NBER WORKING PAPER SERIES

THE SOCIAL VALUE OF HURRICANE FORECASTS

Renato Molina
Ivan Rudik

Working Paper 32548
http://www.nber.org/papers/w32548

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
June 2024, Revised July 2025

We thank Diego Cardoso, Luc Esprabens, Mike Huang, Steven Koller, Brian McNoldy, and Juan Carlos Villaseñor-Derbez for excellent research assistance and comments. We are also grateful for the guidance and support provided by Andrea Schumacher and Frank DeMaria at the Cooperative Institute for Research in the Atmosphere at Colorado State University, as well as the staff at the Hurricane Forecast Improvement Program and the Weather Program Office at the National Oceanic and Atmospheric Administration, especially to Gina Eosco, Frank Marks, and Shirley Murillo. This manuscript benefited from discussions by Jackson Dorsey, Manuel Linsenmeier, and Je Shrader, and comments from Christopher Costello, Gabriel Lade, Derek Lemoine, Cynthia Lin-Lawell, Antony Millner, Christopher Parmeter, Christopher Timmins, and Jinhua Zhao, as well as from feedback by seminar participants at Arizona State University, the University of Alaska Anchorage, Cornell University, St. John's University, Marquette University, the University of Miami, the University of California San Diego, the annual meeting of the American Economic Association, the CESifo Area Conference on Energy and Climate Economics, the Colorado Environmental Economics Workshop, the Kansas City Fed, the Northeast Environmental Workshop, the Occasional Workshop, the Seminar Series of the National Oceanic and Atmospheric Administration, and the AERE Summer Conference. Funding for this project was provided by Grant NA20OAR4320472 from the National Oceanic and Atmospheric Administration. The views expressed in this work do not represent the views of the federal government, nor of the National Bureau of Economic Research.

The Social Value of Hurricane Forecasts
Renato Molina and Ivan Rudik
NBER Working Paper No. 32548
June 2024, Revised July 2025
JEL No. Q54, Q58

ABSTRACT

What is the impact and value of hurricane forecasts? We study this question using newly-collected data for the universe of land-falling US hurricanes between 2005–2022. We find that forecasts drive adaptive protective expenditures, and that erroneous under-forecasts result in a significant increase in total hurricane damage. Our main contribution is a new 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, as well as for all federal weather forecasting.

Renato Molina
University of Miami
renato.molina@rsmas.miami.edu

Ivan Rudik
Cornell University
and NBER
irudik@cornell.edu

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 of damage since 1980, with the majority caused by hurricanes (Weinkle et al., 2018; NOAA, 2022b,a). 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 damages and increased expenditures for post-hurricane recovery, and (3) our primary contribution, estimate the *ex ante* marginal value of a forecast improvement using a newly-developed, theoretically-grounded approach. Our method accounts for unobserved protective actions taken prior to landfall, and it is flexible enough to be applied to other kinds of hazardous weather forecasts. 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 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 is 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

[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).

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, our main contribution is a new 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 uptake 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 first regressing the sum of damages and recovery expenditures on the *ex post* squared error in the forecast, and then multiplying 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.

Overall, 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 (Downey, Lind and Shrader, 2023; Anand, 2024), as well as how forecasts can be used to measure climate damages accounting for adaptation (Shrader).

Two recent papers on pollution and temperature are closest to ours in spirit in aiming to estimate the value forecasts accounting for adaptation. Barwick, Li, Lin and 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. Shrader, Bakkensen and 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 (Noy, 2009; Hsiang, 2010; Strobl, 2011; Hsiang and Jina, 2014; Bakkensen and Barrage, Forthcoming; Auh, Choi, Deryugina and Park, 2022; Jerch, Kahn and Lin, 2023; Young and 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 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).

[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 et al., 2019).

[4]Recent work has shown 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 et al., 2019; Gellman et al., 2024).

Finally, our findings also add to a limited stated-preference literature on the value of hurricane 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 1 provides background information on hurricanes and hurricane forecasts. Section 2 describes the data we use in our analysis. Section 3 presents our methods and results. Section 4 concludes.

1 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 usually done when the hurricane is over water, as it is there where 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), however, the share of damage caused by wind and storm surge tends to be higher for major hurricanes 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 deterministic projections as well as probabilistic guidance intended to convey uncertainty in the storm's evolution. Forecasts are then communicated

[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).

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 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 et al., 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

[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.

[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.

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 and Brennan, 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 forecasts 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 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 impeding 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]

2 Data

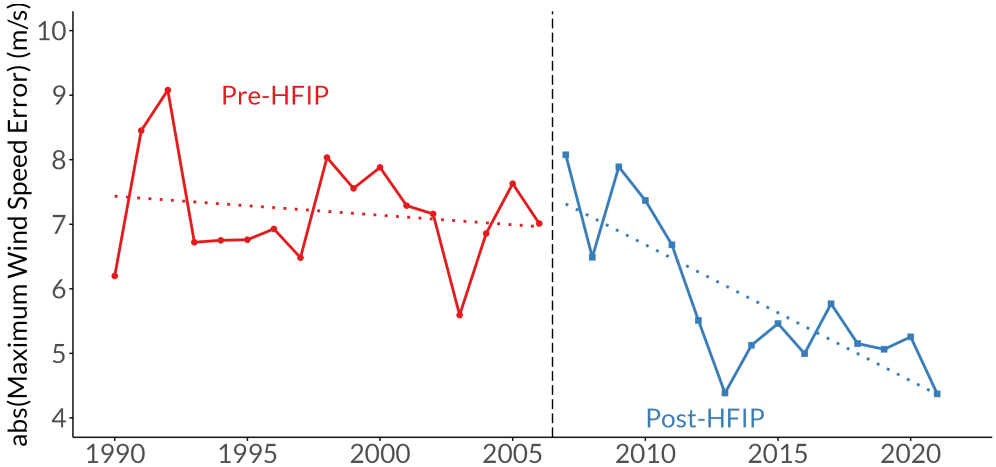
Our analysis focuses on a county-hurricane as the unit of observation (e.g., Kings County, NY and Hurricane Sandy), and uses data on hurricane intensity forecasts, hurricane intensity realizations, protective expenditures, recovery expenditures, and damages at the county-level for all 31 hurricanes that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

[9] Historically, it has been much more difficult to forecast the intensity 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).

[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.

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. The archive for official historical records data used to produce the figure is available at: https://www.nhc.noaa.gov/verification [Last accessed on June 25, 2025].

2.1 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. The determinstic forecast is a prediction of the hurricane track and its maximum wind speed at given times along the track. This forecast is 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

[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.

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 et al., 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.

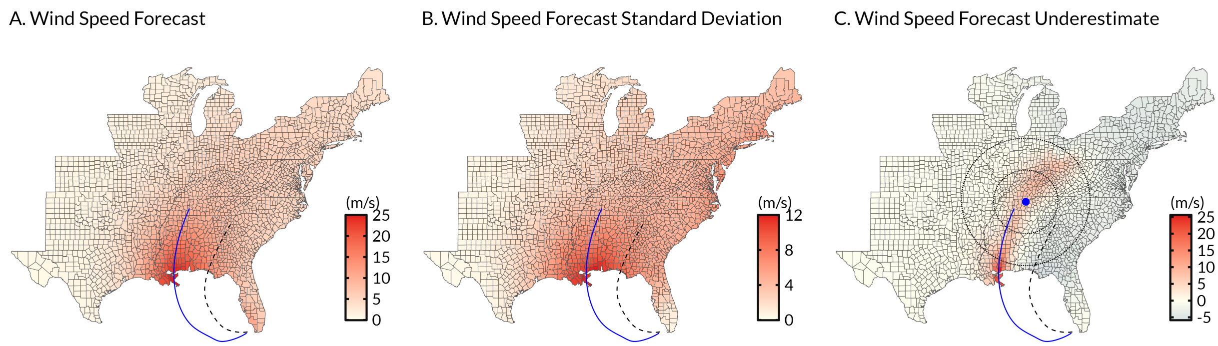
Observed, or realized, wind speed is obtained by evaluating the observed hurricane track and wind speed archived by the NHC in the gridded wind map model. Forecast errors are thus the difference between observed wind speed and the forecast mean across all predictions. For each hurricane, we aggregate 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 et al., 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 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.

[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 et al., 2025) or fluctuations in the El Niño–Southern Oscillation phenomenon (Downey et al., 2023).

[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.

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.

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]

2.2 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 Federal Emergency Management Agency (FEMA)'s Public Assistance Grant Program (PAGM). Administered by FEMA, 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 et al., 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, 2025b). Specifically, expenditures listed as Emergency Work expenditures, we define 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, assists 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.

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

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.

2.3 Economic Damages

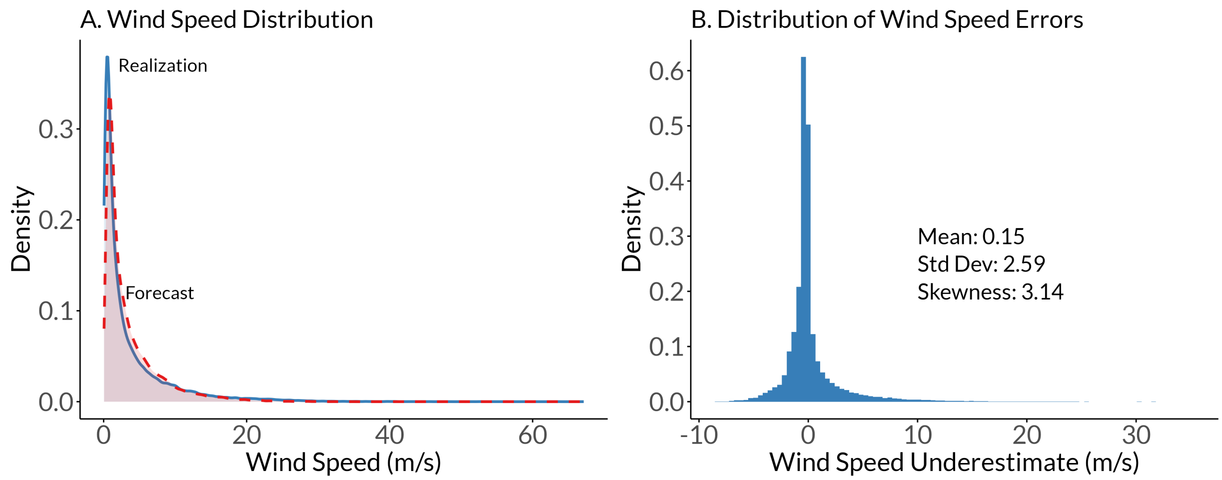
Data on hurricane damages come from the Spatial Hazards Event and Losses Database for the United States (SHELDUS). SHELDUS provides county-level information on the year and month of the hurricane, and the direct losses that stem from fatalities, injuries, and damages to property and crops. Following 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 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.

2.4 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: 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.

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.

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 Exp. (Billion $)	Recovery Exp. (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. "Exp." is short for Expenditure. 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 US$.

13

3 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]

3.1 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:

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

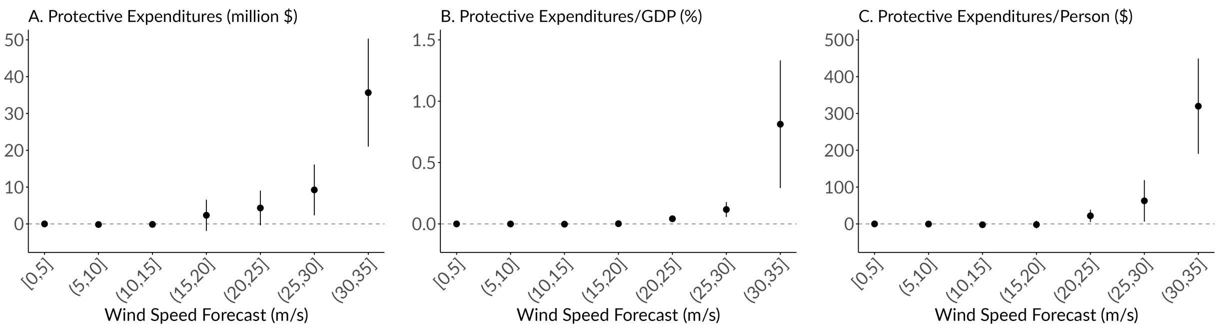
The outcome variable is FEMA protective expenditures. We also present results normalized by county GDP and in per capita terms to adjust for how protective expenditures may be directed toward areas with larger economies or more people. $\mathcal{B}_w$ is a set of 5 m/s bins of wind speed forecasts up 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

[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.

vary across states for the same hurricane, such as the political composition of the state government, and whether states used emergency declarations to marshall local resources. 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 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 increases 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.

[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.

3.2 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:

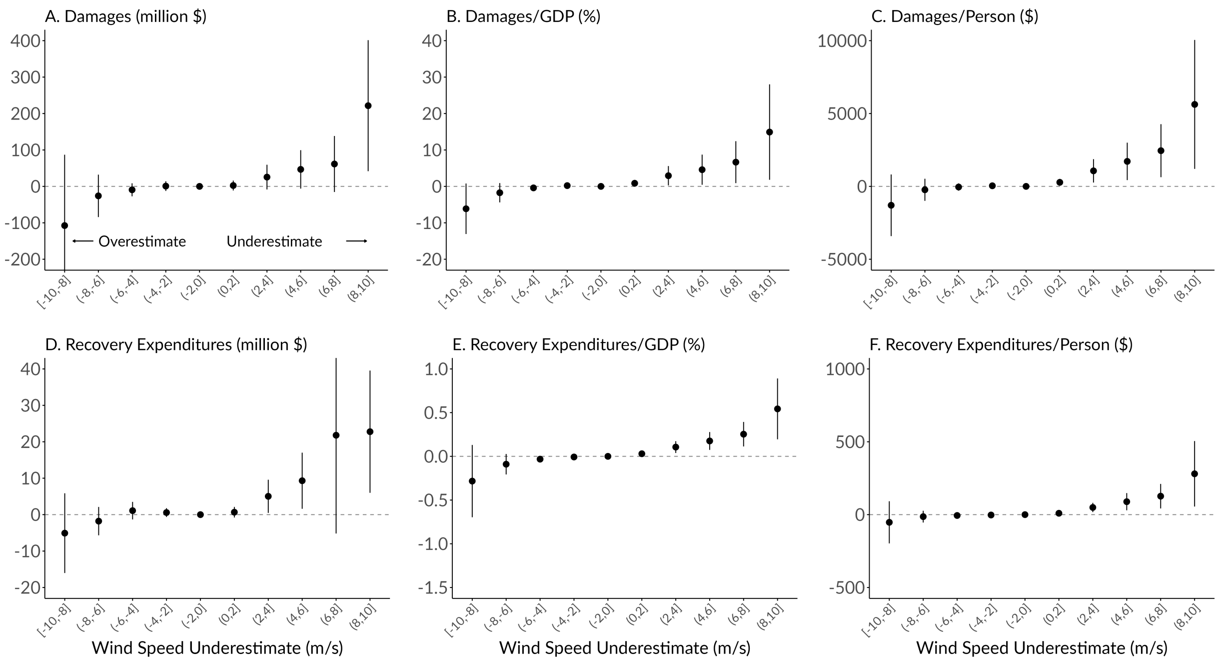
$$\begin{aligned} \mathrm{Y}_{csh} = & \sum_{b \in \mathcal{E}^w} \beta_b^w 1(\text{Wind Error}_{csh} \in b) + \sum_{b \in \mathcal{E}^p} \beta_b^p 1(\text{Precip Error}_{csh} \in b) \\ & + \sum_{b \in \mathcal{E}_i^w} \gamma_b^w 1(\text{Wind Realization}_{csh} \in b) + \sum_{b \in \mathcal{E}_i^p} \gamma_b^p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

Y_{csh} is either damages caused by the hurricane, or FEMA's post-landfall expenditures aimed at 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 uptaken protective actions mitigate damages. Conditional on a storm's intensity, forecast errors only matter through how the forecast directed effective protective actions.

[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.

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.

3.3 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 marshall more costly protective resources to an area. Figure 5 shows that, conditional on realized hurricane intensity, overestimating intensity, through higher forecasts, reduces *ex post* costs. We now formalize the *ex ante* value of improving hurricane forecasts accounting for both of these forces on total costs.

3.3.1 Theoretical Foundation

Suppose a representative agent faces a future hurricane with total after-landfall costs from damages and recovery expenditures, $D(x, a, \mathbf{i}, \mathbf{t})$. To be concise, we will call D damages from hereon. x is the hurricane's deterministic but unobserved intensity (e.g., wind speed, precipitation); $\tilde{x}$ is the forecast of this intensity; a is the agent's continuous choice of before-landfall protective actions to reduce damages (e.g., sandbags, evacuations, structure hardening), which is a function of the forecast and has an associated continuous and increasing cost function $C(a)$; $\mathbf{i}$ is a vector of time-invariant features of the agent's location i (e.g., elevation, proximity to the coast, long-lived capital structures); and $\mathbf{t}$ is a vector of common features across locations in period t. D is continuous and decreasing in a. The agent has access to a forecast $\tilde{x}$ of the realized hurricane intensity x at time t, specific to location i. The forecast is a noisy signal with normally distributed error: $e \sim \mathcal{N}(\mu, \sigma)$. We can write the intensity as a function of forecast and its error: $x = \tilde{x} + e$.[20]

The agent's objective is to minimize their expected total costs:

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

We define the value of a forecast improvement as the 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.[21] Proposition 1 provides an intuitive closed-form expression for this quantity.

Proposition 1 *The value of a forecast improvement is:*

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

$$= 2\sigma\beta_2. \tag{4}$$

Where a^* is the optimized protective action choice, and β_2 is the coefficient from a regression of observed damages $D(\tilde{x} + e, a^*, \mathbf{i}, \mathbf{t})$ on the observed squared demeaned forecast error $(e - \mu)^2$.

Proof: See Appendix B.1. □

Proposition 1 shows that the marginal value of a forecast improvement is proportional to a covariance between realized damages at the optimized protective actions and the squared demeaned forecast error.[22] The value of an improvement and the covariance is positive if damages tend to be higher when the squared demeaned error is higher. Figure 5 provides evidence 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 expenditures and the protective expenditures they would have chosen if they could observe realized hurricane intensity when making their decision.

The second line of Proposition 1 shows the value of a forecast improvement, inclusive of any protective actions, can be recovered by regressing total after-landfall costs on squared demeaned

[20] This setup reflects the fact the underlying physical processes are fundamentally deterministic, and the agent can only observe or predict the hurricane subject to some noise. All observed uncertainty arises from limitations in the forecast signal rather than the physical system itself. Our model can be relaxed if one wanted to allow for randomness in the physical system itself. If realized hurricane intensity is normally distributed, and the forecast is of the mean of this distribution, the agent's distribution of hurricane intensity is still normally distributed, but with a variance that is the sum of the forecast error variance and the variance in the physical system.

[21] 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 hurricane forecasts are approximately unbiased on average (Figure 3). Alternative metrics of forecast quality like root mean squared error are *ex post* and depend 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 (IPCC) Assessment Reports (Masson-Delmotte et al., 2021).

[22] Section B.3 in the Appendix formalizes a version of the result for a risk-averse agent.

errors, and evaluating it at some reference forecast standard deviation. 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 standard deviation of the forecast and forecast error, which turns out is a necessary piece of data to properly calculate the value of a forecast improvement.

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

$$\begin{aligned} \mathrm{D}_{csh} \quad = \quad & \beta_2^w \left(e_{csh}^w - \mu_{csh}^w\right)^2 + \beta_2^p \left(e_{csh}^p - \mu_{csh}^p\right)^2 \\ & + \sum_{b \in \mathcal{E}_i^w} \gamma_b^w 1(x_{csh} \in b) + \sum_{b \in \mathcal{E}_i^p} \gamma_b^p 1(p_{csh} \in b) \\ & + \gamma_c + \eta_{sh} + \varepsilon_{csh}. \end{aligned} \tag{5}$$

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 forecast errors correlation with 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.2, 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.[23] Appendix B.4 shows that this assumption appears reasonable, while Supplemental Appendix C.3 demonstrates that the results are robust to normalizing the error distribution to remove the observed skewness in the data.

3.3.2 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

[23] 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 et al., 2023).

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. Because this is the main contribution of the paper, we show 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 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 ExpendituresPer 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					✓	✓	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ 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, 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.

3.4 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.[24] 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; two times 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.

3.5 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 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

[24]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.

results are not driven by omitted track forecasts and errors.

4 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 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.

Our main contribution is 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 et al., 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 (2024) for example, demonstrates that more precise early forecasts reduce traffic accidents in winter storms. Exploring how precise and early warnings 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.[25] Understanding how public and private insurance design interacts with forecast improvements remains an important area for future research.

Fifth, 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 may 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.

Last, the forecast improvement valuation framework we developed above is reliant upon an independence assumption, specifically that the forecast standard deviation is a constant independent of other forecast characteristics. This assumption is not critical, it can be relaxed to allow forecast uncertainty to depend on functions of *ex ante* observables, such as forecast intensity. We demonstrate how to do this with a linear relationship in the Appendix, but in principle it could be done with other functional forms. In settings where there may be particularly thorny relationships between the forecast standard deviation and other variables, researchers and policymakers could take a local approximation approach to adopt our framework. For example, one could use our constant or linear relationship frameworks locally within bins of some variable that the standard deviation depends upon. If the relationship is constant or linear within some given set of bins, this makes the estimation locally valid and amenable to be aggregated.

[25] 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).

Appendix

A 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, 2025b). 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.[26] 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 of potential actions and investments such as debris removal, temporary levees, and the repair or replacement of disaster-damaged public infrastructure (Moss et al., 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).[27] Protective expenditures

[26]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.

[27]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

associated with pre-landfall emergency declarations are often associated to 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).

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, 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.[28] 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, 2025a). 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 versus 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.

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).

[28] 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).

B Theoretical Foundation

B.1 Proof of Proposition 1

An agent is aiming to minimize the total costs of an incoming hurricane which consist of protective expenditures before the storm, and uncertain damages and recovery costs after the storm. The agent has access to a forecast $\tilde{x}$ of the realized hurricane intensity x. The forecast is a noisy signal with error $e = x - \tilde{x}$ where we can write the intensity as the deviation from the forecast: $x = \tilde{x} + e$. As in Figure 5, the error e measures how much the forecast underestimates the actual intensity. We assume that forecast errors are normally distributed: $e \sim \mathcal{N}(\mu, \sigma^2)$. We denote the probability density function as a function: $\Phi(e, \mu, \sigma)$.

The agent uses the forecast to choose their level of protective actions, a, that mitigate hurricane damage and reduce recovery costs. Protective actions have a cost $C(a)$ which is increasing and convex. Damages and recovery costs are a function D of realized intensity, the chosen level of protective actions, and location-specific and time-specific factors: $D(x, a, \mathbf{i}, \mathbf{t})$. D is decreasing in protective actions. Our agent's objective is to minimize their expected total costs:

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

where the expectation is only over damages since protective actions are determined before the hurricane intensity realizes. We are interested in the reduction in the minimized expected total cost from a marginal decrease in the standard deviation of the forecast error:

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

The envelope theorem gives us that:

$$\frac{\partial \mathcal{C}(\tilde{x}, \mu, \sigma, \mathbf{i}, \mathbf{t})}{\partial \sigma} = \int D(\tilde{x} + e, a^*, \mathbf{i}, \mathbf{t}) \frac{\partial \Phi(e, \mu, \sigma)}{\partial \sigma} de,$$

where a^* is the optimized protective action that is a function of the intensity forecast but not intensity realization. Taking the partial derivative inside the integral then gives:

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

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

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

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

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

where we use $e \sim \mathcal{N}(\mu,\sigma)$ so that $\mathbb{E}\{(e-\mu)^2\} = \sigma^2$. This result proves the first part of the proposition.

Next, we return to the last line in equation (B.2):

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

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

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

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

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

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

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

$$
\frac{\mathrm{d}\mathcal{C}(\tilde{x},\mu,\sigma,\mathbf{i},\mathbf{t})}{\mathrm{d}\sigma} = 2\sigma\beta_2. \qquad \text{(B.5)}
$$

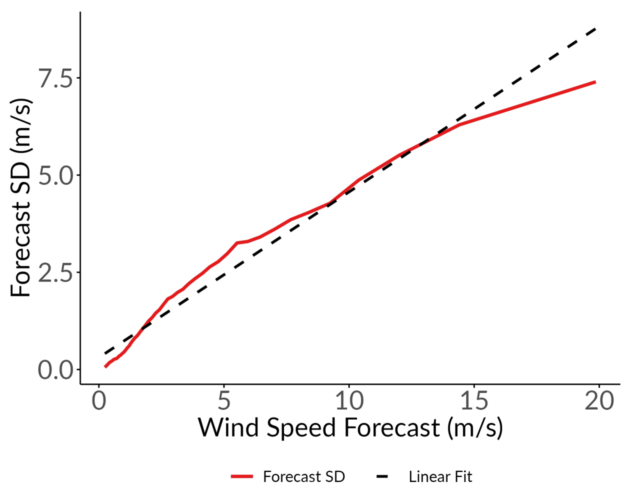
The marginal value of a forecast improvement is the product of this regression coefficient and the standard deviation of forecast errors at which we want to evaluate the marginal value.

Note that this result depends on assuming that the forecast error distribution has constant parameters that do not depend on the actual hurricane intensity. Figure D.1 shows that this is unlikely to be the case: forecast errors and squared demeaned forecast errors are both correlated with realized intensity. This means that we need to flexibly condition on hurricane intensity when performing the regression over our full dataset, otherwise the coefficient on squared errors may just be picking up the fact that stronger hurricanes cause more damage regardless of the forecast error. Appendix B.2 below relaxes this assumption.

B.2 Allowing the Forecast Standard Deviation to Depend on Forecast Intensity

Here we extend the model to allow the forecast error standard deviation to depend on the forecast hurricane intensity $\tilde{x}$. Figure B.1 shows that there is an approximately linear positive relationship between the two.

Figure B.1: 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 standard deviation takes on a linear form:

$$\sigma(\tilde{x}) = \bar{\sigma} + \sigma_{\text{slope}} \cdot \tilde{x}. \tag{B.6}$$

The error, e, is assumed to be normally distributed with mean μ and standard deviation $\sigma(\tilde{x})$, so that:

$$e \sim \mathcal{N}\left(\mu, \sigma^2(\tilde{x})\right) \quad \text{and} \quad x = \tilde{x} + e. \tag{B.7}$$

More intense storms will have greater forecast standard deviations and forecast errors.

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

$$C(\tilde{x}, \mu, \bar{\sigma}, \sigma_{\text{slope}}, i, t) = \min_a \mathbb{E}[D(\tilde{x} + e, a, i, t)] + C(a). \tag{B.8}$$

We are interested in the marginal change in total expected cost from a marginal change in σ_{slope}. This is given in the proposition below.

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

$$\frac{dC(\tilde{x}, \mu, \bar{\sigma}, \sigma_{slope}, i, t)}{d\sigma_{slope}} = \frac{\tilde{x}}{\sigma^3(\tilde{x})} \cdot \text{cov}\left(D(\tilde{x} + e, a^*, i, t), (e - \mu)^2\right) \tag{B.9}$$

$$= 2\tilde{x} \cdot \sigma(\tilde{x}) \cdot \beta_2, \tag{B.10}$$

where a^* is the optimized protective action choice, and β_2 is the coefficient from a regression of observed damages on squared demeaned forecast errors, conditional on forecast intensity and covariates.

Proof: Let a^* denote the optimal protective action. The minimized expected total cost is:

$$C(\tilde{x}, \mu, \bar{\sigma}, \sigma_{\text{slope}}, i, t) = \int D(\tilde{x} + e, a^*, i, t) \cdot \phi(e; \mu, \sigma^2(\tilde{x}))\, de. \tag{B.11}$$

Let $\sigma \equiv \sigma(\tilde{x})$ and differentiate with respect to σ_{slope} using the envelope theorem:

$$\frac{dC}{d\sigma_{\text{slope}}} = \int D(\tilde{x} + e, a^*, i, t) \cdot \frac{\partial \Phi(e; \mu, \sigma^2)}{\partial \sigma_{\text{slope}}}\, de. \tag{B.12}$$

Apply the chain rule:

$$\frac{\partial \Phi}{\partial \sigma_{\text{slope}}} = \frac{\partial \Phi}{\partial \sigma^2} \cdot \frac{d\sigma^2}{d\sigma_{\text{slope}}} \tag{B.13}$$

$$= \frac{\partial \Phi}{\partial \sigma^2} \cdot 2\sigma(\tilde{x}) \cdot \frac{d\sigma}{d\sigma_{\text{slope}}} \tag{B.14}$$

$$= \frac{\partial \Phi}{\partial \sigma^2} \cdot 2\sigma(\tilde{x}) \cdot \tilde{x}. \tag{B.15}$$

As in Proposition 1, the derivative of the normal density with respect to variance is:

$$\frac{\partial \Phi(e; \mu, \sigma^2)}{\partial \sigma^2} = \Phi(e; \mu, \sigma^2) \cdot \left(\frac{(e - \mu)^2 - \sigma^2}{2\sigma^4}\right). \tag{B.16}$$

Combining these results and using the same expectation-covariance substitutions as in the proof for

Proposition 1 gives:

$$\begin{aligned}\frac{dC}{d\sigma_{\text{slope}}} &= \int D(\tilde{x}+e, a^*, i, t)\cdot\Phi(e;\mu,\sigma^2)\cdot\left(\frac{(e-\mu)^2-\sigma^2}{2\sigma^4}\right)\cdot 2\sigma\tilde{x}\,de\\ &= \frac{\tilde{x}}{\sigma^3}\cdot\int D(\tilde{x}+e, a^*, i, t)\cdot\big((e-\mu)^2-\sigma^2\big)\cdot\Phi(e)\,de\\ &= \frac{\tilde{x}}{\sigma^3}\cdot\operatorname{cov}(D(\tilde{x}+e, a^*, i, t), (e-\mu)^2).\end{aligned}$$

We can now express the covariance in terms of the regression coefficient β_2:

$$\operatorname{cov}(D(\tilde{x}+e, a^*, i, t), (e-\mu)^2) = \operatorname{var}((e-\mu)^2)\cdot\beta_2 \tag{B.17}$$

$$= 2\sigma^4\cdot\beta_2 \tag{B.18}$$

and substitute back:

$$\frac{dC}{d\sigma_{\text{slope}}} = \frac{\tilde{x}}{\sigma^3}\cdot 2\sigma^4\cdot\beta_2 \tag{B.19}$$

$$= 2\tilde{x}\cdot\sigma(\tilde{x})\cdot\beta_2 \tag{B.20}$$

□

We estimate this expression using the estimated coefficient β_2 from Table 2, along with observed values of $\tilde{x}$ and 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 yields nearly identical results, with an annual valuation that is only \$20 million lower.

In this generalized framework, we can also obtain $\frac{dC}{d\bar{\sigma}}$. The proof follows almost identically except that in equation (B.14) we have $\frac{d\sigma}{d\bar{\sigma}} = 1$. The marginal value of reducing the intercept term, which captures a uniform reduction across all intensities, just boils down to our expression in the main text:

$$\frac{dC}{d\bar{\sigma}} = 2\sigma\beta_2. \tag{B.21}$$

This provides an alternative interpretation of our main text results.

B.3 Risk Averse Agent

Suppose that now the agent is risk-averse with some continuous, increasing, and concave utility function U. The agent's utility is over their total income Y, less the costs of protective actions $C(a)$, and damages $D(x, a, \mathbf{i}, \mathbf{t})$. The agent maximizes their expected utility:

$$V(\tilde{x}, \mu, \sigma, Y, \mathbf{i}, \mathbf{t}) = \max_a \mathbb{E}\left\{U\left(Y - D(\underbrace{\tilde{x}+e}_{x}, a, \mathbf{i}, \mathbf{t}) - C(a)\right)\right\}.$$

To simplify notation, let $U(\tilde{x}+e, a, Y, \mathbf{i}, \mathbf{t}) \equiv U\left(Y - D(\tilde{x}+e, a, \mathbf{i}, \mathbf{t}) - C(a)\right)$. The value of a forecast improvement is:

$$-\frac{\mathrm{d}V(\tilde{x}, \mu, \sigma, Y, \mathbf{i}, \mathbf{t})}{\mathrm{d}\sigma} = -\frac{\partial V(\tilde{x}, \mu, \sigma, Y, \mathbf{i}, \mathbf{t})}{\partial \sigma}. \tag{B.22}$$

First, note that here we use a decrease in the standard deviation since we are maximizing utility instead of minimizing costs. Second, note that since the agent has a utility function over their (random) payoff, the value of a forecast improvement is in units of utility and will need to be translated back into dollar terms if one wishes to monetize the value of an improvement.

The envelope theorem gives us that:

$$\frac{\partial V(\tilde{x}, \mu, \sigma, Y, \mathbf{i}, \mathbf{t})}{\partial \sigma} = \int U(\tilde{x}+e, a^*, Y, \mathbf{i}, \mathbf{t})\frac{\partial \Phi(e, \mu, \sigma)}{\partial \sigma} de$$

recalling that $x = \tilde{x} - e$.

The rest of the proof follows identically to Proposition 1 except where $D(x, a^*, \mathbf{i}, \mathbf{t})$ is replaced by $U(\tilde{x}+e, a^*, Y, \mathbf{i}, \mathbf{t})$. We can get a closed form solution by using the covariance identity:

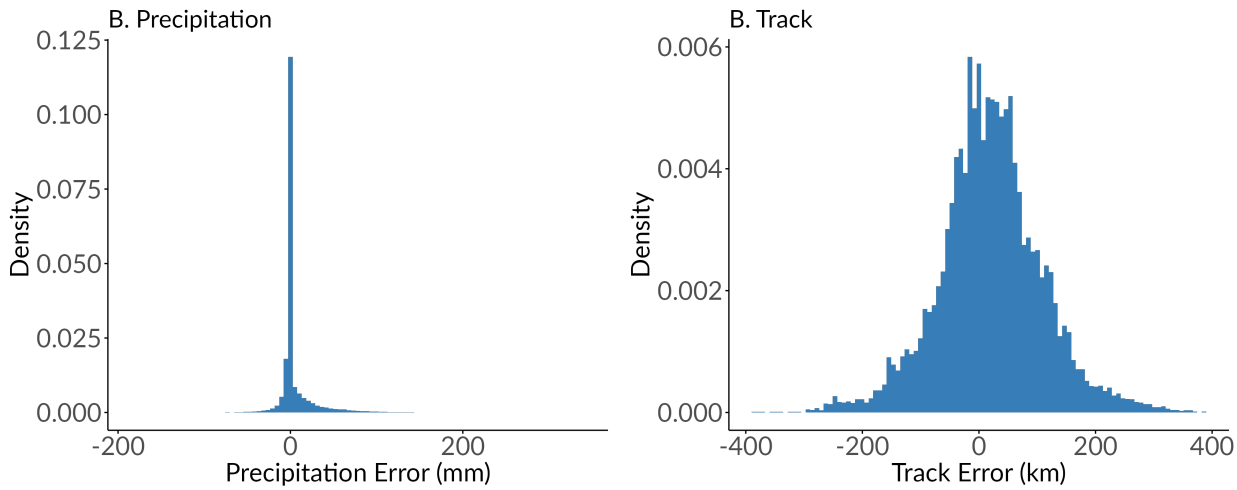
$$\begin{aligned}
-\frac{\partial V(\mu, \sigma, Y, \mathbf{i}, \mathbf{t})}{\partial \sigma} &= -\mathbb{E}\left\{U(\tilde{x}+e, a^*, Y, \mathbf{i}, \mathbf{t}) \times \left[\frac{(e-\mu)^2 - \sigma^2}{\sigma^3}\right]\right\} \\
&= -\frac{1}{\sigma^3}\mathbb{E}\left\{U(\tilde{x}+e, a^*, Y, \mathbf{i}, \mathbf{t}) \times \left[(e-\mu)^2 - \sigma^2\right]\right\} \\
&= -\frac{1}{\sigma^3}\Big[\operatorname{cov}\left(U(\tilde{x}+e, a^*, Y, \mathbf{i}, \mathbf{t}), (e-\mu)^2\right) \\
&\qquad + \mathbb{E}\left\{U(\tilde{x}+e, a^*, Y, \mathbf{i}, \mathbf{t})\right\}\underbrace{\mathbb{E}\left\{(e-\mu)^2 - \sigma^2\right\}}_{=0}\Big] \\
&= -\frac{1}{\sigma^3}\operatorname{cov}\left(U(\tilde{x}+e, a^*, Y, \mathbf{i}, \mathbf{t}), (e-\mu)^2\right).
\end{aligned} \tag{B.23}$$

If errors and utility are negatively correlated, then a decrease in the forecast standard deviation increases maximized utility. Since we do not observe utility like we do damages, to compute $\frac{\partial V(\mu,\sigma,Y,\mathbf{i},\mathbf{t})}{\partial \sigma}$ requires observing protective actions.

B.4 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 B.2 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 B.2: The Distribution of Realized Wind Speeds and Precipitation.



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.

References

Alaka Jr, Ghassan J, Jason A Sippel, Zhan Zhang, Hyun-Sook Kim, Frank D Marks, Vijay Tallapragada, Avichal Mehra, Xuejin Zhang, Aaron Poyer, and Sundararaman G Gopalakrishnan (2024) "Lifetime performance of the operational hurricane weather research and forecasting model (hwrf) for north atlantic tropical cyclones," *Bulletin of the American Meteorological Society*, Vol. 105, No. 6, pp. E932–E961.

Anand, Vaibhav (2024) "The value of forecast improvements: Evidence from advisory lead times and vehicle crashes," *Available at SSRN 4206910*.

Auh, Jun Kyung, Jaewon Choi, Tatyana Deryugina, and Tim Park (2022) "Natural disasters and municipal bonds,"Technical report, National Bureau of Economic Research.

Bakkensen, Laura and Lint Barrage (Forthcoming) "Climate shocks, cyclones, and economic growth: bridging the micro-macro gap," *The Economic Journal*.

Barwick, Panle Jia, Shanjun Li, Liguo Lin, and Eric Yongchen Zou (2024) "From fog to smog: The value of pollution information," *American Economic Review*, Vol. 114, No. 5, pp. 1338–1381.

Beatty, Timothy KM, Jay P Shimshack, and Richard J Volpe (2019) "Disaster preparedness and disaster response: Evidence from sales of emergency supplies before and after hurricanes," *Journal of the Association of Environmental and Resource Economists*, Vol. 6, No. 4, pp. 633–668.

Bhatia, Kieran T, Gabriel A Vecchi, Thomas R Knutson, Hiroyuki Murakami, James Kossin, Keith W Dixon, and Carolyn E Whitlock (2019) "Recent increases in tropical cyclone intensification rates," *Nature Communications*, Vol. 10, No. 1, pp. 1–9.

Bilal, Adrien and Esteban Rossi-Hansberg (2023) "Anticipating climate change across the united states,"Technical report, National Bureau of Economic Research.

Broad, Kenneth, Anthony Leiserowitz, Jessica Weinkle, and Marissa Steketee (2007) "Misinterpretations of the "cone of uncertainty" in florida during the 2004 hurricane season," *Bulletin of the American Meteorological Society*, Vol. 88, No. 5, pp. 651–668.

Cannon, Glenn (2008) "Strengthening the federal emergency management agency's disaster response capabilities," *Journal of Business Continuity & Emergency Planning*, Vol. 2, No. 3, pp. 281–293.

Congressional Research Service (2015) *The National Oceanic and Atmospheric Administration (NOAA) Budget for FY2016*.

——— (2021) *FEMA's Public Assistance Program: A Primer and Considerations for Congress*.

Conley, Timothy G (1999) "Gmm estimation with cross sectional dependence," *Journal of Econometrics*, Vol. 92, No. 1, pp. 1–45.

Craft, Erik D (1998) "The value of weather information services for nineteenth-century great lakes shipping," *American Economic Review*, pp. 1059–1076.

Czajkowski, Jeffrey, Kevin Simmons, and Daniel Sutter (2011) "An analysis of coastal and inland fatalities in landfalling us hurricanes," *Natural Hazards*, Vol. 59, No. 3, pp. 1513–1531.

DeMaria, Mark (1996) "A history of hurricane forecasting for the atlantic basin, 1920–1995," *Historical Essays on Meteorology 1919–1995*, pp. 263–305.

DeMaria, Mark, John A Knaff, Michael J Brennan, Daniel Brown, Richard D Knabb, Robert T DeMaria, Andrea Schumacher, Christopher A Lauer, David P Roberts, Charles R Sampson et al. (2013) "Improvements to the operational tropical cyclone wind speed probability model," *Weather and Forecasting*, Vol. 28, No. 3, pp. 586–602.

DeMaria, Mark, John A Knaff, and John Kaplan (2006) "On the decay of tropical cyclone winds crossing narrow landmasses," *Journal of Applied Meteorology and Climatology*, Vol. 45, No. 3, pp. 491–499.

DeMaria, Mark, John A Knaff, Richard Knabb, Chris Lauer, Charles R Sampson, and Robert T DeMaria (2009) "A new method for estimating tropical cyclone wind speed probabilities," *Weather and Forecasting*, Vol. 24, No. 6, pp. 1573–1591.

Deryugina, Tatyana (2017) "The fiscal cost of hurricanes: Disaster aid versus social insurance," *American Economic Journal: Economic Policy*, Vol. 9, No. 3, pp. 168–98.

Downey, Mitch, Nelson Lind, and Jeffrey G Shrader (2023) "Adjusting to rain before it falls," *Management Science*.

Emanuel, Kerry (2003) "Tropical cyclones," *Annual Review of Earth and Planetary Sciences*, Vol. 31, No. 1, pp. 75–104.

——— (2005) "Increasing destructiveness of tropical cyclones over the past 30 years," *Nature*, Vol. 436, No. 7051, pp. 686–688.

——— (2017) "Will global warming make hurricane forecasting more difficult?" *Bulletin of the American Meteorological Society*, Vol. 98, No. 3, pp. 495–501.

Enten, Harry (2017) "Why Hurricane Maria Surprised Forecasters By Getting So Strong So Fast," https://fivethirtyeight.com/features/why-hurricane-maria-surprised-forecasters-by-getting-so-strong-so-fast/, Accessed: 2025-05-26.

FEMA (2007) "Emergency Declaration Requests for Hurricanes and Typhoons - Disaster Assistance Policy 1001," //www.fema.gov/pdf/hazard/major_disaster_requests.pdf, Accessed: 2025-05-13.

——— (2019) "FEMA Obligates $13.3M for Emergency Protective Measures in Miami-Dade County," https://www.fema.gov/press-release/20250602/more-1-billion-fema-funds-approved-reimburse-hurricane-irma-infrastructure, Accessed: 2025-05-13.

——— (2023) "FEMA Awards Additional $368.5 Million in Hurricane Ida Public Assistance Grants," https://www.fema.gov/press-release/20230606/fema-awards-additional-3685-million-hurricane-ida-public-assistance-grants, Accessed: 2025-05-13.

——— (2024) "Public Assistance Expedited Projects Instructional Guidance," https://www.fema.gov/sites/default/files/documents/fema_pa-expedited-funding-project-guidance.pdf, Accessed: 2025-05-13.

——— (2025a) "Process of Public Assistance Grants," https://www.fema.gov/assistance/public/process, Accessed: 2025-05-13.

——— (2025b) "Public Assistance Program and Policy Guide Version 5.0," https://www.fema.gov/sites/default/files/documents/fema_pa_pappg-v5.0_012025.pdf, Accessed: 2025-05-13.

Fried, Stephie (2022) “Seawalls and stilts: A quantitative macro study of climate adaptation,” *The Review of Economic Studies*, Vol. 89, No. 6, pp. 3303–3344.

Gall, Robert, James Franklin, Frank Marks, Edward N Rappaport, and Frederick Toepfer (2013) “The hurricane forecast improvement project,” *Bulletin of the American Meteorological Society*, Vol. 94, No. 3, pp. 329–343.

Gallagher, Justin (2021) “Natural disasters that cause no damage: Accounting for the selective reporting of weather damage,”Technical report, Working Paper.

Gellman, Jacob, Hannah Hennighausen, Brett Watson, and Kevin Berry (2024) “The cost of hurricane evacuations,” Working Paper.

Grinsted, Aslak, Peter Ditlevsen, and Jens Hesselbjerg Christensen (2019) “Normalized us hurricane damage estimates using area of total destruction, 1900- 2018,” *Proceedings of the National Academy of Sciences*, Vol. 116, No. 48, pp. 23942–23946.

Gudishala, Ravindra and Chester Wilmot (2017) “Modeling emergency managers’ hurricane evacuation decisions,” *Transportation Research Record*, Vol. 2604, No. 1, pp. 82–87.

Hamill, Thomas M, Michael J Brennan, Barbara Brown, Mark DeMaria, Edward N Rappaport, and Zoltan Toth (2012) “Noaa’s future ensemble-based hurricane forecast products,” *Bulletin of the American Meteorological Society*, Vol. 93, No. 2, pp. 209–220.

Hilderbrand, Douglas and Lian Xie (2025) “Relative contributions from wind, storm surge, and inland flooding to tropical cyclone damage from 1925 to 2000 in north carolina,” *Atmosphere*, Vol. 16, No. 4, p. 451.

Hsiang, Solomon M (2010) “Temperatures and cyclones strongly associated with economic production in the caribbean and central america,” *Proceedings of the National Academy of sciences*, Vol. 107, No. 35, pp. 15367–15372.

Hsiang, Solomon M and Amir S Jina (2014) “The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones,” Working Paper.

Hudson, Paul, WJ Wouter Botzen, Jeffrey Czajkowski, and Heidi Kreibich (2017) “Moral hazard in natural disaster insurance markets: Empirical evidence from germany and the united states,” *Land Economics*, Vol. 93, No. 2, pp. 179–208.

Iman, Sara, Yue Ge, Daniel J Klenow, Amanda Savitt, and Pamela Murray-Tuite (2023) “Understanding the decision-making process for hurricane evacuation orders: A case study of florida county emergency managers,” *Sustainability*, Vol. 15, No. 24, p. 16666.

Jerch, Rhiannon, Matthew E Kahn, and Gary C Lin (2023) “Local public finance dynamics and hurricane shocks,” *Journal of Urban Economics*, Vol. 134, p. 103516.

Kantha, Lakshmi (2006) “Time to replace the saffir-simpson hurricane scale?” *Eos, Transactions American Geophysical Union*, Vol. 87, No. 1, pp. 3–6.

Kossin, James P (2018) “A global slowdown of tropical-cyclone translation speed,” *Nature*, Vol. 558, No. 7708, pp. 104–107.

Kossin, James P, Kenneth R Knapp, Timothy L Olander, and Christopher S Velden (2020) "Global increase in major tropical cyclone exceedance probability over the past four decades," *Proceedings of the National Academy of Sciences*, Vol. 117, No. 22, pp. 11975–11980.

Kousky, Carolyn, Brett Lingle, and Leonard Shabman (2015) "Fema public assistance grants: Implications of a disaster deductible,"Technical report, Resources for the Future.

Kruttli, Mathias S, Brigitte Roth Tran, and Sumudu W Watugala (2025) "Pricing poseidon: Extreme weather uncertainty and firm return dynamics," *The Journal of Finance*, Vol. 80, No. 2, pp. 783–832.

Lave, Lester B (1963) "The value of better weather information to the raisin industry," *Econometrica*, pp. 151–164.

Lazo, Jeffrey K and Donald M Waldman (2011) "Valuing improved hurricane forecasts," *Economics Letters*, Vol. 111, No. 1, pp. 43–46.

Lazo, Jeffrey K, Donald M Waldman, Betty Hearn Morrow, and Jennifer A Thacher (2010) "Household evacuation decision making and the benefits of improved hurricane forecasting: Developing a framework for assessment," *Weather and Forecasting*, Vol. 25, No. 1, pp. 207–219.

Lemoine, Derek and Sarah Kapnick (2024) "Financial markets value skillful forecasts of seasonal climate," *Nature Communications*, Vol. 15, No. 1, p. 4059.

Li, Lin and Pinaki Chakraborty (2020) "Slower decay of landfalling hurricanes in a warming world," *Nature*, Vol. 587, No. 7833, pp. 230–234.

Lonfat, Manuel, Robert Rogers, Timothy Marchok, and Frank D Marks Jr (2007) "A parametric model for predicting hurricane rainfall," *Monthly Weather Review*, Vol. 135, No. 9, pp. 3086–3097.

Long Island Press (2014) "Nassau Makes Case for FEMA Funds to Improve Bay Park Plant," https://www.longislandpress.com/2014/05/14/nassau-makes-case-for-fema-funds-to-improve-bay-park-plant/, Accessed: 2025-05-13.

Marks, Frank D, Brian D McNoldy, Mu-Chieh Ko, and Andrea B Schumacher (2020) "Development of a probabilistic tropical cyclone rainfall model: P-rain," in *100th American Meteorological Society Annual Meeting*, AMS.

Marks, Nicole Kurkowski Mark DeMaria, Frank and Michael Brennan (2019) "Hurricane forecast improvement project years ten to fifteen strategic plan,"Technical report, National Oceanic and Atmospheric Administration.

Martinez, Andrew B (2020) "Forecast accuracy matters for hurricane damage," *Econometrics*, Vol. 8, No. 2, p. 18.

Masson-Delmotte, Valérie, Panmao Zhai, Anna Pirani, Sarah L Connors, Clotilde Péan, Sophie Berger, Nada Caud, Y Chen, L Goldfarb, MI Gomis et al. (2021) "Climate change 2021: the physical science basis," *Contribution of working group I to the sixth assessment report of the intergovernmental panel on climate change*, Vol. 2, No. 1, p. 2391.

Mendelsohn, Robert, Kerry Emanuel, Shun Chonabayashi, and Laura Bakkensen (2012) "The impact of climate change on global tropical cyclone damage," *Nature Climate Change*, Vol. 2, No. 3, pp. 205–209.

Michel-Kerjan, Erwann and Howard Kunreuther (2011) "Redesigning flood insurance," *Science*, Vol. 333, No. 6041, pp. 408–409.

Molina, Renato, David Letson, Brian McNoldy, Pallab Mozumder, and Matthew Varkony (2021) "Striving for improvement: The perceived value of improving hurricane forecast accuracy," *Bulletin of the American Meteorological Society*, pp. 1–41.

Moss, Mitchell, Charles Schellhamer, and David A Berman (2009) "The stafford act and priorities for reform," *Journal of Homeland Security and Emergency Management*, Vol. 6, No. 1.

Muñoz-Sabater, Joaquín, Emanuel Dutra, Anna Agustí-Panareda, Clément Albergel, Gabriele Arduini, Gianpaolo Balsamo, Souhail Boussetta, Margarita Choulga, Shaun Harrigan, Hans Hersbach et al. (2021) "Era5-land: A state-of-the-art global reanalysis dataset for land applications," *Earth System Science Data Discussions*, pp. 1–50.

Murnane, Richard J and James B Elsner (2012) "Maximum wind speeds and us hurricane losses," *Geophysical Research Letters*, Vol. 39, No. 16.

NOAA (2022a) "Billion Dollar Weather and Climate Disasters," https://www.ncei.noaa.gov/access/billions/, Accessed: 2025-05-25.

——— (2022b) "Fast Facts: Hurricane Costs," https://coast.noaa.gov/states/fast-facts/hurricane-costs.html, Accessed: 2025-05-25.

——— (2025) "Storm Surge Overview: What Causes Storm Surge?," https://www.nhc.noaa.gov/surge/#CAUSE, Accessed May 19, 2025.

Nolan, David S, Brian D McNoldy, Jimmy Yunge, Forrest J Masters, and Ian M Giammanco (2021) "Evaluation of the surface wind field over land in wrf simulations of hurricane wilma (2005). part ii: Surface winds, inflow angles, and boundary layer profiles," *Monthly Weather Review*, Vol. 149, No. 3, pp. 697–713.

Norcross, Bryan (2018) "Hurricane forecasts are great — as long as the storms themselves behave," https://www.washingtonpost.com/news/capital-weather-gang/wp/2018/06/01/hurricane-forecasts-are-great-as-long-as-the-storms-themselves-behave/, Accessed: 2025-05-26.

Norton, Grady (1951) "Hurricanes of the 1950 season," *Monthly Weather Review*, Vol. 79, pp. 8–15.

Noy, Ilan (2009) "The macroeconomic consequences of disasters," *Journal of Development economics*, Vol. 88, No. 2, pp. 221–231.

Price, Ilan, Alvaro Sanchez-Gonzalez, Ferran Alet, Tom R Andersson, Andrew El-Kadi, Dominic Masters, Timo Ewalds, Jacklynn Stott, Shakir Mohamed, Peter Battaglia et al. (2025) "Probabilistic weather forecasting with machine learning," *Nature*, Vol. 637, No. 8044, pp. 84–90.

Resnick, Brian (2018) "Hurricane Michael and why it's so hard to predict storm intensity," https://www.vox.com/energy-and-environment/2018/10/11/17963958/hurricane-michael-forecast-track-intensity-category, Accessed: 2025-05-26.

Ripberger, Joseph T, Carol L Silva, Hank C Jenkins-Smith, Deven E Carlson, Mark James, and Kerry G Herron (2015) "False alarms and missed events: The impact and origins of perceived inaccuracy in tornado warning systems," *Risk Analysis*, Vol. 35, No. 1, pp. 44–56.

Rudik, Ivan (2020) "Optimal Climate Policy When Damages are Unknown," *American Economic Journal: Economic Policy*, Vol. 12, No. 2, pp. 340–373.

Sheets, Robert C (1990) "The national hurricane center—past, present, and future," *Weather and Forecasting*, Vol. 5, No. 2, pp. 185–232.

Shrader, Jeffrey G, Laura Bakkensen, and Derek Lemoine (2023) "Fatal errors: The mortality value of accurate weather forecasts," Working Paper.

Shrader, Jeffrey"Improving climate damage estimates by accounting for adaptation," *SSRN 3212073*, Working Paper.

Simmons, Kevin M and Daniel Sutter (2009) "False alarms, tornado warnings, and tornado casualties," *Weather, Climate, and Society*, Vol. 1, No. 1, pp. 38–53.

Strobl, Eric (2011) "The economic growth impact of hurricanes: Evidence from us coastal counties," *Review of Economics and Statistics*, Vol. 93, No. 2, pp. 575–589.

Taylor, Harvey Thurm, Bill Ward, Mark Willis, and Walt Zaleski (2010) "The saffir-simpson hurricane wind scale," *Atmospheric Administration: Washington, DC, USA*.

The White House (2022) "Fact Sheet: The Biden Administration Continues to Support Hurricane Fiona Response Efforts in Puerto Rico," https://bidenwhitehouse.archives.gov/briefing-room/statements-releases/2022/09/28/fact-sheet-the-biden-administration-continues-to-support-hurricane-fiona-response-efforts-in-puerto-rico/, Accessed: 2025-05-13.

U.S. Congress (1988) "Robert T. Stafford Disaster Relief and Emergency Assistance Act, Section 102(1), 42 U.S.C. §5122(1)," https://www.fema.gov/disaster/stafford-act, As amended through Public Law 117-103.

US Congressional Budget Office (2019) "Expected costs of damage from hurricane winds and storm-related flooding," pp. 1–48.

US EPA (2024) "Guidelines for Preparing Economic Analyses," https://www.epa.gov/system/files/documents/2024-12/guidelines-for-preparing-economic-analyses_final_508-compliant_compressed.pdf, Accessed: 2025-05-25.

Volusia County Government (2023) "Hurricane Irma FEMA Grant Application Summary," https://www.volusia.org/core/fileparse.php/7189/urlt/Hurrican-Irma-Updat_8.pdf, Accessed: 2025-05-25.

Weinkle, Jessica, Chris Landsea, Douglas Collins, Rade Musulin, Ryan P Crompton, Philip J Klotzbach, and Roger Pielke (2018) "Normalized hurricane damage in the continental united states 1900–2017," *Nature Sustainability*, Vol. 1, No. 12, pp. 808–813.

Willoughby, Hugh E, RWR Darling, and ME Rahn (2006) "Parametric representation of the primary hurricane vortex. part ii: A new family of sectionally continuous profiles," *Monthly Weather Review*, Vol. 134, No. 4, pp. 1102–1120.

Young, Rachel and Solomon Hsiang (2024) "Mortality caused by tropical cyclones in the united states," *Nature*, pp. 1–8.

Supplemental Appendix

C Robustness Checks

Here we show robustness checks for all three sets of main results: how forecasts affect emergency protective expenditures by FEMA, how forecast errors drive damages and emergency recovery expenditures by FEMA, and the value of a forecast improvement. Across these sections, we assess robustness to spatial correlation assumptions; alternative fixed effects, sample restrictions, and functional forms for our variables of interest; and alternative ways of constructing or transforming the data. We also explore robustness to the inclusion of additional hurricane features such as intensity bins, track forecasts, and categorical forecast accuracy. Taken together, these results demonstrate that our main findings are highly robust across a wide range of reasonable empirical choices.

C.1 Does FEMA Respond to Forecasts?

Table C.1 presents estimates of the effect of the forecast wind speed and precipitation on before-landfall FEMA protective expenditures. Our binned estimates in Figure 4 are highly convex, so we include a quadratic term here to capture the convexity. The first column corresponds to the fixed effects in our main results. The second column adds county-by-month-of-year fixed effects to account for potential location-specific seasonality. The third column adds county-by-year effects to flexibly account for variables trending over time but differentially across counties. The fourth column adds both of these additional fixed effects. Consistent with Figure 4, we find that given a sufficiently high wind forecast, protective expenditures is increasing and convex in the forecast. Precipitation estimates are small and often noisy.

Figure C.1 increases our Conley cutoff to 600 km, allowing for spatial correlation over an area over twice as large. This has little effect on our standard errors.

Figures C.2 and C.3 replicate Figure 4 but where we drop "error counties", those with a Presidential Disaster Declaration (PDD) but zero reported damage in SHELDUS, or where we only include Atlantic and Gulf Coast states. These different sample restrictions have essentially no effect on our results.

Figure C.4 shows protective expenditures results, for wind speed and precipitation, when using an inverse hyperbolic sine transformation. Using this alternative outcome, we still find that forecasts of higher wind speeds spur more protective expenditures. This functional form also suggest greater precipitation forecasts increase protective expenditures as well.

Figure C.5 replicates Figure 4 but for precipitation. The plots show mixed, noisy results. Given the lack of a clear relationship between precipitation forecasts and FEMA protective expenditures, we may not expect to find consistent effects for precipitation forecast errors or for the value of improving precipitation forecasts.

Figure C.6 tests whether our results are driven by cases where emergency expenditures may be in response to forecasts issued prior to 3 days before landfall. The FEMA PAGM data do not provide enough information to discern the timing of the protective actions, but they do allow us to identify when an emergency or disaster was declared relative to landfall when combining it with our hurricane dataset. We find that only about 10% of declarations are made more than 3 days before landfall. These 10% of declarations may pose issues for our claims about protective expenditures and forecasts so here we re-produce our protective expenditures results dropping all hurricanes for which there is a declaration more than 3 days before landfall. The results are essentially unchanged.

Figure C.7 tests whether our results are driven by cases where what we classify as protective expenditures may actually be in response to post-landfall outcomes, such as deploying search and rescue. Because forecasts and realized intensity are strongly positively associated, erroneously including post-landfall "protective" expenditures in a variable that we want to only have pre-landfall expenditures may artificially inflate our estimates. We test how severe of a problem this is by flexibly controlling for realized wind and precipitation intensity using the same realized wind speed and precipitation bins as in equation (2) as controls. If post-landfall expenditures are driven by hurricane realizations and damage, these intensity controls will soak up that variation. The figure shows that including these controls does not change our results.

In addition to responding to the forecast intensity, protection actions may also respond to the forecast quality. We test this by estimating equation (1), but including additional sets of bin variables for the standard deviation of the wind speed and precipitation forecasts. We plot the wind speed standard deviation estimates in Figure C.8. Conditional on forecast intensity and the set of fixed effects, a lower standard deviation wind speed forecast—which we interpret as higher quality–is associated with more protective expenditures.

Figure C.9 tests the sensitivity of our results to population-weighting when constructing our county-level measures of hurricane forecasts and intensity. Population-weighting has little effect on the results.

Figures C.10 and C.12 analyze the role of hurricane track forecasts. We define track forecasts distance from the hurricane's eye path to a county centroid. Specifically, the forecast distance is computed using the hurricane's predicted track at 1-, 2-, and 3-day lead times, and then averaged as in our wind speed analysis. Figure C.10 reports estimates of the distance of a county to the forecast hurricane track on protective expenditures. When studying hurricane track, we focus on counties within 400 km of the forecast track. We do so because unlike wind speed and precipitation, even counties thousands of kilometers away (for example, Orange County, CA) can have large track errors despite having no risk of actual hurricane exposure. The blue triangles are estimates that do not condition on binned wind speed or precipitation forecasts, while the black circles condition on both. The blue triangles show that track forecasts are associated with greater protective expenditures. Forecasting a hurricane to be within 40 km results in about $2 million more protective expenditures than a forecast further away. Results are similar in county GDP or per capita terms. Overall, these estimates are smaller than the wind speed forecast effects by about an order of magnitude. Once we condition on wind speed and precipitation forecasts, track forecasts appear to have no effect on protective expenditures as shown in the black circles. Figure C.11 shows that these results are robust to alternative distance cutoffs.

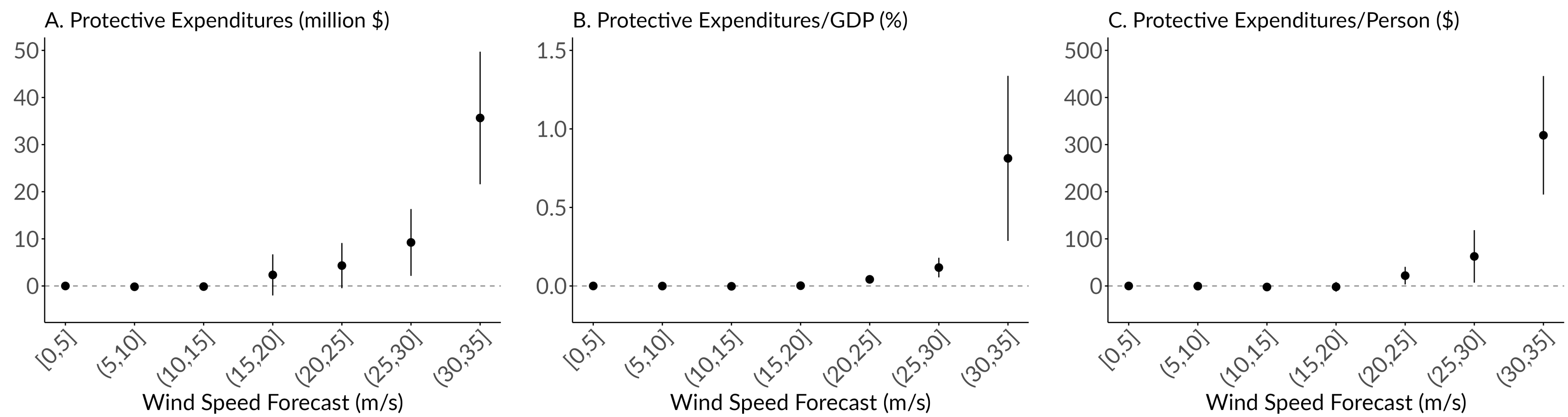
Figure C.12 presents estimates of the effect of wind speed forecasts when conditioning or not conditioning on the distance to the track forecast. Results are nearly identical to our main results. Track forecasts are not driving our findings that wind speed forecasts affect FEMA protective expenditures.

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

	(1)	(2)	(3)	(4)
Protective Expenditures (million \$)				
Wind Forecast (m/s)	-0.4010**	-0.4068***	-0.3599	-0.3393*
	(0.1663)	(0.1404)	(0.2246)	(0.1743)
Wind Forecast^2	0.0399***	0.0395***	0.0407***	0.0385***
	(0.0116)	(0.0111)	(0.0125)	(0.0104)
Precip Forecast (mm)	-0.0754*	-0.0713*	-0.0855*	-0.0765
	(0.0456)	(0.0397)	(0.0496)	(0.0480)
Precip Forecast^2	0.0001	0.0001	0.0002	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Protective Expenditures / GDP (%)				
Wind Forecast (m/s)	-0.0078***	-0.0074***	-0.0080***	-0.0075***
	(0.0026)	(0.0024)	(0.0028)	(0.0023)
Wind Forecast^2	0.0007***	0.0007***	0.0007***	0.0007***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Precip Forecast (mm)	-0.0016***	-0.0016***	-0.0015***	-0.0015***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Precip Forecast^2	0.0000**	0.0000**	0.0000***	0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Protective Expenditures / Person (\$)				
Wind Forecast (m/s)	-4.6397**	-4.2334**	-5.3487*	-4.5687**
	(2.2058)	(1.8434)	(2.8480)	(2.0728)
Wind Forecast^2	0.3558***	0.3426***	0.4022***	0.3564***
	(0.1098)	(0.0954)	(0.1418)	(0.1015)
Precip Forecast (mm)	-0.4730	-0.4930	-0.5331*	-0.5047
	(0.3085)	(0.3000)	(0.3010)	(0.3100)
Precip Forecast^2	0.0017	0.0017	0.0020	0.0026
	(0.0018)	(0.0018)	(0.0017)	(0.0016)
Observations	95,263	95,263	95,263	95,263
State-Hurricane FE	✓	✓	✓	✓
County FE	✓			
County-Month of Year FE		✓		✓
County-Year FE			✓	✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Standard errors are Conley Spatial HAC with a distance radius of 400 km for spatial correlation and arbitrary autocorrelation within counties.

Figure C.1: FEMA Protective Expenditures Responses to Forecasts: 600 km Conley Cutoff.

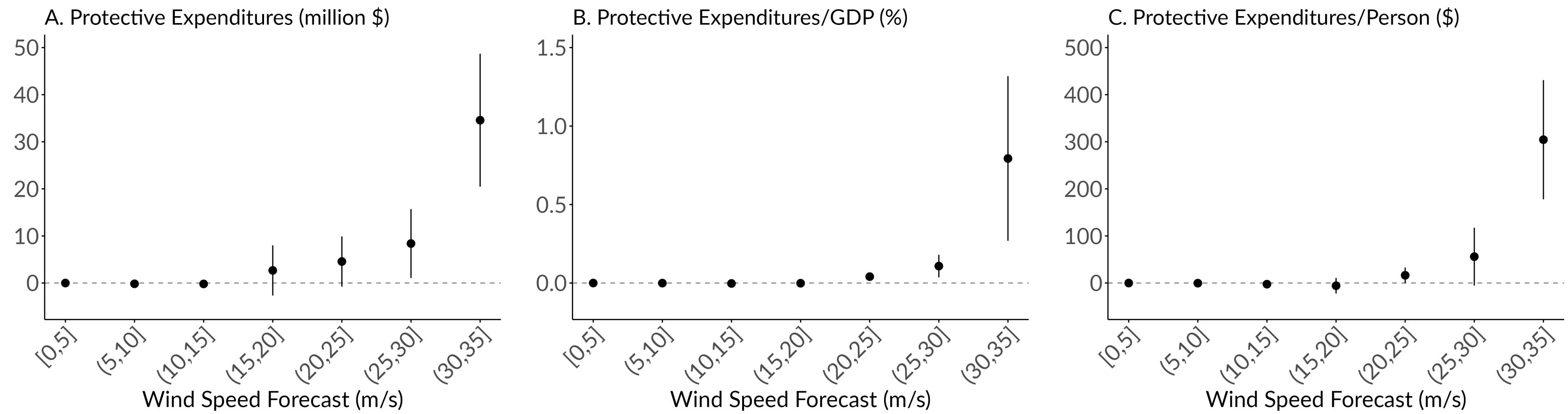


Note: Points are point estimates and the bars are the 95% confidence intervals. The omitted category for each panel is [0,5]. All panels control for bins for the precipitation forecast, and for county and state-by-hurricane fixed effects. Standard errors are Conley Spatial HAC with a distance radius of 600 km for spatial correlation and arbitrary autocorrelation within counties. The number of observations is 95,263.

44

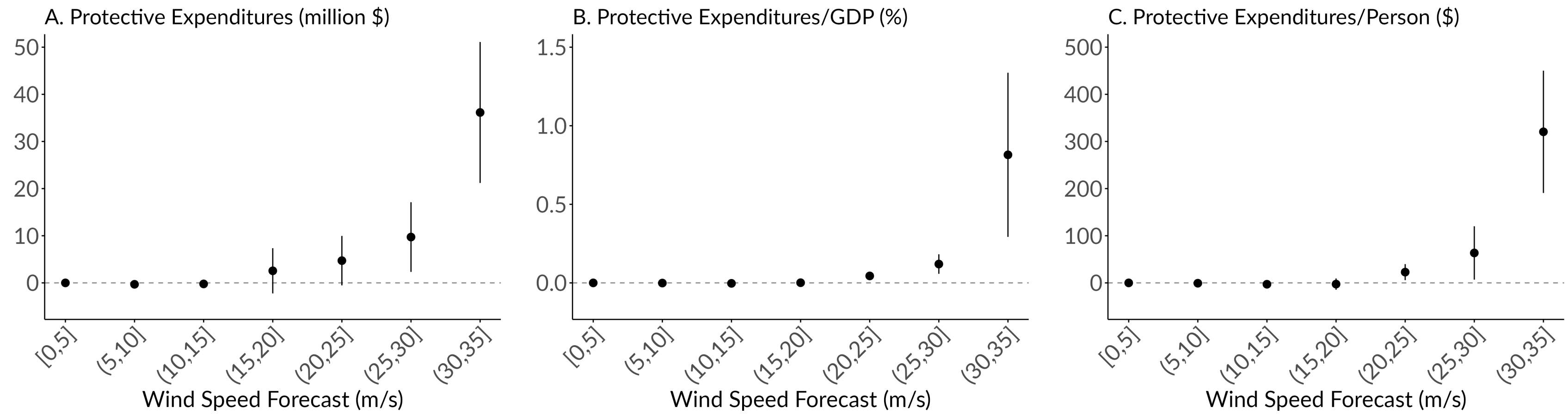
45

Figure C.2: FEMA Protective Expenditures Responses to Forecasts: PDD Robustness.



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 plots drop all "error counties" with a PDD but zero damage. The number of observations is 94,105.

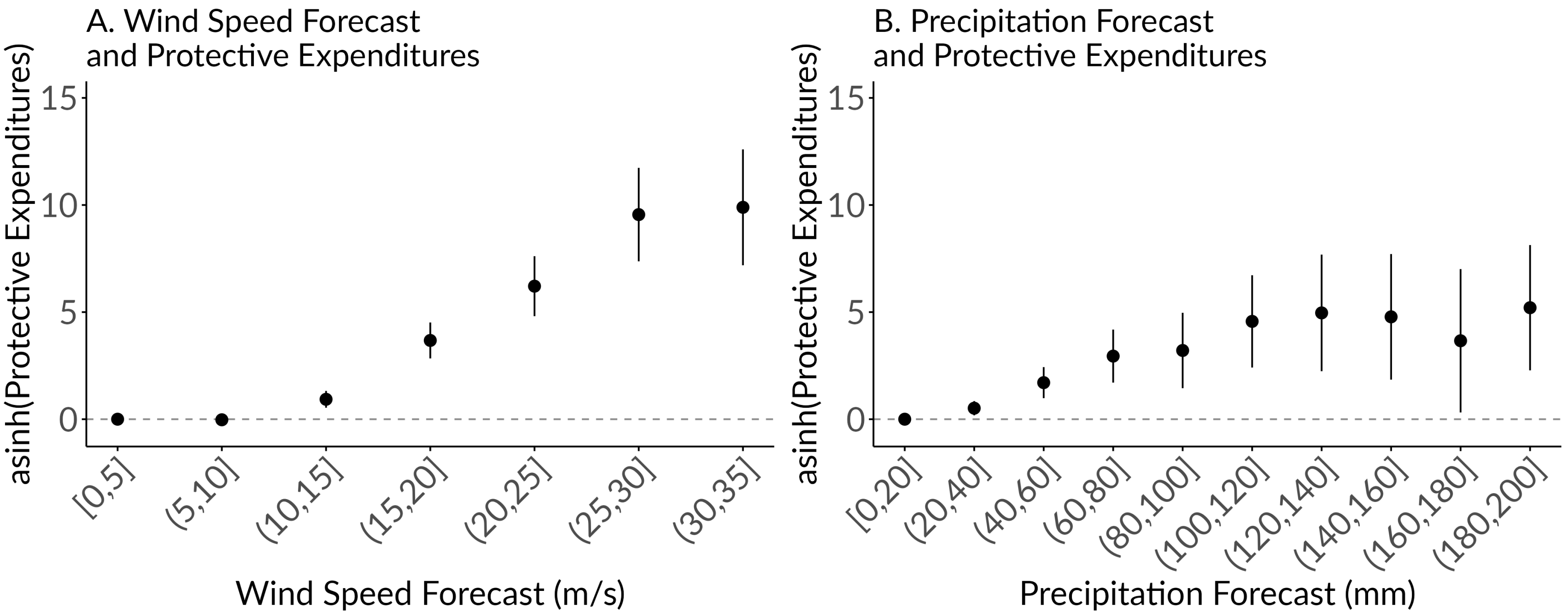
Figure C.3: FEMA Protective Expenditures Responses to Forecasts: Coastal States.



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. Only the following states are included in the sample: Texas, Louisiana, Mississippi, Alabama, Georgia, Florida, South Carolina, North Carolina, Virginia, Maryland, New Jersey, Pennsylvania, Connecticut, Delaware, New York, Rhode Island, Massachusetts, New Hampshire, and Maine. The number of observations is 33,914.

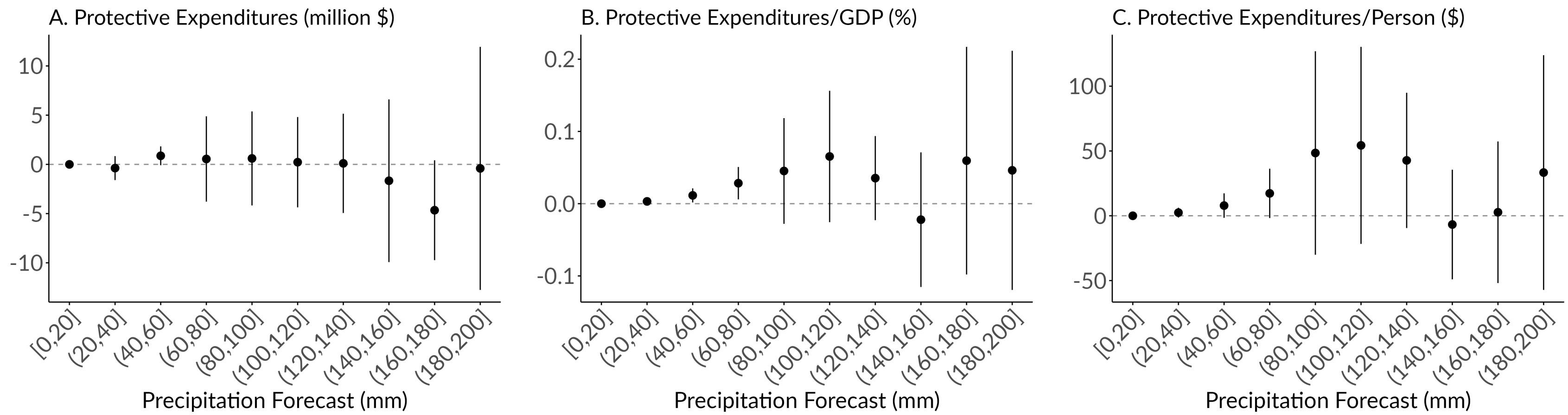
46

Figure C.4: FEMA Protective Expenditures Responses to Forecasts: Inverse Hyperbolic Sine.



Note: Points are point estimates and the bars are the 95% confidence intervals. The omitted category for wind speed is [0,5] and for precipitation is [0,20]. The estimates from both panels are from a single regression. All panels control 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.

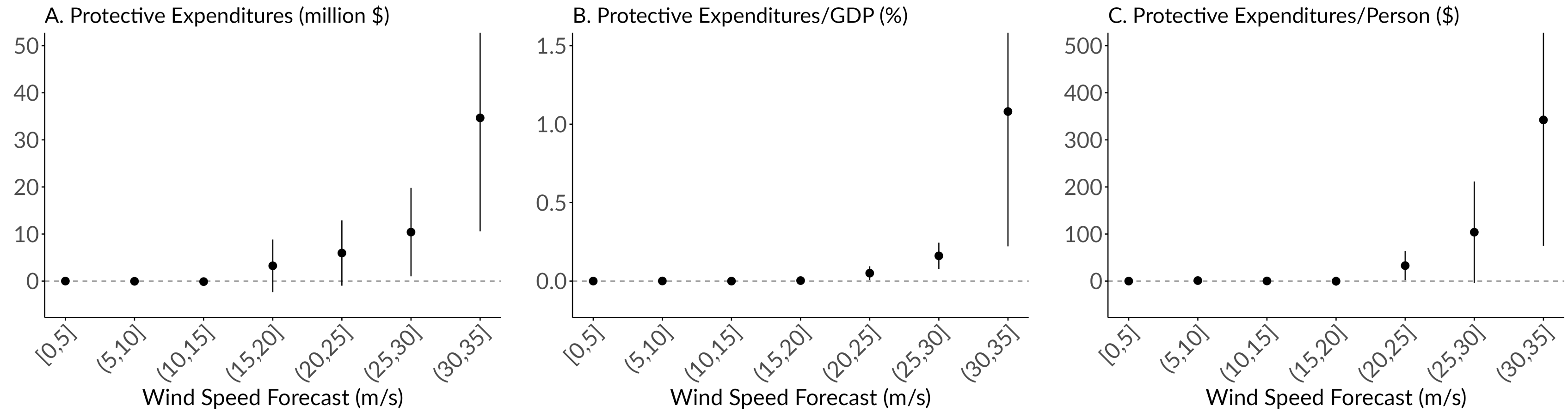
Figure C.5: FEMA Protective Expenditures Responses to Forecasts: Precipitation.



Note: Points are point estimates and the bars are the 95% confidence intervals. The omitted category for each panel is [0,20]. All panels control for bins for the wind speed 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.

48

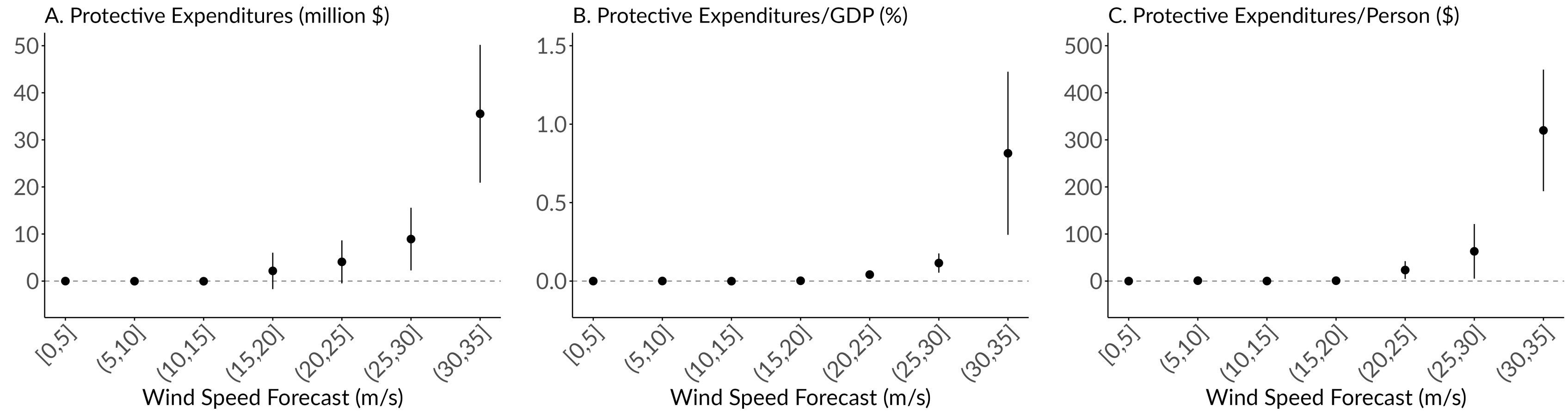
Figure C.6: FEMA Protective Expenditures Responses to Forecasts (No Early Declarations).



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. County-Hurricane combinations with emergency or disaster declarations issued before 3 days before landfall are dropped. 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 70,679.

49

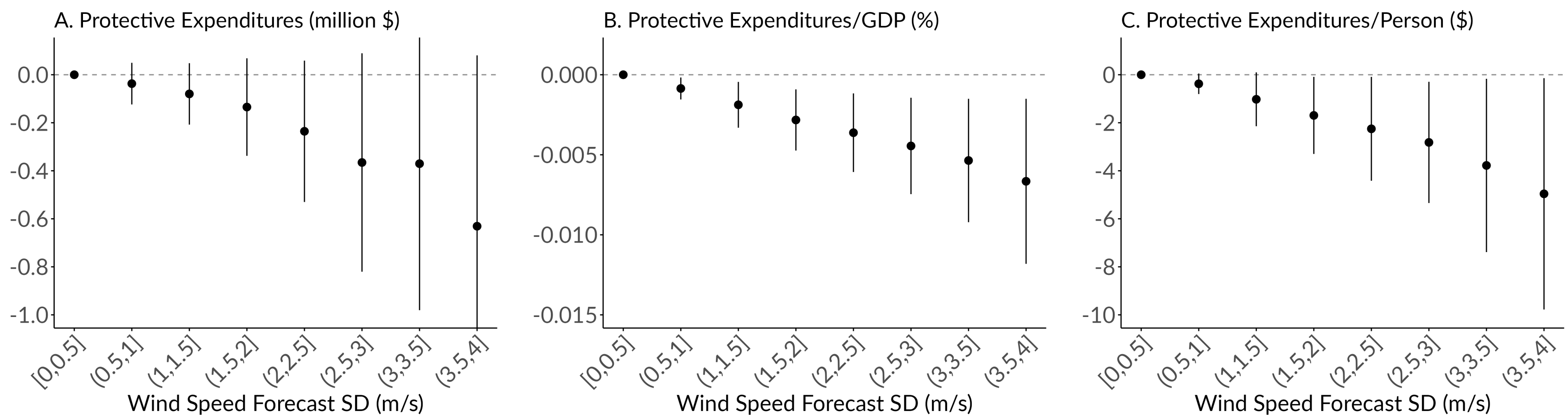
Figure C.7: FEMA Protective Expenditures Responses to Forecasts with Intensity Controls.



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 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.

50

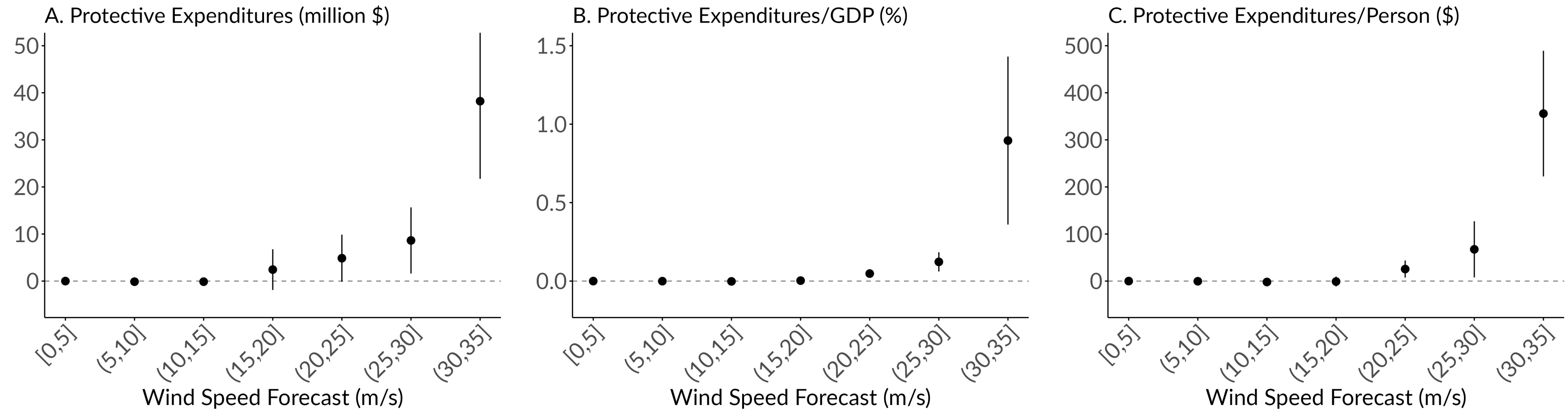
Figure C.8: FEMA Protective Expenditure Responses to Forecast Uncertainty.



Note: Points are point estimates and the bars are the 95% confidence intervals. The omitted category for each panel is [0,0.5]. All panels control for bins for the wind and 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.

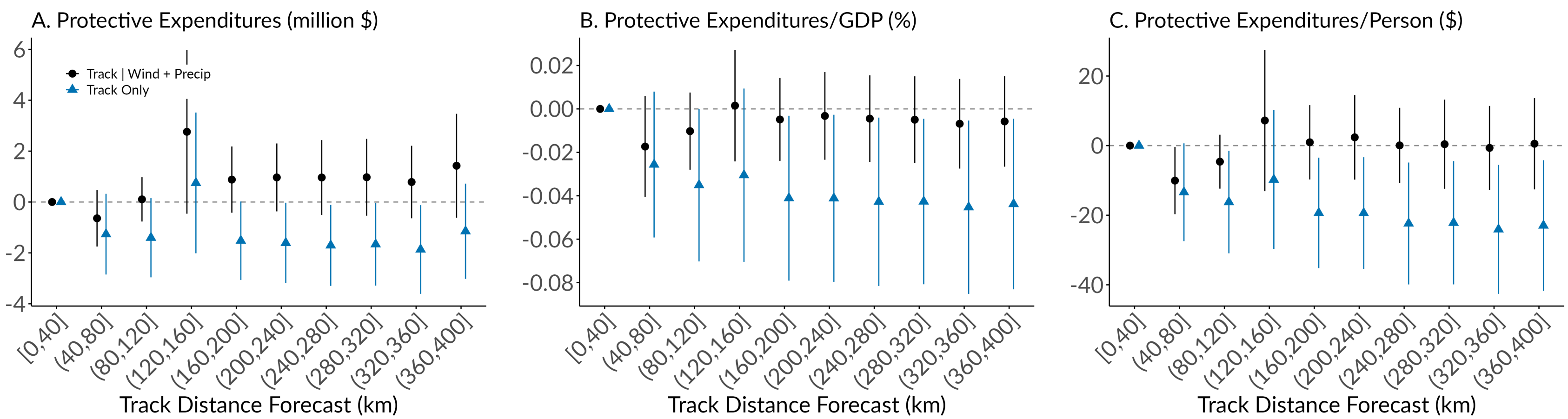
51

Figure C.9: FEMA Protective Expenditures Responses to Forecasts with Population-Weighted Wind Aggregation.



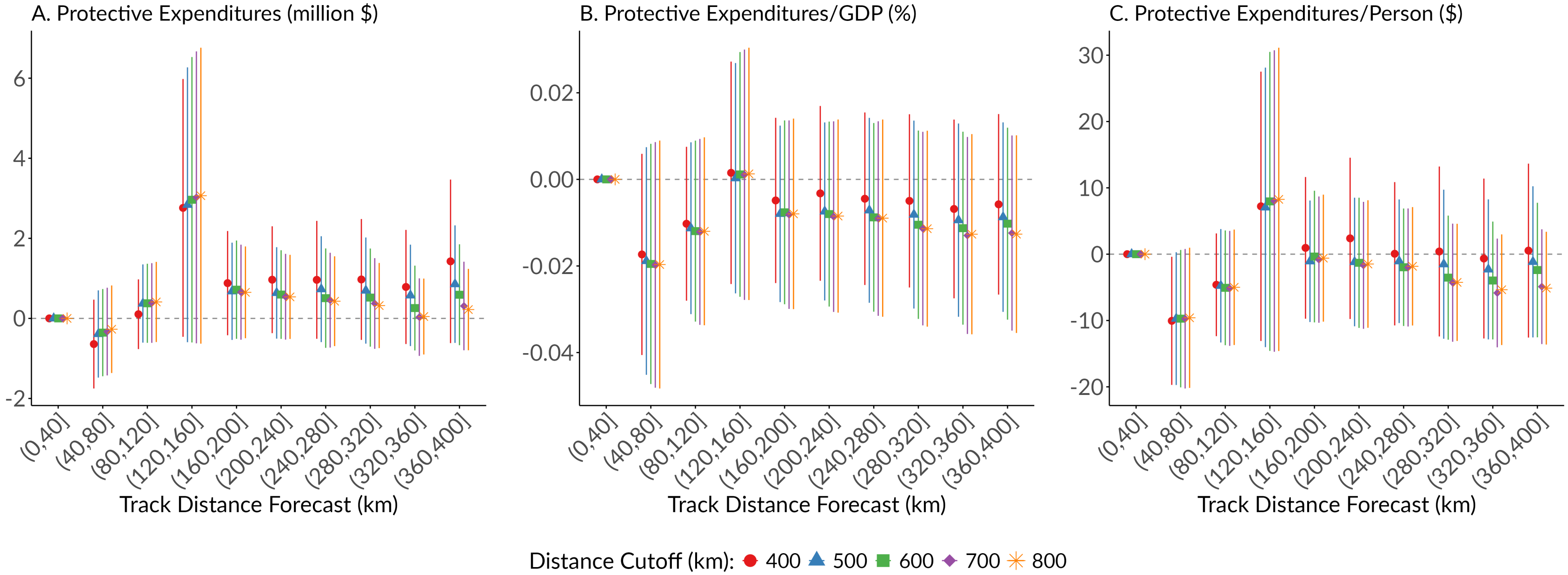
Note: Points are point estimates and the bars are the 95% confidence intervals. The omitted category for each panel is [0,5]. All panels control for bins for the precipitation forecast, and for county and state-by-hurricane fixed effects. Standard errors are Conley Spatial HAC with a distance radius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

Figure C.10: FEMA Protective Expenditures Responses to Track Forecasts.



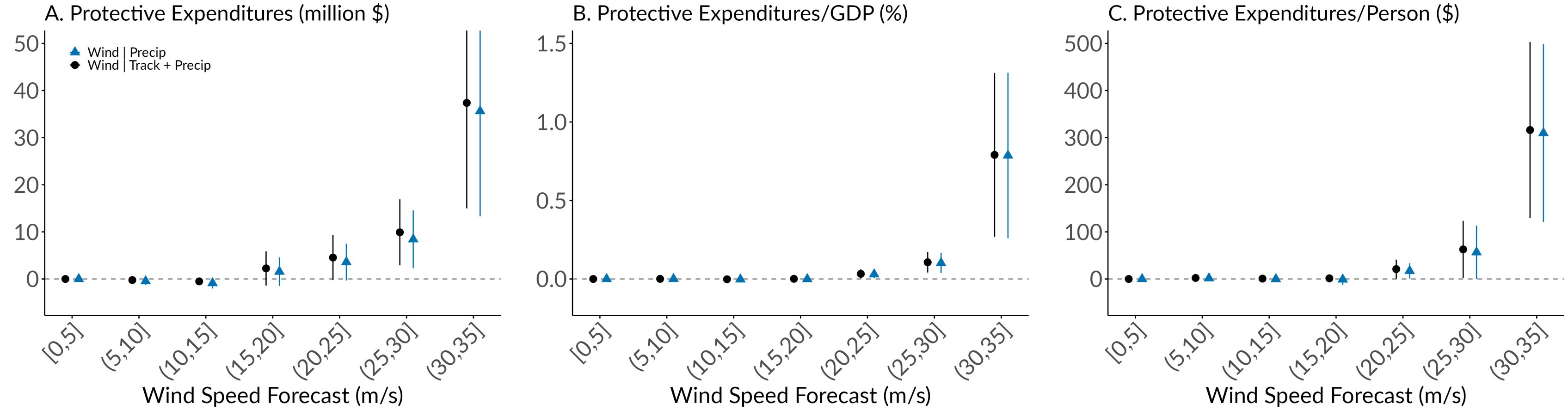
Note: Points are point estimates and the bars are the 95% confidence intervals. The omitted category for each panel is [0,40]. Black circles are estimates that control for bins for the wind and precipitation forecast, while blue triangles are estimates that do not. All estimates control for county and 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 15,018.

Figure C.11: FEMA Protective Expenditures Responses to Track Forecasts with Multiple Distance Cutoffs.



Note: Points are point estimates and the bars are the 95% confidence intervals. The omitted category for each panel is [0,40]. All estimates control for binned wind and precipitation errors, binned realized distance from track, binned realized wind speed, and binned realized precipitation. All estimates control 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 are: 400 km = 15,018; 500 km = 20,072; 600 km = 25,195; 700 km = 30,470; 800 km = 35,874.

Figure C.12: FEMA Protective Expenditures Responses to Forecasts with Track Controls.



Note: Points are point estimates and the bars are the 95% confidence intervals. The omitted category for each panel is [0,5]. Black circles are estimates that control for bins of the track forecast, while blue triangles are estimates that do not. All estimates control for bins of the precipitation forecast, and 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 15,018.

C.2 Does Forecast Accuracy Matter?

Table C.2 presents estimates of the effect of the forecast errors on damages and recovery expenditures. The columns correspond to the same sets of fixed effects as in Table C.1. All specifications show that wind speed underestimates increase damages and recovery expenditures conditional on the realization of wind speed and precipitation. These costs are substantial: for a 1 m/s worse underestimate in a county, costs increase by almost \$30 million per county, or \$700 per person. Precipitation estimates are noisy, negative, and an order of magnitude smaller.

Table C.3 reports the same estimates as Table C.2 but where we also interact the wind speed forecast error with an indicator variable for whether the wind speed was hurricane-force, or sub-hurricane-force. This tests whether errors are more costly for higher-intensity storms. Across all specifications, forecast errors are more costly for hurricane-force winds than for sub-hurricane-force winds.

Figure C.13 presents results using a more conservative 600 km Conley spatial cutoff. The main results are all still statistically significant.

Figures C.14 and C.15 show that our wind speed forecast error results are robust to dropping "error counties" with a Presidential Disaster Declaration (PDD) but zero reported SHELDUS damage, and to only including Atlantic Coast and Gulf Coast states.

Figure C.16 shows the wind speed results are robust to using an inverse hyperbolic sine transformation.

Figure C.17 shows that wind speed forecast underestimates increase all of property damage, crop damage, and mortality damage independently in addition to increasing the aggregate cost. The plot makes clear that aggregate damage is driven by property losses.

Figure C.18 replicates our main results but for precipitation. Precipitation shows no strong pattern. This is consistent with our finding that precipitation forecasts do not have a consistent effect on protective expenditures. This may be because hurricane strength has historically been communicated through its wind speed (Kantha, 2006; Murnane and Elsner, 2012).

Figure C.19 tests the sensitivity of our results to a more comprehensive set of hurricane intensity controls. Specifically, we now include up to a four-way interaction of the wind speed and precipitation intensity control bins, an indicator for whether the county is on the coast, and an indicator for whether a county was to the east or west of a hurricane track. The coastal indicator is to better capture storm surge, and the direction relative to hurricane track is to better capture wind direction. Results are almost identical across the different specifications.

Figure C.20 tests the sensitivity of our results to the more comprehensive set of hurricane intensity controls while increasing the number of wind speed and precipitation intensity bins. The figure reports results from the four-way interaction of the wind speed and precipitation intensity control bins, an indicator for whether the county is on the coast, and an indicator for whether a county was to the east or west of a hurricane track, but varying the number of bins for wind speed and precipitation between 5 and 120. Results are essentially the same regardless of the number of bins, though recovery expenditures are noisy when not normalized by county GDP and/or population.

Figure C.21 tests the sensitivity of our results to population-weighting when constructing our county-level measures of hurricane forecasts and intensity. Population-weighting has little effect on the results.

Figure C.22 presents results from interacting our wind speed error bins with the inverse hyperbolic sine of realized wind speed to test whether errors are more costly for more intense hurricanes. The figure presents the estimates evaluated at six different wind speeds representing the thresholds for classification as a tropical storm, a Category 1 hurricane, and all the way to a Category 5 hurricane. The estimates show that errors tend to be more costly when hurricanes are more intense.

Figures C.23 and C.25 perform analogous track exercises as Figures C.10 and C.12 to understand the role of track errors. As before, the data used for estimation are restricted to be counties within 400 km of the forecast track. Track forecast error is the difference between the forecast and realized distance from the hurricane's eye path to the county centroid. A positive track error indicates that the hurricane was closer to the county than forecast (underprediction), while a negative value reflects overprediction (i.e., the hurricane stayed farther away than expected).

Figure C.23 plots the effect of forecast track errors on damages and recovery expenditures conditioning only on the realized track and fixed effects in blue triangles, and further conditioning on realized wind speed and precipitation as well as wind speed and precipitation errors in black circles. No clear relationship appears in any specification. Figure C.24 shows that these results are robust to alternative distance cutoffs.

Figure C.25 presents wind speed error results as in our main results in blue triangles, and further conditioning on track error and realized track in black circles. The results are essentially identical. Track and track errors do not appear to be driving the effects of wind speed.

Figure C.26 presents estimates of the effect of wind speed forecast errors on protective expenditures. If we have properly classified protective actions as being for before-landfall protection, they should not be correlated with forecast errors. Unlike the results in the main text we condition here on forecasts instead of realizations so that the variation in forecast errors is from variation in the hurricane's intensity realization. This changes the interpretation of the estimates to be that, given a forecast intensity, how much does an (after-landfall) error in this intensity drive protective expenditures? The results show no systematic relationship between forecast error and protective expenditures.

Table C.2: The Effect of Underestimating Wind and Precipitation on Damages and FEMA Recovery Expenditures.

	(1)	(2)	(3)	(4)
Damages + Recovery Expenditures (million \$)				
Wind Forecast Underestimate (m/s)	31.63***	31.95***	31.01**	29.84**
	(11.66)	(10.59)	(13.93)	(12.03)
Precip Forecast Underestimate (mm)	-0.82	-0.93	-1.17	-1.23
	(1.34)	(1.29)	(1.69)	(1.54)
(Damages + Recovery Expenditures) / GDP (%)				
Wind Forecast Underestimate (m/s)	1.91**	1.91**	1.72**	1.82**
	(0.91)	(0.81)	(0.78)	(0.71)
Precip Forecast Underestimate (mm)	-0.08*	-0.09**	-0.09*	-0.10**
	(0.05)	(0.04)	(0.05)	(0.04)
(Damages + Recovery Expenditures) / Person (\$)				
Wind Forecast Underestimate (m/s)	716.12***	722.41***	709.74**	748.70***
	(276.81)	(258.26)	(287.10)	(272.45)
Precip Forecast Underestimate (mm)	-35.21**	-37.40**	-42.94**	-46.98**
	(15.58)	(15.23)	(19.85)	(19.42)
Observations	95,263	95,263	95,263	95,263
Realized Wind/Precip Bins	✓	✓	✓	✓
State-Hurricane FE	✓	✓	✓	✓
County FE	✓			
County-Month of Year FE		✓		✓
County-Year FE			✓	✓

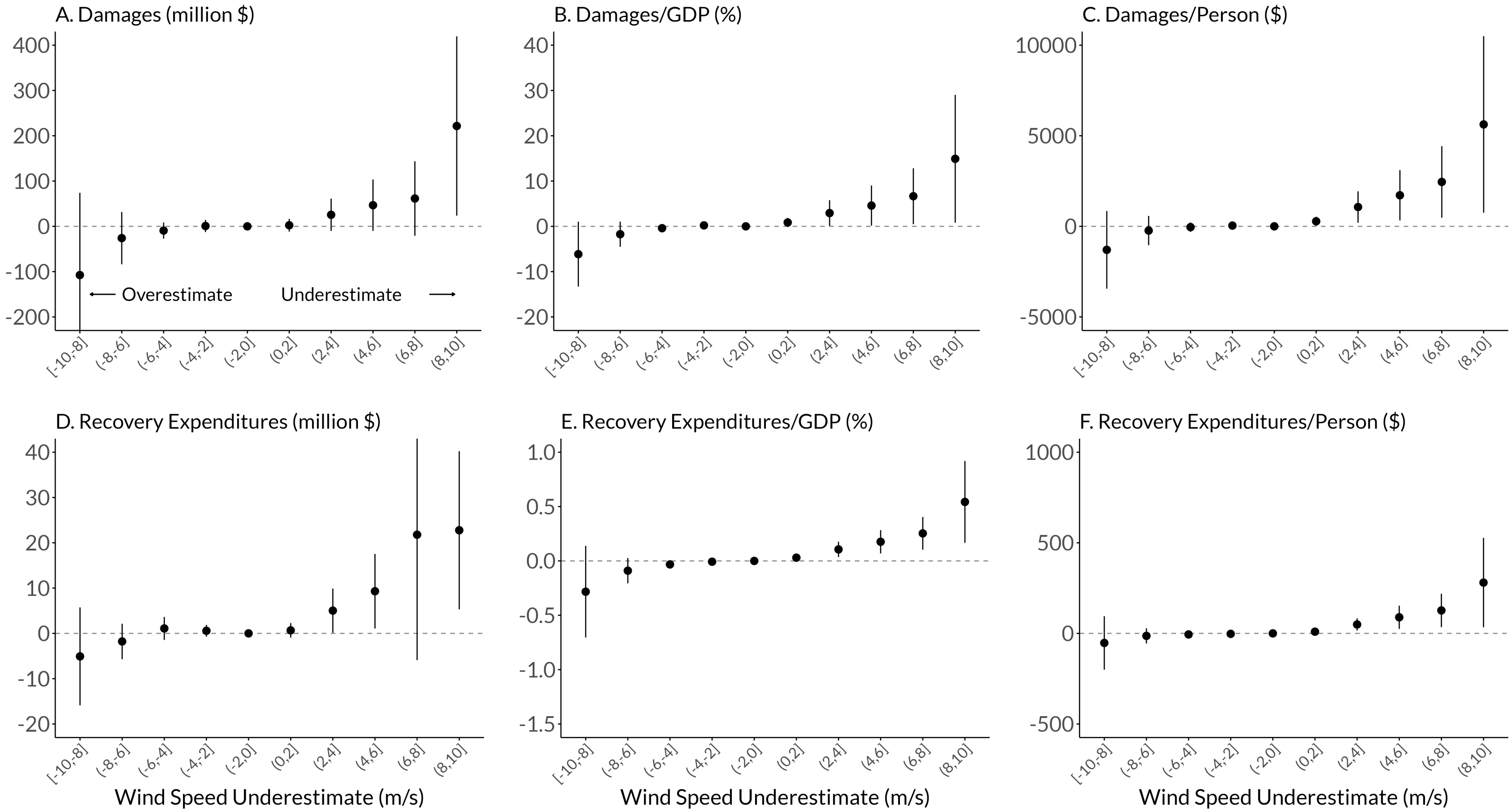
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Standard errors are Conley Spatial HAC with a distance radius of 400 km for spatial correlation and arbitrary autocorrelation within counties.

Table C.3: The Marginal Effect of Underestimating Wind and Precipitation on Damages and FEMA Recovery Expenditures As a Function of Hurricane Intensity.

	(1)	(2)	(3)	(4)
Damages + Recovery Expenditures (million \$)				
Wind Forecast Underestimate (m/s): Hurricane	79.58***	78.71***	81.47**	76.34***
	(25.77)	(22.64)	(31.74)	(25.77)
Wind Forecast Underestimate (m/s): Sub-Hurricane	-3.17	-2.50	-7.61	-5.23
	(4.77)	(4.25)	(6.15)	(4.43)
(Damages + Recovery Expenditures) / GDP (%)				
Wind Forecast Underestimate (m/s): Hurricane	4.21**	4.15***	3.75**	3.81***
	(1.71)	(1.53)	(1.50)	(1.35)
Wind Forecast Underestimate (m/s): Sub-Hurricane	0.25	0.26	0.17	0.32*
	(0.18)	(0.16)	(0.16)	(0.17)
(Damages + Recovery Expenditures) / Person (\$)				
Wind Forecast Underestimate (m/s): Hurricane	1597.38***	1595.02***	1577.65***	1607.76***
	(535.28)	(501.30)	(582.22)	(531.96)
Wind Forecast Underestimate (m/s): Sub-Hurricane	76.51	79.68*	45.42	100.75**
	(50.10)	(46.39)	(54.28)	(50.94)
Observations	95,263	95,263	95,263	95,263
Precipitation Underestimate	✓	✓	✓	✓
Realized Wind/Precip Bins	✓	✓	✓	✓
State-Hurricane FE	✓	✓	✓	✓
County FE	✓			
County-Month of Year FE		✓		✓
County-Year FE			✓	✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Standard errors are Conley Spatial HAC with a distance radius of 400 km for spatial correlation and arbitrary autocorrelation within counties. Hurricane wind speeds are those greater than 33 m/s (74 mph), while Sub-Hurricane wind speeds fall below that threshold.

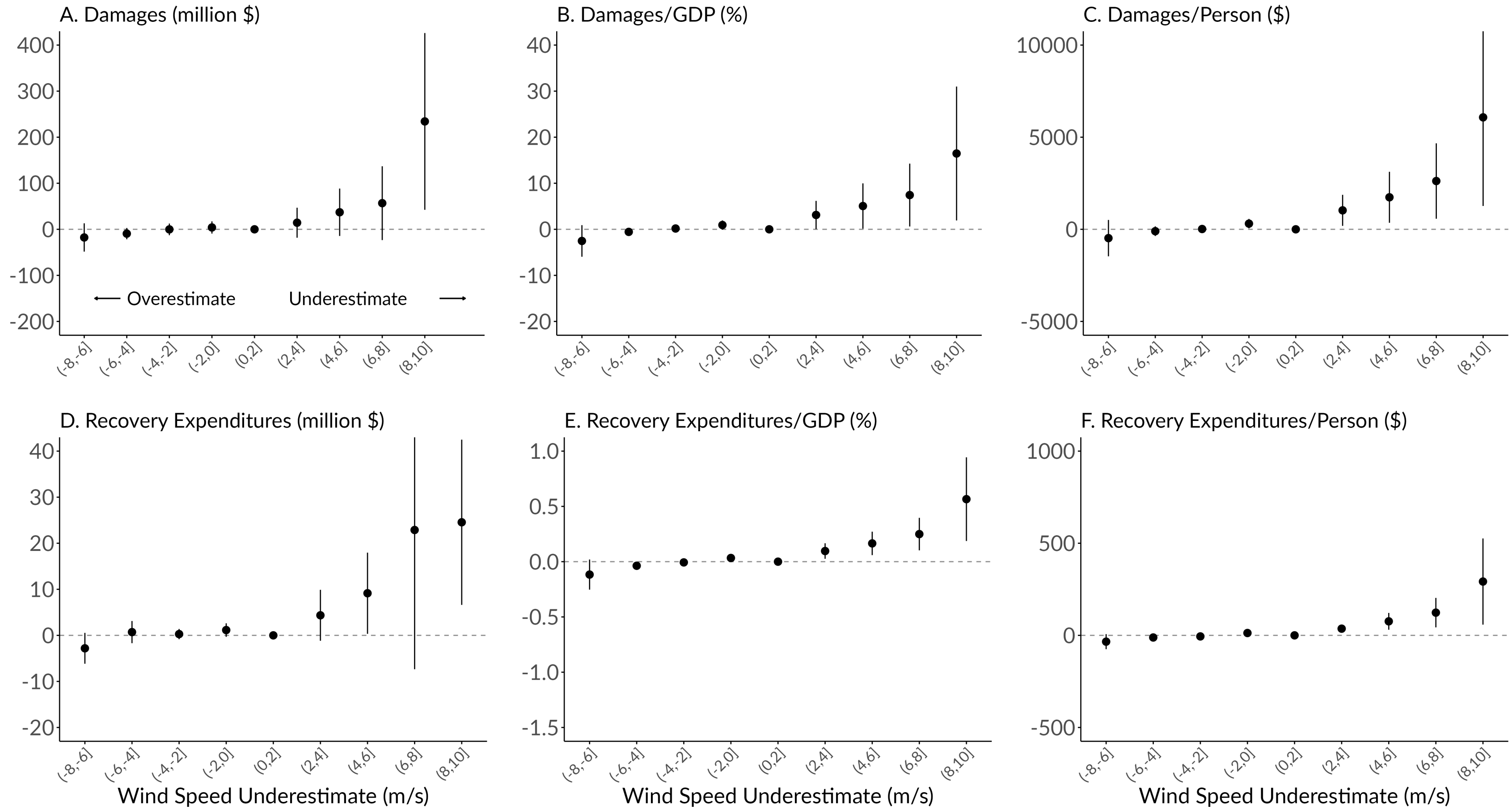
Figure C.13: Forecast Errors, Damages, and *Ex Post* Recovery Expenditures: 600 km Conley Cutoff.



Note: 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 600 km for spatial correlation and arbitrary autocorrelation within counties. The number of observations is 95,263.

60

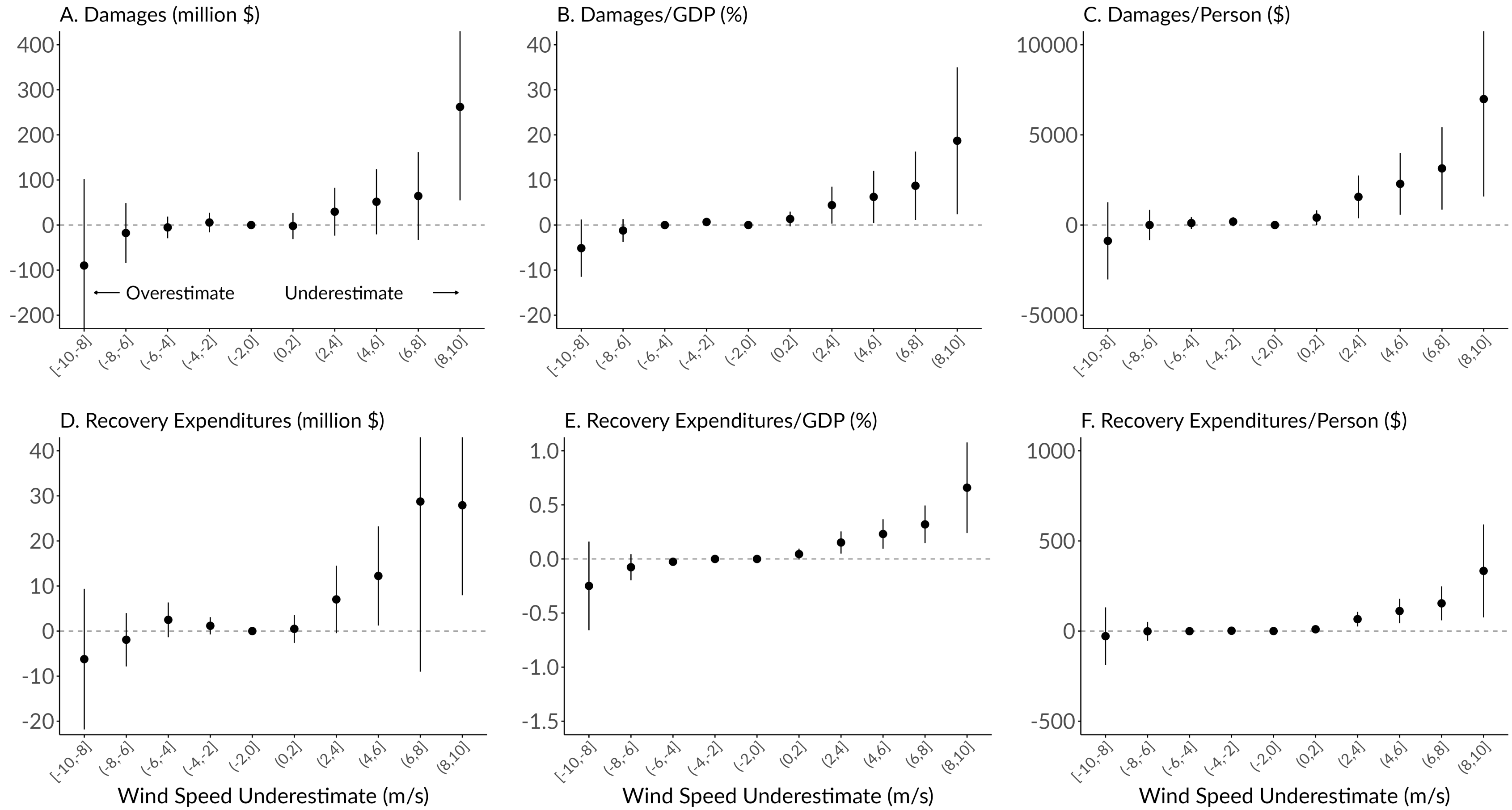
Figure C.14: Forecast Errors, Damages, and *Ex Post* Recovery Expenditures: PDD Robustness.



Note: 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 plots drop all "error counties" with a PDD but zero damage. Dropping error counties results in omitting the lowest bin. The number of observations is 94,105.

61

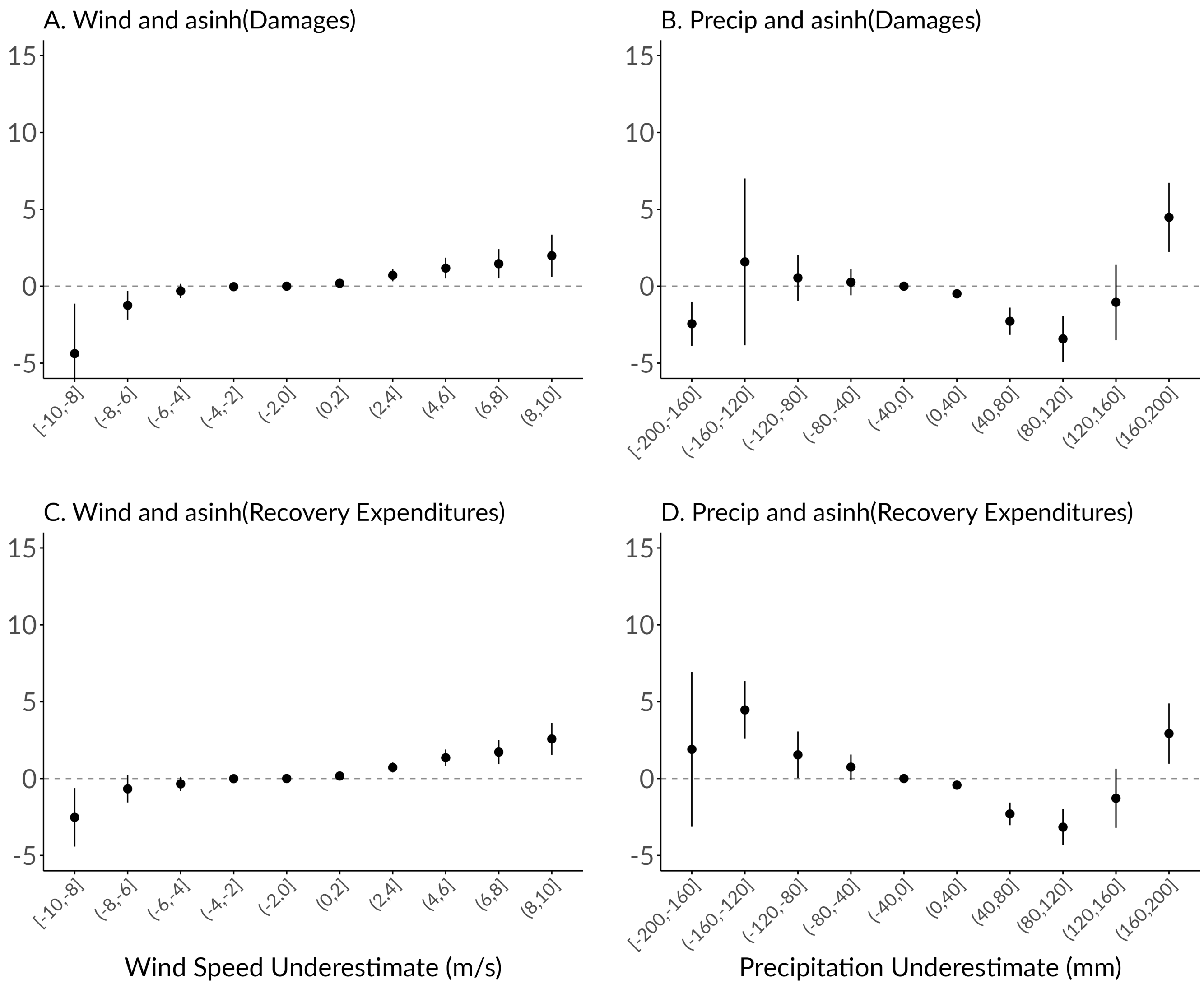
Figure C.15: Forecast Errors, Damages, and *Ex Post* Recovery Expenditures: Coastal States.



Note: 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. Only the following states are included in the sample: Texas, Louisiana, Mississippi, Alabama, Georgia, Florida, South Carolina, North Carolina, Virginia, Maryland, New Jersey, Pennsylvania, Connecticut, Delaware, New York, Rhode Island, Massachusetts, New Hampshire, and Maine. The number of observations is 33,194.

62

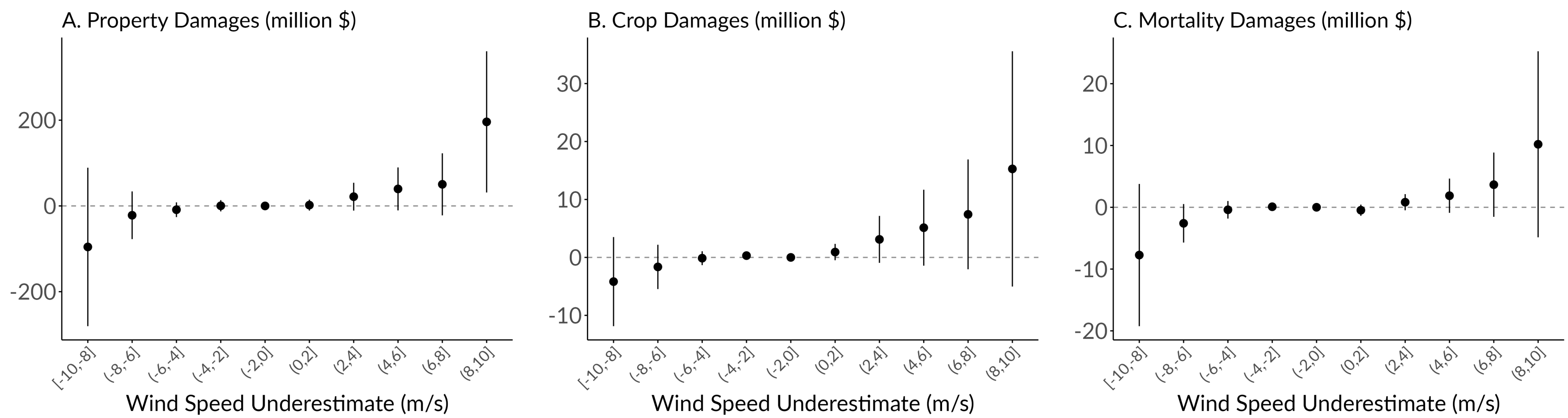
Figure C.16: Forecast Errors, Damages, and *Ex Post* Recovery Expenditures: Inverse Hyperbolic Sine.



Note: Points are point estimates, and the bars are the 95% confidence intervals. The omitted category is $(-2, 0]$ for wind speed and $(-20, 0]$ for precipitation. 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.

63

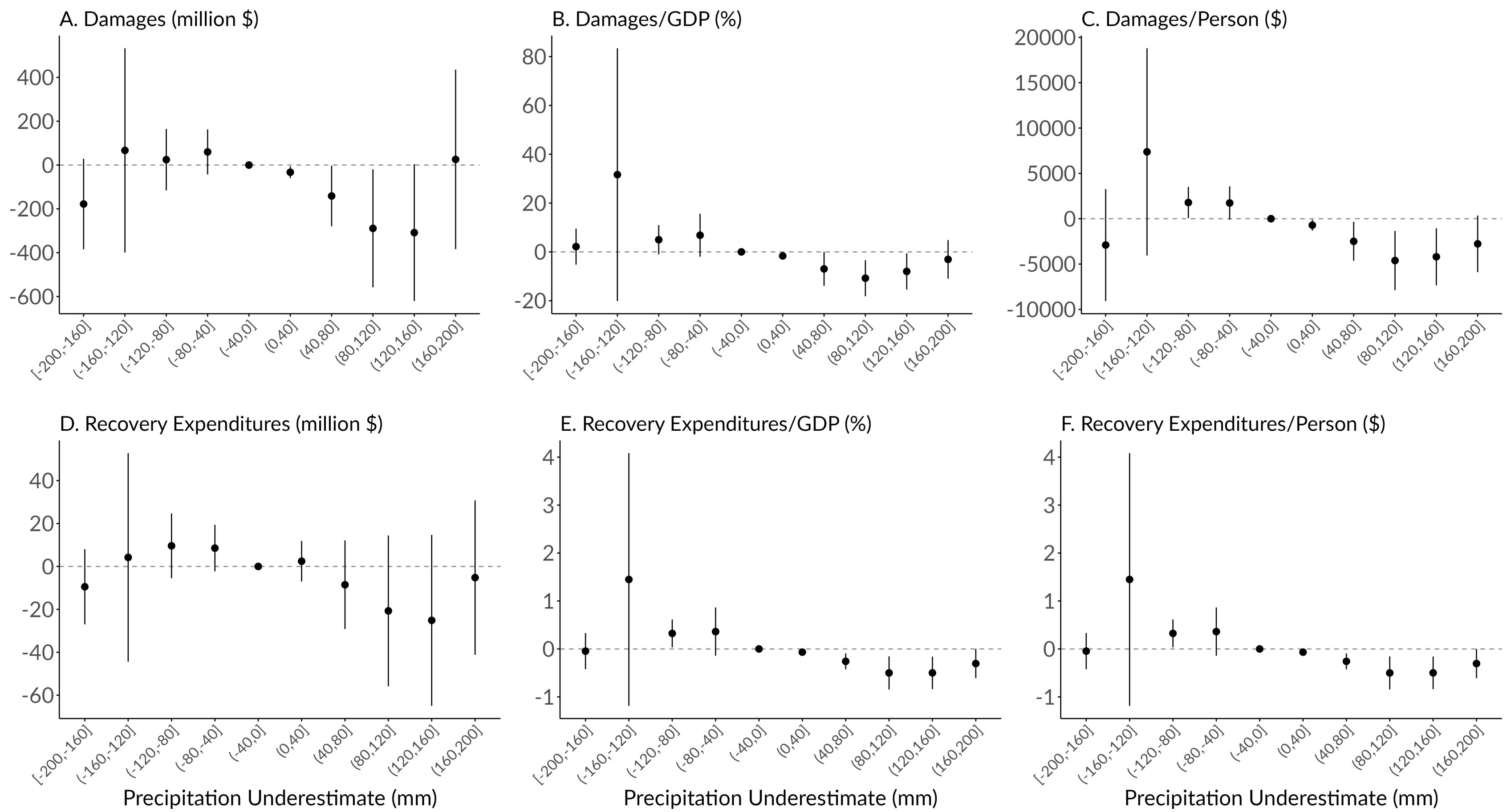
Figure C.17: Forecast Errors, Damages, and *Ex Post* Recovery Expenditures: By Damage Type.



Note: Points are point estimates, and the bars are the 95% confidence intervals. The omitted category is $(-2, 0]$ for wind speed and $(-20, 0]$ for precipitation. 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.

64

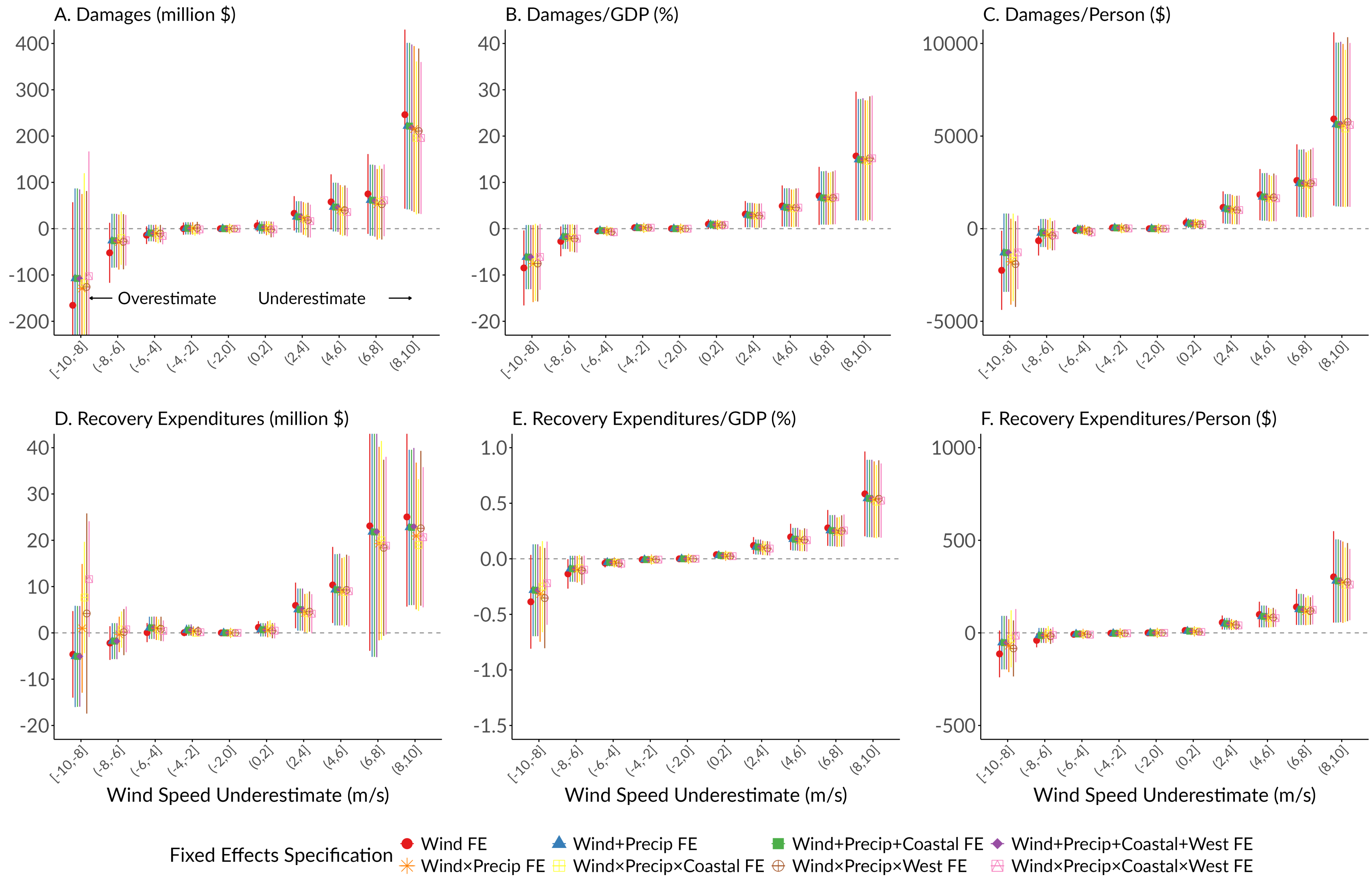
Figure C.18: Forecast Errors, Damages, and *Ex Post* Recovery Expenditures: Precipitation.



Note: Points are point estimates, and the bars are the 95% confidence intervals. The omitted category is $(-20, 0]$. All panels control for binned wind speed 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.

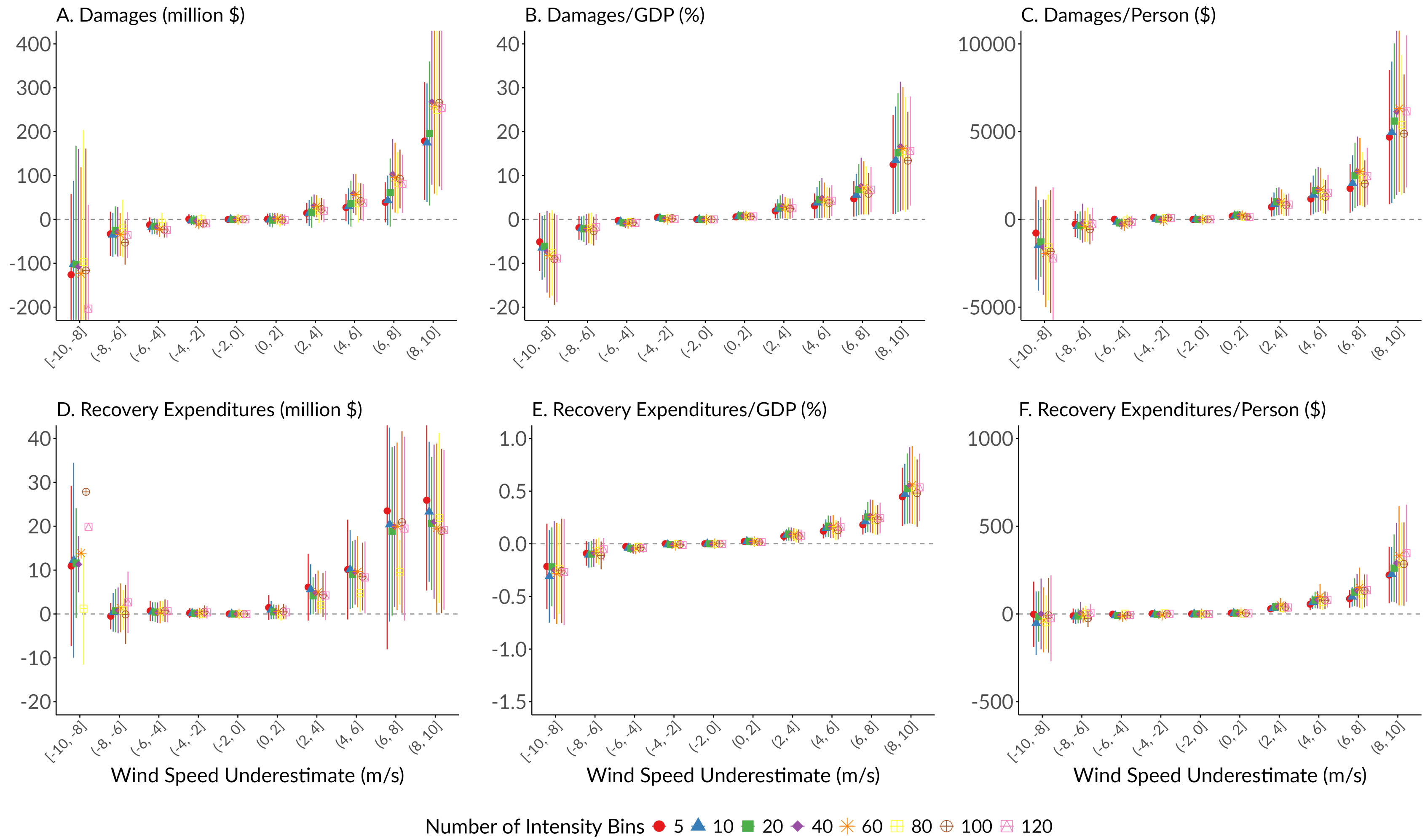
65

Figure C.19: Forecast Errors, Damages, and *Ex Post* Recovery Expenditures with Multiple Fixed Effects.



Note: The points are point estimates, and the bars are the 95% confidence intervals. The omitted category is $(-2, 0]$. Each color represents a different specification varying the hurricane intensity fixed effects. 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.

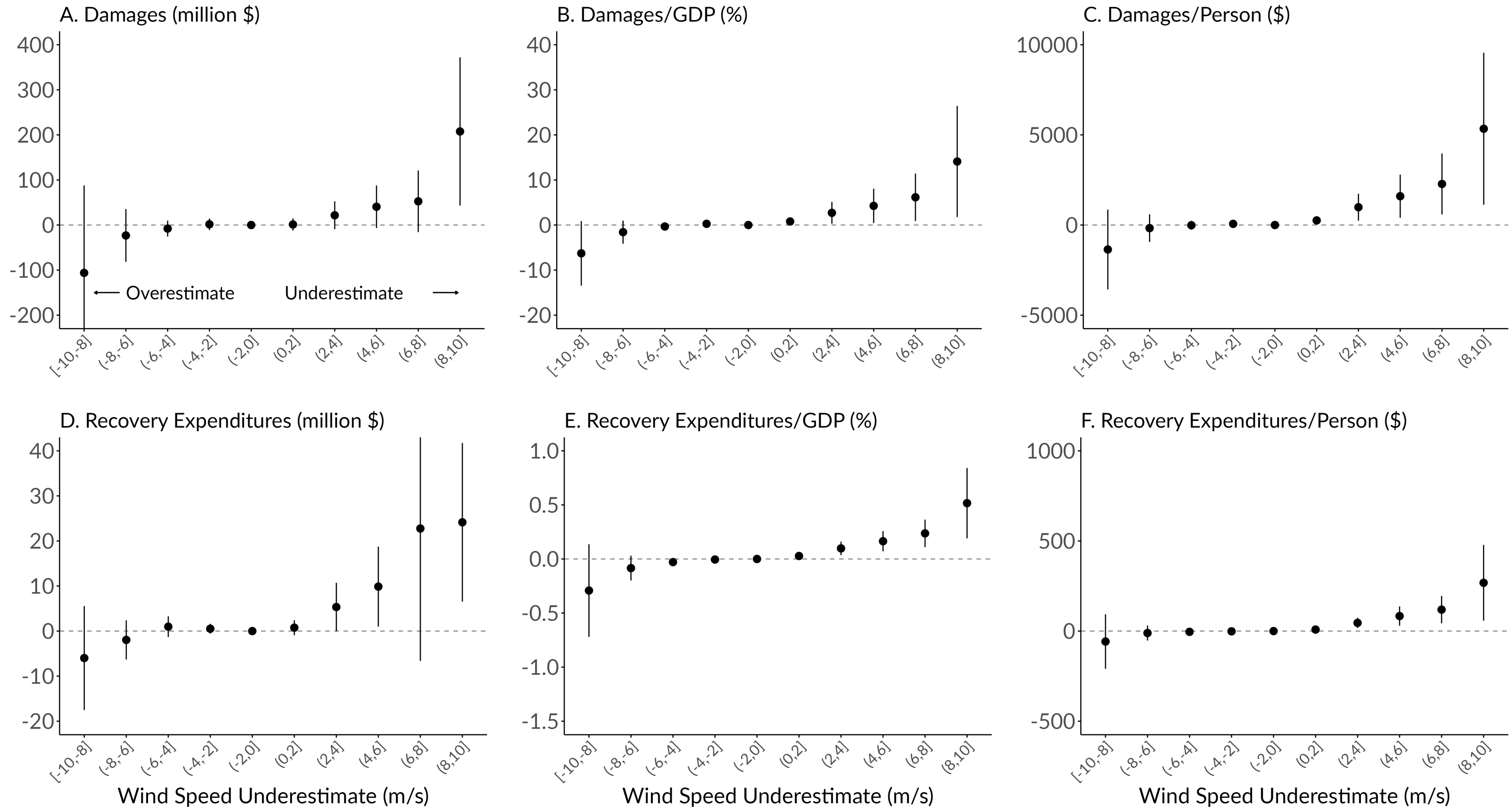
Figure C.20: Forecast Errors, Damages, and *Ex Post* Recovery Expenditures with Multiple Bin Sizes.



Note: The points are point estimates, and the bars are the 95% confidence intervals. The omitted category is $(-2, 0]$. Each color represents a different specification varying the number of bins (from 20 to 120) used to control for wind and precipitation intensity. All panels control for binned precipitation errors; a four-way interaction of binned realized wind speed, binned realized precipitation, a coastal indicator, and a west-of-track indicator; 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.

67

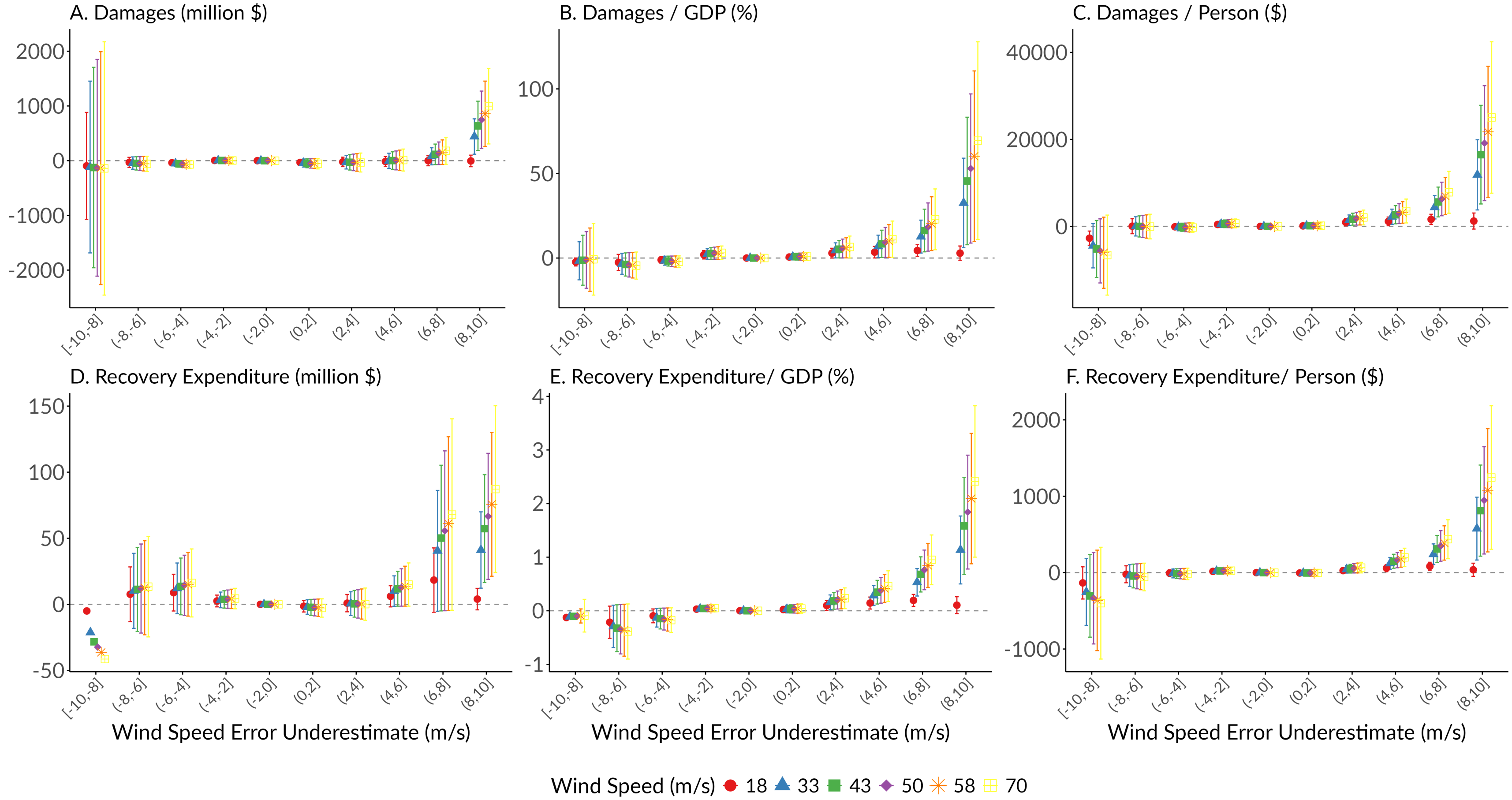
Figure C.21: Forecast Errors, Damages, and *Ex Post* Recovery Expenditures with Population-Weighted Wind Exposure.



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. Wind speed forecasts and wind speed intensities are population-weighted within-county when constructing the county-level variables. The number of observations is 95,263.

68

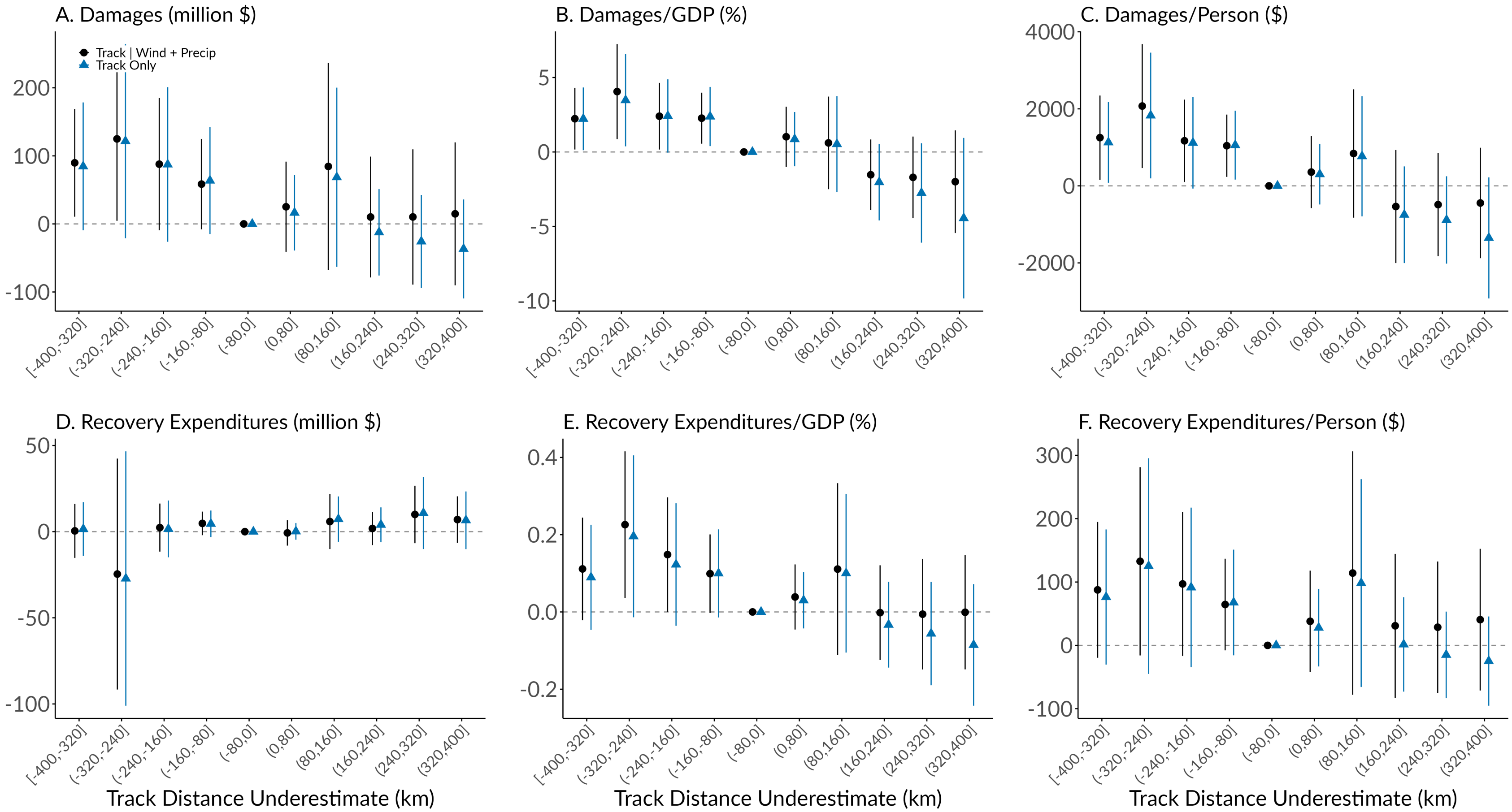
Figure C.22: Wind Forecast Errors, Wind Intensity, and Their Interaction Effects on Damages and Recovery Expenditures



Note: The points are point estimates, and the bars are the 95% confidence intervals. The omitted category is $(-2, 0]$. Estimates are based on a regression specification where wind forecast error bins are interacted with the inverse hyperbolic sine of observed wind speed. 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.

69

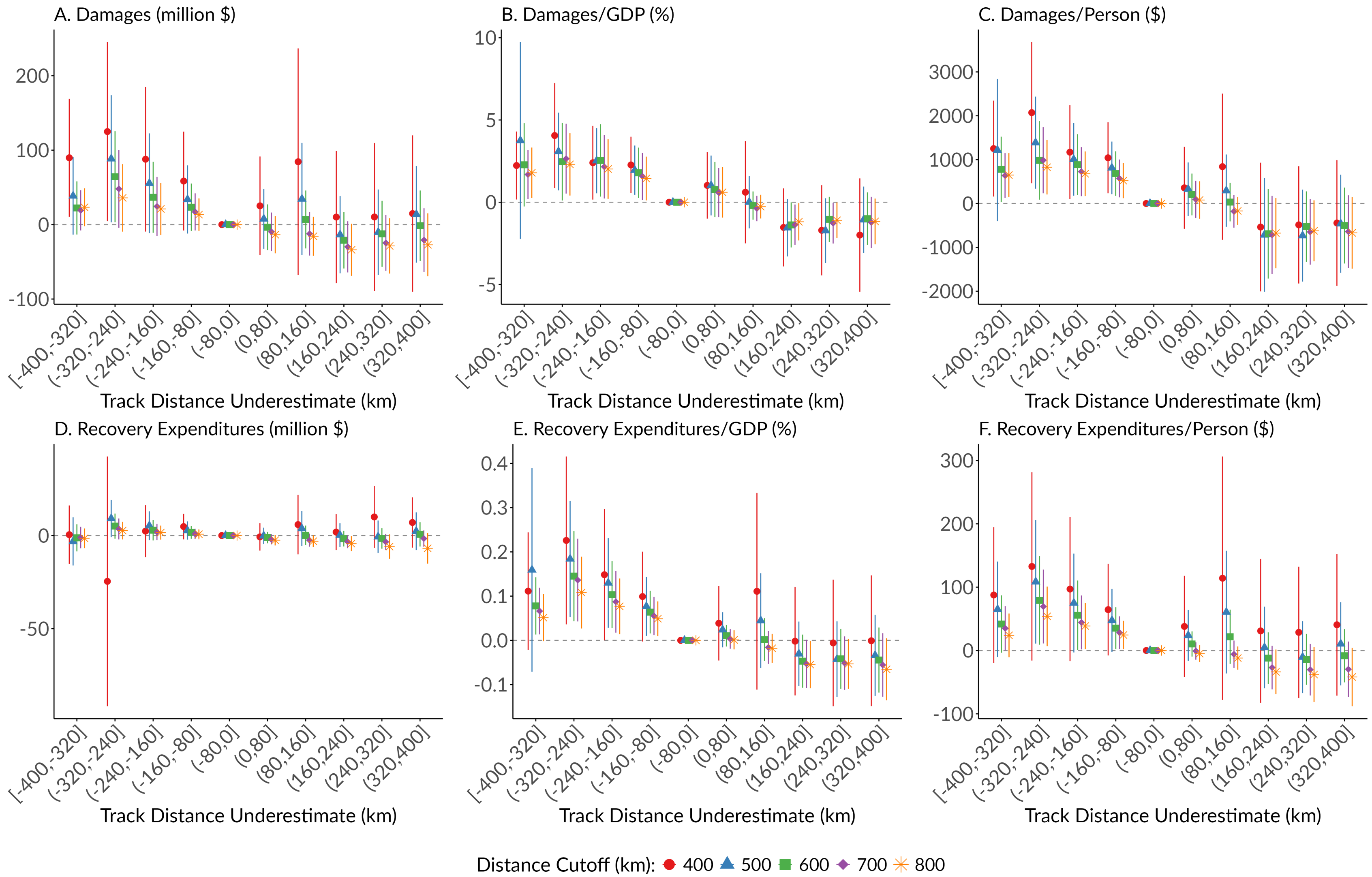
Figure C.23: Track Forecast Errors, Damages, and *Ex Post* Recovery Expenditures.



Note: The points are point estimates, and the bars are the 95% confidence intervals. The omitted category is $(-80, 0]$. Black circles are estimates that control for binned wind and precipitation errors, binned realized distance from track, binned realized wind speed, and binned realized precipitation, while blue triangles are estimates that do not. All estimates control 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 15,018.

70

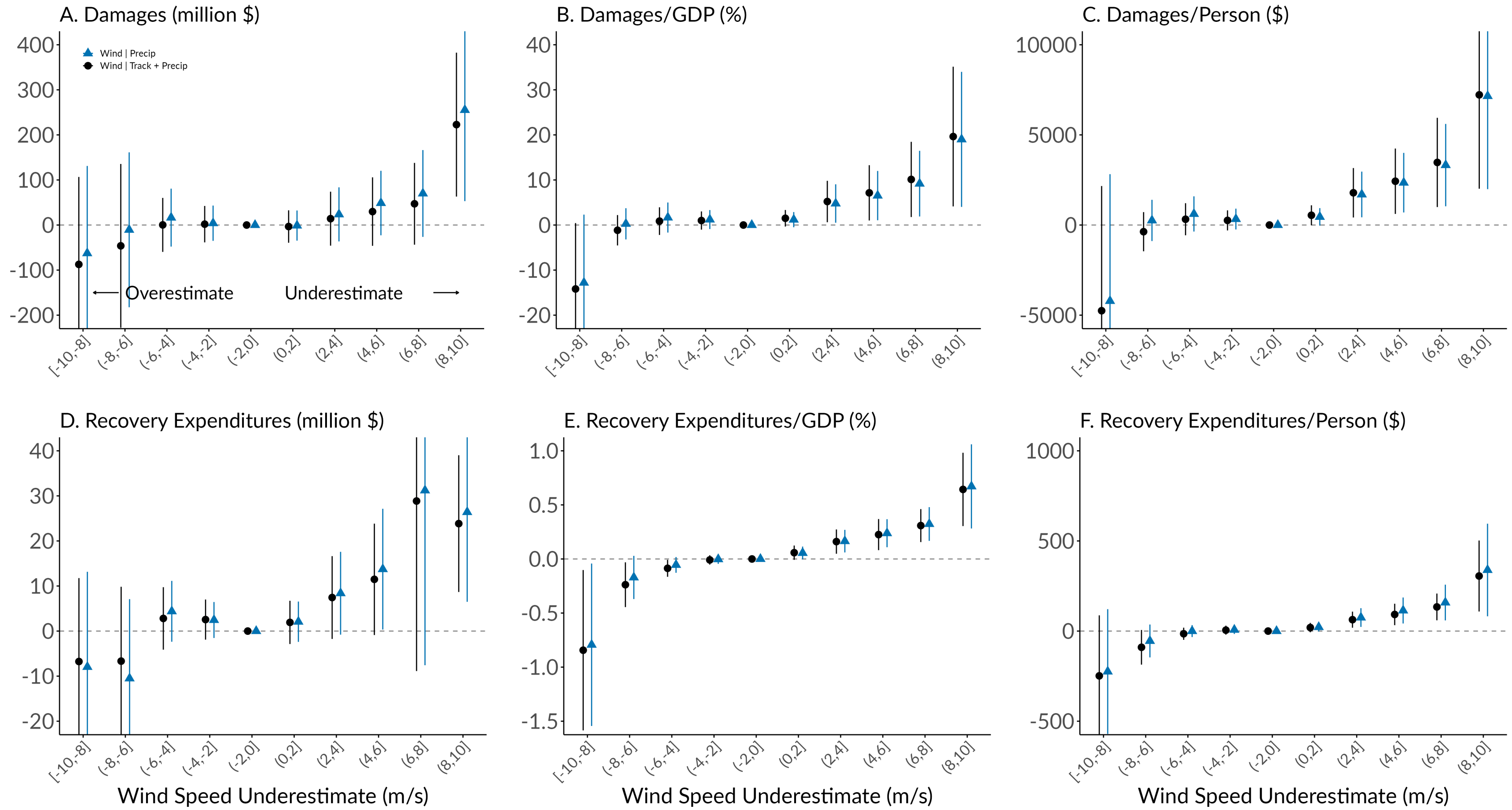
Figure C.24: Track Forecast Errors, Damages, and *Ex Post* Recovery Expenditures with Multiple Distance Cutoffs.



Note: The points are point estimates, and the bars are the 95% confidence intervals. The omitted category is $(-80, 0]$. Each estimate comes from a different sample that retains counties within a certain distance (400-800 km) from the forecast and observed track. All estimates control for binned wind and precipitation errors, binned realized distance from track, binned realized wind speed, and binned realized precipitation. All estimates control 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 are: 400 km = 15,018; 500 km = 20,072; 600 km = 25,195; 700 km = 30,470; 800 km = 35,874.

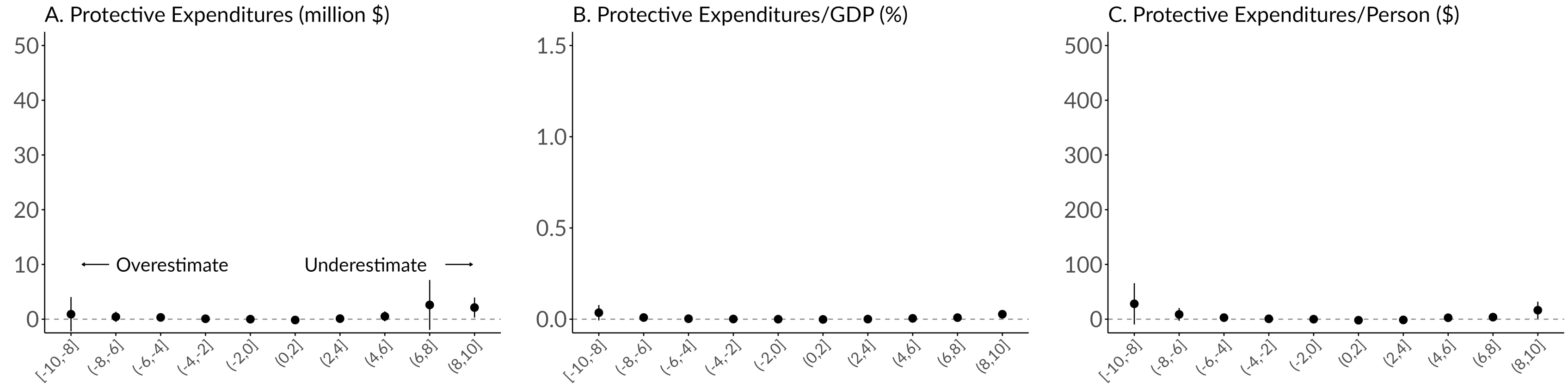
71

Figure C.25: Forecast Errors, Damages, and *Ex Post* Recovery Expenditures with Track Controls.



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. The black circles further control for binned track errors and binned realized distance to the center of the hurricane. 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 15,018.

Figure C.26: Forecast Errors and Protective 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 forecast wind speed, binned forecast 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.

73

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

The fixed effects in all table columns follow similarly to the previous sections. All specifications include binned wind speed and precipitation realizations as well as first-order forecast error terms.

Table C.4 shows our results using the alternative 600 km Conley cutoff. The results are all still statistically significant.

Tables C.5 and C.6 show our results are robust to dropping counties issued a Presidential Disaster Declaration (PDD) but with no reported SHELDUS damage, and working only with coastal counties. The results are robust to either sampling approach.

Table C.7 performs the same exercise as Figure C.17, where we estimate impacts on different types of damage. The value of a forecast improvement is positive for all three, but it is driven by property damage, consistent with Figure C.17.

Table C.8 shows our estimates when we do not demean the error. The results follow the main pattern in the main text and are all statistically significant.

Table C.9 shows our estimates when conditioning on the interaction of two indicator variables: one for whether a county was forecast to experience hurricane-force winds, and one for whether the county actually experienced hurricane-force winds. Conditioning on the interaction of these variables controls for the error in categorizing whether a county would be hit by hurricane-force winds or not. This tests whether the value in a forecast improvement is from solely getting the binary aspect of predicting hurricane-force winds correct, or if there is still remaining value in forecast improvements conditional on getting this binary prediction right. Depending on the specification and outcomes, results are unchanged or up to about 40% smaller indicating that improving wind speed forecasts, conditional on correctly predicting hurricane status, are still highly valuable.

Table C.10 presents the value of improving the precipitation forecasts. We find that they are smaller in magnitude than their equivalent estimates for wind speed forecasts and statistically indistinguishable from zero at the 95% confidence level in all specifications. This is consistent with our results showing that precipitation forecasts do not seem to drive protective expenditures and precipitation forecast errors do not seem to have large effects on damages or recovery expenditures.

Table C.11 tests the sensitivity of our results to a more comprehensive set of hurricane intensity controls where we now do up to a four-way interaction of the wind speed and precipitation intensity control bins, an indicator for whether the county is on the coast, and an indicator for whether a county was to the east or west of a hurricane track. Results are essentially identical.

Table C.12 tests the sensitivity of our results to a more comprehensive set of hurricane intensity controls analogously to Table C.11, but where we increase the number of bins for wind speed and precipitation. Results are similar across all specifications.

Table C.13 tests the sensitivity of our results to population-weighting when constructing our county-level measures of hurricane forecasts and intensity similarly to Figure C.21. Population-weighting again has little effect on the results.

Table C.14 presents results from interacting squared demeaned error with the inverse hyperbolic sine of realized wind speed, analogously to Figure C.22. The table presents the estimates evaluated at six different wind speeds representing the thresholds for classification as a tropical storm, a Category 1 hurricane, all the way to a Category 5 hurricane. The estimates show that the value of a forecast improvement is higher when the hurricane is more intense.

Table C.15 presents estimates of the value of a track forecast improvement, conditional on the wind speed and precipitation error and realization variables included in the main text. The estimates are small and imprecise except for Column 7 of the top panel. Taking this estimate along with the sample standard deviation of a track forecast error of 90 km yields a marginal value of a forecast improvement of $22 million per county per hurricane. Table C.16 presents the same estimates, but when not conditioning on any wind speed or precipitation variables to allow track to pick up on the effects of wind speed and precipitation. The estimates are similar but are more precise in Column 7.

Tables C.17 and C.18 replicate the track analysis above using different distance cutoffs. The result are basically unchanged.

Table C.19 presents estimates of the value of a wind speed forecast improvement, conditional on the analogous track error and realization variables. The estimates are very close to those in the main text. On this restricted sample, the standard deviation of a wind speed forecast is 4.3 m/s, delivering a value of a forecast improvement of $47 million per hurricane per county.

The key assumption underlying the estimate in equation (5) is the normality of forecast errors. A formal Kolmogorov-Smirnov test rejects normality for both wind and precipitation forecast errors, primarily due to skewness, excess kurtosis, and the large sample size. Even small deviations from normality can be rejected with nearly 100,000 observations.

To quantify the deviation from normality, we use the Continuous Ranked Probability Score (CRPS). Given some assumed normal error distribution CDF, F, and some observed error value, e_{obs}, the CRPS is:

$$\mathrm{CRPS}\big(F, e\big) \;=\; \int_{-\infty}^{\infty} \big\{F(z) - \mathbf{1}\{e_{obs} \le z\}\big\}^2 \,\mathrm{d}z,$$

where $\mathbf{1}\{\,\cdot\,\}$ is the indicator function.

What the CRPS does is compare a normal CDF, F, to the empirical CDF of a single error observation. Because this observation is just a point, its CDF boils down to an indicator function. The measure of fit between the two is then the squared area difference between the two CDFs.[29]

We compute the average CRPS in our data across all observations. We do so by having F be a normal distribution that matches the mean and standard deviation for the wind speed error in our dataset. That is, we are comparing our forecast errors to a proposed normal distribution that matches the empirical forecast error distribution's first two moments.

We get that the average CRPS when comparing against this normal distribution is 1.05 m/s: on average, the assumed normal distribution misses the actual error by 1.05 m/s. We can compare this to the CRPS of the actual empirical error distribution as a benchmark. The average CRPS here is

[29]To provide some intuition, the CRPS is a generalization of mean absolute error. Mean absolute error measures the difference between a point (degenerate) distribution and a point outcome. The CRPS measures the difference between a continuous distribution and a point outcome.

0.89 m/s. The difference between the two is 0.17 m/s, which is less than one-tenth of a standard deviation (2.27 m/s). What this comparison suggests, is that while assuming normality is not a perfect fit, it does little in terms of changing the distribution.

Table C.20 and Table C.21 assess the robustness of our results after imposing normality via a rank-based inverse-normal transformation. We transform the data according to the following steps:

1. Compute the empirical mean, $\hat{\mu}$, and standard deviation, $\hat{\sigma}$, of the errors.
2. Rank each county's error from smallest to largest and convert those ranks to percentiles in $(0, 1)$.
3. Map each percentile to a standard normal deviate via the inverse standard-normal cumulative distribution function, $\Phi^{-1}(\cdot)$.
4. Shift and scale those deviates to match the mean and standard deviation of the sample: $\hat{\mu}$ and $\hat{\sigma}$.

This ensures the errors follow a normal distribution and match the mean and variance of the data. Table C.20 applies the transformation across the full sample, while Table C.21 does so within each hurricane. Both sets of estimates corroborate the main finding that improving forecasts has positive and meaningful ex ante value.

Tables C.22 through C.25 present a second transformation that imposes normality within wind speed bins (bin widths of 2, 5, 10, and 20 m/s) for each hurricane, allowing the forecast error distribution to vary with hurricane intensity and better reflect the fact that forecasts are more uncertain and errors are larger when wind speeds are higher. Here we use the following steps to transform the data:

1. Split counties within each hurricane into bins according to their wind speed, e.g., 5 m/s wide bins of wind speed.
2. For each bin in each hurricane, compute the mean and variance of the errors.
3. Apply the same rank-based inverse-normal transform *within* each bin as in the prior results.

These results remain consistent with our main estimates. Note that minor differences in the number of observations across tables are due to counties being dropped during the binning in the data transformation.

Figure C.27 plots the t-statistic from the estimate in Column 7 of Table 2, but when we smoothly vary the distance cutoff for the Conley standard errors. The figure shows that our estimates are significant at the 95% level while allowing for spatial correlation up to over 1,000 km away from the county centroid.

Figure C.28 shows the distribution of estimates corresponding to Column 7 of Table 2, but where we drop hurricanes from the sample, one-by-one. Most of the estimates are tightly clustered around the full sample estimate which is given by the dashed line. The large estimate is when we drop Michael, and the low estimate is when we drop Katrina.

Table C.4: The Value of a Wind Speed Forecast Improvement: Conley Robustness.

	(1)	(2)	(3)	(4)	(5)
Damages + Recovery Expenditures (million \$)					
$\beta_2 : (e-\mu)^2$	3.65***	3.61***	4.25***	4.03***	
	(1.19)	(1.10)	(1.56)	(1.33)	
Hurricane $\beta_2 : (e-\mu)^2$					5.49***
					(1.81)
Sub-Hurricane $\beta_2 : (e-\mu)^2$					-0.39
					(0.48)
(Damages + Recovery Expenditures) / GDP (%)					
$\beta_2 : (e-\mu)^2$	0.32**	0.31***	0.29**	0.29***	
	(0.13)	(0.12)	(0.12)	(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)					
$\beta_2 : (e-\mu)^2$	110.82***	112.76***	113.05***	117.04***	
	(33.24)	(32.05)	(37.02)	(33.63)	
Hurricane $\beta_2 : (e-\mu)^2$					158.61***
					(41.45)
Sub-Hurricane $\beta_2 : (e-\mu)^2$					5.67
					(5.93)
Observations	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			✓	✓	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Standard errors are Conley Spatial HAC with a distance radius of 600 km for spatial correlation and arbitrary autocorrelation within counties. e is the county-hurricane-specific forecast error, 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.

Table C.5: The Value of a Wind Speed Forecast Improvement: PDD Robustness.

	(1)	(2)	(3)	(4)	(5)
Damages + Recovery Expenditures (million \$)					
$\beta_2 : (e-\mu)^2$	3.74***	3.69***	4.26***	3.89***	
	(1.18)	(1.10)	(1.52)	(1.23)	
Hurricane $\beta_2 : (e-\mu)^2$					5.50***
					(1.81)
Sub-Hurricane $\beta_2 : (e-\mu)^2$					-0.44
					(0.50)
(Damages + Recovery Expenditures) / GDP (%)					
$\beta_2 : (e-\mu)^2$	0.33***	0.33***	0.32***	0.31***	
	(0.13)	(0.12)	(0.12)	(0.11)	
Hurricane $\beta_2 : (e-\mu)^2$					0.47***
					(0.16)
Sub-Hurricane $\beta_2 : (e-\mu)^2$					0.01
					(0.02)
Damages + Recovery Expenditures Per Capita (\$/person)					
$\beta_2 : (e-\mu)^2$	115.56***	118.31***	122.54***	114.17***	
	(31.21)	(30.43)	(33.97)	(28.71)	
Hurricane $\beta_2 : (e-\mu)^2$					162.93***
					(39.20)
Sub-Hurricane $\beta_2 : (e-\mu)^2$					3.43
					(6.07)
Observations	94,105	94,105	94,105	94,105	94,105
Realized Wind/Precip Bins	✓	✓	✓	✓	✓
Level Wind/Precip Error	✓	✓	✓	✓	✓
State-Hurricane FE	✓	✓	✓	✓	✓
County FE	✓				✓
County-Month of Year FE		✓		✓	
County-Year FE			✓	✓	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ 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, 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. Counties issued a Presidential Disaster Declaration but without reported SHELDUS damage are dropped from the sample.

Table C.6: The Value of a Wind Speed Forecast Improvement: Coastal States.

	(1)	(2)	(3)	(4)	(5)
Damages + Recovery Expenditures (million \$)					
$\beta_2 : (e-\mu)^2$	3.68***	3.63***	4.34***	4.09***	
	(1.18)	(1.09)	(1.53)	(1.31)	
Hurricane $\beta_2 : (e-\mu)^2$					5.32***
					(1.72)
Sub-Hurricane $\beta_2 : (e-\mu)^2$					-0.22
					(0.52)
(Damages + Recovery Expenditures) / GDP (%)					
$\beta_2 : (e-\mu)^2$	0.36***	0.37***	0.32**	0.32***	
	(0.14)	(0.14)	(0.13)	(0.11)	
Hurricane $\beta_2 : (e-\mu)^2$					0.42***
					(0.15)
Sub-Hurricane $\beta_2 : (e-\mu)^2$					0.02
					(0.02)
Damages + Recovery Expenditures Per Capita (\$/person)					
$\beta_2 : (e-\mu)^2$	131.14***	133.13***	114.11***	121.37***	
	(36.89)	(37.15)	(30.79)	(30.76)	
Hurricane $\beta_2 : (e-\mu)^2$					158.40***
					(38.12)
Sub-Hurricane $\beta_2 : (e-\mu)^2$					9.01
					(7.10)
Observations	33,914	33,914	33,914	33,914	33,914
Realized Wind/Precip Bins	✓	✓	✓	✓	✓
Level Wind/Precip Error	✓	✓	✓	✓	✓
State-Hurricane FE	✓	✓	✓	✓	✓
County FE	✓				✓
County-Month of Year FE		✓		✓	
County-Year FE			✓	✓	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ 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, 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. Only the following states are included in the sample: Texas, Louisiana, Mississippi, Alabama, Georgia, Florida, South Carolina, North Carolina, Virginia, Maryland, New Jersey, Pennsylvania, Connecticut, Delaware, New York, Rhode Island, Massachusetts, New Hampshire, and Maine.

Table C.7: The Value of a Wind Speed Forecast Improvement by Damage Type.

	(1)	(2)	(3)	(4)	(5)
Property Damages (million \$)					
$\beta_2 : (e - \mu)^2$	3.02***	2.99***	3.59***	3.37***	
	(1.06)	(0.97)	(1.31)	(1.13)	
Hurricane $\beta_2 : (e - \mu)^2$					4.55***
					(1.63)
Sub-Hurricane $\beta_2 : (e - \mu)^2$					-0.35
					(0.44)
Crop Damages (million \$)					
$\beta_2 : (e - \mu)^2$	0.28	0.27*	0.21	0.21	
	(0.18)	(0.16)	(0.15)	(0.13)	
Hurricane $\beta_2 : (e - \mu)^2$					0.39*
					(0.23)
Sub-Hurricane $\beta_2 : (e - \mu)^2$					0.03
					(0.02)
Mortality Damages (million \$)					
$\beta_2 : (e - \mu)^2$	0.11	0.11*	0.14	0.13	
	(0.07)	(0.06)	(0.10)	(0.08)	
Hurricane $\beta_2 : (e - \mu)^2$					0.16
					(0.11)
Sub-Hurricane $\beta_2 : (e - \mu)^2$					-0.02
					(0.02)
Observations	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			✓	✓	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ 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, 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.

Table C.8: The Value of a Wind Speed Forecast Improvement without Demeaning.

	(1)	(2)	(3)	(4)	(5)
Damages + Recovery Expenditures (million \$)					
$\beta_2 : (e-\mu)^2$	1.94***	1.93***	2.13**	1.87**	
	(0.69)	(0.66)	(0.84)	(0.73)	
Hurricane $\beta_2 : (e-\mu)^2$					3.51***
					(1.13)
Sub-Hurricane $\beta_2 : (e-\mu)^2$					-0.18
					(0.21)
(Damages + Recovery Expenditures) / GDP (%)					
$\beta_2 : (e-\mu)^2$	0.13*	0.13**	0.12**	0.12**	
	(0.07)	(0.06)	(0.06)	(0.05)	
Hurricane $\beta_2 : (e-\mu)^2$					0.21**
					(0.09)
Sub-Hurricane $\beta_2 : (e-\mu)^2$					0.01
					(0.01)
Damages + Recovery Expenditures Per Capita (\$/person)					
$\beta_2 : (e-\mu)^2$	42.39**	43.15***	42.26**	43.69***	
	(17.63)	(16.45)	(17.56)	(16.20)	
Hurricane $\beta_2 : (e-\mu)^2$					73.29***
					(24.25)
Sub-Hurricane $\beta_2 : (e-\mu)^2$					0.67
					(4.28)
Observations	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			✓	✓	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Standard errors are Conley Spatial HAC with a distance radius of 400 km for spatial correlation and arbitrary autocorrelation within counties. The squared error terms are not demeaned. e is the county-hurricane-specific forecast error, 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.

Table C.9: The Value of a Wind Speed Forecast Improvement: Category Error Controls.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Damages + Recovery Expenditures (million \$)							
$\beta_2 : (e-\mu)^2$	2.36***	2.36***	2.46***	2.46***	2.90***	2.82***	
	(0.70)	(0.70)	(0.74)	(0.74)	(0.84)	(0.85)	
Hurricane $\beta_2 : (e-\mu)^2$							3.83***
							(1.12)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.19
							(0.52)
(Damages + Recovery Expenditures) / GDP (%)							
$\beta_2 : (e-\mu)^2$	0.29**	0.30**	0.29**	0.29**	0.26**	0.27***	
	(0.13)	(0.14)	(0.13)	(0.12)	(0.11)	(0.10)	
Hurricane $\beta_2 : (e-\mu)^2$							0.45**
							(0.18)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.02
							(0.02)
Damages + Recovery Expenditures Per Capita (\$/person)							
$\beta_2 : (e-\mu)^2$	97.35***	100.70***	98.81***	101.52***	98.53***	105.50***	
	(30.38)	(31.01)	(30.05)	(28.29)	(28.96)	(27.21)	
Hurricane $\beta_2 : (e-\mu)^2$							151.80***
							(39.50)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							9.34
							(8.09)
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					✓	✓	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ 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, 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. All specifications control for an interaction between an indicator for forecast hurricane-force winds and an indicator for realized hurricane-force winds.

Table C.10: The Value of a Precipitation Forecast Improvement.

	(1)	(2)	(3)	(4)	(5)
Damages + Recovery Expenditures (million \$)					
$\beta_2 : (e-\mu)^2$	0.00	0.01	0.00	0.01*	
	(0.00)	(0.00)	(0.00)	(0.00)	
Hurricane $\beta_2 : (e-\mu)^2$					0.01
					(0.01)
Sub-Hurricane $\beta_2 : (e-\mu)^2$					0.00
					(0.00)
(Damages + Recovery Expenditures) / GDP (%)					
$\beta_2 : (e-\mu)^2$	-0.00	0.00	0.00	0.00	
	(0.00)	(0.00)	(0.00)	(0.00)	
Hurricane $\beta_2 : (e-\mu)^2$					0.00
					(0.00)
Sub-Hurricane $\beta_2 : (e-\mu)^2$					-0.00
					(0.00)
Damages + Recovery Expenditures Per Capita (\$/person)					
$\beta_2 : (e-\mu)^2$	-0.02	0.00	-0.01	0.05	
	(0.04)	(0.03)	(0.04)	(0.05)	
Hurricane $\beta_2 : (e-\mu)^2$					0.04
					(0.18)
Sub-Hurricane $\beta_2 : (e-\mu)^2$					-0.02
					(0.03)
Observations	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			✓	✓	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ 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, 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.

84

Table C.11: The Value of a Wind Speed Forecast Improvement.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Damages + Recovery Expenditures (million \$)								
Hurricane $\beta_2 : (e-\mu)^2$	5.61***	5.49***	5.49***	5.49***	5.42***	5.10***	5.38***	4.79***
	(1.82)	(1.73)	(1.73)	(1.73)	(1.71)	(1.54)	(1.72)	(1.54)
Sub-Hurricane $\beta_2 : (e-\mu)^2$	-0.38	-0.39	-0.39	-0.41	-0.36	-0.53	-0.35	-0.47
	(0.43)	(0.45)	(0.45)	(0.44)	(0.49)	(0.47)	(0.49)	(0.47)
(Damages + Recovery Expenditures) / GDP (%)								
Hurricane $\beta_2 : (e-\mu)^2$	0.45***	0.45***	0.45***	0.45***	0.45***	0.45***	0.45***	0.45***
	(0.15)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.15)	(0.16)
Sub-Hurricane $\beta_2 : (e-\mu)^2$	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Damages + Recovery Expenditures Per Capita (\$/person)								
Hurricane $\beta_2 : (e-\mu)^2$	159.90***	158.61***	158.61***	158.60***	157.90***	155.18***	157.10***	151.42***
	(38.84)	(38.64)	(38.64)	(38.63)	(38.41)	(37.70)	(38.10)	(37.28)
Sub-Hurricane $\beta_2 : (e-\mu)^2$	5.73	5.67	5.67	5.70	6.38	4.57	7.04	5.10
	(5.44)	(5.57)	(5.57)	(5.61)	(5.77)	(5.30)	(6.23)	(6.18)
Observations	95,263	95,263	95,263	95,263	95,263	95,263	95,263	95,263
State-Hurricane FE	✓	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓	✓	✓
Realized Wind Bins	✓	✓	✓	✓				
Realized Precip Bins		✓	✓	✓				
Coastal Indicator			✓	✓				
West of Track Indicator				✓				
Wind-by-Precip Bins					✓			
Wind-by-Precip-by-Coastal Indicator						✓		
Wind-by-Precip-by-West of Track Indicator							✓	
Wind-by-Precip-by-Coastal-by-West of Track Indicator								✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ 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, 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.

Table C.12: The Value of a Wind Speed Forecast Improvement Under Different Wind Bins.

	5 Bins	10 Bins	20 Bins	40 Bins	60 Bins	80 Bins	100 Bins	120 Bins
Damages + Recovery Expenditures (million $)								
Hurricane $\beta_2 : (e-\mu)^2$	5.30***	5.01***	4.79***	4.74***	4.92***	4.62***	4.89***	4.30***
	(1.77)	(1.62)	(1.54)	(1.49)	(1.45)	(1.24)	(1.40)	(1.19)
Sub-Hurricane $\beta_2 : (e-\mu)^2$	-0.54	-0.57	-0.47	-0.37	-0.42	-0.07	-0.65	-0.40
	(0.49)	(0.47)	(0.47)	(0.46)	(0.43)	(0.69)	(0.61)	(0.67)
(Damages + Recovery Expenditures) / GDP (%)								
Hurricane $\beta_2 : (e-\mu)^2$	0.45***	0.45***	0.45***	0.44***	0.45***	0.44***	0.42***	0.40***
	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.14)	(0.14)	(0.13)
Sub-Hurricane $\beta_2 : (e-\mu)^2$	0.02	0.02	0.02	0.02	0.02	0.01	0.01	0.04
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
Damages + Recovery Expenditures Per Capita ($/person)								
Hurricane $\beta_2 : (e-\mu)^2$	157.75***	153.58***	151.42***	145.69***	145.54***	140.21***	138.28***	123.78***
	(39.06)	(37.60)	(37.28)	(35.29)	(36.92)	(32.14)	(32.48)	(32.08)
Sub-Hurricane $\beta_2 : (e-\mu)^2$	4.92	4.25	5.10	4.69	5.19	0.76	-0.10	20.10*
	(5.76)	(5.60)	(6.18)	(6.54)	(6.69)	(9.96)	(10.10)	(11.61)
Observations	95,263	95,263	95,263	95,263	95,263	95,263	95,263	95,263
State-Hurricane FE	✓	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓	✓	✓
Wind-by-Precip-by-Coastal-by-West of Track Indicator	✓	✓	✓	✓	✓	✓	✓	✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ 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, μ is the hurricane-intensity bin-specific mean forecast error. Each column shows estimates using a different number of bins to control for wind and precipitation intensity, ranging from 5 to 120 bins. Hurricane wind speeds are those greater than 33 m/s (74 mph), while Sub-Hurricane wind speeds fall below that threshold.

Table C.13: The Value of a Wind Speed Forecast Improvement with Population-Weighted Wind Aggregation.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Damages + Recovery Expenditures (million \$)							
$\beta_2 : (e-\mu)^2$	4.51***	4.49***	3.69***	3.66***	4.29***	4.09***	
	(1.42)	(1.43)	(1.14)	(1.06)	(1.49)	(1.29)	
Hurricane $\beta_2 : (e-\mu)^2$							5.50***
							(1.75)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							-0.41
							(0.48)
(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)	(0.12)	(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***	125.94***	111.71***	113.77***	114.01***	118.63***	
	(35.74)	(35.98)	(31.33)	(30.31)	(33.45)	(31.22)	
Hurricane $\beta_2 : (e-\mu)^2$							158.46***
							(38.81)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							5.72
							(5.74)
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					✓	✓	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Wind speed forecasts and wind speed intensities are population-weighted within-county when constructing the county-level variables. Standard errors are Conley Spatial HAC with a distance radius of 400 km for spatial correlation and arbitrary autocorrelation within counties. Estimates are conditional on an interaction between an indicator variable whether the county was forecast to be hit by hurricane-force winds, and an indicator variable whether the county was hit by hurricane-force winds. e is the county-hurricane-specific forecast error, 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.

Table C.14: Marginal Effect of Squared Forecast Error by Wind Intensity

	18 m/s	33 m/s	43 m/s	50 m/s	58 m/s	70 m/s
Damages + Recovery Expenditures (million \$)						
$\beta_2 : (e - \mu)^2$	2.15*	3.39***	3.93***	4.24***	4.54***	4.93***
	(1.11)	(1.15)	(1.26)	(1.34)	(1.44)	(1.57)
(Damages + Recovery Expenditures) / GDP (%)						
$\beta_2 : (e - \mu)^2$	0.14**	0.30***	0.36***	0.40***	0.44***	0.49***
	(0.06)	(0.11)	(0.13)	(0.14)	(0.16)	(0.17)
Damages + Recovery Expenditures Per Capita (\$/person)						
$\beta_2 : (e - \mu)^2$	63.93**	105.81***	124.11***	134.54***	144.80***	157.80***
	(26.74)	(28.87)	(31.64)	(33.58)	(35.71)	(38.65)
Observations	95,263	95,263	95,263	95,263	95,263	95,263
State-Hurricane FE	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓
Wind-by-Precip-by-Coastal-by-West of Track Indicator	✓	✓	✓	✓	✓	✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ 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, μ is the hurricane-intensity bin-specific mean forecast error. Each column reports the marginal effect of squared forecast error $(e - mu)^2$ evaluated at different observed wind speeds, ranging from tropical storm (18 m/s) to major hurricane strength (70 m/s).

87

Table C.15: The Value of a Track Distance Forecast Improvement Conditional on Wind and Precipitation.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Damages + Recovery Expenditures (million \$)							
$\beta_2 : (e-\mu)^2$	0.000	0.000	0.001	0.000	0.001	-0.001	
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	
Hurricane $\beta_2 : (e-\mu)^2$							0.125*
							(0.072)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.000
							(0.000)
(Damages + Recovery Expenditures) / GDP (%)							
$\beta_2 : (e-\mu)^2$	-0.000	-0.000	0.000	0.000	0.000*	0.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Hurricane $\beta_2 : (e-\mu)^2$							0.002
							(0.002)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							-0.000
							(0.000)
Damages + Recovery Expenditures Per Capita (\$/person)							
$\beta_2 : (e-\mu)^2$	0.001	-0.001	0.008	0.011	0.021	0.018	
	(0.008)	(0.008)	(0.008)	(0.010)	(0.016)	(0.036)	
Hurricane $\beta_2 : (e-\mu)^2$							2.166
							(1.387)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.002
							(0.005)
Observations	15,018	15,018	15,018	15,018	15,018	15,018	15,018
Realized Wind/Precip/Track Bins		✓	✓	✓	✓	✓	✓
Level Wind/Precip/Track Error			✓	✓	✓	✓	✓
State-Hurricane FE	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓				✓
County-Month of Year FE				✓		✓	
County-Year FE					✓	✓	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ 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, 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.

Table C.16: The Unconditional Value of a Track Distance Forecast Improvement.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Damages + Recovery Expenditures (million \$)							
$\beta_2 : (e-\mu)^2$	0.001	0.000	0.000	0.000	0.000	-0.001	
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	
Hurricane $\beta_2 : (e-\mu)^2$							0.151**
							(0.075)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.000
							(0.000)
(Damages + Recovery Expenditures) / GDP (%)							
$\beta_2 : (e-\mu)^2$	0.000	-0.000	-0.000	0.000	0.000	0.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Hurricane $\beta_2 : (e-\mu)^2$							0.004**
							(0.002)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							-0.000
							(0.000)
Damages + Recovery Expenditures Per Capita (\$/person)							
$\beta_2 : (e-\mu)^2$	0.013	-0.002	0.003	0.012	0.017	0.019	
	(0.010)	(0.008)	(0.007)	(0.007)	(0.014)	(0.023)	
Hurricane $\beta_2 : (e-\mu)^2$							2.917**
							(1.414)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.004
							(0.006)
Observations	15,018	15,018	15,018	15,018	15,018	15,018	15,018
Realized Wind/Precip/Track Bins		✓	✓	✓	✓	✓	✓
Level Wind/Precip/Track Error			✓	✓	✓	✓	✓
State-Hurricane FE	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓				✓
County-Month of Year FE				✓		✓	
County-Year FE					✓	✓	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ 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, 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.

Table C.17: The Value of a Track Distance Forecast Improvement: Cutoff Robustness.

	400 km	500 km	600 km	700 km	800 km
Damages + Recovery Expenditures (million \$)					
Hurricane $\beta_2 : (e-\mu)^2$	0.125*	0.123*	0.122*	0.121*	0.120*
	(0.072)	(0.073)	(0.072)	(0.072)	(0.072)
Sub-Hurricane $\beta_2 : (e-\mu)^2$	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
(Damages + Recovery Expenditures) / GDP (%)					
Hurricane $\beta_2 : (e-\mu)^2$	0.002	0.002	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Sub-Hurricane $\beta_2 : (e-\mu)^2$	-0.000	-0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Damages + Recovery Expenditures Per Capita (\$/person)					
Hurricane $\beta_2 : (e-\mu)^2$	2.166	2.116	2.077	2.047	2.037
	(1.387)	(1.368)	(1.354)	(1.354)	(1.349)
Sub-Hurricane $\beta_2 : (e-\mu)^2$	0.002	0.000	0.001	0.003	0.002
	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	15,018	20,072	25,195	30,470	35,874
Realized Wind/Precip/Track Bins	✓	✓	✓	✓	✓
Level Wind/Precip/Track Error	✓	✓	✓	✓	✓
State-Hurricane FE	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ 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, 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. Each column corresponds to a different distance cutoff (in kilometers) used to define the maximum allowable distance between county centroids and the hurricane track.

Table C.18: The Value of a Track Distance Forecast Improvement: Cutoff Robustness.

	400 km	500 km	600 km	700 km	800 km
Damages + Recovery Expenditures (million \$)					
Hurricane $\beta_2 : (e-\mu)^2$	0.151**	0.150**	0.150**	0.149**	0.149**
	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)
Sub-Hurricane $\beta_2 : (e-\mu)^2$	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
(Damages + Recovery Expenditures) / GDP (%)					
Hurricane $\beta_2 : (e-\mu)^2$	0.004**	0.004**	0.004**	0.004**	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Sub-Hurricane $\beta_2 : (e-\mu)^2$	-0.000	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Damages + Recovery Expenditures Per Capita (\$/person)					
Hurricane $\beta_2 : (e-\mu)^2$	2.917**	2.865**	2.836**	2.812**	2.805**
	(1.414)	(1.396)	(1.383)	(1.385)	(1.384)
Sub-Hurricane $\beta_2 : (e-\mu)^2$	0.004	0.003	0.005	0.006	0.005
	(0.006)	(0.004)	(0.003)	(0.004)	(0.003)
Observations	15,018	20,072	25,195	30,470	35,874
Realized Wind/Precip/Track Bins	✓	✓	✓	✓	✓
Level Wind/Precip/Track Error	✓	✓	✓	✓	✓
State-Hurricane FE	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ 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, 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. Each column corresponds to a different distance cutoff (in kilometers) used to define the maximum allowable distance between county centroids and the hurricane track.

Table C.19: The Value of a Wind Speed Forecast Improvement with Track Controls.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Damages + Recovery Expenditures (million \$)							
$\beta_2 : (e-\mu)^2$	4.77***	4.63***	3.60***	3.65***	5.06**	4.07**	
	(1.50)	(1.40)	(1.11)	(1.14)	(2.07)	(1.86)	
Hurricane $\beta_2 : (e-\mu)^2$							5.25***
							(1.65)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							-0.59
							(0.56)
(Damages + Recovery Expenditures) / GDP (%)							
$\beta_2 : (e-\mu)^2$	0.37***	0.37***	0.32***	0.32***	0.18**	0.08*	
	(0.13)	(0.13)	(0.12)	(0.10)	(0.07)	(0.05)	
Hurricane $\beta_2 : (e-\mu)^2$							0.43***
							(0.15)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.03
							(0.02)
Damages + Recovery Expenditures Per Capita (\$/person)							
$\beta_2 : (e-\mu)^2$	133.06***	132.34***	111.73***	127.01***	118.36***	65.79**	
	(35.13)	(34.79)	(28.75)	(30.59)	(42.15)	(31.14)	
Hurricane $\beta_2 : (e-\mu)^2$							153.15***
							(36.14)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							7.13
							(6.26)
Observations	15,018	15,018	15,018	15,018	15,018	15,018	15,018
Realized Wind/Precip/Track Bins		✓	✓	✓	✓	✓	✓
Level Wind/Precip/Track Error			✓	✓	✓	✓	✓
State-Hurricane FE	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓				✓
County-Month of Year FE				✓		✓	
County-Year FE					✓	✓	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ 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, 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.

Table C.20: The Value of a Wind Speed Forecast Improvement: Global Inverse Normal Transformation.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Damages + Recovery Expenditures (million \$)							
$\beta_2 : (e-\mu)^2$	7.12***	7.26**	7.27***	7.78***	8.27**	9.45***	
	(2.76)	(2.94)	(2.81)	(2.75)	(3.51)	(3.54)	
Hurricane $\beta_2 : (e-\mu)^2$							29.54***
							(9.57)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.36
							(0.56)
(Damages + Recovery Expenditures) / GDP (%)							
$\beta_2 : (e-\mu)^2$	0.42**	0.46**	0.45**	0.48**	0.42**	0.49***	
	(0.21)	(0.23)	(0.23)	(0.21)	(0.19)	(0.19)	
Hurricane $\beta_2 : (e-\mu)^2$							1.56**
							(0.63)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.11**
							(0.05)
Damages + Recovery Expenditures Per Capita (\$/person)							
$\beta_2 : (e-\mu)^2$	157.77**	169.98**	168.15**	179.86***	175.01**	206.20***	
	(65.79)	(72.31)	(69.43)	(67.81)	(72.26)	(75.99)	
Hurricane $\beta_2 : (e-\mu)^2$							589.11***
							(195.83)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							37.53**
							(14.69)
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					✓	✓	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Standard errors are Conley Spatial HAC with a distance radius of 400 km for spatial correlation and arbitrary autocorrelation within counties. Forecast errors are normalized across hurricanes. e is the county-hurricane-specific forecast error, 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.

Table C.21: The Value of a Wind Speed Forecast Improvement: Inverse Normal Transformation by Hurricane.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Damages + Recovery Expenditures (million \$)							
$\beta_2 : (e-\mu)^2$	2.08**	1.88**	1.78*	1.87**	1.67*	1.61*	
	(0.96)	(0.94)	(0.94)	(0.92)	(0.97)	(0.89)	
Hurricane $\beta_2 : (e-\mu)^2$							10.12*
							(5.54)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							-0.35
							(0.26)
(Damages + Recovery Expenditures) / GDP (%)							
$\beta_2 : (e-\mu)^2$	0.10*	0.09*	0.09*	0.09*	0.09*	0.08**	
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	
Hurricane $\beta_2 : (e-\mu)^2$							0.46
							(0.31)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							-0.00
							(0.01)
Damages + Recovery Expenditures Per Capita (\$/person)							
$\beta_2 : (e-\mu)^2$	39.91**	38.09**	36.42*	37.52**	36.37*	35.72**	
	(19.39)	(19.41)	(18.93)	(18.23)	(19.32)	(18.19)	
Hurricane $\beta_2 : (e-\mu)^2$							179.82
							(115.23)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							-0.30
							(3.43)
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					✓	✓	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Standard errors are Conley Spatial HAC with a distance radius of 400 km for spatial correlation and arbitrary autocorrelation within counties. Forecast errors are normalized by hurricane. e is the county-hurricane-specific forecast error, 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.

Table C.22: The Value of a Wind Speed Forecast Improvement Using Binned Normal Transform with 2 m/s bins.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Damages + Recovery Expenditures (million \$)							
$\beta_2 : (e-\mu)^2$	1.45**	1.52**	1.33*	1.32*	1.50*	1.35*	
	(0.69)	(0.75)	(0.73)	(0.71)	(0.85)	(0.76)	
Hurricane $\beta_2 : (e-\mu)^2$							4.78**
							(1.96)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.04
							(0.12)
(Damages + Recovery Expenditures) / GDP (%)							
$\beta_2 : (e-\mu)^2$	0.07*	0.08*	0.07	0.07	0.06	0.06*	
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.03)	
Hurricane $\beta_2 : (e-\mu)^2$							0.23**
							(0.11)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.01
							(0.01)
Damages + Recovery Expenditures Per Capita (\$/person)							
$\beta_2 : (e-\mu)^2$	23.94**	26.60**	22.09*	21.62*	21.18*	19.48*	
	(11.75)	(13.45)	(13.32)	(12.37)	(12.16)	(11.08)	
Hurricane $\beta_2 : (e-\mu)^2$							76.33**
							(32.50)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							1.96
							(2.46)
Observations	95,186	95,186	95,186	95,186	95,186	95,186	95,186
Realized Wind/Precip Bins		✓	✓	✓	✓	✓	✓
Level Wind/Precip Error			✓	✓	✓	✓	✓
State-Hurricane FE	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓				✓
County-Month of Year FE				✓		✓	
County-Year FE					✓	✓	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ 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, 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.

Table C.23: The Value of a Wind Speed Forecast Improvement Using Binned Normal Transform with 5 m/s bins.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Damages + Recovery Expenditures (million \$)							
$\beta_2 : (e-\mu)^2$	1.92**	2.04**	1.86**	1.86**	2.08**	1.78**	
	(0.77)	(0.84)	(0.86)	(0.82)	(1.01)	(0.89)	
Hurricane $\beta_2 : (e-\mu)^2$							4.72***
							(1.54)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.05
							(0.12)
(Damages + Recovery Expenditures) / GDP (%)							
$\beta_2 : (e-\mu)^2$	0.10**	0.11**	0.10*	0.09*	0.09*	0.09*	
	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	
Hurricane $\beta_2 : (e-\mu)^2$							0.23**
							(0.10)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.01
							(0.01)
Damages + Recovery Expenditures Per Capita (\$/person)							
$\beta_2 : (e-\mu)^2$	38.85**	42.90**	36.25*	35.80**	36.89*	37.03**	
	(17.08)	(19.14)	(19.59)	(18.07)	(19.88)	(18.69)	
Hurricane $\beta_2 : (e-\mu)^2$							90.43**
							(35.56)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							1.80
							(4.31)
Observations	95,238	95,238	95,238	95,238	95,238	95,238	95,238
Realized Wind/Precip Bins		✓	✓	✓	✓	✓	✓
Level Wind/Precip Error			✓	✓	✓	✓	✓
State-Hurricane FE	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓				✓
County-Month of Year FE				✓		✓	
County-Year FE					✓	✓	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ 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, 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.

Table C.24: The Value of a Wind Speed Forecast Improvement Using Binned Normal Transform with 10 m/s bins.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Damages + Recovery Expenditures (million \$)							
$\beta_2 : (e-\mu)^2$	1.85***	1.95***	1.77**	1.77**	2.03**	1.79**	
	(0.68)	(0.73)	(0.74)	(0.70)	(0.91)	(0.81)	
Hurricane $\beta_2 : (e-\mu)^2$							3.75***
							(1.26)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							-0.09
							(0.17)
(Damages + Recovery Expenditures) / GDP (%)							
$\beta_2 : (e-\mu)^2$	0.11**	0.13**	0.12*	0.12*	0.12*	0.11**	
	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.06)	
Hurricane $\beta_2 : (e-\mu)^2$							0.24**
							(0.10)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.02
							(0.01)
Damages + Recovery Expenditures Per Capita (\$/person)							
$\beta_2 : (e-\mu)^2$	40.21**	44.45**	39.06**	38.33**	39.64**	39.92**	
	(16.36)	(18.20)	(18.80)	(17.22)	(19.24)	(17.85)	
Hurricane $\beta_2 : (e-\mu)^2$							79.24***
							(26.93)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							1.13
							(3.86)
Observations	95,256	95,256	95,256	95,256	95,256	95,256	95,256
Realized Wind/Precip Bins		✓	✓	✓	✓	✓	✓
Level Wind/Precip Error			✓	✓	✓	✓	✓
State-Hurricane FE	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓				✓
County-Month of Year FE				✓		✓	
County-Year FE					✓	✓	

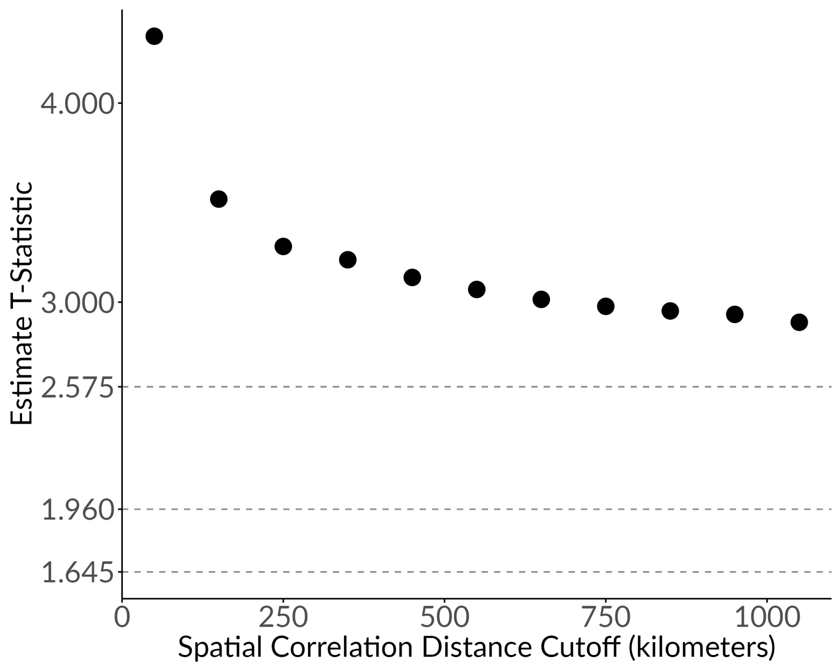
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Standard errors are Conley Spatial HAC with a distance radius of 400 km for spatial correlation and arbitrary autocorrelation within counties. e is the county-hurricane-specific forecast error, μ is the hurricane-intensity bin-specific mean forecast error. Hurricane wind speeds are those greater than 33 m/s (74 mph), while Sub-Hurricane wind speeds fall below that threshold.

Table C.25: The Value of a Wind Speed Forecast Improvement Using Binned Normal Transform with 20 m/s bins.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Damages + Recovery Expenditures (million \$)							
$\beta_2 : (e-\mu)^2$	1.98***	2.01***	1.81**	1.79***	2.00**	1.75**	
	(0.71)	(0.72)	(0.73)	(0.69)	(0.87)	(0.77)	
Hurricane $\beta_2 : (e-\mu)^2$							3.93***
							(1.24)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							-0.08
							(0.13)
(Damages + Recovery Expenditures) / GDP (%)							
$\beta_2 : (e-\mu)^2$	0.12**	0.13**	0.12*	0.12**	0.11*	0.11**	
	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.05)	
Hurricane $\beta_2 : (e-\mu)^2$							0.24**
							(0.09)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.01
							(0.01)
Damages + Recovery Expenditures Per Capita (\$/person)							
$\beta_2 : (e-\mu)^2$	42.07**	44.18**	39.57**	39.28**	39.56**	39.55**	
	(17.11)	(18.20)	(18.46)	(17.13)	(18.80)	(17.61)	
Hurricane $\beta_2 : (e-\mu)^2$							81.92***
							(26.71)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							1.80
							(2.94)
Observations	95,260	95,260	95,260	95,260	95,260	95,260	95,260
Realized Wind/Precip Bins		✓	✓	✓	✓	✓	✓
Level Wind/Precip Error			✓	✓	✓	✓	✓
State-Hurricane FE	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓				✓
County-Month of Year FE				✓		✓	
County-Year FE					✓	✓	

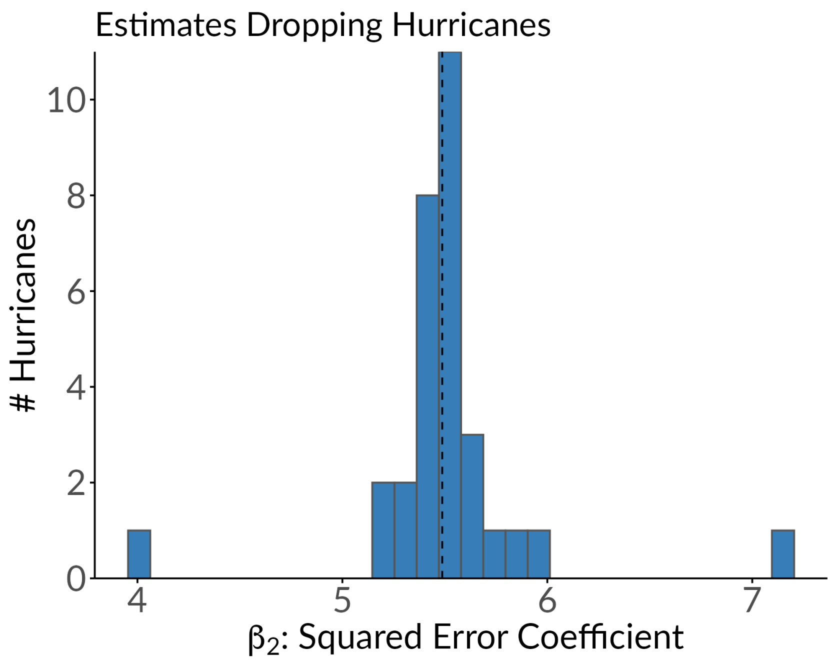
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Standard errors are Conley Spatial HAC with a distance radius of 400 km for spatial correlation and arbitrary autocorrelation within counties. e is the county-hurricane-specific forecast error, μ is the hurricane-intensity bin-specific mean forecast error. Hurricane wind speeds are those greater than 33 m/s (74 mph), while Sub-Hurricane wind speeds fall below that threshold.

Figure C.27: Conley Spatial HAC Distance Cutoff and Conley Spatial HAC T-Statistics.



The figure plots t-statistics of the hurricane-force coefficient estimate from Table 2 Column 7, but using Conley (1999) standard errors that account for arbitrary autocorrelation within counties and spatial correlation up to 1,050 km in 100 km steps. Dashed lines correspond to 10%, 5%, and 1% levels of statistical significance. The number of observations is 95,263.

Figure C.28: The Value of a Wind Speed Forecast Improvement Dropping Individual Hurricanes.



Note: The figure plots a histogram of the distribution of estimates of the value of a forecast improvement for hurricane-force winds corresponding to Column 7 of Table 2 but where we drop individual hurricanes. The lowest value comes from dropping Katrina while the highest values come from dropping Michael.

D Additional Results

D.1 Correlations and Distributions

Table D.1 reports the within-hurricane standard deviations of wind speed, wind speed error, precipitation, and precipitation error across counties. When comparing against the means in Table 1, this table highlights that precipitation is more spatially variable than wind speed, and precipitation forecasts tend to be less accurate. This suggests greater uncertainty and heterogeneity in local precipitation impacts.

Figure D.1 presents correlations between hurricane and forecast attributes. Panels A and B show that higher-intensity hurricanes tend to be under-forecast, while lower-intensity hurricanes were over-forecast but to a lesser extent. Panels C and D show that this results in higher intensity hurricanes having larger squared demeaned forecast errors, which is why we flexibly control for realized hurricane intensity in valuing forecast improvements. Panel E shows that more uncertain forecasts, in terms of the *ex ante* standard deviation, tend to result in larger *ex post* forecast errors. This provides evidence for why reductions in the forecast standard deviation will result in more accurate forecasts ex post. Panel F shows that realized wind speed and realized precipitation are highly positively correlated. Thus, omitting one from a regression may result in omitted variable bias.

Figure D.2 plots the distribution of realizations and forecasts of wind speed in panel A and precipitation in panel B. The distributions are only over those with strictly positive values. The plots show that our data cover a large range of intensities. Most forecasts and realizations fall in the "tropical depression" category with wind speeds under 17 m/s. This is because most counties are not near the coast and end up not experiencing hurricane-force winds. However, our data do include counties experiencing wind speeds of up to 67 m/s, which would correspond to a high-end category 4 storm. Overall, our data covers nearly the entire range of potential intensities.

Figure D.3 shows additional information about the hurricane forecast. Panel A plots the realized wind speed against the forecast wind speed using a 5 percentile binscatter. All the points are essentially on the 45 degree line: forecasts are quite accurate on average. Panel B plots the distribution of wind speed forecast errors as in Figure 3. 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 D.4 presents additional information on hurricane track and its relationship to wind speed to highlight how wind speed and track are only weakly correlated. Here we focus on counties that are within 400 km of a hurricane to isolate counties that are exposed to the hurricane to some degree.[30] Panel A shows the track error is approximately normally distributed. Panel B plots three histograms of wind speed errors. The first, in orange with stripes, is the unconditional wind speed distribution

[30] If we included all counties as in our main analysis, the correlations between wind speed and track would be artificially low because distant counties would still have track error, however, their wind speed error would always be near zero since they are not near the hurricane.

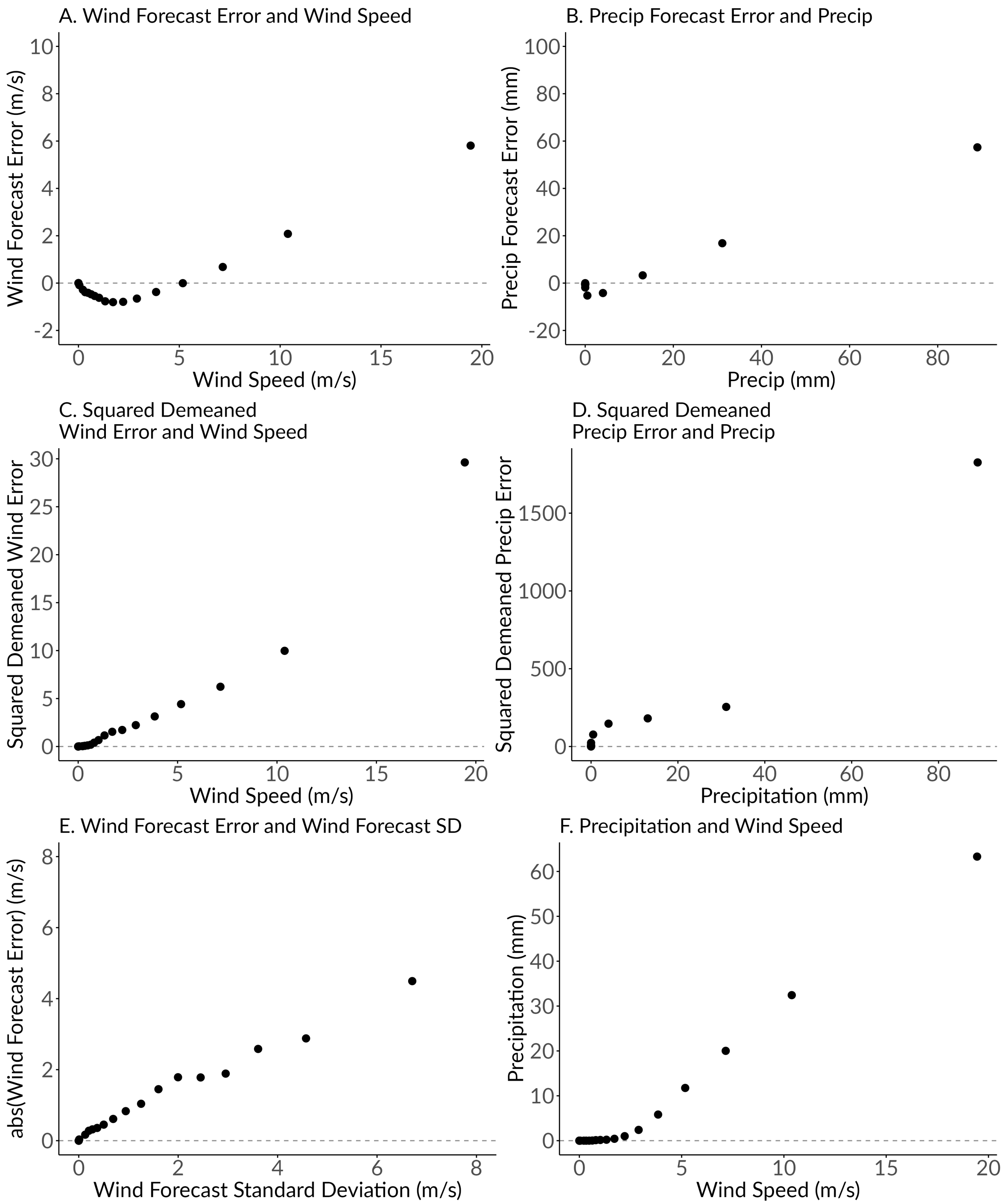
in this restricted sample. The second histogram, in blue with dots, is the distribution of wind speed errors conditional on track errors. This is the distribution of residuals from regressing wind speed errors on track errors. The third histogram in red is the wind speed distribution predicted by track errors, which are just the fitted values from the same regression. The greater dispersion of the wind speed errors conditional on track and the fact that it is a near-perfect match for the unconditional distribution suggests that track errors play a role in wind speed errors, but are not the sole driver. Panel C plots wind speed errors against track errors. They are positively correlated: if the hurricane is closer than expected, the experienced wind speed is also higher than expected. However the relationship is weak, the R^2 is only 0.15. There is substantial variation in wind speed errors not predicted by track errors. Panel D plots damages as a function of track errors and wind speed errors. The plot shows that there is a relatively clear correlation between damages and wind speed errors, but not with track errors.

Table D.1: Standard Deviations of Physical Values by Hurricane.

Hurricane	Year	Wind Speed	Wind Speed Error	Precipitation	Precipitation Error
		(m/s)	abs(m/s)	(mm)	abs(mm)
Cindy	2005	3.64	2.26	18.01	15.92
Dennis	2005	4.19	1.11	19.31	10.64
Katrina	2005	5.58	2.21	26.61	19.41
Rita	2005	4.12	1.79	24.97	17.29
Wilma	2005	2.44	1.06	7.33	5.27
Dolly	2008	2.23	0.68	8.96	4.68
Gustav	2008	4.37	1.35	35.39	29.05
Ike	2008	6.48	4.95	19.92	15.69
Irene	2011	5.63	1.71	30.27	23.98
Isaac	2012	4.01	1.01	27.82	15.73
Sandy	2012	5.26	1.59	18.94	12.33
Arthur	2014	4.42	1.57	6.07	6.81
Hermine	2016	5.48	2.61	19.04	14.57
Matthew	2016	4.93	1.48	30.48	25.54
Harvey	2017	3.74	0.97	39.07	30.82
Irma	2017	4.55	1.25	29.98	18.85
Nate	2017	4.21	1.86	14.26	9.72
Florence	2018	4.69	0.59	36.37	19.46
Michael	2018	7.45	2.37	21.57	15.72
Barry	2019	3.57	1.02	21.84	13.25
Dorian	2019	4.23	0.25	12.64	5.77
Delta	2020	4.11	0.69	17.98	10.96
Hanna	2020	2.51	0.52	7.84	5.49
Isaias	2020	6.84	3.10	14.94	13.27
Laura	2020	5.28	2.14	17.78	10.56
Sally	2020	4.40	1.90	32.63	28.22
Zeta	2020	6.76	3.03	11.05	7.73
Ida	2021	4.95	1.86	24.39	17.48
Nicholas	2021	2.98	0.72	18.17	16.29
Ian	2022	4.61	2.39	19.78	14.46
Nicole	2022	3.49	1.41	11.11	6.07

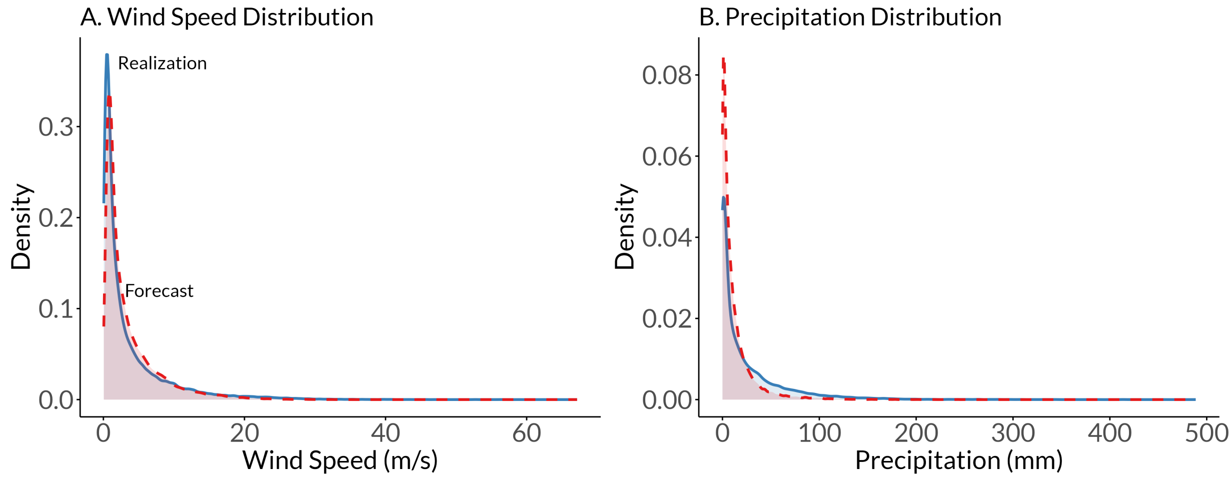
Note:
The table includes all Category 1 and greater hurricanes (maximum wind speeds greater than 33 m/s) that made landfall in the continental US between 2005–2022. Wind speed, precipitation, and their associated errors are averaged across counties to the hurricane level. Wind speed is the maximum sustained 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.

Figure D.1: Relationships Between Different Forecast Attributes and Hurricane Attributes.



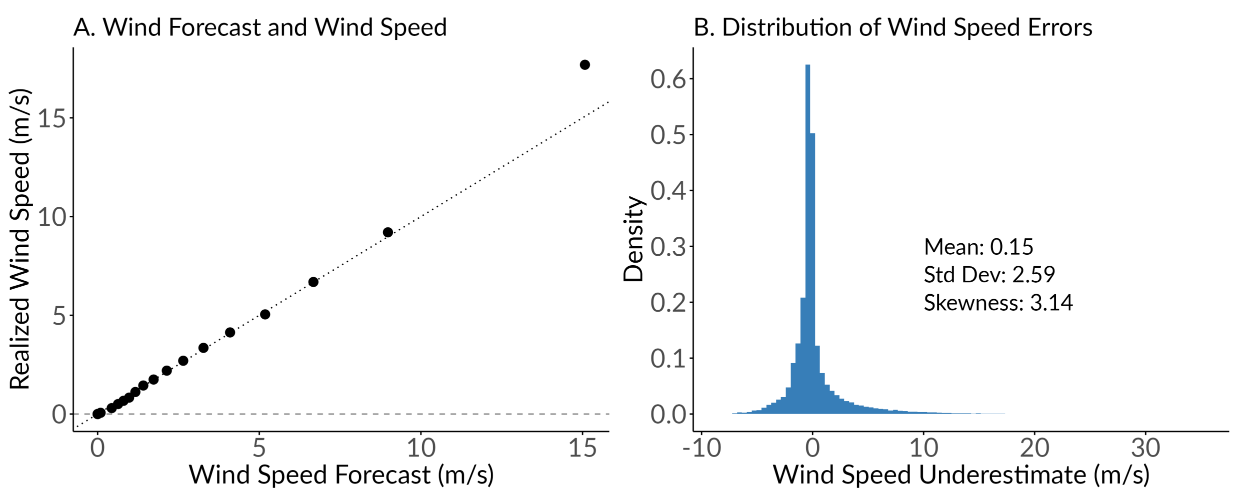
Note: Panel A plots the absolute error in the wind speed forecast (actual wind speed minus predicted wind speed) against the realized wind speed. Panel B plots the absolute error in the precipitation forecast against the realized precipitation. Panel C plots the squared demeaned error in the wind speed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

Figure D.2: The Distribution of Realized Wind Speeds and Precipitation.



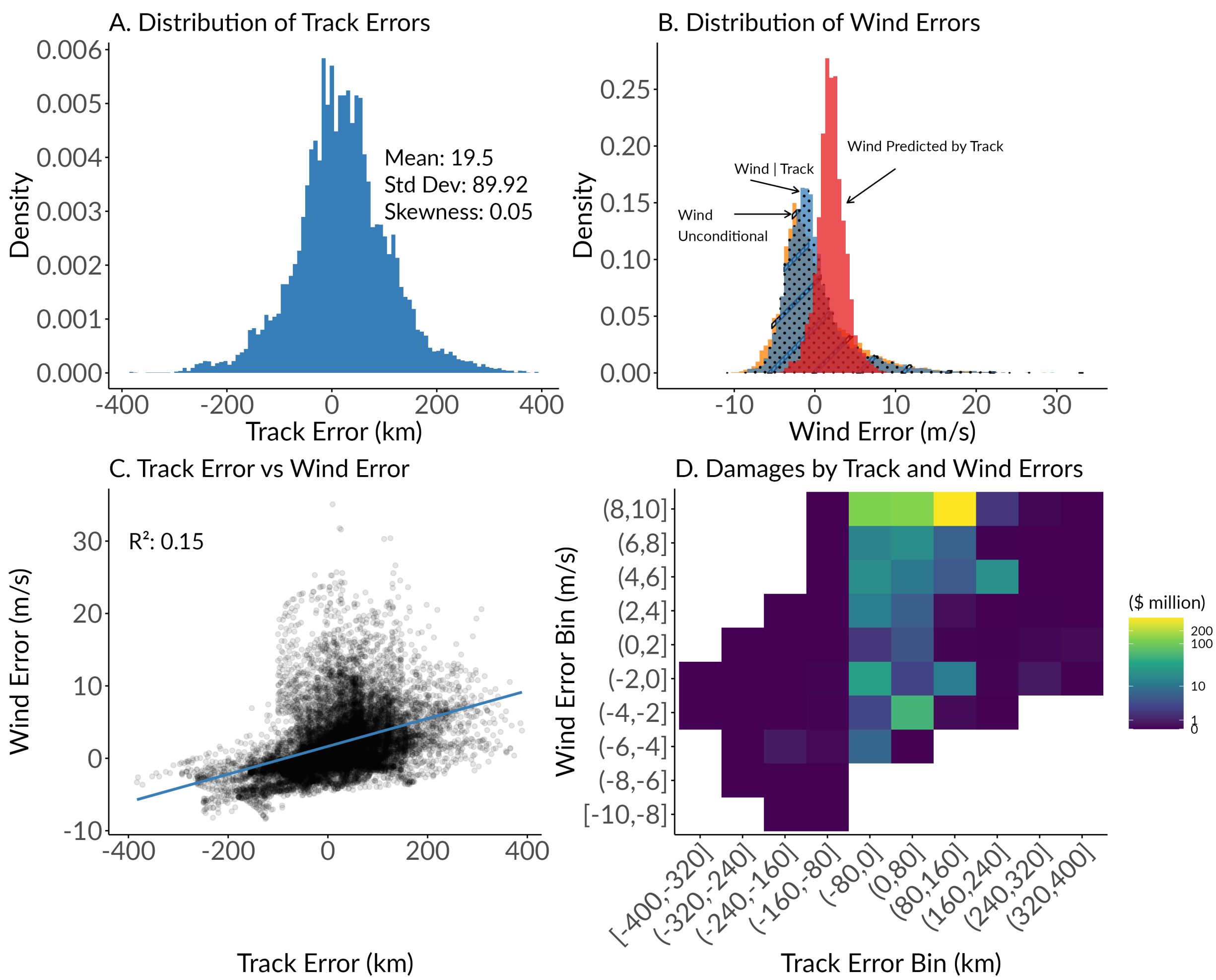
Note: Panel A shows the observed distribution of the realized and forecast wind speed by county-hurricane. Panel B shows the observed distribution of the realized and forecast precipitation by county-hurricane. The red dashed line is the distribution of the forecast and the blue line is the distribution of the realization. Values of 0 are omitted for clarity.

Figure D.3: The Distribution of Wind Speed Errors.



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

Figure D.4: Track Error and its Relationship with Wind Error and Damages.



Note: Panel A shows the distribution of track errors. Panel B shows three histograms of wind speed errors. The orange striped histogram is the unconditional distribution of wind speed errors obtained from a regression of wind speed errors on an intercept term. The blue dotted histogram is the wind speed error distribution conditional on track errors obtained from the residuals of a regression of wind speed errors on an intercept term and track error. The red histogram is the wind speed error distribution predicted by track error, which comes from the fitted values of the same regression used for the blue dotted histogram. Panel C shows the fitted relationship between between wind speed level errors and track distance level errors. Panel D shows a heatmap of total economic damages between wind speed error bins and track distance error bins. Lighter colors imply more higher damage. Data are from counties within 400 km from the forecast and observed hurricane track. The number of observations is 15,018.