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THE SOCIAL VALUE OF HURRICANE FORECASTS

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ABSTRACT

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The Social Value of Hurricane Forecasts

By Renato Molina and Ivan Rudik*

What is the impact and value of hurricane forecasts? We study this question using the universe of landfalling US hurricanes between 2005–2022. We find that forecasts drive adaptive protective expenditures, and that erroneous underforecasts result in a significant increase in total hurricane damage. Using a theoretically-grounded approach for estimating the marginal value of forecast improvements, we find that improvements since 2007, after the implementation of a national policy to improve hurricane forecasts, have reduced total costs by 19%, averaging $2 billion per hurricane. These benefits far exceed the annual budget of the policy and of all federal weather forecasting.

Extreme weather like hurricanes, flooding, and extreme heat has devastated regions around the world. In the United States alone, these events have caused over $700 billion in damage since 2017, and trillions of dollars in damage since 1980, with the majority caused by hurricanes (Weinkle et al., 2018; NOAA, 2022*a*,*b*). One of the key levers for mitigating the destructive impacts of extreme weather, and especially hurricanes, is forecasting. Forecasts provide information on the expected strength, location, and timing of the event, allowing households and government actors to make better preparation decisions. Despite their importance and ubiquity, however, there is limited evidence on the historical value of hurricane forecasts or the potential value of future forecasting improvements.

In this paper, we investigate the value and economic impact of hurricane forecasts in the US.[1] Using the actual models underpinning the national hurricane forecast system, we develop a new county-level dataset of forecasts and realizations of wind speed and precipitation, as well as the *ex ante* uncertainty embedded in the forecasts. Our dataset consists of the 31 Category 1 and greater hurricanes (maximum wind speeds greater than 33 meters per second [m/s]) that made landfall in the continental US between 2005–2022. In total, our dataset accounts for over 70% of direct property damage and about 40% of deaths for all environmental hazards in the US during this time period.

We use these new data to (1) estimate how emergency federal expenditures for protecting against hurricanes respond to forecast information, (2) estimate the costs of forecast errors in terms of dam-

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[1] We focus on hurricane forecasts that are issued in the several days between a hurricane's formation and its landfall. However, there also exist seasonal forecasts of the characteristics of an entire hurricane season. Recent empirical work has found that seasonal hurricane forecasts, issued once per year, do not seem to be priced in options markets (Lemoine and Kapnick, 2024).

ages and increased expenditures for post-hurricane recovery, and (3) estimate the *ex ante* marginal value of a forecast improvement using a structural approach while accounting for unobserved protective actions taken prior to landfall. We then use our estimates to value the dramatic improvements in wind speed forecast accuracy since the 2000s.

The value of hurricane forecasts comes from how they help agents make better protective decisions. We start our analysis by estimating how hurricane forecasts affect the allocation of federal emergency protective expenditures in the days before a hurricane reaches land. The federal government disburses significant resources to reduce the immediate impact of hurricanes. For example, in anticipation of Hurricane Irma, Miami-Dade County was awarded over \$13 million to fund protective measures, including more than 9,500 hours of overtime for police officers to conduct evacuations and implement protective operations before landfall (FEMA, 2019).

In our analysis, we find that a county's allocated federal protective expenditures for an impending hurricane are increasing in its wind speed forecast. Counties forecast to experience hurricane-force winds receive \$36 million more in protective expenditures than counties forecast to have lower, sub-hurricane-force winds. This is equivalent to 0.8% more funding as a share of county GDP, or over \$300 more per person. These findings suggest that forecasts play a significant role in driving protective actions.

We next estimate the consequences of forecast errors. Conditional on hurricane intensity, forecast errors matter only if protective actions respond to forecasts and also mitigate hurricane impacts. We find that there are economically significant increases in damages and post-landfall federal disaster recovery costs from underestimating hurricane wind speed, after flexibly conditioning on realized wind speed and precipitation. Relative to a perfect forecast, underestimating wind speed by 10 m/s – an error that would be a misclassification by up to two categories on the commonly used Saffir-Simpson scale – increases county-specific damages by \$220 million and after-landfall federal emergency expenditures for recovery by \$20 million. For damages, this is about 15% of county GDP or over \$5,500 per person.

Finally, we implement a theoretically-grounded approach to estimate the expected total cost reduction from a marginal decrease in a forecast's *ex ante* standard deviation. We call this the *value of a forecast improvement*. Lower standard deviation forecasts have smaller *ex post* errors, which means agents are less likely to incur excess protective costs from an over-forecast, or incur excess damages and recovery costs from an under-forecast. We show that the marginal value of a forecast improvement can be identified by regressing the sum of damages and recovery expenditures on the *ex post* squared error in the forecast, and then scaling the estimate by the baseline *ex ante* standard deviation at which we are valuing the marginal improvement. This approach does not require observing pre-landfall protective actions, so we are able to establish the value of a forecast improvement without having to track how agents might protect themselves against a hurricane. Properly estimating the value of a forecast improvement does require observing the *ex ante* forecast standard deviation, a feature unique to our newly-constructed forecast dataset.

We find that a marginal reduction in a forecast's squared wind speed error reduces total protective expenditures, damages, and recovery expenditures in a county by \$5.5 million per hurricane, equivalent to about 0.45% of county GDP or \$160 per person. Inserting these estimates into our theoretically-grounded expression for the value of a 1 standard deviation reduction in forecast uncertainty indicates that this value is about \$16 million per hurricane per county when evaluated at our sample average forecast standard deviation. This value of a forecast improvement is driven entirely by counties that experience hurricane-force winds. We then use our estimates to value the historical improvements in forecasting over 2007-2022, and find that they led to a 19% reduction in total hurricane costs, about \$2 billion per hurricane. The average benefit *per hurricane* is larger than the budget for *all* federal weather forecasting in the US in 2015 (Congressional Research Service, 2015).

Overall, our paper adds to a sparse and relatively new literature on environmental forecasts.

Some of the earliest work studied the role of weather forecasts in agriculture and shipping (Lave, 1963; Craft, 1998). More recently, researchers have studied the economic effects of precipitation forecasts in construction and automobile accidents (Mitch Downey, Nelson Lind and Jeffrey G Shrader, 2023; Vaibhav Anand, Forthcoming), as well as how forecasts can be used to measure climate damages accounting for adaptation (Shrader, 2021).

Two recent papers on pollution and temperature are closest to ours in spirit in aiming to estimate the value of forecasts accounting for adaptation. Panle Jia Barwick, Shanjun Li, Liguo Lin and Eric Yongchen Zou (2024) 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. Jeffrey Shrader, Laura Bakkensen and Derek Lemoine (2023) evaluates the benefits of improving routine temperature forecasts – inclusive of protective costs – and finds that cutting errors in half would save thousands of lives per year, generating benefits of billions of dollars.

We contribute to this literature in several ways. First, we provide a novel overall assessment of the US hurricane forecast system and the improvements in its accuracy.[2] Second, we provide a general method to value any kind of hazard forecast, inclusive of all *ex ante* adaptation or protective costs. Third, after taking a stand on the distributional family of a forecast, our approach can value changes in the second moment of the forecast. This allows us to go beyond aggregate cost-benefit analysis and provide marginal values that could be used to analyze optimal levels of investments for improving 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, municipal financing, mortality, and welfare (Ilan Noy, 2009; Solomon M Hsiang, 2010; Eric Strobl, 2011; Solomon M Hsiang and Amir S Jina, 2014; Laura Bakkensen and Lint Barrage, Forthcoming; Jun Kyung Auh, Jaewon Choi, Tatyana Deryugina and Tim Park, 2022; Rhiannon Jerch, Matthew E Kahn and Gary C Lin, 2023; Rachel Young and Solomon Hsiang, 2024). Historically, the US has suffered abnormally high damages due to hurricanes, and climate change is expected to amplify them while also making hurricane forecasting more difficult (Mendelsohn et al., 2012; Emanuel, 2017; Kossin et al., 2020).[3] Recent research suggests that damages caused by storms like hurricanes significantly magnify the impacts of climate change (Bilal and Rossi-Hansberg, 2023), but that a third of the climate change-induced damages in the US could be offset by appropriate investments into long-run adaptation capital (Fried, 2022).

We add to this literature by studying the role of accurate 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. 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.[4] Our theoretical results indicate that the expected decrease in hurricane forecastability under climate change will make future improvements more valuable on the margin, while our empirical results suggest the avoided costs from the actual hurricane forecast improvements since 2007 are half the size of the avoided climate change-induced costs from optimal long-run adaptive capital investments (Fried, 2022).

Finally, our findings also add to a limited stated-preference literature on the value of hurricane

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

[3]Hurricanes have recently been both moving slower across space while also intensifying much more rapidly (Kossin, 2018; Bhatia et al., 2019), potentially leading to their observed rising destructiveness in recent decades (Emanuel, 2005; Grinsted, Ditlevsen and Christensen, 2019).

[4]Recent work has shown that individuals stock up on emergency supplies before a hurricane and that the costs of before-landfall evacuations can exceed tens of millions of dollars per hurricane (Beatty, Shimshack and Volpe, 2019; Gellman et al., 2024).

forecasts. This literature finds that, in the aggregate, households in hurricane-vulnerable areas value recent forecast improvements at about $300 million per year (Lazo et al., 2010; Lazo and Waldman, 2011; Molina et al., 2021). Using data on actual damages, we find the value of hurricane forecast improvements is significantly larger.

The paper proceeds as follows. Section I provides background information on hurricanes and hurricane forecasts. Section II describes the data we use in our analysis. Section III presents our methods and results. Section IV concludes.

I. Background

Hurricanes are a type of tropical cyclone, a rotating storm system that forms over warm tropical or subtropical waters and with 1-minute maximum sustained wind speeds (from hereon "wind speed") of at least 17.5 m/s (39 mph). When maximum wind speeds reach 17.5–32.9 m/s (39–73 mph), the system is classified as a tropical storm and receives an official name. If maximum wind speeds exceed 33 m/s ($\geq$ 74 mph), it becomes a hurricane (in the Atlantic and Eastern Pacific), a typhoon (in the Western Pacific), or a cyclone (in the Indian Ocean and South Pacific). In the rest of the paper, we will refer to the hurricanes in our analysis as hurricanes or storms.

Hurricanes are further categorized on the Saffir-Simpson Hurricane Wind Scale to provide a heuristic for hurricane intensity. The scale ranges from Category 1 (33–42 m/s or 74–95 mph) to Category 5 ($\geq$ 70 m/s or $\geq$ 157 mph). The potential for damages increases with Category (Emanuel, 2003). The Saffir-Simpson categorization is done when the hurricane is over water, as it is during that phase that maximum wind speeds are developed, particularly around the eye wall. An important feature of hurricanes, however, is that they weaken considerably and rapidly after making contact with land (Li and Chakraborty, 2020; Nolan et al., 2021). This drives a disconnect between a hurricane's reported category and the realized and forecast wind speeds over land.

Despite the historical reliance upon wind speed for hurricane classification, hurricanes are multi-dimensional disasters. Hurricanes cause damage through wind exposure, inland flooding caused by extreme precipitation, and coastal flooding caused by storm surge. Recent analyses estimate that wind causes about 40% of damage, with flooding accounting for the other 60% (US Congressional Budget Office, 2019; Hilderbrand and Xie, 2025), though the share of damage caused by wind and storm surge tends to be higher for "major" hurricanes ($\geq$ 50–58 m/s or $\geq$ 130 mph) like those in our data (Hilderbrand and Xie, 2025).[5]

The National Hurricane Center (NHC) issues official forecasts every six hours during an active tropical cyclone, providing forecasts of the storm's track (the path that the eye of the hurricane will follow), intensity, and size. Each forecast includes a deterministic forecast—a single best-guess of trajectory and intensity—as well as probabilistic guidance intended to convey uncertainty in the storm's evolution. Forecasts are then communicated to the public in several ways, with some focusing on the track and others focusing on intensity. One well-known communication tool is the cone of uncertainty. This is a graphical representation of the probable path of the center of a storm over time. The cone is constructed so that, given the recent history of forecast errors, the actual path will fall inside the cone about two-thirds of the time.[6]

Forecasts are also used to issue official watches and warnings, which guide emergency response and public communication. A tropical storm warning is issued when winds between 17.5–32.9 m/s (39–73 mph) are expected within a specific area, typically within 36 hours. Hurricane warnings are

[5]Although we do not have data on storm surge forecasts and realizations, storm surge is primarily caused by wind so our wind realization variables will be picking up some of the effects of unobserved storm surge realizations (NOAA, 2025).

[6]The size of the cone reflects historical forecast skill rather than real-time uncertainty in any specific storm. Importantly, the cone does not represent the size of the storm or the extent of damaging conditions, which can occur far outside its boundaries (Broad et al., 2007). See the official documentation of the cone of uncertainty, as well as the guidelines for interpretation here: https://www.nhc.noaa.gov/aboutcone.shtml.

issued when expected wind speeds exceed 33 m/s (74 mph).[7]

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 hurricanes in the 1954 and 1955 seasons, which led Congress to create the National Hurricane Research Project in 1956 (DeMaria, 1996). The eventual coordination and collocation of the Research Project, the Warning Office, and Aircraft Operations resulted in what is now known as the NHC (Sheets, 1990). The advent of computer modeling and meteorological satellites resulted in significant improvements in forecasting capabilities after 1970, setting the foundation for modern forecasts (Sheets, 1990).

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 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, Simmons and Sutter, 2011; Strobl, 2011).[8]

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 and extend the forecast lead time from five 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 guidance, and improved communication of risk and uncertainty (Marks et al., 2019). From 2009 to 2019, the HFIP budget for research and operations totaled approximately $250 million.

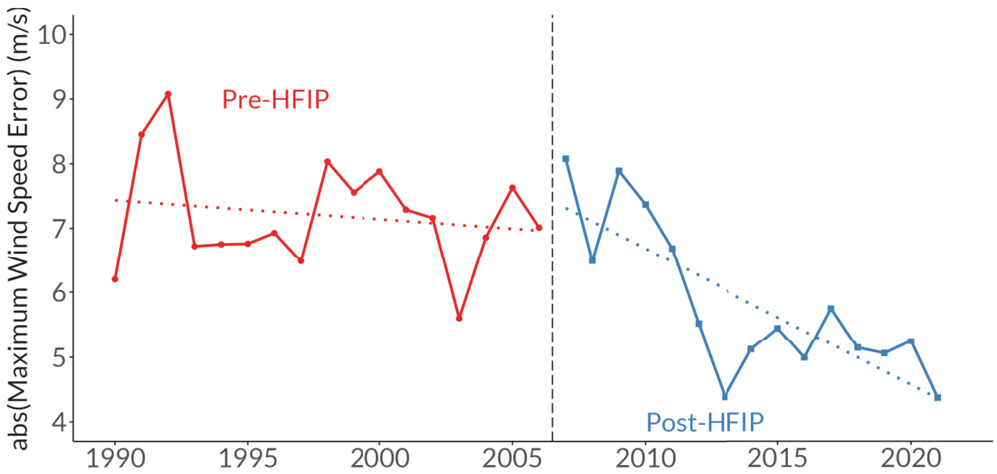
By any measure, these recent efforts to improve forecasts have been successful. Figure 1 plots the average of the errors in the official 1-, 2-, and 3-day ahead forecasts, as reported by the NHC at the storm level. The figure shows that prior to the HFIP in 2007, wind speed forecast errors were declining by 0.03 m/s each year, or about a 0.4% annual improvement. Since the inception of the HFIP in 2007, there has been a dramatic increase in the quality of the forecasts. Wind speed forecast errors have been declining by 0.21 m/s each year since 2007, or 3% annually.[9] These improvements can be attributed to advances in remote sensing, direct observations, model physics, and data assimilation techniques (Alaka Jr et al., 2024). In our valuation exercises, we will estimate

[7]Storm surge and extreme wind warnings are issued separately, depending on local risk. See the official glossary for warnings here: https://www.weather.gov/safety/hurricane-ww.

[8]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 hurricanes ever recorded at that time) also struck.

[9]Historically, it has been much more difficult to forecast the intensity of a storm 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 hurricanes will go under rapid intensification as they near landfall (Enten, 2017; Norcross, 2018).

FIGURE 1. WIND SPEED FORECAST ERROR ANNUAL TREND.



Note: The figure shows the average absolute value error in NOAA's maximum wind speed forecasts. The figure presents the average between the 1, 2, and 3-day ahead forecast errors across all hurricanes and tropical storms in a given year. Dotted lines represent the best linear fits for the time series before and after 2007, while the vertical dashed line marks the implementation of the HFIP in 2007, which expanded funding for forecast research and development. Source: NOAA (2024).

the value of this change in the rate of forecast improvement.

For forecasts to have value, decision-makers need to use them. A small academic literature finds that forecasts are important inputs into decisions of local emergency managers facing an impending hurricane. Their decisions are well-predicted by storm surge, hurricane category (wind), and timing of landfall (Gudishala and Wilmot, 2017), while surveys find they focus on flooding, storm surge, wind speed, and precipitation (Iman et al., 2023). The historical reliance on the Saffir-Simpson scale and wind speed as an overall measure of hurricane intensity suggests that wind speed may be a key factor in driving protective expenditures.[10,11]

II. Data

Our analysis focuses on a county-hurricane as the unit of observation (e.g., Kings County, NY and Hurricane Sandy), and uses data on hurricane intensity forecasts, hurricane intensity realizations, protective expenditures, recovery expenditures, and damages at the county-level for all 31 hurricanes that made landfall in the continental US from 2005 to 2022. We focus on wind speed as our measure of hurricane intensity.

A. *Forecasts*

For our analysis, we reconstruct the NHC forecast products from their raw data and models to replicate the contemporaneous official NOAA forecast. Here, we outline the data construction procedure. The process starts with the baseline "deterministic forecast," which we obtain from the NHC archives for each hurricane (NOAA, 2024). The deterministic forecast is a prediction of the hurricane track and its maximum wind speed at given times along the track. This forecast is

[10] The National Hurricane Center and National Weather Service did not begin issuing storm surge warnings until 2017, 12 years into our 17-year sample, making it unlikely that emergency actions were based on storm surge forecasts for many hurricanes in our sample.

[11] Assigning hurricanes to categories is based upon the hurricane's maximum sustained wind speed at a single point, however this will be strongly correlated with wind speeds in other parts of the hurricane.

produced with the input of leading weather models such as the US's Global Forecast System model or Europe's European Centre for Medium-Range Weather Forecasts model, as well as the expert judgment of forecasters at the NHC. These forecasts also incorporate real-time observational data from satellite imagery, aircraft reconnaissance, and surface measurements (Hamill et al., 2012). A probabilistic forecast is then derived from the baseline deterministic forecast. The process consists of sampling 1,000 time series of track and maximum wind speed errors from the distribution of errors over the previous 5-year forecast history, and then adding them to the current deterministic track forecast to produce a distribution of hurricane tracks and maximum wind speeds along these tracks.[12] We secure the official 1,000 track and maximum wind speed predictions at different lead times for the hurricanes in our sample through a collaboration with the Cooperative Institute for Research in the Atmosphere at Colorado State University. These predictions are created using the data and model vintage available at the time of each hurricane. We then produce 1,000 gridded wind speed forecast maps (i.e., rasters) by combining the 1,000 track forecasts and the maximum wind speeds with a high resolution hurricane wind model. Given a hurricane's maximum wind speed and track, the model generates gridded wind speed forecasts at different distances from the eye of the hurricane across the entire US (Willoughby, Darling and Rahn, 2006; DeMaria et al., 2009, 2013). The variability across the 1,000 maps captures errors and uncertainties that are specific to each hurricane because of the relative history of forecast accuracy, the hurricane's movement and location, and the local climate.[13]

For the purpose of this study, we focus on the 1- to 3-day-ahead forecast. This encompasses the time window followed by NOAA and the National Weather Service to issue watches and warnings to areas potentially exposed to hurricane wind hazard. The wind speed forecast's mean and standard deviation are calculated across all 1,000 maps for forecasts one, two, and three days prior to landfall. By relying on the official inputs, we ensure that our forecast data are in essence identical to the official predictions for the hurricanes in our sample. It is worth noting that on average, the standard deviation of the wind forecast has consistently declined over time. This is because progress in computing power, measurement and data collection, and forecasters' skill has made contemporaneous forecasts more precise (Alaka Jr et al., 2024). As more precise forecasts accumulate over time, smaller errors will be sampled to produce the probabilistic model.

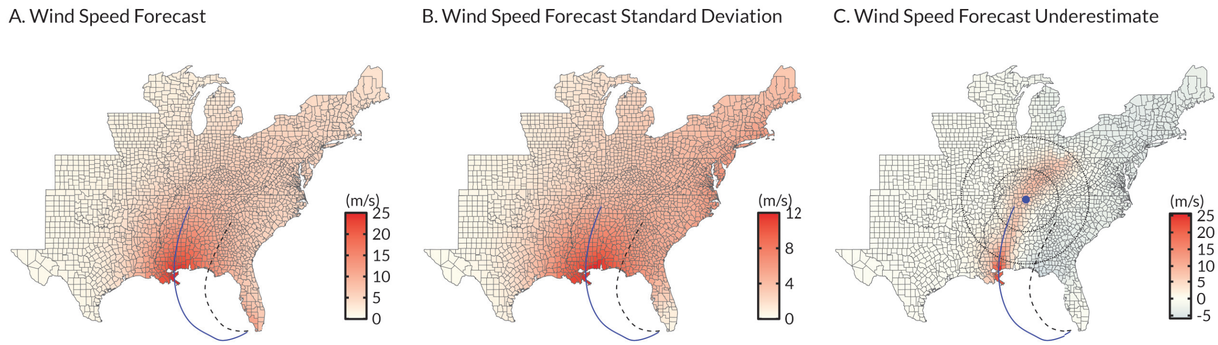
Observed, or realized, wind speed is obtained by evaluating the observed hurricane track and wind speed archived by the NHC in the gridded wind map model. Forecast errors are thus the difference between observed wind speed and the forecast mean across all predictions. For each hurricane, we aggregate these forecast statistics and errors to the county-level using an unweighted average across the forecast's grid cells within the county. In the Supplemental Appendix, we test the robustness of our results to population-weighted wind exposure.

To complete the data construction, we extend the framework above to cover precipitation forecasts and realizations for each storm in our data. This consists of using the official deterministic forecast, as well as the 1,000 track and maximum wind forecasts, in conjunction with a high-resolution hurricane precipitation model (Lonfat et al., 2007; DeMaria, Knaff and Kaplan, 2006; Marks et al., 2020). This model predicts spatial rainfall intensity based on storm intensity, size, forward speed, and terrain effects. The model produces a gridded map of precipitation forecasts for each lead time and hurricane in our sample. As with wind, we calculate the mean and standard deviation of precipitation forecasts across the 1,000 realizations, and compute forecast errors as the difference between observed precipitation and the gridded forecast mean. Observed precipitation is obtained

[12]The construction of the probabilistic forecast uses an auto-regressive procedure that allows for serial correlation in forecast errors (DeMaria et al., 2009, 2013). This captures important features of actual forecasts where if, for example, the 3-day ahead forecast underestimates the maximum wind speed, the 2-day ahead forecast is likely to underestimate it as well.

[13]Most environmental economics research only uses aggregated forecast data instead of the full distribution. For example, previous work has used probabilities of hurricane force winds (Kruttli, Tran and Watugala, 2025) or fluctuations in the El Niño–Southern Oscillation phenomenon (Downey, Lind and Shrader, 2023).

Figure 2. An Illustrative Example: Hurricane Katrina.



Note: Panels A, B, and C show Hurricane Katrina's 1-3 day ahead average landfall forecast wind speed, the forecast's *ex ante* standard deviation, and the forecast's errors. The dashed line shows the 3-day ahead forecast track, while the blue line is the realized track. Positive values in Panel C are underestimates of the actual wind speed. The dotted circles in Panel C display radii of 400 km and 600 km, centered around Nashville, TN, which is marked by the blue dot. For our empirical results we use Conley Spatial HAC standard errors with a distance radius of 400 km. In the Supplemental Appendix, we show robustness of our main results to the alternative radius.

from the European Centre for Medium-Range Weather Forecasts (Muñoz-Sabater et al., 2021).[14] As with wind speed, precipitation is aggregated up to the county-hurricane level.

Our final dataset includes forecasts, realizations, and forecast errors for wind speed and precipitation at the county-hurricane level, measured one, two, and three days before landfall. For the analysis, we use the average forecast across this three-day lead period. This approach reflects the range of protective actions available: some, such as installing temporary levees, require more lead time, while others, like deploying emergency generators to hospitals, can be implemented on shorter notice. Averaging the forecasts over a county provides a parsimonious way to capture the influence of forecasts on a mix of protective responses. We focus primarily on wind speed in the main text since it directly causes damage and is the basis for the Saffir-Simpson hurricane scale, one of the most common ways for conveying hurricane information. We also analyze hurricane track and precipitation in the Supplemental Appendix.

Figure 2 illustrates the variation in our data using Hurricane Katrina as an example. Panel A in the figure shows that winds over 25 m/s (50 mph) were expected to hit the northern Gulf Coast, with a sharp decrease to 5 m/s (11 mph) as the hurricane moved inland and dissipated. Panel B shows that, overall, Katrina's forecast was most uncertain around the predicted point of landfall, because of uncertainty about the degree of intensification before the storm's arrival. Panel C shows that the forecast had errors in both directions, but the underestimates tended to be much larger than the overestimates. The asymmetry arises because Katrina intensified more than expected just before landfall. If the forecast error was solely from incorrectly predicting the forecast track, wind speed underestimates along the realized track would be symmetrically offset by wind speed overestimates along the forecast track. However, since the overall intensity of the storm was also underestimated, counties along the realized track had even larger underestimates, while counties along the forecast track had smaller overestimates.

Supplemental Appendix D. contains several additional figures highlighting the distribution of forecast outcomes. There, we show that errors are correlated with intensity, that wind speed and precipitation are positively correlated, and that the *ex ante* uncertainty in the forecast is highly correlated with the *ex post* error.[15]

[14]Following expert guidance, only precipitation within 500 km of the hurricane center is considered when computing observed precipitation in order to avoid confounding hurricane-induced precipitation with precipitation caused by routine weather.

[15]These correlations will inform our analysis, for example, we will condition on precipitation forecasts when estimating the

B. *Expenditures for Pre-Hurricane Protection and Post-Hurricane Recovery*

We obtain data on publicly funded expenditures for hurricane-related protection and recovery efforts through the Public Assistance Grant Program (PAGM) (FEMA, 2024*a*). Administered by the Federal Emergency Management Agency (FEMA), the PAGM provides financial assistance to state, local, tribal, and territorial governments, as well as certain nonprofit organizations, to support response and recovery activities for major disasters (Kousky, Lingle and Shabman, 2015). Funding is available across a broad range of eligible activities, including debris removal, emergency protective measures, and the repair or replacement of damaged infrastructure.

The program distinguishes between *Emergency Work*, which includes immediate actions such as debris removal and emergency protective measures, and *Permanent Work*, which involves infrastructure restoration and rebuilding. Funding requests are submitted through FEMA's Public Assistance Grants Portal, evaluated for eligibility, and obligated based on estimated costs, with final reconciliation after project completion. For large projects, funds are disbursed incrementally; for small projects, funding is often provided upfront (See Appendix A for background and institutional details of the PAGM).

We assign PAGM expenditures to hurricanes in our data using FEMA's own categorizations (FEMA, 2025*b*). Specifically, we define expenditures listed as Emergency Work as *protective expenditures*. Some examples of protective expenditures include: transporting and pre-positioning equipment and other resources for response; search and rescue; emergency evacuations; constructing emergency berms or temporary levees to provide protection from floodwaters or landslides; and use or lease of temporary generators for facilities that provide essential community services. In a specific example, $2 million was allocated to Louisiana for a request titled "Emergency Evacuation Measures-Police Department Equipment Use" during Hurricane Katrina. This funded over 170,000 hours of Police Department vehicles and apparatus to reduce and eliminate threats to life and public safety, assist with the relocation of people to secure shelters, and facilitate response and recovery operations.

We define expenditures classified under Permanent Work as *recovery expenditures.* Some examples of recovery expenditures are permanent repair and replacement of roads, permanent repair of fish and wildlife habitat, repair of buildings and structures, and repair of utilities facilities. Some projects may serve multiple purposes and some measures could provide immediate protection, as well as contribute to longer-term resilience. This makes a strict separation between protective and recovery expenditures imperfect.

A limitation of the FEMA PAGM data is that they do not report the date when funding was requested or when the work was done. One consequence of this is that protective expenditures may occur prior to the forecasts captured in our data. Another consequence is that protective expenditures that are allocated post-landfall—for example, for search and rescue—may be incorrectly attributed to the forecast instead of the realized hurricane intensity. We test whether these are major concerns for our results in our robustness checks in the Supplemental Appendix.

C. *Economic Damages*

Data on hurricane damages come from the Spatial Hazards Event and Losses Database for the United States (SHELDUS). SHELDUS provides county-level information on the year and month of the hurricane, and the direct losses that stem from fatalities, injuries, and damages to property and crops (SHELDUS, 2024). Following the Environmental Protection Agency's guidelines, we estimate the losses from deaths using a value of a statistical life of $9.39 million in 2019 dollars (US

effects of wind speed forecasts to disentangle the two, and we will condition on realized hurricane intensity to ensure that we are not confounding greater forecast errors with simply more intense storms.

EPA, 2024). Because we do not observe the types of injuries incurred, and have no way to clearly monetize them, we ignore injuries in our analysis.

SHELDUS estimates damages based on data from sources such as NOAA's Storm Events Database, the National Climatic Data Center, and FEMA. SHELDUS provides county-level records of fatalities, injuries, and property damage, often supplemented with information from federal disaster declarations and insurance claims data. SHELDUS is updated retroactively, so past records incorporate newly available information and ensure consistency across a given version. We note that while SHELDUS has implemented multiple procedures over time to ensure consistency and improve data quality, some degree of underreporting may occur, for example, in counties with resource constraints, or in counties that were exposed to low hurricane intensity. This will introduce unobserved measurement error in our outcome variable that may be systematically correlated with forecast errors, our main variable of interest in our analysis. Some, but not necessarily all, of this measurement error will be absorbed by county fixed effects and hurricane intensity controls in our regressions. Although imperfect, SHELDUS is widely-used, and is typically thought of as the best available dataset for measuring direct damages at a county-level (Gallagher, 2021; Auh et al., 2022). All values in our analysis are in 2019 dollars.

County-level demographic and economic data come from the US Census Bureau and the Bureau of Economic Analysis (USCB, 2024; BEA, 2024). Census tract-level population data come from the Spatial Epidemiology and Ecology Research Laboratory (SEER, 2024).

D. *Summary Statistics*

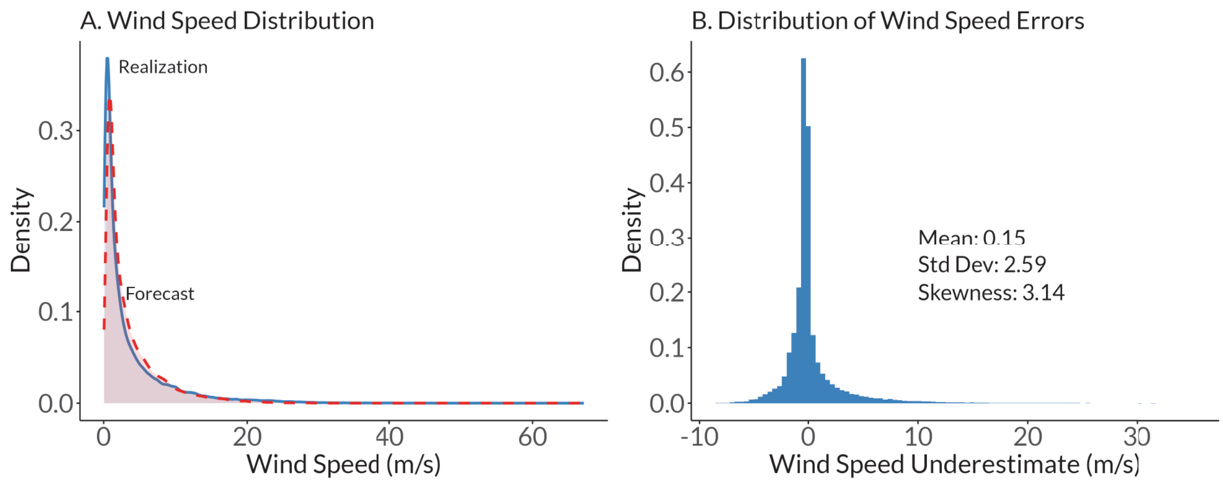
Table 1 shows summary statistics for the 31 hurricanes in our sample. The wind speed and precipitation columns are averages across all counties, the wind speed and precipitation error columns are averages of the absolute value of the errors across all counties, and the damages and expenditures columns are summed across all counties. The table shows that there is substantial heterogeneity in mean wind speed, precipitation, and forecast errors across storms. The total damages associated with all hurricanes is \$377 billion. Total protective and recovery expenditures are about \$45 billion, about one-tenth of the reported damages. Standard deviations associated with the reported means are provided in the Supplemental Appendix, Table D.1.

Figure 3 presents the distributions of wind speeds and wind speed forecasts across our county-hurricane observations. Panel A shows the distribution of both realized and forecast wind speeds. While our data cover a wide range of intensities—including county-level wind speeds as high as 67 m/s (e.g., Hurricane Michael)—most observations fall below 17 m/s. This pattern reflects the fact that hurricane intensity decays rapidly over land, and that the majority of counties are not coastal.

The forecast wind speeds in Figure 3 are predominantly below the 33 m/s threshold for classifying a tropical cyclone as a hurricane. This follows from categorizations being done over water. Our analysis, on the other hand, uses predicted and realized wind speed at the county level on land. In practice, this means that even coastal counties will show attenuated predicted and observed wind speeds relative to the ones used to categorize the hurricanes that hit them.

Panel B plots the distribution of wind forecast errors. The average forecast error is only 0.15 m/s with a standard deviation of 2.59. 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 3. THE DISTRIBUTION OF REALIZED WIND AND WIND SPEED ERROR.



Note: Panel A shows the observed distribution of the realized and forecast wind speed by county-hurricane. The red dashed line is the distribution of the forecast and the blue line is the distribution of the realization. Values of 0 are omitted for clarity. Panel B plots the underestimate of wind speed by a forecast. We omit observations where the forecast and realized wind speed was zero for clarity.

Table 1—Summary Statistics by Hurricane.

Hurricane	Year	Wind Speed (m/s)	Wind Speed Error abs(m/s)	Precipitation (mm)	Precipitation Error abs(mm)	Total Damage (Billion $)	Protective Expenditures (Billion $)	Recovery Expenditures (Billion $)
Cindy	2005	3.02	1.83	8.25	9.05	2.39	0.00	0.00
Dennis	2005	2.84	1.24	9.79	5.99	2.39	0.02	0.13
Katrina	2005	4.05	1.70	11.63	10.13	110.54	1.96	11.45
Rita	2005	3.35	1.30	9.86	8.52	15.56	0.14	0.42
Wilma	2005	1.10	0.55	0.70	0.71	13.81	0.17	1.11
Dolly	2008	0.80	0.16	1.01	0.50	1.68	0.01	0.05
Gustav	2008	2.71	0.76	11.22	9.72	21.26	0.12	0.28
Ike	2008	6.41	3.81	8.01	7.09	21.26	0.24	1.17
Irene	2011	3.10	0.75	8.97	6.88	5.12	0.19	0.86
Isaac	2012	2.45	0.89	7.63	5.23	0.82	0.11	0.21
Sandy	2012	3.00	0.78	6.57	4.21	29.16	2.26	12.49
Arthur	2014	2.52	0.64	1.54	1.99	0.00	0.00	0.00
Hermine	2016	3.28	1.27	5.81	4.28	0.46	0.01	0.05
Matthew	2016	2.63	0.68	8.68	7.16	4.64	0.14	0.76
Harvey	2017	1.27	0.46	6.87	5.54	55.30	0.43	1.86
Irma	2017	2.44	1.12	11.31	7.05	5.97	0.41	1.77
Nate	2017	4.07	1.36	8.19	5.63	0.06	0.01	0.03
Florence	2018	3.11	0.37	9.54	5.76	2.54	0.15	0.54
Michael	2018	4.65	1.12	9.12	6.44	21.11	0.21	1.38
Barry	2019	2.02	0.95	6.22	5.02	0.02	0.02	0.02
Dorian	2019	2.41	0.32	2.26	1.35	0.02	0.06	0.12
Delta	2020	2.43	0.67	6.38	3.95	3.86	0.02	0.03
Hanna	2020	0.92	0.13	0.87	0.73	0.00	0.00	0.00
Isaias	2020	4.06	1.34	4.89	4.46	12.42	0.02	0.18
Laura	2020	3.71	1.77	6.40	5.05	12.42	0.30	1.31
Sally	2020	2.69	1.11	10.95	11.04	0.61	0.02	0.36
Zeta	2020	5.17	1.54	6.34	4.64	3.86	0.02	0.18
Ida	2021	3.35	1.23	11.48	9.63	12.05	0.61	1.43
Nicholas	2021	1.35	0.51	3.70	4.06	1.50	0.00	0.00
Ian	2022	2.22	1.19	4.86	5.02	15.98	0.19	0.57
Nicole	2022	2.29	0.91	4.35	2.89	0.51	0.03	0.07

Note:
The table includes all category 1 and greater hurricanes (maximum wind speeds greater than 33 m/s) that made landfall in the continental US between 2005–2022. Wind speed, precipitation, and their associated errors are averaged across counties to the hurricane level. Damages and expenditures are summed across counties to the hurricane level. Wind speed is the maximum sustained wind speed in m/s, precipitation is the total precipitation in mm. Wind speed and precipitation errors are averages of the absolute values of county-level errors. All damage and expenditures are reported in billions of (2019) US$.

III. Methods and Results

We present our results in three steps. First, we show that FEMA, the federal agency responsible for allocating before-landfall protective emergency funding, responds to forecasts of hurricane intensity. Second, we provide evidence that the forecasts generated economic value by showing that larger underestimates of hurricane intensity lead to larger damages and recovery costs, conditional on the actual hurricane intensity. Third, we develop a theoretical model to guide estimation of the *ex ante* value of reducing uncertainty in hurricane forecasts, which gives us the value of a forecast improvement. While in the main text we focus on wind speed, the Supplemental Appendix expands these results to track and precipitation.[16]

A. *Does FEMA Respond to Forecasts?*

First, we provide evidence that forecasts drive protective actions by estimating how FEMA's pre-landfall, protective emergency expenditures respond to the wind speed forecast.[17] Here, and for the rest of the paper, we will use c, s, and h to index county, state, and hurricane, respectively.

Our model is:

$$\begin{aligned}\text{FEMA Protective Expenditures}_{csh} = &\sum_{b\in\mathcal{B}_w}\beta_b^w 1(\text{Wind Forecast}_{csh}\in b)\\ &+\sum_{b\in\mathcal{B}_p}\beta_b^p 1(\text{Precip Forecast}_{csh}\in b)\\ &+\gamma_c+\eta_{sh}+\varepsilon_{csh}.\end{aligned} \tag{1}$$

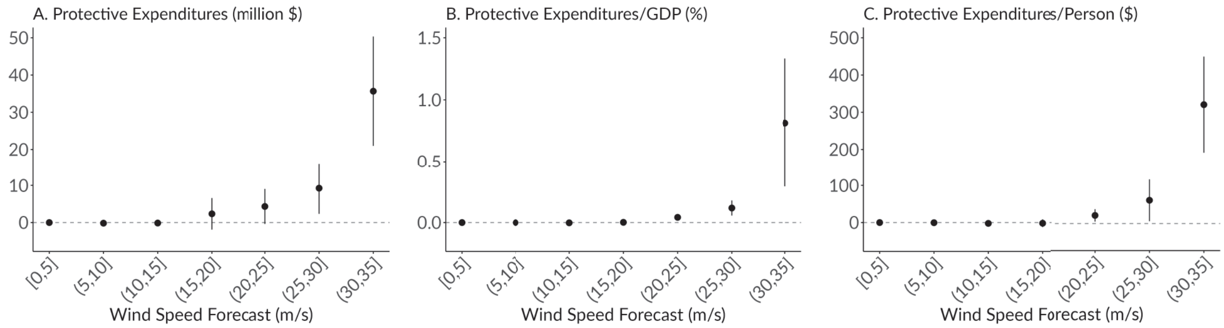
The outcome variable is FEMA protective expenditures. We also present results normalized by county GDP and in per capita terms to adjust for how protective expenditures may be directed toward areas with larger economies or more people. $\mathcal{B}_w$ is a set of 5 m/s bins of wind speed forecasts up to 35 m/s, with forecasts of 0-5 m/s as the omitted category. $\mathcal{B}_p$ is a set of 20 mm bins of precipitation forecasts up to 200 mm. Recall that these forecasts are averages of the 1-3 day prior to landfall forecasts. We include both wind and precipitation forecasts in the same regression as they are positively correlated (Supplemental Appendix D.), and omitting one may result in omitted variable bias.

All specifications include county fixed effects, γ_c, and state-by-hurricane fixed effects, η_{sh}. γ_c controls for time-invariant factors that vary across counties that may drive protective expenditures and forecast hurricane intensity, like distance to the coast or elevation. η_{sh} addresses factors that vary across states for the same hurricane, such as the political composition of the state government, and whether states used emergency declarations to marshal local resources. Following other papers in the literature (Hsiang, 2010; Deryugina, 2017), we compute spatial heteroskedasticity and autocorrelation consistent (HAC) standard errors using the approach documented by Conley (1999). Our standard errors account for arbitrary serial correlation within a county, and spatial correlation across all other counties that are within 400 km of a county's centroid. We note that this radius is about double the values used in this prior literature, and thus more conservative. The area traced out by this radius is larger than Florida, Georgia, and Alabama combined. Figure

[16]In the main results we will include both wind speed and precipitation in our specifications since both can directly cause damage. We omit track because the location of the hurricane only matters for damage through how it affects a county's exposure to the hurricanes other characteristics like wind speed. The analyses in the Supplemental Appendix include all three.

[17]One channel through which FEMA protective expenditures are able to respond rapidly to new forecast information is the Hurricane Liaison Team. Its purpose is to connect local and federal officials with scientists and meteorologists at the NHC. The Hurricane Liaison Team assists with properly communicating the forecast in order to better guide response operations, including evacuations, sheltering, and mobilizing manpower and equipment (Cannon, 2008).

FIGURE 4. FEMA PROTECTIVE EXPENDITURES RESPONSES TO FORECASTS.



Note: Points are point estimates and the bars are the 95% confidence intervals. The omitted category for each panel is [0,5]. All panels control for bins for the precipitation forecast, and for county and state-by-hurricane fixed effects. Standard errors are Conley Spatial HAC with a distance radius of 400 km for spatial correlation and arbitrary autocorrelation within counties. The number of observations is 95,263.

2 Panel C illustrates the geographical span of this radius along with an additional 600 km radius that we use as a robustness check in the Supplemental Appendix.

Figure 4 plots the estimates from equation (1). Panel A shows the effect of wind speed forecasts on pre-landfall protective expenditures. The results indicate that the effects of the wind speed forecast are negligible until above 20 m/s and increase rapidly up to 35 m/s, about the threshold for hurricane-force winds that would trigger an official hurricane warning.[18] Relative to counties forecast to have winds of 0-5 m/s, counties predicted to experience wind speeds over 30 m/s receive $36 million more, while counties predicted to only experience wind speeds of 20-25 m/s – a low-end tropical storm forecast – receive only $4 million more. Overall, these estimates show that protective expenditures increase monotonically with the anticipated wind speed, and that protective expenditures are targeted toward areas predicted to experience hurricane-force winds.

Panels B and C plot estimates for protective expenditures as a share of county GDP and per capita. Relative to 15-20 m/s or lower forecasts, expenditures increase by over 0.1% of county GDP or $60/person for wind speed forecasts of 25-30 m/s, and by over 0.8% of county GDP or $300 per person for hurricanes forecast above 30 m/s.

B. *Does Forecast Accuracy Matter?*

Next, we test whether forecast errors affect hurricane damages and after-landfall recovery expenditures, conditional on realized hurricane intensity. As in Figure 2, we define a forecast error as how much the forecast *underestimated* realized wind speeds. We estimate the effect of forecast errors on damages and FEMA recovery expenditures using the following model:

$$\begin{aligned} \mathrm{Y}_{csh} = & \sum_{b\in\mathcal{E}^w} \beta_b^w 1(\text{Wind Error}_{csh} \in b) + \sum_{b\in\mathcal{E}^p} \beta_b^p 1(\text{Precip Error}_{csh} \in b) \\ & + \sum_{b\in\mathcal{E}_i^w} \gamma_b^w 1(\text{Wind Realization}_{csh} \in b) + \sum_{b\in\mathcal{E}_i^p} \gamma_b^p 1(\text{Precip Realization}_{csh} \in b) \\ & + \gamma_c + \eta_{sh} + \varepsilon_{csh}. \end{aligned} \tag{2}$$

Y_{csh} is either damages caused by the hurricane, or FEMA's post-landfall expenditures aimed at

[18] About 18% of protective expenditures go to counties with realized wind speeds below 20 m/s. If officials have accurate beliefs that damages (and thus the benefits of protective expenditures) are negligible under this threshold, this suggests that 18% of pre-landfall protective expenditures may be misallocated ex post.

recovering the damaged area. As before, we also report results scaled as a percentage of county GDP and per capita. $\mathcal{E}^w$ and $\mathcal{E}^p$ are sets of bins of forecast errors (realization minus forecast) and $\mathcal{E}_i^w$ and $\mathcal{E}_i^p$ are sets of bins of intensity realizations. The omitted error bin for wind is (-2,0]. We flexibly control for hurricane wind speed and precipitation realizations using 20 quantile-based bins each to ensure we are picking up the effect of forecast errors and not just that more intense hurricanes tend to have larger errors as shown in Figure 3.[19] The fixed effects and standard errors are identical to equation (1).

Figure 5 plots the results. Panels A and D plot the effect of wind speed forecast underestimates on damages and after-landfall recovery expenditures, Panels B and E plot the effect in terms of share of county GDP, while panels C and F plot the effect in per capita terms. All six panels show an increasing relationship between the outcome and wind speed underestimates. County damages are \$47 million higher if wind speed is underestimated by 4-6 m/s, and over \$220 million higher if underestimated by 8-10 m/s. To put this into context, an 8-10 m/s error would result in misclassifying a hurricane by 1-2 categories and only occurs for about 1.7% of the observations in our data. In county GDP or per capita terms, a 10 m/s underestimate increases damages by about 15% of county GDP or \$5,600/person. The effects on recovery expenditures follow the same pattern: underestimating wind speed by 4-6 m/s increases expenditures by \$9 million, while underestimating by 8-10 m/s increases expenditures by over \$20 million; the precision of these estimates increases considerably once we normalize by county GDP and population. An 8-10 m/s error increases recovery expenditures by about 0.5% of county GDP or about \$300/person. These estimates provide indirect evidence that forecasts drive protective actions and that the undertaken protective actions mitigate damages. Conditional on a storm's intensity, forecast errors only matter through how the forecast directed effective protective actions.

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

Figures 4 and 5 provide evidence for how the information in forecasts generates social value. Figure 4 shows that higher forecasts marshal more costly protective resources to an area. Figure 5 shows that, conditional on realized hurricane intensity, overestimating intensity reduces *ex post* costs. We now formalize the *ex ante* value of improving hurricane forecasts accounting for both of these forces on total costs. Our model builds on a cost-loss approach in the forecast literature (Katz and Murphy, 1997), where a decision-maker optimizes over taking a costly adaptive action in the face of an uncertain, but costly event (Katz, Murphy and Winkler, 1982; Lee and Lee, 2007; Millner, 2009). We complement this literature by allowing damages and adaptive actions to be continuous and empirically measurable.[20]

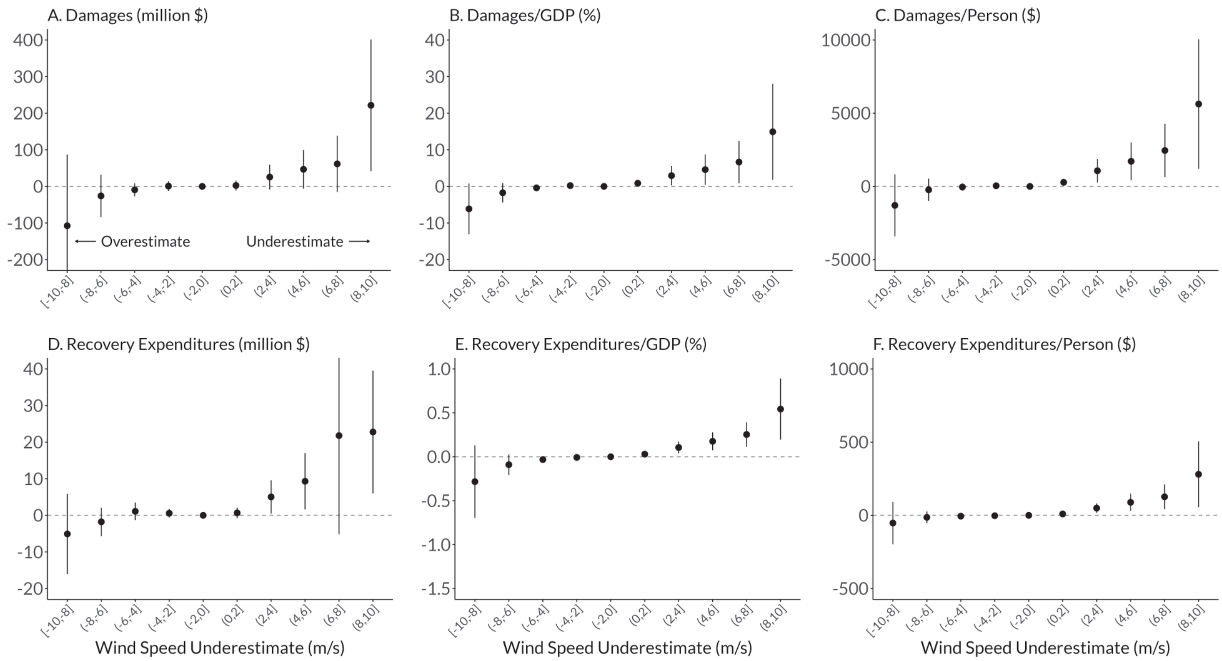
Theoretical Foundation. — An expected cost-minimizing representative agent faces a hurricane with total after-landfall costs, $D(x, a, \mathbf{i}, \mathbf{t})$, where x is the realized intensity (e.g., wind speed), a is the agent's choice of protective actions (e.g., sandbags, evacuations), $\mathbf{i}$ represents location-specific features (e.g., elevation), $\mathbf{t}$ denotes time-specific features, and where $D(x, a, \mathbf{i}, \mathbf{t})$ is increasing in x and decreasing in a. $D(x, a, \mathbf{i}, \mathbf{t})$ includes direct hurricane damages as well as other after-landfall costs, but for simplicity we refer to it as damages from hereon.

The timing of the model is such that first a hurricane with unobserved intensity x forms. The intensity is a draw from some arbitrary distribution F such that $x \sim F$. The agent then receives a

[19]Since we are not visualizing the intensity realizations, we use quantile-based bins to ensure good data coverage across all the bins. In the Supplemental Appendix, we test the robustness of our results to between 5–120 bins for each, including full interactions of the wind speed and precipitation bins, as well as interactions with indicators capturing wind direction and potential exposure to storm surge.

[20]This literature has primarily relied on binary state and action frameworks, with extensions to jointly normally distributed weather and forecast variables (Katz, Murphy and Winkler, 1982) and continuous action models (Lee and Lee, 2007), along with behavioral extensions (Millner, 2009).

FIGURE 5. FORECAST ERRORS, DAMAGES, AND AFTER-LANDFALL RECOVERY EXPENDITURES.



Note: The points are point estimates, and the bars are the 95% confidence intervals. The omitted category is $(-2, 0]$. All panels control for binned precipitation errors, binned realized wind speed, binned realized precipitation, and for county and state-by-hurricane fixed effects. Standard errors are Conley Spatial HAC with a distance radius of 400 km for spatial correlation and arbitrary autocorrelation within counties. The number of observations is 95,263.

forecast $\tilde{x}$ of the realized intensity x. The relationship between the two is defined by the forecast error, $e = x - \tilde{x}$. We model this error as being drawn from a normal distribution, $e \sim \mathcal{N}(\mu, \sigma^2)$, where μ is a potential forecast bias and σ^2 is the variance of the forecast error.[21] We assume that the agent knows this error distribution and knows when the distribution changes. The agent takes the de-biased forecast as her conditional expectation of intensity so that her conditional beliefs about hurricane intensity having observed some forecast $\tilde{x}$ are given by: $x \mid \tilde{x} \sim \mathcal{N}(\tilde{x} + \mu, \sigma^2)$.[22] After the forecast is issued, the agent chooses the level of protective action $a(\tilde{x})$ as a function of the forecast, incurring cost $C(a(\tilde{x}))$ which is increasing in the protective action. Lastly, the hurricane makes landfall, intensity x is observed, and the agent incurs total damage $D(x, a(\tilde{x}), \mathbf{i}, \mathbf{t})$.

The agent's objective is to minimize expected total cost given her conditional beliefs about hurricane intensity:

$$\mathcal{C}(\tilde{x}; \mu, \sigma) = \min_a \mathbb{E}[D(x, a(\tilde{x})) \mid \tilde{x}] + C(a(\tilde{x})). \tag{3}$$

We define the value of a forecast improvement as the *ex ante* reduction in minimized expected total cost — inclusive of both before-landfall protective expenditures and after-landfall damages — from a marginal reduction in the standard deviation of the forecast error: $(\mathrm{d}\mathbb{E}_{\tilde{x}}[\mathcal{C}(\tilde{x}; \mu, \sigma)]) / (\mathrm{d}\sigma)$.[23]

[21] This setup assumes all underlying physical processes are deterministic, and the agent can only predict the hurricane subject to some noise. All observed uncertainty arises from limitations in the forecast rather than the physical system itself. Our model can be relaxed if one wanted to allow for physical uncertainty. We include this extension in Supplemental Appendix D..D.3.

[22] This formulation for conditional beliefs could also be generated from a Bayesian model with an uninformative prior. Modeling a Bayesian with an informative prior would require taking a stand on the agent's pre-forecast beliefs.

[23] In principle, forecast improvements can arise from reducing either the bias (μ) or the standard deviation (σ) of forecast errors. We focus on σ as our measure of forecast quality because, while hurricane forecasts may exhibit small biases in some cases, they are approximately unbiased on average (Figure 3). Alternative metrics like root mean squared error are *ex post* and depend

Importantly, this value averages the expected total cost $\mathcal{C}(\tilde{x};\mu,\sigma)$ over possible forecasts $\tilde{x}$, as reducing σ improves forecast precision and changes the forecasts that the agent receives given the (yet-to-be-observed) hurricane intensity.

Proposition 1 provides an intuitive analytical expression for this quantity.

PROPOSITION 1: *The value of a forecast improvement, defined as the ex ante reduction in expected minimized total costs from a marginal decrease in the forecast error standard deviation, σ, is:*

$$\frac{\mathrm{d}}{\mathrm{d}\sigma}\mathbb{E}_{\tilde{x}}\left[\mathcal{C}(\tilde{x};\mu,\sigma)\right] = \frac{1}{\sigma^3}\mathbb{E}_{\tilde{x}}\left[\mathrm{Cov}\left(D(x,a^*(\tilde{x})),(e-\mu)^2 \mid \tilde{x}\right)\right] \tag{4}$$

$$= 2\sigma \cdot \mathbb{E}_{\tilde{x}}[\beta_2(\tilde{x})], \tag{5}$$

where $\beta_2(\tilde{x})$ is the coefficient from a regression of damages $D(x,a^*(\tilde{x}))$ on the squared demeaned error $(e-\mu)^2$, defined as:

$$\beta_2(\tilde{x}) = \frac{\mathrm{Cov}\left(D(x,a^*(\tilde{x})),(e-\mu)^2 \mid \tilde{x}\right)}{\mathrm{Var}\left((e-\mu)^2 \mid \tilde{x}\right)}. \tag{6}$$

PROOF:

See Appendix B.B1.

Proposition 1 shows that the value of a forecast improvement is proportional to a covariance between realized damage at the optimized protective action and the squared demeaned forecast error. The value of an improvement and the covariance is positive if damages tend to be higher when the squared demeaned error $(e-\mu)^2$ is higher, where μ is the forecast bias. Figure 5 provides evidence that the covariance is positive: damages are increasing and convex in errors, conditional on intensity. Better forecasts help the agent reduce the difference between the *ex ante* optimized level of protective actions and the protective actions they would have chosen if they could observe realized hurricane intensity when making their decision.

Equation (5) indicates the value of a forecast improvement can be recovered by combining estimates of the effect of squared demeaned errors on damage, $\beta_2(\tilde{x})$, averaged over the distribution of forecasts, with some reference forecast error standard deviation σ. Formally, $\beta_2(\tilde{x})$ corresponds to the coefficient from a regression of damage on squared demeaned errors where the data are from different realizations of hurricane intensity, holding the forecast fixed. We then can recover $\mathbb{E}_{\tilde{x}}[\beta_2(\tilde{x})]$ by averaging these estimated coefficients over the distribution of forecasts the agent could receive given the forecast error distribution. In practice, however, we only observe one realization for any given hurricane. To approximate $\mathbb{E}_{\tilde{x}}[\beta_2(\tilde{x})]$, we pool data across counties and hurricanes (and their associated forecasts), treating each county-hurricane combination as a realization of the forecast process. This approximates the *ex ante* expectation by averaging over the empirical distribution of forecasts.[24]

Equation (5) also indicates that a higher standard deviation baseline, reflecting more *ex ante* forecast uncertainty, tends to raise the value of a forecast improvement. Unlike prior work, our new dataset reports the ex ante standard deviation of the forecast error, which turns out to be a necessary piece of data to properly calculate the value of a forecast improvement.

on the realized hurricane intensity, which complicates their use in formal *ex ante* valuation frameworks. The use of standard deviations to measure model spread and uncertainty is common in other scientific areas, including the Intergovernmental Panel on Climate Change Assessment Reports (Masson-Delmotte et al., 2021).

[24]In Supplemental Appendix D..D.2 we provide a formal proof that a slightly modified approach is able to recover a *weighted* expectation of $\beta_2(\tilde{x})$ and that this approach generates attenuated but qualitatively similar estimates.

In the empirical analysis, we derive estimates of β_2 with the following model:

$$\begin{aligned} \mathrm{D}_{csh} \quad = \quad & \beta_2^w \left(e_{csh}^w - \mu_{csh}^w\right)^2 + \beta_2^p \left(e_{csh}^p - \mu_{csh}^p\right)^2 \\ & + \sum_{b \in \mathcal{E}_i^w} \gamma_b^w 1(x_{csh} \in b) + \sum_{b \in \mathcal{E}_i^p} \gamma_b^p 1(p_{csh} \in b) \\ & + \gamma_c + \eta_{sh} + \varepsilon_{csh}. \end{aligned} \tag{7}$$

D_{csh} is observed post-landfall damages (i.e., economic damages and recovery expenditures), which we will normalize by county GDP or population in some specifications. $\left(e_{csh}^w - \mu_{csh}^w\right)^2$ is the observed squared demeaned error in wind speed, and $\left(e_{csh}^p - \mu_{csh}^p\right)^2$ is the observed squared demeaned error in precipitation. We compute the mean error terms within each hurricane and within each of our hurricane intensity bins to account for the correlation between forecast errors and realized intensity. To further ensure that our estimates isolate the impact of forecast uncertainty rather than hurricane severity, we flexibly control for realized intensity by including binned indicators for wind and precipitation realizations. This design ensures that the identifying variation arises from forecast errors conditional on hurricane intensity, consistent with the structure of equation (2). The model also includes the same set of fixed effects and standard errors used in earlier specifications.

Before presenting the results, we highlight two key assumptions that make this approach work. First, the theoretical model assumes constant and independent distributional parameters for forecasts. Figure D.1 shows that forecast errors tend to increase with hurricane intensity, and that the forecast standard deviation increases with the forecast intensity. In Appendix B.B2, we relax this assumption to allow the forecast standard deviation to depend on the forecast intensity and find similar quantitative results. Second, we assume that forecast errors are normally distributed. This parametric assumption allows us to quantify how expectations change as σ changes.[25] Appendix B.B3 shows that this assumption appears reasonable, while Supplemental Appendix C..C.3 demonstrates that the results are robust to normalizing the error distribution to remove the observed skewness in the data.

Estimation Results. — Table 2 reports our results corresponding to Proposition 1. The first panel shows the results assuming the agent is minimizing total costs, while the second and third panels show results if the agent is minimizing costs as a share of county GDP or per capita costs. Within each panel, we report the coefficient estimate on squared demeaned wind errors. The sample average forecast standard deviation is 1.4, so the marginal value of an improvement of the average forecast is 2.8 times the coefficient. The table shows robustness of our results to a variety of specification choices. These include county-by-month of year effects which address county-specific seasonality in exposure or forecastability, county-by-year effects which control for things like prior hurricane experience and damage that may change how forecast errors affect current damages, as well as linear forecast errors. Our preferred specification is in column 7, which has our base fixed effects along with controls for intensity realizations and linear forecast errors. This specification allows for heterogeneous effects for hurricane versus sub-hurricane-force winds in a county, reflecting how protective expenditures increase significantly at this level in Figure 4.

The first panel shows that a one unit increase in the squared error of wind speed forecasts increases damages. For the sample average, the value of a forecast improvement is about \$15.5 million per hurricane per county in our preferred specification, but only for counties experiencing hurricane-force winds. A forecast improvement of 0.046 standard deviations, about 3% of the sample mean and an improvement that occurs annually on average, reduces total costs by over \$500,000 for

[25] Since forecast errors are often substantial for wind speed, we make a distributional assumption instead of using local approaches like Taylor approximations (e.g., Shrader, Bakkensen and Lemoine, 2023).

the average county hit with hurricane-force winds. This result suggests that every year, forecast improvements are generating hundreds of millions of dollars of benefits per hurricane.

The second and third panels show that the value of a 1 standard deviation forecast improvement is about 0.45% of county GDP, or $160 in per-person terms. Using the same thought experiment as in the top panel, the annual average forecast improvement reduces costs by 0.04% of county GDP, or $15 per person. The estimates in Column 7 also demonstrate that the value of improvements comes entirely from places experiencing hurricane-force winds.

TABLE 2—THE VALUE OF A WIND SPEED FORECAST IMPROVEMENT.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Damages + Recovery Expenditures (million \$)							
$\beta_2 : (e-\mu)^2$	4.51	4.49	3.65	3.61	4.25	4.03	
	(1.42)	(1.43)	(1.13)	(1.04)	(1.45)	(1.25)	
Hurricane $\beta_2 : (e-\mu)^2$							5.49
							(1.73)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							-0.39
							(0.45)
(Damages + Recovery Expenditures) / GDP (%)							
$\beta_2 : (e-\mu)^2$	0.34	0.35	0.32	0.31	0.29	0.29	
	(0.14)	(0.14)	(0.13)	(0.11)	(0.11)	(0.10)	
Hurricane $\beta_2 : (e-\mu)^2$							0.45
							(0.16)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.02
							(0.02)
Damages + Recovery Expenditures Per Capita (\$/person)							
$\beta_2 : (e-\mu)^2$	124.30	126.29	110.82	112.76	113.05	117.04	
	(35.74)	(36.05)	(30.88)	(29.82)	(32.92)	(30.50)	
Hurricane $\beta_2 : (e-\mu)^2$							158.61
							(38.64)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							5.67
							(5.57)
Observations	95,263	95,263	95,263	95,263	95,263	95,263	95,263
Realized Wind/Precip Bins		✓	✓	✓	✓	✓	✓
Level Wind/Precip Error			✓	✓	✓	✓	✓
State-Hurricane FE	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓				✓
County-Month of Year FE				✓		✓	
County-Year FE					✓	✓	

Standard errors are Conley Spatial HAC with a distance radius of 400 km for spatial correlation and arbitrary autocorrelation within counties. e is the county-hurricane-specific forecast error, and μ is the hurricane-intensity bin-specific mean forecast error. Hurricane wind speeds are those greater than 33 m/s (74 mph), while Sub-Hurricane wind speeds fall below that threshold.

D. The Value of Historical Forecast Improvements

We now use our estimates in Table 2 to value historical improvements in forecast accuracy. Specifically, we estimate the value of the sudden increase in the rate of forecast improvement in 2007, as depicted in Figure 1.[26] For each of the 26 hurricanes after 2007, we compute its counterfactual forecast uncertainty if forecasts had continued to follow only the pre-HFIP 0.4% annual improvement, and then use the estimate in Column 7 of the top panel of Table 2 to value the increase in costs compared to the actual forecast uncertainty.

Our findings suggest that accelerated improvements in forecast accuracy since 2007 reduced hurricane costs – damages, recovery expenditures, and protective expenditures – by 19% or $2 billion per hurricane. How large is this value? $2 billion is about 30% of NOAA's budget; twice the 2015 budget of the National Weather Service, the weather forecasting arm of NOAA; and more than ten times the cumulative budget of the HFIP since its inception in 2007, which was tasked with accelerating forecast improvements.

E. Robustness

Our Supplemental Appendix contains a large number of robustness checks that we list here. First, we show all of our results are robust to using more conservative Conley standard errors, more granular fixed effects, more granular controls for hurricane intensity, population-weighting the forecast data when aggregating to the county-level, and alternative transformations of our outcome variables. Second, we show our results are robust to subsamples of the data that focus on coastal areas, and subsamples that aim to purge our analysis of issues with mismeasurement in our damages and protective expenditures data. Third, we show that protective expenditures respond to the forecast standard deviation, suggesting that decision-makers respond to forecast quality. Fourth, we show that our measure of before-landfall protective expenditures does *not* respond to after-landfall forecast errors as we should expect if we have classified expenditures correctly into before-landfall protective expenditures and after-landfall recovery expenditures. Fifth, we show that forecast errors are more costly and that forecast improvements are more valuable for stronger hurricanes. Sixth, we show that transforming our data so that it precisely fits a normal distribution does not meaningfully affect our results. Seventh, we show that our results for the value of a forecast improvement are not solely driven by errors in whether wind speeds are below or above the 33 m/s hurricane threshold, and are not solely driven by any particular hurricane. Eighth, we show that precipitation forecasts and track forecasts have little effect on FEMA emergency protective expenditures, but that the value of a track forecast improvement may be non-negligible. The limited impact of precipitation forecasts may be because the widely-used Saffir-Simpson categories for classifying hurricanes are based entirely on wind speed, and also the way in which hurricane strength has historically been communicated (Kantha, 2006; Murnane and Elsner, 2012). Last, we show that our wind speed forecast and error results are not driven by omitted track forecasts and errors.

IV. Conclusion

In this paper we estimate the economic impact of hurricane forecasts and the value of improving them. We find forecasts are major determinants of the allocation of emergency resources, both before and after the storm. Counties projected to face the strongest wind speeds receive millions more in protective expenditures, while those that experienced the largest forecast underestimates had

[26] Note that Figure 1 shows the decline in absolute wind speed error which is not quite the same as wind speed uncertainty. The wind speed forecast standard deviation shows a 4.5% annual decline since the first hurricane in our dataset.

several times higher after-landfall recovery expenditures. We also find that forecasts affect realized hurricane damages. Conditional on realized intensity, an under-forecast can increase damages by tens or hundreds of millions of dollars compared to an accurate one. These results suggest that forecasts direct valuable protective resources and actions.

We also provide an estimate of the marginal value of reducing forecast uncertainty, inclusive of observed hurricane damages, observed after-landfall recovery costs, and unobserved before-landfall protective costs. Per-hurricane benefits from forecast improvements since 2007 amount to $2 billion – a figure that exceeds the total budget for all federal weather forecasting.

We conclude with several limitations that we leave for future work. First, our data do not capture all forms of damages, recovery costs, and before-landfall protection. Accounting for additional factors, such as longer-run social insurance costs (Deryugina, 2017), or longer-run mortality impacts (Young and Hsiang, 2024), would only increase the value of a forecast improvement. Individuals can take before-landfall protective actions such as evacuating (Gellman et al., 2024), or buying emergency supplies (Beatty, Shimshack and Volpe, 2019). Although our valuation exercise is not specific to any protective action and thus accounts for the private choices individuals may make in responding to a forecast, there is little to no existing work studying the efficacy of different protective actions, private or public.

Second, our estimates in the main text 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. Storm surge forecasting is in its infancy and likely less accurate compared to predicting hurricane track and wind speed, so there may be significant gains from further forecasting improvements along these additional dimensions of a hurricane.

Third, here we focus on the aggregate effect of forecasting up to 3 days ahead of landfall. This is well ahead of the 36-hour window used by the NHC to issue official warnings, and it ensures that the full range of actionable forecast information is accounted for. The timeliness of the forecast, however, undoubtedly plays an important role. Anand (Forthcoming), for example, demonstrates that early forecasts reduce traffic accidents in winter storms. Exploring how the timing of forecasts may reduce the impact of hurricanes is an area ripe for future research and policy impact. This issue is of particular relevance as recent advances in machine learning techniques and methods show promise in supporting early forecasting efforts (Price et al., 2025).

Fourth, our analysis does not directly account for the interactions between forecasts, insurance markets, and moral hazard. We find that improved forecasts reduce damages, which in principle should be reflected in lower insurance premia. However, fully insured households may have diminished incentives to undertake protective measures since they do not bear as much hurricane risk, potentially muting the benefits of improved forecast accuracy.[27] Understanding how public and private insurance design interacts with forecast improvements remains an important area for future research.

Fifth and final, our results show asymmetric impacts of forecast errors, with under-predictions leading to significantly greater damages and recovery costs, while over-predictions do not. In fact, over-predictions lead to modest reductions in damages as one might expect. This result should not be interpreted as evidence that systematically inflating forecasts would be socially beneficial. Overstated forecasts may lead to costly protective actions that we have not measured in this paper. Over time, overstated forecasts may also erode trust in forecast information. As agents form beliefs about forecast accuracy, persistent overestimation may reduce compliance with future warnings. This dynamic tradeoff underscores the importance of maintaining forecast credibility. Modeling how agents learn and respond to forecast bias over time is a promising direction for future work.

[27]Insurance coverage is often incomplete, and delays or uncertainty in payouts may preserve incentives to respond (Michel-Kerjan and Kunreuther, 2011; Hudson et al., 2017).

Additional Details on the FEMA PAGM Program

PAGM disburses funds through Stafford Act procedures to assist state, local, tribal, and territorial governments and certain private nonprofit organizations in responding to and recovering from major disasters or emergencies. The background on the FEMA PAGM process described here follows from official federal documents (U.S. Congress, 1988; Congressional Research Service, 2021; FEMA, 2024*b*, 2025*b*). Under the Stafford Act, emergency declarations and disaster declarations are made by the President after a governor's request. These declarations are issued when the hurricane is beyond state and local capabilities and federal assistance is needed. A declaration request must include information on state and local resources already allocated and the type and amount of federal aid that is needed. Requests for emergency versus disaster declarations differ in two ways. The first is that emergency declarations can be issued prior to landfall, but disaster declarations are issued after landfall.[28] The second is that disaster declaration requests require estimates of the damage caused by a disaster, which is often determined by a Preliminary Damage Assessment done jointly between the state and FEMA.

PAGM provides funding for a variety of potential actions and investments such as debris removal, temporary levees, and the repair or replacement of disaster-damaged public infrastructure (Moss, Schellhamer and Berman, 2009). We break PAGM funding into two groups in our paper following FEMA's own classifications. What FEMA calls "Category B - Emergency Work" corresponds to our protective expenditures. FEMA explicitly categorizes protective expenditures for actions taken before, during, and immediately after a disaster to save lives, protect public health and safety, and prevent damage to property. Protective expenditures include pre-disaster and immediate response actions, such as activating emergency operations centers, deploying emergency personnel, providing medical care, setting up emergency shelters, and conducting search-and-rescue operations.

Funding for protective expenditures can be authorized under either an emergency or disaster declaration. These funds are often authorized prior to hurricane landfall, as the assistance is intended to "[...] supplement State and local efforts and capabilities to save lives and to protect property and public health and safety, or to lessen or avert the threat of a catastrophe in any part of the United States." (U.S. Congress, 1988; Congressional Research Service, 2021).[29] Protective expenditures associated with pre-landfall emergency declarations are often associated with expedited funding given the short timeframe for action. To support legal responsibility, eligibility, and determine costs, applicants for protective expenditures must provide detailed information describing the work to be done, the timeframe, and who will conduct the work (FEMA, 2024*b*).

Protective expenditures follow federal cost-share guidelines, with FEMA typically covering at least 75% of eligible costs. However, under extraordinary circumstances, this percentage can be increased. Funding is not provided upfront for protective expenditures, but is instead typically disbursed after the hurricane as a reimbursement.

What FEMA calls "Categories C-G - Permanent Work" corresponds to our recovery expenditures. These are expenditures that are to rebuild an area such as restoring a facility like a building,

[28]FEMA policy during our sample period states that pre-landfall emergency declarations require that "[...] the State, or a portion thereof, is threatened by landfall of a major hurricane or typhoon [...]" providing a clear link between hurricane forecasts, pre-landfall emergency declarations, and protective expenditures (FEMA, 2007). Historically, pre-landfall emergency declarations were rare prior to Hurricanes Katrina and Rita, however they have become much more common.

[29]Volusia County, FL specifically enumerates the pre-landfall actions taken in their cost recovery documents for Hurricane Irma (Volusia County Government, 2023). These include "[...] preparations to secure locations, hand out sandbags, stage essential personnel and equipment, evacuate patients from hospitals and other facilities, and prepare evacuation shelters as well as other pre-storm activities. It also includes activities during the hurricane including staffing the Emergency Operations Center with extra personnel to answer phones, personnel to work in shelters, extra sheriff patrols, and fire services as well as other services." The Biden White House also reports that the pre-landfall emergency declaration for Hurricane Fiona was to "[...] to save lives and to protect property and public health and safety and fund emergency protective measures" such as "prepositioning supplies on the island including four strategically located warehouses throughout the island, more than 7 million liters of water, more than 4 million ready-to-eat meals, more than 215 generators, more than 100,000 tarps, more than 28,000 plastic covers and more than 10,300 cots and other emergency supplies." (The White House, 2022).

road, dam, or natural gas transmission facility to its pre-hurricane design and function. Recovery expenditures can be authorized after a post-hurricane disaster declaration.[30] After a disaster is declared, states conduct briefings with local applicants to inform them of the application process. Applicants can then submit requests for public assistance through the FEMA Public Assistance Grant Portal. These applications are then reviewed by the state and FEMA for eligibility. After an application is approved, a Program Delivery Manager is assigned by FEMA who works with the local applicant through the granting process which consists of several steps, including damage documentation and identification, project formulation, and a final review by FEMA (FEMA, 2025*a*). For large projects, funding is released incrementally based on actual incurred costs. For small projects, funds are often provided upfront based on estimated costs. As with protective expenditures, recovery expenditures also follow federal cost-share guidelines.

The timing of expenditures follows specific regulatory deadlines. Emergency work funding is available for up to six months from the disaster declaration date. Permanent work must generally be completed within 18 months, with possible extensions granted for factors like permitting delays or environmental compliance.

It is important to note that protective expenditures may serve dual purposes so that the distinction from recovery expenditures is not sharp. For instance, protective expenditures like reinforced temporary flood barriers may also contribute to long-term resilience if left in place, blurring the lines between immediate protective measures and recovery work. Emergency protective expenditures can also be incurred after landfall, potentially being a function of hurricane realizations instead of just the forecast.

[30]For example, recovery expenditures were authorized for Louisiana to repair utility lines in the wake of Hurricane Ida (FEMA, 2023), and Nassau County received funds to repair a wastewater treatment plant damaged during Hurricane Sandy (Long Island Press, 2014).

Theoretical Foundation

B1. Proof of Proposition 1

PROOF:
The agent minimizes expected total costs, given by:

$$\mathcal{C}(\tilde{x};\mu,\sigma) = \min_a \mathbb{E}\left[D(x,a(\tilde{x})) \mid \tilde{x}\right] + C(a(\tilde{x})),$$

where x is the true intensity, $\tilde{x}$ is the forecast, and the forecast error is $e = x - \tilde{x} \sim \mathcal{N}(\mu,\sigma^2)$. Thus, $x \mid \tilde{x} \sim \mathcal{N}(\tilde{x}+\mu,\sigma^2)$. The optimal protective action is $a^*(\tilde{x};\mu,\sigma)$. The value of a forecast improvement is the *ex ante* reduction in expected minimized costs from a marginal decrease in σ:

$$\frac{\mathrm{d}}{\mathrm{d}\sigma}\mathbb{E}_{\tilde{x}}\left[\mathcal{C}(\tilde{x};\mu,\sigma)\right].$$

By the envelope theorem, since $a^*(\tilde{x})$ minimizes $\mathcal{C}$:

$$\frac{\mathrm{d}\mathcal{C}}{\mathrm{d}\sigma} = \frac{\partial\mathcal{C}}{\partial\sigma} = \frac{\partial}{\partial\sigma}\mathbb{E}\left[D(x,a^*(\tilde{x})) \mid \tilde{x}\right].$$

Denote the normal probability density function as $\phi(\cdot)$. Expected damages are:

$$\mathbb{E}\left[D(x,a^*(\tilde{x})) \mid \tilde{x}\right] = \int D(x,a^*(\tilde{x}))\cdot\phi(x \mid \tilde{x};\mu,\sigma^2)\,dx,$$

where $\phi(x \mid \tilde{x};\mu,\sigma^2)$ denotes the normal probability density function with mean $\tilde{x}+\mu$ and variance σ^2. Differentiating with respect to σ:

$$\frac{\partial\mathcal{C}}{\partial\sigma} = \int D(x,a^*(\tilde{x}))\cdot\frac{\partial\phi(x \mid \tilde{x};\mu,\sigma^2)}{\partial\sigma}\,dx.$$

Using the chain rule and noting the demeaned error is $e-\mu = x-(\tilde{x}+\mu)$, we get:

$$\frac{\partial\phi}{\partial\sigma} = \phi(x \mid \tilde{x};\mu,\sigma^2)\cdot\frac{(e-\mu)^2-\sigma^2}{\sigma^3}.$$

The partial derivative then becomes:

$$\frac{\partial\mathcal{C}}{\partial\sigma} = \int D(x,a^*(\tilde{x}))\cdot\phi(x \mid \tilde{x};\mu,\sigma^2)\cdot\frac{(e-\mu)^2-\sigma^2}{\sigma^3}\,dx,$$

which can then be expressed as an expectation:

$$\frac{\partial\mathcal{C}}{\partial\sigma} = \frac{1}{\sigma^3}\mathbb{E}\left[D(x,a^*(\tilde{x}))\cdot\left((e-\mu)^2-\sigma^2\right) \mid \tilde{x}\right]. \tag{B1}$$

Noting that, by definition, the conditional variance is $\sigma^2 = \mathbb{E}\left[(e-\mu)^2 \mid \tilde{x}\right]$, we can rewrite the expectation from equation (B1) as:

$$\mathbb{E}\left[D(x,a^*(\tilde{x}))\cdot\left((e-\mu)^2-\mathbb{E}[(e-\mu)^2 \mid \tilde{x}]\right) \mid \tilde{x}\right].$$

This expression is the definition of the conditional covariance, and is therefore equal to:

$$\mathrm{Cov}\left(D(x, a^*(\tilde{x})), (e-\mu)^2 \mid \tilde{x}\right).$$

So, equation (B1) then becomes:

$$\frac{\partial \mathcal{C}}{\partial \sigma} = \frac{1}{\sigma^3} \mathrm{Cov}\left(D(x, a^*(\tilde{x})), (e-\mu)^2 \mid \tilde{x}\right). \tag{B2}$$

It follows then that the *ex ante* value of improving the forecast is:

$$\frac{\mathrm{d}}{\mathrm{d}\sigma}\mathbb{E}_{\tilde{x}}\left[\mathcal{C}(\tilde{x};\mu,\sigma)\right] = \mathbb{E}_{\tilde{x}}\left[\frac{1}{\sigma^3}\mathrm{Cov}\left(D(x, a^*(\tilde{x})), (e-\mu)^2 \mid \tilde{x}\right)\right].$$

This completes the first part of the proof.

Next, because $e \mid \tilde{x} \sim \mathcal{N}(\mu, \sigma^2)$, the fourth moment of the demeaned error is $\mathbb{E}\left[(e-\mu)^4 \mid \tilde{x}\right] = 3\sigma^4$. It follows that the variance of the demeaned error is given by:

$$\mathrm{Var}\left((e-\mu)^2 \mid \tilde{x}\right) = \mathbb{E}\left[(e-\mu)^4 \mid \tilde{x}\right] - \left(\mathbb{E}\left[(e-\mu)^2 \mid \tilde{x}\right]\right)^2 = 3\sigma^4 - \sigma^4 = 2\sigma^4.$$

Define the regression coefficient:

$$\beta_2(\tilde{x}) = \frac{\mathrm{Cov}\left(D(x, a^*(\tilde{x})), (e-\mu)^2 \mid \tilde{x}\right)}{\mathrm{Var}\left((e-\mu)^2 \mid \tilde{x}\right)} = \frac{\mathrm{Cov}\left(D(x, a^*(\tilde{x})), (e-\mu)^2 \mid \tilde{x}\right)}{2\sigma^4},$$

and rearrange:

$$\mathrm{Cov}\left(D(x, a^*(\tilde{x})), (e-\mu)^2 \mid \tilde{x}\right) = 2\sigma^4 \cdot \beta_2(\tilde{x}).$$

We can then substitute into (B2):

$$\frac{\partial \mathcal{C}}{\partial \sigma} = \frac{1}{\sigma^3} \cdot 2\sigma^4 \cdot \beta_2(\tilde{x}) = 2\sigma \cdot \beta_2(\tilde{x}),$$

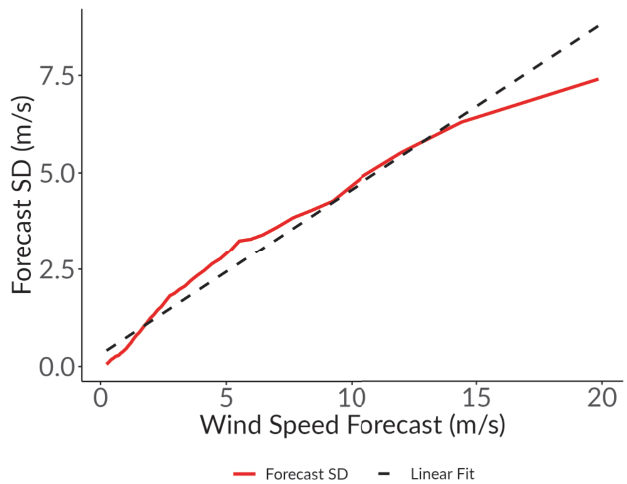
and take expectations over $\tilde{x}$:

$$\frac{\mathrm{d}}{\mathrm{d}\sigma}\mathbb{E}_{\tilde{x}}\left[\mathcal{C}(\tilde{x};\mu,\sigma)\right] = \mathbb{E}_{\tilde{x}}\left[2\sigma \cdot \beta_2(\tilde{x})\right] = 2\sigma \cdot \mathbb{E}_{\tilde{x}}\left[\beta_2(\tilde{x})\right].$$

B2. Allowing the Forecast Standard Deviation to Depend on Forecast Intensity

This section extends the model to allow the forecast standard deviation to depend on the forecast hurricane intensity, $\tilde{x}$. As Figure B1 shows, there is an approximately linear positive relationship between the two:

FIGURE B1. FORECAST UNCERTAINTY BY WIND SPEED FORECAST



Note: The red line shows a binscatter of the standard deviation of wind forecast errors as a function of forecast wind speed. The black dashed line is the linear fit from a regression of standard deviation on forecast wind speed.

Given this empirical relationship, we generalize our model so that the forecast error standard deviation is a linear function of the forecast, $\sigma(\tilde{x}) = \bar{\sigma} + \sigma_{\text{slope}} \cdot \tilde{x}$, with $\sigma_{\text{slope}} > 0$. The forecast error is $e = x - \tilde{x} \sim \mathcal{N}(\mu, \sigma^2(\tilde{x}))$. More intense storms thus have greater forecast uncertainty.

The agent's objective is to minimize expected total cost:

$$\mathcal{C}(\tilde{x}, \mu, \bar{\sigma}, \sigma_{\text{slope}}, \mathbf{i}, \mathbf{t}) = \min_a \mathbb{E}[D(\tilde{x} + e, a, \mathbf{i}, \mathbf{t}) \mid \tilde{x}] + C(a).$$

We are interested in the *ex ante* marginal change in expected total cost from a marginal change in σ_{slope}, which is given by:

$$\frac{\mathrm{d}}{\mathrm{d}\sigma_{\text{slope}}} \mathbb{E}_{\tilde{x}} \left[\mathcal{C}(\tilde{x}, \mu, \bar{\sigma}, \sigma_{\text{slope}}, \mathbf{i}, \mathbf{t})\right].$$

This is derived in the proposition below.

PROPOSITION 2: *The* ex ante *marginal value of a forecast improvement from reducing σ_{slope} is:*

$$\begin{aligned}\frac{\mathrm{d}}{\mathrm{d}\sigma_{slope}} \mathbb{E}_{\tilde{x}}\left[\mathcal{C}\right] &= \mathbb{E}_{\tilde{x}}\left[\frac{\tilde{x}}{\sigma^3(\tilde{x})} \cdot \mathrm{Cov}\left(D(\tilde{x}+e, a^*, \mathbf{i}, \mathbf{t}), (e-\mu)^2 \mid \tilde{x}\right)\right] \\ &= \mathbb{E}_{\tilde{x}}\left[2\tilde{x} \cdot \sigma(\tilde{x}) \cdot \beta_2(\tilde{x})\right],\end{aligned}$$

where $\beta_2(\tilde{x})$ is the coefficient from a regression of damages $D(\tilde{x} + e, a^*, \mathbf{i}, \mathbf{t})$ on squared demeaned forecast errors $(e-\mu)^2$, conditional on $\tilde{x}$ and the optimal action a^*.

PROOF:

Let a^* denote the optimal protective action. Using the envelope theorem, the marginal change in cost is:

$$\frac{\partial \mathcal{C}}{\partial \sigma_{\text{slope}}} = \int D(\tilde{x}+e, a^*, \mathbf{i}, \mathbf{t}) \cdot \frac{\partial \phi(e;\mu,\sigma^2(\tilde{x}))}{\partial \sigma_{\text{slope}}}\, de.$$

We can apply the chain rule to get:

$$\frac{\partial \phi(\bullet)}{\partial \sigma_{\text{slope}}} = \frac{\partial \phi(\bullet)}{\partial \sigma^2} \cdot \frac{\mathrm{d}\sigma^2}{\mathrm{d}\sigma_{\text{slope}}}.$$

The derivative of the variance with respect to σ_{slope} is:

$$\frac{\mathrm{d}\sigma^2}{\mathrm{d}\sigma_{\text{slope}}} = \frac{\mathrm{d}}{\mathrm{d}\sigma_{\text{slope}}}\left[(\bar{\sigma}+\sigma_{\text{slope}}\cdot\tilde{x})^2\right] = 2(\bar{\sigma}+\sigma_{\text{slope}}\cdot\tilde{x})\cdot\tilde{x} = 2\sigma(\tilde{x})\cdot\tilde{x}.$$

The partial derivative of the normal density with respect to its variance is:

$$\frac{\partial \phi(e;\mu,\sigma^2(\tilde{x}))}{\partial \sigma^2} = \phi(e;\mu,\sigma^2(\tilde{x}))\cdot\frac{(e-\mu)^2-\sigma^2}{2\sigma^4}.$$

Combining these terms then gives:

$$\frac{\partial \phi(e;\mu,\sigma^2(\tilde{x}))}{\partial \sigma_{\text{slope}}} = \phi(e;\mu,\sigma^2(\tilde{x}))\cdot\frac{(e-\mu)^2-\sigma^2}{2\sigma^4}\cdot 2\sigma(\tilde{x})\cdot\tilde{x}.$$

Substituting this back into the integral and using the covariance identity yields:

$$\frac{\partial \mathcal{C}}{\partial \sigma_{\text{slope}}} = \frac{\tilde{x}}{\sigma^3(\tilde{x})}\cdot \operatorname{Cov}\left(D(\tilde{x}+e,a^*,\mathbf{i},\mathbf{t}),(e-\mu_f)^2 \mid \tilde{x}\right).$$

It follows then that the *ex ante* marginal change in expected total cost from a marginal change in σ_{slope} is given by:

$$\frac{\mathrm{d}}{\mathrm{d}\sigma_{\text{slope}}}\mathbb{E}_{\tilde{x}}\left[\mathcal{C}\right] = \mathbb{E}_{\tilde{x}}\left[\frac{\tilde{x}}{\sigma^3(\tilde{x})}\cdot \operatorname{Cov}\left(D(\tilde{x}+e,a^*,\mathbf{i},\mathbf{t}),(e-\mu)^2 \mid \tilde{x}\right)\right].$$

For the second part of the proof, define the regression coefficient $\beta_2(\tilde{x})$ as:

$$\beta_2(\tilde{x}) = \frac{\operatorname{Cov}\left(D(\tilde{x}+e,a^*,\mathbf{i},\mathbf{t}),(e-\mu_f)^2 \mid \tilde{x}\right)}{2\sigma^4(\tilde{x})}.$$

Substituting this in gives the marginal effect:

$$\frac{\partial \mathcal{C}}{\partial \sigma_{\text{slope}}} = \frac{\tilde{x}}{\sigma^3(\tilde{x})}\cdot\left(2\sigma^4(\tilde{x})\beta_2(\tilde{x})\right) = 2\tilde{x}\cdot\sigma(\tilde{x})\cdot\beta_2(\tilde{x}).$$

Taking the expectation over $\tilde{x}$ gives the final result:

$$\frac{\mathrm{d}}{\mathrm{d}\sigma_{\text{slope}}}\mathbb{E}_{\tilde{x}}\left[\mathcal{C}\right] = \mathbb{E}_{\tilde{x}}\left[2\tilde{x}\cdot\sigma(\tilde{x})\cdot\beta_2(\tilde{x})\right].$$

We estimate the expression using the coefficient β_2 from Table 2, along with observed values of $\tilde{x}$ and the standard deviation $\sigma(\tilde{x})$. We compute the marginal value for each county that experienced hurricane-force winds in the dataset, and average across years to obtain an annualized estimate. The results indicate that a 1-unit reduction in σ_{slope} generates an average annual benefit of approximately \$42 billion. This magnitude reflects the disproportionate impact from reducing uncertainty in high-intensity storms, which have both greater damages and higher baseline variance.

To facilitate a comparison with the constant-variance model in our main analysis, we also compute the value of a 1-unit reduction in $\sigma(\tilde{x})$ at the mean forecast intensity through reducing σ_{slope}. This yields an annual benefit of approximately \$1.7 billion. Performing a similar calculation under the constant and independent variance assumption used in the main text yields nearly identical results, with an annual valuation that is only \$20 million lower.

Finally, this generalized framework can also be used to find the effect of changing the intercept, $\bar{\sigma}$. The proof for $(\mathrm{d}C)\,/\,(\mathrm{d}\bar{\sigma})$ is analogous to the one above. The key difference is that the derivative of the variance term simplifies, since $(\mathrm{d}\sigma(\tilde{x}))\,/\,(\mathrm{d}\bar{\sigma}) = 1$. The marginal value of a uniform reduction in uncertainty across all storm intensities is then given by:

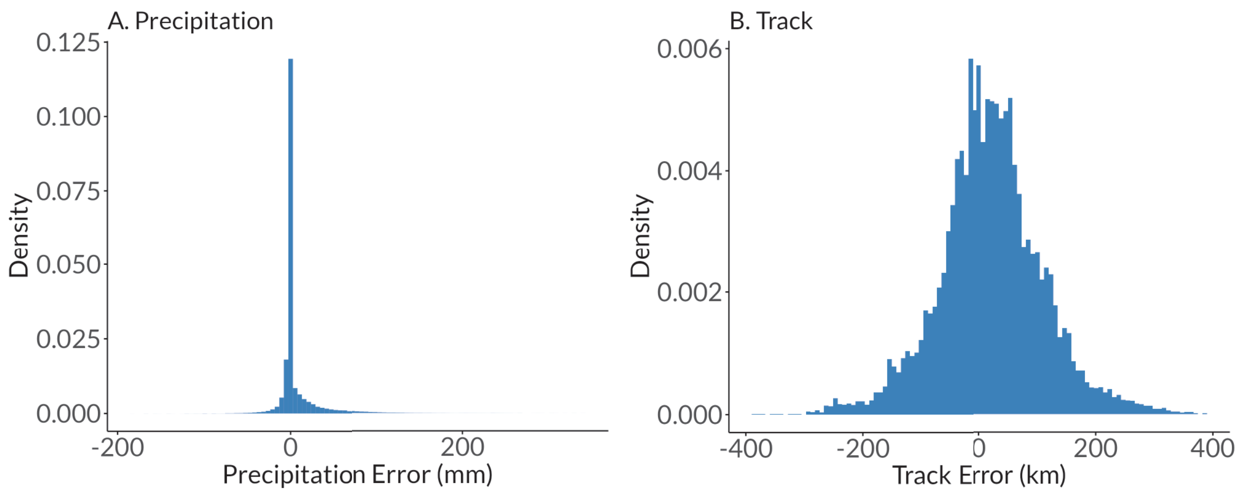
$$\frac{\mathrm{d}}{\mathrm{d}\bar{\sigma}}\mathbb{E}_{\tilde{x}}\left[\mathcal{C}\right] = \mathbb{E}_{\tilde{x}}\left[2\sigma(\tilde{x})\cdot\beta_2(\tilde{x})\right],$$

which is equivalent to the expression derived in the main text.

B3. Model Assumption

The assumption in our theoretical model is that the hurricane intensity errors should be normally distributed. Figure 3 plots the empirical distribution of wind speed forecast errors, while Figure B2 below plots the empirical distribution of precipitation and track errors. Both appear to be roughly normal, although with a slight right skew indicating that the average forecast slightly underestimates both precipitation and distance from track.

Figure B2. The Distribution of Realized Precipitation and Track Error.



Note: Panel A shows the observed distribution of the realized precipitation error by county-hurricane. The panel omits observations where the forecast and realized precipitation was zero for clarity. Panel B shows the observed distribution of the realized distance from track error by county-hurricane.

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