CESifo WORKING PAPERS

10049
2022

October 2022

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CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
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CESifo *Working Paper No. 10049*

The Social Value of Predicting Hurricanes

Abstract

Hurricanes are among the costliest natural disasters in the world, with a significant portion of their impact linked to the accuracy of their forecasts. In this paper, we estimate the economic impacts of the official hurricane forecasts in the US and develop a new approach for measuring the social value of forecast improvements. We find that pre-landfall federal protective expenditures exponentially increase with the forecast wind speed and with the degree of uncertainty about the forecast. Correspondingly, we find that forecast errors are costly: underestimating wind speed results in damages and post-landfall recovery spending up to an order of magnitude larger than if the forecast had been accurate. Our main contribution is to develop a new theoretically-grounded approach for estimating the marginal value of information and we apply it to establish the social value of improving hurricane forecasts. On the margin, the value of hurricane information is large and has increasing returns. We find that forecast improvements since 2009 reduced total costs associated with hurricanes by 5%, totalling hundreds of millions of dollars per hurricane. When aggregated, these benefits are over an order of magnitude greater than the cumulative budget for operating and improving the hurricane forecast system.

JEL-Codes: Q540, Q580, C530.

Keywords: natural disasters, hurricanes, tropical cyclones, forecasts, information, climate change.

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October 22, 2022
We thank Diego Cardoso, Luc Esprabens, Mike Huang, Steven Koller, Brian McNoldy, and Juan Carlos Villaseñor-Derbez for excellent research assistance. We are also grateful for the guidance and support provided by Andrea Schumacher and the staff at the Hurricane Forecast Improvement Program and the Weather Program Office at the National Oceanic and Atmospheric Administration, especially to Gina Eosco and Frank Marks. This manuscript benefited from comments from Christopher Costello, Gabriel Lade, Derek Lemoine, Cynthia Lin-Lawell, Christopher Parmeter, Christopher Timmins, Jinhua Zhao, and numerous seminar participants. Funding for this project was provided by Grant NA20OAR4320472 from the National Oceanic and Atmospheric Administration.

1 Introduction

Hurricanes are among the costliest natural disasters in the world. In the US, individual hurricanes regularly cause tens of billions of dollars in damages, totaling over $1 trillion since 1980 (Weinkle et al., 2018; NOAA Office for Coastal Management, 2022). Both academic research and US government projections indicate that hurricane damages will likely grow to more than $50 billion a year in the long run, exceeding 0.25% of GDP (Mendelsohn et al., 2012; US Congressional Budget Office, 2019).

One of our key tools for mitigating the destructive impacts of hurricanes is forecasting. Through the National Hurricane Center (NHC), the US government funds the operation, development, and improvement of hurricane forecast products. Prior to landfall, forecasts provide information on the expected strength and path of a hurricane, and they offer measures of forecast uncertainty. Following the devastating 2004 and 2005 hurricane seasons hurricane forecasting came under intense scrutiny which led congress to create the Hurricane Forecast Improvement Program (HFIP) in 2007.[1] The HFIP has a budget of approximately $25 million per year and goals of improving forecasts of storm track (i.e., location of the storm center) and wind speeds (Gall et al., 2013).

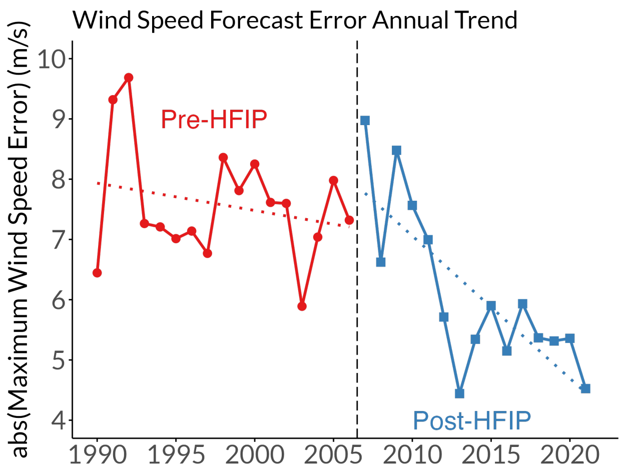
By any measure, the efforts to improve the forecast have been highly successful. Figure 1 shows that prior to the HFIP in 2007, hurricane wind speed forecast errors were declining by 0.05 meters per second each year, or about a 0.8% annual improvement. Since the inception of the HFIP in 2007, there has been a dramatic increase in the quality of the forecasts. Hurricane wind speed forecasts errors have been declining by 0.24 m/s each year since 2007, or 4% annually.[2] Despite the long-running existence of hurricane forecasts and these recent dramatic improvements, there is limited evidence of the economic value of hurricane forecasts or the social benefits accrued from previous and future investments to improve their accuracy.

In this paper, we fill this gap by measuring the economic impacts of hurricane forecasts, providing one of the first estimates of the social value of the US hurricane forecast system and the marginal value of increasing hurricane forecast precision. Using the actual models underpinning the hurricane forecast system, we develop a novel dataset of county-level forecasts of hurricane wind speed and precipitation 24, 48, and 72 hours before landfall, as well as the *ex ante* uncertainty embedded in each forecast. Our dataset accounts for about

[1] Hurricane Charley, which struck in 2004, was the strongest hurricane to reach land in the US since 1992. In 2005, Katrina struck, becoming one of the costliest hurricanes in US history. That same year, Rita and Wilma (two of the strongest Atlantic storms ever recorded at that time) also struck.

[2] Historically, it has been much more difficult to forecast the intensity a storm will have than to forecast the track it will follow (Resnick, 2018). This is due to a combination of many factors, including previously poor computational resolutions, and difficulties in predicting which storms will go under rapid intensification as they near landfall (Enten, 2017; Norcross, 2018).

Figure 1: Trends in Atlantic Hurricane Wind Speed Forecast Errors Before and After the Hurricane Forecast Improvement Program.



Note: The data are the absolute values of forecasting errors for wind speed, averaged across 24, 48, and 72 hour ahead forecasts for all Atlantic tropical cyclones in a given year. The data are reported by the National Hurricane Center. Dotted lines are the best linear fits to each time series. The vertical dashed line is when the Hurricane Forecast Improvement Program was implemented in 2007. The archive for official historical records data is available at: https://www.nhc.noaa.gov/verification [Last visited on July 26, 2022].

two-thirds of the landfalling hurricanes in the US from 2005 to 2020, including all hurricanes that either were classified at Category 3 or above (maximum wind speeds greater than 50 meters per second [m/s]), or generated at least $20 billion in damage.[3] With these new data, we (1) estimate how emergency federal expenditures for protecting against hurricane damages respond to forecast information, (2) estimate the costs of forecast errors in terms of damages and increased expenditures for after-storm recovery, and (3) – our primary contribution – develop a new theoretically-grounded approach to recover the *ex ante* marginal value of forecast improvements, a quantity we call the value of information. Our method accounts for unobserved protective actions taken prior to landfall, and it is flexible enough to be applied to forecasts of any kind of hazard.

How do forecasts create economic benefits? We first show that hurricane forecasts influence how the government allocates emergency protective funding across counties before

[3]We focus on larger and more damaging hurricanes because of computational constraints to simulate the hurricane forecast models described in Section 3. While all hurricanes produce life-threatening winds, hurricanes rated Category 3 and higher are known as major hurricanes, and they can cause devastating to catastrophic wind damage and significant loss of life simply due to the strength of their winds. We included lower-category storms (i.e., Ike, Sandy and Florence) because neither deadly hurricane-related hazards, such as storm surge and tornadoes, nor damages from a hurricane are fully captured by a given storm's category. See the NOAA categorization criteria at https://www.nhc.noaa.gov/aboutsshws.php [Last visited June 06, 2022].

hurricanes reach land. We show that pre-landfall, federal protective funding was targeted toward areas predicted to experience higher wind speeds. Counties that were forecast to experience Category 1 winds (33–42 m/s) received over double the protective funding made available to areas where forecasts indicated that lower, sub-hurricane force wind speeds were likely. Counties that were forecast to be hit by Category 2 winds (43–49 m/s) received over an order of magnitude more funding as those forecast to face sub-hurricane force winds. We also find that, conditional on the forecast wind speed, emergency funding has tended to be allocated to places where wind speed forecasts' were most uncertain. Unlike wind speed, however, we find little to no relationship between precipitation forecasts and the amount of protective emergency funding allocated to a county. This result is likely because the Saffir-Simpson categories commonly used for classifying hurricanes are based entirely on wind speed, as well as the way in which hurricane strength has historically been communicated (Kantha, 2006; Murnane and Elsner, 2012).

Once we establish that protective actions are guided by wind speed forecasts, we then estimate the consequences of forecast errors. We find that there were no additional costs from overestimating wind speed relative to a perfect forecast, but exponential increases in damages and post-landfall federal recovery costs from underestimating wind speed.[4] When the hurricane was stronger than the forecast, affected counties incurred larger property, crop, and mortality damages. These same counties also used larger amounts of emergency recovery spending allocated after the hurricane to rebuild a disaster area. Conditional on realized wind speed and precipitation, underestimating wind speed by 4 m/s doubles damages relative to a perfect forecast, and underestimating wind speed by 15 m/s increases damages by over an order of magnitude. Unlike wind speed, we do not find a clear effect of precipitation forecast errors on damages or recovery spending. This result is consistent with the fact that forecasts can only affect damages and after-landfall recovery spending through their effect on before-landfall protective actions, and our findings that federal protective expenditures do not respond to precipitation forecasts.

Finally, the main contribution of the paper is we develop a new theoretically-grounded approach to measure the marginal net benefits of improving forecasts, a quantity we call the *value of information*. Our approach begins with a model of a representative agent who has access to a hurricane forecast and aims to minimize the total expected costs of before-landfall protective expenditures, hurricane damages, and after-landfall expenditures to rebuild and recover. We use the model to derive a sufficient statistic for the value of information, which

[4]This is not to say that there are no costs from overestimating hurricane intensity. Overestimates will lead to excessive protective actions and costs. For example, overestimating hurricane intensity may lead mothers to cancel prenatal care appointments which worsens birth outcomes (Hochard et al., 2021).

we define as the total cost reduction from a 1 unit decrease in the forecast's *ex ante* standard deviation.[5] The sufficient statistic for the value of information is simply the product between a monomial function of the forecast's *ex ante* standard deviation, and the covariance between the forecast's squared error and the sum of damages and recovery spending. This quantity can be identified by simply regressing the sum of damages and recovery spending on the squared error in the forecast. An important feature of this approach is it does not hinge upon us observing pre-landfall protective actions, freeing us from pinning down precisely how agents might protect themselves against a hurricane.

Overall, we find that for the average county, reducing wind speed forecast uncertainty by 10% – the observed improvement every two years – is worth $40,000 in reduced protective spending, damages, and recovery spending. Moreover, we find that there are increasing returns to forecast improvements for the average county and forecast in our sample. Our headline policy result is that the increased forecast precision since the inception of the HFIP has generated large net benefits: the forecast improvements since 2009 have led to $7 billion of avoided damages and costs, or twenty times the cumulative 2009–2020 NHC budget that funds the operation of the forecasting system and the research conducted to improve it. The combination of large marginal net benefits and increasing marginal returns to further forecast improvements also suggests that the optimal level of hurricane forecast improvement funding is higher than current levels.

Our paper adds to a sparse and relatively new literature on environmental forecasts. In two early papers, Lave (1963) estimates the value of perfect weather forecasts for California raisin growers, while Craft (1998) uses a quasi-experimental approach to estimate the value of the existence of storm-warning stations in the Great Lakes. More recently, Shrader (2021) provides a new method for estimating damages accounting for adaptation and finds that El Niño-Southern Oscillation (ENSO) forecasts have major effects in the North Pacific albacore tuna fishery. Other papers have shown routine precipitation forecasts are valuable to construction firms (Downey et al., Forthcoming), and for avoiding winter automobile accidents (Anand, 2022). Two recent papers on temperature and pollution are closest to ours in spirit. Shrader, Bakkensen and Lemoine (2022) evaluates the consequences of errors in routine temperature forecasts and and finds that the gross avoided mortality benefits of cutting errors

[5] Uncertainty in a hurricane forecast comes from the fact that the atmosphere consists of features across different scales, from large and strong (e.g., sea surface temperature, pressure systems and fronts) to small and weak (e.g., localized dry vertical atmosphere layers and wind shear). These features evolve and interact with each other to determine the track and intensity of hurricanes. In general, when larger and stronger features, which are easier to measure and predict, are the main drivers for steering and strengthening hurricanes, the forecast tends to be more straightforward and more certain (Kalnay, 2003). When subtle features are more prevalent, they may not even be captured in the forecast model, making the overall forecast less certain (Kalnay, 2003).

in half – ignoring adaptation costs – are billions of dollars per year. Barwick, Li, Lin and Zou (2020) estimates the value of air pollution monitoring in China – accounting for some adaptation costs by directly estimating them – and finds that the benefits of the monitoring system exceed the costs by an order of magnitude.

We contribute to this literature in several ways. First, we provide a novel overall assessment of the US hurricane forecast system and improvements in its accuracy.[6] We find that the forecast system is extremely valuable. Over the past decade, the avoided damage and emergency expenditures have eclipsed the costs to fund operation and improvement of the forecast system by a factor of 20. Second, we provide a general methodological approach to value any kind of hazard forecast, inclusive of all *ex ante* adaptation or protective costs. Our approach only requires data on the forecast, the realization of the forecast variable, and the realized *ex post* costs like damages and recovery spending. The benefit of this method is that we do not need to observe *ex ante* protective actions, and yet we can still recover the marginal value of the information in a forecast.[7] The prior literature has often focused on the special case of the value of a forecast relative to not having one at all. In contrast, our general approach allows for valuation of arbitrary improvements in forecast systems which allows users to go beyond aggregate cost-benefit analysis and do marginal analyses that can speak to optimal investments in forecasts.

This paper also contributes to a broader literature on the economic impacts of hurricanes and natural disasters. Hurricanes and tropical cyclones have been shown to be strongly associated with negative impacts on industrial production, national income, and welfare (Noy, 2009; Hsiang, 2010; Strobl, 2011; Hsiang and Jina, 2014; Bakkensen and Barrage, Forthcoming), and that the effectiveness of local institutions is a key determinant of the ultimate damage caused by a hurricane (Tennant and Gilmore, 2020). Although most countries at risk of hurricanes or cyclones have taken steps to adapt to these risks and to protect themselves from incurring such losses, the US remains an exception (Bakkensen and Mendelsohn, 2016; Bakkensen and Barrage, Forthcoming).[8] Historically, the US has suffered abnormally high damages, and climate change is expected to further amplify them (Mendelsohn et al., 2012; Kossin et al., 2020).[9] Recent research suggests that about a third of the climate

[6] Martinez (2020) performs a similar exercise but only for 12 hour ahead forecasts of hurricane track, and using less than 100 observations of outcomes aggregated to the hurricane level.

[7] This is similar to Shrader (2021) who shows how to identify damages and adaptation value using only *ex post* data.

[8] In this vein, US households' emergency purchases like flashlights tend to be highly responsive to forecasts right before landfall, suggesting that they do not follow government advice to maintain stockpiles of necessary goods in hurricane-prone areas (Beatty et al., 2019). Previous research has also shown that investors tend to underestimate hurricane uncertainty (Kruttli et al., 2021), and that environmental uncertainty can deteriorate market functioning (Rehse et al., 2019).

[9] Hurricanes have recently been both moving slower across space while also intensifying much more rapidly

change-induced damages in the US could be offset by appropriate investments into long-run adaptation capital (Fried, Forthcoming).

We add to this literature by studying short-run hurricane risk and the role of information. Because the US has made only limited long-run hurricane adaptation investments, accurate forecasts are even more critical to reduce the impacts of hurricanes.[10] Good forecasts help households and governmental agencies better allocate the necessary adaptive resources in the short window of time between the formation of a hurricane and its landfall. To put our estimates into another context, the forecast improvements since 2009 have led to reductions in total costs that are equal to 5% of those achieved from the entire US adaptive capital stock (Fried, Forthcoming).

Finally, our findings also add to a limited stated-preference literature, which finds that, in the aggregate, households in hurricane-vulnerable areas consider the value of recent improvements in forecasts to be more than $50 million per year (Lazo and Waldman, 2011; Molina et al., 2021). Our observational evidence indicates that the actual value of hurricane forecast improvements is significantly larger.

The paper proceeds as follows. Section 2 provides background information on hurricane forecasts. Section 3 describes the data we use in our analysis. Section 4 presents our methods and results. Section 5 concludes.

2 Background

Officially sanctioned forecasts for hurricanes in the US date back to the late 1800s. Initially, forecasts and warnings were the responsibility of the US Weather Bureau, which relied on land-based weather stations and observations from vessels along the Atlantic coast and in the Gulf of Mexico (DeMaria, 1996). The detection of hurricanes and the ability to predict their paths significantly improved following World War II, with advances in the understanding of atmospheric processes, and access to aircraft reconnaissance and radar. These advances eventually led to the establishment of the Miami Hurricane Warning Office to provide yearly hurricane season summaries for the US (Norton, 1951).

Further federal commitment to hurricane forecasts came after a series of devastating storms in the 1954 and 1955 seasons, leading Congress to create the National Hurricane

(Kossin, 2018; Bhatia et al., 2019), potentially leading to their observed rising destructiveness in recent decades (Emanuel, 2005; Grinsted et al., 2019).

[10] One possible adaptation mechanism would be to no longer rebuild high risk areas following a hurricane and instead incentivize households to move to safer areas. For a variety of reasons, including federal and state monetary incentives that lower the costs of coastal infrastructure and reduce the costs of rebuilding after disasters, this typically is not the case (Young, 2022).

Research Project in 1956 (DeMaria, 1996). The eventual coordination and collocation of the Research Project, the Warning Office, and Aircraft Operations led to what is now known as the National Hurricane Center (NHC) (Sheets, 1990).

The advent of computer modeling and meteorological satellites resulted in significant improvements in forecasting capabilities after 1970, thereby setting the foundation for modern forecasts (Sheets, 1990). Nonetheless, while forecasts of hurricane tracks continued to improve gradually over the years, generating reliable forecasts of wind speed remained a challenge. These limitations became evident to US policy makers when the country experienced 13 hurricane landfalls during the 2002-2005 hurricane seasons – 10 of them in 2004 and 2005. The 2004 and 2005 hurricanes alone were responsible for at least 5,200 deaths and $229 billion in damages, underscoring the need for more aggressive forecast improvements (Czajkowski et al., 2011; Strobl, 2011).

Following these catastrophic seasons, Congress mandated the creation of the Hurricane Forecast Improvement Project (HFIP) in 2007 by the National Oceanic and Atmospheric Administration (NOAA). The goal of the HFIP was to improve both storm-track and wind-intensity forecasts through coordinated efforts from the research and operational communities (Gall et al., 2013). Initially, the project was intended to continue for 10 years. It funded research and operations and made significant investments in high-performance computing to support both these aims. The original 10-year goals were to reduce average track errors by 50%, and to reduce average wind speed errors by 50%. In addition, the project was also expected to improve the prediction of rapid intensification of hurricanes by increasing the probability of detection, reducing the false-alarm rate, and extending the forecast lead time from five days to seven days.

In 2017 the project was given a new name, the Hurricane Forecast Improvement Program, and funding was renewed and extended through at least 2024. The goals of the extension include an emphasis on an advanced, unified-modeling system, probabilistic-hazard guidance, and improved communication of risk and uncertainty (Marks and Brennan, 2019). From 2009 to 2019, the HFIP budget for research and operations totaled approximately $250 million.

3 Data

Our analysis focuses on a county-hurricane as the unit of observation (e.g., Kings County, NY and Hurricane Sandy), and it uses data on hurricane forecasts, protective spending, recovery spending, and damages at the county-level for landfalling hurricanes from 2005 to 2020. Our data cover 18 out of the 29 total hurricanes from 2005–2020, including 7 of the 10 costliest hurricanes on record. Our data sources, data construction steps, and summaries are presented below.

3.1 Forecasts

For our analysis, we reconstruct several NHC forecast products from the raw data and models. For wind speed, we use the surface wind swath model described in Anderson et al. (2020). The forecast wind swath model starts from the base NHC forecast, which reports predictions of storm track (storm center) and its maximum wind speed beginning one, two, and three days prior to landfall. Following DeMaria et al. (2009) and DeMaria et al. (2013), we then sample 1,000 time series of track errors from the previous 5-year forecast history and add them to the current track forecast to produce a distribution of potential storm tracks. We allow for serial correlation by linking errors over time within each time series through an AR(1) process that relies on the 5 year forecast error history, as well as the residuals of the estimated AR(1) process. This generates 1,000 different forecasts of the storm track. We then generate an ensemble of the hurricane's maximum wind speed using a nearly identical Monte Carlo approach. The primary difference is that for maximum wind speed, the AR(1) process for the errors also accounts for other factors such as realized wind speed and distance inland.

We generate wind speed swath ensembles by combining the 1,000 forecasts of track and maximum wind speed with the radii-climatological and persistence (CLIPER) model. Given a storm's maximum wind speed, the distance of that maximum from the center of the storm, and a storm's translational speed and location, CLIPER generates wind speed forecasts at different radii from the storm's center. These predictions are potentially asymmetrical about the center of the storm. For the purpose of this study, we focus on the maximum sustained wind in a county, which is defined as the maximum average wind speed over one minute. From here on we call this measure "wind speed."

This process generates 1,000 swaths of wind speed forecasts across the entire US, where the variability across the swaths captures errors and uncertainties that are specific to each storm because of the recent history of forecast accuracy, the hurricane's movement and location, and the local climate.[11] The forecast mean and standard deviation are calculated across all 1,000 swaths for forecasts one, two, and three days prior to landfall. On average, the standard deviation of the ensemble has declined over time as forecasts improve and the statistical models are updated.

[11]Most economics research in this areas only uses aggregated data instead of the full distribution of outcomes. For example, previous work has used probabilities of hurricane force winds (Kruttli et al., 2021), expected temperature (Lemoine, 2021), or fluctuations in the ENSO phenomenon (Downey et al., Forthcoming).

Observed wind speed is obtained by evaluating the observed storm track and wind speed in the wind swath model. Forecast errors are thus the difference between observed wind speed and the forecast ensemble mean. For each hurricane, we aggregate the forecast statistics and errors to the county-level.

Precipitation is handled similarly to Molina et al. (2021). Using the same Monte Carlo ensembles as those for wind speed, we create 1,000 rainfall forecast swaths for each lead time and hurricane using the probabilistic version of the Parametric Hurricane Rainfall Model (PHRaM) (Lonfat et al., 2007; Marks et al., 2020). We then use the European Centre for Medium-Range Weather Forecasts fifth generation atmospheric reanalysis of the global climate dataset to create the observed precipitation swath (Muñoz-Sabater et al., 2021).[12] To match observed precipitation with the forecast, only rainfall within 500 km of the storm center is considered. As with wind speed, precipitation is aggregated up to the county-hurricane level.

Our final dataset reports forecasts, realizations, and errors for storm track, wind speed, and precipitation by county-hurricane pairs one, two, and (if available) three days prior landfall.[13]

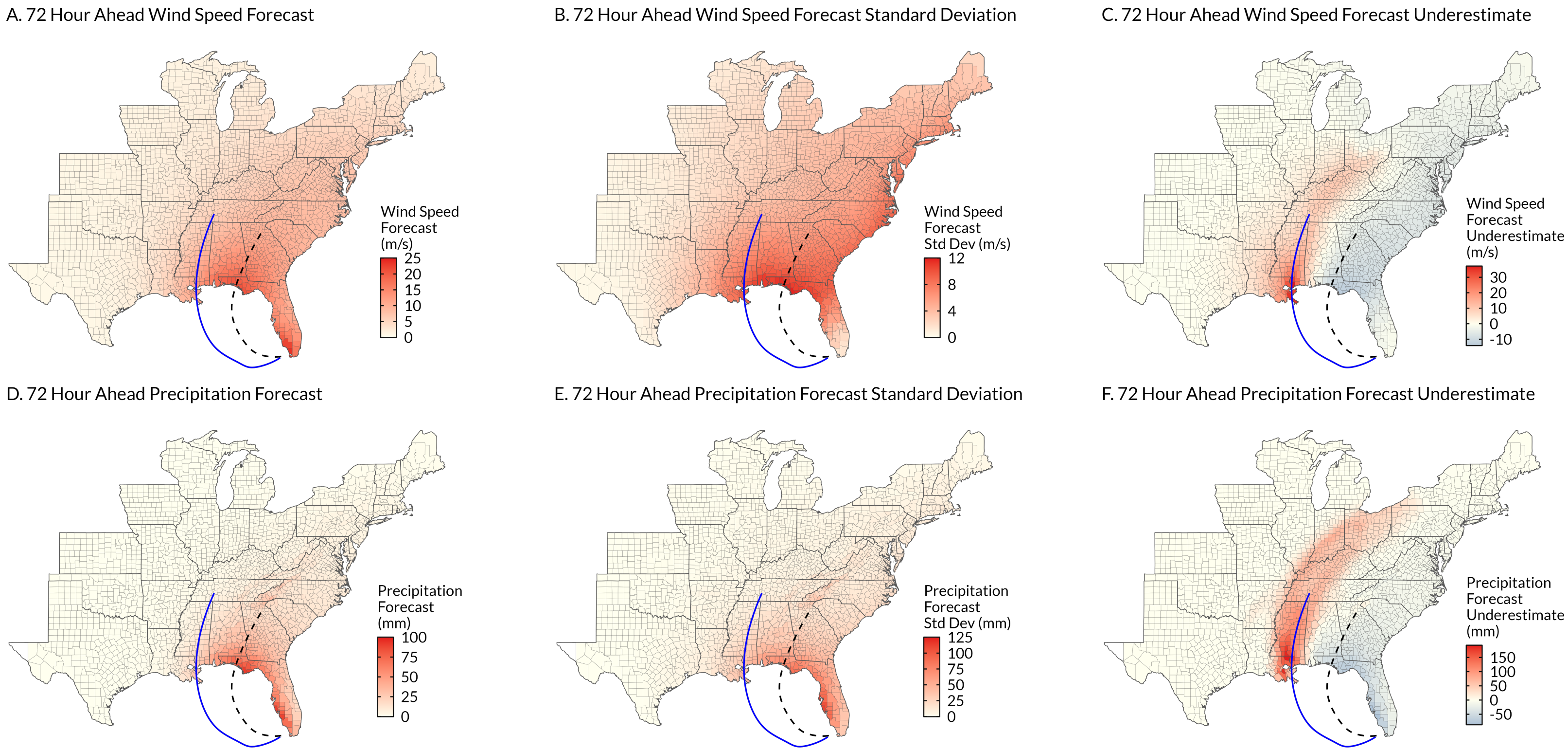
Figure 2 plots an example of our data. Panel A maps the ensemble-mean wind speed forecast 72 hours ahead of landfall for Hurricane Katrina. Darker shades of red denote higher predicted wind speeds. The blue line represents the actual storm track. The black dashed line is the storm track that was forecast. The predictions show that winds over 25 m/s (50 mph) were expected to hit the Florida Gulf Coast, but that wind speed would decrease as the hurricane moved inland and dissipated.

Panel B shows the wind speed forecast's *ex ante* standard deviation by county. The forecast was most uncertain around the predicted point of landfall because of uncertainty about the degree of intensification before the storm's arrival. After landfall when the hurricane moves inland, uncertainty in the forecast tends to decline as hurricanes consistently and rapidly weaken over land.

[12]While the data from the National Center for Environmental Prediction (NECP) would be the default choice for observed precipitation, the National Weather Service radar network experiences significant outages during some landfalling hurricanes that result in incomplete or poor NECP data coverage (e.g., radar stations KLIX during Katrina 2005, KMHX during Florence 2018, and KLCH during Laura 2020).

[13]Some storms intensify rapidly and may not have forecasts generated three days before landfall.

Figure 2: Forecasts, Forecast Uncertainty, and Forecast Errors for Hurricane Katrina 72 Hours Before Landfall.



Note: The figure is split in six panels. Panels A, B, and C show the predicted wind speed, the forecast's *ex ante* standard deviation, and the errors for the wind speed that was forecast for hurricane Katrina 72 hours ahead of landfall. Positive values in Panel C are underestimates of the actual wind speed. Panels D, E, and F show the predicted precipitation, the forecast's *ex ante* standard deviation, and errors for the precipitation forecast for hurricane Katrina 72 hours ahead of landfall. Positive values in Panel F are also underestimates of the actual precipitation. For all panels, the solid blue line indicates the actual hurricane track, and the dashed black line indicates the hurricane track that was forecast 72 hours ahead of landfall.

10

The differences between the predicted and actual wind speeds are shown in Panel C. Underestimates of the severity of the storm are shown in red, and overestimates of severity are shown in blue. In the case of Katrina, the forecast had errors in both directions – underestimating wind speed along the path of the hurricane, with errors of nearly 35 m/s in New Orleans, and overestimating wind speed throughout most of the Southeast.

Panels D, E, and F repeat the analysis for precipitation. The findings are similar in that precipitation was underestimated by over half a foot in Louisiana and Mississippi. However, unlike wind speed, precipitation was forecast to be highly concentrated near the coast.

The appendix contains several figures highlighting the distribution of forecast errors. Figure D.5 shows that the standard deviation of a forecast is strongly correlated with realized forecast errors. Figure D.6 shows there is a near one-to-one relationship between forecast wind speed and realized wind speed with an average error of only 0.1 m/s. The error distribution is slightly skewed because forecasts underestimate wind speed more than they overestimate it. The combination of these two results suggest that the *ex ante* distribution of hurricane intensity in the forecast is a close match to the distribution of the *ex post* realized outcomes.

3.2 Expenditures for Pre-Storm Protection and Post-Storm Recovery

We use a Freedom of Information Act (FOIA) request to obtain data on measures and funding for public protection under the Public Assistance Grant Program (PAGM). PAGM is administered by the Federal Emergency Management Agency (FEMA) and provides grant assistance for eligible disasters (Kousky et al., 2016). PAGM supports the removal of debris and helps fund emergency protective measures such as the establishment of shelters and emergency power generation. These funds are allocated prior to a storm's landfall, and they are aimed at reducing overall storm impacts. We call these kinds of expenditures *protective expenditures*. PAGM also funds the repair, replacement, or restoration of disaster-damaged, publicly-owned facilities and facilities owned by certain nonprofit organizations, as well the administrative expenses associated with these grants. These funds, which are allocated after the storm has concluded, are provided for restoring an already damaged area. We call these kinds of expenditures *recovery expenditures*.

Typical beneficiaries of the PAGM include local governments and nonprofit organizations. The federal government provides a minimum of 75% of the cost of eligible assistance for these entities. From FY2000 to FY2013, more than 90% of major disaster declarations received some assistance through the PAGM. According to data obtained through a separate FOIA request, 98% of the federal funding requests through PAGM end up being approved by FEMA.

3.3 Economic Damages

We measure the economic impact of hurricanes using data from the Spatial Hazards Event and Losses Database for the United States (SHELDUS). SHELDUS provides information on the year and month of the event, the affected US counties, and the direct losses that stem from fatalities, injuries, and damages to property and crops at the county-level for each hurricane. The database covers the period from January 1960 to December 2020. SHELDUS obtains the storm data from National Centers for Environmental Information (NCEI) and the estimates of mortality, injuries, and losses to crops and properties from various authorities, including insurance companies, the US Geological Survey, and the US Department of Agriculture (USDA). All damages are in 2019 dollars. It is important to note that the economic losses reported by SHELDUS are only the lower bound of the damage costs; this is because SHELDUS tries to maintain the most conservative estimate of losses (Borden and Cutter, 2008). Following EPA guidelines, we estimate the losses from deaths using a value of a statistical life of $9.39 million in 2019 dollars (US EPA, 2022). Because we do not observe the type of injuries incurred and have no way to clearly monetize them, we ignore injuries in our analysis.

3.4 Summary Statistics

Table 1 shows summary statistics for the 18 storms in our sample. Note that these statistics are generated using only counties that experienced positive wind from the hurricane. In the table, the third column shows the average wind speed across counties and reports the standard deviation of average wind speed in parentheses. As described above, we measure wind speed as the maximum sustained wind speed in meters per second (m/s). The column reveals that there is substantial heterogeneity in mean wind speed across storms, and the wind speed across counties for the same storm. The average county-hurricane pair experiences wind speeds of only around 10 m/s. Comparing the absolute value of the difference between the forecast wind speed and actual wind speed in the fourth column reveals that average errors can also vary significantly across different storms, and across different counties for the same storm.

The fifth and sixth columns in Table 1 show similar patterns in terms of the total amount of precipitation and absolute errors in the precipitation forecast. The average county receives about 25 millimeters of precipitation. Compared to wind speed, precipitation tends to be

Table 1: Summary Statistics by Storm.

Hurricane	Year	Wind Speed (m/s)	abs(Wind Error) (m/s)	Precip. (mm)	abs(Precip. Error) (mm)	Total Damage (Billion USD)	Protective Exp. (Billion USD)	Recovery Exp. (Billion USD)
Dennis	2005	6.56 (4.89)	1.94 (1.74)	28.49 (24.22)	14.94 (14.36)	0.17	0.05	0.39
Katrina	2005	8.99 (6.48)	3.15 (3.44)	30.71 (35.8)	24.55 (27.21)	20.92	4.37	34.03
Rita	2005	7.14 (4.89)	3.49 (2.88)	28.06 (35.55)	22.72 (24.42)	2.72	0.42	1.26
Wilma	2005	10.85 (9.33)	3.13 (5.31)	24.16 (35.96)	16.74 (26.39)	0.47	0.50	3.33
Ike	2008	11.45 (6.17)	7.02 (5.84)	17.16 (26.32)	14.89 (20.82)	7.27	0.72	3.55
Sandy	2012	10.86 (6.51)	2.8 (2.75)	30.68 (30.86)	19.94 (21.69)	87.59	3.57	10.89
Harvey	2017	10.91 (8.22)	2.37 (3.77)	90.06 (117.13)	68.83 (90.87)	188.20	0.87	3.59
Irma	2017	7.62 (6.51)	2.57 (2.23)	43.9 (44.92)	26.28 (30.7)	14.80	1.24	5.32
Florence	2018	9.75 (5.45)	1.82 (1.62)	41.73 (68.11)	22.43 (35.63)	5.71	0.45	1.59
Michael	2018	12.87 (8.75)	3.14 (4.11)	29.48 (30.29)	21.49 (23.64)	31.83	0.62	3.90
Barry	2019	6.37 (5.19)	1.8 (1.47)	26.38 (38.78)	18.48 (22.95)	0.00	0.04	0.03
Dorian	2019	10.76 (5.08)	0.57 (0.61)	15.59 (30.79)	8.61 (14)	0.09	0.13	0.37
Delta	2020	6.55 (5.42)	1.48 (1.25)	20.92 (27.47)	12.83 (17.33)	12.02	0.05	0.07
Hanna	2020	9.36 (6.42)	0.91 (2.15)	17.3 (30.64)	14.39 (20.09)	0.00	0.00	0.00
Isaias	2020	13.65 (7.7)	4.8 (4.77)	19.48 (24.55)	17.66 (22.1)	0.70	0.03	0.23
Laura	2020	7.54 (6.46)	2.38 (2.61)	15.45 (24.97)	11.05 (14.63)	36.99	0.63	1.80
Sally	2020	8.5 (5.31)	3.14 (2.98)	43.34 (53.54)	42.18 (43.12)	0.95	0.07	0.78
Zeta	2020	10.1 (7.55)	3.89 (4.1)	14.71 (12.67)	10.81 (8.73)	12.09	0.00	0.01

Note: Wind speed, precipitation, and their associated errors are averaged across counties that experienced positive wind speeds only. Standard deviations for these variables are reported in parentheses. Damages and expenditures are summed across counties for each storm. "Precip" is short for precipitation, and "Exp" is short for Expenditure.

more variable within a given storm relative to its mean, and precipitation forecasts tend to have larger relative errors.

The next column in Table 1 shows the total economic impact across all counties in terms of losses, which include deaths, and damages to properties and crops. The total costs from the losses associated with all storms is nearly half a trillion dollars, which highlights the economic importance of hurricanes in the continental US. Finally, the last two columns show the total amount of protective and recovery emergency FEMA spending across all counties for each hurricane. Overall, total emergency spending on this set of 18 hurricanes is about $100 billion, about one-fifth of the reported costs in terms of mortality and damages to property and crops. Notably, for virtually every storm, and especially for the most damaging ones, recovery spending exceeds protective spending.

4 Methods and Results

We present our results in four steps. First, we demonstrate that hurricane forecasts contain more information than a benchmark naive forecast. Second, we show that FEMA, the federal agency responsible for allocating protective emergency funding, responds to the mean and standard deviation of the forecast. Third, we provide evidence that the forecasts generated economic value by showing that larger underestimates of storm intensity lead to larger damages and recovery costs, conditional on the actual storm intensity. Last, we use our theoretical model to estimate the *ex ante* value of reducing uncertainty in hurricane forecasts, the value of information.

4.1 Are Hurricane Forecasts Skillful?

For forecasts to have value, they must be accurate and contain information that can be used by government and individuals to reduce the damages from hurricanes. Here, we measure forecast accuracy by computing forecast-skill scores. Skill scores are a measure of accuracy of a forecast relative to some benchmark forecast in terms of mean-squared error (MSE). For our analysis, we use the following score:

$$\text{skill score} = 1 - \frac{\text{MSE}_{\text{forecast}}}{\text{MSE}_{\text{benchmark}}}.$$

Under this metric, a skill score of one implies a perfect forecast (i.e., zero error), while a score of zero implies that the forecast performed no better than the benchmark, while a negative skill score would imply the forecast was worse than the benchmark.

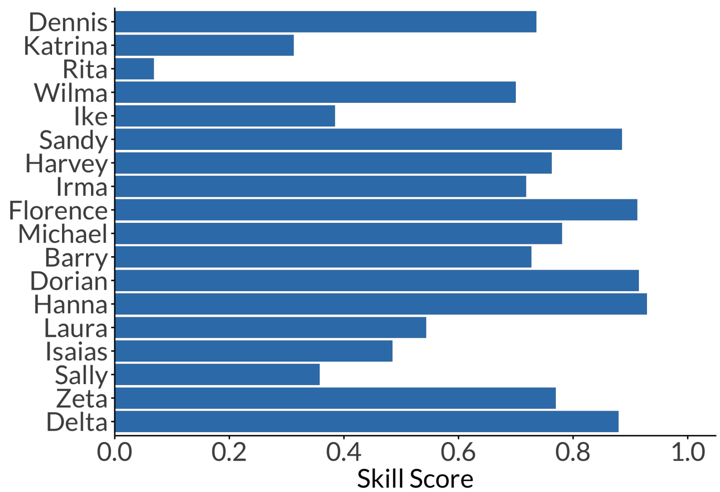
We follow NOAA's benchmark and use the Operational 120-hr Climatology and Persistence Track Forecast and 20-hr Decay Statistical Model Intensity Forecast (OCD5) model as the reference forecast. The model merges the 5-Day Statistical Climatology and Persistence model (CLIPER5) for track, and the Decay-Statistical Hurricane Intensity Forecast model (SHIFOR5) for wind intensity (Cangialosi, 2019).

OCD5 is what is known as a persistence forecast. The model initially assumes that the storm continues at the same direction, speed, and intensity, but then it smoothly transitions to climatology-based projections; for example, projecting the forecast based on the average storm behavior at a given location and at a certain time of year (Cangialosi, 2019). In other words, it ignores the current atmospheric conditions, and assumes that the storm's trajectory and speed will not change in the immediate future.

Figure 3 plots the forecast-skill score for wind speed for the storms in the sample. Overall, the scores range from about 0.1 to nearly 1, and the average across hurricanes is about 0.6. This distribution implies that the actual forecast outperformed OCD5 with a mean-squared error that was, on average, one-third the size of the reference. On average, skill scores improved by approximately 4% per year between 2005 and 2020, which is consistent with the data shown in Figure 1.

While these scores suggest that forecasts are skillful on average, it is important to highlight that there is substantial variation in accuracy within a given forecast. Consider the three-day-ahead forecast error for Hurricane Katrina (Figure 2, panels B and D). For most

Figure 3: Hurricane Skill Scores.



Note: Each bar shows a hurricane forecast's wind speed skill score relative to NOAA's benchmark, no-skill, persistence-based OCD5 forecast. A skill score of zero means that the forecast has the same mean-squared error as the no-skill forecast. A skill score of one means that the forecast was perfect.

counties the forecast is accurate with errors under 5 m/s (10 mph), however it consistently underestimated the strength of winds and precipitation along the actual track of the storm. This error was extremely acute near the landfall area (i.e., New Orleans).

4.2 Does FEMA Respond to Forecasts?

Next we analyze how protective actions taken before landfall respond to forecasts. We estimate the degree to which FEMA's pre-landfall, protective emergency expenditures respond to the mean and standard deviation of the predicted wind speed and precipitation. We use the following flexible model for our main results:

$$\begin{aligned} \log\big(\text{Protective FEMA Spending}_{cshf} + 1\big) = & \sum_{b \in \mathcal{B}_M} \beta_m^b 1(\text{Forecast Mean}_{cshf} \in b) \\ & + \sum_{b \in \mathcal{B}_{SD}} \beta_{sd}^b 1(\text{Forecast SD}_{cshf} \in b) \\ & + \gamma_c + \eta_{sh} + \upsilon_f + \varepsilon_{cshf}. \end{aligned} \tag{1}$$

$\mathcal{B}_M$ is a set of bins of forecast means, and $\mathcal{B}_{SD}$ is a set of bins of forecast standard deviations. We estimate the effects jointly for means and standard deviations because, as shown in Figure D.5 in the Appendix, higher wind speed forecasts tend to also have higher standard deviations; thus, estimating the effect of means and standard deviations separately may lead to omitted variable bias. The omitted category for the mean and standard deviation is 0 m/s.

All of our specifications in Section 4 use county fixed effects γ_c, state-by-hurricane fixed effects η_{sh}, and a fixed effect υ_f for whether a forecast is 24, 48, or 72 hours ahead of landfall. γ_c controls for time-invariant factors that vary across counties like distance to the coast or elevation. η_{sh} addresses shocks that vary across states for the same hurricane, such as the political composition of the state government, and whether states used emergency declarations to marshall local resources. υ_f ensures we are comparing forecasts with the same lead time. We account for arbitrary serial correlation within a county and arbitrary spatial correlation across counties within the same state by clustering standard errors two ways at the county and state-by-hurricane levels.

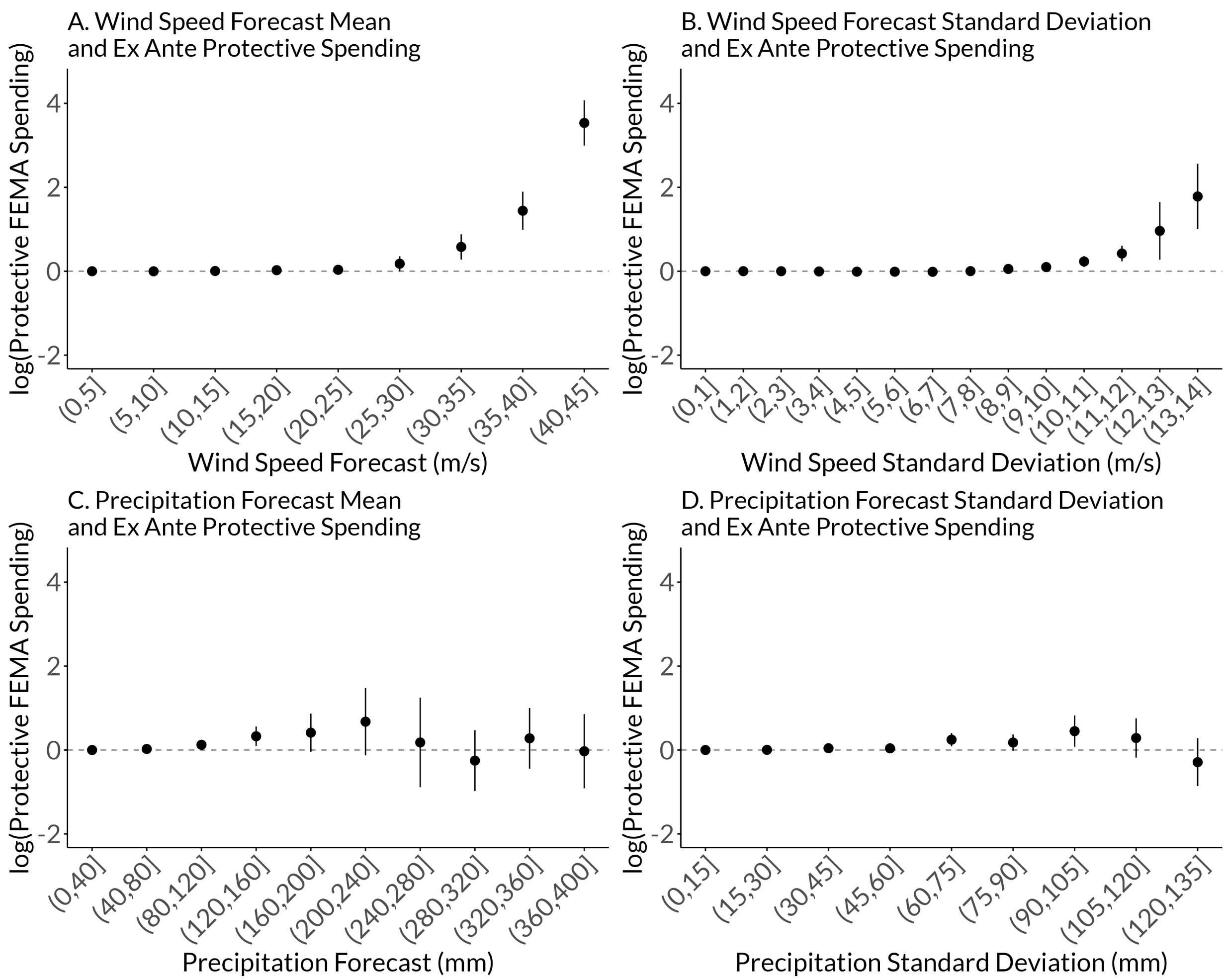
Figure 4 plots the estimates from Equation (1).[14] Panel A shows the effect of wind speed forecasts, conditional on the standard deviation, on pre-landfall protective expenditures. The estimates can be interpreted as the effect of a forecast in a particular 5 m/s bin relative to a forecast of 0 m/s. Note that since the coefficient estimates are large, they are not a good approximation for percentage changes and we must perform the exact transformation on the coefficients. The results indicate that the effects of the mean wind speed forecast are negligible until about 25-30 m/s, the threshold for a Category 1 hurricane, and that the effect then grows rapidly. On average, locations predicted to experience wind speeds of 35-40 m/s receive approximately 75% more FEMA funding for protective measures than locations predicted to experience wind speeds of 20 m/s or less. Locations predicted to experience wind speeds above 40 m/s receive over an order of magnitude more protective funding. Overall, these estimates show that protective emergency spending increases exponentially with the anticipated amount of wind, and that protective expenditures are targeted toward storms above the threshold to be designated as a hurricane.

Panel B of Figure 4 plots the effect of the standard deviation of the wind speed forecast (conditional on the forecast mean). The relationship shows a similar pattern to the forecast mean. The difference in spending is significant for standard deviations above 10 m/s, and it increases rapidly beyond the 10 m/s threshold. Locations with standard deviations of 13-14 m/s have about 3 times more protective spending than areas with standard deviations of 9 m/s or lower.

Panels C and D of Figure 4 replicate the analysis above for the precipitation forecast. Unlike wind speed, neither set of estimates for precipitation show a clear pattern. These results suggest that pre-storm federal emergency expenditures do not consistently respond to precipitation forecasts.

[14] Table C.1 in the appendix shows results for different choices of fixed effects in tabular form.

Figure 4: FEMA Protective Spending Responses to Forecast Means and Standard Deviations.



Note: Points are point estimates and the bars are the 95% confidence intervals. The omitted category for each panel is zero. The top row shows the effect of the mean and standard deviation of a forecast's wind speed on protective FEMA spending. The estimates in panels A and B are from the same regression. The bottom row shows the effect of the mean and standard deviation of a forecast's precipitation on protective FEMA spending. The estimates in panels C and D are from the same regression. All panels account for county, state-by-hurricane, and hours-ahead fixed effects. Standard errors in all panels are clustered two ways at the county and state-by-hurricane levels.

4.3 Does Forecast Accuracy Matter?

Thus far we have seen that forecasts are skillful, and that emergency protective spending responds to forecast information about hurricane strength. Next, we test whether forecasts matter for the ultimate damages that are incurred, and for after-landfall recovery expenditures.

As in Figure 2, we define forecast error as how much the forecast *underestimated* realized wind speeds or precipitation levels. We estimate the effect of forecast errors on damages and FEMA recovery spending using the following flexible model:

$$\begin{aligned}\log\left(\mathrm{Y}_{cshf}+1\right) = &\sum_{b\in\mathcal{B}}\beta^{b}1(\text{Wind or Precip Error}_{cshf}\in b)\\ &+\log(\text{Wind or Precip}_{cshf}+1)\\ &+\gamma_c+\eta_{sh}+\upsilon_f+\varepsilon_{cshf}.\end{aligned} \tag{2}$$

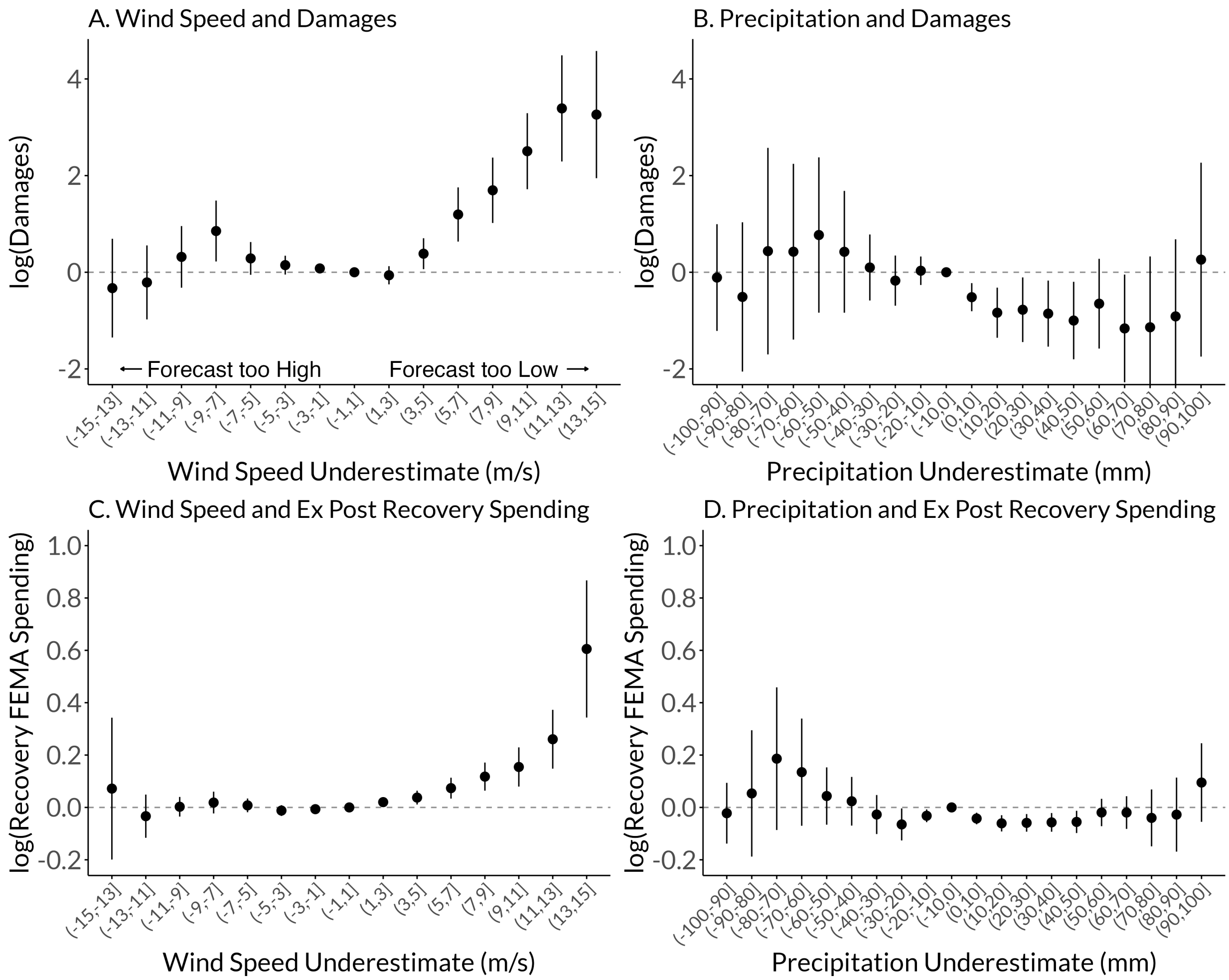
$\mathcal{B}$ is a set of bins of forecast errors (actual minus forecast). The omitted category is (-1,1] for wind speed, and (-10,0] for precipitation. Y_{cshymd} is either damages caused by the hurricane, or FEMA's post-landfall spending aimed at recovering the damaged area. We condition on the realization of log wind speed or log precipitation because, as shown in Appendix Figure D.5, higher-intensity storms tend to have larger errors and because we do not want to confound the effect of forecast errors with with the effect of greater storm intensity. The fixed effects are identical to equation (1) and standard errors are also clustered two ways at the county and state-by-hurricane levels.

The estimates from Equation 2 are shown in Figure 5.[15] Recall that positive errors are underestimates of wind speed, and that negative errors are overestimates of wind speed. Panel A plots the effect of wind speed forecast errors on damages and shows that overestimating wind speed has no effect on damages relative to a nearly perfect forecast with an absolute error of less than 1 m/s. In contrast, incorrectly underestimating wind speed exponentially increases damages. Damages are 300% higher if wind speed is underestimated by 6 m/s, and over an order of magnitude higher if underestimated by 12 m/s.[16] Contrary to our findings on the impacts of errors in wind speed forecasts, Panel B shows that there is no clear relationship between precipitation forecast errors and damages. The lack of a relationship is consistent with our results in Section 4.2 that emergency spending does not seem to be driven by precipitation forecasts. Forecasts only matter in that they provide information to

[15]Tables C.2 and C.3 present the estimates in tabular form and show the robustness to different sets of fixed effects. Figure C.2 shows that damages from forecast errors are driven by property losses.

[16]A 12 m/s error would result in misclassifying a storm by 1-2 categories.

Figure 5: Forecast Errors, Damages, and *Ex Post* Recovery Spending.



Note: The points are point estimates, and the bars are the 95% confidence intervals. Panel A shows the effect of wind speed forecast underestimates on damages, Panel B shows the effect of precipitation forecast underestimates on damages, Panel C shows the effect of wind speed forecast underestimates on FEMA recovery funds provided after landfall. Panel D shows the effect of precipitation forecast underestimates on FEMA recovery funding provided after landfall. The omitted category is $(-1, 1]$ for wind speed and $(-10, 0]$ for precipitation. All panels account for county, state-by-hurricane, and hours-ahead fixed effects. Standard errors in all panels are clustered two ways at the county and state-by-hurricane levels.

better allocate protective resources and actions. If protective resources and actions do not respond to a forecast, then an error in that forecast will not have negative consequences.

The bottom two panels in Figure 5 repeat the analysis but for post-hurricane recovery spending by FEMA. The results show that FEMA recovery spending exhibits a similar pattern. Underestimating actual wind speeds leads to greater emergency expenditures targeted for rebuilding damaged areas after the hurricane. A 10 m/s underestimate of wind speed results in 20% higher expenditures. A 12 m/s underestimate results in 25% higher expenditures. A 14 m/s underestimate results in 80% higher expenditures. As with damages, there is no clear effect of precipitation errors on recovery spending.

Before proceeding, it is important to note that our results in Figure 5 do not imply that there are no costs from overestimating hurricane wind speed. Indeed, Figure 4 shows that emergency expenditures increase in the forecast wind speed, and thus will tend to be higher even in cases where the forecast is an overestimate of the realized wind speed.[17] This means that although we find no evidence that overestimating a hurricane's intensity leads to additional costs from damages and recovery spending, it will still lead to additional costly protective actions before landfall.

4.4 What is the *Ex Ante* Value of Improving Hurricane Forecasts?

Finally, we now turn to the *ex ante* value associated with improving the hurricane forecast. The previous section shows that underestimating wind speed increases hurricane damages and *ex post* recovery spending, but that overestimating wind speed has virtually no effect relative to a perfect forecast. Figure 4 suggests this asymmetry occurs because higher-intensity forecasts induce greater *ex ante* protective expenditures that mitigate damages. To understand the value of improving a hurricane, we must account for changes in both of these costs. To do so, we develop a model of a planner facing an impending hurricane. We first use the model to derive an sufficient statistic for the social value of a reduction in forecast uncertainty, and then we use the storms in our sample to quantify the value of reductions in forecast uncertainty observed during this time frame.

4.4.1 Theoretical Foundation

Suppose a representative agent faces a future hurricane with total after-landfall costs from damages and recovery spending given by a function $D(x, a, \mathbf{i}, \mathbf{t})$. x is some measure of the hurricane's realized intensity (e.g., wind speed, precipitation); a is the planner's continuous

[17] This will also likely be true for protective actions that we do not observe such as evacuations and individual expenditures at stores.

choice of before-landfall protective actions to reduce damages with associated continuous cost function $C(a)$ (e.g., sandbags, evacuations, structure hardening); $\mathbf{i}$ is a vector of time-invariant features of the planner's location i (e.g., elevation, proximity to the coast, long-lived capital structures); and $\mathbf{t}$ is a vector of common features across locations in period t. D is continuous in a. The agent has access to forecasts about x at time t specific to location i. The forecast reports a distribution of potential values of x. We assume this distribution is lognormal: $x \sim \log \mathcal{N}(\mu, \sigma)$. μ is the location parameter and σ is the scale parameter, and these are the mean and standard deviation of $\log x$. To examine whether the lognormal assumption is reasonable, B.1 in the appendix plots the distributions of realized log wind speed and log precipitation. Log wind speed appears to be normally distributed, suggesting that wind speed is lognormally distributed in the data. Log precipitation is significantly left-skewed suggesting that precipitation is not lognormally distributed in the data. Given this discrepancy between the precipitation data and our model assumption, we focus solely on wind speed for this analysis.

The agent's objective is to minimize her total expected costs, which can be written as:

$$\mathcal{C}(\mu, \sigma, \mathbf{i}, \mathbf{t}) = \min_a \mathbb{E}\left\{[D(x, a, \mathbf{i}, \mathbf{t})] + C(a)\right\},$$

where $\mathcal{C}(\mu, \sigma, \mathbf{i}, \mathbf{t})$ is the minimized expected cost inclusive of damages, recovery costs, and protective costs. The expectation about damages and recovery costs is constructed using the forecast distribution, so the expectation is a function of μ and σ. We define the value of a forecast improvement as the *ex ante* reduction in minimized expected cost from a marginal reduction in the uncertainty of the forecast. Our first proposition provides an intuitive closed-form expression for this quantity.

Proposition 1 *The value of information – the decrease in minimized expected costs from a marginal reduction in the forecast standard deviation – is given by:*

$$\frac{\mathrm{d}\mathcal{C}(\mu, \sigma, \mathbf{i}, \mathbf{t})}{\mathrm{d}\sigma} = \frac{1}{\sigma^3} \operatorname{cov}\left(D(x, a^*, \mathbf{i}, \mathbf{t}), (\log x - \mu)^2\right). \tag{3}$$

Proof: See Appendix A.1. □

Proposition 1 shows that the marginal value of information is proportional to a covariance.[18] The first term in the covariance, $D(x, a^*, \mathbf{i}, \mathbf{t})$, is realized damages at the optimized

[18]The proposition still holds if hurricane realizations also have fundamental randomness in addition to the forecast, i.e. even with a "perfect" forecast there is still remaining uncertainty about hurricane intensity. Suppose we have a forecast about the hurricane's ultimate realization or a forecast about the mean of the

protective actions, conditional on time-invariant and common factors. The second term, $(\log x - \mu)^2$ is the realized squared error of log wind speed.

The value of information and the covariance is positive if damages tend to be higher when the squared error is higher. Suppose, as we might expect, that damages are increasing and convex in wind speed. Then conditional on the expected hurricane intensity, greater variability in hurricane intensity realizations increases forecast errors and also damages because of a Jensen's inequality argument.[19] Figure 5 provides some direct evidence of the sign of the covariance: damages are weakly increasing and convex in *errors* conditional on wind speed, so the covariance between damages and squared errors is positive. Some economic intuition for this result is that the value of information comes from the policymaker being able to reduce the difference between the *ex ante* optimized level of protective spending and the protective spending the policymaker would have chosen if she observed hurricane intensity. In cases where the forecast was too high, a better forecast reduces the amount of excess protective costs. In cases where the forecast was too low, it and reduces excess damages and recovery costs.

Now we show how to take this insight to the data. First, to simplify future notation let β_p be the coefficient from regressing observed damages $D(x, a^*, \mathbf{i}, \mathbf{t})$ on a power p of the observed log wind speed error $(\log x - \mu)^p$. The following corollary shows how we can recover the value of information from a regression coefficient, forecast data, and damage and recovery spending data.

Corollary 1.1 *The value of information is:*

$$\frac{\mathrm{d}\mathcal{C}(\mu, \sigma, \mathbf{i}, \mathbf{t})}{\mathrm{d}d} = 2\sigma\beta_2. \tag{4}$$

Proof: See Appendix A.2. □

The value of information is the marginal effect of squared errors in log wind speed on damages, scaled up by two times the standard deviation. This result implies that simply regressing total after-landfall costs on squared errors and knowing the forecast standard deviation is sufficient for capturing the *ex ante* value of a forecast improvement, inclusive of any protective actions. Importantly, we do not need to know the shape of the damage

distribution. In the former case, we can think of the forecast as introducing an uncorrelated additive error, in the latter case we can think of the problem as there being a distribution over the mean of the hurricane intensity distribution. If all distributions are normal, both yield prior distributions with mean μ and variance equal to the sum of the variance of the hurricane distribution and the forecast.

[19] Forecast errors will be larger when the forecast has a higher standard deviation, and this is borne out in the data as shown in Figure D.5.

function, the protective cost function, or precisely how local agents protect themselves against incoming hurricanes. There are, however, two key assumptions that make this approach work. The first is that that wind intensity is lognormally distributed. This parametric assumption on beliefs lets us quantify how beliefs change as σ changes.[20] The second is that agents are minimizing their expected total costs, so that we can use the envelope theorem and ignore second-order action responses.[21]

So far we have only shown how to recover the value of information. Next we show how the value of information changes in the baseline quality of the forecast, allowing us to measure whether there are increasing or decreasing returns to forecast improvements.

Proposition 2 *The change in the value of information from a marginal increase in the standard deviation of log wind speed is:*

$$\frac{\mathrm{d}^2\mathcal{C}(\mu,\sigma,\mathbf{i},\mathbf{t})}{\mathrm{d}\sigma^2} = \frac{1}{\sigma^6}\mathrm{cov}\left(D(x,a^*,\mathbf{i},\mathbf{t}),(\log x-\mu)^4\right) - \frac{5}{\sigma^4}\mathrm{cov}\left(D(x,a^*,\mathbf{i},\mathbf{t}),(\log x-\mu)^2\right).$$

This is equivalent to:

$$\frac{\mathrm{d}^2\mathcal{C}(\mu,\sigma,\mathbf{i},\mathbf{t})}{\mathrm{d}\sigma^2} = 96\sigma^2\beta_4 - 10\beta_2, \tag{5}$$

where the coefficients come from separate regressions.

Proof: See Appendix A.3. □

Proposition 2 shows that the average slope of the value of information is the difference between two covariances, and we can estimate it by combining two regressions: one where we regress damages on quartic errors, and the regression of damages on squared errors in Corollary 1.1. By the same arguments used for the covariance in Proposition 1 being positive, may expect that both β_4 and β_2 are positive, so that the overall sign may be negative. This implies that the value of information may have increasing returns as σ declines and the forecast improves. In our empirical results this is what we will find.

Why might there be increasing returns to hurricane information? First, the mechanical reason is that Proposition 1 shows that the value of information is the product of a covariance

[20] Our approach would also work with normally distributed hurricane intensity.

[21] A necessary, and often overlooked point is that this also requires continuity in actions. If actions are not continuous then a marginal change in the forecast can lead to a non-marginal change in actions (Guo and Costello, 2013). If real-world individuals are making discrete actions, these can be aggregated up into continuous actions for a representative agent under common assumptions about heterogeneity and idiosyncratic payoff shocks (Rudik et al., 2021).

Table 2: The Value of a Marginal Reduction in the Wind Speed Forecast Standard Deviation: The Wind Speed Value of Information.

	(1)	(2)	(3)	(4)
β_2: $(\log x - \mu)^2$	1.07*	1.07*	1.59*	2.03*
	(0.596)	(0.596)	(0.881)	(1.16)
$2\sigma\beta_2$: VOI	1.02*	1.02*	1.52*	1.93*
	(0.57)	(0.57)	(0.84)	(1.11)
Observations	118,750	118,750	118,750	118,750
County Fixed Effects	✓	✓	✓	
State-Hurricane Fixed Effects	✓	✓	✓	✓
Hours Ahead Fixed Effects	✓	✓	✓	✓
Year Fixed Effects		✓		
Year-Month-Day Fixed Effects			✓	✓
County-Year Fixed Effects				✓

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors are clustered two ways at the county and state-by-hurricane levels.

and a function that is strictly decreasing in the forecast standard deviation. If $1/\sigma^3$ shrinks faster than the covariance grows, then the value of information declines in σ.[22]

Second, the economic intuition is that for sufficiently noisy forecasts, the marginal value of information – i.e., a reduction in forecast standard deviation – may be zero (Radner and Stiglitz, 1984; Chade and Schlee, 2002). This seemingly innocuous result has significant consequences: if information does eventually carry positive value for more informative forecasts because it allows for better choices of actions, then over some range of forecast standard deviations, the marginal value of information must have been increasing in information.[23] In our context, this result means that the marginal value of information may be falling in the standard deviation of the forecast ($96\sigma^2\beta_4 - 10\beta_2 < 0$), implying that there are *increasing returns* to forecast improvements through smaller σ.

4.4.2 Estimation Results

Table 2 reports our results corresponding to Corollary 1.1. The first row shows the coefficient estimate, and the second row of the table lists our estimates of the value of information $2\sigma\widehat{\beta}_2$, where we use the sample average standard deviation of $\bar{\sigma} = 0.47$.[24] The first row shows that under a variety of fixed effects to address the location-specific and common factors in the damage function, a one unit increase in the squared error of log wind speed increases damages. More granular fixed effects tend to increase the magnitude of the estimate. The second row shows that for the sample average σ, the value of information takes on the same values, about \$1 million per county to \$2 million per county. How large is this estimate in the context of the real world forecast improvements? A forecast improvement of 0.04, about 10% of the sample mean σ and an improvement that occurs just over every 2 years in our sample, reduces total costs by \$40,000 – \$80,000 for the average county. This suggests that every year, forecast improvements are generating tens of millions of dollars of benefits per hurricane when aggregated over the entire US.

Table 3 reports estimates of β_2 and β_4, which combined tell us the average change in the value of information. Both estimates are positive: larger quadratic and quartic errors are both associated with higher damages although the estimates on β_4 alone are noisy. The relative size of these estimates will then determine whether the value of information is increasing or decreasing in the forecast standard deviation. At the sample average standard deviation, the value of information is decreasing in σ, meaning that as the forecast improves (σ declines), the value of information rises: there are increasing returns to improving hurricane forecasts. To put this result into context, the value of a 0.04 standard deviation improvement for a forecast with a standard deviation of 0.3 (about the 25th percentile in our sample) is \$120,000 – \$200,000 higher than the same improvement for a forecast with a standard deviation of 0.6 (about the 75th percentile in our sample).

4.5 The Value of Historical Forecast Improvements

We now use our estimates in Table 2 to value the historical improvements in forecast accuracy since the HFIP. Figure 6 shows that for the storms in our dataset, forecasts improved by

[22] Since β_2 is the ratio of the covariance between damages and squared errors to the variance of errors, we can use the regression form of the expression to see the logic as well. If the variance in squared errors increases faster than its covariance with damages, then the value of information may decline in σ.

[23] With normally distributed information like what we have over log wind speed, the marginal value of information is quasi-concave: it rises convexly before peaking, and then eventually falls convexly toward zero (Keppo et al., 2008).

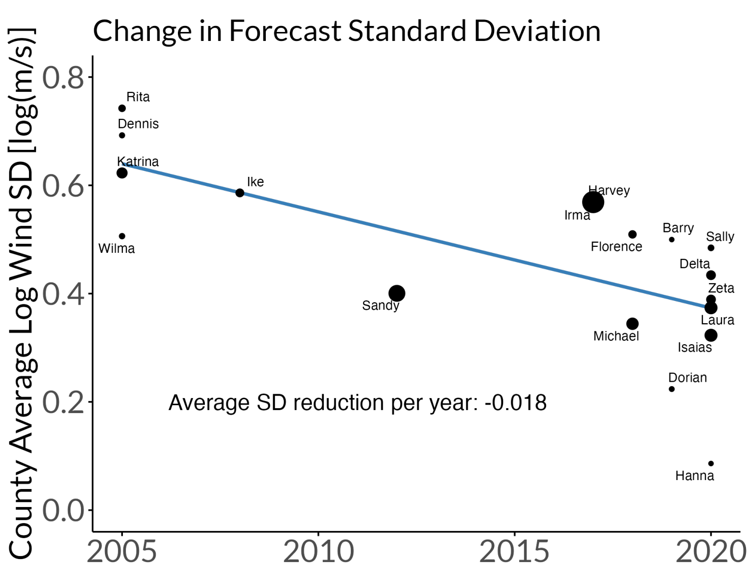
[24] Even though the precipitation forecast data do not seem to satisfy our model assumptions, we present the equivalent precipitation estimates in Tables C.6 and C.7 in the appendix.

Table 3: The Slope of the Wind Speed Value of Information.

	(1)	(2)	(3)	(4)
β_2: $(\log x - \mu)^2$	1.07*	1.07*	1.59*	2.03*
	(0.596)	(0.596)	(0.881)	(1.16)
β_4: $(\log x - \mu)^4$	0.024	0.024	0.031	0.125
	(0.023)	(0.023)	(0.029)	(0.097)
$96\sigma^2\beta_4 - 10\beta_2 : \partial\text{VOI}/\partial\sigma$	-10.15*	-10.15*	-15.22*	-17.54*
	(5.53)	(5.53)	(8.26)	(9.64)
Observations	118,750	118,750	118,750	118,750
County Fixed Effects	✓	✓	✓	
State-Hurricane Fixed Effects	✓	✓	✓	✓
Hours Ahead Fixed Effects	✓	✓	✓	✓
Year Fixed Effects		✓		
Year-Month-Day Fixed Effects			✓	✓
County-Year Fixed Effects				✓

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors are clustered two ways at the county and state-by-hurricane levels.

Figure 6: The Change in Wind Speed Forecast Standard Deviations and Errors Over Time.



Note: The figure plots the county average log wind speed forecast standard deviation. The size of each dot is proportional to the damage caused by the hurricane. The -0.018 estimate is from regressing the log wind speed standard deviation on a linear time trend.

about 0.018 of a standard deviation each year, or about a 4% annual improvement.[25]

First, consider the 12 hurricanes from 2017 to 2020. We ask: what would have been the social cost of these hurricanes if forecast quality remained at its 2005 pre-HFIP level? To answer this question, we compute the benefits of forecast improvements by taking the value of information estimate in Column 1 of Table 2, and multiplying it by the improvement in forecasts since 2007 for each of the 12 hurricanes. The average log wind speed forecast standard deviation prior to the HFIP was about 0.64. On average, the forecast improvements since the HFIP reduced this standard deviation by a third. Our results indicate that the value of these improvements was $7 billion dollars in in the aggregate for only these twelve hurricanes, or about $600 million per hurricane. This is approximately 5% of the sum of damages, *ex post* recovery spending, and *ex ante* protective spending. Over the same time frame, expenditures by NOAA on forecast operations and improvements were under $300 million. The benefits from forecast improvements for a single hurricane exceed the total cumulative cost of the operation and improvement of the entire forecast system, and the total benefits across all twelve hurricanes generated benefits twenty times larger than cumulative costs.[26]

Next, we consider the six hurricanes between 2005 and 2016 and ask how much less damaging they would have been if forecasts had been as good as they were in 2020. Following the same procedure above, we find that the future forecast improvements would have reduced damages by about $12 billion, or $2 billion per hurricane, had said improvements happened sooner. In total, this improvement would have lowered hurricane damages between 2005 and 2016 by nearly 10%.

4.6 Robustness

Section C contains a number of robustness checks of our main results that we summarize here. First, we show all of our results are robust to inclusion of additional fixed effects including county-by-year and date fixed effects. Second, we show our results are robust to restricting our sample to only states on the Atlantic coast. Third, we show that no individual hurricane is entirely driving our main results by re-estimating the marginal value of improving a forecast on subsamples where we drop individual hurricanes. Fourth, we test

[25] Figure D.5 shows that the hurricanes with the most *ex ante* uncertain forecasts also tended to have the largest *ex post* forecast errors indicating that forecast uncertainty translates into larger *ex post* errors.

[26] Assuming that forecast accuracy is held fixed at 2005 levels may overstate the benefits since forecasts were improving prior to the HFIP, albeit at a slow rate. We do not have county-level data prior to the HFIP except for 2005, so we cannot estimate a pre-HFIP improvement trend using our main data. But, if we use the pre-HFIP improvement trend of 0.8% from 1 and use that as the counterfactual improvement trend, we still obtain benefits of $450 million per hurricane and $6 billion in total.

whether there is heterogeneity in the effects of forecast errors and we find suggestive evidence that damages rise faster in errors (in percentage terms) for more populous, richer, and less white counties, but we find no evidence that recent forecast errors drive current effects of forecast errors.

5 Conclusion

In this paper, we estimate the economic impact of hurricane forecasting and the value of improving these forecasts. Our findings indicate that forecasts are extremely important for managing some of the largest natural disasters on the planet. First, these forecasts are major determinants of the allocation of emergency resources, both before and after the storm. Counties projected to face the strongest wind speeds and counties that face forecasts with the most uncertainty receive multiple times more protective funding than the median county. Second, accurate forecasts reduce hurricane damages. Conditional on the exact same wind speed, counties in which the forecast underestimated storm wind speed had damages up to an order of magnitude larger than other counties with accurate forecasts.

Our main contribution is that we develop a new approach for estimating the marginal value of reducing forecast uncertainty. Our approach is grounded in a theoretical model of a representative agent minimizing the sum of expected hurricane damages, after-landfall recovery costs, and before-landfall protective costs. We show that the average county would benefit by $200,000 from a wind speed forecast that is better by one-fifth of a standard deviation, which is approximately equivalent to the average improvement observed over the first decade of the federal Hurricane Forecast Improvement Project. Per-hurricane benefits amount to over half a billion dollars – a figure that dwarfs the annual expenditures on operating and improving the US hurricane forecasting system by nearly twenty-fold. Importantly, we also find evidence that, given current forecast quality, there are increasing returns to forecast improvements. Given that our estimates suggest the marginal value of information for a single hurricane is over an order of magnitude greater than the current costs of thew whole program, it is likely that the optimal level of hurricane forecast funding is still larger than current levels.

Our results also show that hurricane forecasts are more valuable than has been suggested previously (Lazo and Waldman, 2011; Martinez, 2020; Molina et al., 2021). We take a sufficient statistics approach that accounts for damages, after-landfall recovery expenditures, and pre-landfall protective actions. As such, our methodology provides a credible, robust, and flexible approach for quantifying the social value of future hurricane forecasting improvements, and also for valuing forecasts of other hazards for which *ex ante* decision making is crucial.

We conclude with several limitations that we leave for future work. First, our data only capture damages through deaths and damages to property and crops, and only captures recovery expenditures through PAGM. Our quantitative results thus omit other costs such as injuries and hospitalizations, household-level recovery expenditures, and lost time working. Accounting for these additional factors, as well as accounting for the universe of hurricanes, would only increase our estimates of the value of predicting forecast. Second, our estimates only cover the value generated by wind speed forecasts. While wind speed is arguably one of the leading attributes when it comes to hurricane damage (Murnane and Elsner, 2012), flooding and storm surge are important as well.[27] Storm surge forecasting is in its infancy and likely less accurate compared to predicting storm track and wind speed. Our theoretical results suggest that there may be significant gains from further improvements along these additional dimensions of a hurricane.

[27]Some hurricanes, such as Katrina and Ike, had storm surges that raised water levels up to 20 feet (National Hurricane Center, 2022).

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Appendix

A Proofs

A.1 Proof of Proposition 1

Let a^* be the optimal choice of protective spending, x be realized storm intensity, and $\Phi(\frac{\log x-\mu}{\sigma})$ be the lognormal probability density function with location parameter μ and scale parameter σ so that μ is the mean of log wind speed, and σ is its standard deviation. We are interested in the marginal effect of an increase in the standard deviation on the minimized total cost.

The objective is:

$$\mathcal{C}(\mu, \sigma, \mathbf{i}, \mathbf{t}) = \min_a \mathbb{E}\left[D(x, a, \mathbf{i}, \mathbf{t})\right] + C(a).$$

The value of an increase in the standard deviation is:

$$\frac{\mathrm{d}\mathcal{C}(\mu, \sigma, \mathbf{i}, \mathbf{t})}{\mathrm{d}\sigma} = \frac{\partial \mathcal{C}(\mu, \sigma, \mathbf{i}, \mathbf{t})}{\partial \sigma} \tag{A.1}$$

The envelope theorem gives us that:

$$\frac{\partial \mathcal{C}(\mu, \sigma, \mathbf{i}, \mathbf{t})}{\partial \sigma} = \int D(x, a^*, \mathbf{i}, \mathbf{t}) \frac{\partial \Phi(\frac{\log x-\mu}{\sigma})}{\partial \sigma} ds.$$

Taking the partial derivative inside the integral then gives:

$$\frac{\partial \mathcal{C}(\mu, \sigma, \mathbf{i}, \mathbf{t})}{\partial \sigma} = \int D(x, a^*, \mathbf{i}, \mathbf{t}) \left[\frac{(\log x-\mu)^2-\sigma^2}{\sigma^3}\right] \Phi\left(\frac{\log x-\mu}{\sigma}\right) dx.$$

Since the lognormal density is still in the expression, it can go back into expectation notation as:

$$\frac{\partial \mathcal{C}(\mu, \sigma, \mathbf{i}, \mathbf{t})}{\partial \sigma} = \mathbb{E}\left\{D(x, a^*, \mathbf{i}, \mathbf{t}) \left[\frac{(\log x-\mu)^2-\sigma^2}{\sigma^3}\right]\right\},$$

where the expectation is again with respect to the lognormal distribution over x. We can get a closed form solution by using the covariance identity:

$$\begin{aligned}
\frac{\partial \mathcal{C}(\mu,\sigma,\mathbf{i},\mathbf{t})}{\partial \sigma} &= \mathbb{E}\left\{D(x,a^*,\mathbf{i},\mathbf{t}) \times \left[\frac{(\log x-\mu)^2-\sigma^2}{\sigma^3}\right]\right\} \\
&= \frac{1}{\sigma^3}\mathbb{E}\left\{D(x,a^*,\mathbf{i},\mathbf{t}) \times \left[(\log x-\mu)^2-\sigma^2\right]\right\} \\
&= \frac{1}{\sigma^3}\left[\operatorname{cov}\left(D(x,a^*,\mathbf{i},\mathbf{t}),(\log x-\mu)^2\right) + \mathbb{E}\left\{D(x,a^*,\mathbf{i},\mathbf{t})\right\}\underbrace{\mathbb{E}\left\{(\log x-\mu)^2-\sigma^2\right\}}_{=0}\right] \\
&= \frac{1}{\sigma^3}\operatorname{cov}\left(D(x,a^*,\mathbf{i},\mathbf{t}),(\log x-\mu)^2\right) \qquad \text{(A.2)}
\end{aligned}$$

where we use $\log x \sim \mathcal{N}(\mu,\sigma)$ so that $\mathbb{E}\{(\log x-\mu)^2\} = \sigma^2$.

A.2 Proof of Corollary 1.1

To begin, return to the last line in equation (A.2):

$$\frac{\mathrm{d}\mathcal{C}(\mu,\sigma,\mathbf{i},\mathbf{t})}{\mathrm{d}\sigma} = \frac{1}{\sigma^3}\operatorname{cov}\left(D(x,a^*,\mathbf{i},\mathbf{t}),(\log x-\mu)^2\right).$$

First, compute the variance of $(\log x-\mu)^2$:

$$\begin{aligned}
\operatorname{var}\left((\log x-\mu)^2\right) &= \mathbb{E}\left[\left((\log x-\mu)^2-\mathbb{E}\left[(\log x-\mu)^2\right]\right)^2\right] \\
&= \mathbb{E}\left[\left((\log x-\mu)^2-\sigma^2\right)^2\right] \\
&= \mathbb{E}\left[(\log x-\mu)^4\right]-2\sigma^4+\sigma^4 \\
&= 3\sigma^4-2\sigma^4+\sigma^4 \\
&= 2\sigma^4. \qquad \text{(A.3)}
\end{aligned}$$

where the last line uses the fact that the fourth central moment of a normal variable ($\log x$) is $3\sigma^4$.

Use this to result to rewrite the last line in equation (A.2) as:

$$\frac{\mathrm{d}\mathcal{C}(\mu,\sigma,\mathbf{i},\mathbf{t})}{\mathrm{d}\sigma} = 2\sigma\frac{\operatorname{cov}\left(D(x,a^*,\mathbf{i},\mathbf{t}),(\log x-\mu)^2\right)}{\operatorname{var}\left((\log x-\mu)^2\right)}. \qquad \text{(A.4)}$$

The covariance-variance ratio term is just a coefficient from a regression of damages on the squared error in log wind speed. Denote this regression coefficient as: β_2. The final expression is:

$$\frac{\mathrm{d}\mathcal{C}(\mu,\sigma,\mathbf{i},\mathbf{t})}{\mathrm{d}\sigma} = 2\sigma\beta_2.$$

A.3 Proof of Proposition 2

Begin by differentiating the first line of equation (A.2):

$$\frac{\mathrm{d}^2\mathcal{C}(\mu,\sigma,\mathbf{i},\mathbf{t})}{\mathrm{d}\sigma^2} = \mathbb{E}\left\{D(x,a^*,\mathbf{i},\mathbf{t})\left(\frac{(\log x-\mu)^2-\sigma^2}{\sigma^3}\right)^2\right\} + \mathbb{E}\left\{D(x,a^*,\mathbf{i},\mathbf{t})\frac{\sigma^2-3\left(\log x-\mu\right)^2}{\sigma^4}\right\}.$$

Begin with the first term. Use the covariance identity to get:

$$\begin{aligned}\mathbb{E}\left\{D(x,a^*,\mathbf{i},\mathbf{t})\left(\frac{(\log x-\mu)^2-\sigma^2}{\sigma^3}\right)^2\right\} &= \operatorname{cov}\left(D(x,a^*,\mathbf{i},\mathbf{t}),\left(\frac{(\log x-\mu)^2-\sigma^2}{\sigma^3}\right)^2\right)\\ &\quad+\mathbb{E}\left\{D(x,a^*,\mathbf{i},\mathbf{t})\right\}\mathbb{E}\left\{\left(\frac{(\log x-\mu)^2-\sigma^2}{\sigma^3}\right)^2\right\},\end{aligned}$$

where, after using the definition of the fourth central moment of a normal distribution, $\mathbb{E}\left\{\left(\frac{(\log x-\mu)^2-\sigma^2}{\sigma^3}\right)^2\right\}$ is just $2/\sigma^2$ so we have:

$$\mathbb{E}\left\{D(x,a^*,\mathbf{i},\mathbf{t})\left(\frac{(\log x-\mu)^2-\sigma^2}{\sigma^3}\right)^2\right\} = \operatorname{cov}\left(D(x,a^*,\mathbf{i},\mathbf{t}),\left(\frac{(\log x-\mu)^2-\sigma^2}{\sigma^3}\right)^2\right)+\frac{2}{\sigma^2}\mathbb{E}\left\{D(x,a^*,\mathbf{i},\mathbf{t})\right\}$$

Following the same procedure for the second term:

$$\begin{aligned}\mathbb{E}\left\{D(x,a^*,\mathbf{i},\mathbf{t})\frac{\sigma^2-3\left(\log x-\mu\right)^2}{\sigma^4}\right\} &= \operatorname{cov}\left(D(x,a^*,\mathbf{i},\mathbf{t}),\frac{\sigma^2-3\left(\log x-\mu\right)^2}{\sigma^4}\right)\\ &\quad+\mathbb{E}\left\{D(x,a^*,\mathbf{i},\mathbf{t})\right\}\mathbb{E}\left\{\frac{\sigma^2-3\left(\log x-\mu\right)^2}{\sigma^4}\right\},\end{aligned} \tag{A.5}$$

where $\mathbb{E}\left\{\frac{\sigma^2-3(\log x-\mu)^2}{\sigma^4}\right\}=-2/\sigma^2$.

Combining the two, and moving the σ terms outside the covariances gives us:

$$\frac{\mathrm{d}^2\mathcal{C}(\mu,\sigma,\mathbf{i},\mathbf{t})}{\mathrm{d}\sigma^2} = \frac{1}{\sigma^6}\operatorname{cov}\left(D(x,a^*,\mathbf{i},\mathbf{t}),\left((\log x-\mu)^2-\sigma^2\right)^2\right)+\frac{1}{\sigma^4}\operatorname{cov}\left(D(x,a^*,\mathbf{i},\mathbf{t}),\sigma^2-3\left(\log x-\mu\right)^2\right).$$

Expand the square in the first covariance, and remove the constant σ^2 from the second covariance to get the first part of the proposition:

$$\begin{aligned}
\frac{\mathrm{d}^2\mathcal{C}(\mu,\sigma,\mathbf{i},\mathbf{t})}{\mathrm{d}\sigma^2} &= \frac{1}{\sigma^6}\mathrm{cov}\left(D(x,a^*,\mathbf{i},\mathbf{t}),(\log x-\mu)^4\right) \\
&\quad - \frac{2\sigma^2}{\sigma^6}\mathrm{cov}\left(D(x,a^*,\mathbf{i},\mathbf{t}),(\log x-\mu)^2\right) \\
&\quad - \frac{3}{\sigma^4}\mathrm{cov}\left(D(x,a^*,\mathbf{i},\mathbf{t}),(\log x-\mu)^2\right) \\
&= \frac{1}{\sigma^6}\mathrm{cov}\left(D(x,a^*,\mathbf{i},\mathbf{t}),(\log x-\mu)^4\right) - \frac{5}{\sigma^4}\mathrm{cov}\left(D(x,a^*,\mathbf{i},\mathbf{t}),(\log x-\mu)^2\right).
\end{aligned} \tag{A.6}$$

To put the two covariances in regression terms, we need to compute the variance of the terms in the second argument:

$$\begin{aligned}
\mathrm{var}\left((\log x-\mu)^4\right) &= \mathbb{E}\left\{\left[(\log x-\mu)^4 - \mathbb{E}\left\{(\log x-\mu)^4\right\}\right]^2\right\} \\
&= \mathbb{E}\left\{(\log x-\mu)^8\right\} - 6\sigma^4\mathbb{E}\left\{(\log x-\mu)^4\right\} + 9\sigma^8 \\
&= 105\sigma^8 - 18\sigma^8 + 9\sigma^8 \\
&= 96\sigma^8
\end{aligned} \tag{A.7}$$

where we use the fact that the fourth central moment is $3\sigma^4$ and the eighth central moment is $105\sigma^8$.

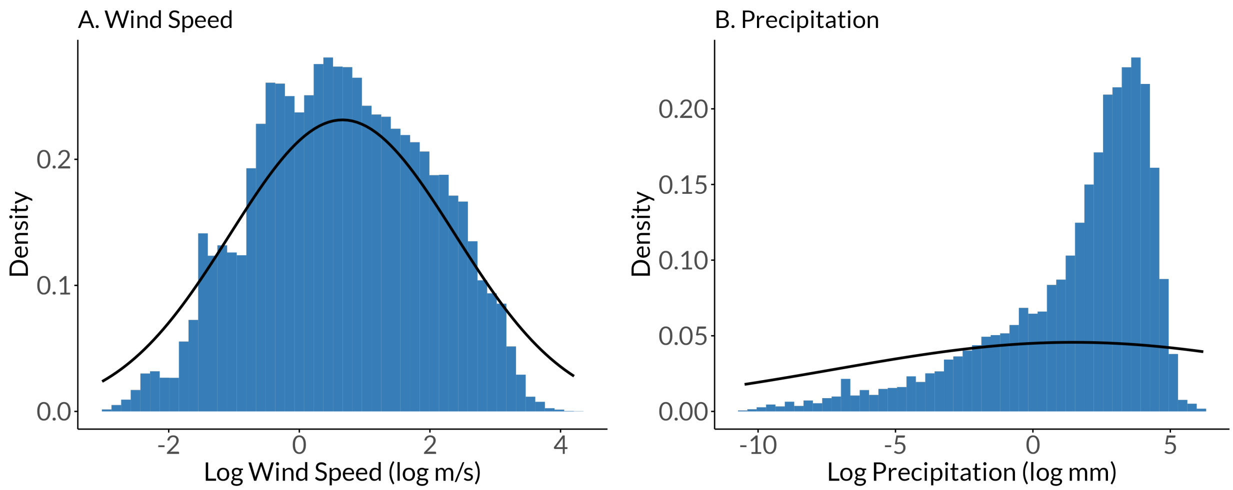
Finally, let β_p be the coefficient from regressing $D(x,a^*,\mathbf{i},\mathbf{t})$ on $(\log x-\mu)^p$. We can use equations A.3 and A.7 to show that:

$$\begin{aligned}
\frac{\mathrm{d}^2\mathcal{C}(\mu,\sigma,\mathbf{i},\mathbf{t})}{\mathrm{d}\sigma^2} &= \frac{1}{\sigma^6}\mathrm{cov}\left(D(x,a^*,\mathbf{i},\mathbf{t}),(\log x-\mu)^4\right) - \frac{5}{\sigma^4}\mathrm{cov}\left(D(x,a^*,\mathbf{i},\mathbf{t}),(\log x-\mu)^2\right) \\
&= \frac{96\sigma^2}{96\sigma^8}\mathrm{cov}\left(D(x,a^*,\mathbf{i},\mathbf{t}),(\log x-\mu)^4\right) - \frac{10}{2\sigma^4}\mathrm{cov}\left(D(x,a^*,\mathbf{i},\mathbf{t}),(\log x-\mu)^2\right) \\
&= 96\sigma^2\frac{\mathrm{cov}\left(D(x,a^*,\mathbf{i},\mathbf{t}),(\log x-\mu)^4\right)}{\mathrm{var}\left((\log x-\mu)^4\right)} - 10\frac{\mathrm{cov}\left(D(x,a^*,\mathbf{i},\mathbf{t}),(\log x-\mu)^2\right)}{\mathrm{var}\left((\log x-\mu)^2\right)} \\
&= 96\sigma^2\beta_4 - 10\beta_2.
\end{aligned} \tag{A.8}$$

B Checking the Normality Assumption

Figure B.1 plots the empirical distribution of log wind speed and log precipitation in blue, and the estimated normal densities in black. Log wind speed is a tight fit to the normal distribution, suggesting that the lognormal distribution assumption in the theoretical model is appropriate. Log precipitation does not appear to be governed by a normal distribution so our sufficient statistic approach may not be appropriate for precipitation.

Figure B.1: The Distribution of Realized Wind Speeds and Precipitation.



Note: The figure is split in two panels. Panel A shows the observed distribution of the log of the realized wind speeds by county-hurricane. Panel B shows the observed distribution of the log of the realized precipitation by county-hurricane. The black line shows the estimated normal distribution using maximum likelihood for each histogram.

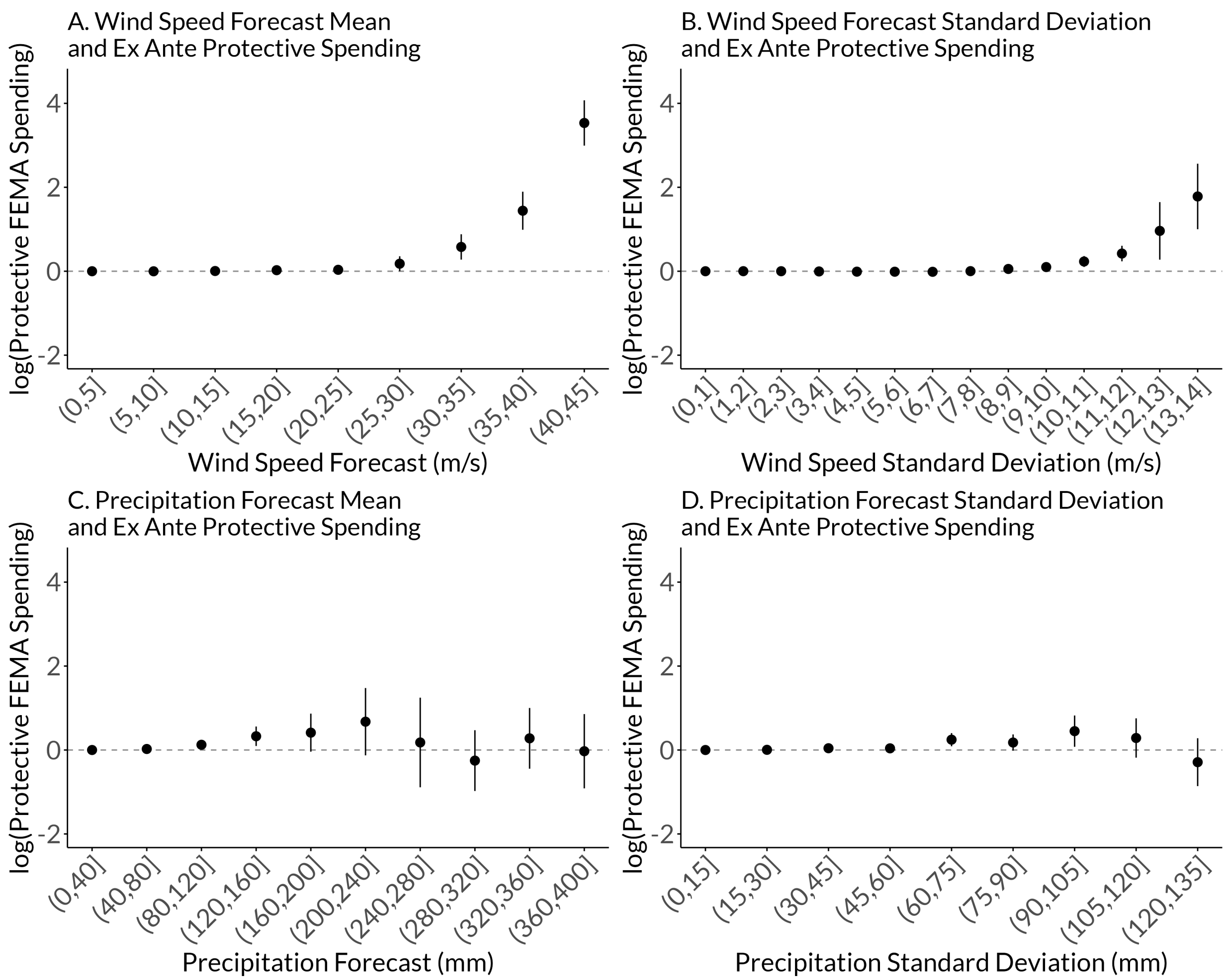
C Robustness Checks

C.1 Does FEMA Respond to Forecasts?

Table C.1 presents estimates of the effect of the expected wind speed, wind speed standard deviation, expected precipitation, and precipitation standard deviation on log protective spending. We include quadratic terms to allow for curvature in the relationship. Consistent with Figure 4, we find protective spending increases the expected wind speed and the wind speed standard deviation. If anything, expected precipitation decreases spending.

Figure C.1 replicates Figure 4 but only for states on the Gulf or Atlantic coasts: Texas, Louisiana, Mississippi, Alabama, Georgia, Florida, South Carolina, North Carolina, Virginia, Maryland, New Jersey, Pennsylvania, Connecticut, Delaware, New York, Rhode Island, Massachusetts, New Hampshire, and Maine. We find results are nearly identical.

Figure C.1: FEMA Protective Spending Responses to Forecast Means and Standard Deviations for Coastal States.



Note: Points are point estimates and the bars are the 95% confidence intervals. The omitted category for each panel is zero. The top row shows the effect of the mean and standard deviation of a forecast's wind speed on protective FEMA spending. The estimates in panels A and B are from the same regression. The bottom row shows the effect of the mean and standard deviation of a forecast's precipitation on protective FEMA spending. The estimates in panels C and D are from the same regression. All panels account for county, state-by-hurricane, and hours-ahead fixed effects. Standard errors in all panels are clustered two ways at the county and state-by-hurricane levels. Only the following states are included in the sample: Texas, Louisiana, Mississippi, Alabama, Georgia, Florida, South Carolina, North Carolina, Virginia, Maryland, New Jersey, Pennsylvania, Connecticut, Delaware, New York, Rhode Island, Massachusetts, New Hampshire, and Maine.

Table C.1: The Effect of Forecast Attributes on Before-Landfall FEMA Protective Spending.

	log(Protective Spending)			
	(1)	(2)	(3)	(4)
Wind Forecast (m/s)	-0.021***	-0.021***	-0.022***	-0.018***
	(0.006)	(0.006)	(0.007)	(0.005)
Wind Forecast Squared	0.001***	0.001***	0.001***	0.0009***
	(0.0004)	(0.0004)	(0.0004)	(0.0003)
Wind Forecast SD (m/s)	-0.007	-0.007	-0.007	-0.002
	(0.009)	(0.009)	(0.009)	(0.007)
Wind Forecast SD Squared	0.002**	0.002**	0.002**	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Precip Forecast (mm)	1.49×10^{-5}	1.49×10^{-5}	1.5×10^{-5}	1.79×10^{-5}
	(1.51×10^{-5})	(1.51×10^{-5})	(1.52×10^{-5})	(1.18×10^{-5})
Precip Forecast Squared	$-2 \times 10^{-10*}$	$-2 \times 10^{-10*}$	$-2.02 \times 10^{-10*}$	$-2.23 \times 10^{-10**}$
	(1.05×10^{-10})	(1.05×10^{-10})	(1.07×10^{-10})	(8.86×10^{-11})
Precip Forecast SD (mm)	6.29×10^{-6}	6.29×10^{-6}	3.72×10^{-6}	-9.85×10^{-6}
	(3.12×10^{-5})	(3.12×10^{-5})	(3.36×10^{-5})	(2.62×10^{-5})
Precip Forecast SD Squared	4.75×10^{-9}	4.75×10^{-9}	4.96×10^{-9}	$5.87 \times 10^{-9*}$
	(3.73×10^{-9})	(3.73×10^{-9})	(3.88×10^{-9})	(3.51×10^{-9})
Observations	157,150	157,150	157,150	157,150
County Fixed Effects	✓	✓	✓	
State-Hurricane Fixed Effects	✓	✓	✓	✓
Hours Ahead Fixed Effects	✓	✓	✓	✓
Year Fixed Effects		✓		
Year-Month-Day Fixed Effects			✓	✓
County-Year Fixed Effects				✓

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered two ways at the county and state-by-hurricane levels.

C.2 Does Forecast Accuracy Matter?

Tables C.2 and C.3 present estimates of the effect of wind speed and precipitation errors on damages and after-storm recovery spending. Tables C.4 and C.5 do the same, but let underestimates and overestimates have different magnitude marginal effects. Consistent with the main text, wind speed forecast underestimates increase damages, but we find little effect of precipitation errors in either direction except for recovery spending when we allow for heterogeneous effects by overestimates versus underestimates.

Figure C.2 decomposes the effect of forecast errors across the three damage categories. Errors are costly primarily because of increased property damages, although all three kinds of damage increase in the extent of the underestimation of realized wind speed.

Figure C.3 replicates Figure 5 but only for states on the Gulf or Atlantic coasts: Texas, Louisiana, Mississippi, Alabama, Georgia, Florida, South Carolina, North Carolina, Virginia, Maryland, New Jersey, Pennsylvania, Connecticut, Delaware, New York, Rhode Island, Massachusetts, New Hampshire, and Maine. We find results are nearly identical.

Table C.2: Effect of Underestimating Wind and Precipitation on Mortality, and Property and Crop Damages.

	log(Damages)			
	(1)	(2)	(3)	(4)
Wind Speed Underestimate (m/s)	0.100***	0.100***	0.110***	0.103***
	(0.038)	(0.038)	(0.041)	(0.027)
Precip Underestimate (mm)	0.004	0.004	0.004	0.004
	(0.009)	(0.009)	(0.009)	(0.006)
Observations	156,400	156,400	156,400	156,400
County Fixed Effects	✓	✓	✓	
State-Hurricane Fixed Effects	✓	✓	✓	✓
Hours Ahead Fixed Effects	✓	✓	✓	✓
Year Fixed Effects		✓		
Year-Month-Day Fixed Effects			✓	✓
County-Year Fixed Effects				✓

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered two ways at the county and state-by-hurricane levels. All regressions control for log wind speed and log precipitation.

Table C.3: Effect of Underestimating Wind and Precipitation on FEMA Recovery Spending.

	log(Recovery Spending)			
	(1)	(2)	(3)	(4)
Wind Speed Underestimate (m/s)	0.023***	0.023***	0.025***	0.021***
	(0.006)	(0.006)	(0.007)	(0.005)
Precip Underestimate (mm)	0.0009	0.0009	0.0008	0.0005
	(0.0008)	(0.0008)	(0.0008)	(0.0006)
Observations	156,400	156,400	156,400	156,400
County Fixed Effects	✓	✓	✓	
State-Hurricane Fixed Effects	✓	✓	✓	✓
Hours Ahead Fixed Effects	✓	✓	✓	✓
Year Fixed Effects		✓		
Year-Month-Day Fixed Effects			✓	✓
County-Year Fixed Effects				✓

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered two ways at the county and state-by-hurricane levels. All regressions control for log wind speed and log precipitation.

Table C.4: Effect of Underestimating Wind and Precipitation on Mortality, and Property and Crop Damages.

	log(Damages)			
	(1)	(2)	(3)	(4)
Wind Speed Error (m/s) × 1(Overestimate)	-0.070***	-0.070***	-0.075***	-0.033**
	(0.020)	(0.020)	(0.023)	(0.016)
Wind Speed Error (m/s) × 1(Underestimate)	0.204***	0.204***	0.212***	0.202***
	(0.049)	(0.049)	(0.050)	(0.033)
Precip Error (mm) × 1(Overestimate)	-0.010	-0.010	-0.010	-0.011
	(0.009)	(0.009)	(0.009)	(0.007)
Precip Error (mm) × 1(Underestimate)	0.009	0.009	0.009	0.009
	(0.012)	(0.012)	(0.012)	(0.008)
Observations	156,400	156,400	156,400	156,400
County Fixed Effects	✓	✓	✓	
State-Hurricane Fixed Effects	✓	✓	✓	✓
Hours Ahead Fixed Effects	✓	✓	✓	✓
Year Fixed Effects		✓		
Year-Month-Day Fixed Effects			✓	✓
County-Year Fixed Effects				✓

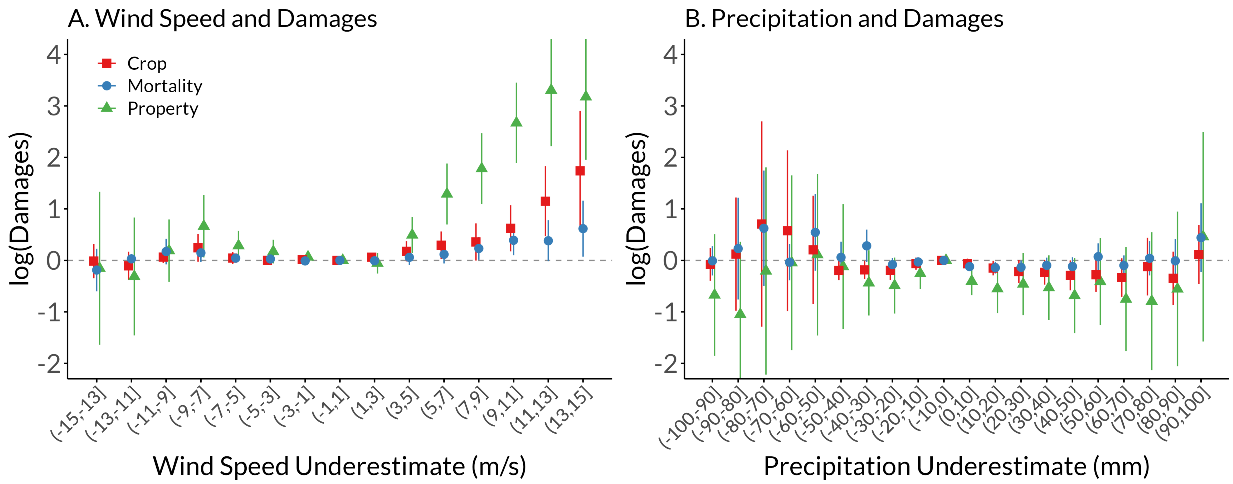
Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered two ways at the county and state-by-hurricane levels. All regressions control for log wind speed and log precipitation.

Table C.5: Effect of Underestimating Wind and Precipitation on FEMA Recovery Spending.

	log(Recovery Spending)			
	(1)	(2)	(3)	(4)
Wind Speed Error (m/s) $\times$ 1(Overestimate)	-0.001	-0.001	-0.0002	-0.0008
	(0.003)	(0.003)	(0.003)	(0.003)
Wind Speed Error (m/s) $\times$ 1(Underestimate)	0.039***	0.039***	0.041***	0.038***
	(0.009)	(0.009)	(0.009)	(0.007)
Precip Error (mm) $\times$ 1(Overestimate)	-0.003**	-0.003**	-0.003**	-0.003***
	(0.001)	(0.001)	(0.001)	(0.0008)
Precip Error (mm) $\times$ 1(Underestimate)	0.002**	0.002**	0.002**	0.002**
	(0.0010)	(0.0010)	(0.0010)	(0.0008)
Observations	156,400	156,400	156,400	156,400
County Fixed Effects	✓	✓	✓	
State-Hurricane Fixed Effects	✓	✓	✓	✓
Hours Ahead Fixed Effects	✓	✓	✓	✓
Year Fixed Effects		✓		
Year-Month-Day Fixed Effects			✓	✓
County-Year Fixed Effects				✓

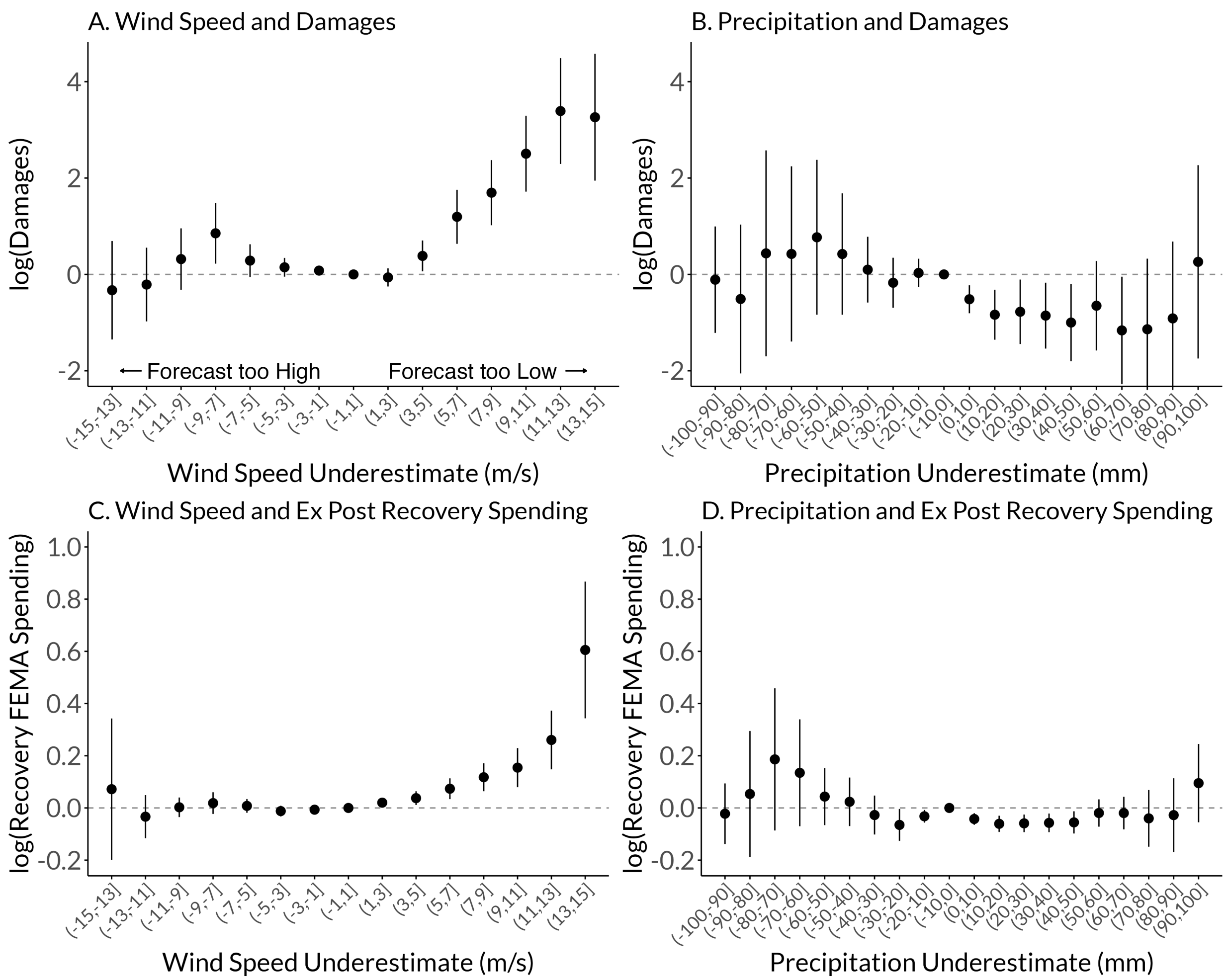
Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered two ways at the county and state-by-hurricane levels. All regressions control for log wind speed and log precipitation.

Figure C.2: Forecast Errors and Damage by Type of Damage.



Note: The points are point estimates, and the bars are the 95% confidence intervals. Panel A shows the effect of wind speed forecast underestimates on damages, Panel B shows the effect of precipitation forecast underestimates on damages. Each panel shows results from three regressions, one for each type of damage in our dataset. The omitted category is $(-1, 1]$ for wind speed and $(-10, 0]$ for precipitation. All panels account for county, state-by-hurricane, and hours-ahead fixed effects. Standard errors in all panels are clustered two ways at the county and state-by-hurricane levels.

Figure C.3: Forecast Errors, Damages, and *Ex Post* Recovery Spending for Coastal States.



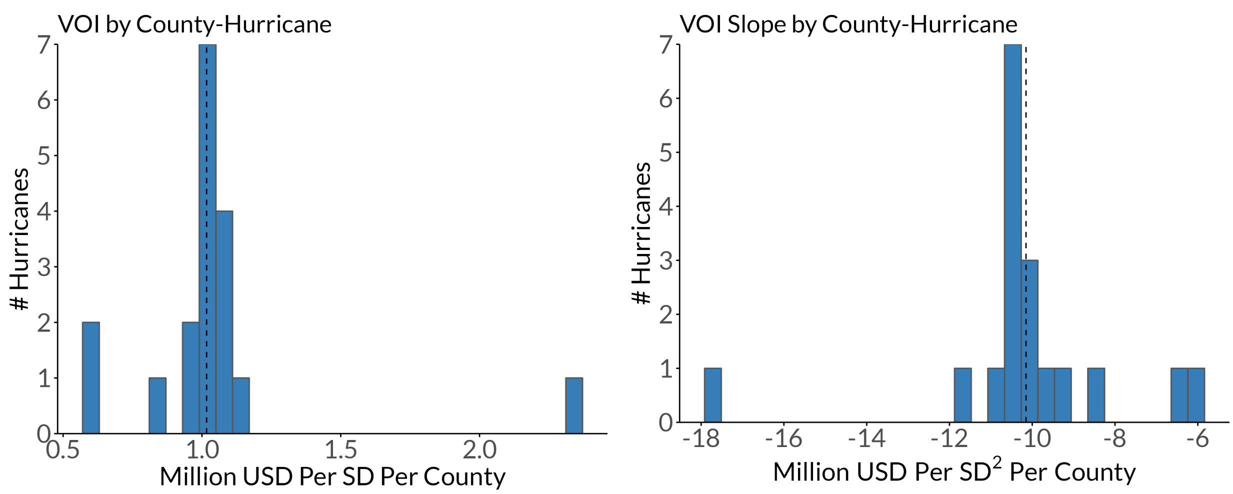
Note: The points are point estimates, and the bars are the 95% confidence intervals. Panel A shows the effect of wind speed forecast underestimates on damages, Panel B shows the effect of precipitation forecast underestimates on damages, Panel C shows the effect of wind speed forecast underestimates on FEMA recovery funds provided after landfall. Panel D shows the effect of precipitation forecast underestimates on FEMA recovery funding provided after landfall. The omitted category is $(-1, 1]$ for wind speed and $(-10, 0]$ for precipitation. All panels account for county, state-by-hurricane, and hours-ahead fixed effects. Standard errors in all panels are clustered two ways at the county and state-by-hurricane levels. Only the following states are included in the sample: Texas, Louisiana, Mississippi, Alabama, Georgia, Florida, South Carolina, North Carolina, Virginia, Maryland, New Jersey, Pennsylvania, Connecticut, Delaware, New York, Rhode Island, Massachusetts, New Hampshire, and Maine.

C.3 What is the *Ex Ante* Value of Improving Hurricane Forecasts?

Panel A of Figure C.4 shows the distribution of estimates corresponding to Column 1 of Table 2 but where we drop hurricanes from the sample, one-by-one. Most of the estimates are tightly clustered around the full sample estimate except for three. The large estimate is when we drop Ike, and the two low estimates are when we drop Katrina and Harvey. Panel B performs the same exercise for the slope estimate. Here, the largest estimate corresponds to dropping Harvey while the smallest two are Harvey and Michael.

Tables C.6 and C.7 present value of information estimates for precipitation forecasts. Recalling that precipitation is not lognormally distributed like our model assumption, we caution against interpreting the exact point estimates as the true value of information for forecasts. With this in mind, we do find that they are smaller in magnitude than their equivalent estimates for wind speed forecasts and statistically indistinguishable from zero in all specifications. This is consistent with our main text results showing that precipitation forecasts do not seem to drive protective spending and precipitation forecast errors do not seem to have large effects on damages or recovery spending.

Figure C.4: The Value of a Marginal Reduction in Wind Speed Forecast Uncertainty Dropping Individual Hurricanes.



Note: Panel A plots a histogram of the distribution of estimates of the value of information corresponding to Column 1 of Table 2 but where we drop individual hurricanes. Panel B plots estimates of the slope of the value of information corresponding to Column 1 of Table 3 but where we drop individual hurricanes.

Table C.6: The Value of a Marginal Reduction in the Precipitation Forecast Standard Deviation: The Precipitation Value of Information.

	(1)	(2)	(3)	(4)
β_2: $(\log x - \mu)^2$	0.256	0.256	0.271	-0.051
	(0.271)	(0.271)	(0.286)	(0.058)
$2\sigma\beta_2$: Precip VOI	0.78	0.78	0.83	-0.16
	(0.83)	(0.83)	(0.88)	(0.18)
Observations	43,830	43,830	43,830	43,830
County Fixed Effects	✓	✓	✓	
State-Hurricane Fixed Effects	✓	✓	✓	✓
Hours Ahead Fixed Effects	✓	✓	✓	✓
Year Fixed Effects		✓		
Year-Month-Day Fixed Effects			✓	✓
County-Year Fixed Effects				✓

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors are clustered two ways at the county and state-by-hurricane levels.

Table C.7: The Slope of the Precipitation Value of Information.

	(1)	(2)	(3)	(4)
β_2: $(\log x - \mu)^2$	0.256	0.256	0.271	-0.051
	(0.271)	(0.271)	(0.286)	(0.058)
β_4: $(\log x - \mu)^4$	0.0005	0.0005	0.0005	0.0001
	(0.0005)	(0.0005)	(0.0005)	(0.0001)
$96\sigma^2\beta_4 - 10\beta_2 : \partial\text{Precip VOI}/\partial\sigma$	-2.46	-2.46	-2.6	0.54
	(2.61)	(2.61)	(2.76)	(0.56)
Observations	43,830	43,830	43,830	43,830
County Fixed Effects	✓	✓	✓	
State-Hurricane Fixed Effects	✓	✓	✓	✓
Hours Ahead Fixed Effects	✓	✓	✓	✓
Year Fixed Effects		✓		
Year-Month-Day Fixed Effects			✓	✓
County-Year Fixed Effects				✓

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors are clustered two ways at the county and state-by-hurricane levels.

D Additional Results

D.1 Heterogeneous Effects of Forecast Errors

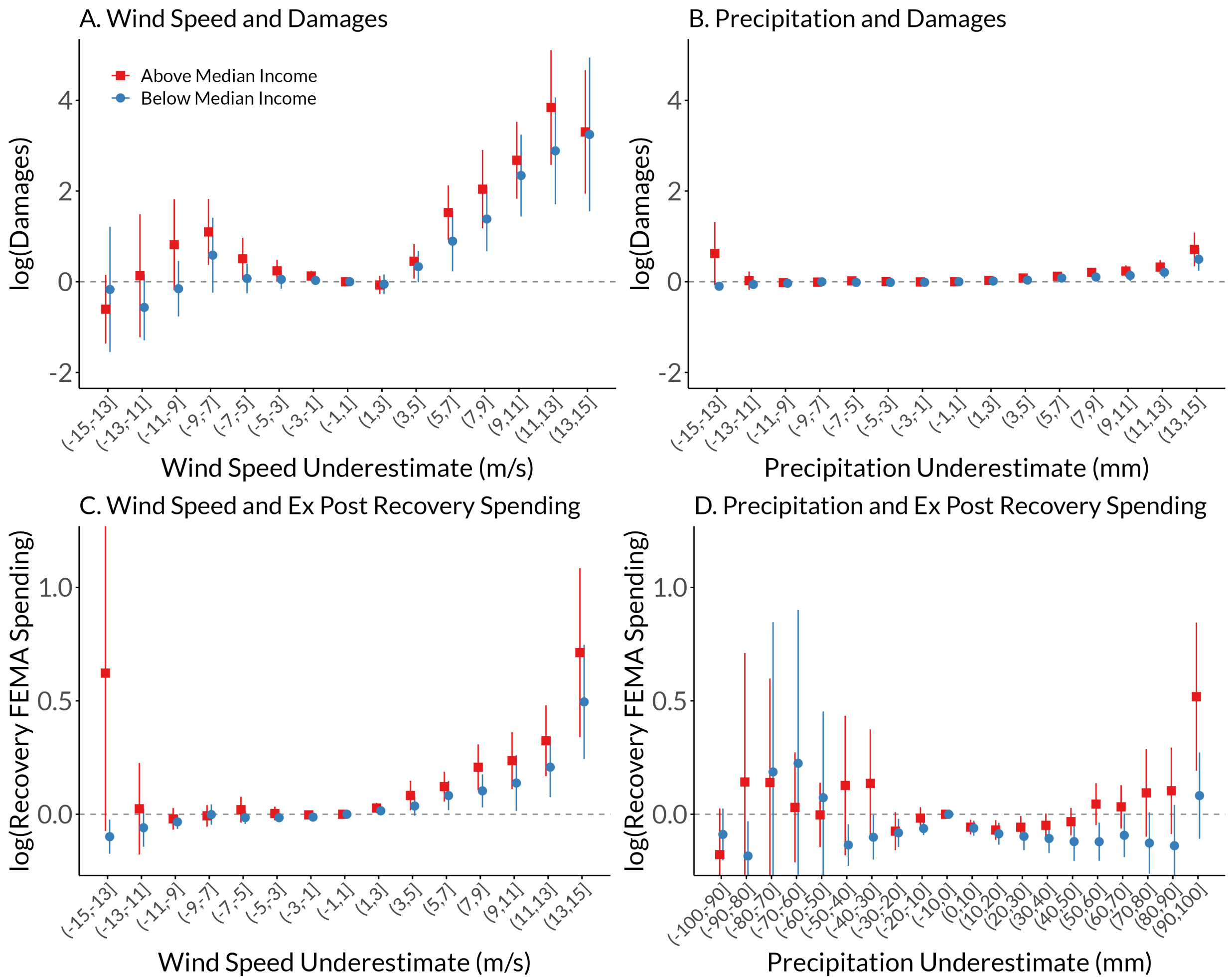
Figures D.2–D.4 show heterogeneous effects of forecast errors by whether a county is below or above the median income, the median population, the median share white, and the median forecast error for the last hurricane. The first three test for socioeconomic differences in forecast errors while the last tests for whether previous errors may affect current outcomes if, for example, households or local governments are less responsive to forecasts if the last hurricane's forecast was bad. Areas that are higher income and have larger populations tend to have greater damages and recovery spending from the same forecast error, while areas that are less white tend to have greater damages and similar recovery spending. We find little evidence for heterogeneity in damages or recovery spending in the size of the last forecast error.

D.2 Correlations and Distributions

Figure D.5 presents correlations between storm and forecast attributes. Panel A shows that higher intensity storms tend to have forecasts that are too low, creating a correlation between storm intensity and forecast errors. Panel B shows that there is a strong positive correlation between the predicted intensity of the storm and the uncertainty of the forecast. Panel C shows that more uncertain forecasts tend to result in larger forecast errors, showing why reductions in forecast standard deviations will result in more accurate forecasts ex post. Panel D shows that realized wind speed and realized precipitation are highly positively correlated.

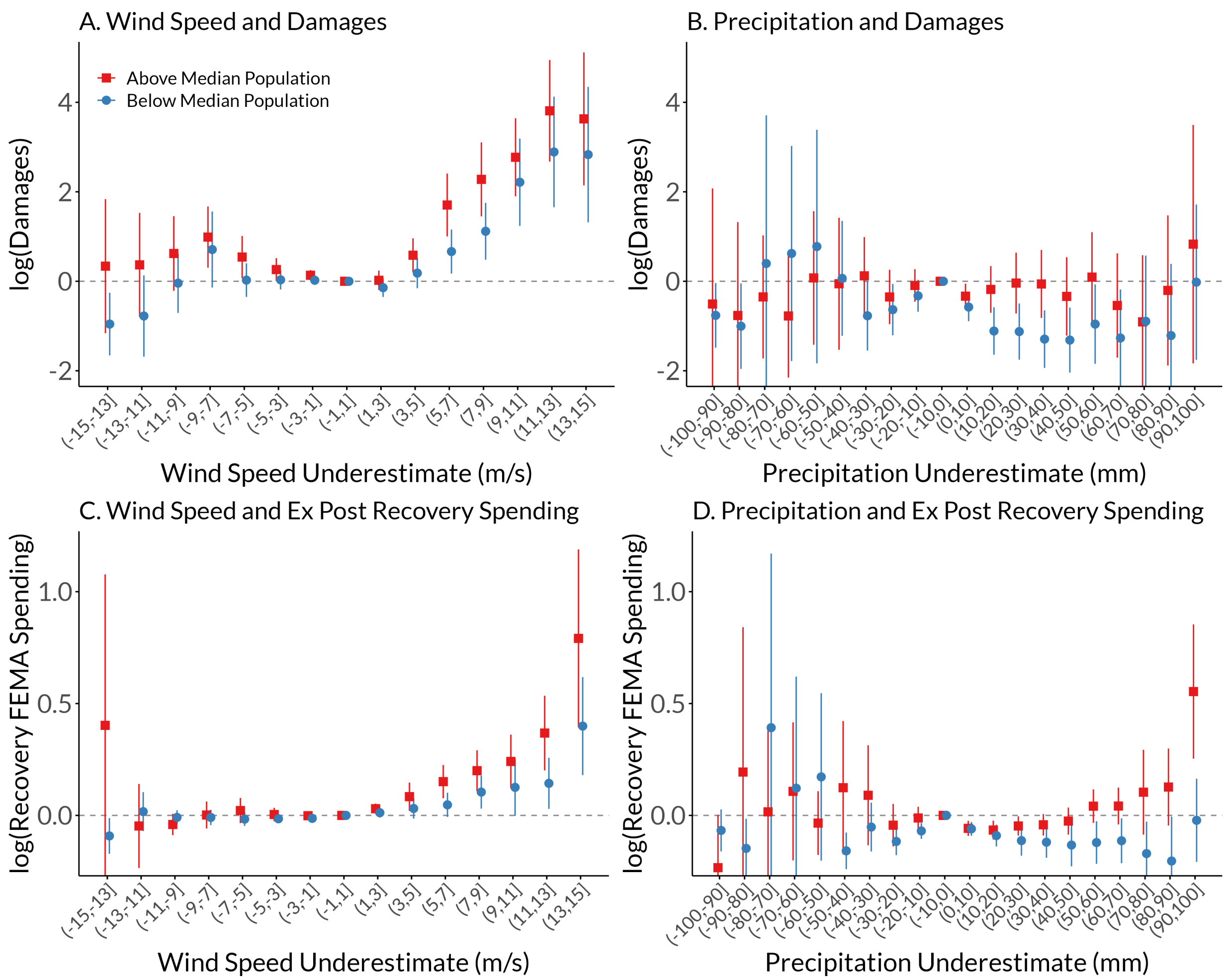
Figure D.6 shows additional information about the hurricane forecast. Panel A shows that forecasts are quite accurate on average, plotting the realized wind speed against the forecast wind speed using a 5 percentile binscatter shows all the points essentially on the 45 degree line. Panel B plots the distribution of wind speed forecast errors. The average forecast error is only 0.1 m/s with a standard deviation of over 3. The distribution is right-skewed: there are slightly more underestimates of wind speed than overestimates, likely driven by difficulties with forecasting rapidly intensifying storms.

Figure D.1: Forecast Errors, Damages, and *Ex Post* Recovery Spending by Median Income.



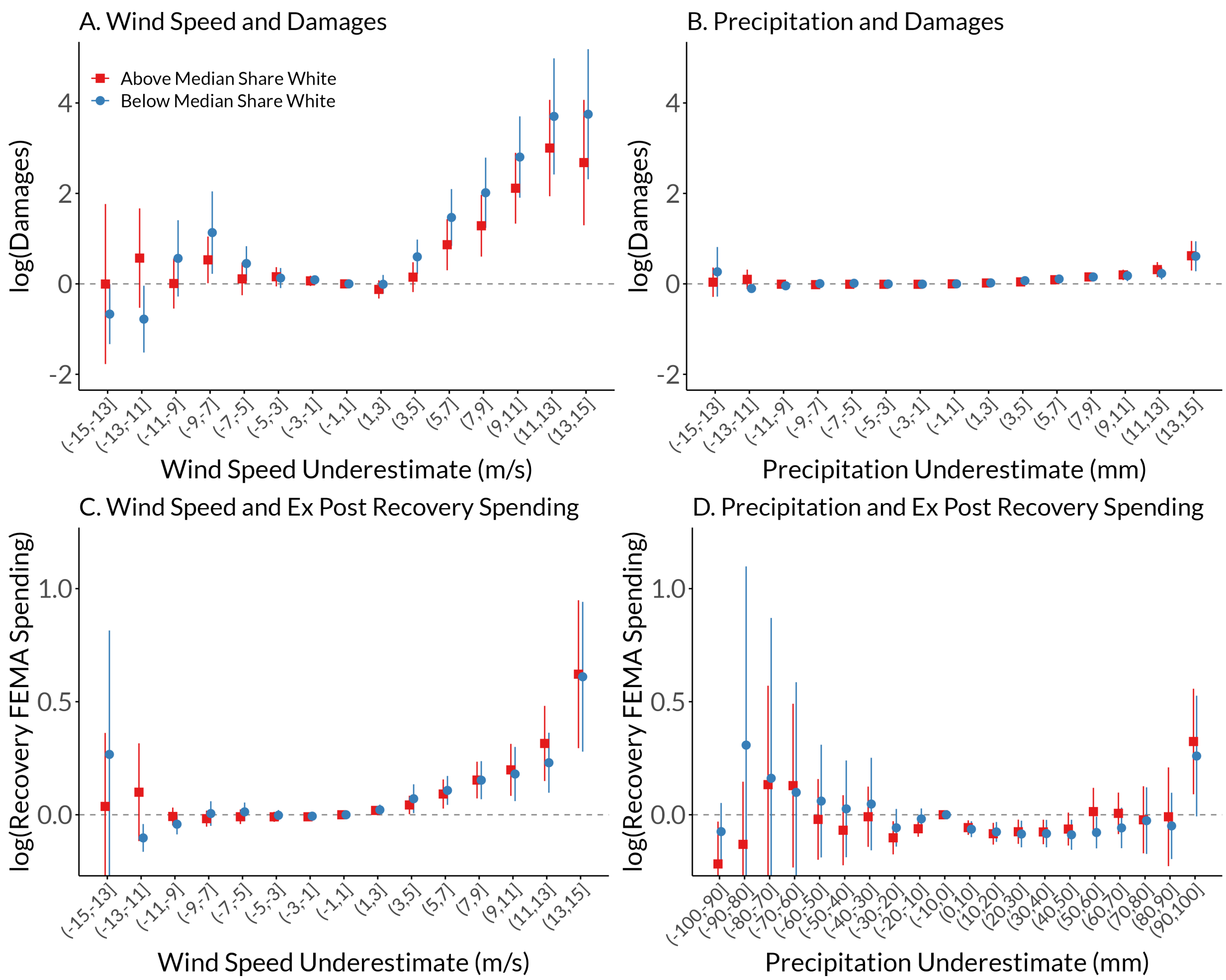
Note: The points are point estimates, and the bars are the 95% confidence intervals. Panel A shows the effect of wind speed forecast underestimates on damages, Panel B shows the effect of precipitation forecast underestimates on damages, Panel C shows the effect of wind speed forecast underestimates on FEMA recovery funds provided after landfall. Panel D shows the effect of precipitation forecast underestimates on FEMA recovery funding provided after landfall. The omitted category is $(-1, 1]$ for wind speed and $(-10, 0]$ for precipitation. All panels account for county, state-by-hurricane, and hours-ahead fixed effects. Standard errors in all panels are clustered two ways at the county and state-by-hurricane levels.

Figure D.2: Forecast Errors, Damages, and *Ex Post* Recovery Spending by Median Population.



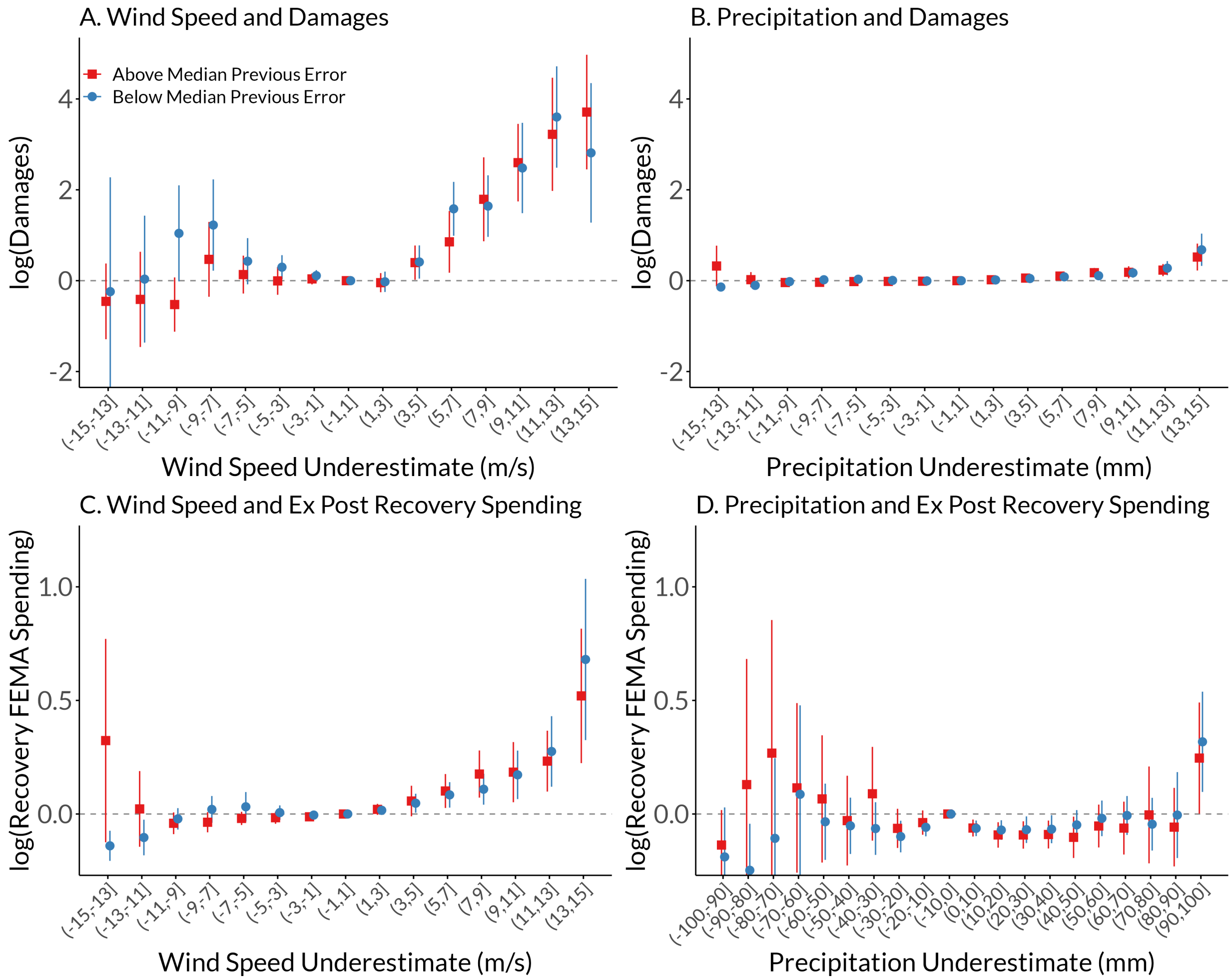
Note: The points are point estimates, and the bars are the 95% confidence intervals. Panel A shows the effect of wind speed forecast underestimates on damages, Panel B shows the effect of precipitation forecast underestimates on damages, Panel C shows the effect of wind speed forecast underestimates on FEMA recovery funds provided after landfall. Panel D shows the effect of precipitation forecast underestimates on FEMA recovery funding provided after landfall. The omitted category is $(-1, 1]$ for wind speed and $(-10, 0]$ for precipitation. All panels account for county, state-by-hurricane, and hours-ahead fixed effects. Standard errors in all panels are clustered two ways at the county and state-by-hurricane levels.

Figure D.3: Forecast Errors, Damages, and *Ex Post* Recovery Spending by Median Share White.



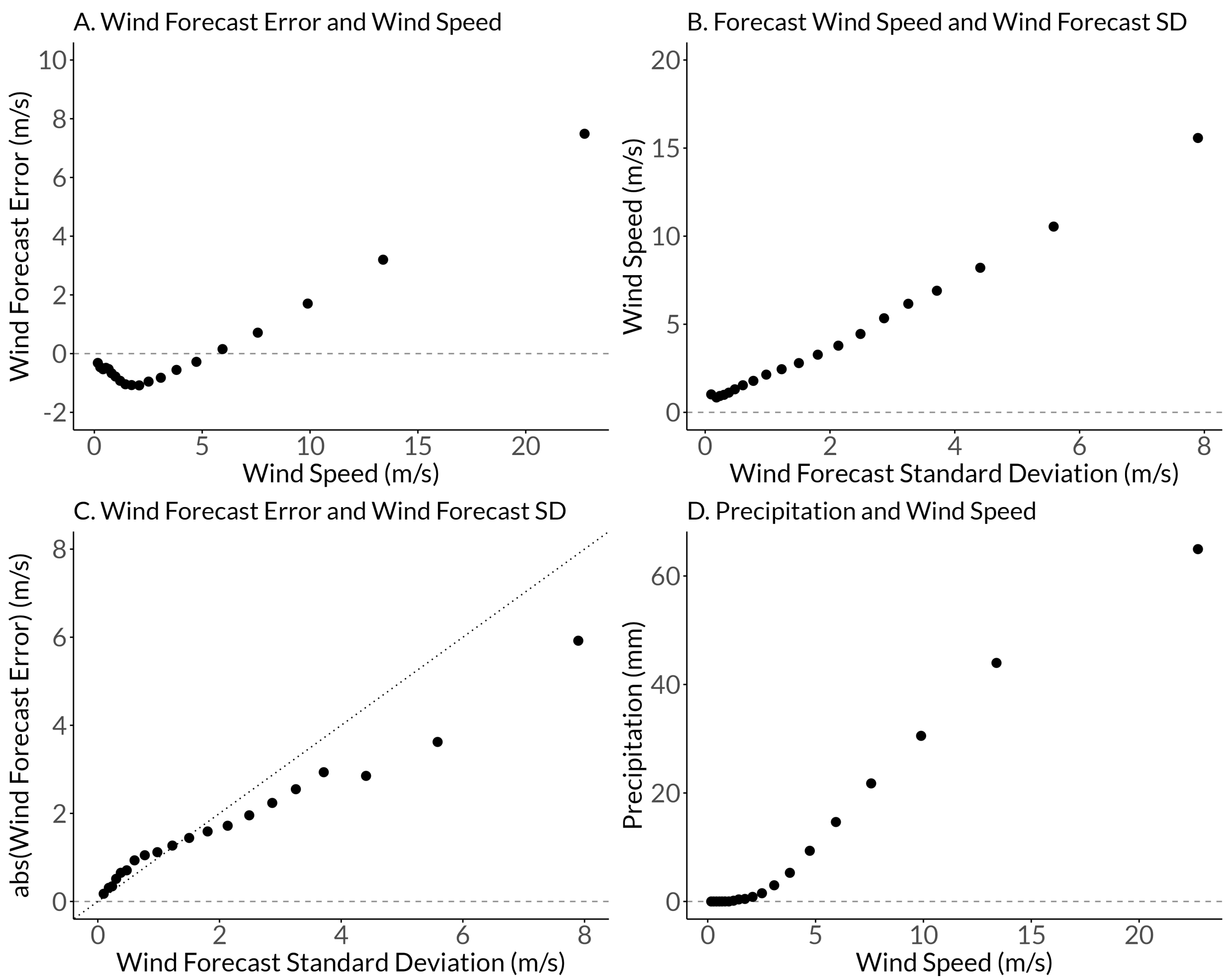
Note: The points are point estimates, and the bars are the 95% confidence intervals. Panel A shows the effect of wind speed forecast underestimates on damages, Panel B shows the effect of precipitation forecast underestimates on damages, Panel C shows the effect of wind speed forecast underestimates on FEMA recovery funds provided after landfall. Panel D shows the effect of precipitation forecast underestimates on FEMA recovery funding provided after landfall. The omitted category is $(-1, 1]$ for wind speed and $(-10, 0]$ for precipitation. All panels account for county, state-by-hurricane, and hours-ahead fixed effects. Standard errors in all panels are clustered two ways at the county and state-by-hurricane levels.

Figure D.4: Forecast Errors, Damages, and *Ex Post* Recovery Spending by Median Error of Last Forecast.



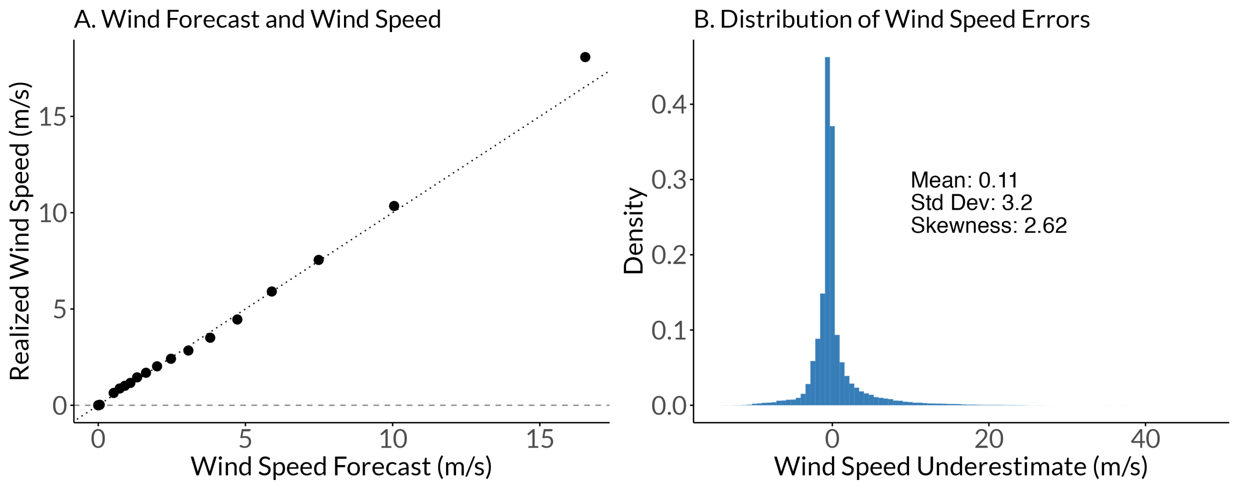
Note: The points are point estimates, and the bars are the 95% confidence intervals. Panel A shows the effect of wind speed forecast underestimates on damages, Panel B shows the effect of precipitation forecast underestimates on damages, Panel C shows the effect of wind speed forecast underestimates on FEMA recovery funds provided after landfall. Panel D shows the effect of precipitation forecast underestimates on FEMA recovery funding provided after landfall. The omitted category is $(-1, 1]$ for wind speed and $(-10, 0]$ for precipitation. All panels account for county, state-by-hurricane, and hours-ahead fixed effects. Standard errors in all panels are clustered two ways at the county and state-by-hurricane levels.

Figure D.5: Relationships Between Different Forecast Attributes and Storm Attributes.



Note: The figure is split in four panels. Panel A plots the error in the wind speed forecast (actual wind speed minus predicted wind speed) against the realized wind speed. Panel B plots the predicted wind speed against the forecast's standard deviation. Panel C plots the absolute value of the wind speed forecast's error against the forecast's standard deviation. The dotted line is the 45 degree line. Panel D plots realized precipitation against realized wind speed. For all panels, each point is the mean of the x and y-axis variable within each viginile of the x-axis variable (i.e. a 20 bin binscatter).

Figure D.6: The Distribution of Wind Speed Errors.



Note: Panel A plots a 20 point binscatter of realized wind speed against the wind speed forecast. The dotted line is the 45 degree line. Panel B plots the underestimate of wind speed by a forecast. We omit observations where the forecast was for zero wind speed and the realized wind speed was zero.