’ and ‘replication crisis’ gained currency in conversation and in print over the last decade …, as disappointing results emerged from large scale reproducibility projects in various medical, life and behavioural sciences” (p. 1). In addition, replication appears to be rarely undertaken in the social sciences and, while we did not search extensively for such, we are not aware of any specific replication studies in social sciences related to the “Weather Enterprise.”[3]

We feel that this raises several broader questions (which we are not attempting to answer) about the role of replication in the social sciences and the weather enterprise. Some of these questions relate to the purpose of undertaking social science research in this realm as we have advocated for several years as being necessary to the field.[4] As the creation, communication, and use of weather information (and climate and water) information are framed in terms of helping society, we feel there continues to be insufficient understanding of the “societal” end of the information value process ((Lazo and Mills 2021)). This has led to a relatively meager (yet perhaps slowly increasing) investment in social science research. Some of this research has then been used to make changes to the weather information process (e.g., (Demuth et al. 2013); (Morrow and Lazo 2015)). It is unclear though the extent to which any of this research has been critically reviewed or replicated before making operational changes. As a fundamental tenet of science is the “reproducibility of research,” this seems to be a serious shortcoming in the application of social science research in the weather enterprise where the use of weather information can significantly impact lives and livelihoods.

In a widely cited article on issues of replication in the social sciences, Stefan Schmidt reviews prior definitions of replication and suggests a more functional approach:

> “Therefore, I suggest differentiating at a fundamental level between two basic notions of replication: 1. Narrow bounded notion of replication: Repetition of an experimental procedure. Henceforth, this notion will be termed direct replication. 2. Wider notion of replication: Repetition of a test of a hypothesis or a result of earlier research work with different methods. Henceforth, this will be referred to as a conceptual replication.” (Schmidt 2009, p. 91)

As a central tenet of the scientific method, “conceptual replication” is the key tool for supporting or rejecting any given study and thus advancing knowledge.[5] That said, our

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[3]NAS 2018 defines the “Weather Enterprise” as “… the ecosystem of government agencies and private enterprise responsible for weather service provision.” (National Academies of Sciences, E., and Medicine, 2018: *Integrating Social and Behavioral Sciences Within the Weather Enterprise*. The National Academies Press, 198 pp., p. xiii). Alternatively the same report states that “The ‘weather enterprise’ includes the network of government agencies, private-sector companies, and academic institutions that provide weather services to the nation.” (ibid.) p. 1.

[4] “…a true commitment by the weather enterprise to improve the societal benefits derived from forecast information requires a much better understanding of the value-creation process from communication by various sources through to end-user perceptions and their uses of this information.” (Lazo et al. 2009, p. 786).

[5] “…a cumulative science should be built on its foundations in a systematic way. Adding a brick here and another brick there without much regard for the space between them may result in an unstable building with weak parts, leakages and unnecessary parts that will require a major effort later on to effect their removal. Replication addresses precisely this connection between existing and new knowledge.” (Schmidt,

2022 effort represents more of a "direct replication" as we attempted to use the same methods for implementing the survey. While we are not necessarily attempting to retest specific hypotheses, we are interested in the extent to which our findings remain the same or change and how that may relate to the weather information communication process. Schmidt goes on to discuss the following five functions of a replication study.

> "Replications serve several different functions. The general function of replication is, as mentioned above, to verify a fact or piece of knowledge. However, this implies the following more specific functions: 1. To control for sampling error (chance result); 2. To control for artifacts (lack of internal validity); 3. To control for fraud; 4. To generalize results to a larger or to a different population; 5. To verify the underlying hypothesis of the earlier experiment. (Schmidt 2009, p. 93)

We hope that with our sample sizes that sampling error is minimized although we note that with current sampling methods sampling bias is a real possibility in most survey research. Further, as discussed in our evaluation of the sample in the section on Dynata's methods and survey implementation, we feel we have a high degree of internal validity. Our current (2022) efforts thus pursue the fourth and fifth functions more than the first three.[6] We are interested in assessing the stability of our prior findings across the national sample (in this case re-generalizing to the same population) as well as to support or refine our prior hypothesis and findings.

2.3. Difficulty in replication of social sciences

We feel that replication in the social sciences is fundamentally different or more difficult than in the physical sciences.[7] First, in general there are not "universal laws" of human behavior as there are for physical processes (e.g., universal law of gravity). Therefore, in some social sciences there are not well-defined sets of expectations or quite often even hypothesis-driven research.[8]

There is also the added complication that humans can and do change behavior in response to prior events. The rational expectations theory in economics in fact assumes that "… individuals base their decisions on human rationality, information available to them, and their past experiences."[9] Thus, behavioral responses to situations as well as

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S., 2009: Shall we Really do it Again? The Powerful Concept of Replication is Neglected in the Social Sciences. *Review of General Psychology*, **13,** 90-100., p. 96).

[6] With respect to item 3, i.e. fraud, we assert we have not committed fraud although from the perspective of replication science that is for others to determine.

[7] As noted by Rodney Beard "A recent paper on replicability in particle physics, demonstrated that there are also barriers to replicability in physics" (Junk, T., and L. Lyons, 2020: Reproducibility and Replication of Experimental Particle Physics Results. *Harvard Data Science Review*, **2,** 63.).

[8] "…the grounded theory method consists of a set of systematic, but flexible, guidelines for conducting inductive qualitative inquiry aimed toward theory construction." (Charmaz, K., and A. Bryant, 2008: Gounded Theory. *The SAGE Encyclopedia of Qualitative Research Methods: Volumes 1 & 2*, L. M. Given, Ed., SAGE , p. 374). This seems to suggest theory driven by data based research rather than theory directing collection of data to test theory.

[9] Source: https://www.investopedia.com/terms/r/rationaltheoryofexpectations.asp.

preferences can be expected to change with time and experience and thus "perfect" methodological (i.e., direct) replication may not even produce the same results.[10]

In some areas of the social sciences there may be a greater expectation of reproducibility. In psychology for instance there are controlled experiments related to specific hypotheses that may be expected to generate replicable outcomes (as well as perhaps in experimental economics). Even here, in a large study of 100 replications of prior results, Nosek (2015) seemed to find that less than half of prior findings replicated and the effect size of many that did replicate were in general smaller than the original studies.[11] Similarly, Camerer et al. (Camerer et al. 2018) replicated selected experimental social sciences studies published in *Nature* and *Science* between 2010 and 2015. They find significant effects for 62% of studies. Similar to Nozek et al.'s findings, the effect size in replications was on average about 50% of the original study's effect size.

For the current effort we did not make a priori hypothesis about which prior findings we would try to replicate, and we did not create a "replication package." The lead author (Lazo) on this report was not aware of that literature and procedures prior to undertaking the 2022 survey. It seems reasonable that if any specific information is important for policy or decision-making (e.g., would be used to make operational changes in forecast communications) that such findings should be evaluated in more depth with a fully documented and preplanned replication effort (Heers 2021); see also: http://www.socialsciencesreplicationproject.com/).

In conclusion, we feel that we are replicating the 2006 study at least in terms of implementation of essentially the same survey, by the same researchers, using the same research methods (i.e., direct replication). We are pursuing two objectives that confound the issue of a true replication to test prior hypotheses or findings (i.e., conceptual replication):

1. What has changed since the 2006 survey? One area we expect this to have changed is in the value of current forecasts—at least when not adjusted for inflation and wealth changes.
2. What has stayed the same, and thus we can provide additional support for the finding reported in prior articles? One area this seems feasible is in the analysis of the weather saliency concept (see Stewart 2009).

With respect to replication in social science research for the weather enterprise it seems that an assessment of the purpose of such research would indicate whether replication is an issue. As a relatively young field of research, the integration of multiple fields of the social sciences into applied research for the weather enterprise may not have reflected

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[10] Rodney Beard commented that "However, contemporary theories of causation in some social sciences rely on a theory of causality, the Neyman–Rubin approach, which is based on counterfactuals rather than conditioning on past events. This stands in contrast to fields like medicine and epidemiology that employ the Bradford hill criteria which are time dependent, and also in physics which employs a temporal concept of causality." While beyond the capacity of this report or research to fully explore issues of causation, we feel this would be worthy of further discussion in the weather–social sciences realm to enhance understanding on the limitations and capacities of the social sciences.

[11] "Replication effects were half the magnitude of original effects." (Nosek, B. A., 2015: Estimating the reproducibility of psychological science. *Science*, **349**., p. 1)

significant levels of hypothesis testing (thus, potentially making replication a moot point) nor having been explicitly based on specific theoretical models or model testing. In a broader sense, and as previously noted, replication in the social sciences is fundamentally different than in the physical sciences.

> "...human minds are so complex that building clear, practical, testable theories can be a long process, often well beyond the scope of a single research report. Many social problems are similarly complex: it is prudent to accumulate detailed demonstrations of empirical phenomena in the literature before making confident recommendations about solutions to big problems." (Burke and Moss-Racusin 2023, p. 536)

The question of the need for replication of social science studies for the weather enterprise should be driven in part by the importance and impact of the use of results of such research. If operational changes are being made that affect the safety or welfare of millions of people, then confirmation of research results would seem prudent.

3. Survey design

3.1. Original survey design

The following information on the original survey design and implementation is taken largely verbatim from Morss et al. (2008, 2010). The 2006 survey development process largely followed methods and principles accepted at that time for writing survey questions (Dillman 2000) as well as general principles of survey research, pretesting, and revision (Schuman and Presser 1996); (Tourangeau et al. 2000)). The survey instrument was drafted initially through multiple iterations among the research team and then underwent peer review for structure, content, and clarity. Hard copy versions of the survey were pretested with nonmeteorologists using one-on-one verbal protocols using the methods developed by (Ericsson and Simon 1993). These evaluations were then used to finalize the survey for programming. Survey data were collected in November 2006 using a controlled-access Internet-based implementation programmed and hosted by the survey research company (which was no longer in business in 2022). ResearchExec managed the data collection and quality control while Survey Sampling International (SSI) provided the sample.

The sample was drawn from SSI's 2006 U.S. internet panel. At that time, we understood that the panel was regularly screened, and that SSI maintained the database of people, recruited from multiple sources, who had actively indicated their willingness to respond to online surveys on a variety of topics. The only people permitted to access the survey were those invited by SSI via an email containing a specific link to the survey website.

After pretesting ResearchExec's internet version of the survey, the survey was implemented in three stages. First, approximately 100 responses were obtained to confirm survey functionality and basic data quality. This then proceeded directly with full data collection designed to be limited to the first 1200 complete responses. Analysis of the initial complete dataset indicated that Caucasians were overrepresented, and so an additional 300 responses were obtained from non-Caucasians. Upon full implementation, we had 1891 responses, 371 of which were incomplete. We began our analysis with the 1520 completed surveys.

The survey was implemented with one question per screen, with questions in the same order for all respondents. Respondents were required to provide responses to each question other than the demographic questions, and they could not return to previous questions. The order of response options was randomized for those questions in which the options did not follow a logical sequence. The median time to complete the survey was 21 min; because respondents could start the survey and complete it later without stopping the clock. A few long completion times skew the mean upward to 28 min.

The 2006 respondent population included people from every U.S. state and the District of Columbia. Based on qualitative comparisons, we determined that the sociodemographic characteristics were generally similar to that of the U.S. population (U.S. Census Bureau 2006)[1], except that it was somewhat older and more educated and

[1] As referenced in Morss et al. 2010. U.S. Census Bureau. 2006. 2006 American Community Survey. Available online at http://www.census.gov/acs/www/.

underrepresented people with very low and high incomes. While the respondent population was not a random sample of the general U.S. population, it was more diverse and representative than previous related work with convenience samples or students.

3.2. Redesign with new research topics

In 2022 we reviewed the 2006 survey instrument and compared questions therein to questions analyzed in the five papers resulting from that effort. It was determined that every question in the 2006 instrument was used in some form in those papers and thus we did not eliminate any questions. The original survey questions were thus retained as implemented in 2006 but five additional topics were included at the end of the instrument to begin to assess these related concepts:

- Cultural risk theory
- Numeracy
- Perceived vulnerability
- Political preferences
- Risk preferences

The current report does not deal with these new topics at this time but does use some scales or factor scores from these questions in our analysis of other topics. Future work will undertake analysis of these new topics. The survey instrument is available from the authors.

3.3. Changes in price offer in Willingness-to-Pay question

A minor change was made to the question assessing individuals' Willingness-to-Pay for current weather information. While the question format was the exact same as 2006, additional price points were added to the randomization to try to cover the higher values not covered in the 2006 analysis. Table 2 shows the different price levels offered in each survey. With 2022 we included a larger number of price points in an attempt to have the highest price point be above the median WTP level (the point where 50% would answer yes and 50% answer no to the "are you willing to pay" question). Dynata provided the researchers with data from the first 100 respondents in the soft launch even though a total of 120 had participated in that. With the responses to the 2022 soft launch, even at the highest offer price ($320) less than 50% of respondents indicated "No." Thus, we increased the highest offer level to $508. We also reduced the total number of price points from 12 to 6 price points. Analysis of the WTP responses includes respondents from both the soft launch and the final implementation.

Table 2: Offer Price Levels (Total number of respondents at each price level)		
2006 Survey (n = 1,465)	2022 Soft Launch (n = 120) *	2022 Final (n = 1082) *
2	5	2
5	10	52
10	30	109
30	60	204
60	90	407
90	120	508
120	150	
150	180	
180	210	
210	240	
240	286	
	320	
* Includes respondents who answered that they don't use forecasts and thus were not offered the Willingness-to-Pay question.		

3.4. Reordering sociodemographic questions for sample screening

To allow for screening for respondents' sociodemographic characteristics to meet the desired sample distribution, several sociodemographic questions were moved to the beginning of the survey (see Figure 1).[2] Zip code was first asked to screen for regional distribution of respondents, then gender, age, and race. Gender for the 2022 survey included response options of "fluid/nonbinary" and "other," which were not offered in the 2006 implementation. The only characteristic screened for in the 2006 survey was age to ensure no respondents were younger than 18 years old.

Although Dynata has sociodemographic information on their panelists in their database the sociodemographics were elicited through the survey instrument.

> It is not deem[ed] reliable to solely base collection via the panel data as there are possible changes to a panelist not reflected in the panel database (such as their region or marital status). It is understood that data such as gender, age, ethnicity and race shouldn't change, but we also know that panelists tend to share their account with their spouses/partners; and the person who is registered in the panel may not be the person completing the survey. If we do a match between database vs survey–we will encounter mismatch and will reduce our sample feasibility. (J. Grodzicki, Dynata, 2023, personal communication)

Figure 1 provides a flowchart of the survey as implemented in 2022. We note that Figure 1 needs some minor updating including adding Cultural Risk Theory in the bottom row boxed labeled "New Analysis Scales." The file survey flowchart_2023_06_19[3] contains a pdf of the complete survey flow listing each question (but not response options).

[2] This approach may technically make the sampling process a "quota sample."

[3] This link is: https://drive.google.com/file/d/1yLsPXcgGSSQP9IuHTbDbJF2VlPnuOfF7/view

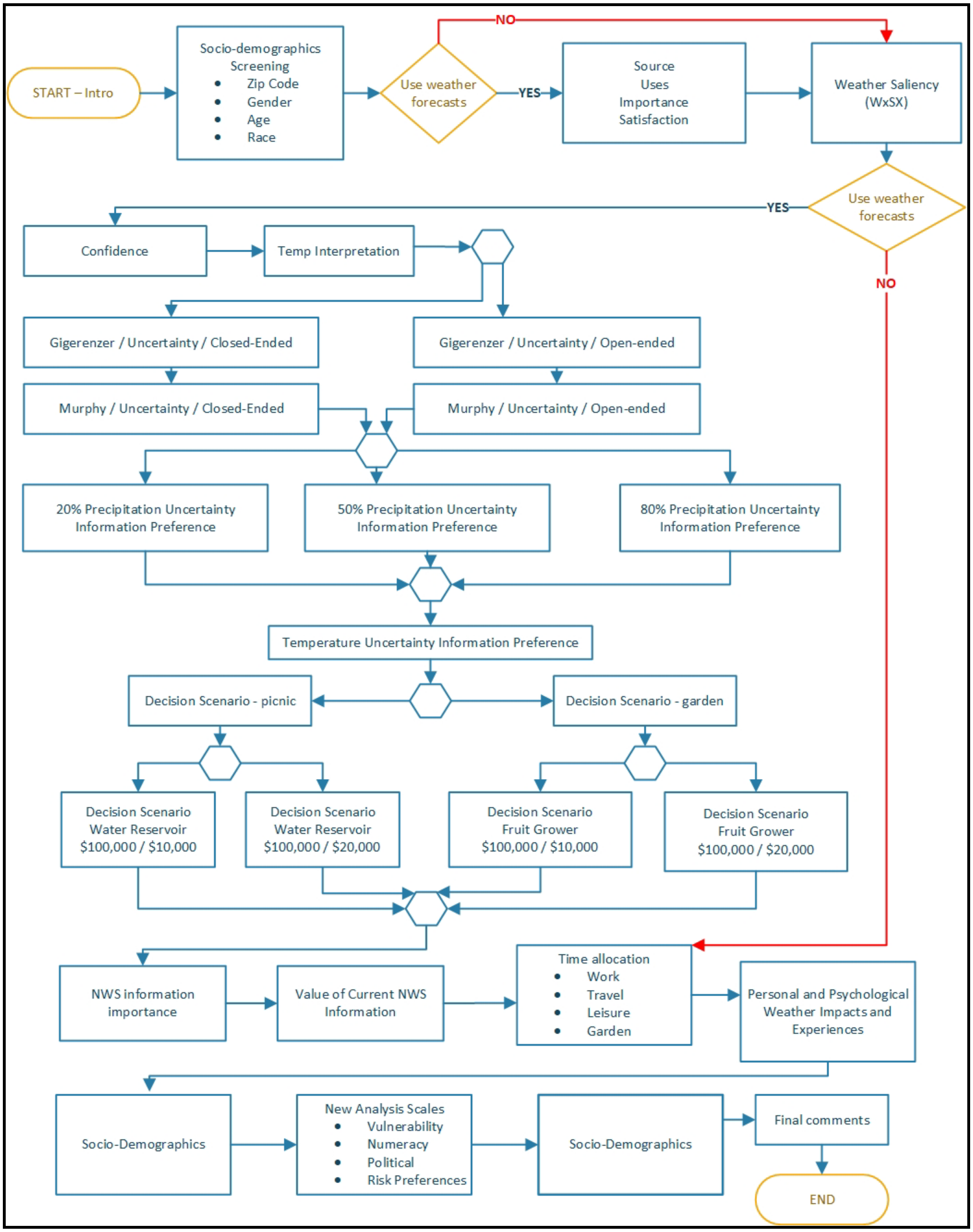

Figure 1: 2022 Survey Flowchart

4. Survey Implementation

4.1. Contracting and information about Dynata

The survey was contracted with Dynata (https://www.dynata.com/) for programming, sampling, and hosting. As per their home page Dynata is "the world's largest first-party data company for insights, activation & measurement." Dynata generously offered a significant price discount due to the nonprofit research nature of the survey.[1] Communication was entirely through email.

A potential concern is the quality of the data obtained from a panel where we do not control access and cannot track response rates, etc. Given logistical and budget constraints, in choosing Dynata we felt that the data quality would be acceptable. Research by (Peer et al. 2021) compared data quality from several survey platforms and panels including MTurk, CloudResearch, Prolific, Qualtrics, and Dynata and recommended against using Qualtrics or Dynata. As three of the five authors were Prolific employees (one is the cofounder and CEO of Prolific) and even though they profess no bias, it seems reasonable to be cautious with respect to their findings. Alternatively the Behavioral Research Lab of MIT recommends using Dynata for studies stating "We especially encourage researchers to conduct studies through Dynata, our preferred panel vendor" (BRL ND). Dynata is listed first in 2022 in the GreenBook Research Industry Trends (GRIT) Business & Innovation 2022: GRIT Top 50 Most Innovative Suppliers (https://www.greenbook.org/mr/grit/top-50-most-innovative-market-research-companies/). Additional information on Dynata practices and resources is available in the Dynata document "Panel Quality: Our Values Answers to ESOMAR's 28 Questions." (Survey Sampling International 2018). ESOMAR is the European Society for Opinion and Market Research (https://esomar.org/) (see also (Dynata 2020)).

Dynata implemented the survey through their survey router rather than an email invitation as used by ResearchExec in the 2006 survey. As defined by (Peterson 2016)[2] "A router at its basic level is technology that acts as a hub that respondents pass through to be directed to a survey they have a higher likelihood for which to qualify." As explained in Survey Sampling International (2018), in response to ESOMAR Question 9 "If you use a router: Please describe the allocation process within your router. How do you decide which surveys might be considered for a respondent? On what priority basis are respondents allocated to surveys?"

> Dynata's routing technology uses weighted randomization to assign surveys to participants. Upon entry into the system, panelists are checked to ensure they have not exceeded survey participation limits. A list of potential survey matches is determined for each panelist based upon the information we know about them. Panelists may be asked additional screening questions within the system to ensure they meet the project criteria. Priority may be given to surveys that are behind schedule; however, this is kept to a minimum as survey randomization must remain in place as a key element for preventing bias.

[1] The total survey cost was $6,680—30% off of Dyanata's baseline cost.

[2] https://emi-rs.com/2016/11/18/survey-routing-good-thing-bad-thing-just-thing/.

4.2. Dynata QA/QC, privacy, and confidentiality

As this survey was supported by nongovernment resources and implemented by Lazo through Jeffrey K. Lazo Consulting LLC, we did not process the 2022 effort through any sort of human subjects' approval.

Dynata maintains their own privacy policy provided to panel participants through the various websites used for panelist contact. While we could not access the panel U.S. site, in response to ESOMAR question #24 (Survey Sampling International 2018).

> We follow all national, regional and local laws with respect to privacy and data protection. As such, the privacy policy for each panel adheres to local law. We ensure our panels comply with all applicable industry standards set by ESOMAR, MRS (UK), AMSRS (Australia), BVM (Germany), Insights Association (U.S.), etc. Among others, this includes observing the following guidelines:
>
> • Voluntary cooperation of panelists
>
> • Protection of researchers' and participants' identities
>
> • Terms & conditions and privacy policies compliant with local laws
>
> • State-of-the-art data security policies and measures
>
> • Reliable and validated data procedures
>
> • Strict adherence to rules governing the interviewing of children and young people.

No information was provided in either survey dataset (2006 or 2022) that would allow for individual identification. Location information is at the zip code level. In both implementations the introductory page stated "All your responses will remain anonymous. None of the information or opinions you provide can be linked back to you, so please respond as honestly as you can."

4.3. Dynata panel

Dynata used their online panel for the sample.[3] As explained in their responses to ESOMAR's 28 Questions (Survey Sampling International 2018):

> Dynata has a variety of sample sources such as panel, web intercept sample, and specialty lists available to meet our clients' unique project requirements. All panels are actively managed, online access panels built from two decades of experience. All our panels are localized–not just translated–with native language panel support and country-specific reward choices. We run "open enrollment" and "by-invitation-only" ® recruitment campaigns, via direct email and through online marketing channels, utilizing hundreds of diverse, online affiliate partners and targeted websites. "By-Invitation-Only" is a proprietary method of exclusively inviting pre-validated individuals, or individuals who share known characteristics, to enroll into our market research panels. We achieve "By-Invitation-Only" by partnering with a diverse set of globally recognized consumer and business-facing brands.

The Dynata sampling process and panel is described further in Dynata (2020). In response to a request for an example of the manner in which respondents are invited to the panel, Dynata indicated that

[3] In response to a clarification question Dynata indicated "We used all sources within the Dynata panel detailed in the ESOMAR document" (J. Grodzicki, Dynata, 2023, personal communication).

> By default, the panelists receives a simple invite that details the survey topic (i.e. healthcare, auto, finance, etc.), the survey length and the reward they will receive upon completion. As there are so many panel sources–they are all slightly different in set-up and wording. There isn't a template version to share (J. Grodzicki, Dynata, 2023, personal communication).

Further, in response to a request for information on the reward or incentive offered to respondents, Dynata indicated that, similar to other companies offering similar panel resources, this information is proprietary:

> The incentive offered to the respondents is based on the panel source they registered, be it points, cash, air miles, etc. Dynata cannot share this information (J. Grodzicki, Dynata, 2023, personal communication).

4.4. Survey population

The intended population for this research is the entire population of the United States 18 years old or older. Throughout this report we refer to this as the U.S. general public or some variation of that terminology.

Race is included as a screening variable and is used as a variable in the analysis in this report. As noted in (Bureau 2022): "An individual's response to the race question is based upon self-identification." This report further states "The racial categories included in the census questionnaire generally reflect a social definition of race recognized in this country and not an attempt to define race biologically, anthropologically, or genetically. In addition, it is recognized that the categories of the race item include racial and national origin or sociocultural groups. People may choose to report more than one race to indicate their racial mixture, such as 'American Indian' and 'White.' People who identify their origin as Hispanic, Latino, or Spanish may be of any race." The authors of this report feel that the use of race as an explanatory variable requires further consideration and discussion and are reviewing additional literature to better understand this potentially controversial topic including: (Bureau 2022; Dirette 2014; Flanagin et al. 2021; Giannini et al. 2022; Ross et al. 2020; VanEenwyk 2010).

We also note that gender was used as a screening variable in the survey implementation with a target of 50% male/50% female and with no target on "fluid/nonbinary" or "other" responses to the gender question. For the 2022 survey we implemented the gender question as suggested by Dynata compared to the binary question asked in the 2006 survey. The purpose of this is not to identify sexual orientation or gender identity and thus we use a "female" indicator variable for analysis without specific expectations as to how or why responses would vary by gender. As suggested in the National Institutes of Health style guide[4]:

> Because there are many different gender identities, avoid using binary language that indicates there are only two. Use all genders instead of both genders, opposite sex, or either sex. If referring only to sex, use female, male, or intersex.

Like our initial consideration of "race" as an explanatory variable, the authors of this report feel that the use of gender (or a "female" indicator variable in particular) as an

[4] https://www.nih.gov/nih-style-guide/inclusive-gender-neutral-language#:~:text=Use%20all%20genders%20instead%20of,female%2C%20male%2C%20or%20intersex.

explanatory variable requires further consideration and discussion and a review of the extant literature to better understand this potentially controversial topic. We did review several recent peer-reviewed publications in weather-related social science studies and note that the use of a "male/female" indicator variable is still a relatively common practice.

4.5. Survey requirements

The sociodemographic criteria provided to Dynata included 1) a roughly 50/50 split on gender and 2) as representative of the general U.S. population as possible based on current census data. Table 3 shows the sociodemographic variables used for screening respondents for entry into the survey. The target distribution in each category was determined by Dynata based on current census data (other than gender for which we requested a 50/50 split with unlimited entry for nonbinary respondents). We have entered our calculations for each variable based on Census data.

After a brief introductory slide, respondents were thus screened in or out of the survey through the first four questions on zip code (converted by Dynata lookup tables to regions), gender, age, and race. Respondents under 18 years of age were terminated from further responses. If respondents were screened out or the quota was full, they were informed: *"Thank you for your interest in our study. Unfortunately, we are looking for individuals with characteristics different than your own."*

Table 3: Respondent Quotas Used by Dynata for 2022 Survey

	Target Sample Size		Actual		Census Estimates of National Percent
TOTAL	1200		1202		
Region - Decennial Census (2020) [1]					
Northeast	18%	216	18.30%	220	17%
Midwest	22%	264	20.88%	251	21%
South	37%	444	38.02%	457	38%
West	23%	276	22.80%	274	24%
	100.00%	1200	100.00%	1,202	100%
Gender - American Community Survey (2021) [2]					
Female	50%	600	51.41%	618	
Male	50%	600	47.5%	571	49.52%
Fluid/Nonbinary	Inf		0.83%	10	
Other	Inf		0.25%	3	
	100.00%	1200	99.99%	1202	
			Percent non-male: 52.5%		Percent non-male: 50.48%
Age - American Community Survey (2021) [2]					
18-24yrs	13%	156	12.98%	156	12%
25-34yrs	18%	216	17.89%	215	17%
35-44yrs	18%	216	18.05%	217	17%
45-54yrs	19%	228	17.30%	208	16%
55-64yrs	16%	192	16.39%	197	17%
65yrs+	17%	204	17.39%	209	22%
	101.00%	1212	100.00%	1,202	101%
Race – Population Estimates: Race and Hispanic Origin [3]					
White	70%	840	70.30%	845	76%

Table 3: Respondent Quotas Used by Dynata for 2022 Survey					
Black/AA	13%	156	13.89%	167	14%
Hispanic/Latino	20%	240	13.98%	168	19%
Asian	5%	60	5.41%	65	6%
American India/Alaska Native	Inf		1.83%	22	1%
Other	Inf		1.41%	17	3%
	108.00%	1296	106.82% [4]	1284 [4]	119%

[1] https://data.census.gov/table?q=population+by+Region+-+Decennial+Census&tid=DECENNIALPES2020.F_REGIONS Accessed May 18, 2023
[2] https://data.census.gov/table?q=S0101&tid=ACSST5Y2021.S0101 Accessed May 18, 2023
[3] https://www.census.gov/quickfacts/fact/table/US/PST045222 - Population Estimates Accessed May 18, 2023
[4] Sums to more than 100% and more than 1,202 as respondents were instructed to "Please select all that apply to you"

4.6. Pretesting, soft launch and full implementation

Once Dynata had programmed the survey into their system based on the Word document provided by the researchers, various members of the team tested the survey on multiple different platforms. Once we had approved the programming, Dynata soft-launched the survey to obtain 100 respondents within the desired sociodemographic criteria.

The soft launch was implemented on May 3, 2022 with 100 responses to be provided to the research team for analysis. Based on analysis of the start dates in the raw dataset, 120 responses were obtained by the end of May 3rd that were included in the final dataset. The first soft-launch response was started May 3, 2022 at 7:59:00 PM and the 120th response at May 3, 2022 at 8:42:00 PM for a period of 43 minutes to obtain the first 120 responses.[5] After a quick evaluation of the soft launch data and the requested revision to the price offers on the Willingness-to-Pay question, the complete launch began May 5, 2022 at 3:56:00 PM. The final response (n = 1,202 including the soft launch) was started May 11, 2022 at 7:57 PM. It is noted that the response rate slows as the survey proceeds as a higher and higher percentage of starts are screened out as the quotas for age, gender, region, and race are filled. (Based on our calculations there was a completed start for the full implementation every 8 minutes, 16 seconds).

4.7. Final raw dataset

The final dataset was provided by Dynata on May 12, 2022. This contained the raw data and a datamap for the 1,202 responses. Within the folder CoFU/Analysis – 2023/Dataset/Raw Data/ORD-713020-P3C0 Final Data 051122[6] the file "CoFU 2 Raw Data from Dynata" contains the raw data as provided by Dynata on May 5, 2022. This data file was used for all initial data QA/QC, variable renaming, and merging with the CoFU1 data for further analysis.

While 1,202 complete and valid responses were provided, we note that the first data field labeled "record" had a maximum number of 3,930. As only complete responses

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[5] All times are Eastern Standard Time (EST) (J. Grodzicki, Dynata, 2023, personal communication).

[6] We are currently (April 17, 2024) not providing external access to the data pending the primary researchers completing their initial analysis.

were provided and there were 3,930 starts of which only 1,202 qualified and completed the survey, we calculate a completion rate of 30.59%.[7]

Dynata provided the survey activity report with the information shown in Table 4. This has been reordered to show our calculations based on this information. (Note that this has to be specifically requested from Dynata as part of the survey implementation and would recommend others make sure to request this if using this service). It is not clear why there is a difference between the "Click ins" of 3,199 and the 3,930 of apparent starts according to the number of records. It is also not clear to us why the activity report indicates 1,205 completes whereas the raw dataset included 1,202 completes.

The "terminates" includes those individuals who were screened out for sociodemographic reasons to meet our region, gender, and race requirements as well as the minimum age of 18 years. The last four rows show responses that were dropped as part of Dynata's QA/QC process of identifying respondents who do not appear to be providing useful answers. These individuals may have been speeding through too quickly (suggesting they were not actually reading the questions or were providing the same answers on a number of questions (e.g., just clicking on a single response option in order to complete the survey without processing the information).

Overall, we feel that this process provides a sample that comes from a well-developed panel, which meets our population requirements, and removes respondents who are not providing useful information.

Table 4: Activity Report from Dynata

Click ins	3199
Dropoffs / partials	459
Overquota	985
Terminates	550
Total drop-offs, over quota and terminates	1994
Completes	1205
Terminates Summary	550
No DMA matched	31
dAge: under 18	95
Speeder Auto Check Failed	113
QualityScore Check Failed	100
Disqualified: Straight liner	151
Disqualified: Bad open ends	60

[7] "...the 'record' field register each entry into the survey regardless of their final status–be it, complete, terminated, quotafull, dropout, etc" (J. Grodzicki, Dynata, 2023, personal communication).

4.8. Appending datasets

Following data cleaning and various adjustments and the calculation of new variables such as the "Weather Impact Scale" and fitted income as described below (Section 6.1 and following), the two datasets were joined using SAS® append.[8] The two datasets stacked with the same number of variables except the new questions added in CoFU2. The compiled dataset has 267 variables and 2,722 observations.

[8] SAS is a suite of software with a range of statistical processes. SAS and all other SAS Institute Inc. product or service names are registered trademarks or trademarks of SAS Institute Inc. in the USA and other countries. ® indicates USA registration. The majority of analysis using SAS was performed using SAS Enterprise Guide 7.15. Additional analysis was performed mainly using Microsoft 365 Excel Version 2406.

5. Results

In this section we discuss statistical considerations in analyzing the survey, efforts to fit income for individuals who did not answer the income question, inflation adjustments to income and the Willingness-to-Pay price points, and the characteristics of the sample.

5.1. Analytical and statistical considerations

In this section we present an initial analysis of some aspects of the survey. A complete analysis of some specific topics will be left to the development of individual manuscripts focusing on topics similar to those covered in the original articles from the CoFU1 analysis (see Table 1}. For the current analysis we note that the margin of error is not specifically discussed with each result but in general is ±3% as indicated in Table 5. The margin of errors were calculated using an online calculator from Survey Monkey the year each survey was implemented (accounting for that year's U.S. population and the difference in sample size between the full sample and the smaller sample of only those indicating that they use weather forecasts. Thus, for either survey for the full sample or "use forecasts" subsamples, the 95% confidence interval margin of error is plus or minus 3%.

Table 5: Margin of Error

Confidence Level 95%

Survey Year	U.S. Population	Total Sample	Margin of Error	Use Forecasts	Margin of Error
2006	299,398,484	1520	3%	1465	3%
2022	338,289,857	1202	3%	1092	3%

Calculated using: https://www.surveymonkey.com/mp/margin-of-error-calculator/

In our analysis and reporting we generally use a 10% level as the relevant level of significance. This is a subjective decision and has not accounted for potential multiple-related significance tests. In general, we also provide the resulting statistical tests and levels of significance so the reader can make their own judgments and so that a result that is significant for instance at the 10.001% level is not ignored erroneously. As (Lachlan and Spence 2006) note "corrections for Type I error are seldom utilized, even in designs so complicated as to almost guarantee erroneous rejection of null hypotheses." Given the large number of statistics reported here there are almost certainly cases of "erroneous rejection of null hypotheses" when the null is in general that there is "no effect." This provides additional motivation for our suggestion that any results reported here (or in most scientific literature) be reevaluated and replicated especially if decisions based on those results may affect peoples' safety or welfare as communication of weather information certainly does.[1]

[1] A reviewer commented that a discussion or calculation of effect sizes and power could be useful. This analyst is not familiar enough with effect size calculations to include that here but feels it would be worthwhile to discuss effect sizes in terms of whether statistically "significant" findings are significant in any real world sense. The inclusion of standardized regression coefficients as shown in Table 7 does this to some degree.

We note that comparing results or drawing inferences for the samples as a whole, basically assumes that the samples were both random and representative. To further explore various results, we undertake regression analysis including sociodemographic explanatory variables as well as the CoFU_Version indicator variable.[2] Regression analysis is an analysis of individual responses where a significant explanatory variable is such after controlling for all of the other included independent variables. In this sense, we feel that regression analysis where the version indicator is still significant suggests that there is more likely a real difference in behavior, perceptions, or values between 2006 and 2022 than just comparing sample means.

We further note that many of the response options provided in the surveys are Likert item or Likert scale type response options.[3] In general, we treat these as interval scale responses when used as a dependent variable (i.e., we use ordered probit analysis) but treat them as continuous variables when used as an independent variable. We understand there may statistical issues in doing so (Sullivan and Artino 2013) and are open to suggestions for improved analysis, but we also feel that results presented are unlikely to change much.

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[2] We note that we use of the word "indicator" in reference to a variable that is generally coded as a 0/1 variable (binary) indicating the absence or presence of the particular characteristic. This is commony called a "dummy" variable in the economic statistical analysis literature. (See https://en.wikipedia.org/wiki/Dummy_variable_(statistics) accessed June 25, 2024).

[3] "Developed in 1932 by Rensis Likert to measure attitudes, the typical Likert scale is a 5- or 7-point ordinal scale used by respondents to rate the degree to which they agree or disagree with a statement…" (Sullivan, G. M., and A. R. Artino, Jr., 2013: Analyzing and interpreting data from likert-type scales. *J Grad Med Educ*, **5,** 541-542.p. 543).

5.2. Time to complete survey

We compared individuals' time to complete the survey between the 2006 and 2022 implementations. We further split this into those who indicated they do and do not use weather forecasts as those who indicated they do not use forecasts answered considerably fewer questions. Table 6 shows summary statistics by implementation year and by use or do not use weather forecasts. The mean time is almost identical for those who do use forecasts (28.95 minutes versus 28.97 minutes). The mean time to complete was a little less in 2022 for those who do not use forecasts (13.22 minutes in 2006 versus 11.01 minutes in 2022). Statistical tests showed no significant difference for time to complete the survey between the 2006 and 2022 respondents in those using forecasts ($t = -0.01$, $df = 2555$, $Pr>|t| = 0.9951$) or between those not using forecasts ($t = 0.66$, $df = 163$, $Pr>|t| = 0.5075$). The similarity in time to complete is a little surprising as the 2022 survey included the additional five topic areas that were not included in the 2006 survey (asked of all survey respondents and not just those using forecasts (see Figure 1)).

Table 6: Time to Complete Survey (in Minutes)

CoFU Version	2006 (CoFU1)			2022 (CoFU2)		
Use Forecasts	Yes	No	All	Yes	No	All
N	1465	55	1520	1092	110	1202
Mean	28.954	13.218	28.384	28.968	11.014	27.325
Std Dev	57.960	32.450	57.305	57.630	9.050	55.240
Minimum	4.000	3.000	3.000	4.770	3.850	3.850
Maximum	1543.000	247.000	1543.000	1174.970	78.580	1174.970
Median	21.000	7.000	21.000	18.870	8.340	17.717

5.2.1. Time to complete regression analysis

Table 7 shows an ordinary least squares regression of the natural log of the time to complete (TTC) the survey on various sociodemographic and survey characteristics. The natural log of TTC was taken as the distribution is highly skewed to the right.[4] The natural log provided a much more normal distribution on the dependent variables. The standardized estimates in the last column are standardized regression coefficients meant to give an indication of which variables have the largest impact on time to complete.[5]

[4] As noted by Rodney Beard "One might be able to defend this from the perspective of queueing theory, where often one assumes Poisson arrivals and exponential inter arrivals, time to complete might be exponentially distributed, in this case it would be a dequeue not a queue."

[5] Standardized regression coefficients are "…the estimates resulting from a regression analysis where the underlying data have been standardized so that the variances of dependent and independent variables are equal to 1. Therefore, standardized coefficients are unitless and refer to how many standard deviations a dependent variable will change, per standard deviation increase in the predictor variable." (Source: Wikipedia article on "Standardized coefficient" https://en.wikipedia.org/wiki/Standardized_coefficient; accessed June 7, 2023) "A standardized parameter estimate predicts the change in the response variable

The estimates suggest, after accounting for the other variables included in the model, it took respondents in the 2022 implementation a little less time to complete the survey than in 2006—even though the 2022 survey included the additional variables. As was expected the largest impact on TTC is that individuals who indicated they do not use forecasts took significantly less time as they were routed to simply skip a significant portion of the survey.

Other significant (at the 10% level) coefficients, suggest that individuals who are female, older, or less educated took more time to complete the survey. Of the employment indicator variables, only "student" was not significant suggesting perhaps that students took less time that all the other respondents. Of all the race indicator variables only "Asian" was not significant again suggesting perhaps that "Asian" took less time than all the other respondents.

Also shown in Table 7 is the same regression on time to complete but adding the factor scores from the numeracy questions.[6] As these questions were only asked in the 2022 survey this analysis only includes respondents from that implementation. The SNS_Ability_Subscale is the self-rated measure of numeracy ability or competency. Individuals with higher "ability" scores took a little longer to complete the survey. The SNS_Preference_Subscale is the self-rated preferences for numerical over non-numerical information in communication. Individuals higher rated on this scale took less time to complete the survey. At this time, we do not have a reasonable explanation for this difference, but suggest it would be interesting for further examination in relation to how individuals respond to surveys questions (i.e., being more or less invested in evaluating numerical information in the survey).

(in standard deviations) for one standard deviation of change in the explanatory variable (while controlling for the other variables)." (https://blogs.sas.com/content/iml/2018/08/22/standardized-regression-coefficients.html Accessed December 19, 2023).

[6] Note that this and the other "new factors" will be examined in follow-on research.

Table 7: OLS Regression on Natural Log of Time to Complete

		Both Survey Implementations			CoFU2 with SNS Scales		
		N = 2,772; Adj R-Sq = 0.164			N = 1,202; Adj R-Sq = 0.174		
	Variable	Param. Est.	Pr > |t|	Stand. Est.	Param. Est.	Pr > |t|	Stand. Est.
	Intercept	3.370	<.0001	0.000	3.417	<.0001	0.000
	CoFU_Version CoFU1 = 1; CoFU2 = 2)	-0.090	0.000	-0.067	Not in this model		
	Use Wx Forecast (Yes = 1; No = 2)	-0.801	<.0001	-0.288	-0.709	<.0001	-0.273
Sociodemographics	Income_2021_Median_Thousands	0.000	0.983	0.000	0.001	0.128	0.052
	Years in Current Residence	0.001	0.280	0.021	0.001	0.456	0.022
	Female	0.083	0.001	0.062	0.177	<.0001	0.118
	Age (Years)	0.009	<.0001	0.200	0.009	<.0001	0.210
	Household Size	0.001	0.905	0.002	-0.008	0.475	-0.020
	Education (Years)	-0.013	0.016	-0.048	-0.016	0.062	-0.059
Employed (No-1; Yes=1)	Fulltime	0.126	0.069	0.094	-0.172	0.013	-0.114
	Parttime	0.152	0.029	0.074	-0.084	0.312	-0.035
	Retired	0.204	0.005	0.132	-0.076	0.345	-0.043
	Homemaker	0.175	0.015	0.078	-0.035	0.712	-0.012
	Student	0.065	0.451	0.016	-0.288	0.027	-0.067
	Unemployed	0.239	0.001	0.108	Linear combination of other variables		
Race (No-1; Yes=1)	White	0.122	0.038	0.081	0.166	0.058	0.101
	Black	0.247	0.000	0.126	0.206	0.033	0.095
	Latino	0.161	0.005	0.069	0.169	0.031	0.078
	Asian	0.070	0.355	0.022	0.052	0.662	0.016
	Native	0.185	0.034	0.039	0.178	0.239	0.032
	Other	0.260	0.008	0.054	0.286	0.115	0.045
Numeracy	SNS_Ability_Subscale				0.051	0.047	0.064
	SNS_Preference_Subscale				-0.098	0.026	-0.066

More time to complete may indicate the individual invested more cognitive effort in the survey or may indicate the individual had more difficulty with understanding or answering the questions. We have no causal explanation for these relationships. It would be more interesting to have measures of the quality of the survey responses such as measures of internal reliability or validity.

As a way to explore the possibility of improved quality with more time spent on survey completion, we compare the standard deviation on a number of different scales and factor scores based on splitting the sample based on median time to complete (TTC) the survey. First, we created an indicator variable splitting the sample (across both survey implementations) between those who completed in less than median completion time (Short TTC) and those who took more than the median completion time (Longer TTC). We then conducted a *t* test of the means that also generates a test of the "equality of the variances." Results of this test of variances for a selection of scales and factor scores as shown in Table 8 indicates that the standard deviation of responses is smaller for all 11 measures for those who took longer to complete the survey (see the column labeled "Longer TTC Smaller Std Dev?"). The standard deviations are significantly smaller in five of the cases for those who took longer to complete the survey. While not definitive, we take this as a possible indication that those who took longer to complete the survey may have been more careful in doing so and thus more "precise" in their responses as indicated by the lower standard deviations. Note that we do not explain in this report what some of these scales or factors are. Also note that some of these are scales and some are factor scores.

Table 8: Comparison of Standard Deviation of Various Scales as a Function of Time to Complete (TTC)

Scale / Factor	Std Dev - Shorter TTC	Std Dev – Longer TTC	Longer TTC Smaller Std Dev?	T-test output for equality of variance (Folded F method)			
				Num DF	Den DF	F Value	Pr F
Source Total Freq	96.528	79.259	Y	1209	1346	1.48	<.0001
WxSQ Salience Total[1]	21.699	17.905	Y	1360	1360	1.47	<.0001
Factor1 – Discretionary Act[2]	1.025	0.964	Y	1209	1346	1.13	0.028
Factor – Non-disrectionary Act[2]	0.997	0.985	Y	1209	1346	1.02	0.682
Attrib Fact_1 Precipitation[3]	0.953	0.938	Y	1209	1346	1.03	0.577
Attrib Fact_2 Wind Clouds[3]	0.933	0.922	Y	1209	1346	1.03	0.651
Attrib Fact_3 Time of Temp[3]	1.009	0.991	Y	1209	1346	1.04	0.514
Attrib Fact_4 Temp Extreme[3]	0.907	0.875	Y	1209	1346	1.08	0.191
SNS Ability Subscale[4]	0.9414	0.9406	Y	686	514	1.00	0.99
SNS Preference Subscale[4]	0.514	0.477	Y	686	514	1.16	0.08
SNS Total[4]	0.633	0.586	Y	686	514	1.17	0.06

[1] Weather Salience - scale
[2] Use of Fx for Activities – factor scores
[3] Importance of forecast attributes – factor scores
[4] Subjective Numeracy Scale - scale

5.3. Fitting income for 2022 survey

The income question was reworded slightly from 2006 to ask, "What was your total household income (before taxes) in 2021?" (rather than 2005). Dynata added a "Prefer not to answer" response option, which we did not provide in 2006. A total of 73 respondents (6.07% of the total) declined to provide their income (i.e., answered "Prefer not to answer"). As in CoFU1, we fitted a value for income for respondents who declined to respond to the income question. We first recoded the categorical responses into midpoints for the range offered in each response category. We then regressed income on sociodemographics using the same regression model as in CoFU1 used to fit missing income. Table 9 shows the regression model for the nonmissing values. Income is higher for individuals who are older, more educated, fully employed, and White. Individuals with a larger household also have a larger income, which may be a matter of two or more earners in the household. We did not include gender as an explanatory variable in this model as we had not done so in the 2006 analysis and wanted to maintain consistency with that income fitting exercise.

Table 9: OLS Regression on Income 2021

(n = 1129; nmiss = 73)

Variable	Est.	Std Err	t-stat	Pr>|t|
Intercept	-106,953.00	7,935.64	-13.48	<.0001
Age (in years)	548.73	81.37	6.74	<.0001
Household Size	2,781.81	666.57	4.17	<.0001
Education (in years)	8,053.08	468.45	17.19	<.0001
Employed Full Time (Employed Full Time = 1; Else = 0)	25,930.00	2,651.19	9.78	<.0001
Race White (White = 1; Non-White = 0)	13,056.00	2,763.35	4.72	<.0001
Adj R-Sq	0.3476			

In running the regression analysis in SAS, for each respondent predicted income is generated based on the estimated regression coefficients including for those who had not reported their income. These values were saved. For respondents who had provided their income, the reported income was retained as well as the fitted income for those who had not provided their income and retained as the variable "Income_2021" corresponding to the income variable from the 2006 survey adjusted for inflation.

5.4. Inflation adjustments from 2005 to 2021 for WTP price points and income

The income and Willingness-to-Pay price points ("NWS_Cost") were adjusted from 2005 values (as asked in the survey) to 2021 values using the Consumer Price Index (a multiplier of 1.41668).[1] Alternatively, we used the increase in median income rather than the consumer price index to inflate income (and the NWS price point) from 2005 to 2021. This represented a 9.867% increase rather than 41.668% using the CPI. This

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1 U.S. Bureau of Labor Statistics - CPI Inflation Calculator: https://www.bls.gov/data/inflation_calculator.htm December 2005 to December 2021, $1,000.00 to $1,416.68 for a factor of 1.41668

created new variables "Income_2021_CPI," "Income_2021_Median," "NWS_Cost_2021," and "NWS_Cost_2021_Median," as well as "Income_2021_CPI_Thousands," which is simply "Income_2021" divided by 1,000, which is easier to use in regression analysis (and a similar variable for "Income_2021_Median_Thousands").

Table 10 provides summary statistics and a *t* test of the difference in mean income between 2005 and 2021 using the different adjustment factors—the CPI and the difference in median income. Using the CPI adjustment, the adjusted mean income from 2005 is $15,074.50 more than 2021 respondents, which is significant at less than 0.01%. Using the median income adjustment, adjusted mean income from 2005 is $3,341.70 more than 2021 respondents, which is significant at the 6.33% level. This difference in income adjustments using the CPI versus using median income suggests that median income has not kept up with inflation. One possible cause of this could be an increasing income disparity between the more and less wealthy.

Table 10: Comparison of Mean Income between 2005 and 2021 Using CPI and Median Income

Variable	Version	Mean	Std Dev	Minimum	Maximum	N
Income_2021 CPI Adjusted Income from 2005 to 2021	CoFU1	82,048.95	53,794.41	7,083.40	255,002.40	1520
	CoFU2	66,974.42	50,126.18	4,382.94	180,000.00	1202
		Mean	Std Err	DF	t Value	Pr > |t|
t-test	Diff (1-2)	15,074.50	1,998.60	2,648.10	7.54	<.0001
Variable	Version	Mean	Std Dev	Minimum	Maximum	N
Income_2021_Median Income adjusted to 2021 using median income as the metric	CoFU1	63,632.70	41,720.02	5,493.50	197,766.00	1520
	CoFU2	66,974.42	50,126.18	4,382.94	180,000.00	1202
		Mean	Std Err	DF	t Value	Pr > |t|
t-test	Diff (1-2)	-3,341.70	1,798.70	2,325.50	-1.86	0.0633

A simple comparison of mean income assumes that the samples are essentially comparable. Regression analysis of a mix of sociodemographic variables (also interacted with the CoFU version indicator) on mean income (using both adjustment methods) shows very complex interactions between the version of the survey and sociodemographic characteristics and income.[2] It is not clear at this point which adjustment factor is best (if either). This will be explored further as income is a key explanatory variable in analysis of the current value of weather forecasts.

5.5. Location and sociodemographics of respondents

5.5.1. Location of respondents

As noted above, in CoFU1 we had respondents from all 50 states (and the District of Columbia assuming zip codes have not changed significantly between 2006 and 2024

[2] This regression is not included in this report.

when we crossed checked this). In CoFU2 we have respondents from all states except Alaska and Delaware. Further we have no respondents from American Samoa, Federated States of Micronesia, Guam, Marshall Islands, Northern Mariana Islands, Palau, Puerto Rico, or the U.S. Virgin Islands.

We also note that while we do have zip code information from CoFU1 respondents this has not been recoded into state or other regional identifiers in the current working dataset. For the CoFU2 dataset, Dynata did code this into states as well as variables for a 4—region assignment, 9—region assignment, and Designated Marketing Area (DMA) codes for city assignments.

5.5.2. Sociodemographics of respondents

Table 11 shows summary statistics for most of the sociodemographic variables for the two versions of the survey.[3] The last columns indicate results of the Kruskal–Wallis *H* test for each variable.[4] We used this rather than a *t* test as many of the variables (e.g., income and the indicator variables) likely do not have normally distributed error terms. The tests were conducted in SAS using the NPAR1WAY procedure, which implements the Kruskal–Wallis *H* test, where the classification variable is CoFU_Version. For now, we have retained the variables names used in the final compiled analysis dataset. Note that several of the variables are indicator variables. Some of these are identified with a minimum of 0 and maximum of 1, while others are identified with a minimum of 1 and maximum of 2.

There is no significant difference (at the 10% level) between samples on several measures including income (adjusted using the median value); gender; education; full-time or part-time employment, retired, or student; or the portion of the sample that identifies their race as Black or Native. The 2022 survey included additional response

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[3] For many of the variables these are indicator variables (e.g., "female") where the variable is coded as "1" if that characteristic is present or the response is "yes" and zero otherwise. As indicated in Table 7 CoFU_Versions is coded as "1" for the 2006 survey and "2" for the 2022 survey; and Use Wx Forecast is coded Yes = 1 and No = 2.

[4] "The Kruskal–Wallis test by ranks, Kruskal–Wallis *H* test (named after William Kruskal and W. Allen Wallis), or one-way ANOVA on ranks is a nonparametric method for testing whether samples originate from the same distribution. It is used for comparing two or more independent samples of equal or different sample sizes. It extends the Mann–Whitney *U* test, which is used for comparing only two groups. The parametric equivalent of the Kruskal–Wallis test is the one-way analysis of variance (ANOVA). A significant Kruskal–Wallis test indicates that at least one sample stochastically dominates one other sample. The test does not identify where this stochastic dominance occurs or for how many pairs of groups stochastic dominance obtains. For analyzing the specific sample pairs for stochastic dominance, Dunn's test, pairwise Mann–Whitney tests with Bonferroni correction, or the more powerful but less well known Conover–Iman test are sometimes used. Since it is a nonparametric method, the Kruskal–Wallis test does not assume a normal distribution of the residuals, unlike the analogous one-way analysis of variance. If the researcher can make the assumptions of an identically shaped and scaled distribution for all groups, except for any difference in medians, then the null hypothesis is that the medians of all groups are equal, and the alternative hypothesis is that at least one population median of one group is different from the population median of at least one other group. Otherwise, it is impossible to say, whether the rejection of the null hypothesis comes from the shift in locations or group dispersions. This is the same issue that happens also with the Mann–Whitney test." Source: https://en.wikipedia.org/wiki/Kruskal%E2%80%93Wallis_one-way_analysis_of_variance .

options for gender to be more inclusive, but such a small percentage responded with these options that statistically there was still no difference in the distribution.

There is a significant difference (at the 10% level) between samples on several measures including years in current residence; age; being a homemaker or unemployed; and the portion of the sample that identifies their race as Asian, Latino, White, or other. We feel that these differences reflect that we have reached a somewhat more representative sample with the 2022 survey including better reaching younger respondents and those from racial groups not as well represented in the 2006 sample.

In 2006 8.1% of respondents indicated they were unemployed. The official US unemployment rate in November 2006 was 4.3%.[5] A total of 12.1% of respondents to the 2022 survey indicated they were unemployed. The unemployment rate in June 2022 was only 3.8%. Respondents thus reported a much higher rate of unemployment in both surveys than in the official statistics for the corresponding period. This may be accounted for in part as some retired individuals also indicated themselves as unemployed, but this was only 7 of the 288 (or 2.61%) unemployed respondents across both surveys.

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[5] Source: https://beta.bls.gov/dataViewer/view/timeseries/LNU04000000. Labor Force Statistics from the Current Population Survey.

Table 11: Sociodemographics Summary Stats and Difference Test

	CoFU 1 (n = 1520)					CoFU 2 (n = 1202)					Kruskal–Wallis Test (df = 1)	
Variable	Mean	Std Dev	Min	Max	Median	Mean	Std Dev	Min	Max	Median	Chi-Square	Pr > Chi-Square
Inc_2021_Med	63632.7	41720.0	5493.0	197766	49441.5	66974.4	50126.2	4382.9	180000	55000	0.617	0.432
yrs_residence	24.878	19.208	0	100	22	21.745	18.320	0	88	17	17.119	<.0001
gender*	1.490	0.500	1	2	1	1.499	0.531	1	4	1	0.003	0.958
female	0.510	0.500	0	1	1	0.514	0.500	0	1	1	0.049	0.825
age	50.543	13.388	18	93	51	46.042	17.052	18	99	45	52.332	<.0001
household_size	2.531	1.303	1	9	2	2.768	1.919	1	25	2	6.921	0.009
educ_yrs	14.759	2.321	10	22	14	14.937	2.726	10	22	14	1.955	0.162
emp_fulltime	0.454	0.498	0	1	0	0.443	0.497	0	1	0	0.300	0.584
emp_parttime	0.124	0.329	0	1	0	0.110	0.313	0	1	0	1.244	0.265
emp_retired	0.253	0.435	0	1	0	0.226	0.419	0	1	0	2.545	0.111
emp_homemaker	0.118	0.322	0	1	0	0.068	0.252	0	1	0	18.998	<.0001
emp_student	0.026	0.160	0	1	0	0.032	0.175	0	1	0	0.677	0.411
emp_unemployed	0.081	0.273	0	1	0	0.121	0.326	0	1	0	11.921	0.001
race_white	0.767	0.423	0	1	1	0.703	0.457	0	1	1	14.291	0.000
race_black	0.124	0.329	0	1	0	0.139	0.346	0	1	0	1.376	0.241
race_latino	0.051	0.219	0	1	0	0.140	0.347	0	1	0	65.047	<.0001
race_asian	0.039	0.193	0	1	0	0.054	0.226	0	1	0	3.594	0.058
race_native	0.021	0.144	0	1	0	0.018	0.134	0	1	0	0.261	0.610
race_other	0.024	0.152	0	1	0	0.014	0.118	0	1	0	3.199	0.074

* Gender in the 2022 survey had 4 response options rather than binary. For analysis we generally use only the “female” indicator variable.

5.5.3. Sociodemographics for analysis

For analysis throughout this report, we use various sociodemographic and behavioral information generally as explanatory variables. These include sociodemographic characteristics (income, age, education, gender, etc.). As the 2022 survey included 4 response options for the “gender” question and the 2006 survey did not, we instead use a “female” indicator variable (1 if female, 0 otherwise). For income we generally use income adjusted to current (2021) values using the median income adjustment as explained in Table 10. We feel this deserves further investigation as to the best approach for adjusting income (and offer prices on the WTP question). We also have a series of indicator variables for employment status. These are not necessarily exclusive as for instance of the 78 respondents identifying as students, 66 are unemployed (84.6%), while 12 are employed full-time (15.4%), and another 5 are employed part-time (6.4%). Similarly, we use indicator variables for race identifiers that are not necessarily exclusive. For instance, of the 2,011 identifying as “White” (across both survey implementations), 57 (or 2.83%) also identify as Latino. Finally, we include a series of self-assessed measures of time allocation including percent of leisure time or work time spent outside and how many hours per week spent traveling to work or being outside at home (which may or may not include leisure time).

Table 12: Sociodemographic Measures Used for Analysis							
N = 2722; N Miss = 0							
		Label	Mean	Std Dev	Minimum	Maximum	Median
Sociodemographics	Income (2021_Median_Adjusted_Thousands)	Q41	65.108	45.645	4.383	197.766	55
	Yrs in current residence	Q33	23.495	18.882	0	100	19
	Age (yrs)	Q36	0.512	0.500	18	99	50
	Female (no = 0; yes = 1)	Q35	48.556	15.277	0	1	1
	Household size	Q37	2.636	1.609	1	25	2
	Education (yrs)	Q38	14.838	2.509	10	22	14
Employment	Fulltime	Q39	0.449	0.498	0	1	0
	Parttime	Q39	0.118	0.322	0	1	0
	Retired	Q39	0.241	0.428	0	1	0
	Homemaker	Q39	0.096	0.294	0	1	0
	Student	Q39	0.029	0.167	0	1	0
	Unemployed	Q39	0.098	0.298	0	1	0
Race	White	Q40	0.739	0.439	0	1	1
	Black	Q40	0.130	0.337	0	1	0
	Latino	Q40	0.090	0.286	0	1	0
	Asian	Q40	0.046	0.209	0	1	0
	Native	Q40	0.020	0.139	0	1	0
	Other	Q40	0.019	0.138	0	1	0
Time allocation	Percent of job outside	Q23	3.240	3.125	1	11	1
	Hours traveling to work	Q24	6.971	14.813	0	168	1
	Percent of leisure time outside	Q25	5.354	2.377	1	11	5
	Hours at home spent outside	Q26	10.232	16.474	0	167	5

6. Analysis

In this section we discuss the analysis of questions on sources, uses, and perceptions of forecasts. Section 7 discusses values for forecasts.

6.1. Personal weather impact scale

A new measure we labelled the "Personal Wx Impact Scale" was developed in a preliminary manner here based on a series of questions asking respondents if they have experienced personal (or household level) weather-related impacts. While respondents who answered "yes" to the question were then followed up to ask the level of impact, we focus here on the four yes/no questions related to weather-related property damage, motor vehicle injury, non-motor vehicle injury, and weather-related medical conditions. Table 13 shows the four dichotomous questions used for this preliminary scale (and not the follow-up questions for those who answered yes and were asked follow-up questions on the level of impacts).

Table 13 Dichotomous Questions on Personal/Household Weather-Related Impacts

Question Number	Question in Survey (Response Options: Yes = 1; No = 2)
27	Within the last five years, have you or members of your household sustained weather-related damage to your property (e.g., house, fence, vehicle, boat)?
28	Within the last five years, have you sustained any injuries from a motor vehicle crash that was caused by weather?
29	Within the last five years, have you sustained any injuries caused by the weather that are not related to a motor vehicle crash?
30	Do you have a medical or health condition that is affected by changes in the weather?

As the yes responses were coded as 1 and the no responses coded as 2, we "reversed" the total scores on the four questions so that zero would mean the respondent answered "no" to all four impacts and a score of 4 means they had experienced all four types of impacts. Table 14 shows the percent of respondents from each survey in each summed score level.

Table 14: Personal Weather Impact Scale (Personal Wx Impact Scale_Reversed)

Summed Score	Percent	
	CoFU1	CoFU2
0	46.6	51.4
1	37.9	24.8
2	12.6	8.9
3	2.4	4.5
4	0.5	10.4
Total percent	100	100

Figure 2 shows this information graphically. There is some variation between the two survey versions (we have not undertaken statistical tests of these differences at this time) especially with respect to apparently significantly more CoFU2 respondents indicating they had experienced all four of the impacts (10.4% for CoFU2 versus 0.5% in CoFU1).

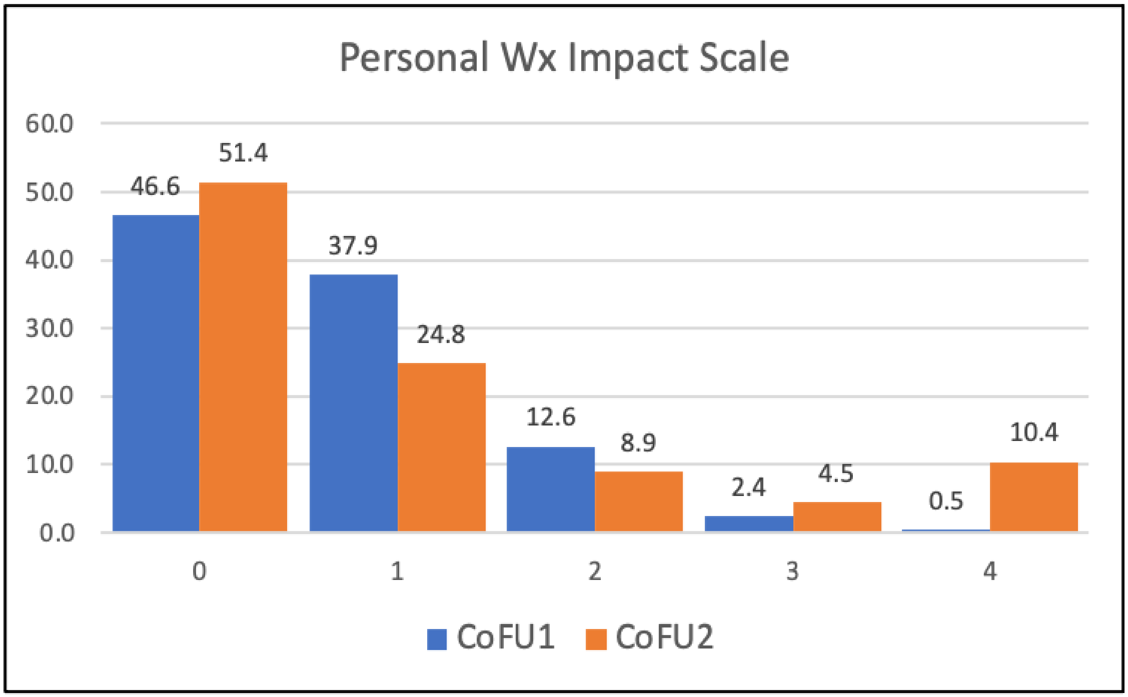

Figure 2: Percent of Total Impacts by Survey Version

Table 15 shows an ordered probit regression analysis on the total personal weather impact scale. The regression was on the highest level (4) so positive parameter estimates indicated the individual is more likely to have experienced more personal weather impacts. Overall CoFU2 respondents are less likely to have experienced negative weather impacts as indicated by the negative parameter estimate on CoFU_Version. This seems odd given the higher percent of CoFU2 respondents who have experienced all four impacts, but after controlling for all the other independent variables, CoFU2 respondents have fewer personal impacts.

Those with lower income, older, nonfemale, larger household, more education, who spend more job or leisure time outside, do not get forecasts for their own city but do so for other states or countries, and use forecasts in the early morning but not in the midmorning (8 to 11 am), and those who use forecasts to get to work or who feel NWS information is more important are more likely to experience personal weather impacts. No employment or race variables were significant nor were satisfaction or confidence in forecasts.

Table 15: Ordered Probit Regression on Personal Weather Impact Scale

(n=2,557)

		Intercept	Pr>ChiSq
Intercept	Intercept	-2.926	<.0001
	Intercept	-2.579	<.0001
	Intercept	-1.945	<.0001
	Intercept	-0.932	0.005
	CoFU_Version	-0.123	0.021
Sociodemographics	Income	-0.002	0.010
	Yrs in current residence	0.001	0.610
	Age (yrs)	0.099	0.052
	Female (no = 0; yes = 1)	-0.007	0.001
	Household size	0.075	<.0001
	Education (yrs)	0.033	0.002
Employment	Fulltime	-0.141	0.288
	Parttime	-0.053	0.691
	Retired	0.137	0.326
	Homemaker	-0.027	0.846
	Student	-0.145	0.378
	Unemployed	0.054	0.708
Race	White	0.062	0.589
	Black	-0.019	0.879
	Latino	-0.151	0.172
	Asian	-0.175	0.243
	Native	0.222	0.172
	Other	-0.030	0.879
Time allocation	Percent of job outside	0.064	<.0001
	Hours traveling to work	0.000	0.859
	Percent leisure time outside	0.029	0.009
	Hrs at home spent outside	-0.001	0.400
Geographic Area	City you live	-0.153	<.0001
	City in state	-0.029	0.133
	City other state	0.045	0.052
	City world	0.088	0.000
Use by time of day	Time 12 to 6	0.205	0.000
	Time 6 to 8	0.017	0.733
	Time 8 to 11	-0.126	0.012
	Time 11 to 1	0.059	0.263
	Time 1 to 4	0.047	0.395
	Time 4 to 7	0.056	0.281

Table 15: Ordered Probit Regression on Personal Weather Impact Scale (n=2,557)			
		Intercept	Pr>ChiSq
	Time 7 to 12	0.072	0.155
Use Fx for Activities	Dress	0.010	0.568
	Get work	0.033	0.049
	Yardwork	0.025	0.149
	Job activities	-0.003	0.857
	Social activities	0.008	0.694
	Travel	0.020	0.285
	Weekend activities	-0.034	0.126
	Simply know weather	-0.025	0.284
Fx Qual	Satisfaction	-0.017	0.543
	Confidence 1d	-0.033	0.229
	Import of NWS info	0.186	<.0001
	Personal Wx Impact Scale	N.A.	N.A.
	Max-rescaled R-Sq	0.1886	
	Likelihood Ratio (DF = 45)	484.0831	<.0001
	Percent Concordant	66.8	

We note again that the Personal Weather Impact Scale developed here scale is preliminary and is mainly used as an explanatory variable in several other regressions in this report. The regression above though does indicate that substantial useful information may be revealed by these questions especially when combined with the responses to the follow-up questions on levels or personal impacts.[1]

6.2. Use forecasts

As shown in Figure 3, the first survey question other than screening questions asked "A weather forecast is a prediction about future weather conditions with respect to temperature, cloudiness, winds, and precipitation (such as rain, snow, hail, or sleet). Do you ever use weather forecasts?" offering Yes/No response options. This question is critical in the calculation of the total number of forecasts accessed by the public (e.g., 300 billion) as it reduces the number of people we multiply by the frequency of use to derive an estimate (lower bound) of the total annual forecasts accessed.

[1] In response to a comment from Labanyalata Roy we undertook additional regression analysis with respect to respondent's location and the weather impact scale. Section 10.4 Climate zones and weather impact explores this further with respect to the weather impact scale based on climate zones finding significantly more impacts experienced for those in temperate climates compared to those in tropical climates.

ASK ALL
SC
1 **A weather forecast is a prediction about future weather conditions with respect to temperature, cloudiness, winds, and precipitation (such as rain, snow, hail, or sleet).**

Do you ever use weather forecasts?

1. Yes
2. No

Figure 3: Do You Use Weather Forecasts Question [2]

Table 16 shows the frequencies of the Yes/No responses by version. Whereas in 2006, 3.62% of respondents indicated they never used forecasts, this had changed to 9.15% in 2022. A statistical test rejects the hypothesis that the frequency of use is the same in the two implementations (chi-square = 36.09; df = 1; Prob < 0.0001).[3] This would seem to be a very significant change in use of weather information and strongly suggests the need for a better understanding of these responses. If this is an indication of an actual change in use we feel this is a strong suggestion for further research. The bottom rows of Table 16 show the 95% confidence intervals for the binomial proportions (using exact confidence limits as calculated in SAS). As would be indicated by the chi-square test noted above, the 95% confidence intervals do not overlap.

Table 16: Do You Use Weather Forecasts?

	CoFU1		CoFU2		Combined	
use_wx_fcst	Frequency	Percent	Frequency	Percent	Frequency	Percent
Yes (1)	1465	96.38	1092	90.85	2557	93.94
No (2)	55	3.62	110	9.15	165	6.06
Total	1520	100	1202	100	2722	100
95% Exact Confidence Limits on Percent Yes						
Lower Bound	95.32		89.08		92.98	
Mean	96.38		90.85		93.94	
Upper Bound	97.26		92.42		94.81	

To explore this issue further we reexamined data from the Lazo and Chestnut (2002) study. This work did not have a binary question on use/do not use weather information

[2] In general figures showing the questions as asked in the various surveys are the content of the question and not necessarily the format respondents saw. Questions asked online in general are formatted differently than shown and possibly even between different platforms used by respondents to access the survey.

[3] Using a slightly different test of a difference of proportions the Mantel–Haenszel chi-square statistic is 36.0730 with a probability of <.0001 (df = 1), thus rejecting the null hypothesis of no difference in proportions by treatment (i.e., by survey version). Note: Throughout this report “df” or “DF” is an abbreviation for “degrees of freedom.”

as the CoFU surveys did, but did include a frequency question similar to those studies as shown in Figure 4.

3 **How often do you obtain weather forecasts from each of the following sources?**
Circle the number of your answer for each item.

	Rarely or never	Once or more a month	Once or more a week	Daily	Twice a day	Three or more times a day
Local TV newscasts	1	2	3	4	5	6
Cable TV stations	1	2	3	4	5	6
Newspaper	1	2	3	4	5	6
Commercial or public radio .	1	2	3	4	5	6
NOAA Weather Radio	1	2	3	4	5	6
Internet	1	2	3	4	5	6
Other people	1	2	3	4	5	6

Figure 4: Frequency of Use Question from Lazo and Chestnut (2002)

We created a variable that is the simple sum of the response (i.e., not recoded to monthly frequencies) to determine what percent of respondents indicated “Rarely or never” to all eight sources. Of the 381 respondents in the 2002 study only 1 indicated “Rarely or never” to all 8 sources (a sum of 8). This represents 0.26% of the respondents. Another 4 respondents (1.05%) had a sum of 9 and 6 respondents (1.57%) had a sum of 10. We note that the 2002 had a much smaller and geographically limited sample (all respondents were from one of nine urban areas around the United States). We also note that the maximum sum possible from Lazo and Chestnut is 42 (7 sources times a maximum response of 6 for each source). The maximum possible sum in CoFU is 60 (10 sources times a maximum of 6 for each source).

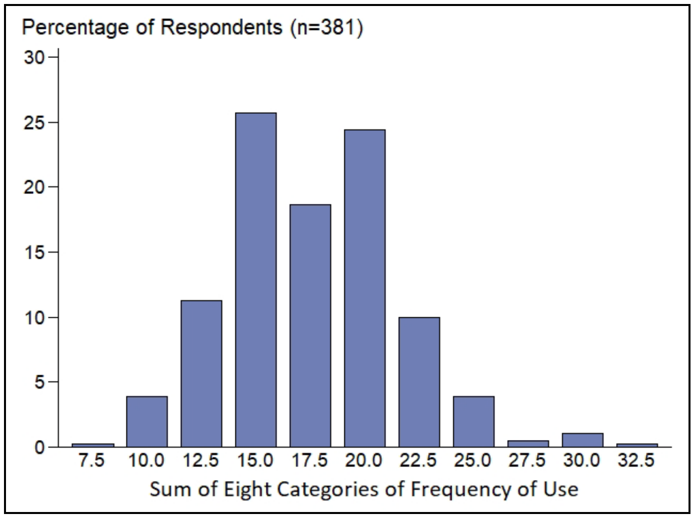

Figure 5: Distribution of Sum of Frequency of Use from Lazo and Chestnut (2002)

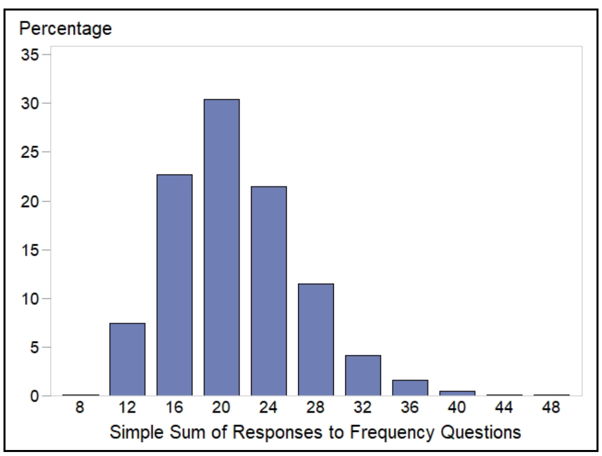

Figure 6: Distribution of Sum of Frequency of Use—CoFU1

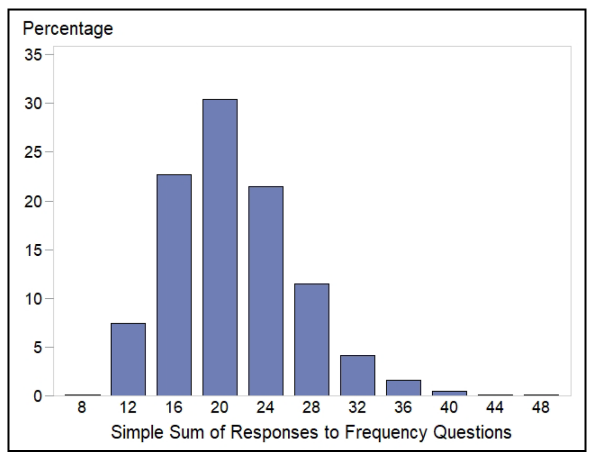

Figure 7: Distribution of Sum of Frequency of Use—CoFU2

Figure 5 shows a frequency distribution of the simple sum of the responses to the frequency of use question from Lazo and Chestnut (2002). Figure 6 and Figure 7 show the corresponding frequency distributions for the 2006 and 2022 survey, respectively. Table 17 shows the relevant statistics—the percent of respondents indicating that they do not use weather forecasts—from the three studies. The simple average across the three studies is 4.34%. Counting the number of individuals in each survey who do not use forecasts (1, 55, and 110, respectively) and the total number of respondents (381, 1520, and 1202, respectively, for a total of 3,103) yields 5.35% not using forecasts. Which number is the correct one to use is indeterminate. When making calculations using this as a factor, it is likely best to indicate the range or several options explicitly. Future research is likely needed to determine the true proportion of the population not using forecasts. It would likely also be useful to better define what "not using" forecasts means in terms of not seeking information, not using weather information for decision-making, not hearing anything, or some more precise way of characterizing not using weather forecasts.

For purposes of further analysis and aggregation in this report we use 5.35% as the baseline value for those not accessing weather information in the U.S. general public.

Table 17: Percent Not Using Weather Forecasts from Three Studies

Survey	Year	Sample Size	Number of "No"	Percent of "No"
Storm 2	2002	381	1	0.26
CoFU1	2006	1520	55	3.62
CoFU2	2022	1202	110	9.15
Total		3103	166	5.35

Table 18 shows a probit regression on the "Yes" response to the use forecasts questions. The yes responses are coded "1" and the no responses are coded as "2."[4] The negative and significant estimate on CoFU_Version indicates that, even after controlling for the included sociodemographic characteristics, significantly fewer people used forecasts in 2022 compared to 2006. Marginally insignificant (10.3%), those with higher income are (potentially) more likely to access weather information. Female, more highly educated, White, Black, Asian, Native (p = 10.4%), and those who spend more of their leisure time outdoors are more likely to use forecasts.[5]

An F test of the joint significance of the employment variables fails to reject the null hypothesis of no joint significance $F = 0.6083$. This does not exceed the critical value of the F statistic, which is $F_{1,6,2697} = 1.776$.[6] On the other hand, an F test of the joint significance of the race variables does reject the null hypothesis of no joint significance $F = 2.106$. Given that the White and Asian race variables were already significant at the 10% level and Native very nearly so this is not surprising. We can thus conclude that there is a race component related to the use of weather forecasts but, rather unexpectedly, not a relationship to employment status. Given that this could be a very complex and potentially a politically and socially sensitive topic, we do not have a hypothesis at this time as to why racial group would influence whether respondents use weather forecasts. This may be worth further discussion and research though in the realm of environmental justice.[7]

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[4] Although "use_wx_fcsts" is coded a Yes = 1; No = 2, the probit regression in on probability of answering Yes so it is irrelevant how the responses are actually coded.

[5] In response to a comment by a reviewer we indicated that the choice of probit models over logit models was purely a matter or habit of preferring the assumption of a normally distributed error in the probit model. As a comparison though we replicate the regression in Table 18 using a logit model. These results are shown in Table 50 in Section 10.2. The results are very similar between the two models with generally the same signs and all of the same significant variables as shown in Table 18.

[6] From the "critical F-value calculator" at https://www.danielsoper.com/statcalc/calculator.aspx?id=4. Both tests have the same number of restrictions (6) and same sample size, so have the same critical value.

[7] In response to a comment from Labanyalata Roy we undertook additional regression analysis with respect to respondent's location. Section 10.3 Climate zones and use of forecasts explores this further with

Table 18: Probit Regression on Use Forecasts (Yes = 1; No = 2)

	Parameter	Estimate	Pr>ChiSq
	Intercept	0.141	0.781
	CoFU_Version	-0.477	<.0001
Sociodemographics	Income (2021_Median_Adjusted_Thousands)	0.002	0.103
	Yrs in current residence	0.004	0.149
	Age (yrs)	0.005	0.195
	Female (no = 0; yes = 1)	0.184	0.038
	Household size	0.003	0.922
	Education (yrs)	0.046	0.017
Employment	Fulltime	0.042	0.875
	Parttime	-0.067	0.802
	Retired	0.230	0.420
	Homemaker	0.016	0.956
	Student	0.085	0.789
	Unemployed	-0.018	0.949
Race	White	0.592	0.008
	Black	0.402	0.089
	Latino	0.270	0.211
	Asian	0.642	0.029
	Native	0.648	0.104
	Other	0.378	0.264
Time allocation	Percent of job outside	-0.007	0.644
	Hours traveling to work	0.003	0.342
	Percent of leisure time outside	0.061	0.002
	Hours at home spent outside	0.004	0.207
Percent Concordant = 72.9% / Max-rescaled R-Square = 0.107			

respect to the use of forecasts based on climate zones finding significantly more use by those in temperate or continental climates compared to those in arid climates.

6.3. *Sources*

6.3.1. Frequency by source

Figure 8 shows the question asking how often respondents obtain forecasts from a number of different information sources.[8] Even though we are aware of technical developments since 2006 we retained the identical question from 2006 to maintain consistency.

2 How often do you get weather forecasts from the sources listed below?

Rarely or never	Once or more a month	Once a week	Two or more times a week	Once a day	Two or more times a day
1	2	3	4	5	6

1	Local TV stations
2	Cable TV stations (e.g., CNN, The Weather Channel)
3	Newspapers
4	Telephone (dial-in) weather information source
5	Commercial or public radio
6	NOAA Weather Radio
7	National Weather Service (NWS) webpages
8	Other webpages
9	Cell phone, personal desk assistant (PDA), pager, or other electronic device
10	Friends, family, co-workers, etc.

Figure 8: Question on Frequency of Different Forecast Sources

As shown, Question 2 asked "How often do you get weather forecasts from the sources listed below?" with responses options from "Rarely or never" = 1 to "Two or more times a day" = 6 for 10 potential information sources (local TV stations; cable TV stations (e.g., CNN, The Weather Channel); newspapers; telephone (dial-in) weather information source ; commercial or public radio; NOAA Weather Radio; National Weather Service (NWS) web pages; other web pages; cell phone, personal desk assistant (PDA), pager, or other electronic device; friends, family, coworkers, etc.).

The CoFU1 dataset contained created variables for the frequency of use of the 10 different sources of weather forecasts from Question 2. Corresponding variables were created in the CoFU2 dataset prior to appending. These were recoded from the offered qualitative response options to lower-bound uses per month as shown in Table 19. The variable "src_tot_freq"(for sources total frequency) was also created, which is the sum of the monthly uses for the 10 sources for each respondent.

[8] For this question and most questions where there was not a logical order of response options, the response options were randomized. For instance, while some people saw "local TV stations" first, 9 out of 10 other respondents saw 1 of the 9 other information sources first.

Table 19: Recoding of Q2 on Frequency of Use for Weather Information Sources	
Response Option	Recoding to develop conservative lower-bound frequency by source as "times per month"
Rarely or never	0
Once or more a month	1
Once a week	4
Two or more times a week	8
Once a day	30
Two or more times a day	60

Table 20 shows the frequency of use for each source by survey version (CoFU1 or CoFU2) as well as the mean frequency and a *t* test of the difference between versions. For the *t* tests we report the *t* value and probability based on the assumption the variances are different using the "Satterthwaite" method. While some variances are not statistically different, this approach is more conservative and maintains consistency in reporting the results across all sources.[9]

The last column indicates whether the average usage for each source increased or decreased since 2006. It appears that the more "traditional" sources (local and cable TV stations, commercial or public radio, other web pages, and newspapers) have all decreased in usage at the expense of more "modern" or "social" sources [i.e., NWS web pages, friends, family, coworkers, etc., NOAA Weather Radio (NWR), cell phone, PDA, pager, or other electronic device, and telephone weather information source].

[9] We conducted the same *t* tests on differences between survey versions by source using the "raw" data (e.g., the responses before recoding to frequencies) and reached the same statistical results on each source.

Table 20: Frequency of Use by Source and Survey Version (reported as Percent of Source Total) and t-Test of Differences

Source	Survey Version	Rarely or never	Once or more a month	Once a week	Two or more times a week	Once a day	Two or more times a day	Mean times per month	t-Test			Change
Recoding to develop conservative lower-bound frequency by source as "times per month"		0	1	4	8	30	60		DF	t Value	Pr > |t|	
Local TV stations	1	6	5	4	14	36	36	33.7	2001.7	15.73	<.0001	Decreased
	2	20	10	10	16	27	18	20.7				
Cable TV stations	1	35	15	16	19	11	4	18.9	2351.6	5.76	<.0001	Decreased
	2	36	13	14	17	13	8	14.5				
Commercial or public radio	1	22	13	9	17	22	18	18.5	2438.1	11.38	<.0001	Decreased
	2	32	12	10	15	20	11	9.9				
Other Web pages	1	39	11	12	12	24	3	12.7	2412.7	2.83	0.0046	Decreased
	2	59	9	8	10	11	4	10.2				
Newspapers	1	88	6	2	2	1	1	10.3	2414.7	9.54	<.0001	Decreased
	2	70	5	5	7	8	5	6.8				
NWS web pages	1	29	8	8	16	21	18	8.3	2266.7	-6.6	<.0001	Increased
	2	46	10	9	15	13	7	11.7				
Friends, family, coworkers, etc.	1	80	9	3	3	3	1	8.1	2231.2	-1.81	0.0708	Increased
	2	64	9	7	9	8	3	10.5				
NOAA Weather Radio (NWR)	1	48	17	8	10	11	6	2.1	1820.4	-10.47	<.0001	Increased
	2	38	13	10	13	17	8	5.6				
Cell phone, PDA, pager, or other electronic device	1	39	11	9	13	17	10	1.6	1492.3	-40.55	<.0001	Increased
	2	42	11	11	15	13	8	21.7				
Telephone weather information source	1	90	3	2	2	2	1	1.2	1508.9	-13.17	<.0001	Increased
	2	23	6	8	15	26	20	6.2				

Figure 9 shows the average monthly frequency for each source by survey version (plotting the data from Table 20).

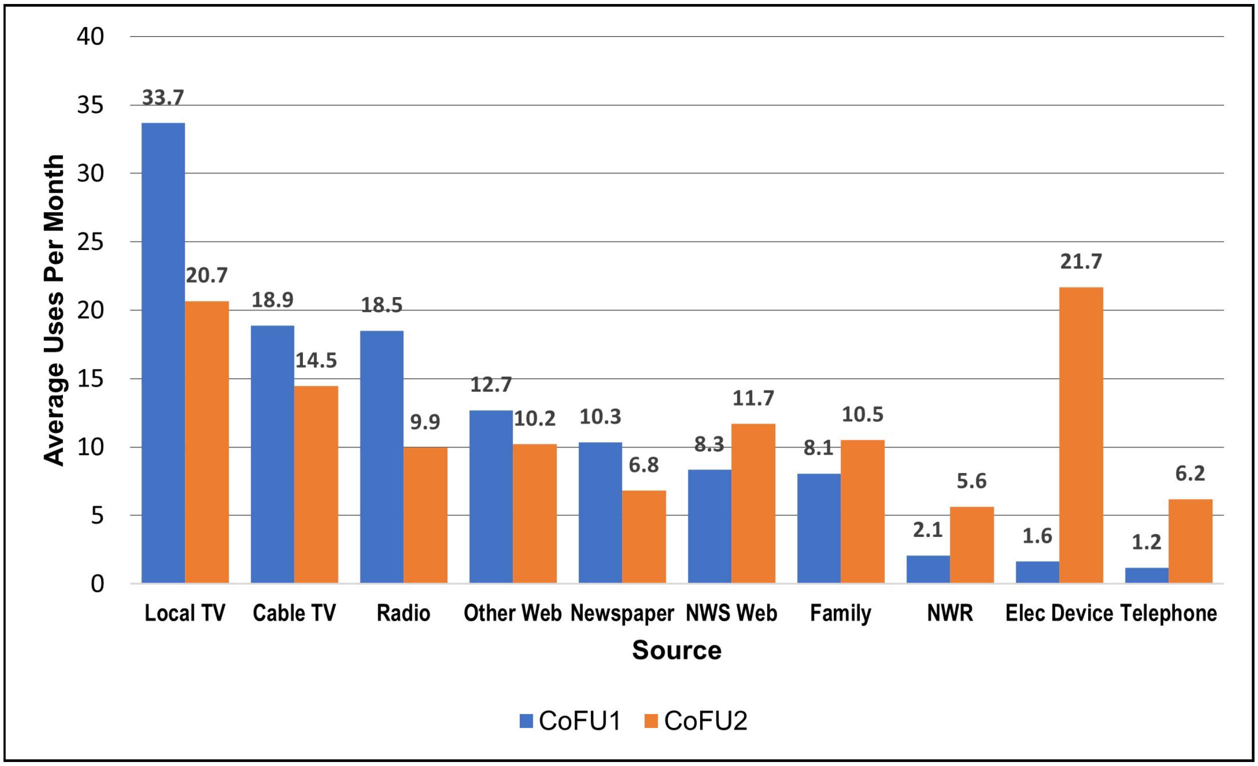

Figure 9: Frequency of Use by Source by Survey Version

6.3.2. Total monthly frequency

For each individual we summed their monthly uses for each of the sources to derive a total monthly frequency. Table 21 shows the mean monthly frequency of use for those individuals who do use forecasts (the *n*-miss indicates the portion of each survey indicating not using forecasts). The right-hand two columns show a t *t*-test of the difference between the means indicating no statistical difference. The mean monthly uses are thus statistically the same—falling between 115 and 120 times a month on average.

Table 21: Total Monthly Frequency by Survey Version

	CoFu1	CoFU2	t-test of difference by version	
Mean	115.40	117.80	Diff (1-2)	-2.47
Std Dev	77.46	100.60	T Value	-0.70
n	1465	1092	Pr>|t|	0.48
n-miss	55	110	DF	2555

For comparison, a survey conducted April 14–20, 2023 by YouGov[1] sampled 1000 U.S. adult citizens (with a reported margin of error ±3.4%). As shown in Table 22, we use conservative values to translate responses to monthly frequencies. For instance, for the response "hourly or more often" we assume individuals access weather forecasts once an hour daily after subtracting 8 hours for "sleep time." This is thus calculated as 486.67 times a month rather than based on 730 hours in a month or even more if accessed more than once an hour. We then weigh the monthly frequency by percent of respondents in each response option and sum this to suggest (a conservative) total monthly frequency of 57.03 for this sample. We also note that the question asked how often they access forecasts for their "local" area (see also Table 32). While most respondents access weather information for their own city, many also access weather information for other cites, states, and even countries. Thus, it seems likely that the monthly average calculated in Table 22 is a lower bound.

Table 22: YouGov Poll Indicating Frequency of Accessing Weather Forecasts

How often do you read, watch, or listen to the weather forecast for your local area?	% of Respondents	Coded to Monthly	Monthl y	Weighted Monthly
Hourly or more often	2	(24-8)*(365/12)	486.67	9.73
Multiple times a day	18	2*(365/12)	60.83	10.95
Daily	40	365/12	30.42	12.17
A few times a week	18	2*52	104.00	18.72
About once a week	7	52	52.00	3.64
Less often than once a week	7	52/2	26.00	1.82
Never	4	0	0.00	0.00
Not sure	3	0	0.00	0.00
Calculated Average Monthly Frequency				57.03

In an earlier but similar question but with less information available on sampling and question formatting, AYTM used their online panel on January 20, 2014 to develop the article "Weather Updates Survey: Online Forecasts More Popular Than TV."[2] As indicated in Table 23, the AYTM poll did not include two of the response options used in the YouGov poll. We note again that this question asked about "local" access and thus is likely a lower bound estimate of total weather forecast use.

[1]Article about the survey available at https://today.yougov.com/topics/health/articles-reports/2023/05/08/how-and-where-americans-get-information-weather. This article includes a link to the data crosstabs. Question 1 in that survey asked "How often do you read, watch, or listen to the weather forecast for your local area?"

[2] Article at https://aytm.com/post/weather-updates-survey.

Table 23: AYTM Poll Indicating Frequency of Accessing Weather Forecasts				
Frequency derived from text description of results.	% of Respondents	Coded to Monthly	Monthly	Weighted Monthly
Hourly or more often	NA	(24-8)*(365/12)	486.67	NA
Multiple times a day	24	2*(365/12)	60.83	14.60
Daily	41	365/12	30.42	12.47
A few times a week	19	2*52	104.00	19.76
About once a week	5	52	52.00	2.60
Less often than once a week	10	52/2	26.00	2.60
Never	3	0	0.00	0.00
Not sure	NA	0	0.00	NA
Calculated Average Monthly Frequency				52.03

Table 24 shows an ordinary least squares regression (OLS) on total frequency of use. The last column shows the standardized estimates to suggest the strength of effect of the variable on total frequency. The estimate on CoFU_version is not significant.[3] This confirms the results from Table 21 of a simple test of frequencies showing no difference by version. Showing the result in the regression analysis is a somewhat stronger test as it also controls for potential variation in the samples (e.g., age, gender, income, etc.) that may have masked a difference in use.

Those individuals who have lived in his/her house longer use more forecasts. Individuals using forecasts more for any of the four geographic levels access more forecasts. Those who spend a larger percentage of their time outside on the job or for leisure access more forecasts. Individuals using forecast information to get dressed, get to work, or for weekend activities all use more forecasts. "Travel" is not significant. Those with a higher level of confidence in 1-day precipitation forecasts access more forecasts but those with more confidence in less than 1-day forecasts in general do not. Finally, as may be expected, those who place a higher level of importance on NWS forecast information access more of that information. The largest standardized coefficient estimate is 0.139 for "percent of job outside" suggesting that weather forecasts are very important or useful for outside work activities or possibly that those activities also require more frequent updating of weather information.

Overall, the significant results seem internally consistent. Some of the nonsignificant results suggest that individuals' uses of forecasts are complex and may entail further investigation—for instance it would seem logical that a higher level of satisfaction with forecasts would be related to greater use, but this was not a significant result. See section 6.5.1 for more analysis on satisfaction with weather information.

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[3] We note also that the standardized coefficient estimates on indicator variables changes their interpretation from categorical to continuous variables ("if you standardize indicator variables, you lose this interpretation. Instead, the regression procedure treats the standardized variables as if they were continuous." https://blogs.sas.com/content/iml/2023/07/17/standardize-reg-coeff-class.html.

Table 24: OLS Regression on Total Frequency				
N = 1,908; Adj R-Sq = 0.294				
	Variable	Para. Est.	Pr>|t|	Std. Est.
	Intercept	-161.280	<.0001	0.000
	CoFU_Version	-0.412	0.922	-0.002
Sociodemographics	Income (2021_Median_Adjusted_Thousands)	0.000	0.453	0.017
	Years in current residence	0.327	0.003	0.064
	Female	-1.885	0.633	-0.010
	Age	-0.016	0.927	-0.003
	Household size	1.072	0.340	0.020
	Education (Years)	0.279	0.728	0.008
Employment	Fulltime	8.690	0.400	0.046
	Parttime	3.052	0.768	0.011
	Retired	9.768	0.373	0.038
	Homemaker	-6.565	0.554	-0.017
	Student	-1.321	0.917	-0.003
	Unemployed	-2.112	0.859	-0.006
Race	White	3.032	0.732	0.015
	Black	15.223	0.118	0.056
	Latino	1.691	0.844	0.005
	Asian	-3.616	0.750	-0.008
	Native	-8.898	0.504	-0.014
	Other	-6.442	0.663	-0.010
Time allocation	Percent of job outside	3.927	<.0001	0.139
	Hours traveling to work	0.029	0.806	0.005
	Percent of leisure time outside	2.299	0.012	0.058
	Hours at home spent outside	0.135	0.231	0.025
Geographic Area of Forecast Use	City you live	5.726	0.007	0.061
	City in state	6.681	<.0001	0.103
	City other state	7.586	<.0001	0.110
	City world	12.007	<.0001	0.163
Use Fx for Planning	How to dress yourself or your children	3.828	0.005	0.062
	How to get to work or school	6.292	<.0001	0.113
	Travel	1.177	0.415	0.019
	Weekend activities	6.519	<.0001	0.098
Forecast Quality	Satisfaction with weather forecast information	2.258	0.305	0.021
	Confidence in forecasts of less than 1 day	0.574	0.809	0.006
	Confidence in 1 day chance of precipitation forecast	5.688	0.014	0.058
	Importance of NWS Information	11.356	<.0001	0.108

6.3.3. Aggregate forecasts accessed annually by the U.S. public

The title of the Lazo et al. (2009) BAMS paper "300 Billion Served" was based on the calculation of total forecasts accessed by the U.S. public in 2006. As calculated in Lazo et al. (2009) footnotes 2 and 3 (p. 789):

> The estimated 2006 U.S. population is 299,398,485. Of this, 75.4% are 18 years of age and older, which corresponds to an adult population of 225,746,458. An adult population of 225,746,458 × 115.374 times per month × 12 months per year × 0.9638 (to account for the 3.62% who do not use forecasts) equates to 301,229,196,054 forecasts a year—about 300 billion forecasts a year.

Following the same approach, we calculate the total based on the 2022 responses and recalculate the 2006 total in Table 25. From Table 17 we use the value of 5.35% as the percent of the U.S. population not using weather forecasts for recalculating the aggregate number of forecasts accessed by the public annually and apply this for both surveys.

Table 25: Aggregation of Annual Forecasts Accessed by the U.S. Public

	Survey	CoFU1	CoFU2
	Year	2006	2022
a	Population[1]	299,398,485	332,403,650
b	Percent 18+	75.40%	74.30%
c	Over 18 population (line a x line b)	225,746,458	246,975,912
d	Percent Not Using Forecasts (see Table 17)	5.35%	5.35%
e	Population Using Forecasts (line c x [1- line d])	213,669,022	233,762,701
f	Times per month (see Table 21)	115.37	117.85
g	Months	12	12
h	Times Per Year (line f x line g)	1,384.49	1,414.16
j	Total Per Year (line e x line h)	295,822,354,644	317,306,934,363
	Total Per Year (rounded)	295 Billion	317 Billion

[1] After obtaining population data we returned to attempt to identify the exact source of this information. We found it impossible to locate U.S. total population estimates exactly matching the numbers we used and for any given year found multiple different estimates all within a few percentage points of the values indicated. For instance, the U.S. Census website at https://data.census.gov/table/ACSSPP1Y2022.S0201?q=s0201&g=010XX00US indicates a total U.S. population in 2022 of 333,287,562 which is 0.27% larger than the value we originally obtained from the U.S. Census website.

The 2006 estimate is slightly reduced to 295 billion from the 300 billion number due to the use of a different fraction of respondents not using weather forecasts. The 2022 estimate is roughly 317 billion forecasts accessed annually by members of the U.S. public. We note again that the monthly use is likely a lower bound because the maximum offered in the frequency question was "twice or more a day" and this is conservatively treated as twice a day.

There has thus been a 7.26% increase in aggregate use between 2006 and 2022.[4] This is driven partly by the slight increase in "times per month" (a 2.14% increase) and more so by the increase in U.S. population over 18 (a 9.40% increase). This was offset by a slight (1.46% decrease in the percentage of 18+ population.

6.4. Time of day obtaining forecasts

Figure 10 shows Question 4 that asked how often people obtained weather forecasts during different times of the day. Note that these time periods are not of equal length but were determined in the development of the 2006 survey as the likely time for different relative uses of weather information (e.g., during normal commuting or lunch periods).

4 Do you normally get weather forecasts during the time periods listed below?

		No	Yes
1	From midnight to before 6 am	1	2
2	From 6 am to before 8 am	1	2
3	From 8 am to before 11 am	1	2
4	From 11 am to before 1 pm	1	2
5	From 1 pm to before 4 pm	1	2
6	From 4 pm to before 7 pm	1	2
7	From 7 pm to before midnight	1	2

Figure 10: Question on Use Forecasts by Time of Day

Table 26 shows the percent of respondents indicating that they access weather forecast during the time periods offered by survey version. We also present the chi-square statistic for a test of the difference of proportions between versions. The last column indicates the direction of change for significant (10%) differences suggesting there has been a shift toward using forecasts earlier in the day away from evening periods. These average uses by time of day by survey version are shown graphically in Figure 11.

[4] The value of 7.26% is calculated from the "raw" total estimates of 295,822,354,644 and 317,306,934,363 for 2006 and 2022, respectively. Similarly, the value of 2.14% is calculated from the unrounded estimates of 115.3740614 and 117.8470696 and the value of 9.40% calculated from population numbers of 225,746,458 and 246,975,912.

Table 26: Precent Responding Yes for Each Time of Day by Survey Version and Test of Difference of Proportions					
	Percent Yes				
Time Period	CoFU1	CoFU2	Mantel-Haenszel Chi-Square	Probability	Change from CoFU1 to CoFU2
12 to 6 am	20.5	29.8	29.189	<.0001	Increase
6 to 8 am	67.9	65.1	2.113	0.146	No change
8 to 11 am	53.2	58.6	7.292	0.007	Increase
11 am to 1 pm	42.7	52.4	23.391	<.0001	Increase
1 to 4 pm	34.9	50.0	58.956	<.0001	Increase
4 to 7 pm	71.6	62.6	23.481	<.0001	Decrease
7 to 12 pm	72.4	57.7	60.592	<.0001	Decrease

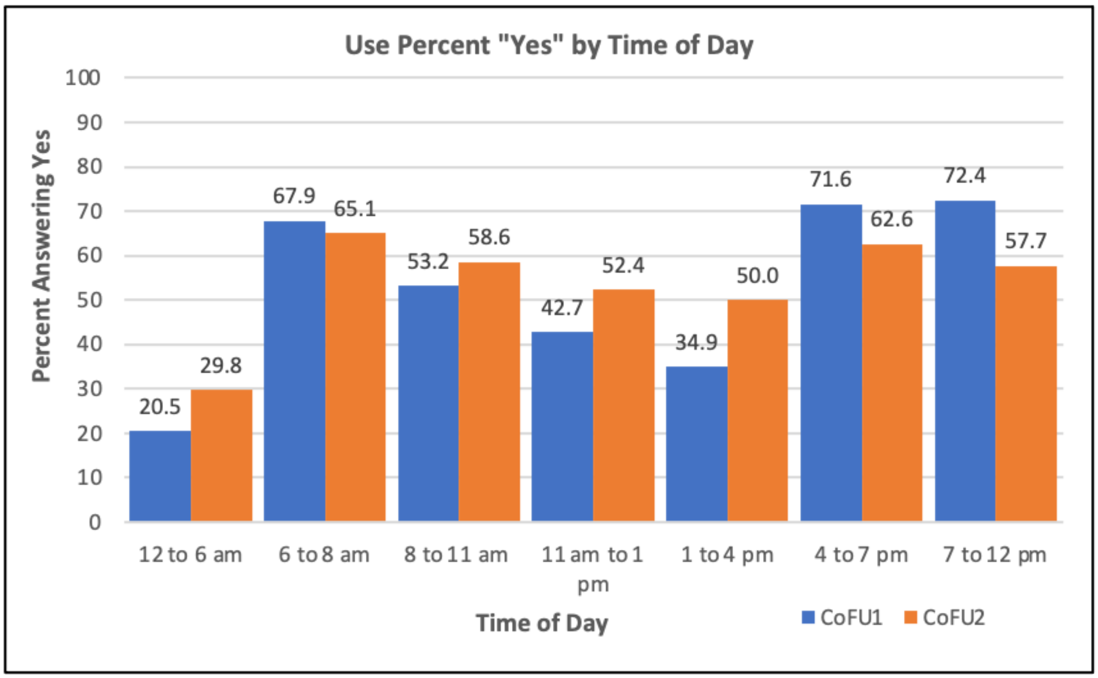

Figure 11: Difference in Time of Day for Use of Forecasts between CoFU1 and CoFU2

6.4.1. Probit regression on use forecasts by time of day

Table 27 shows the results of a probit regression on yes responses to using weather forecasts for each of the seven time periods. Positive parameter estimates indicate the individuals are more likely to use forecasts during that time period. Also note that the lengths of the time periods are not all equal.

Of particular interest is that in five of the seven time periods, the CoFU version parameter is positive even controlling for all the other included variables. Three of these are positive suggesting that there has been a significant increase in the use of forecasts for those time periods (12–6 am; 11am–1pm; 1–4pm) between 2006 and 2022. Two of those significant estimates are negative (4–7pm; 7–12pm), suggesting there has been a significant decrease in the use of forecasts for those time periods. We do not have a specific hypothesis of why this would be the case.

We do not discuss the results in depth here but make a few notes below to suggest how the results may (or may not) inform when and why people use (or do not use) weather forecasts. For instance, while some sociodemographics are significant in certain time periods, there is no consistent use of forecasts across all time periods related to the socio-demographics other than that household size and education level are <u>not</u> significant in any of the regressions.

Employment status is also not consistent across time periods except that being employed fulltime, part time or unemployed are not significant in any of the time periods (although close to 10% in some cases). We expected full time employment to perhaps be related to forecast use outside of “normal” working hours (8am to 5pm) but this was not the case.

In each regression we included the other time periods as explanatory variables (NA indicates that the dependent variable in that regression is not included as an explanatory variable for that specific regression). Several of the parameter estimates are significant indicating that individual’s use of weather forecasts during a time period are related to their use of the forecasts during other time periods. We may expect positive estimates as individuals using forecasts more simply use them more during several time periods. Interestingly though, some of the estimates are negative, suggesting individuals using forecasts more in one time period do use them less in other time periods. For instance in the second regression on the 6–8 am time period, the estimate on “time 8–11” is negative and significant suggesting that those who do get forecasts between 8 am and 11 am are less likely to also have obtained them earlier in the morning.

An interesting mix of the uses of forecasts for specific activities relates to use during specific times of the day. For instance, as may be expected, those who use forecasts to “get to work” are significantly more likely to access forecasts between midnight and 8 am. Perhaps unexpectedly, those who are simply interested in knowing what the weather is are significantly more likely to get forecasts between 6 am and 8 am but not during any other time of the day.

We undertook an exploratory regression, not shown here, using only the 7–12 time period and adding “frequency by source” (raw responses) for the 10 different sources (e.g., local TV, NWS website, etc.—see section 6.3.1). In total, 4 of the 10 sources were significant at the 10% level—3 with positive and 1 with negative parameter estimates. Individuals accessing weather information from local or cable TV or electronic devices are more likely to access information in the 7 pm to midnight time period whereas those accessing weather information from newspapers are less likely to access information in the 7 pm to midnight time period. This seems to be a reasonable result that also suggests that there is more useful information in these data than we discuss here regarding where and when people get weather information.

We note also that it may be interesting to assess the applicability of a Generalized Estimating Equation (GEE) model for combining these regressions while accounting for repeated responses from individuals.

Table 27: Probit Regression Comparison of Use Forecasts by Time of Day (n = 2,557)

		time_12to6 = '2'		time_6to8 = '2'.		time_8to11 = '2'.		time_11to1 = '2'.		time_1to4 = '2'.		time_4to7 = '2'.		time_7to12 = '2'.	
	Parameter	Est.	Prob	Est.	Prob	Est.	Prob	Est.	Prob	Est.	Prob	Est.	Prob	Est.	Prob
	Intercept	-2.930	<.0001	-0.554	0.144	-1.949	<.0001	-3.203	<.0001	-4.496	<.0001	-2.274	<.0001	-1.657	<.0001
	CoFU_Version	0.196	0.004	0.003	0.955	0.089	0.157	0.112	0.086	0.347	<.0001	-0.327	<.0001	-0.351	<.0001
Sociodemographics	Income	-0.002	0.008	0.002	0.012	0.000	0.525	-0.001	0.285	0.000	0.880	0.000	0.819	0.000	0.511
	Yrs in current residence	0.001	0.534	0.001	0.396	0.001	0.521	0.004	0.017	-0.002	0.155	0.004	0.009	0.005	0.002
	Age (yrs)	0.023	0.723	0.058	0.331	-0.015	0.802	-0.022	0.722	-0.163	0.011	0.055	0.373	0.026	0.660
	Female (no = 0; yes = 1)	-0.012	<.0001	0.002	0.530	-0.007	0.008	-0.010	0.001	0.005	0.106	0.007	0.010	0.002	0.369
	Household size	0.008	0.653	-0.002	0.908	0.015	0.413	-0.005	0.778	0.014	0.490	0.002	0.918	0.022	0.230
	Education (yrs)	-0.003	0.841	-0.015	0.236	-0.012	0.348	0.013	0.305	-0.003	0.830	-0.003	0.820	0.004	0.732
Employment	Fulltime	0.214	0.198	0.058	0.713	-0.038	0.808	-0.189	0.252	-0.278	0.119	-0.045	0.788	0.157	0.370
	Parttime	0.186	0.264	-0.027	0.863	0.197	0.211	-0.110	0.504	-0.289	0.106	0.120	0.473	0.354	0.043
	Retired	0.271	0.123	-0.111	0.497	0.360	0.029	0.196	0.256	-0.599	0.001	-0.090	0.605	0.080	0.661
	Homemaker	-0.013	0.939	-0.107	0.508	0.145	0.370	0.072	0.671	-0.320	0.080	0.053	0.757	0.241	0.181
	Student	-0.179	0.387	-0.051	0.791	-0.175	0.374	-0.129	0.529	-0.070	0.749	0.030	0.882	0.514	0.018
	Unemployed	0.274	0.129	-0.200	0.234	0.029	0.868	0.097	0.587	-0.308	0.110	-0.169	0.343	0.145	0.439
Race	White	0.137	0.331	-0.003	0.982	0.044	0.749	-0.089	0.524	-0.072	0.625	0.359	0.012	-0.203	0.132
	Black	0.311	0.041	0.301	0.041	-0.021	0.886	0.128	0.403	-0.137	0.386	0.136	0.375	-0.186	0.205
	Latino	0.129	0.341	-0.104	0.421	-0.113	0.390	-0.044	0.747	0.063	0.654	0.207	0.137	0.008	0.951
	Asian	-0.092	0.633	0.082	0.634	0.130	0.458	-0.405	0.029	0.077	0.685	0.127	0.475	-0.249	0.146
	Native	-0.185	0.391	0.071	0.716	0.045	0.821	0.110	0.590	0.003	0.987	0.408	0.065	-0.070	0.723
	Other	0.123	0.609	0.075	0.737	0.211	0.360	-0.223	0.348	0.044	0.858	0.520	0.034	0.373	0.132
Time allocation	Percent of job outside	0.037	0.002	-0.002	0.826	0.010	0.378	-0.004	0.716	-0.002	0.837	-0.020	0.088	-0.018	0.104
	Hours traveling to work	0.000	0.867	0.007	0.002	0.003	0.145	0.001	0.706	-0.002	0.311	0.001	0.755	0.000	0.832
	Percent leisure time outside	-0.017	0.234	0.032	0.014	-0.003	0.815	-0.007	0.613	0.003	0.837	-0.005	0.742	0.021	0.113
	Hrs at home spent outside	0.001	0.500	-0.002	0.193	0.000	0.885	-0.002	0.328	0.001	0.625	-0.001	0.699	-0.001	0.527
Geographic	city you live	0.076	0.039	0.036	0.275	0.081	0.015	-0.003	0.935	-0.015	0.676	0.007	0.825	0.036	0.273
	city in state	0.046	0.063	0.010	0.644	-0.001	0.966	0.054	0.023	-0.020	0.407	0.058	0.015	0.049	0.031

Table 27: Probit Regression Comparison of Use Forecasts by Time of Day (n = 2,557)															
		time_12to6 = '2'		time_6to8 = '2'.		time_8to11 = '2'.		time_11to1 = '2'.		time_1to4 = '2'.		time_4to7 = '2'.		time_7to12 = '2'.	
	Parameter	Est.	Prob	Est.	Prob	Est.	Prob	Est.	Prob	Est.	Prob	Est.	Prob	Est.	Prob
	city other state	0.051	0.080	0.033	0.222	0.061	0.027	-0.007	0.801	0.067	0.021	0.019	0.514	0.064	0.022
	city world	0.025	0.427	-0.064	0.032	-0.050	0.099	0.023	0.466	0.032	0.313	0.033	0.309	-0.080	0.009
Use by time of day	time 12 to 6	NA	NA	0.071	0.288	-0.194	0.004	0.065	0.344	0.287	<.0001	0.119	0.088	0.375	<.0001
	time 6 to 8	0.073	0.252	NA	NA	-0.098	0.094	-0.036	0.557	-0.144	0.020	0.128	0.031	0.001	0.989
	time 8 to 11	-0.209	0.001	-0.107	0.066	NA	NA	0.394	<.0001	0.741	<.0001	-0.042	0.478	0.117	0.046
	time 11 to 1	0.058	0.392	-0.048	0.446	0.408	<.0001	NA	NA	1.012	<.0001	0.517	<.0001	-0.074	0.240
	time 1 to 4	0.298	<.0001	-0.140	0.029	0.799	<.0001	1.042	<.0001	NA	NA	0.438	<.0001	0.197	0.003
	time 4 to 7	0.127	0.062	0.126	0.036	-0.059	0.325	0.496	<.0001	0.415	<.0001	NA	NA	0.094	0.117
	time 7 to 12	0.345	<.0001	-0.004	0.950	0.112	0.057	-0.079	0.198	0.191	0.003	0.113	0.059	NA	NA
Use Fx for Activities	dress	0.017	0.445	0.006	0.759	0.017	0.390	0.010	0.627	-0.017	0.427	0.019	0.365	0.027	0.176
	get work	0.063	0.003	0.077	0.000	-0.009	0.652	-0.042	0.044	0.000	0.993	-0.017	0.426	0.005	0.803
	yardwork	0.013	0.576	0.003	0.882	-0.007	0.741	0.046	0.031	0.001	0.981	0.058	0.006	-0.021	0.296
	job activities	0.032	0.157	-0.015	0.481	0.031	0.136	0.031	0.158	0.003	0.908	-0.018	0.405	0.037	0.079
	social activities	-0.013	0.634	0.052	0.028	0.043	0.069	-0.002	0.931	0.016	0.534	0.067	0.007	-0.010	0.667
	travel	-0.047	0.051	-0.001	0.965	0.016	0.458	0.015	0.521	0.017	0.483	-0.038	0.093	-0.001	0.956
	weekend activities	0.006	0.842	-0.002	0.942	0.016	0.532	0.034	0.217	-0.028	0.312	0.005	0.844	0.017	0.507
	simply know weather	0.001	0.966	0.075	0.004	0.026	0.328	0.039	0.175	-0.002	0.958	-0.008	0.761	0.035	0.186
Fx Qual	Satisfaction	0.019	0.589	-0.024	0.457	0.011	0.731	-0.034	0.316	0.016	0.636	0.009	0.799	-0.015	0.653
	confidence 1d	-0.037	0.291	0.002	0.956	0.034	0.289	-0.044	0.193	0.049	0.161	-0.002	0.941	0.032	0.311
	Import of NWS info	0.050	0.181	0.034	0.295	-0.029	0.391	0.052	0.140	0.000	0.999	0.044	0.193	0.134	<.0001
	Personal Wx Impact Scale	0.114	<.0001	0.015	0.588	-0.061	0.029	0.040	0.169	0.013	0.664	0.016	0.574	0.027	0.328
	Max-rescaled R-Sq	0.190		0.091		0.238		0.367		0.407		0.202		0.136	
	Likelihood Ratio (DF = 45)	348.209	<.0001	173.998	<.0001	500.469	<.0001	821.901	<.0001	919.508	<.0001	399.004	<.0001	263.345	<.0001
	Percent Concordant	73.		65.7		74.5		81.0		83.1		73.5		68.8	

6.5. Perceptions

As stated in Lazo et al. (2009):

> We explored respondents' perceptions by examining their satisfaction with and confidence in the forecasts they currently receive. Although satisfaction and confidence are related, asking about both yields important distinct information. People's stated overall "satisfaction" [defined by Merriam-Webster (2005) as "fulfillment of a need or want"] may indicate their perception of the ability of forecasts to meet their needs. People's stated "confidence" ["the quality or state of being certain," Merriam-Webster (2005)] in weather forecasts may reflect their perceptions of the quality, reliability, and accuracy of forecasts. Confidence is discussed in the risk perception literature as "the expectation of not being disappointed" (Siegrist et al. 2005, p. 146) and is intimately tied to trust in the provider of risk information. It is important to note, though, that respondents' actual interpretations of these words may vary from these formal definitions (Lazo et al. 2009, p. 790).

6.5.1. Satisfaction

Figure 12 shows the question asked about respondents' satisfaction with current weather information in both surveys' implementations. We recognize that this is a relatively simplistic evaluation of satisfaction and recommend more in-depth research to further explore the multidimensionality of the public's satisfaction with weather information.

7 Overall, to what extent are you satisfied or dissatisfied with the weather forecast information that you currently receive?

Very dissatisfied	Dissatisfied	Neither satisfied nor dissatisfied	Satisfied	Very satisfied
1	2	3	4	5

Figure 12: Question on Satisfaction with Forecasts

Figure 13 shows the frequency distribution of responses to the satisfaction question by survey version with percentages of responses above each respective bar. Visually it appears that there is a high level of satisfaction and that this has increased somewhat since the 2006 survey.

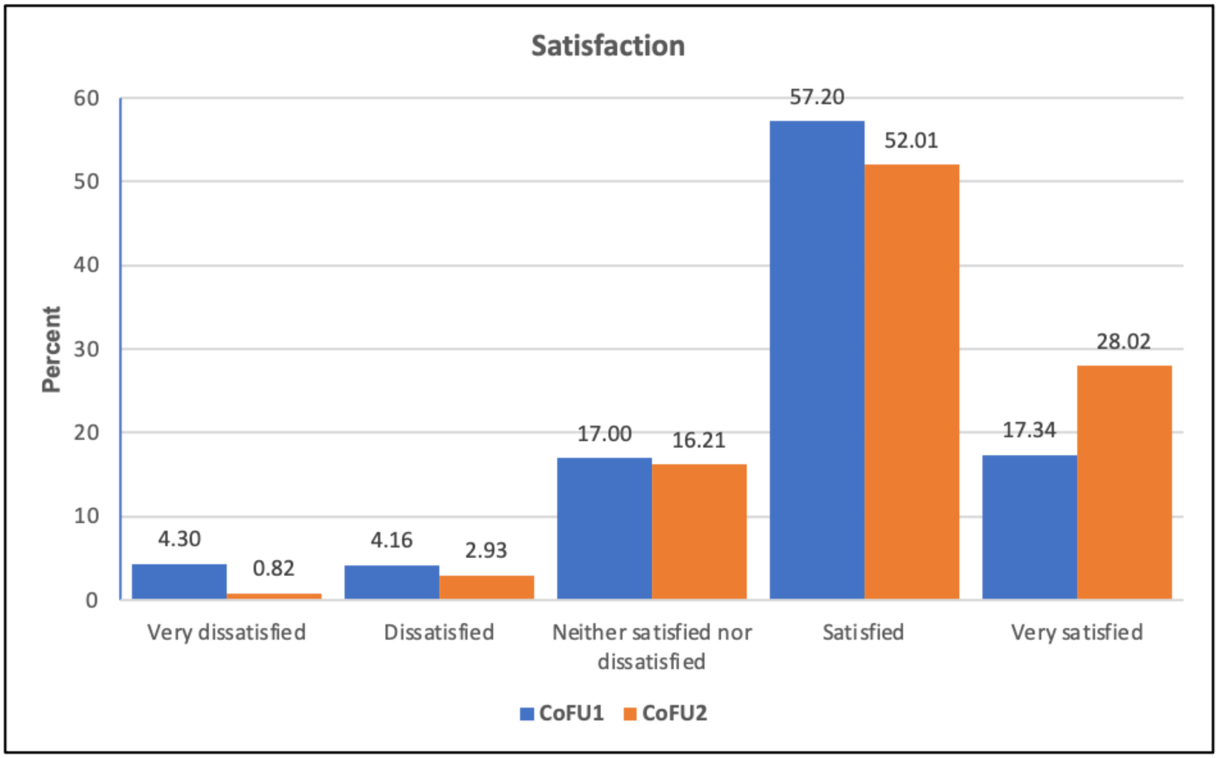

Figure 13: Satisfaction with Forecasts by Survey Version

The mean response in the 2006 survey was 3.791 and in 2022 it was 4.035. This was significantly higher in 2022 (Mantel–Haenszel chi-square 48.006, DF- = 1, Pr Chi Sq < 0.0001).

A probit model of satisfaction is shown in Table 28. Of particular significance is that even controlling for various sociodemographic aspects, confidence in and use and importance of forecasts, the level of satisfaction in 2022 is still significantly greater than 2006 (as indicated by the positive parameter estimate on CoFU_Version).

Those with higher education are more satisfied with weather information as are Latinos and those who use forecasts for the city where they live or for cities in other parts of the world. Conversely, those who spend more time outside while at home or use forecasts for social activities are *less* satisfied with weather forecasts. This seems to suggest that current weather information does not meet expectations or needs for some people. Finally, those who access forecasts simply to know what the weather will be like are more satisfied with forecast information.

Table 28: Ordered Probit Regression on Satisfaction with Forecasts

	Parameter	Parameter Estimate	Pr>ChiSq
Intercepts	Intercept (5)	-3.205	<.0001
	Intercept (4)	-1.625	<.0001
	Intercept (3)	-0.805	0.005
	Intercept (2)*	-0.401	0.166
	CoFU_Version	0.344	<.0001
Sociodemographics	Income (2021_Median_Adjusted_Thousands)	0.000	0.911
	Yrs in current residence	0.000	0.718
	Age (yrs)	0.002	0.472
	Female (no = 0;yes = 1)	-0.010	0.844
	Household size	-0.003	0.860
	Education (yrs)	0.018	0.079
Employment	Fulltime	0.130	0.313
	Parttime	0.098	0.446
	Retired	0.204	0.131
	Homemaker	0.104	0.432
	Student	-0.097	0.544
	Unemployed	0.126	0.368
Race	White	0.036	0.749
	Black	0.092	0.451
	Latino	0.332	0.002
	Asian	-0.198	0.165
	Native	-0.006	0.970
	Other	-0.236	0.205
Time allocation	Percent of job outside	0.010	0.300
	Hours traveling to work	0.001	0.724
	Percent of leisure time outside	0.014	0.202
	Hours at home spent outside	-0.003	0.050
Geographic Area of Forecast	City You Live	0.199	<.0001
	City In State	0.023	0.220
	City Other State	-0.024	0.290
	City World	0.043	0.082
Use Fx for Activities	Dress	0.015	0.365
	Get Work	0.003	0.867
	Yardwork	-0.001	0.937
	Job Activities	0.017	0.323
	Social Activities	-0.039	0.049
	Travel	0.001	0.946
	Weekend Activities	0.030	0.166
	Simply Know Weather	0.047	0.032
	Personal Weather Impact Scale	0.037	0.107

Max-rescaled R-Sq: 0.079; Likelihood Ratio (DF = 45) Chi-Square: 189.18 / Pr > ChiSq < 0.0001; Percent Concordant: 62.0

* Response level "1" was deleted due to missing or invalid values for its explanatory, frequency, or weight variables.

Using the regression model we "fitted" the satisfaction level for the "average" CoFU2 respondent using the means of all sociodemographics and other explanatory variables used in the regression model—except we fit this value for a CoFU1 response versus a CoFU2 response (i.e., calculating the level of satisfaction by only varying which version of the survey they answered and thus only the parameter estimate on version affected the difference in fitted satisfaction). The average CoFU1 level of satisfaction was calculated as 3.78 and for CoFU2 as 4.03 for a 0.26-point increase in satisfaction on the 5-point scale. Adjusting for the fact that the scale starts at "1" this represents a 9.29% increase in satisfaction with forecasts between 2006 and 2022.

6.5.2. Confidence in weather forecasts

Figure 14 shows the question about confidence in weather forecasts as asked in both survey versions. The response time periods were not randomly presented as response categories were in most other questions.

11 Weather forecasts are available for up to 14 days into the future. This means that a 1-day forecast is for the weather 1 day (24 hours) from now, that a 2-day forecast is for the weather 2 days (48 hours) from now, and so on.

How much confidence do you have in weather forecasts for the times listed below?

	Forecasts for weather…	Very low	Low	Medium	High	Very high
1	Less than 1 day from now	1	2	3	4	5
2	1 day from now	1	2	3	4	5
3	2 days from now	1	2	3	4	5
4	3 days from now	1	2	3	4	5
5	5 days from now	1	2	3	4	5
6	7 to 14 days from now	1	2	3	4	5

Figure 14: Question on Confidence in Forecasts by Time Period

Figure 15 (page 60) shows the average confidence by time period for each version of the survey. For both implementations there is a declining trend for the longer time periods. But confidence was higher for shorter time periods for the 2006 respondents and then lower for longer time periods.

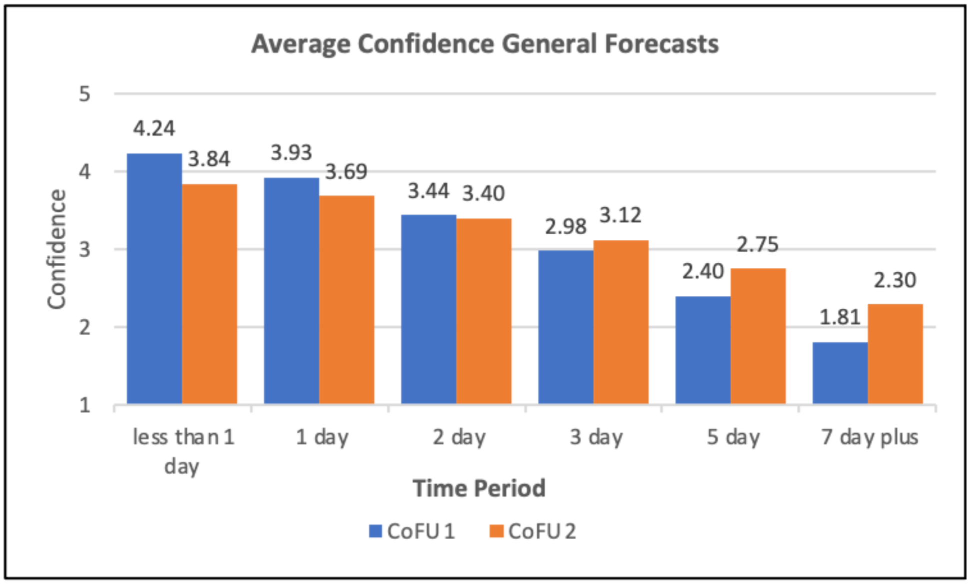

Figure 15: Average Confidence in Forecasts by Time Period and Survey Version

Table 29 shows these data as well as the statistical test of difference between survey implementations. As stated in Lazo et al. (2009) with respect to this question:

> These results provide empirical information about people's perceptions of weather forecasts. Our interpretation of these results is that respondents' lower confidence in longer lead-time forecasts reflects their understanding that these forecasts tend to be less accurate. This understanding—which likely comes about through experience with weather and forecasts—coupled with respondents' stated satisfaction levels, suggests that people do have well-formed judgments and understanding about weather forecasts (Lazo et al. 2009, p. 790).

As shown in the final column in Table 29, confidence in shorter-term weather forecasts (1 day or less) appears to have decreased, while confidence in 3-day or longer forecasts has increased.

Table 29: Confidence in Weather Forecasts by Time Period: Mean Responses by Version and Chi-Sq Test of Differences

	Mean Response		Mantel–Haenszel Chi-Square (df = 1)		Direction of Change
Time Period	CoFU1	CoFU2	Value	Prob	
less than 1 day	4.237	3.844	110.065	<.0001	Decreased
1 day	3.929	3.691	43.183	<.0001	Decreased
2 day	3.444	3.402	1.235	0.267	No Change
3 day	2.985	3.123	12.457	0.000	Increased
5 day	2.399	2.751	75.086	<.0001	Increased
7 day plus	1.811	2.299	126.067	<.0001	Increased

Figure 16 shows the follow-up question on confidence levels in various attributes of forecasts at three different time periods (1 day shown in Figure 16, but 3-day and 7-day questions also followed).

12a **For forecasts of weather 1 day (24 hours) from now, how much confidence do you have in forecasts of the weather elements listed below?**

		Very low	Low	Medium	High	Very high
1	Temperature	1	2	3	4	5
2	Chance of precipitation	1	2	3	4	5
3	Amount of precipitation	1	2	3	4	5

Figure 16: Question on Confidence in Forecast Weather Elements

Table 30 shows the mean response by survey version for each of the forecast attributes and time periods. Using a nonparametric one-way ANOVA test for differences in the responses to this set of questions, we show the most conservative Kruskal–Wallis test with one degree of freedom. All of the responses were significantly different between the two survey implementations but not all in the same direction. As the last column indicates, confidence in short-term forecasts (1-day) has decreased since 2006 but increased for the 3-day and 7-day forecasts for all attributes. Note that the Kruskal–Wallis test is not really a test of the difference of means but a test of where the two subsamples come from the same distribution.

Table 30: Confidence in Different Attributes of Weather Forecasts at Different Time Periods

	Mean		Test of Difference Kruskal–Wallis (df = 1)		
Variable	CoFU1	CoFU2	Value	Prob	Change
1 day temp	4.094	3.820	56.486	<.0001	Decreased
1 day chance precip	3.856	3.534	69.429	<.0001	Decreased
1 day amount precip	3.610	3.352	39.419	<.0001	Decreased
3 day temp	3.333	3.406	4.963	0.026	Increased
3 day chance precip	3.004	3.173	19.853	<.0001	Increased
3 day amount precip	2.833	2.995	16.495	<.0001	Increased
7 day temp	2.367	2.875	132.111	<.0001	Increased
7 day chance precip	2.050	2.637	188.584	<.0001	Increased
7day amount precip	1.930	2.501	165.583	<.0001	Increased

Table 31 shows results of an exploratory factor analysis on the combined confidence in forecast questions. This analysis generated four factors. Also shown are columns "breaking down" the variables by time, weather attribute, and forecast details (e.g., amount or chance). The second row provides potential labels for the factors based on the forecast components.

Table 31: Confidence in Forecasts Exploratory Factor Analysis: Rotated Factor Pattern

Variable	Time	Attribute	Detail	Factor1	Factor2	Factor3	Factor4
				Long Term	Short Term	General	Amount Precip
conf7d_t	7 days	temp	general	0.936	0.219	-0.009	-0.258
conf7d_ch_p	7 days	precip	chance	0.832	-0.127	0.093	0.104
conf7d_amt_p	7 days	precip	amount	0.730	-0.237	0.171	0.204
conf3d_t	3 days	temp	general	0.540	0.568	-0.044	-0.006
conf3d_ch_p	3 days	precip	chance	0.421	0.221	0.096	0.388
conf1d_t	1 day	temp	general	0.100	0.775	-0.185	0.160
conf_lt_1d	less than 1 day	general	general	-0.137	0.756	0.089	0.076
conf_1d	1 day	general	general	-0.140	0.724	0.297	0.056
conf_2d	2 days	general	general	0.005	0.524	0.524	0.014
conf1d_ch_p	1 day	precip	chance	-0.038	0.463	-0.109	0.621
conf_3d	3 days	general	general	0.080	0.313	0.717	-0.035
conf_5d	5 days	general	general	0.262	0.025	0.704	-0.031
conf_7d_pls	7 days plus	general	general	0.398	-0.218	0.577	0.001
conf_1d_amt_p	1 day	precip	amount	-0.075	0.236	-0.025	0.789
conf3d_amt_p	3 days	precip	amount	0.335	0.052	0.139	0.548

6.6. *Uses*

6.6.1. Geographic area of forecast use

Figure 17 shows the question about the use of weather forecasts for different geographic areas as asked in both survey versions. The response options were not randomly presented as response categories were in most other questions.

3 **When you get weather forecasts, how often do you get them for the cities or areas listed below?**

		Rarely or never	Less than half of the time	About half the time	More than half the time	Usually or always
1	The city or area where you live	1	2	3	4	5
2	Other cities or areas in the state where you live	1	2	3	4	5
3	Cities or areas in other U.S. states	1	2	3	4	5
4	Cities or areas in other countries around the world	1	2	3	4	5

Figure 17: Question on Use of Forecasts by Geographic Area

Table 32 shows average responses by survey version and geographic area and chi-square tests of difference in the distributions between implementations. It is interesting that local use (in one's own city) has decreased while interest in other cities or areas in other countries has increased. This is in the context that use in one's own city is on average close to usually or always, while in more distant areas it is still less than half of the time.

Table 32: Use of Forecasts by Geographic Area

	Mean		Test of Difference (Mantel–Haenszel Chi-Square (df = 1))		
Area	CoFU1	CoFU2	Value	Prob	Change
city you live	4.775	4.353	126.9614	<.0001	Decreased
city in state	2.848	2.810	0.4122	0.5209	No Change
city other state	2.476	2.516	0.5381	0.4632	No Change
city world	1.593	2.124	<.0001	<.0001	Increased

Figure 18 shows these data in a bar chart for the four geographic areas by survey version. This further suggests that there has been a shift in interest from local areas to broader geographic areas between the two survey implementations.

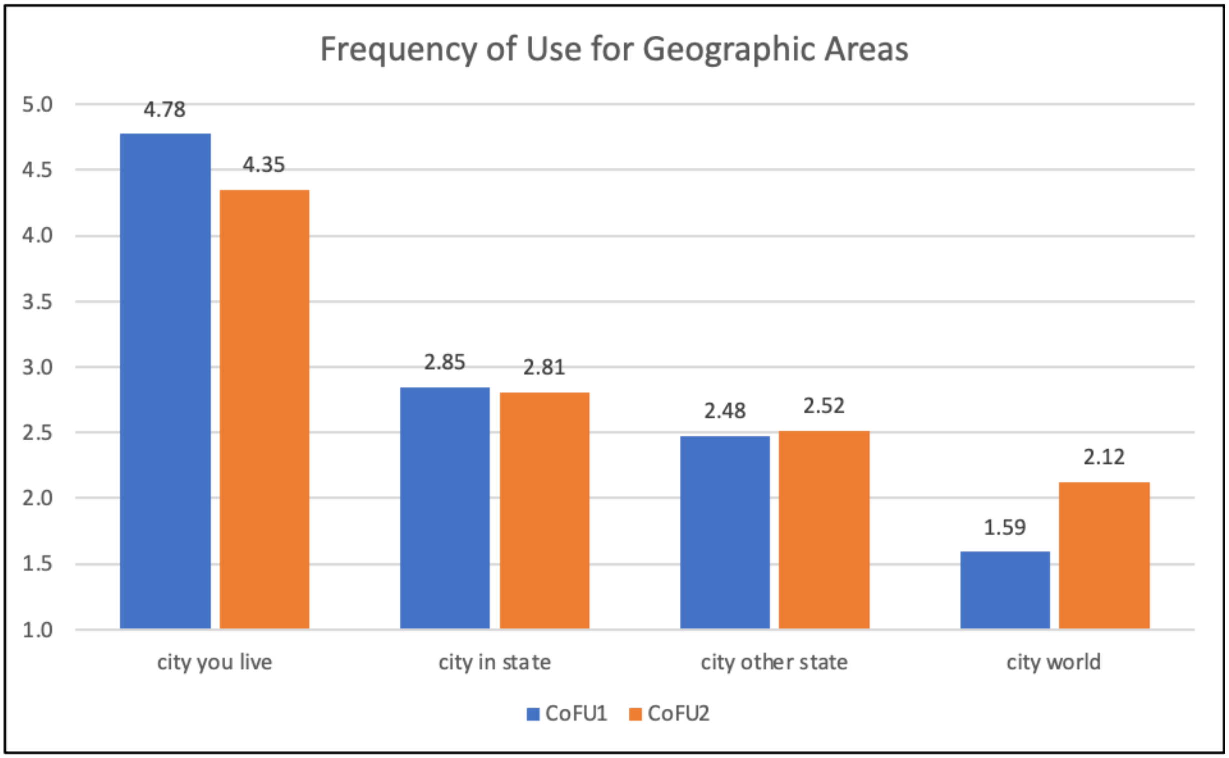

Figure 18: Frequency of Use by Geographic Area and Survey Version

An ordered probit regression model on the use of forecasts for the geographic area of "cities or other countries around the world" yielded the estimates shown in Table 33. We note that even after controlling for the other independent variables included in the model the variable "CoFU_Version" is still significant and positive indicating that individuals are using weather forecasts more in 2022 than in 2006 for geographic areas outside of the United States.

More educated, younger people, Asian, those who spend more of their worktime outside, use forecasts to get to work or for job activities or whom have had more weather-related personal impacts all access forecasts for international areas more. Those who access local ("your city") forecast more or access forecasts later in the day (7–12pm) access international forecasts *less*.

Table 33: Ordered Probit Regression on Use of Forecasts for Cities or Other Countries around the World

	Parameter	Parameter Estimate	Pr>ChiSq
Intercepts	Intercept (5)	-4.471	<.0001
	Intercept (4)	-3.774	<.0001
	Intercept (3)	-3.200	<.0001

Table 33: Ordered Probit Regression on Use of Forecasts for Cities or Other Countries around the World			
	Parameter	Parameter Estimate	Pr>ChiSq
	Intercept (2)*	-2.333	<.0001
	CoFU_Version	0.365	<.0001
Sociodemographics	Income (2021_Median_Adjusted_Thousands)	0.001	0.392
	Yrs in current residence	-0.001	0.574
	Age (yrs)	-0.010	<.0001
	Female (no = 0;yes = 1)	-0.028	0.616
	Household size	0.004	0.797
	Education (yrs)	0.033	0.003
Employment	Fulltime	0.055	0.712
	Parttime	0.010	0.946
	Retired	0.119	0.451
	Homemaker	0.094	0.541
	Student	-0.061	0.739
	Unemployed	0.012	0.944
Race	White	-0.058	0.638
	Black	0.036	0.786
	Latino	0.013	0.910
	Asian	0.362	0.019
	Native	-0.033	0.854
	Other	0.413	0.046
Time allocation	Percent of job outside	0.038	0.000
	Hours traveling to work	-0.001	0.520
	Percent of leisure time outside	0.000	0.991
	Hours at home spent outside	0.000	0.963
Geographic Area of Forecast Use	City You Live	-0.151	<.0001
	City In State	0.167	<.0001
	City Other State	0.504	<.0001
	City World	NA	NA
Use Fx for Activities	Dress	-0.001	0.955
	Get to Work	0.042	0.027
	Yardwork	-0.006	0.772
	Job Activities	0.056	0.004
	Social Activities	-0.018	0.451
	Travel	0.018	0.386
	Weekend Activities	-0.001	0.962
	Simply Know Weather	-0.003	0.897
Use by time of day	time 12 to 6	0.019	0.760
	time 6 to 8	-0.036	0.511
	time 8 to 11	-0.049	0.380
	time 11 to 1	0.051	0.380
	time 1 to 4	0.072	0.231
	time 4 to 7	0.092	0.117
	time 7 to 12	-0.098	0.081
Forecast Quality	Satisfaction with weather forecast information	0.049	0.111
	Confidence in 1 day forecast	-0.039	0.198
	Importance of NWS Information	-0.003	0.922
	Personal Weather Impact Scale	0.059	0.017

N=2,557; Max-rescaled R-Sq: 0.4753; Likelihood Ratio (DF = 44) Chi-Square: 1447.07 / Pr > ChiSq < 0.0001; Percent Concordant: 83.4

* Response level "1" was deleted due to missing or invalid values for its explanatory, frequency, or weight variables.

One interesting observation is that those who use forecasts between 7pm and 12pm are less likely to use weather information about international locations. To explore this further Table 34 shows the Pearson correlations between frequency of sources and the four different geographic areas. It is interesting to note a negative correlation between weather radio and "city where you live" and a strong positive correlation between weather radio and "world" as it seems a primary purpose of NOAA Weather Radio is to inform people on local conditions.[1] It is also interesting to note that the only correlations that are not significant are between "city where you live" and with newspapers or NWS websites.

Table 34: Correlations between Geographic Areas of Use and Sources of Information

Pearson Correlation Coefficients, N = 2557
Prob > |r| under H0: Rho = 0

	cty_you_live	cty_in_state	cty_othr_state	cty_world
src_local_tv_freq	0.203	0.227	0.188	0.045
	<.0001	<.0001	<.0001	0.023
src_cable_tv_freq	0.078	0.210	0.271	0.179
	<.0001	<.0001	<.0001	<.0001
src_newspaper_freq	0.022	0.183	0.251	0.211
	0.271	<.0001	<.0001	<.0001
src_telephone_freq	-0.121	0.138	0.186	0.312
	<.0001	<.0001	<.0001	<.0001
src_radio_freq	0.106	0.147	0.147	0.119
	<.0001	<.0001	<.0001	<.0001
src_wx_radio_freq	-0.133	0.155	0.200	0.294
	<.0001	<.0001	<.0001	<.0001
src_nws_web_freq	0.002	0.180	0.187	0.211
	0.926	<.0001	<.0001	<.0001
src_othr_web_freq	0.057	0.118	0.135	0.145
	0.004	<.0001	<.0001	<.0001

[1] This suggests that people who get forecasts for the city where they live are *less* likely to access NOAA Weather Radio than those who don't get forecasts for the city where they live. Although not shown here, this held up in a regression analysis parallel to that shown in Table 33 but on "city where you live" that included frequency of use for the different sources. The parameter on "NOAA Weather Radio" was negative and significant.

6.6.2. Importance of specific attributes of weather forecasts

Figure 19 shows the question about the importance of different "attributes" of weather forecasts as asked in both survey versions. The different attribute options were randomly presented.

6 **A weather forecast can provide several types of information about temperature, cloudiness, winds, and precipitation (such as rain, snow, hail, or sleet).**

How important is it to you to have the information listed below as part of a weather forecast?

Not at all important	A little important	Somewhat important	Very important	Extremely important
1	2	3	4	5

1	Chance of precipitation
2	Amount of precipitation
3	Type of precipitation
4	When precipitation will occur
5	Where precipitation will occur
6	Chance of different amounts of precipitation (e.g., greater than ½ inch, 1 inch, 6 inches)
7	Low temperature
8	High temperature
9	What time of day the high temperature will occur
10	What time of day the low temperature will occur
11	How cloudy it will be
12	Wind speed
13	Wind direction
14	Humidity levels

Figure 19: Question on Importance of Forecast Information

Table 35 shows the mean responses for the two different survey implementations in descending order of CoFU2 responses (i.e., from most to most to least important to CoFU2 respondents). Also shown is the statistical test of difference between 2006 and 2022 and the direction of change if significant. "High temperature" is considered most important in 2022 compared to when precipitation would occur considered most important by 2006 respondents. Most of the forecast attributes are considered as important or more important to the 2022 respondents (only two attributes decreased in importance–type and location of precipitation). It does seem possible that these changes in relative importance of forecast attributes are related to the time of year of survey implementation as CoFU1 was implemented in November 2006 and CoFU2 in June 2022.

Table 35: Importance of Forecast Attributes (from most to least important as ranked by CoFU2 respondents)					
	Mean		Test of Difference (Mantel–Haenszel Chi-Square (df = 1))		
Forecast Attribute	CoFU1	CoFU2	Value	Prob	Change
high temperature	3.725	3.819	6.104	0.014	Increased
when precipitation	3.859	3.805	0.973	0.324	Unchanged
chance of precipitation	3.855	3.802	0.341	0.559	Unchanged
where precipitation	3.831	3.735	4.185	0.041	Decreased
amount of precipitation	3.699	3.697	0.051	0.822	Unchanged
type of precipitation	3.823	3.646	17.019	<.0001	Decreased
low temperature	3.524	3.570	1.033	0.310	Unchanged
chance of amount of precipitation	3.567	3.495	2.278	0.131	Unchanged
time of high temperature	3.014	3.456	88.513	<.0001	Increased
wind speed	3.186	3.342	13.286	0.000	Increased
time of low temperature	2.928	3.317	66.091	<.0001	Increased
humidity	3.025	3.234	21.799	<.0001	Increased
cloudy	2.743	3.039	41.701	<.0001	Increased
wind direction	2.565	2.875	37.329	<.0001	Increased

Figure 20 shows the mean importance ratings by survey version. The attributes are arranged from largest to smallest difference between the CoFU1 and CoFU2 implementations. Note also that the scale is only shown from 1 to 4 (the response scale was 1 to 5).

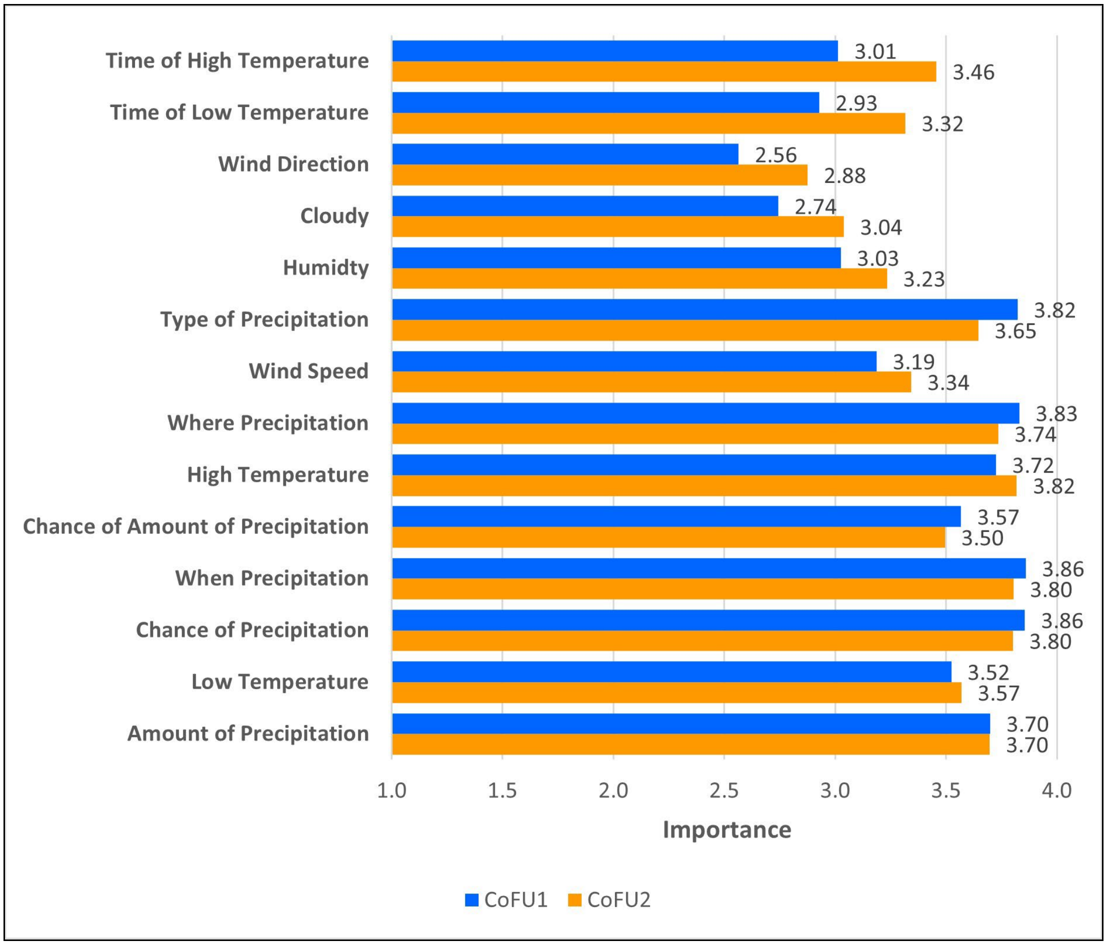

Figure 20: Mean Importance of Forecast Attributes Ranked by Difference between Surveys

Table 36 shows a probit regression on preference for time of high temperature, which had the largest change from 2006 to 2022. Of note again here is that the CoFU indicator variable is still significant after accounting for the other independent variables suggesting that there has been an increase in the importance of this forecast attribute since 2006.

The younger a person is, using forecasts to dress, get to work, job, social activities, or simply to know the weather, getting information on weather in other cities in one's own state or the world are all positively and significantly related to increased preferences for information on the time of day of high temperature. As may be expected, using forecasts from 11am to 1pm and 1pm to 4pm also are positively and significantly related to increased preferences for information on the time of day of high temperature (the afternoon typically being when high temperatures occur). The percentage of leisure time spent outside is negatively related to wanting to know the time of the high temperature, which is unexpected. Finally, all forecast quality measures (satisfaction with weather forecast information, confidence in 1-day forecast, and Importance of NWS information) are all positively and significantly related to increased preferences for information on the time of day of high temperature.

Table 36: Probit Regression on Preference for "Time of High Temperature"			
	Variable	Para. Est.	Pr>|t|
Intercepts	Intercept (5)	-4.217	<.0001
	Intercept (4)	-3.228	<.0001
	Intercept (3)	-2.299	<.0001
	Intercept (2)*	-1.500	<.0001
	CoFU_Version	0.399	<.0001
Sociodemographics	Income (2021_Median_Adjusted_Thousands)	-0.001	0.130
	Years in current residence	0.001	0.413
	Age	-0.008	0.000
	Female	0.074	0.121
	Household size	0.006	0.694
	Education (Years)	0.001	0.914
Employment	Fulltime	-0.135	0.278
	Parttime	-0.047	0.709
	Retired	0.038	0.772
	Homemaker	-0.042	0.743
	Student	-0.018	0.910
	Unemployed	-0.048	0.725
Race	White	-0.168	0.119
	Black	-0.163	0.164
	Latino	0.026	0.804
	Asian	-0.081	0.559
	Native	0.246	0.118
	Other	-0.167	0.357
Use Fx for Planning	Dress	0.052	0.001
	Get to Work	0.046	0.004
	Yardwork	0.019	0.233
	Job Activities	0.053	0.001
	Social Activities	0.052	0.006
	Travel	0.023	0.193
	Weekend Activities	0.075	0.000
	Simply Know Weather	0.056	0.009
Time allocation	Percent of job outside	0.010	0.242
	Hours traveling to work	0.001	0.534
	Percent of leisure time outside	-0.028	0.007
	Hours at home spent outside	0.002	0.283
Geog Area Fx Use	city you live	0.043	0.104
	city in state	0.041	0.023
	city other state	0.017	0.438
	city world	0.064	0.007
Use by time of day	time 12 to 6	0.015	0.769
	time 6 to 8	0.013	0.780
	time 8 to 11	-0.048	0.306
	time 11 to 1	0.099	0.046
	time 1 to 4	0.103	0.047
	time 4 to 7	-0.021	0.663
	time 7 to 12	0.030	0.521
Forecast Quality	Satisfaction with weather forecast information	0.058	0.022
	Confidence in 1 day forecast	0.045	0.078
	Importance of NWS Information	0.158	<.0001

Table 36: Probit Regression on Preference for "Time of High Temperature"			
	Personal Weather Impact Scale	0.030	0.173
	Max-rescaled R-Sq	0.24	
	Likelihood Ratio (DF = 46)	679.78	<.0001
	Percent Concordant	70.4	
* Response level "1" was deleted due to missing or invalid values for its explanatory, frequency, or weight variables			

Next, we conducted an exploratory factor analysis with maximum-likelihood factor analysis. All Kaiser's measure of sampling adequacy (MSA) were greater than 0.87 and the overall MSA was 0.93. After examining the scree plot and initial factor pattern it was determined to retain four factors. The analysis was run again with maximum-likelihood factor analysis and a Heywood correction setting any communality greater than one equal to one. Oblique promax rotation was used to generate the reference structure and factor structure that were examined to confirm the retention of four factors. Table 37 shows the rotated factor pattern and highlights loadings greater than 0.40. Based on the attributes loading in each factor we name the four factors:

- Factor1: Precipitation
- Factor2: Wind and clouds
- Factor3: Time of temperature
- Factor4: Temp extreme

We retained factor scores for further analysis. We note that the loading on "time low temperature" for the third factor is 1.007 (i.e., larger than 1.0) which this author had not seen before in a factor analysis. Further investigation indicates that this is possible with oblique rotation (which was used here) but that such a case may also suggest problems with the analysis. We have not delved into this literature at this point to determine if this is the case (Cooperman and Waller 2022; Costello and Osborne 2005).

Table 37: Importance of Weather Forecast Attributes—Rotated Factor Pattern				
	Factor 1: Precipitation	Factor 2: Wind and Clouds	Factor 3: Time of Temperature	Factor 4: Temp Extreme
chance precipitation	0.738	-0.082	-0.001	0.099
amount of precipitation	0.708	0.120	-0.015	-0.019
type of precipitation	0.685	0.070	0.038	-0.037
when precipitation	0.827	-0.072	-0.001	0.022
where precipitation	0.785	0.005	-0.014	0.022
chance amount of precipitation	0.593	0.157	0.053	-0.039
low temperature	0.127	0.067	0.240	0.410
high temperature	0.026	0.008	-0.023	0.817
time high temperature	-0.028	0.201	0.417	0.306
time low temperature	0.023	0.009	1.007	-0.038
cloudy	0.004	0.523	0.083	0.149
wind speed	0.134	0.658	-0.074	0.088
wind direction	-0.033	0.923	0.030	-0.140
humidty	0.082	0.419	0.073	0.243

6.6.3. Weather forecast—related decisions and activities

Figure 21 shows the question about one's use of forecast information for various activities as asked in both survey versions. The activity options were randomly presented.

5 On average, year round, how often do you use weather forecasts for the activities listed below?

Rarely or never	Less than half of the time	About half the time	More than half the time	Usually or always	Not applicable to me
1	2	3	4	5	9

1	Planning how to dress yourself or your children
2	Planning how to get to work or school
3	Planning to do yard work or outdoor house work
4	Planning job activities
5	Planning social activities
6	Planning travel
7	Planning weekend activities
8	Simply knowing what the weather will be like

Figure 21: Question on Use of Forecasts for Different Activities

For individuals who responded that the item was not applicable to them we recoded their response as a "1" or "rarely or never" for purposes of statistical analysis. Table 38 shows the mean responses by survey version and a statistical test of the difference in response profiles. We note that the Mantel–Haenszel chi-square is essentially a test of the distributions of the responses being the same and not a test of the central tendency. The last column indicates the direction of change (if any) from 2006 to 2022 survey implementations.

Table 38: Use of Weather Forecasts for Different Activities

	Mean		Mantel–Haenszel Chi-Square (df = 1)Test of Difference		
Use Forecasts for:	CoFU1	CoFU2	Chi-Square	Pr > Chi-Square	Change
dress	3.846	3.584	18.046	<.0001	Decreased
get work	2.778	2.750	0.174	0.6770	No change
yardwork	3.329	3.360	0.236	0.6270	No change
job activities	2.362	2.549	8.344	0.0039	Increased
social activities	3.261	3.426	7.544	0.0060	Increased
travel	3.450	3.401	0.634	0.4258	No change
weekend activities	3.732	3.693	0.490	0.4840	No change
simply know weather	4.453	4.129	50.854	<.0001	Decreased

Figure 22 shows the mean use of forecasts for the different activities by survey version from highest to lowest by CoFU2 responses from left to right. Although this decreased somewhat from CoFU1 to CoFU2, accessing forecasts "simply to know what the weather will be like" is the most frequent use of forecasts.

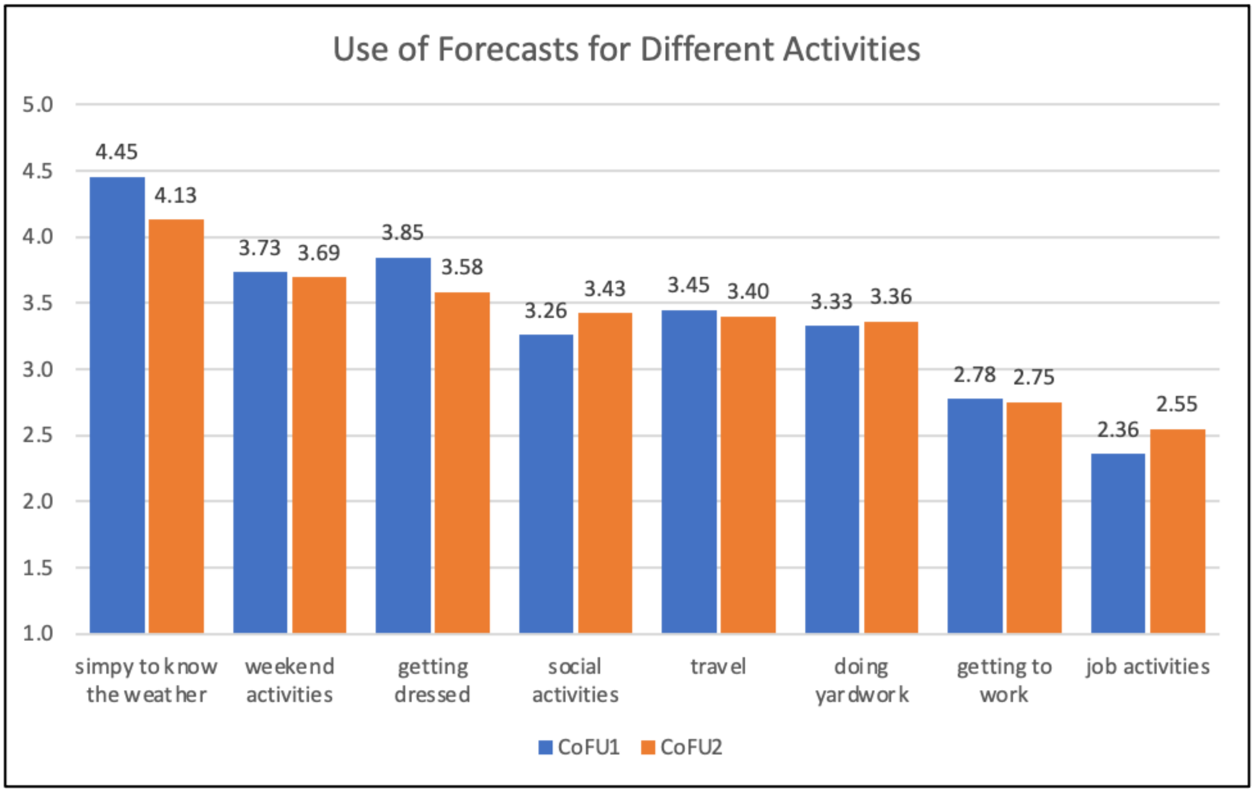

Figure 22: Mean Use of Forecasts for Different Activities by Survey Version

A probit regression model on the use of forecasts to get dressed yielded the estimates shown in Table 39. We note that even after controlling for the other independent variables included in the model the variable "CoFU_Version" is still significant and negative indicating that individuals are using weather forecasts less in 2022 than in 2006 when getting dressed. One conjecture on this would be that post-COVID, fewer people are going into a workplace requiring any sort of formal dress (or even going into a specific workplace).

As noted above some differences here could be related to the time of year of survey implementation (CoFU1 implemented in November and CoFU2 in June).

Those who are longer in their current residence, female, of larger household size, more educated, homemakers, or Black, use forecasts to help get to work, job, social, or weekend activities, travel, or simply to know weather, use forecasts for the city where they live, or rate NWS forecasts of greater importance, all use forecasts more to help them make decisions on what to wear. Those who spend more hours outside around the house use forecasts *less* to help them decide what to wear.

Table 39: Probit Regression on Use of Forecasts to Get Dressed

	Variable	Para. Est.	Pr>|t|
Intercepts	Intercept (5)	-3.833	<.0001
	Intercept (4)	-3.316	<.0001
	Intercept (3)	-2.941	<.0001
	Intercept (2)*	-2.658	<.0001
	CoFU_Version	-0.140	0.010
Sociodemographics	Income (2021_Median_Adjusted_Thousands)	-0.001	0.256
	Years in current residence	0.002	0.091
	Age	-0.003	0.176
	Female	0.355	<.0001
	Household size	0.056	0.001
	Education (Years)	0.020	0.060
Employment	Fulltime	0.088	0.544
	Parttime	0.021	0.886
	Retired	0.102	0.503
	Homemaker	0.305	0.046
	Student	0.038	0.830
	Unemployed	0.184	0.243
Race	White	0.179	0.143
	Black	0.284	0.033
	Latino	0.035	0.767
	Asian	0.152	0.336
	Native	0.184	0.288
	Other	-0.037	0.849
Use Fx for Planning	Dress	NA	NA
	Get to Work	0.169	<.0001
	Yardwork	0.067	0.000
	Job Activities	-0.018	0.360
	Social Activities	0.095	<.0001
	Travel	0.036	0.058
	Weekend Activities	0.111	<.0001
	Simply Know Weather	0.172	<.0001
Time allocation	Percent of job outside	0.002	0.830
	Hours traveling to work	0.001	0.525
	Percent of leisure time outside	-0.014	0.243
	Hours at home spent outside	-0.003	0.033
Geog Area Fx Use	City you live	0.090	0.002
	City in state	0.019	0.345
	City other state	-0.018	0.458
	City world	-0.027	0.316
Use by time of day	Time 12 to 6	0.044	0.454
	Time 6 to 8	0.052	0.302
	Time 8 to 11	0.039	0.448
	Time 11 to 1	0.027	0.624
	Time 1 to 4	-0.068	0.235
	Time 4 to 7	0.053	0.321
	Time 7 to 12	0.078	0.129
Forecast Quality	Satisfaction with weather forecast information	0.008	0.790
	Confidence in 1 day forecast	0.023	0.424
	Importance of NWS Information	0.059	0.042

Table 39: Probit Regression on Use of Forecasts to Get Dressed			
	Variable	**Para. Est.**	**Pr>|t|**
	Personal Weather Impact Scale	-0.004	0.884
	Max-rescaled R-Sq	0.303	
	Likelihood Ratio (DF = 46)	851.23	<.0001
	Percent Concordant	75.3	
* Response level "1" was deleted due to missing or invalid values for its explanatory, frequency, or weight variables			

An exploratory factor analysis on the use of forecasts for different activities items did not yield a clear and reasonably interpretable result. The Kaiser's MSA ranged from 0.77 to 0.89 and the overall MSA was 0.83, which are not overly strong results.[2] Instead we conducted a principal component analysis with a varimax orthogonal rotation—primarily as a data reduction effort—and yielded the two factors shown in Table 40. We have named the two factors "discretionary" and "nondiscretionary" and retained the factor scores for further analysis. We consider job, school, and travel activities as "nondiscretionary" as quite often these activities related to specific schedules not determined by the respondents. Simply knowing the weather and weekend, social, or yard work seem more "discretionary" with respect to timing and participation.

Table 40: Principal Component Analysis—Use of Forecasts for Different Activities		
Rotated Factor Pattern		
Use Forecasts for planning:	**Factor1: Discretionary**	**Factor2: Non-Discretionary**
simply know weather	0.757	-0.247
weekend activities	0.687	0.393
how to dress yourself or your children	0.609	0.199
social activities	0.562	0.518
yardwork or outdoor housework	0.479	0.461
job activities	0.470	0.506
planning on how to get to work or school	0.123	0.725
travel	0.021	0.811

Table 41 shows OLS regressions on the factor scores from the principal component analysis. The variable "CoFU_Version" was not significant in either regression indicating that, after controlling for the other included independent variables, there was

[2] "Kaiser proposed that a KMO > 0.9 was marvelous, in the 0.80s, meritorious, in the 0.70s, "middling" source:
https://en.wikipedia.org/wiki/Kaiser%E2%80%93Meyer%E2%80%93Olkin_test#:~:text=The%20Kaiser%E2%80%93Meyer%E2%80%93Olkin%20(,that%20might%20be%20common%20variance.

no significant difference in the use of forecasts for discretionary or nondiscretionary activities between the two survey implementations.

Female (compared to other genders) use forecasts more for discretionary activities but less so for nondiscretionary activities. Less educated, those who spend *less* time on the job outside, spend more leisure time or other time outside at home, use forecasts for their city or other cities in their state, use forecasts more during the 6am-to-1pm or 4pm-to-7pm time frames, have more confidence in 1-day forecast, or rate NWS information as more important use forecasts more for discretionary purposes.

In addition, female, retired, or White respondents use forecasts *less* for nondiscretionary purposes. Those with any more time allocation in any of the four categories (percent of job outside, hours traveling to work, percent of leisure time outside, and hours at home spent outside) use forecasts more for nondiscretionary purposes. In addition, those getting forecasts for other cities in the world or using forecasts any time from midnight until 1 pm, and those with more personal weather impacts use forecasts more for nondiscretionary purposes.

Table 41: OLS on Use of Forecasts Factor Scores

		Use for Activities Factor1 Discretionary		Use for Activities Factor2 Non- Discretionary	
	Obs	1908		1908	
	Adj R-Sq	0.2404		0.2440	
	Variable	Param. Est.	Pr>|t|	Param. Est.	Pr>|t|
	Intercept	-3.351	<.0001	-1.235	<.0001
	CoFU_Version	-0.041	0.379	-0.050	0.282
Sociodemographics	Income (2021_Med_Adj_Th)	0.001	0.026	0.001	0.218
	Years in current residence	0.001	0.461	0.000	0.764
	Age	0.003	0.161	-0.002	0.345
	Female	0.186	<.0001	-0.076	0.081
	Household size	0.010	0.436	0.011	0.399
	Education (Years)	-0.017	0.052	-0.003	0.771
Employment	Fulltime	-0.094	0.412	0.052	0.651
	Parttime	-0.017	0.885	-0.131	0.254
	Retired	-0.033	0.787	-0.409	0.001
	Homemaker	0.086	0.486	-0.041	0.737
	Student	0.068	0.631	0.008	0.958
	Unemployed	-0.146	0.268	-0.126	0.339
Race	White	-0.079	0.422	-0.162	0.098
	Black	-0.034	0.752	-0.047	0.661
	Latino	0.014	0.883	0.013	0.895
	Asian	-0.055	0.663	0.078	0.537
	Native	-0.137	0.352	-0.040	0.789

	Table 41: OLS on Use of Forecasts Factor Scores				
		Use for Activities Factor1 Discretionary		Use for Activities Factor2 Non- Discretionary	
	Other	-0.148	0.368	-0.239	0.146
Use Fx for Planning	Dress *	NA	NA	NA	NA
	Get to Work	NA	NA	NA	NA
	Yardwork	NA	NA	NA	NA
	Job Activities	NA	NA	NA	NA
	Social Activities	NA	NA	NA	NA
	Travel	NA	NA	NA	NA
	Weekend Activities	NA	NA	NA	NA
	Simply Know Weather	NA	NA	NA	NA
Time allocation	Percent of job outside	-0.031	<.0001	0.060	<.0001
	Hours traveling to work	0.001	0.511	0.004	0.008
	Percent of leisure time outside	0.039	0.000	0.030	0.003
	Hours at home spent outside	0.002	0.067	0.003	0.031
Geog Area Fx Use	city you live	0.252	<.0001	-0.020	0.393
	city in state	0.082	<.0001	0.075	<.0001
	city other state	0.032	0.126	0.026	0.211
	city world	-0.001	0.961	0.052	0.018
Use by time of day	time 12 to 6	0.002	0.961	0.144	0.003
	time 6 to 8	0.192	<.0001	0.115	0.008
	time 8 to 11	0.132	0.003	0.120	0.006
	time 11 to 1	0.122	0.010	0.081	0.087
	time 1 to 4	-0.011	0.825	-0.003	0.953
	time 4 to 7	0.103	0.021	0.069	0.123
	time 7 to 12	0.054	0.216	0.052	0.240
Forecast Quality	Satisfaction with weather forecast information	-0.017	0.474	-0.031	0.197
	Confidence in 1 day forecast	0.116	<.0001	0.013	0.576
	Importance of NWS Information	0.125	<.0001	0.037	0.129
	Personal Weather Impact Scale	-0.007	0.711	0.037	0.067

* All the "Use Fx for Planning" variables are indicated as NA as the dependent variables (factor scores) are linear combinations of these variables.

7. Value of current forecasts

7.1. Elicitation of Willingness-to-Pay for current forecast information

To elicit the respondents' value for current forecast information we implemented a contingent valuation method (CVM) question. There is a vast literature on CVM and nonmarket valuation methods (Ekstrand and Draper 2000; Haab et al. 2020; Hoyos and Mariel 2010; Johnston et al. 2017). We note here that the implementation of this question does not meet many of the standard guidelines for CVM studies. Given the limitations of this implementation we can most likely interpret responses as indications of the strength of preferences for current forecasts rather than a reasonably valid and reliable benefit estimate. That said, at the end of this section we treat the valuation estimate as valid and provide a national aggregate value—subject to the relevant caveats described here. Some of the limitations on this implementation include:

- We did not specifically indicate a counter-factual—i.e., what the state of forecast information would be in the event it was not provided by the NWS and others. Respondents thus would have to default to some indeterminate other information level including possibly "persistence" or "climatological averages." It is also possible some respondents would default to "I'll use my weather app" or "I'll just watch the Weather Channel" if told that the NWS information was no longer funded and available.
- We did not include a budget reminder as suggested in some CVM guidelines. This is believed to help the respondents better frame their marginal utility of income.
- We did not include any debriefing questions following the valuation question and thus cannot identify potential scenario rejection. Given the overwhelming number of positive responses at all price points we do not believe scenario rejection to have been an issue—and if it was then our benefit estimates could be underestimates.

Haab et al. (2020, p. 8) notes the findings of the NOAA Contingent Valuation Panel (which focused mainly on the use of CVM in oil spill damage litigation) made several recommendations for implementation of CVM surveys:

> The NOAA panel "guidelines for value elicitation surveys" included 12 items. CVM studies needed to follow these guidelines: (1) use research designs that generate conservative WTP estimates; (2) elicit WTP instead of WTA; (3) use the referendum format; (4) develop accurate descriptions of the program or policy; (5) pretest photographs; (6) remind respondents of substitutes; (7) be conducted after a period of time after an oil spill; (8) test for temporal reliability; (9) include a "no answer" alternative in the referendum question; (10) debrief after the referendum questions; (11) examine WTP responses relative to key determinants (e.g., income); and (12) make sure respondents understand and accept the scenario.

While focusing primarily on the use of CVM for resource damage assessment (and thus putting very high standards on the methodology for legal proceedings), the guidelines generally hold for current CVM and stated preference studies as best practice. Assessment of our implementation could be made in reference to these guidelines as noted above.

Of particular relevance we note that our implementation is essentially a referendum CVM where individuals are given a set price point and asked to "vote" yes or no on that option as they may in a referendum on a tax policy.

As we implemented essentially the same nonmarket valuation method in the CoFU2 survey as in the 2006 survey, we quote at length from Lazo et al. (2009, 792–793)

> Understanding the economic value of forecasts is vital for policy analysis and for making decisions about priorities for forecast provision. As a result, after eliciting respondents' sources, perceptions, and uses of forecasts, we explored the value households place on the forecasts they currently receive. Through this analysis, we can begin to make an order-of-magnitude quantitative estimate of the dollar value to U.S. households for all weather

> forecasting services currently provided, across a range of situations. We shift our discussion here to households instead of individuals because the question was framed in terms of household taxes rather than individual costs.
>
> As is necessary for commodities—like weather forecasts—that have a large public good component, we implemented a nonmarket valuation approach. That is, we asked respondents what the commodity is worth (i.e., “stated” preference) rather than using market data as an indication of worth (i.e., “revealed” preference). To do this, we first informed respondents that the NWS is the primary U.S. source for all basic data for weather forecasting and information services, including severe weather forecasts, watches, and warnings. The survey was thus designed to elicit household values for all forecast information, including severe weather watches and warnings. We also clarified that all NWS information is disseminated to media and private weather services.
>
> The valuation question then presented or “offered” respondents a hypothetical amount that they are currently paying in taxes for all NWS activities and asked if the services they are receiving are worth more than, worth exactly, or worth less than the amount indicated. Each individual was randomly presented 1 of 11 dollar amounts ranging from $2 a year to $240 a year. By varying the amount that different respondents are told they are paying, we can derive a profile of the percentage of people willing to pay different dollar amounts for weather information. Based on Lazo and Chestnut (2002)—who estimated a median household value of $109 per household per year for all current weather information using a similar question but with lower “offered” amounts— we expected that $240 a year would be high enough that at least 50% of individuals would indicate that NWS weather services were worth less than the amount indicated. However, the range of values we selected did not extend high enough to include the median value, and therefore, we extrapolated the results to derive a median value.

The 2022 (CoFU2) survey was essentially identical except that we inserted a different set of offer prices. Figure 23 shows the WTP for current value as asked (in the 2022 soft launch before adjusting the offer prices).

SELECT AND INSERT ‘N’ VALUE BASED ON LEAST-FILLED:
2, 5, 10, 30, 60, 90, 120, 150, 180, 210, 240, 286, 320, 360.

22 **All of the activities of the National Weather Service (NWS) are paid for through taxes as a part of the federal government. This money pays for all of the observation equipment (such as satellites and radar), data analysis, and products of the NWS (including all the forecasts, watches, and warnings).**

Suppose you were told that every year about $[INSERT VALUE] of your household’s taxes goes toward paying for all of the weather forecasting and information services provided by the NWS. Do you feel that the services you receive from the activities of the NWS are worth more than, exactly, or less than $[INSERT VALUE] a year to your household? *Please select only one option.*

1. Worth more than **$[INSERT VALUE]** a year to my household
2. Worth exactly **$[INSERT VALUE]** a year to my household
3. Worth less than **$[INSERT VALUE]** a year to my household

Figure 23: Question on Willingness-to-Pay for Current Forecast Information

As discussed in section 3.3 (Changes in price offer in Willingness-to-Pay question) we revised the offer prices for the 2022 survey. With 2022 we included a larger number of price points in an attempt to have the highest price point be above the median WTP level (the point where 50% would answer yes and 50% answer no to the “are you willing to pay” question). Dynata provided the researchers with data from the first 100 respondents in the soft launch even though a total of 120 had participated in that. With the responses to the 2022 soft launch, even at the highest offer price ($320) less than 50% of respondents indicated “No.” Thus, we increased the highest offer level to $508. For purposes of current analysis we also adjusted the offer price levels from 2006 to 2022 dollars based on the change in median income as discussed in section 5.4 (Inflation adjustments from 2005 to 2021 for WTP price points and income). Table 42 shows the offer price levels (adjusted to 2021 dollars using median income change from 2006) and the frequency of respondents seeing that price offer.

Table 42: Offer Price Levels

(Total number of respondents at each price level)

Adjusting 2005 WTP cost to 2021$ using median income change 9.867%					
2006 Survey		2022 Soft Launch		2022 Final	
Offer Price 2021$	Frequency	Offer Price 2021$	Frequency	Offer Price 2021$	Frequency
2.20	132	5.00	5	2.00	171
5.49	135	10.00	11	52.00	163
10.99	132	30.00	6	109.00	165
32.96	132	60.00	7	204.00	164
65.92	131	90.00	4	407.00	165
98.88	132	120.00	5	508.00	164
131.84	136	150.00	12		
164.80	135	180.00	6		
197.76	134	210.00	6		
230.72	134	240.00	11		
263.68	132	286.00	16		
		320.00	6		
		360.00	5		
Total	1465	Total	100	Total	992

7.2. Estimation of median Willingness-to-Pay

In analyzing the response data, we combined the “worth exactly” and “worth more” into a “worth It” response (we treat this simply as “Yes” response hereafter). Figure 24 show the percent of “Yes” responses at each price point noting that for some price points we have as few as 4 observations. The red dashed line is the fitted trend line as determined from Excel graphical plotting. It shows a negative trend as would be expected for a demand curve but still does not cross the 50% point we would like to determine the median value. With respect to interpreting this as a demand curve we also point out that economists usually put the price or cost on the vertical axis and quantity on the horizontal axis. We have the reverse in this graph, which has the dependent variable on the vertical axis as most sciences (other than economics for historical reasons) tend to do.

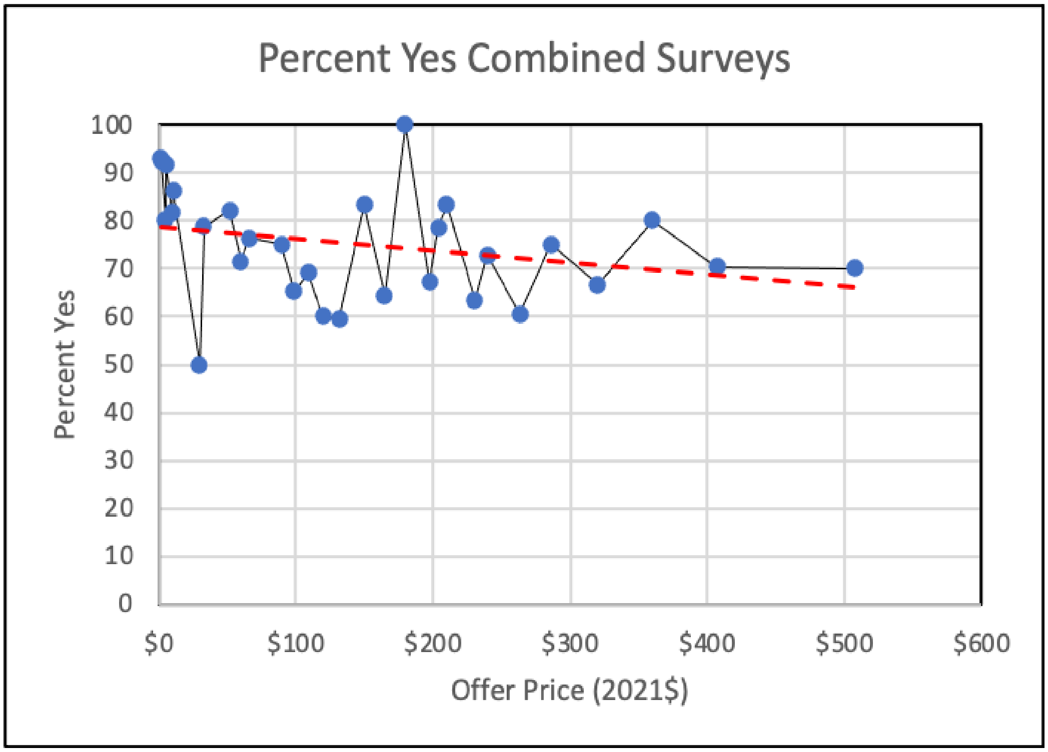

Figure 24: Percent of "Yes" Responses at Each Price Point Combined Surveys

To estimate median WTP in a manner similar to the analysis presented in Lazo et al. (2009) we first only focused on the offer prices (NWS cost) for which we had a significant number of responses—in other words only the revised offer prices following the CoFU2 pretest. Table 43 shows the number at each price level and the percent yes for these. Dropping the pretest responses removes 100 responses, but significantly improves the "look" of the data given the wide variation in "yes" response rates at the smaller response levels.

Table 43: Percent of "Yes" Responses to Offer Prices

(n = 992)

N	NWS Cost	Yes
171	2	92.98
163	52	82.21
165	109	69.09
164	204	78.66
165	407	70.30
164	508	70.12

Figure 25 show a plot of these responses and the line fitted automatically using Excel.

Figure 25: Percent of "Yes" Responses—CoFU2 Final Sample (excluding pretest)

Using these data, we used Excel to fit a linear regression of "Percent Yes" responses on the NWS cost (offer price). The NWS cost parameter estimate is significant at the 11.6% level and negative as expected. Table 44 shows the regression results.

Table 44: Regression on Percent of "Yes"				
N = 992; Adjusted R Square: 0.376				
	Coefficients	Standard Error	t Stat	P-value
Intercept	84.211	4.618	18.236	0.000
NWS Cost	-0.033	0.016	-2.002	0.116

Table 45 shows the results of using the Excel goal seek function to derive the NWS cost that would generate a median value to the Yes responses (50%). This was derived by using the parameter estimates from Table 44 and then seeking the NWS costs that would generate the "goal" of 50%. The lower rows indicate the same NWS cost estimates resulting from using the 80% lower and upper bound parameter estimates from the Excel regression. We use the 80% confidence interval as the parameter estimate is only 11.6% significant and we want to constrain the NWS costs parameter to be negative as would be expected for a normal good.

Table 45: Derivation of NWS Cost to Fit Median				
	Goal	Intercept	NWS Cost Parameter	NWS Cost
Central Parameter Estimate	50.0000	84.2105	-0.0327	1046.6470
80% Lower Bound Parameter Estimate	50.0000	84.2105	-0.0577	527.3620
80% Upper Bounder Parameter Estimate	50.0000	84.2105	-0.0077	4470.5218

As shown in Table 45, the NWS cost that would generate the median response is $1,046.65. This is the result from the 2022 survey equivalent to the "$286 per household per year" reported in Lazo et al. (2009, p. 793). We note that there is a significant 80% confidence interval ranging from $527.36 to $4,470.52. The large range is partially a result of uncertainty in the parameter estimates and is likely even larger given how far out of sample (i.e., out of the range of offer prices) this projection is made. Figure 26 repeats Figure 25 with the line extended to the median point at $1,046.65.

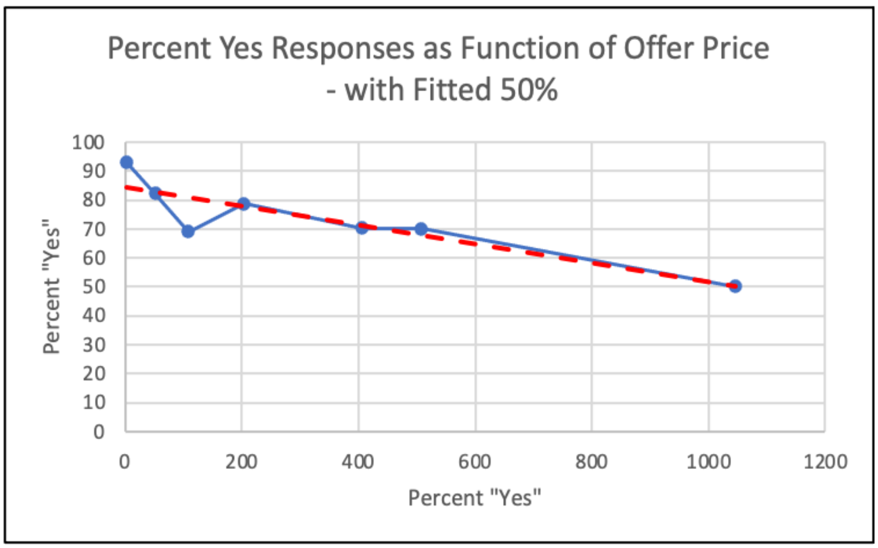

Figure 26: Percent of "Yes" Response Line Extended to Median Value

Using 5.35% as the percent of the U.S. population not using weather forecasts from Table 17, Table 46 shows an aggregation to a national value of current weather forecast information using the same method as presented in Lazo et al. (2009). While the year of the survey is 2022, the WTP question and income question are based on 2021 income and thus we represent the value in 2021 dollars. Aggregating over a population 4.91% larger than in 2006, using a different percent "not using forecasts" (5.35% versus 3.62% in 2006) and a significantly larger median value ($1,046.65 vs $285.64 in 2006) generates a rounded national value of $118.9 billion (versus $31.5 billion from the 2006 survey analysis). The 80% confidence interval on this aggregation estimate using the parameters indicated in Table 45 is $59.9 to $507.8 billion.

Table 46: Aggregation to National Value for Current Forecasts (2021 Dollars)	
Survey	CoFU2
Year	2022
Population	332,403,650
Household Size	2.77
Number of Households	120,001,318
Percent Not Using Forecasts	5.35%
Households Using Forecasts*	113,581,247
Per HH WTP	$1,046.65
Total U.S. Value of Current Forecasts (Current Dollars)	$118,879,477,114.85
Total U.S. Value of Current Forecasts (Billions)	$118.9
* note an assumption here that if the individual respondent indicate not using forecasts we apply this to the entire household. This would overstate the percent of households not using forecasts if someone else in the household does use forecasts.	

7.3. Regression analysis of household WTP

To better understand the responses to the WTP question we undertake a regression analysis on the response variable "Yes." These are probit regressions as the response variable is a dichotomous variable (No = 0; Yes = 1) where we regress on the "Yes" value so positive parameter estimates indicate more likely to respond Yes.

Table 47 shows two models on the CoFU2 (2022) data as it includes some explanatory variables from the new factors not included in the 2006 analysis. In these models we dropped the "unemployed" variable as it is a linear combination of the other variables in the dataset. The first model is a full model with all desired explanatory variables. The second is a backward selection model starting with all of the same variables, but with the restriction of an 0.15 significance level to stay in the model. "NWS cost" and "income" were "forced" into the selection model but were both significant anyway.

In both models "NWS_Cost" is negative and highly significant, which conforms to economic theory of a downward-sloping demand curve—the higher the price the fewer people are willing to pay for the commodity. This result can also serve as an internal validity check in CVM studies. We would expect income to be positive, which it is in both models. This is generally an expected outcome for normal goods where people with higher incomes are generally willing (and able) to pay more for them. (And was suggested by the NOAA CVM panel as discussed earlier in this section).

All variables significant in the full model are also significant and of the same sign in the selection model. Interestingly, some of the parameters significant in the selection model were not significant in the full model though.

In the full model, other than income and "simply know weather" the sociodemographic, employment, race, forecast uses, geographic uses, and time of day accessing forecasts, and factors of confidence in forecasts are all insignificant. Age, full-time and homemaker employment, White, use forecasts for social activities, and the factor for importance of temperature extremes are all negative and significant in the selection model indicating people with higher values on these parameters are less willing to pay for current forecasts.

Using forecasts to “simply know weather and “hours at home spent outside” are negative and significant in both models indicating lower Willingness-to-Pay.

The greater the “percent of job outside,” the more frequent use of forecasts (src_total_freq), the greater the “importance of NWS information,” the more personal weather impacts, the more important information on wind and clouds, and the greater total weather salience are all related to greater Willingness-to-Pay for current forecast information.

While not explained in this report, of the five new factors in the CoFU2 survey (political leanings, cultural risk theory, vulnerability, risk preferences, and numeracy), the individualist factor from cultural risk theory is significant and negative in both models, and political leaning is significant and negative in the selection model. One explanation of the individualist factor is that “people with more individualist worldviews perceive lower risks arising from the environment” (Lazo et al. 2015, p. 1880). If so, this may suggest that they feel less threat from the weather and thus less value in knowing what it will be. The higher the value on the political-leaning scale the more conservative an individual is (the lower indicates the more liberal). While political leaning is highly correlated with individualism (Pearson correlation coefficient = 0.355; Prob>|r| under H0: Rho = 0 = < 0.0001), they are both significant in the selection model suggesting they measure something somewhat different. One possibility is that more conservative individuals may be less inclined to want to pay taxes, which the question asked and thus there may be some scenario rejection due to this. A more complete future CVM analysis could include “debriefing questions” to assess such possibilities (as also suggested by the NOAA CVM panel).

Table 47: Probit Regression on "Yes" to Value of Current Weather Information

<table>
<tr><th></th><th></th><th colspan="2">Full Model</th><th colspan="2">Selection Model</th></tr>
<tr><th></th><th>Variable</th><th>Param. Est.</th><th>Pr>|t|</th><th>Param. Est.</th><th>Pr>|t|</th></tr>
<tr><td></td><td>Intercept</td><td>-0.344</td><td>0.658</td><td>0.181</td><td>0.673</td></tr>
<tr><td></td><td>NWS_Cost_2021_Median</td><td>-0.001</td><td><.0001</td><td>-0.001</td><td><.0001</td></tr>
<tr><td rowspan="6">Sociodemographics</td><td>Income (2021_Med_Adj_Th)</td><td>0.003</td><td>0.020</td><td>0.004</td><td>0.000</td></tr>
<tr><td>Years in current residence</td><td>-0.003</td><td>0.322</td><td></td><td></td></tr>
<tr><td>Age</td><td>-0.002</td><td>0.629</td><td>-0.006</td><td>0.081</td></tr>
<tr><td>Female</td><td>0.004</td><td>0.972</td><td></td><td></td></tr>
<tr><td>Household size</td><td>0.002</td><td>0.955</td><td></td><td></td></tr>
<tr><td>Education (Years)</td><td>0.011</td><td>0.637</td><td></td><td></td></tr>
<tr><td rowspan="6">Employment</td><td>Fulltime</td><td>-0.077</td><td>0.666</td><td>-0.210</td><td>0.062</td></tr>
<tr><td>Parttime</td><td>0.117</td><td>0.587</td><td></td><td></td></tr>
<tr><td>Retired</td><td>0.036</td><td>0.854</td><td></td><td></td></tr>
<tr><td>Homemaker</td><td>-0.210</td><td>0.357</td><td>-0.341</td><td>0.068</td></tr>
<tr><td>Student</td><td>4.579</td><td>0.961</td><td></td><td></td></tr>
<tr><td>Unemployed</td><td colspan="4">dropped as linear combo</td></tr>
</table>

Table 47: Probit Regression on "Yes" to Value of Current Weather Information					
		Full Model		Selection Model	
	Variable	Param. Est.	Pr>|t|	Param. Est.	Pr>|t|
Race	White	-0.272	0.225	-0.387	0.001
	Black	0.070	0.784		
	Latino	0.103	0.599		
	Asian	0.057	0.848		
	Native	0.222	0.565		
	Other	0.784	0.216		
Use Fx for Planning	Dress	-0.033	0.374		
	Get to Work	0.006	0.884		
	Yardwork	0.015	0.692		
	Job Activities	-0.003	0.951		
	Social Activities	-0.069	0.119	-0.062	0.076
	Travel	-0.019	0.625		
	Weekend Activities	0.002	0.972		
	Simply Know Weather	-0.106	0.032	-0.116	0.010
Time allocation	Percent of job outside	0.040	0.061	0.050	0.008
	Hours traveling to work	0.002	0.596		
	Percent of leisure time outside	0.017	0.480		
	Hours at home spent outside	-0.006	0.064	-0.005	0.099
Geog Area Fx Use	city you live	-0.078	0.191		
	city in state	0.027	0.548		
	city other state	0.021	0.696		
	city world	-0.028	0.632		
Use by time of day	time 12 to 6	-0.010	0.933		
	time 6 to 8	0.051	0.626		
	time 8 to 11	0.137	0.217		
	time 11 to 1	0.100	0.388		
	time 1 to 4	-0.274	0.024		
	time 4 to 7	0.015	0.896		
	time 7 to 12	0.133	0.198		
Forecast Quality	src_total_freq	0.002	0.001	0.003	0.000
	Satisfaction with weather forecast information	-0.041	0.557		
	Importance of NWS Information	0.222	0.001	0.210	0.000
Confidence in Wx Fx - Factors	Factor1 - Long Term	0.029	0.680		
	Factor2 - Short Term	0.003	0.968		
	Factor3 - General	0.105	0.115	0.079	0.133
	Factor4 - Amount Precip	-0.054	0.409		
	Personal Weather Impact Scale	0.175	0.001	0.179	0.000

Table 47: Probit Regression on "Yes" to Value of Current Weather Information					
		Full Model		Selection Model	
	Variable	Param. Est.	Pr>|t|	Param. Est.	Pr>|t|
Importance of Wx Fx Attributes - Factors	Factor 1: Precipitation	-0.037	0.627		
	Factor 2: Wind and Clouds	0.136	0.096	0.133	0.046
	Factor 3: Time of Temperature	-0.005	0.940		
	Factor 4: Temp Extreme	-0.140	0.122	-0.191	0.008
	Weather Saliency (total)	0.007	0.029	0.008	0.015
	Political (higher score more conservative)	-0.026	0.220	-0.032	0.102
Cultural Risk Theory Factors	CRT_Factor_1_Hierarchist	-0.011	0.907		
	CRT_Factor_2_Individualitsic	-0.180	0.083	-0.162	0.012
	CRT_Factor_3_Egalitarian	0.017	0.848		
	CRT_Factor_4_Fatalist	0.036	0.709		
Vulnerability Factors	Factor 1: Monetary	-0.060	0.512		
	Factor 2: Health	0.056	0.564		
Risk Preferences - Factors and Risk2 Scale	Factor 1: Active	0.030	0.761		
	Factor 2: Passive	0.032	0.732		
	RISK2	-0.014	0.542		
Numeracy	SNS (Subjective Numeracy Scale - Total)	0.086	0.383		
	Obs	1092		1092	
	Max-rescaled R-Square	0.3079		0.2751	
	Percent Concordant	80.5		79.0	

Figure 27 shows the SAS-generated graph of the response curve fitted at the mean values of all included independent variables from the selection model shown in Table 47. The 95% confidence intervals are shaded in light blue. We note that the regression line would intercept the 0.50 probability line far to the right of this range of offer prices shown here.

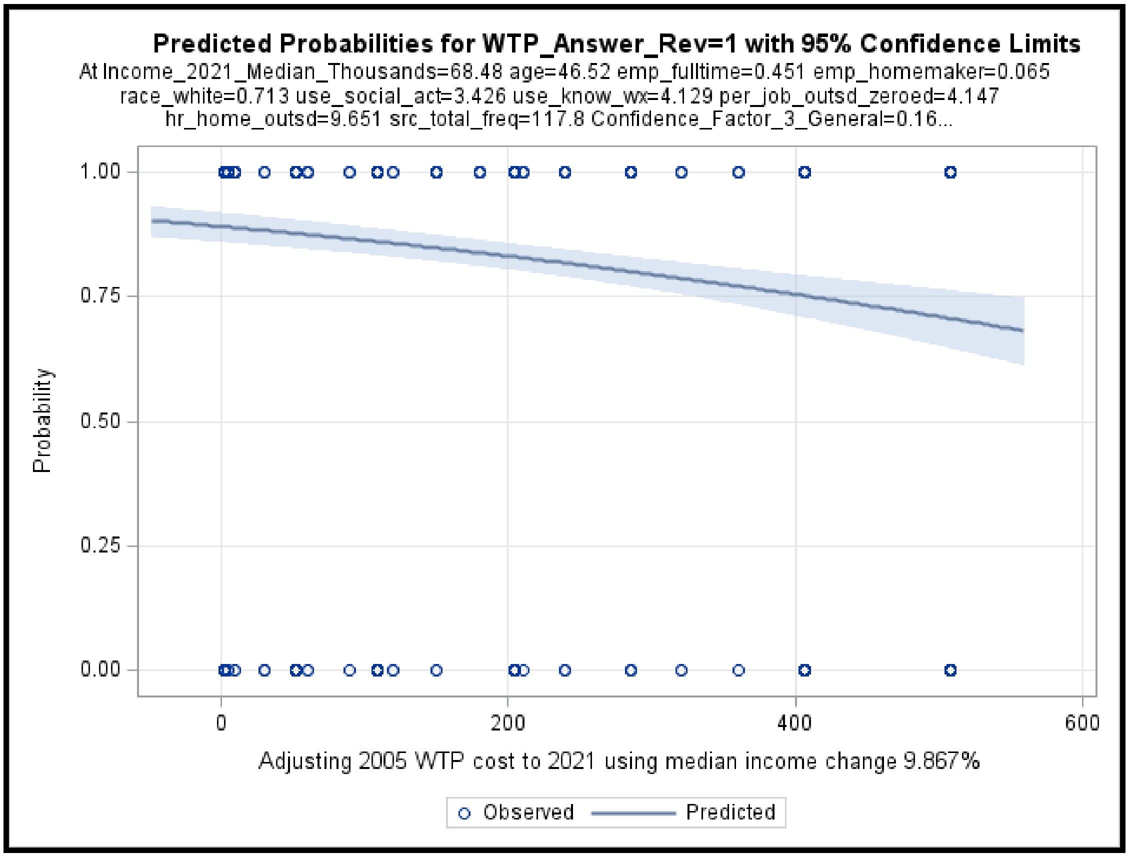

Figure 27: Probit Selection Model Fitted Curve

Using average values for all independent variables included in the regression model, we created a synthetic dataset to run in SAS for model predictions as a step in the probit modeling. In this dataset we entered the price offer level for a range of values to determine the price level where 50% would be predicted to respond yes and 50% would respond no. The median fitted value using this approach is $898.50 (rounded to the nearest penny).

To explore inter-subject differences in values we repeated the process discussed above for estimating the median value but changed the input level for the single attribute of personal weather impacts as this was one of the most significant explanatory variables in the probit model. The fitted median WTP for individuals with personal impacts of 0 is approximately $769.42. For individuals with all personal impacts, or personal impacts = 4, their median fitted price would be approximately $1,298.06.

To examine the potential impact of model form on the mean WTP estimate we ran the exact same backward selection model shown in Table 47 using a logit specification rather than a probit specification. All the same parameters were significant and of the same sign as in the probit model. We then calculated the median WTP using the same synthetic dataset approach. The median WTP using the logit specification was $891.32 (rather than the $898.50 using the probit model). This represents only a 0.80% (that is

8/10 of 1%) difference leading us to conclude that model specification (with respect to probit versus logit does not make a significant difference).

7.4. National aggregation

Building on Figure 27, Figure 28 extrapolates the confidence intervals to the 50% Yes/No line to derive a confidence interval on the median WTP. First, in Figure 28 we have extended a lower and upper limit line to intersect the 0.50 line. We then used a graphics editing program's grid to calculate values on the horizontal axis.

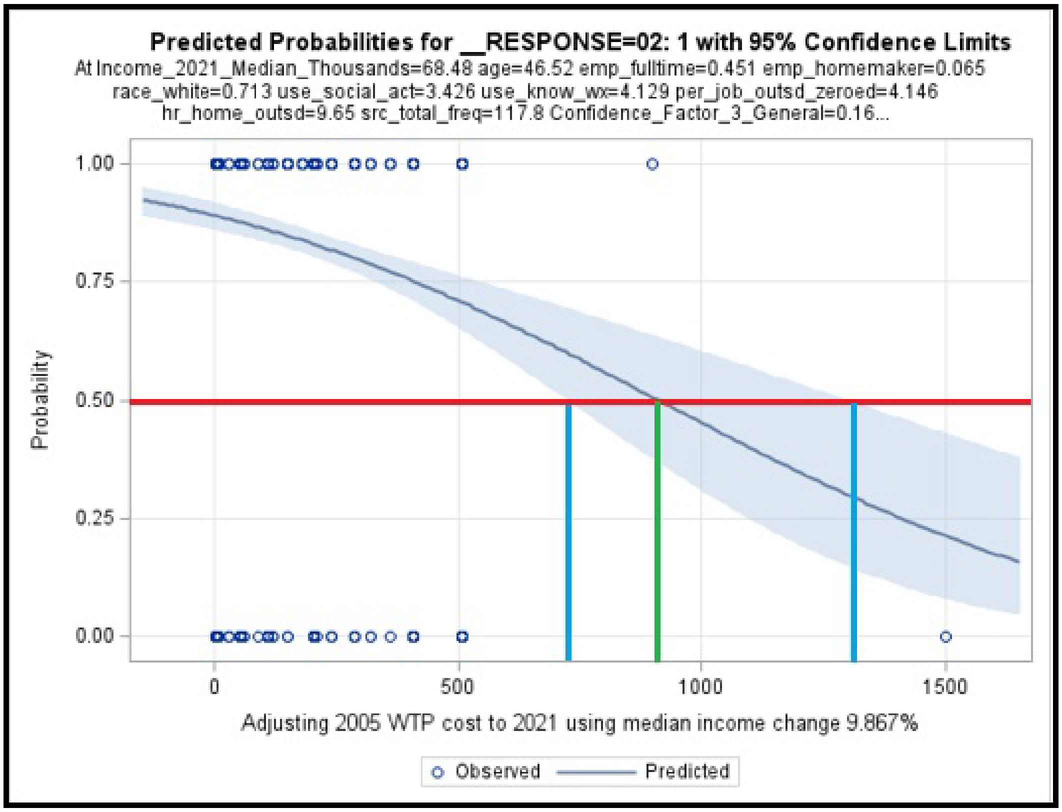

Figure 28: Fitted Demand Curve from Probit Selection Model Extrapolated to Median WTP 95% Confidence Interval

For the time being ignoring all the limitations of this question as a valid stated preference elicitation, we use the median point estimate to aggregate to a national WTP for current forecast information. The green vertical line is the median WTP, the blue lines show the lower and upper bound of the 95% CI. These values are shown in Table 48. The $898.50 value of the point estimate was taken from the synthetic dataset calculation described above. While shown to two digits, given that these are the median value (rather than the mean value) and the confidence intervals as visually derived from the SAS output it is probably more reasonable to round to the nearest increments as shown in the lower row. Undoubtedly this could be derived analytically from the regression estimates at some point in the future.

Table 48: 95% Confidence Interval for Median WTP			
	Lower Bound	Point Estimate	Upper Bound
Derived WTP 95% CI	$709.98	$898.50	$1,300.14
WTP 95% CI (Rounded)	$700	$900	$1,300

The WTP confidence interval is based on many assumptions including that the sample is representative of the U.S. population and that the median value reflects the average WTP. We thus take $898.50 as the average U.S. WTP for current forecasts' information in 2021 with a $709.98–$1,300.14 95% confidence interval.

Table 49 shows the aggregation of the WTP values from the 2006 and 2022 surveys. As noted above this is based on the assumption that the median value is equal to the average and that this is representative of the general population. This is aggregated assuming that the WTP value derived in the survey is for the household and not the individual. We adjust for population and household size as well as the percent of individuals indicating that they do not use weather information (see Table 17). In the second column we replicate the analysis from Lazo et al. (2009). In the third column, the CoFU1 column information is taken from the 2009 BAMS manuscript and then adjusted to 2021 dollars using the consumer price index (CPI) as well as adopting 5.35% as the portion of the population not using forecasts considering results from the three surveys discussed in Table 17. The last three columns present aggregations for the 2022 survey results (in 2021 dollars) indicating the central point estimate and upper and lower bounds of the 95% confidence interval from Table 48.

Table 49: U.S. National Aggregtation of WTP for Current Forecast Information

Survey	**CoFU1 (from BAMS paper)**	**CoFU1 (from BAMS Paper)**	**CoFU2**	**CoFU2**	**CoFU2**
			Point Estimate	Lower Bound	Upper Bound
Year	2006	2006	2022	2022	2022
Population			332,403,650	332,403,650	332,403,650
Household Size			2.77	2.77	2.77
Number of Households	114,384,000	114,384,000	120,001,318	120,001,318	120,001,318
Percent Not Using Forecasts	3.62%	5.35%	5.35%	5.35%	5.35%
Households Using Forecasts	110,243,299	108,264,456	113,581,247	113,581,247	113,581,247
Per HH WTP	$285.64	$285.64	$898.50	$709.98	$1,300.14
Total U.S. Value of Current Forecasts (Current Dollars	$31,489,895,983.49	$30,924,659,211.84	$102,053,204,928.03	$80,640,346,850.63	$147,671,902,571.17
CPI Adjustment to 2021		1.41668			
Total U.S. Value of Current Forecasts (Billions)	$31.5	$43.8	$102.1	$80.6	$147.7

Using a value of 5.35% of the population as not using forecasts, this generates an estimate of the value of current forecasts (in 2021) of $102.1 billion dollars with a $80.6–$147.7 billion 95% confidence interval.

7.5. Average WTP calculated as the area under the demand curve

As an alternative approach to deriving average Willingness-to-Pay for current forecasts, we generated a synthetic dataset with price offers from $0 to $6,000 at $1 increments and used the SAS regression analysis of the selection model (Table 47) to generate fitted probabilities at each dollar level. The probabilities at each dollar level are plotted in Figure 29. While the probabilities were generated out to $6,000, at $3,000 the probability was only 0.22% and continued to decline after that so we only graph this out to $3,000.

This is a demand curve with price on the horizontal axis. As these probabilities are calculated in $1 increments, we believe we can treat the probability at each offer price as the marginal Willingness-to-Pay and aggregate the area under the curve as the total benefit of current forecast information. This total is the shaded green area under the curve and totals to $938.82.

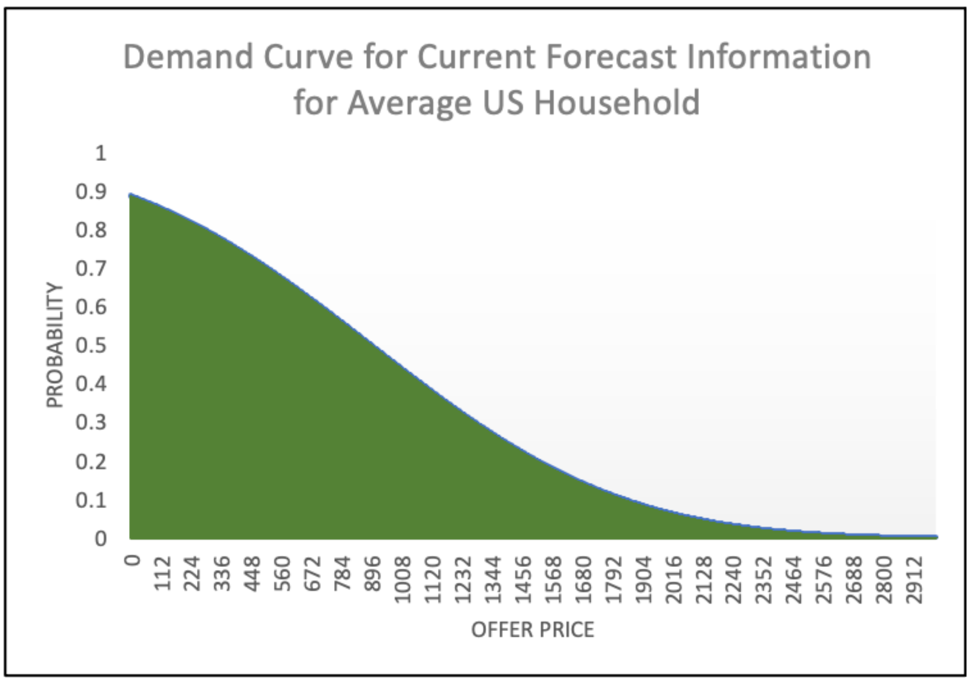

Figure 29: (Inverse) Demand Curve for Current Forecast Information for Average U.S. Household

This may be a better estimate of average WTP than assuming the median as the average as it is more consistent with the basic concept of WTP as the total area under the marginal benefit curve. It is well within the 80% CI discussed above and only 4.43%

larger than the $898.50 value used in the aggregation above. We retain the aggregation using the $898.50 value to be somewhat conservative.

8. Discussion and future work

8.1. Summary

Rather than recap each and every finding, we mention two that we feel are specifically relevant to the Weather Enterprise and related to key findings from Lazo et al. (2009).

- First, with respect to the weather information sources and frequency, the results of the 2022 survey largely supported the 2006 findings with some key differences. These include an understandable shift in sources from more "traditional" sources such as print and TV to more "modern" electronic and social media sources. In terms of total annual forecasts accessed by the public this has increased slightly from roughly 300 billion a year to roughly 317 billion a year mainly due to the increase in population.
- Second, with respect to the value of current forecasts and aggregation to a national value we derive a significantly larger estimate of per household benefit of current forecasts in 2022 ($898) than we did in 2006 ($286). This is related in part to limitations on the valuation question itself and the inherent difficulty in eliciting such values. Even while fully recognizing the limitations of the elicitation and analysis, it is notable that we generate an estimate of the national value of current forecasts (in 2021) of $102.1 billion with a $81–$148 billion 95% confidence interval. At roughly 32 cents per forecast, while large in aggregate this seems a viable estimate. Future work in improving this benefit estimate seems potentially important for the weather enterprise for continued funding and public support.

8.2. Future work

There is a plethora of future research that could use the current dataset as well as build on findings discussed here. This includes but is not limited to the following:

- Alan Stewart's work on weather salience (Stewart 2009) was supported and extended in the 2006 survey (Stewart et al. 2012). Although the question as asked in the 2022 survey had an apparent coding error (missing the middle response option) the data still appear robust and should be further explored.
- The current report has not examined anything related to the decision scenarios or communication of uncertainty included in the survey. Analysis presented in Morss et al. (2008, 2010) shows that these are important areas in the weather information process and these data should be analyzed.
- As suggested by analysis presented in sections 10.2 and 10.3, using the climate zone data suggests support for the findings in Stewart et al. (2012) relating weather experiences and perceptions to climatic zones.
- As suggested by initial analysis using the "weather impact scale" discussed in section 6.1 and analysis on the scale in Table 15, people's stated experience with

weather impacts relates to their use of weather information and their rating of the importance of this information. Further use of the responses to this question beyond the simple initial scale used here seems warranted.

- The 2022 survey included five new sets of questions related to cultural risk theory (CRT), vulnerability, numeracy, political leanings, and risk preferences that have only been touched on in the current report. For instance, the finding that the CRT measure "individualist" is highly and negatively correlated with Willingness-to-Pay for current forecasts (Table 47) suggests the importance of world views on values for weather information.
- Future work will also focus on analysis of specific concepts and questions such as measures of confidence and an in-depth analysis of 2022 WTP values using the five new factors/concepts included in the 2022 survey. This will also entail a closer look at the validity of the WTP elicitation approach and developing a concept to improve this elicitation with a future survey.

9. Acknowledgments

We would like to thank Paul Higgins, Associate Executive Director of the American Meteorological Society and Director of the American Meteorological Society's Policy Program, for providing support for survey implementation. We thank the staff at Dynata, especially Jenna Grodzicki, for their implementation of the survey and response to follow-up questions. We thank our colleagues Alan Stewart, Rebecca Morss, and Julie Demuth for input on the survey revisions as well as the original work on the Communicating Forecast Uncertainty project. We also thank participants in the American Geophysical Union 2023 meetings for input on a poster presented there and participants at the American Meteorological Society 2023 and 2024 annual meetings and the 2023 AMS Summer Community Meeting for input during oral presentations. We thank Labanyalata Roy (Middle Tennessee State University) and Rodney Beard, Ph.D., for editing and peer-review input. Finally, we thank Andrea Schein for editing the final draft report. All remaining errors are the author's.

10. Appendices

10.1. *Dataset cleaning and appending*

10.1.1. *Raw data CoFU1*

Data files will be made available once the primary authors have completed their planned research based on this survey. The primary CoFU1 data is an Excel spreadsheet with the raw data from 2006. Developed from the raw data, the CoFU1 SAS database was appended to the CoFU2 (2022) data to create the merged dataset. This file was constructed from the original raw data from the 2006 implementation. The file names from this dataset were used to rename the variables in the 2022 dataset. This dataset includes 243 variables across 1,520 observations. A number of minor adjustments were made to the 2006 dataset prior to appending with the 2022 data.

- A new variable CoFU_Version was added creating an indicator variable to indicate which survey implementation the observation is. CoFU_Version = 1 for the 2006 implementation and = 2 for the 2022 implementation (the corresponding variable was created for the 2022 data).
- To fill out the sociodemographic information on length of residence, the variable yrs_residence_no_miss was created replacing 3 missing values with the median of nonmissing values of 22 years.
- The variable "dAgeRe-coded" was created assigning individuals into one of the six age brackets defined by Dynata for the sociodemographic screening for the 2022 survey (see the age variable in Table 3).
- The variable "per_job_outsd" was recoded to "per_job_outsd_re-coded" to replace responses of "12" to missing. The response "12" represented "not applicable to me."
- A number of variables were dropped from the 2006 dataset including "finish18," "round," "ssi_pid," and "over_18," which were all survey control variables from the 2006 implementation that were not needed for further analysis.
- The categorical income variable "income2005" was dropped as the continuous variable "income" converted that to the dollar level and included fitted income for those individuals from 2006 that did not provide a response to the income question. Additional explanation of the treatment of income variables and renaming is included in section 5.3.
- In examining the data, it was determined that responses to Q24 (asking "On average, year round, how many hours per week do you spend traveling outside to and from work or school in a mode that could be affected by the weather?") in CoFU1 were never coded numerically. Responses were entered as text and numerical variable in the dataset was simply an indicator variable as to whether or not an individual had responded. For merging the datasets, we recoded the text responses into hours per week. To do so a number of judgment calls were made about how to convert to numbers including taking the simple average when a range was entered (e.g., 2–4 hours a week was recoded as 3 hours). Eight responses indicating more than 168 hours a week were converted to the median of the subsample (7.0 hours) indicating a response once the other responses had been quantified. In addition, three verbal responses were also recoded to the median of the subsample indicating

a response once the other responses had been quantified. This adjustment was made to the SAS dataset "CoFU_1_final_data," which was the final dataset from the CoFU1 analysis.

- In the CoFU1 dataset, for the variables used in forecasts (e.g., "use_dress"), we recoded "6" responses indicating "not applicable to me" to "1" indicating "rarely or never" to be consistent with CoFU2 data. In the CoFU1 survey the "NA" option indicates "9," but was coded in the dataset as "6."

10.1.2. Raw data CoFU2

The raw data provided from Dynata on May 5, 2022 were imported into SAS Enterprise Guide Version 7.15[1] (and some earlier versions) for data cleaning and analysis. This file includes 267 variables, which includes several variables coded by Dynata for quality control and survey flow. The file includes 1,202 observations. For the CoFU2 dataset we made several changes to variables to recode them to be consistent with CoFU1 and to convert a number of categorical responses into continuous or other more meaningful or useful responses (e.g., indicator variables as needed for analysis). These included the following:

- The variable "CoFU_Version" was created with the value of "2" for all 2022 respondents.
- A number of variables were dropped including "psid," "dTrack," "Status," "Date," "Start_date," "noanswerQ33_r999," "noanswerQ37_r999," and "Time Using LOI." A series of 8 "dFlag" variables were also dropped as these were all Dynata survey control variables used for identifying random responding, illogical or inconsistent responding, or overuse of item nonresponse from the 2022 implementation that were not needed for further analysis.
- Due to the two-step process in implementation the raw data included two variables on the price (NWS_Cost) offered to respondents (one for the soft launch and one for the full implementation). A new single variable of "NWS_Cost" was created from these to use in the analysis.
- As in the 2006 dataset, a variable "WTP_Answer_Rev" was created from the responses to the WTP question so that responses of "worth more than $N a year to my household" and "worth exactly $N a year to my household" are coded as "1" and responses of "worth less than $N a year to my household" are coded as "0."
- The source of uses was recoded from a categorical variable into a continuous variable of times per month as in CoFU1. And a total frequency of use was calculated from these new variables.
- Education was recoded from a categorical variable into a continuous variable of number of years of schooling. We then recoded the 21 responses of "do not want to answer" to the median value of 14 years.
- For the variable on household size, we replaced 95 missing responses with a median value of "2."

[1] Full version number as indicated by SAS is HF9 (7.100.5.6226) (32-bit).

- For the variable on employment, we created indicator variables from numeric responses and recoded responses of “prefer not to answer” to median value of “emp_fulltime.”
- For the variable on years living in their current residence we replaced 3 missing values with the median value of 17 years.
- For the variable on education, we recoded the 21 responses of “do not want to answer” to the median value of 14 years.
- For the variable hr_home_outsd for those respondents who indicated this did not apply to them (n = 351), we recoded their responses to “0” hours a week.
- In both datasets we recoded the variables “per_leis_outsd” and “per_job_outsd” to include new variables “per_leis_outsd_re-coded” and “per_job_outsd_re-coded” that treats the “not applicable to me” responses as missing. We also created new variables “per_leis_outsd_zeroed” and “per_job_outsd_zeroed” that treat the “not applicable to me” responses as zero hours or zero percent (response level “1”).
- In the CoFU2 dataset, for the variables used in forecasts (e.g., “use_dress”), we recoded “9” responses indicating “not applicable to me” to “1” indicating “rarely or never” to be consistent with CoFU1 data.

For purposes of data analysis we created indicator variables for male (male = 1 ; nonmale = 0) and female (female = 1; nonfemale = 0).

For the variables Q14 and Q15, which explored individuals’ interpretation of forecast uncertainty following prior work by Gigerenzer and Murphy, in CoFU we elicited open-ended comments from 100 respondents for each question and then provided categorical response options to the rest of the sample. For CoFU2, the sample was split equally between the open-ended and close-ended alternatives (for those individuals who do use forecasts). The close-ended alternatives did include the option of providing an open-ended response as well, which some respondents did. In addition, we recoded the numbering of the categorical responses used in CoFU2 to match those used in CoFU1.

10.2. Comparison of probit and logit models on "use forecasts"

Table 50: Comparison of Probit and Logit Regression on Use Forecasts

Modeled on Probability of "Yes"

		probit		logit	
	Parameter	**Estimate**	**Pr>ChiSq**	**Estimate**	**Pr>ChiSq**
	Intercept	0.141	0.781	-0.064	0.952
	CoFU_Version	-0.477	<.0001	-0.990	<.0001
Sociodemographics	Income (2021_Median_Adjusted_Thousands)	0.002	0.103	0.004	0.093
	Yrs in current residence	0.004	0.149	0.008	0.156
	Age (yrs)	0.005	0.195	0.009	0.218
	Female (no = 0; yes = 1)	0.184	0.038	0.359	0.047
	Household size	0.003	0.922	0.002	0.973
	Education (yrs)	0.046	0.017	0.090	0.026
Employment	Fulltime	0.042	0.875	0.063	0.913
	Parttime	-0.067	0.802	-0.186	0.746
	Retired	0.23	0.42	0.466	0.447
	Homemaker	0.016	0.956	-0.023	0.969
	Student	0.085	0.789	0.114	0.865
	Unemployed	-0.018	0.949	-0.041	0.946
Race	White	0.592	0.008	1.264	0.008
	Black	0.402	0.089	0.876	0.080
	Latino	0.27	0.211	0.676	0.148
	Asian	0.642	0.029	1.369	0.029
	Native	0.648	0.104	1.281	0.127
	Other	0.378	0.264	0.835	0.234
Time allocation	Percent of job outside	-0.007	0.644	-0.010	0.763
	Hours traveling to work	0.003	0.342	0.007	0.322
	Percent of leisure time outside	0.061	0.002	0.129	0.001
	Hours at home spent outside	0.004	0.207	0.010	0.180
		Percent Concordant = 72.9% / Max-rescaled R-Square = 0.107		Percent Concordant = 72.8% / Max-rescaled R-Square = 0.107	

10.3. Climate zones and use of forecasts

As an exploratory analysis we conducted a probit regression on “use forecasts” including indicator variables for Köppen main climate groups. “The Köppen climate classification scheme divides climates into five main climate groups: A (tropical), B (arid), C (temperate), D (continental), and E (polar).”[1] Dr. Alan Stewart coded the data for climate zone for respondents based on zip codes. None of the respondents resided in a “polar” zone. We developed indicator variables for the remaining four climate zones (0 = not in the zone; 1 = in the zone). At this time, we only had this information for the CoFU2 respondents. Table 51 replicates the probit analysis on “do you use forecasts” for the CoFU2 respondents as in Table 16 and then adds three climate zone indicator variables. Climate zone B (arid) is the excluded indicator variable so the results on the other indicator variables are relative to this excluded variable. Also shown in Table 51, after each climate zone label is the percent of the sample living in that climate zone (i.e., 3.85% of the 1.194 respondents for whom we have climate zone information live in a tropical climate zone).

Based on these regression results, compared to those living in arid regions, those living in temperate or in continental climate regions use forecasts significantly more after controlling for the other sociodemographic and behavioral variables included in the model. At this time, we have not calculated the numerical difference based on the probit model—only that there are significant climate zone differences in forecast use. There is not a significant difference in use between those in tropical and arid climate zones.

[1] Source:
https://en.wikipedia.org/wiki/K%C3%B6ppen_climate_classification#:~:text=The%20K%C3%B6ppen%20climate%20classification%20scheme,indicates%20the%20level%20of%20heat.

Table 51: Probit Regression on Use Forecasts (Yes = 1; No = 2)—and Climate Zones—for CoFU2 only

	Parameter	Estimate	Pr>ChiSq	Estimate	Pr>ChiSq
	Intercept	-0.657	0.217	-0.925	0.105
Climate Zone Dummy	Climate Zone A (Tropical) (3.85)			0.169	0.582
	Climate Zone B (Arid) (8.79)			Excluded indicator variable	
	Climate Zone C (Temperate) (62.9)			0.304	0.095
	Climate Zone D (Continental) (24.46)			0.448	0.032
Sociodemographics	Income (2021_Median_Adjusted_Thousands)	0.001	0.454	0.001	0.384
	Yrs in current residence	0.003	0.448	0.001	0.762
	Age (yrs)	0.006	0.167	0.007	0.116
	Female (no = 0; yes = 1)	0.038	0.743	0.027	0.817
	Household size	-0.003	0.928	0.005	0.882
	Education (yrs)	0.036	0.144	0.034	0.167
Employment	Fulltime	0.198	0.254	0.210	0.236
	Parttime	-0.032	0.873	-0.038	0.852
	Retired	0.274	0.195	0.229	0.283
	Homemaker	0.017	0.940	-0.001	0.995
	Student	0.140	0.655	0.169	0.595
Race	White	0.561	0.054	0.529	0.072
	Black	0.240	0.430	0.194	0.528
	Latino	0.516	0.057	0.560	0.042
	Asian	0.684	0.068	0.701	0.062
	Native	0.748	0.206	0.766	0.198
	Other	0.013	0.977	-0.067	0.883
Time allocation	Percent of job outside	0.001	0.961	0.000	0.983
	Hours traveling to work	-0.001	0.726	-0.002	0.575
	Percent of leisure time outside	0.060	0.015	0.058	0.019
	Hours at home spent outside	0.009	0.072	0.009	0.058
	N = / Percent Concordant / Max-rescaled R-Square	1202/ 70.1 / 0.093		1194/ 70.3 / 0.098	

10.4. Climate zones and weather impact scale

Similar to 10.3, as an exploratory analysis we regressed "weather impact scale" on our standard set of explanatory variables now including indicator variables for Köppen main climate groups as described above. Climate zone A (tropical) is the excluded indicator variable so the results on the other indicator variables are relative to this excluded variable. Also shown in Table 52, after each climate zone label is the percent of the sample living in that climate zone (i.e., 3.85% of the 1.194 respondents for whom we have climate zone information live in a tropical climate zone).

Based on these regression results, compared to those living in tropical regions, those living in temperate climate regions experienced significantly more weather impacts after controlling for the other sociodemographic and behavioral variables included in the model. There is not a significant difference in impacts between those in tropical zones and those in arid or continental climate zones.

Table 52: Probit Regression on Weather Impact Scale and Climate Zones–for CoFU2 only					
	Parameter	**Estimate**	**Pr>ChiSq**	**Estimate**	**Pr>ChiSq**
Intercepts	Intercept	-2.672	<.0001	-2.992	<.0001
	Intercept	-2.395	<.0001	-2.715	<.0001
	Intercept	-1.996	<.0001	-2.314	<.0001
	Intercept	-1.194	0.000	-1.509	<.0001
Climate Zone Dummy	Climate Zone A (Tropical) (3.85)			Excluded indicator	
	Climate Zone B (Arid) (8.79)			0.141	0.509
	Climate Zone C (Temperate) (62.9)			0.332	0.075
	Climate Zone D (Continental) (24.46)			0.222	0.258
Sociodemographics	Income (2021_Median_Adjusted_Thousands)	-0.001	0.147	-0.001	0.134
	Yrs in current residence	-0.002	0.265	-0.002	0.297
	Age (yrs)	0.026	0.721	0.025	0.734
	Female (no = 0; yes = 1)	-0.010	0.001	-0.010	0.001
	Household size	0.109	<.0001	0.110	<.0001
	Education (yrs)	0.039	0.008	0.041	0.005
Employment	Fulltime	-0.122	0.312	-0.114	0.349
	Parttime	0.021	0.884	0.029	0.839
	Retired	0.245	0.081	0.246	0.080
	Homemaker	-0.004	0.981	0.011	0.945
	Student	0.160	0.452	0.175	0.410
Race	White	0.095	0.520	0.085	0.565
	Black	0.065	0.692	0.044	0.788
	Latino	0.080	0.542	0.099	0.456
	Asian	-0.017	0.936	-0.009	0.965
	Native	0.277	0.264	0.249	0.316
	Other	-0.208	0.506	-0.220	0.484
Time allocation	Percent of job outside	0.096	<.0001	0.096	<.0001
	Hours traveling to work	-0.001	0.626	-0.001	0.521
	Percent of leisure time outside	0.066	<.0001	0.066	<.0001

Table 52: Probit Regression on Weather Impact Scale and Climate Zones–for CoFU2 only					
	Hours at home spent outside	0.003	0.153	0.003	0.154
	n = / Percent Concordant / Max-rescaled R-Square	1194/ 70.2 / 0.233		1194 / 70.4 / 0.237	

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