The Social Value of Hurricane Forecasts
Supplemental Appendix

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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 are 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 suggests 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 reproduce 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.

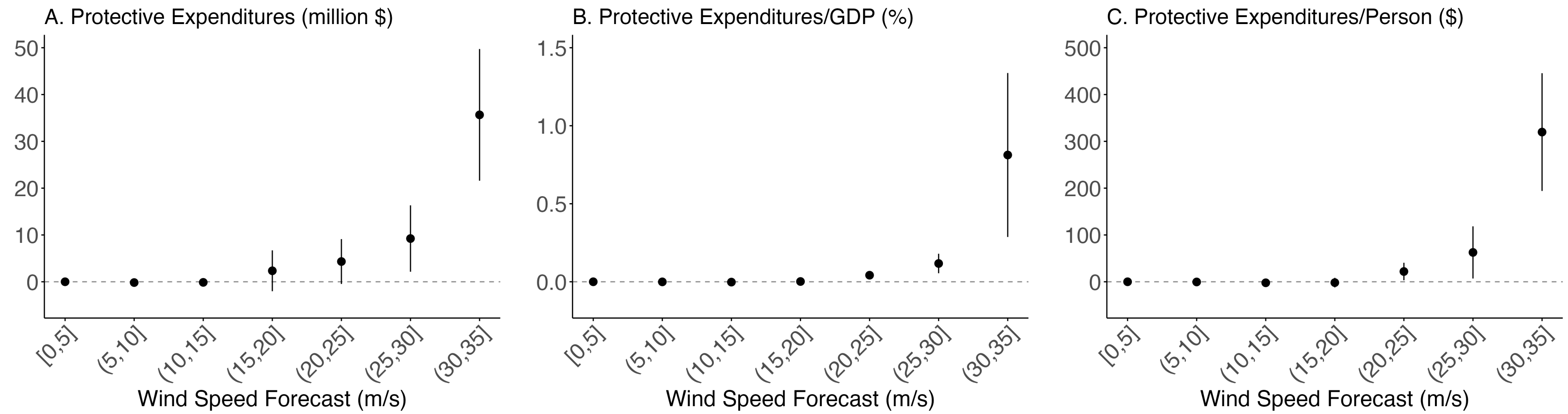
Figure C.12 presents estimates of the effect of wind speed forecasts when conditioning or not conditioning on the distance to the track forecast. Results are nearly identical to our main results. Track forecasts are not driving our findings that wind speed forecasts affect FEMA protective expenditures.

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			✓	✓

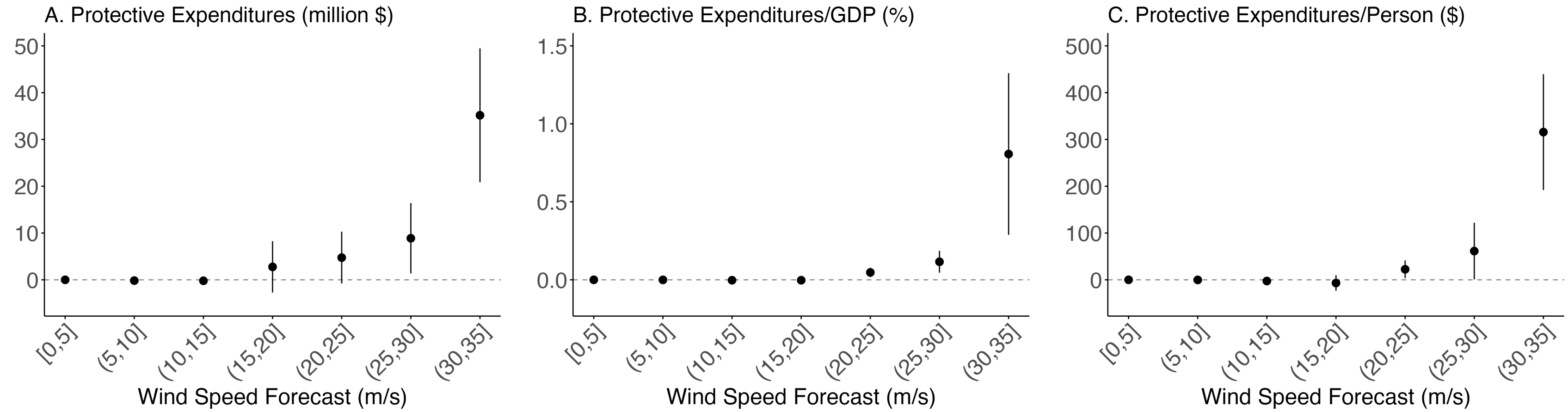
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Standard errors are Conley Spatial HAC with a distance radius of 400 km for spatial correlation and arbitrary autocorrelation within counties.

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.

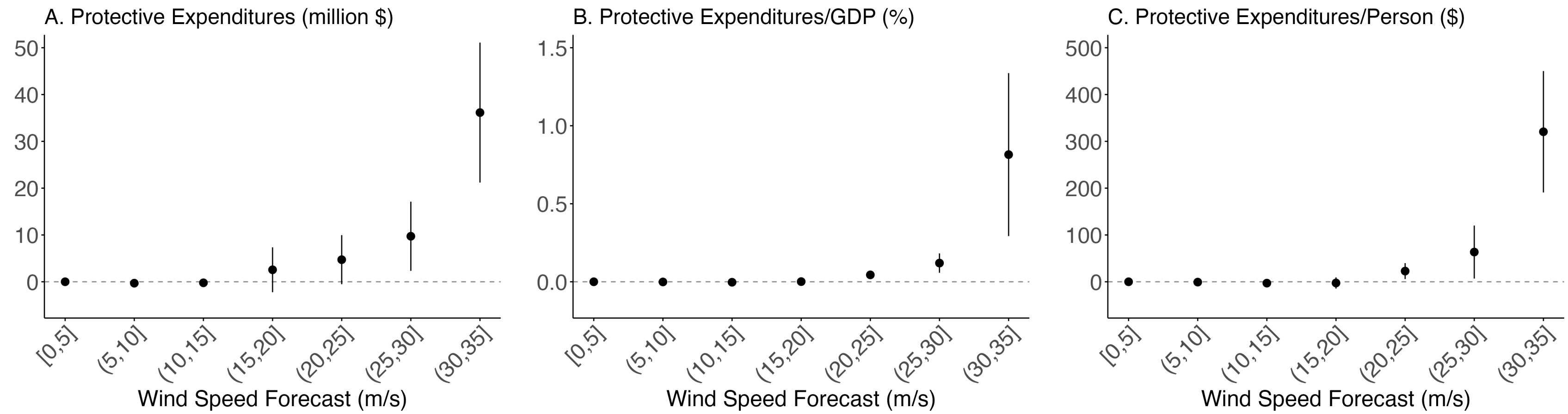
Figure C.2. FEMA Protective Expenditures Responses to Forecasts: PDD Robustness.



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.

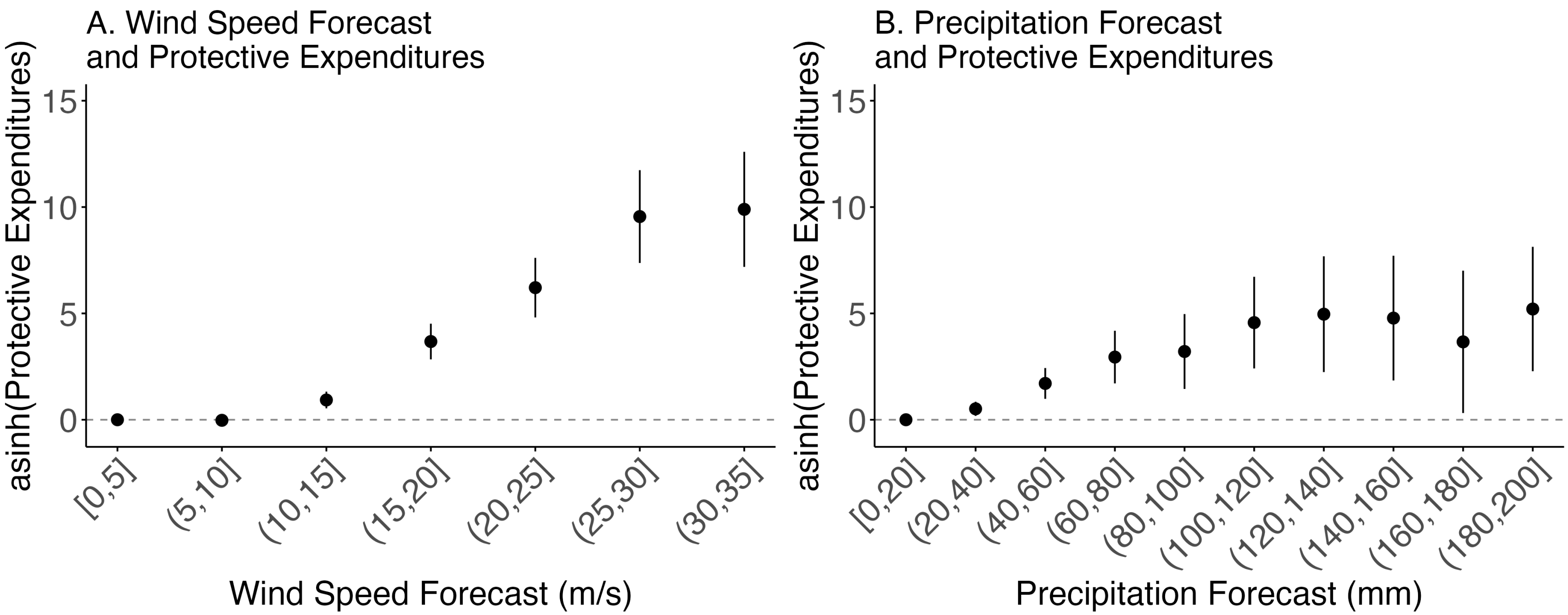
5

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



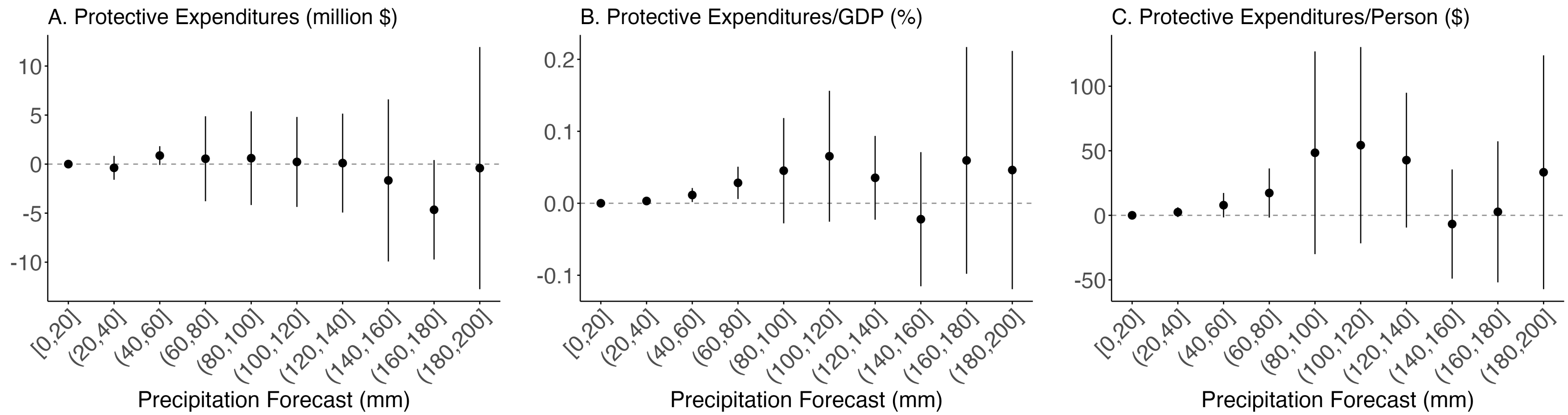
Note: Points are point estimates and the bars are the 95% confidence intervals. The omitted category for each panel is [0,5]. All panels control for bins for the precipitation forecast, and for county and state-by-hurricane fixed effects. Standard errors are Conley Spatial HAC with a distance radius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

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.

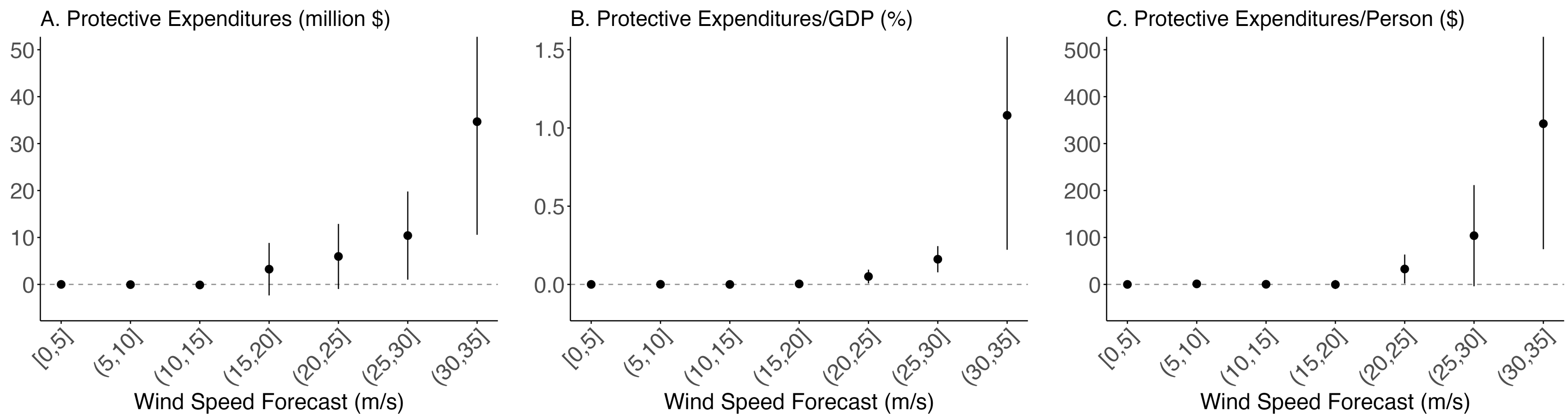
Figure C.5. FEMA Protective Expenditures Responses to Forecasts: Precipitation.



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.

8

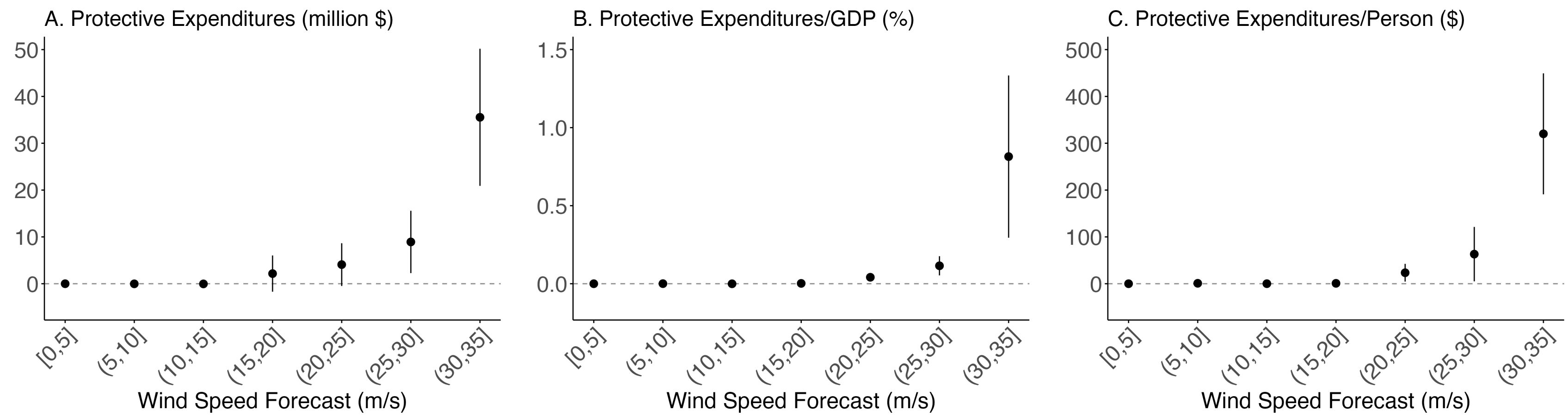
Figure C.6. FEMA Protective Expenditures Responses to Forecasts (No Early Declarations).



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.

9

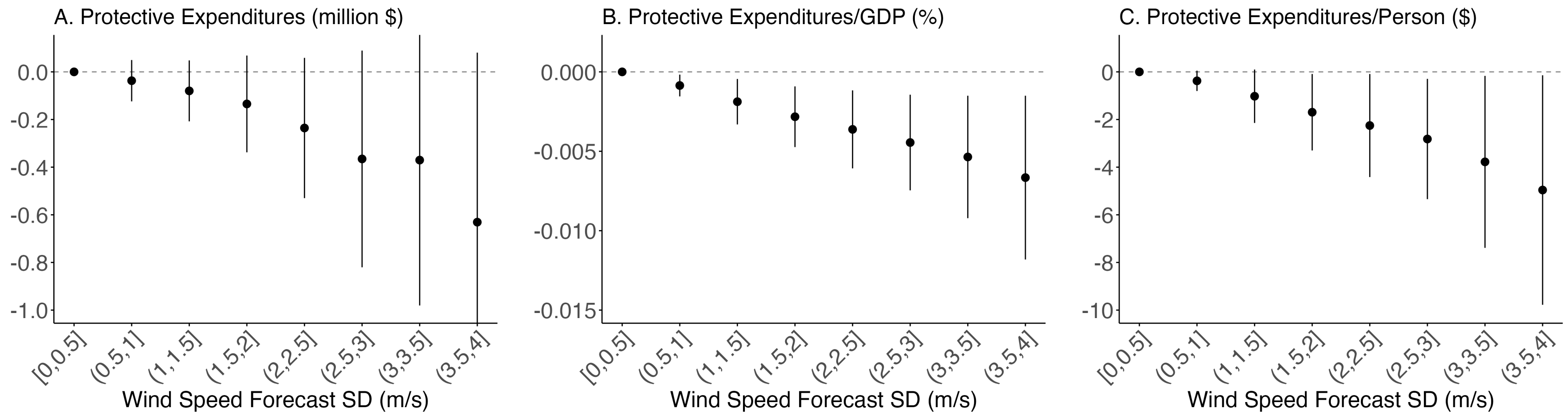
Figure C.7. FEMA Protective Expenditures Responses to Forecasts with Intensity Controls.



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.

10

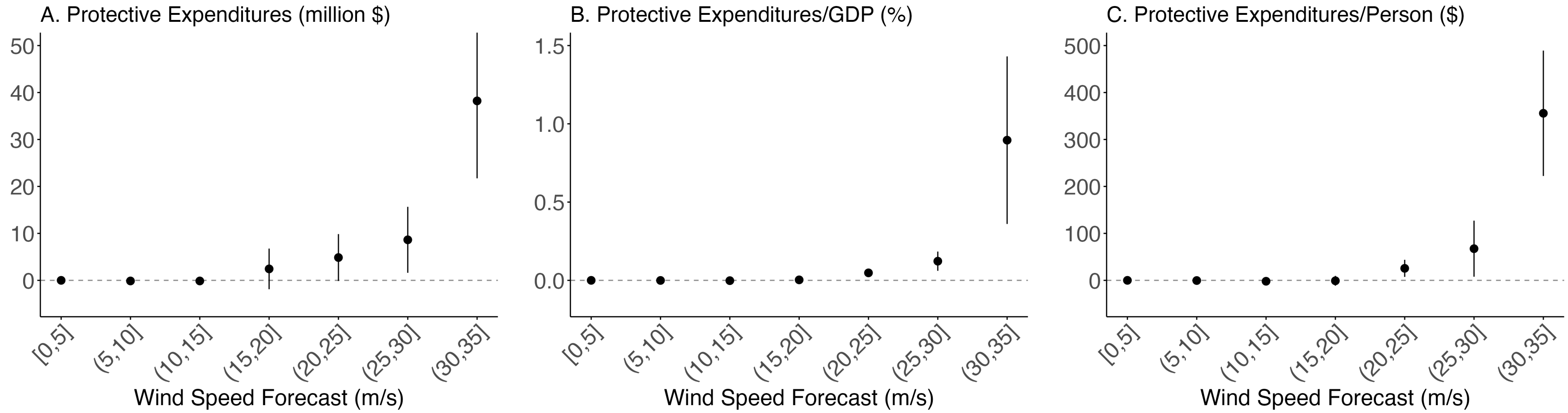
Figure C.8. FEMA Protective Expenditure Responses to Forecast Uncertainty.



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.

11

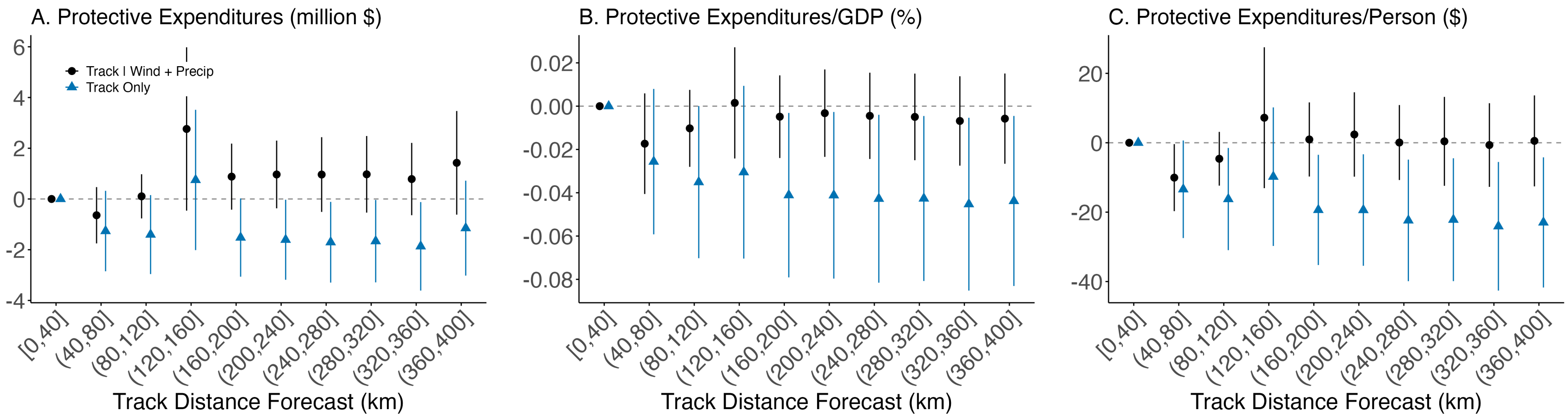
Figure C.9. FEMA Protective Expenditures Responses to Forecasts with Population-Weighted Wind Aggregation.



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.

12

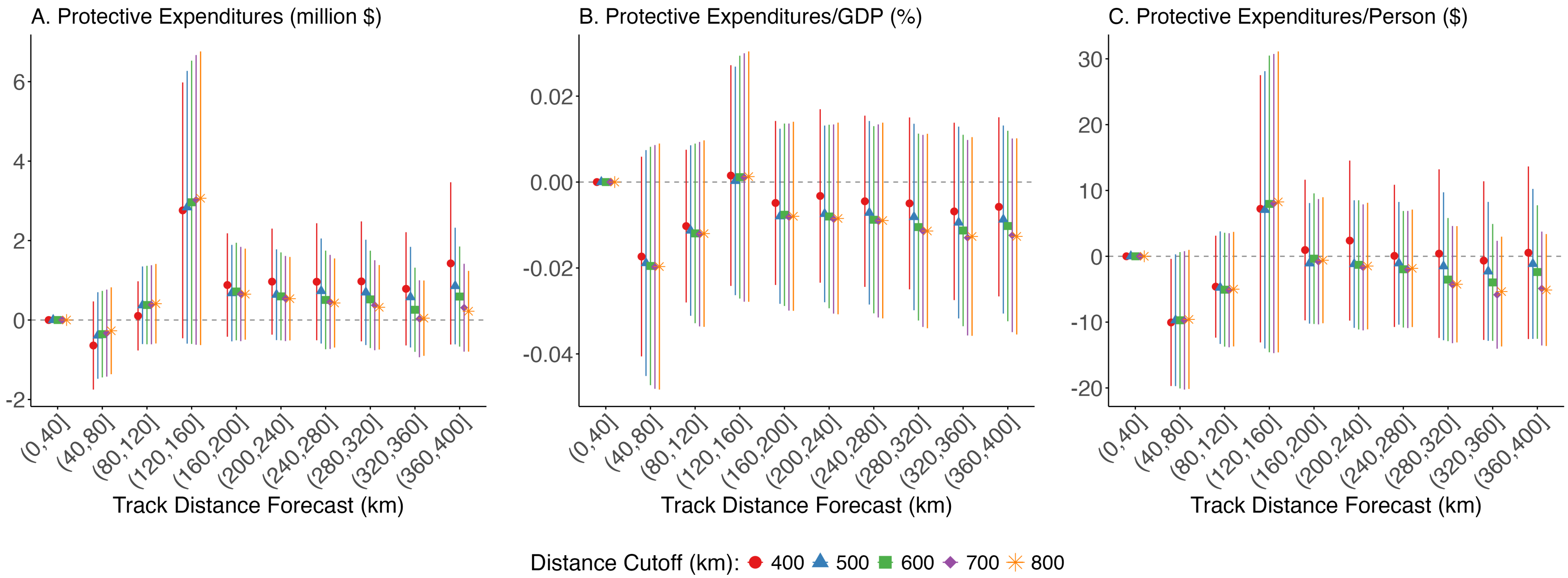
Figure C.10. FEMA Protective Expenditures Responses to Track Forecasts.



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.

13

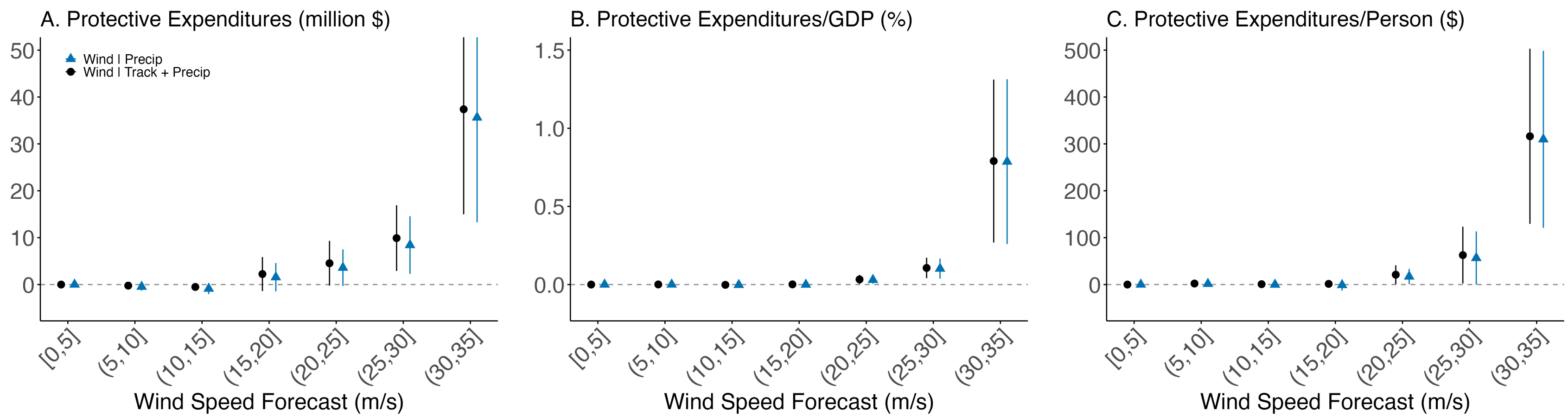
Figure C.11. FEMA Protective Expenditures Responses to Track Forecasts with Multiple Distance Cutoffs.



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.

14

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.

15

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 over $27 million per county, or $567 per person. Precipitation estimates are noisy, negative, and orders 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 remain 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 stems 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 $)				
Wind Forecast Underestimate (m/s)	26.77**	27.51***	27.89**	27.13**
	(11.72)	(10.67)	(13.93)	(12.14)
Precip Forecast Underestimate (mm)	-0.51	-0.68	-0.97	-1.11
	(1.31)	(1.27)	(1.67)	(1.53)
(Damages + Recovery Expenditures) / GDP (%)				
Wind Forecast Underestimate (m/s)	1.26**	1.28***	1.22**	1.29***
	(0.50)	(0.45)	(0.48)	(0.43)
Precip Forecast Underestimate (mm)	-0.05*	-0.06**	-0.06*	-0.07**
	(0.03)	(0.03)	(0.03)	(0.03)
(Damages + Recovery Expenditures) / Person ($)				
Wind Forecast Underestimate (m/s)	513.10***	519.61***	535.96**	566.91***
	(189.61)	(177.48)	(216.57)	(200.81)
Precip Forecast Underestimate (mm)	-25.56**	-27.80**	-33.25**	-37.30**
	(11.54)	(11.61)	(15.79)	(15.82)
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			✓	✓

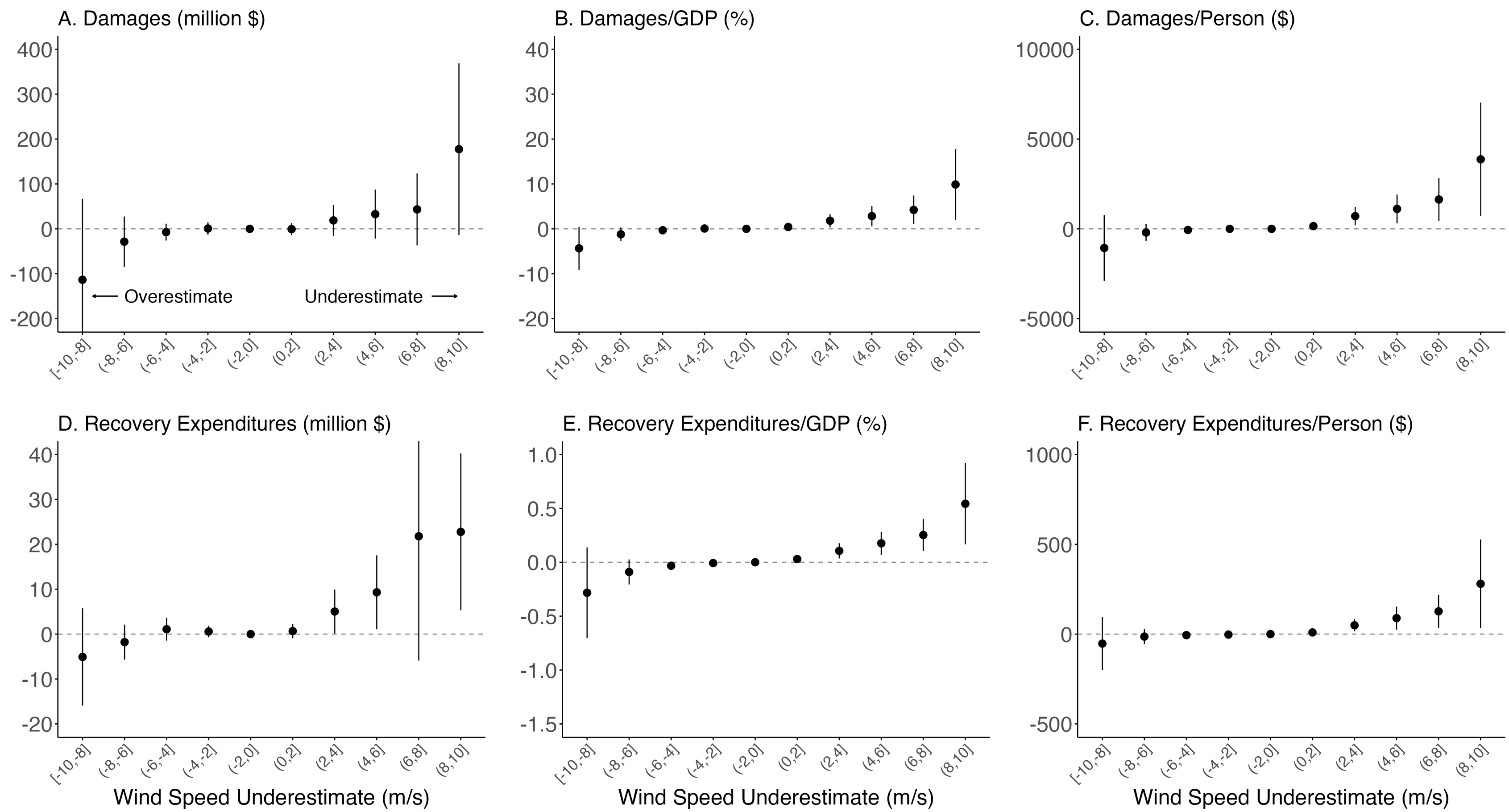
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Standard errors are Conley Spatial HAC with a distance radius of 400 km for spatial correlation and arbitrary autocorrelation within counties.

Table C.3—The 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 $)				
Wind Forecast Underestimate (m/s): Hurricane	68.99***	68.82***	75.20**	71.13***
	(26.43)	(23.20)	(31.92)	(25.89)
Wind Forecast Underestimate (m/s): Sub-Hurricane	-3.87	-2.93	-8.32	-6.07
	(4.74)	(4.11)	(6.18)	(4.46)
(Damages + Recovery Expenditures) / GDP (%)				
Wind Forecast Underestimate (m/s): Hurricane	2.81***	2.80***	2.69***	2.74***
	(0.93)	(0.83)	(0.92)	(0.79)
Wind Forecast Underestimate (m/s): Sub-Hurricane	0.14	0.15	0.09	0.19*
	(0.11)	(0.10)	(0.11)	(0.11)
(Damages + Recovery Expenditures) / Person ($)				
Wind Forecast Underestimate (m/s): Hurricane	1153.73***	1156.30***	1211.46***	1241.08***
	(383.31)	(353.06)	(455.64)	(394.79)
Wind Forecast Underestimate (m/s): Sub-Hurricane	48.12	50.65	18.91	58.42
	(34.43)	(32.19)	(43.57)	(36.14)
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			✓	✓

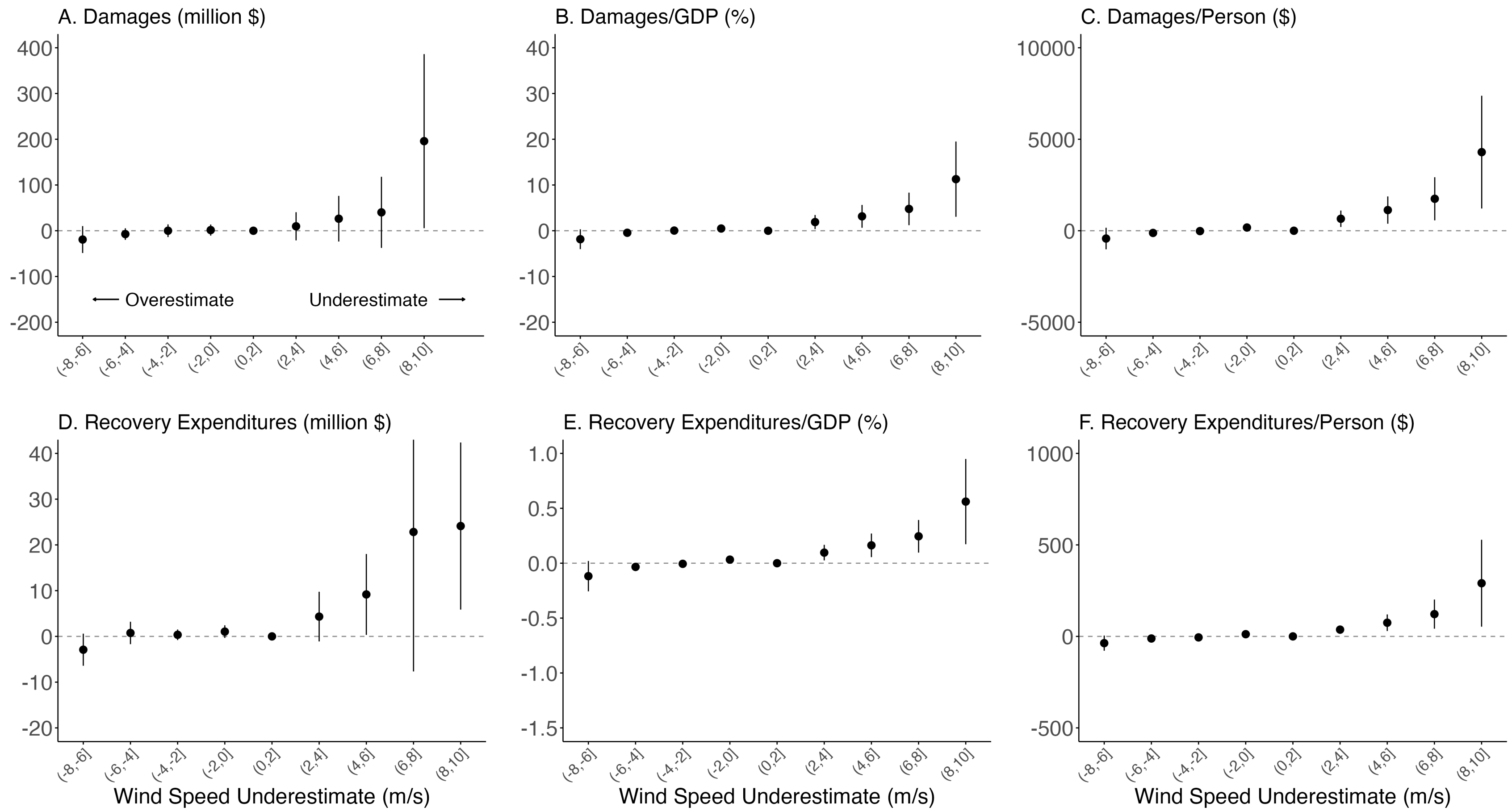
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Standard errors are Conley Spatial HAC with a distance radius of 400 km for spatial correlation and arbitrary autocorrelation within counties. Hurricane wind speeds are those greater than 33 m/s (74 mph), while Sub-Hurricane wind speeds fall below that threshold.

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.

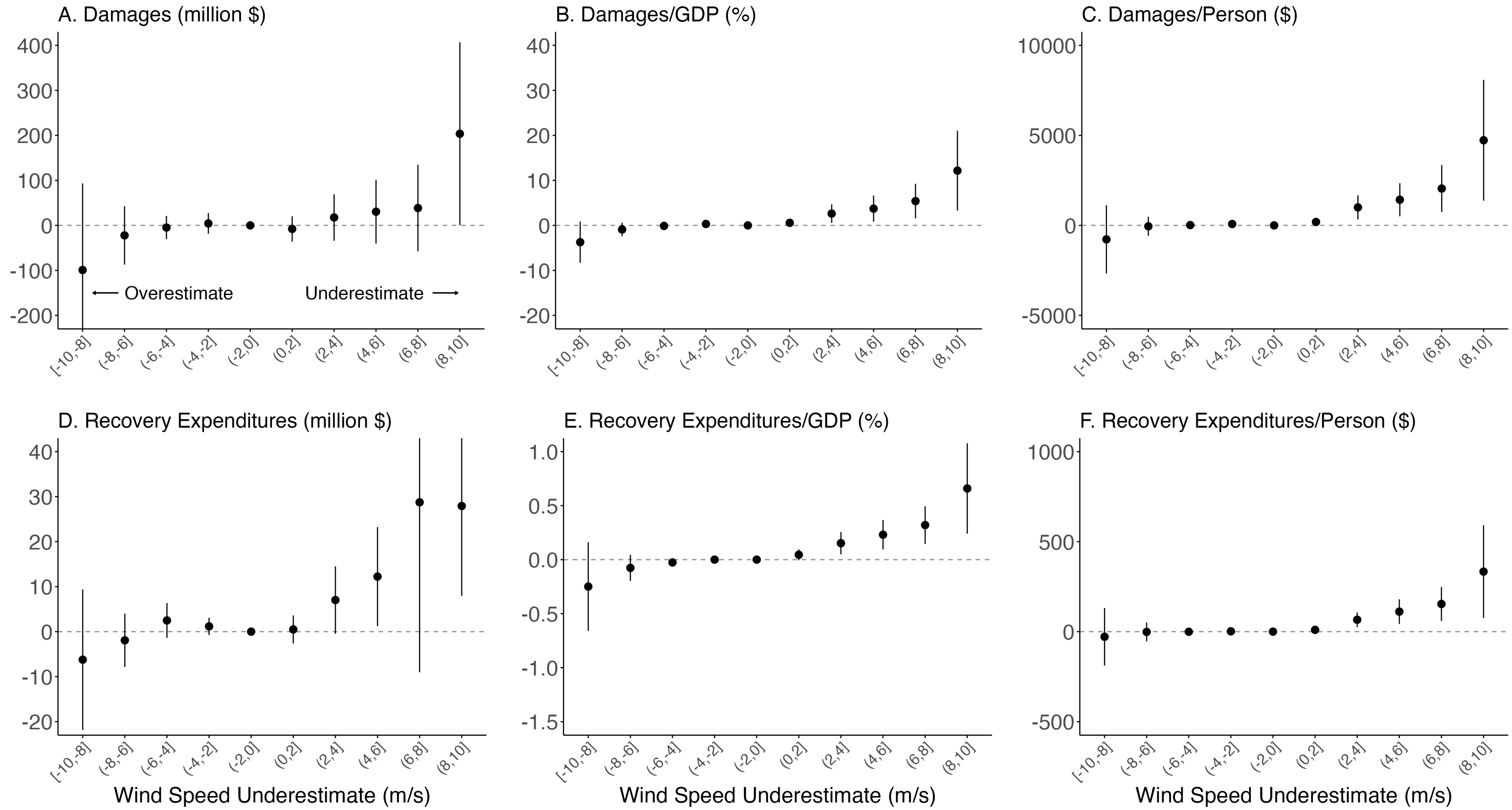
Figure C.14. Forecast Errors, Damages, and *Ex Post* Recovery Expenditures: PDD Robustness.



21

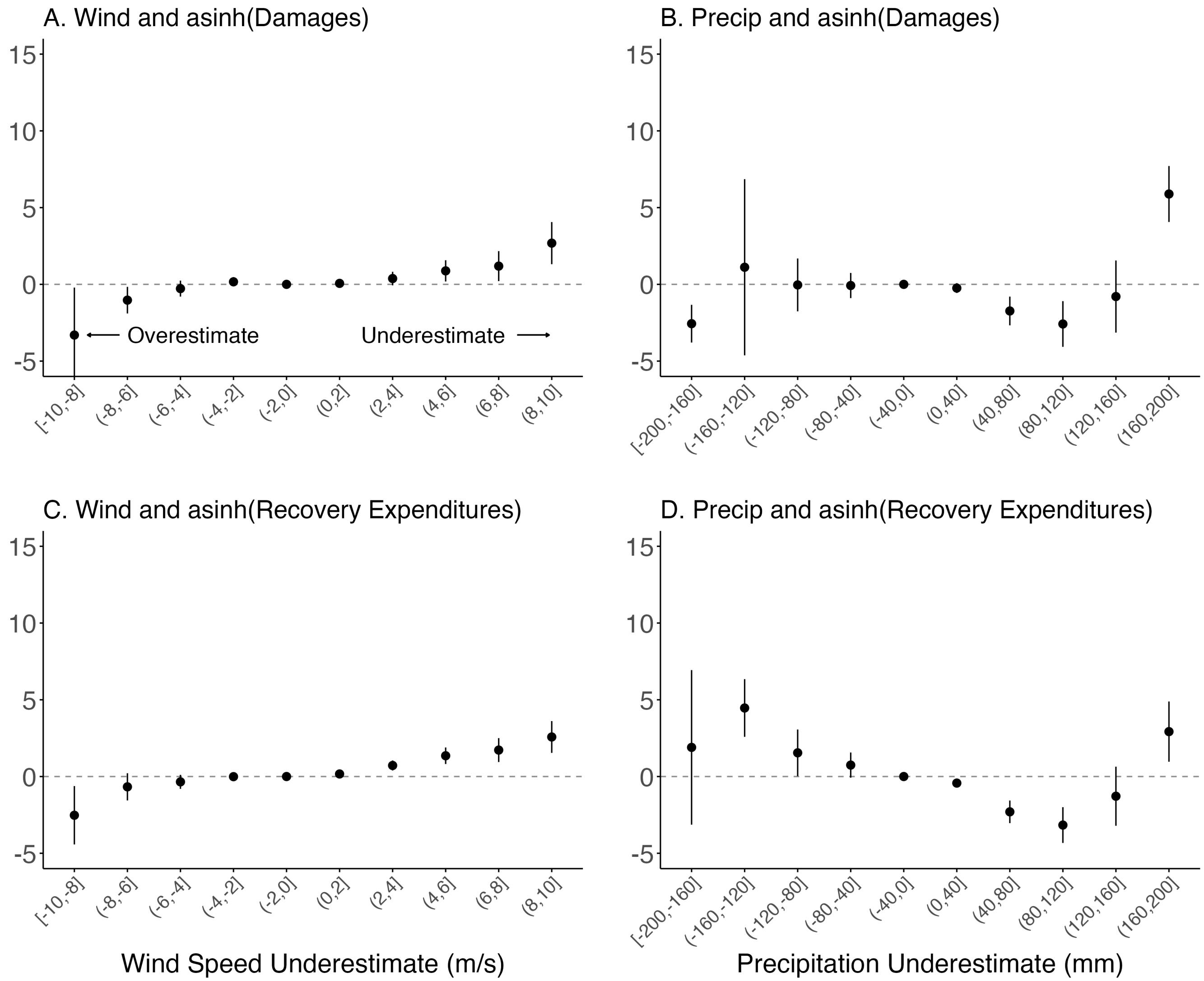
Note: Points are point estimates, and the bars are the 95% confidence intervals. The omitted category is $(-2, 0]$. All panels control for binned precipitation errors, binned realized wind speed, binned realized precipitation, and for county and state-by-hurricane fixed effects. Standard errors are Conley 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.

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.

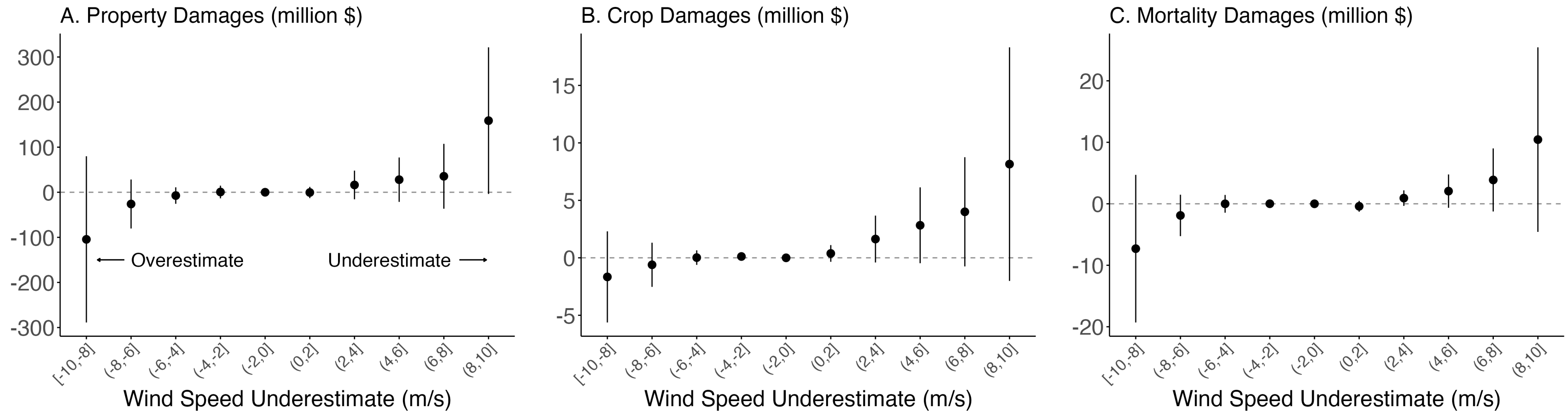
Figure C.16. Forecast Errors, Damages, and *Ex Post* Recovery Expenditures: Inverse Hyperbolic Sine.



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.

23

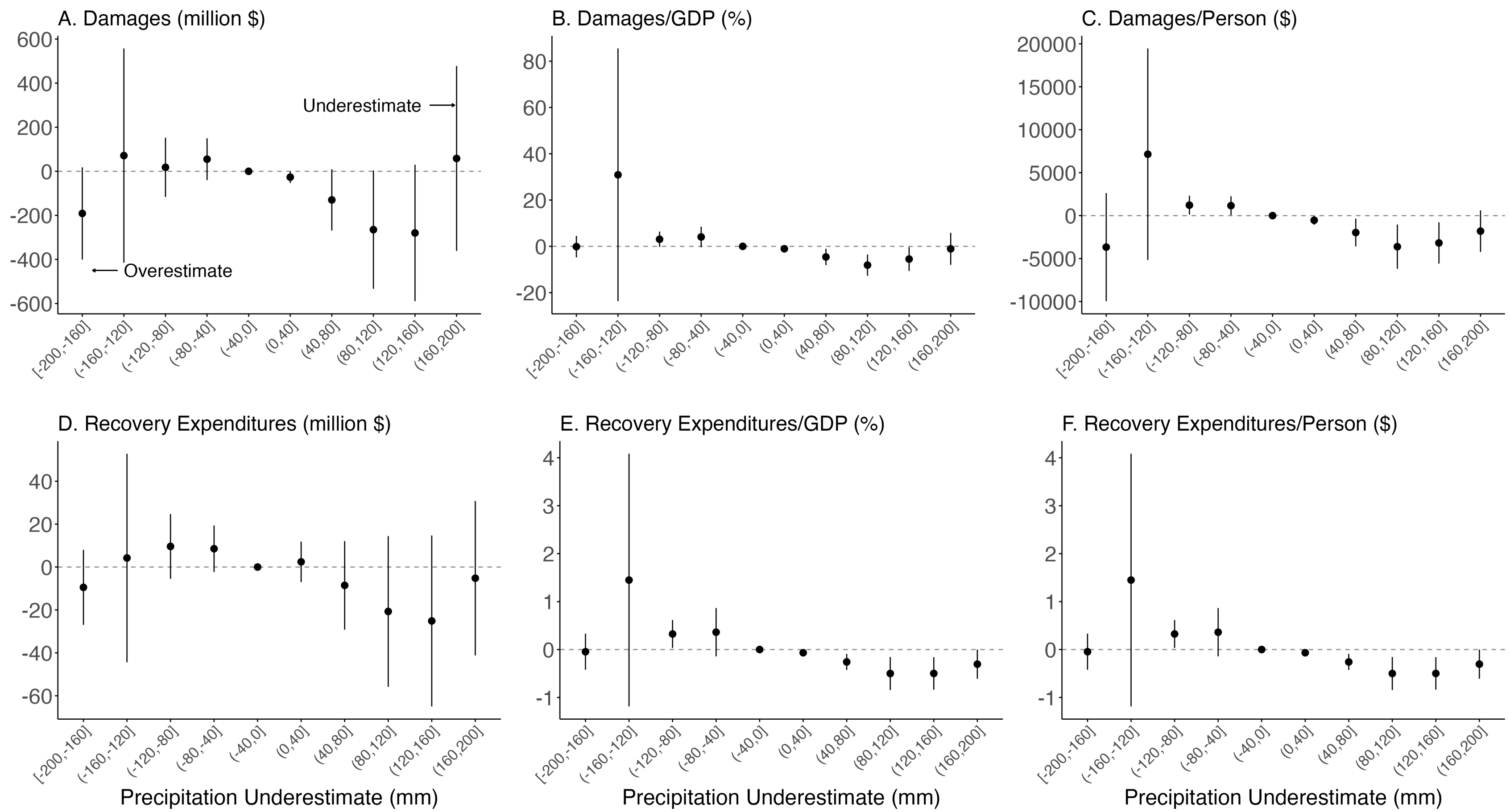
Figure C.17. Forecast Errors, Damages, and *Ex Post* Recovery Expenditures: By Damage Type.



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.

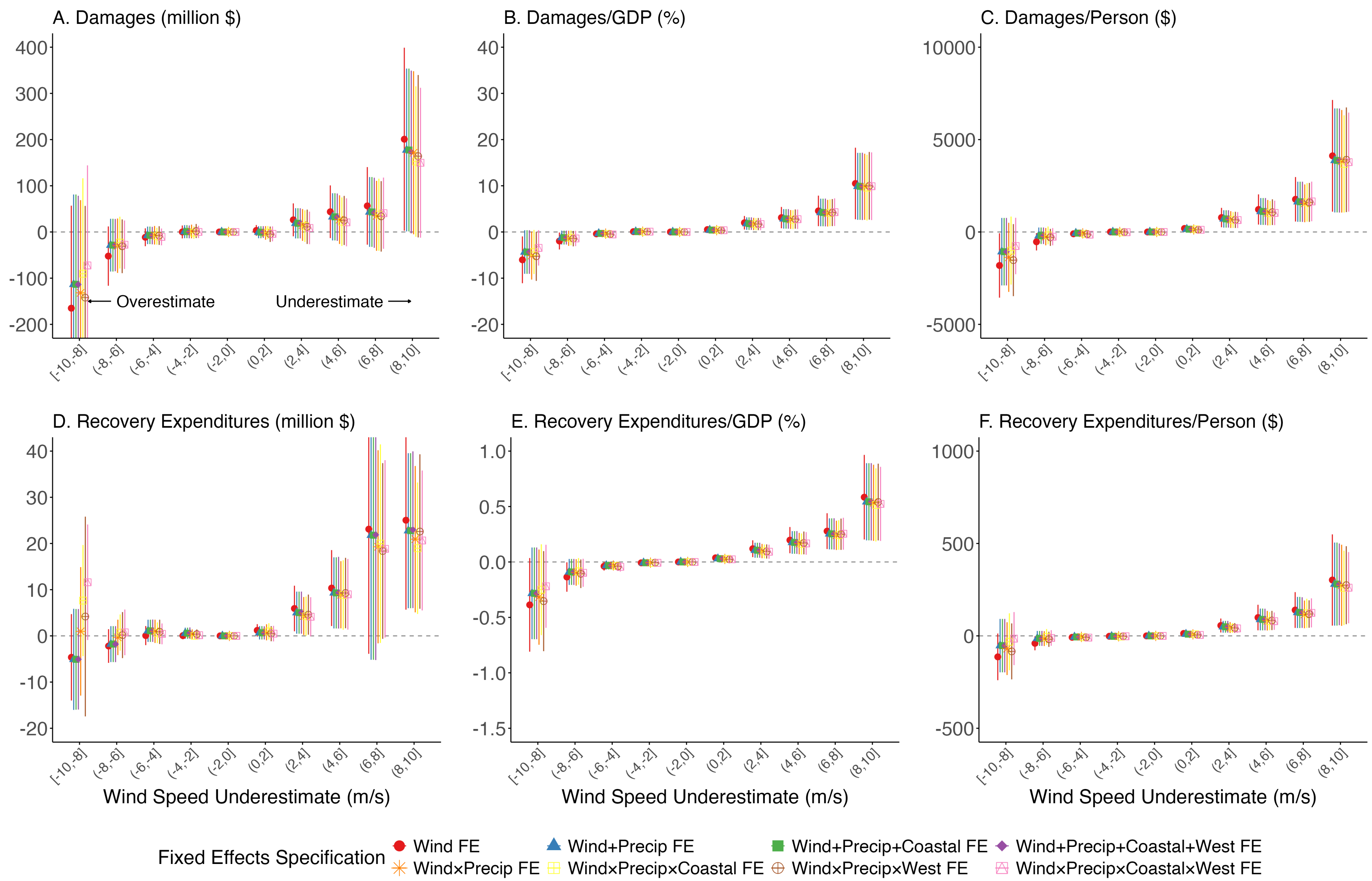
24

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.

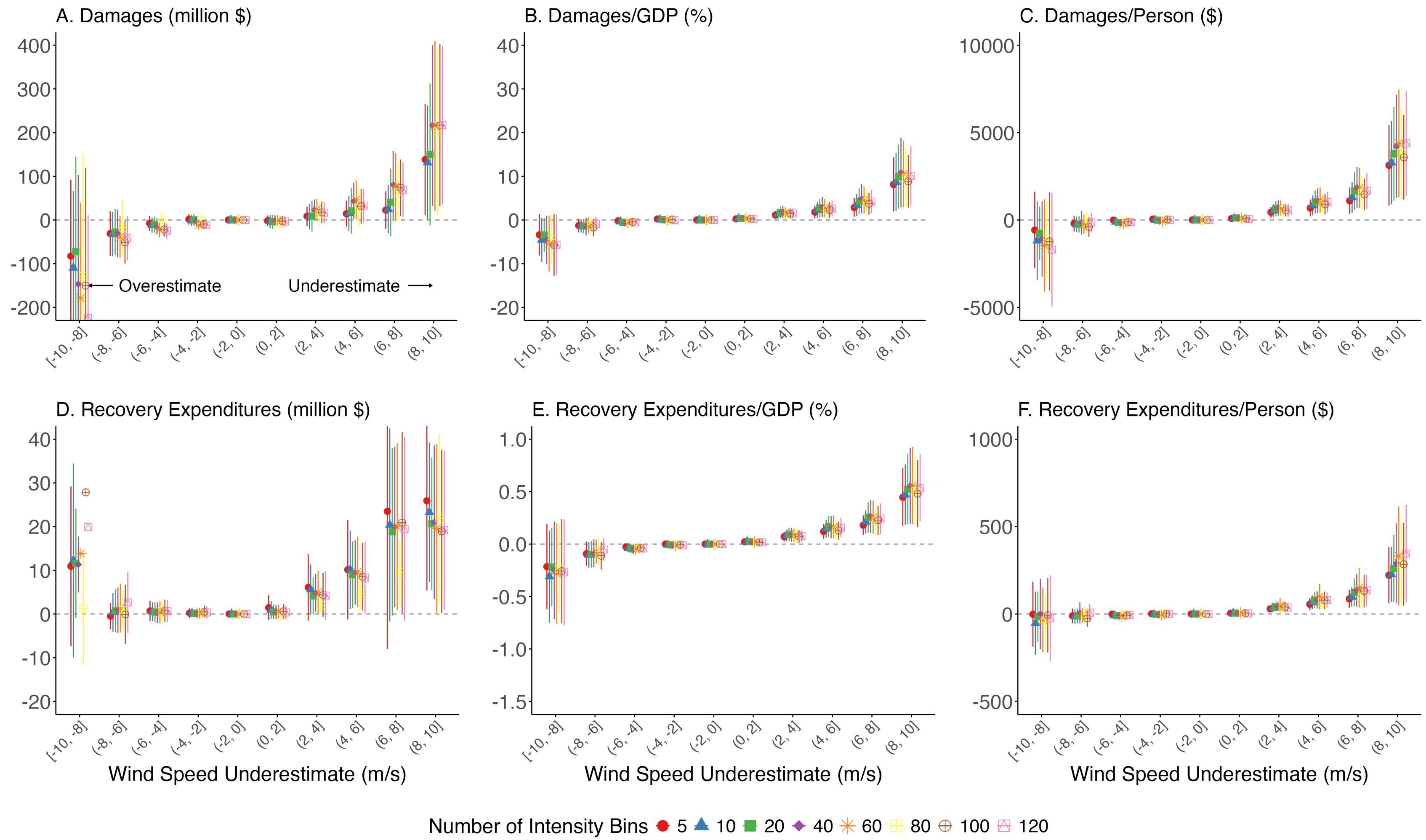
FIGURE C.19. FORECAST ERRORS, DAMAGES, AND *Ex Post* RECOVERY EXPENDITURES WITH MULTIPLE FIXED EFFECTS.



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.

26

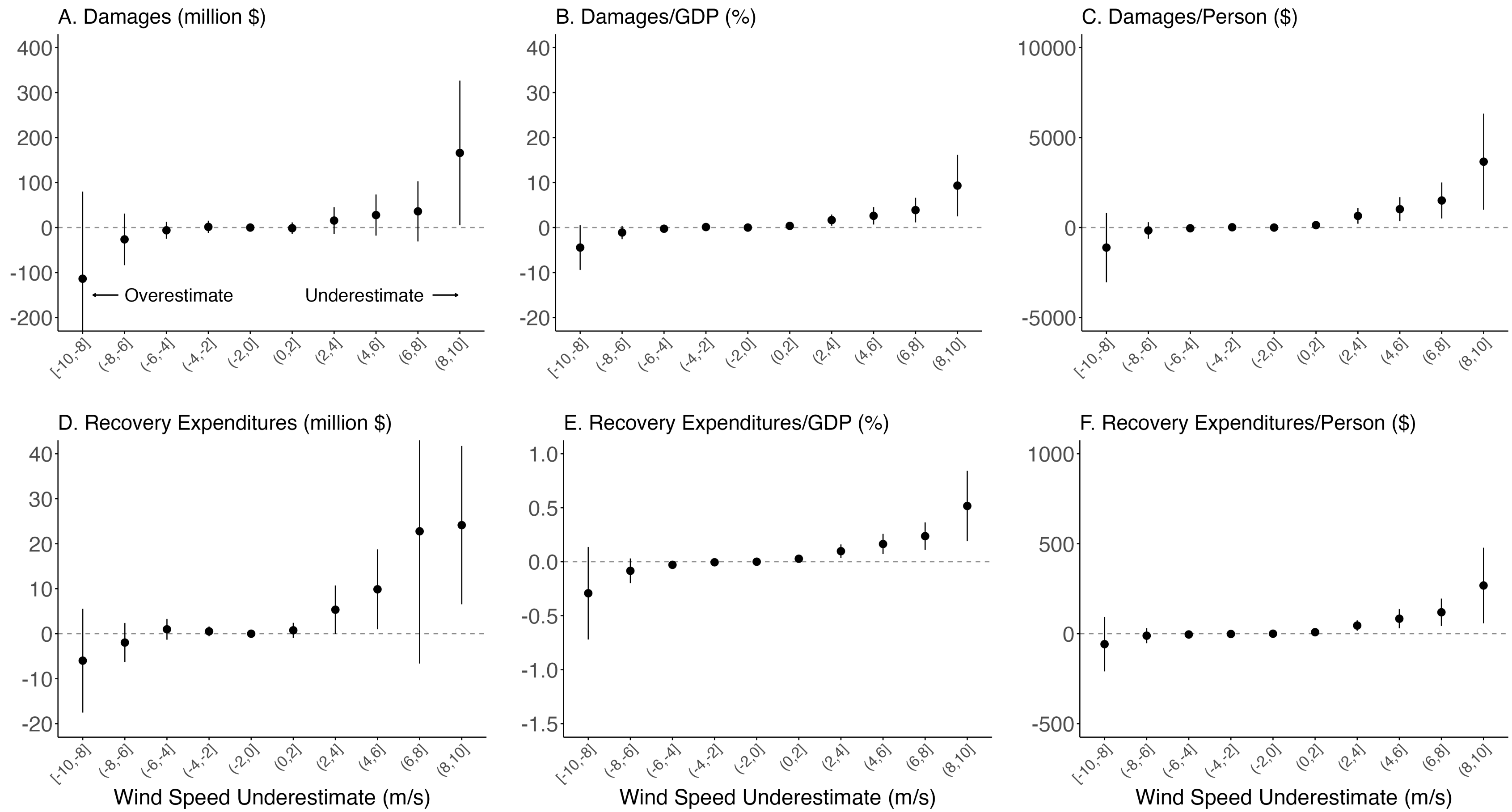
Figure C.20. Forecast Errors, Damages, and *Ex Post* Recovery Expenditures with Multiple Bin Sizes.



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.

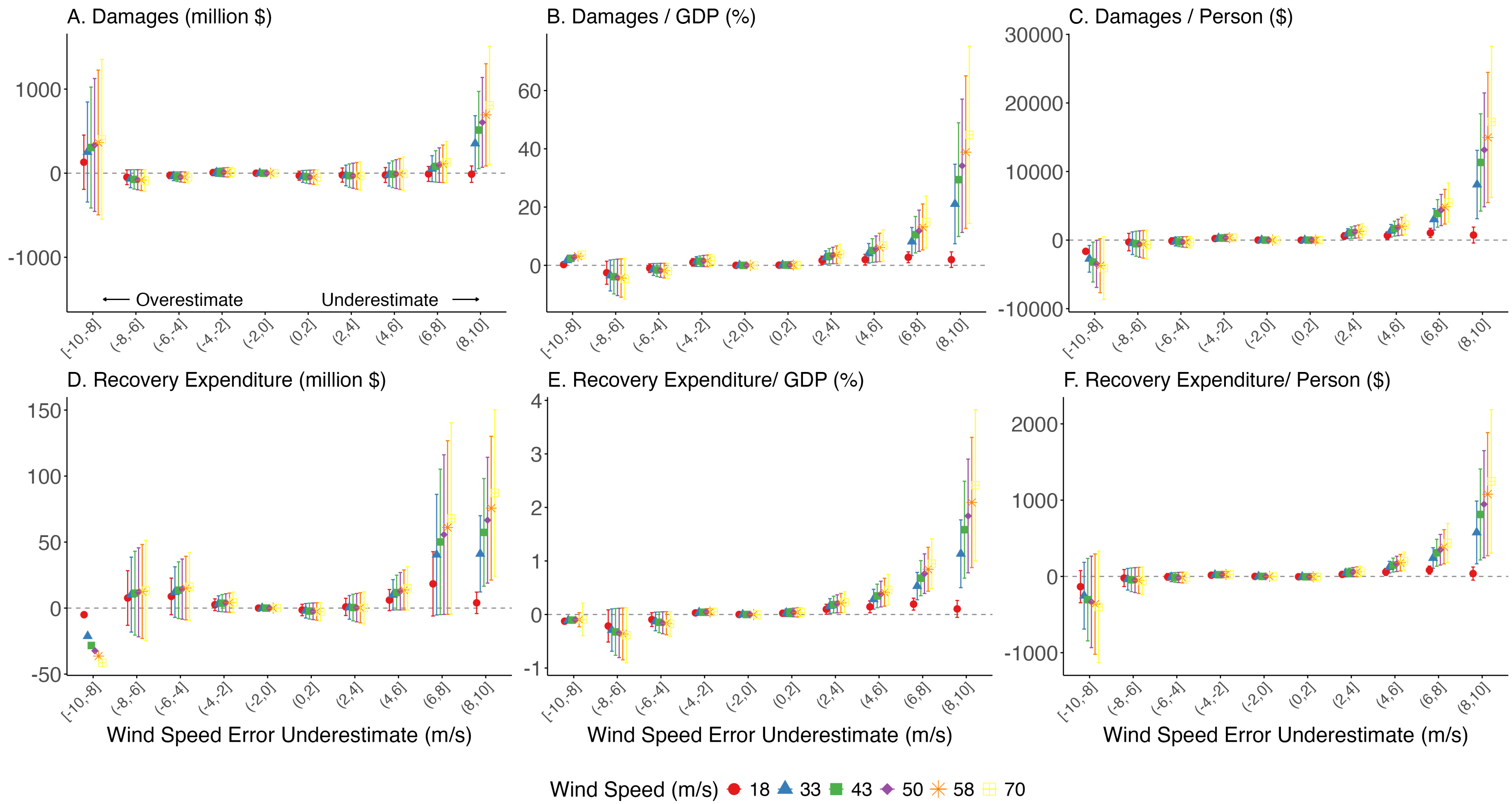
27

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.

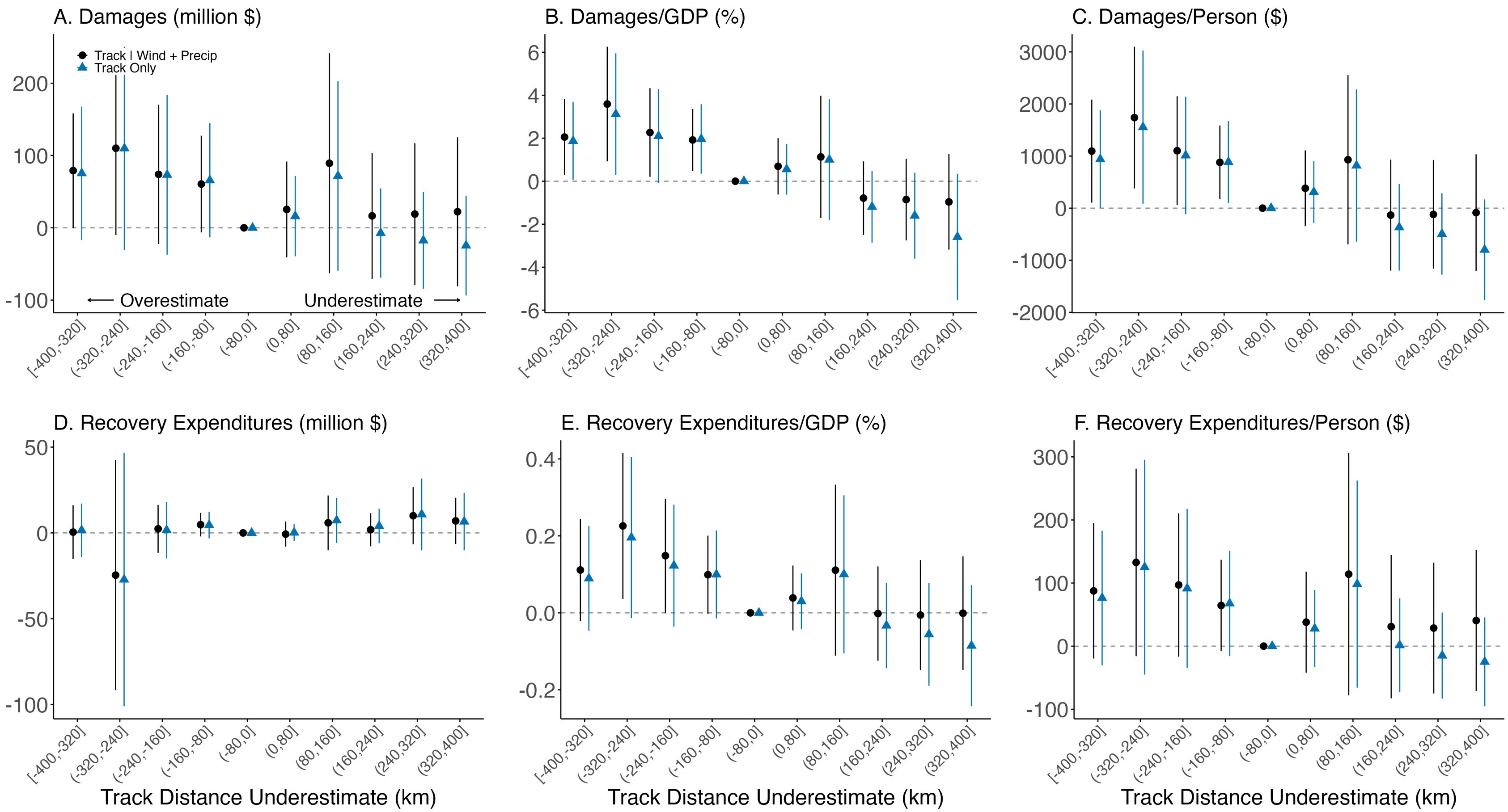
Figure C.22. Wind Forecast Errors, Wind Intensity, and Their Interaction Effects on Damages and Recovery Expenditures



29

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. Each color represents a different 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.

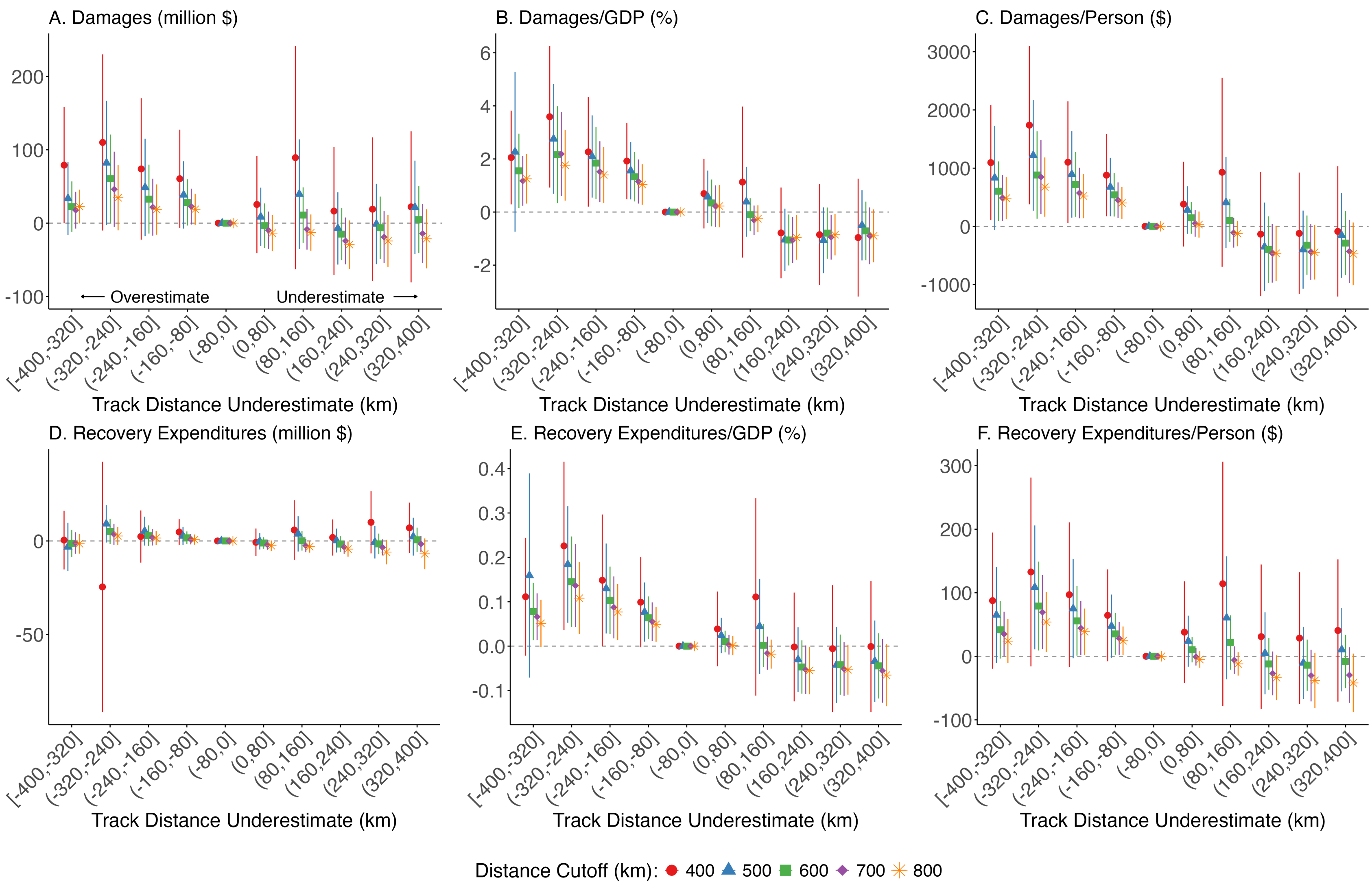
Figure C.23. Track Forecast Errors, Damages, and *Ex Post* Recovery Expenditures.



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.

30

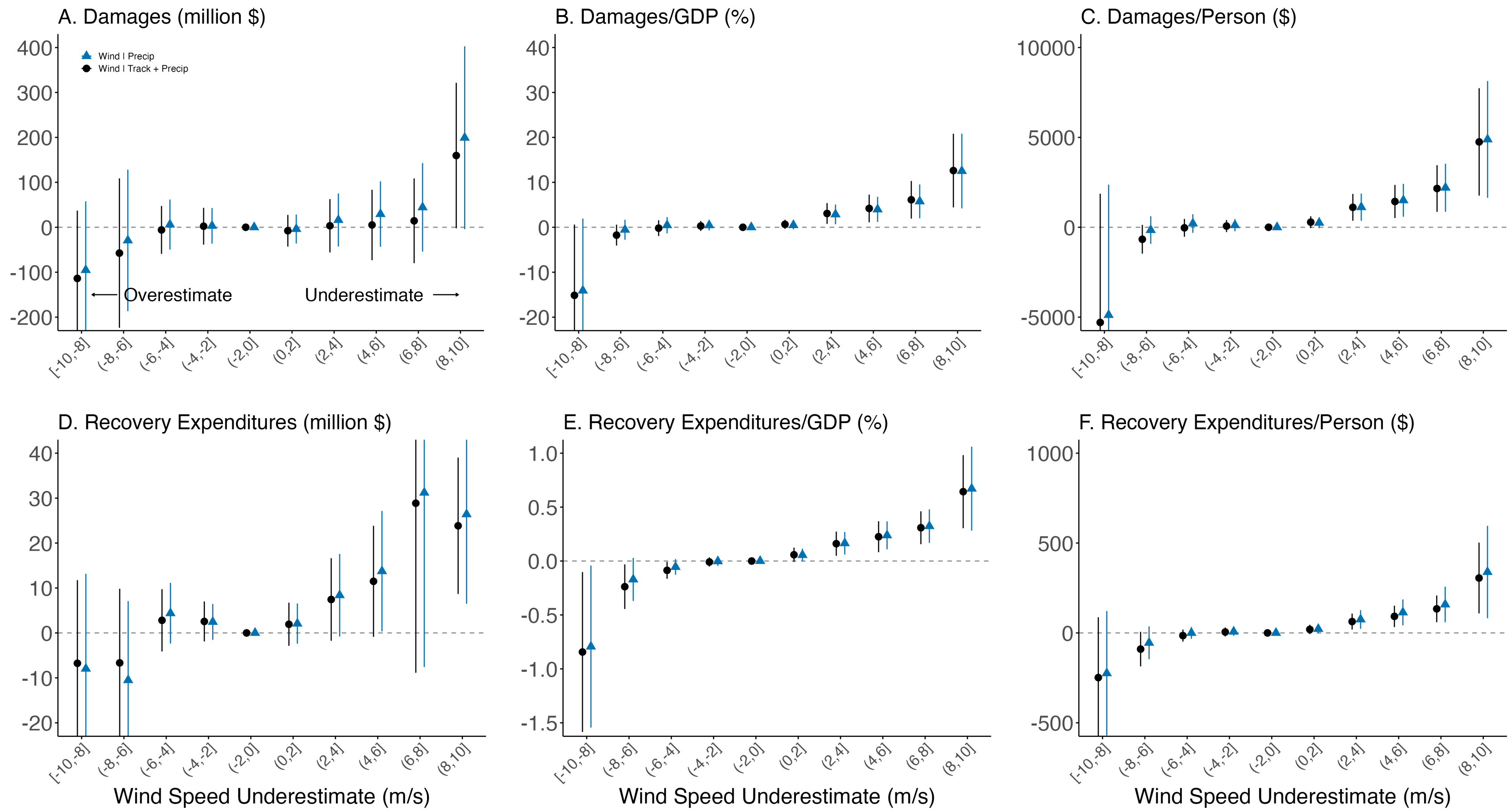
Figure C.24. Track Forecast Errors, Damages, and *Ex Post* Recovery Expenditures with Multiple Distance Cutoffs.



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.

31

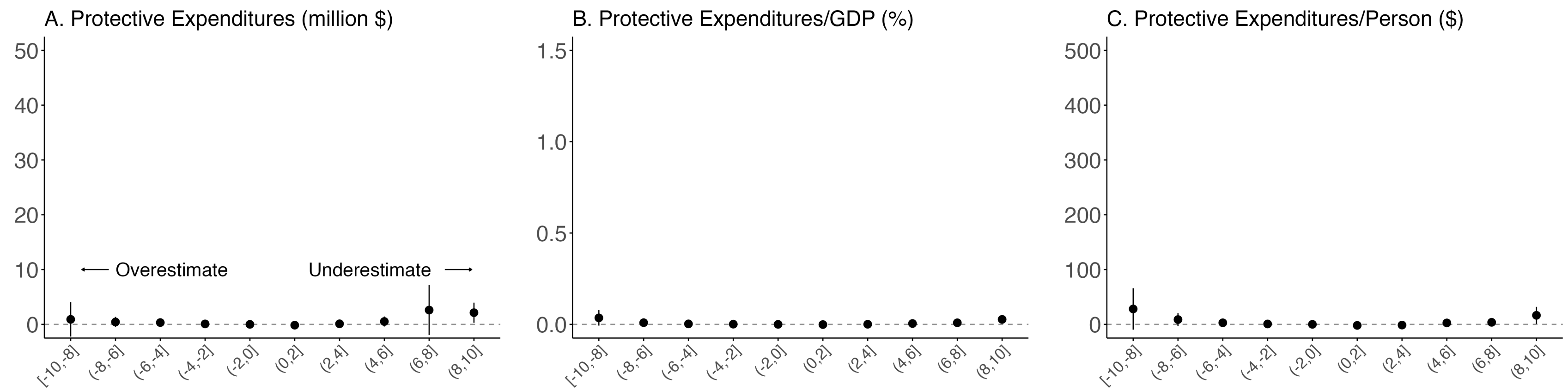
Figure C.25. Forecast Errors, Damages, and *Ex Post* Recovery Expenditures with Track Controls.



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.

32

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.

33

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 main 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 comes solely from 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. Across specifications and outcomes, the estimated effects are attenuated by up to about 40%, but remain large and statistically significant. This indicates that improving wind speed forecasts, conditional on correctly predicting hurricane status, continues to generate substantial economic value.

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 most 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 bottom 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 over $300 per person 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 results 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 $44 million per hurricane per county.

The key assumption underlying the estimate in equation (7) 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:

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

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.[31]

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 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

[31] 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.

each hurricane. Both sets of estimates corroborate the 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 \$)					
$\beta_2 : (e-\mu)^2$	3.57***	3.54***	4.19***	4.03***	
	(1.24)	(1.13)	(1.57)	(1.32)	
Hurricane $\beta_2 : (e-\mu)^2$					5.16***
					(1.94)
Sub-Hurricane $\beta_2 : (e-\mu)^2$					0.06
					(0.51)
(Damages + Recovery Expenditures) / GDP (%)					
$\beta_2 : (e-\mu)^2$	0.20***	0.20***	0.20***	0.20***	
	(0.07)	(0.06)	(0.07)	(0.06)	
Hurricane $\beta_2 : (e-\mu)^2$					0.29***
					(0.08)
Sub-Hurricane $\beta_2 : (e-\mu)^2$					0.01
					(0.01)
Damages + Recovery Expenditures Per Capita (\$/person)					
$\beta_2 : (e-\mu)^2$	79.61***	81.31***	86.95***	91.12***	
	(22.92)	(22.39)	(28.94)	(25.82)	
Hurricane $\beta_2 : (e-\mu)^2$					114.02***
					(31.53)
Sub-Hurricane $\beta_2 : (e-\mu)^2$					3.90
					(4.27)
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, and μ is the hurricane-intensity bin-specific mean forecast error. Hurricane wind speeds are those greater than 33 m/s (74 mph), while Sub-Hurricane wind speeds fall below that threshold.

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

	(1)	(2)	(3)	(4)	(5)
Damages + Recovery Expenditures (million \$)					
$\beta_2 : (e-\mu)^2$	3.71***	3.72***	4.30***	4.09***	
	(1.29)	(1.20)	(1.65)	(1.29)	
Hurricane $\beta_2 : (e-\mu)^2$					5.25***
					(2.02)
Sub-Hurricane $\beta_2 : (e-\mu)^2$					-0.02
					(0.54)
(Damages + Recovery Expenditures) / GDP (%)					
$\beta_2 : (e-\mu)^2$	0.22***	0.22***	0.22***	0.22***	
	(0.06)	(0.06)	(0.07)	(0.06)	
Hurricane $\beta_2 : (e-\mu)^2$					0.30***
					(0.08)
Sub-Hurricane $\beta_2 : (e-\mu)^2$					0.01
					(0.01)
Damages + Recovery Expenditures Per Capita (\$/person)					
$\beta_2 : (e-\mu)^2$	84.36***	87.04***	96.20***	93.52***	
	(22.25)	(21.85)	(28.34)	(22.98)	
Hurricane $\beta_2 : (e-\mu)^2$					118.16***
					(31.41)
Sub-Hurricane $\beta_2 : (e-\mu)^2$					1.97
					(4.68)
Observations	94,031	94,031	94,031	94,031	94,031
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, and μ is the hurricane-intensity bin-specific mean forecast error. Hurricane wind speeds are those greater than 33 m/s (74 mph), while Sub-Hurricane wind speeds fall below that threshold. 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 \$)					
$\beta_2 : (e-\mu)^2$	3.63***	3.59***	4.31***	4.13***	
	(1.26)	(1.15)	(1.58)	(1.34)	
Hurricane $\beta_2 : (e-\mu)^2$					5.06***
					(1.88)
Sub-Hurricane $\beta_2 : (e-\mu)^2$					0.25
					(0.53)
(Damages + Recovery Expenditures) / GDP (%)					
$\beta_2 : (e-\mu)^2$	0.24***	0.24***	0.21***	0.21***	
	(0.07)	(0.07)	(0.06)	(0.06)	
Hurricane $\beta_2 : (e-\mu)^2$					0.29***
					(0.08)
Sub-Hurricane $\beta_2 : (e-\mu)^2$					0.02
					(0.02)
Damages + Recovery Expenditures Per Capita (\$/person)					
$\beta_2 : (e-\mu)^2$	94.30***	95.82***	82.05***	94.83***	
	(26.14)	(26.40)	(21.71)	(24.55)	
Hurricane $\beta_2 : (e-\mu)^2$					113.91***
					(29.61)
Sub-Hurricane $\beta_2 : (e-\mu)^2$					6.45
					(4.81)
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, and μ is the hurricane-intensity bin-specific mean forecast error. Hurricane wind speeds are those greater than 33 m/s (74 mph), while Sub-Hurricane wind speeds fall below that threshold. 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 \$)					
$\beta_2 : (e-\mu)^2$	3.08***	3.05***	3.63***	3.48***	
	(1.10)	(1.01)	(1.34)	(1.14)	
Hurricane $\beta_2 : (e-\mu)^2$					4.43**
					(1.72)
Sub-Hurricane $\beta_2 : (e-\mu)^2$					0.10
					(0.46)
Crop Damages (million \$)					
$\beta_2 : (e-\mu)^2$	0.14	0.14*	0.11	0.11*	
	(0.09)	(0.08)	(0.08)	(0.07)	
Hurricane $\beta_2 : (e-\mu)^2$					0.20*
					(0.12)
Sub-Hurricane $\beta_2 : (e-\mu)^2$					0.02
					(0.01)
Mortality Damages (million \$)					
$\beta_2 : (e-\mu)^2$	0.10	0.10	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, and μ is the hurricane-intensity bin-specific mean forecast error. Hurricane wind speeds are those greater than 33 m/s (74 mph), while Sub-Hurricane wind speeds fall below that threshold.

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

	(1)	(2)	(3)	(4)	(5)
Damages + Recovery Expenditures (million \$)					
$\beta_2 : (e-\mu)^2$	1.76**	1.76***	2.04**	1.79**	
	(0.70)	(0.66)	(0.85)	(0.74)	
Hurricane $\beta_2 : (e-\mu)^2$					3.15***
					(1.17)
Sub-Hurricane $\beta_2 : (e-\mu)^2$					-0.12
					(0.20)
(Damages + Recovery Expenditures) / GDP (%)					
$\beta_2 : (e-\mu)^2$	0.08**	0.08**	0.08**	0.08**	
	(0.04)	(0.03)	(0.04)	(0.03)	
Hurricane $\beta_2 : (e-\mu)^2$					0.14***
					(0.05)
Sub-Hurricane $\beta_2 : (e-\mu)^2$					0.01
					(0.01)
Damages + Recovery Expenditures Per Capita (\$/person)					
$\beta_2 : (e-\mu)^2$	31.07**	31.84***	33.79**	35.08***	
	(12.30)	(11.77)	(14.12)	(13.04)	
Hurricane $\beta_2 : (e-\mu)^2$					53.53***
					(17.84)
Sub-Hurricane $\beta_2 : (e-\mu)^2$					0.74
					(2.32)
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, and μ is the hurricane-intensity bin-specific mean forecast error. Hurricane wind speeds are those greater than 33 m/s (74 mph), while Sub-Hurricane wind speeds fall below that threshold.

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 \$)							
$\beta_2 : (e-\mu)^2$	2.39***	2.39***	2.58***	2.58***	2.97***	2.95***	
	(0.74)	(0.74)	(0.79)	(0.79)	(0.91)	(0.90)	
Hurricane $\beta_2 : (e-\mu)^2$							3.82***
							(1.31)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.52
							(0.56)
(Damages + Recovery Expenditures) / GDP (%)							
$\beta_2 : (e-\mu)^2$	0.18***	0.19***	0.18***	0.18***	0.18***	0.18***	
	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	
Hurricane $\beta_2 : (e-\mu)^2$							0.29***
							(0.09)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.01
							(0.01)
Damages + Recovery Expenditures Per Capita (\$/person)							
$\beta_2 : (e-\mu)^2$	69.78***	72.41***	70.99***	73.42***	75.99***	82.55***	
	(18.97)	(19.48)	(18.84)	(18.62)	(21.72)	(20.93)	
Hurricane $\beta_2 : (e-\mu)^2$							109.42***
							(27.43)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							6.67
							(5.22)
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, and μ is the hurricane-intensity bin-specific mean forecast error. Hurricane wind speeds are those greater than 33 m/s (74 mph), while Sub-Hurricane wind speeds fall below that threshold. 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	0.00	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)					
$\beta_2 : (e - \mu)^2$	-0.00	0.02	0.00	0.06	
	(0.03)	(0.03)	(0.03)	(0.05)	
Hurricane $\beta_2 : (e - \mu)^2$					0.19
					(0.14)
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, and μ is the hurricane-intensity bin-specific mean forecast error. Hurricane wind speeds are those greater than 33 m/s (74 mph), while Sub-Hurricane wind speeds fall below that threshold.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Damages + Recovery Expenditures (million \$)								
Hurricane $\beta_2 : (e-\mu)^2$	5.24***	5.16***	5.16***	5.17***	5.12***	4.83***	5.07***	4.52***
	(1.95)	(1.88)	(1.88)	(1.88)	(1.86)	(1.70)	(1.86)	(1.68)
Sub-Hurricane $\beta_2 : (e-\mu)^2$	0.06	0.06	0.06	0.03	0.10	-0.07	0.09	-0.03
	(0.45)	(0.48)	(0.48)	(0.47)	(0.53)	(0.53)	(0.53)	(0.51)
(Damages + Recovery Expenditures) / GDP (%)								
Hurricane $\beta_2 : (e-\mu)^2$	0.29***	0.29***	0.29***	0.29***	0.29***	0.29***	0.29***	0.29***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Sub-Hurricane $\beta_2 : (e-\mu)^2$	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Damages + Recovery Expenditures Per Capita (\$/person)								
Hurricane $\beta_2 : (e-\mu)^2$	115.39***	114.02***	114.02***	114.04***	113.53***	111.31***	113.17***	109.05***
	(30.04)	(29.66)	(29.66)	(29.67)	(29.53)	(28.32)	(29.35)	(27.53)
Sub-Hurricane $\beta_2 : (e-\mu)^2$	4.06	3.90	3.90	3.83	4.52	3.16	4.62	3.47
	(3.80)	(3.97)	(3.97)	(3.97)	(4.13)	(3.66)	(4.29)	(4.05)
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, and μ is the hurricane-intensity bin-specific mean forecast error. Hurricane wind speeds are those greater than 33 m/s (74 mph), while Sub-Hurricane wind speeds fall below that threshold.

44

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 $\beta_2 : (e-\mu)^2$	4.96***	4.69***	4.52***	4.58***	4.72***	4.50***	4.81***	4.25***
	(1.89)	(1.75)	(1.68)	(1.65)	(1.59)	(1.38)	(1.52)	(1.26)
Sub-Hurricane $\beta_2 : (e-\mu)^2$	0.00	-0.07	-0.03	-0.00	-0.15	0.30	-0.23	-0.11
	(0.52)	(0.52)	(0.51)	(0.46)	(0.42)	(0.66)	(0.54)	(0.66)
(Damages + Recovery Expenditures) / GDP (%)								
Hurricane $\beta_2 : (e-\mu)^2$	0.29***	0.29***	0.29***	0.28***	0.29***	0.28***	0.27***	0.26***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)
Sub-Hurricane $\beta_2 : (e-\mu)^2$	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Damages + Recovery Expenditures Per Capita (\$/person)								
Hurricane $\beta_2 : (e-\mu)^2$	113.93***	110.64***	109.05***	104.64***	106.00***	100.86***	102.30***	94.03***
	(29.72)	(27.96)	(27.53)	(25.26)	(25.95)	(22.09)	(23.84)	(21.68)
Sub-Hurricane $\beta_2 : (e-\mu)^2$	3.08	2.55	3.47	3.03	2.79	0.86	0.63	15.22*
	(4.08)	(3.94)	(4.05)	(4.37)	(4.33)	(6.25)	(7.01)	(8.37)
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, and 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 \$)							
$\beta_2 : (e-\mu)^2$	4.15***	4.14***	3.60***	3.58***	4.22***	4.08***	
	(1.48)	(1.49)	(1.21)	(1.11)	(1.53)	(1.31)	
Hurricane $\beta_2 : (e-\mu)^2$							5.16***
							(1.89)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.06
							(0.52)
(Damages + Recovery Expenditures) / GDP (%)							
$\beta_2 : (e-\mu)^2$	0.22***	0.23***	0.21***	0.20***	0.20***	0.20***	
	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	(0.05)	
Hurricane $\beta_2 : (e-\mu)^2$							0.29***
							(0.08)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.01
							(0.01)
Damages + Recovery Expenditures Per Capita (\$/person)							
$\beta_2 : (e-\mu)^2$	89.41***	90.61***	80.28***	82.07***	87.72***	92.33***	
	(25.05)	(25.26)	(21.65)	(21.22)	(26.78)	(24.48)	
Hurricane $\beta_2 : (e-\mu)^2$							113.99***
							(29.79)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							3.86
							(4.14)
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, and μ is the hurricane-intensity bin-specific mean forecast error. Hurricane wind speeds are those greater than 33 m/s (74 mph), while Sub-Hurricane wind speeds fall below that threshold.

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 $)						
$\beta_2 : (e - \mu)^2$	2.33**	3.24***	3.64***	3.86***	4.09***	4.37**
	(1.06)	(1.19)	(1.35)	(1.46)	(1.57)	(1.72)
(Damages + Recovery Expenditures) / GDP (%)						
$\beta_2 : (e - \mu)^2$	0.10***	0.19***	0.23***	0.26***	0.28***	0.31***
	(0.04)	(0.05)	(0.06)	(0.07)	(0.08)	(0.08)
Damages + Recovery Expenditures Per Capita ($/person)						
$\beta_2 : (e - \mu)^2$	46.20**	75.99***	89.01***	96.42***	103.72***	112.97***
	(18.36)	(20.81)	(22.94)	(24.35)	(25.86)	(27.90)
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, and 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).

47

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	0.000	-0.002	
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.002)	
Hurricane $\beta_2 : (e-\mu)^2$							0.115
							(0.074)
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)							
$\beta_2 : (e-\mu)^2$	0.004	0.001	0.007	0.007	0.015	-0.003	
	(0.007)	(0.006)	(0.006)	(0.007)	(0.012)	(0.024)	
Hurricane $\beta_2 : (e-\mu)^2$							1.722*
							(1.023)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.003
							(0.004)
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, and μ is the hurricane-intensity bin-specific mean forecast error. Hurricane wind speeds are those greater than 33 m/s (74 mph), while Sub-Hurricane wind speeds fall below that threshold.

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 $\beta_2 : (e-\mu)^2$							0.137*
							(0.077)
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 $\beta_2 : (e-\mu)^2$							0.003**
							(0.002)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.000
							(0.000)
Damages + Recovery Expenditures Per Capita (\$/person)							
$\beta_2 : (e-\mu)^2$	0.012	0.001	0.003	0.009	0.014	0.006	
	(0.009)	(0.006)	(0.005)	(0.006)	(0.012)	(0.015)	
Hurricane $\beta_2 : (e-\mu)^2$							2.245**
							(1.098)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.005
							(0.004)
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, and μ is the hurricane-intensity bin-specific mean forecast error. Hurricane wind speeds are those greater than 33 m/s (74 mph), while Sub-Hurricane wind speeds fall below that threshold.

TABLE C.17—THE VALUE OF A TRACK DISTANCE FORECAST IMPROVEMENT CONDITIONAL ON WIND AND PRECIPITATION: CUTOFF ROBUSTNESS.

	400 km	500 km	600 km	700 km	800 km
Damages + Recovery Expenditures (million \$)					
Hurricane $\beta_2 : (e - \mu)^2$	0.115	0.113	0.112	0.111	0.110
	(0.074)	(0.074)	(0.073)	(0.073)	(0.073)
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 $\beta_2 : (e - \mu)^2$	1.722*	1.688*	1.661	1.637	1.628
	(1.023)	(1.019)	(1.016)	(1.016)	(1.013)
Sub-Hurricane $\beta_2 : (e - \mu)^2$	0.003	0.000	0.001	0.002	0.002
	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
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 forecast error per county for a given hurricane, μ is the mean forecast error per hurricane/hurricane-intensity bin. 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 Unconditional Value of a Track Distance Forecast Improvement: Cutoff Robustness.

	400 km	500 km	600 km	700 km	800 km
Damages + Recovery Expenditures (million \$)					
Hurricane $\beta_2 : (e - \mu)^2$	0.137*	0.136*	0.135*	0.135*	0.134*
	(0.077)	(0.077)	(0.077)	(0.076)	(0.076)
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 $\beta_2 : (e - \mu)^2$	0.003**	0.003**	0.003**	0.003**	0.003**
	(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 $\beta_2 : (e - \mu)^2$	2.245**	2.205**	2.185**	2.165**	2.158**
	(1.098)	(1.091)	(1.089)	(1.088)	(1.087)
Sub-Hurricane $\beta_2 : (e - \mu)^2$	0.005	0.003	0.004	0.005*	0.004*
	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)
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 forecast error per county for a given hurricane, μ is the mean forecast error per hurricane/hurricane-intensity bin. 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 \$)							
$\beta_2 : (e - \mu)^2$	4.49***	4.37***	3.68***	3.73***	5.47***	4.31**	
	(1.58)	(1.49)	(1.23)	(1.20)	(2.08)	(1.82)	
Hurricane $\beta_2 : (e - \mu)^2$							5.06***
							(1.81)
Sub-Hurricane $\beta_2 : (e - \mu)^2$							0.18
							(0.71)
(Damages + Recovery Expenditures) / GDP (%)							
$\beta_2 : (e - \mu)^2$	0.24***	0.24***	0.21***	0.21***	0.16**	0.08**	
	(0.07)	(0.07)	(0.06)	(0.06)	(0.07)	(0.03)	
Hurricane $\beta_2 : (e - \mu)^2$							0.28***
							(0.08)
Sub-Hurricane $\beta_2 : (e - \mu)^2$							0.02
							(0.01)
Damages + Recovery Expenditures Per Capita (\$/person)							
$\beta_2 : (e - \mu)^2$	96.76***	95.92***	81.59***	93.06***	105.36***	73.43***	
	(25.83)	(25.33)	(21.20)	(22.99)	(37.43)	(27.12)	
Hurricane $\beta_2 : (e - \mu)^2$							112.06***
							(28.99)
Sub-Hurricane $\beta_2 : (e - \mu)^2$							4.66
							(4.24)
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 forecast error per county for a given hurricanes, μ is the mean forecast error per hurricane/hurricane-intensity bin. 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 \$)							
$\beta_2 : (e-\mu)^2$	6.15**	6.28**	6.32**	6.81**	7.50**	8.62**	
	(2.68)	(2.87)	(2.76)	(2.72)	(3.48)	(3.55)	
Hurricane $\beta_2 : (e-\mu)^2$							25.85***
							(9.79)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.26
							(0.51)
(Damages + Recovery Expenditures) / GDP (%)							
$\beta_2 : (e-\mu)^2$	0.28**	0.30**	0.30**	0.32***	0.30**	0.35***	
	(0.12)	(0.13)	(0.13)	(0.12)	(0.12)	(0.12)	
Hurricane $\beta_2 : (e-\mu)^2$							1.05***
							(0.34)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.07**
							(0.03)
Damages + Recovery Expenditures Per Capita (\$/person)							
$\beta_2 : (e-\mu)^2$	113.36**	122.02**	120.48**	129.21***	132.94**	157.56***	
	(45.12)	(49.60)	(47.54)	(46.80)	(55.52)	(57.84)	
Hurricane $\beta_2 : (e-\mu)^2$							426.76***
							(140.12)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							25.45***
							(9.09)
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. Forecast errors are normalized across hurricanes. e is the county-hurricane-specific forecast error, and μ is the hurricane-intensity bin-specific mean forecast error. Hurricane wind speeds are those greater than 33 m/s (74 mph), while Sub-Hurricane wind speeds fall below that threshold.

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 \$)							
$\beta_2 : (e-\mu)^2$	1.55*	1.36	1.30	1.41	1.40	1.35	
	(0.91)	(0.91)	(0.92)	(0.90)	(0.96)	(0.88)	
Hurricane $\beta_2 : (e-\mu)^2$							7.48
							(5.61)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							-0.29
							(0.21)
(Damages + Recovery Expenditures) / GDP (%)							
$\beta_2 : (e-\mu)^2$	0.07*	0.06*	0.06*	0.06*	0.06*	0.06**	
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	
Hurricane $\beta_2 : (e-\mu)^2$							0.29
							(0.21)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							-0.00
							(0.01)
Damages + Recovery Expenditures Per Capita (\$/person)							
$\beta_2 : (e-\mu)^2$	27.88*	26.51*	25.56*	26.89*	27.32*	27.43*	
	(14.57)	(14.88)	(14.68)	(14.31)	(15.48)	(14.73)	
Hurricane $\beta_2 : (e-\mu)^2$							124.46
							(87.86)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.24
							(2.71)
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, and μ is the hurricane-intensity bin-specific mean forecast error. Hurricane wind speeds are those greater than 33 m/s (74 mph), while Sub-Hurricane wind speeds fall below that threshold.

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 \$)							
$\beta_2 : (e-\mu)^2$	1.24*	1.30*	1.17*	1.16*	1.41*	1.25*	
	(0.67)	(0.74)	(0.71)	(0.68)	(0.84)	(0.74)	
Hurricane $\beta_2 : (e-\mu)^2$							4.16**
							(2.01)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.06
							(0.12)
(Damages + Recovery Expenditures) / GDP (%)							
$\beta_2 : (e-\mu)^2$	0.05**	0.06**	0.04*	0.04*	0.04*	0.04*	
	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	
Hurricane $\beta_2 : (e-\mu)^2$							0.16**
							(0.06)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.00
							(0.00)
Damages + Recovery Expenditures Per Capita (\$/person)							
$\beta_2 : (e-\mu)^2$	17.61**	19.39**	15.78*	15.66*	15.99*	14.73*	
	(7.91)	(8.98)	(8.87)	(8.35)	(8.95)	(8.12)	
Hurricane $\beta_2 : (e-\mu)^2$							55.39***
							(20.94)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							1.07
							(1.63)
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, and μ is the hurricane-intensity bin-specific mean forecast error. Hurricane wind speeds are those greater than 33 m/s (74 mph), while Sub-Hurricane wind speeds fall below that threshold.

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 $)							
$\beta_2 : (e-\mu)^2$	1.69**	1.79**	1.72**	1.72**	1.97**	1.65*	
	(0.76)	(0.83)	(0.84)	(0.80)	(1.00)	(0.87)	
Hurricane $\beta_2 : (e-\mu)^2$							4.27***
							(1.59)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.09
							(0.13)
(Damages + Recovery Expenditures) / GDP (%)							
$\beta_2 : (e-\mu)^2$	0.07**	0.07**	0.07*	0.07**	0.07*	0.07**	
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	
Hurricane $\beta_2 : (e-\mu)^2$							0.16***
							(0.06)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.01
							(0.01)
Damages + Recovery Expenditures Per Capita ($/person)							
$\beta_2 : (e-\mu)^2$	28.48**	31.36**	27.03*	26.98**	29.01*	28.83*	
	(12.49)	(13.98)	(14.53)	(13.55)	(16.37)	(14.99)	
Hurricane $\beta_2 : (e-\mu)^2$							66.79**
							(26.47)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							1.74
							(2.89)
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, and μ is the hurricane-intensity bin-specific mean forecast error. Hurricane wind speeds are those greater than 33 m/s (74 mph), while Sub-Hurricane wind speeds fall below that threshold.

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 \$)							
$\beta_2 : (e-\mu)^2$	1.59**	1.67**	1.61**	1.61**	1.89**	1.63**	
	(0.67)	(0.73)	(0.73)	(0.69)	(0.90)	(0.79)	
Hurricane $\beta_2 : (e-\mu)^2$							3.34**
							(1.30)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							-0.03
							(0.17)
(Damages + Recovery Expenditures) / GDP (%)							
$\beta_2 : (e-\mu)^2$	0.07**	0.08**	0.08**	0.08**	0.08**	0.08**	
	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	
Hurricane $\beta_2 : (e-\mu)^2$							0.15***
							(0.05)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.01
							(0.01)
Damages + Recovery Expenditures Per Capita (\$/person)							
$\beta_2 : (e-\mu)^2$	28.54**	31.43**	27.85**	27.75**	30.33**	30.37**	
	(11.44)	(12.72)	(13.15)	(12.35)	(15.37)	(14.11)	
Hurricane $\beta_2 : (e-\mu)^2$							56.37***
							(20.21)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.93
							(2.42)
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					✓	✓	

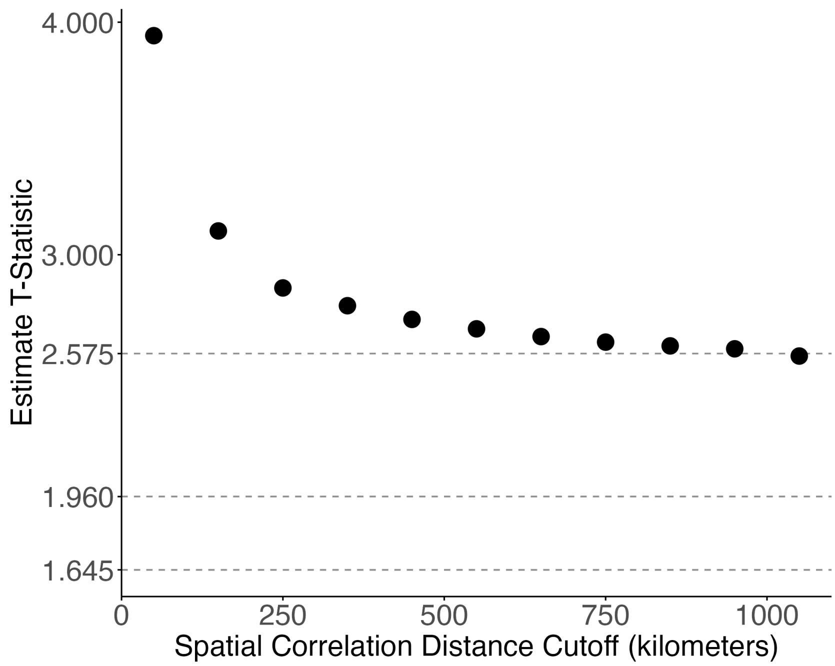
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Standard errors are Conley Spatial HAC with a distance radius of 400 km for spatial correlation and arbitrary autocorrelation within counties. e is the county-hurricane-specific forecast error, and μ is the hurricane-intensity bin-specific mean forecast error.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

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 \$)							
$\beta_2 : (e-\mu)^2$	1.72**	1.74**	1.67**	1.67**	1.93**	1.68**	
	(0.70)	(0.72)	(0.72)	(0.69)	(0.87)	(0.78)	
Hurricane $\beta_2 : (e-\mu)^2$							3.54***
							(1.30)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.00
							(0.13)
(Damages + Recovery Expenditures) / GDP (%)							
$\beta_2 : (e-\mu)^2$	0.08**	0.08**	0.08**	0.08**	0.08**	0.08**	
	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	
Hurricane $\beta_2 : (e-\mu)^2$							0.15***
							(0.05)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							0.01
							(0.01)
Damages + Recovery Expenditures Per Capita (\$/person)							
$\beta_2 : (e-\mu)^2$	30.01**	31.40**	28.54**	28.66**	30.55**	30.36**	
	(12.05)	(12.79)	(13.13)	(12.40)	(15.05)	(13.86)	
Hurricane $\beta_2 : (e-\mu)^2$							58.72***
							(20.38)
Sub-Hurricane $\beta_2 : (e-\mu)^2$							1.62
							(2.03)
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					✓	✓	

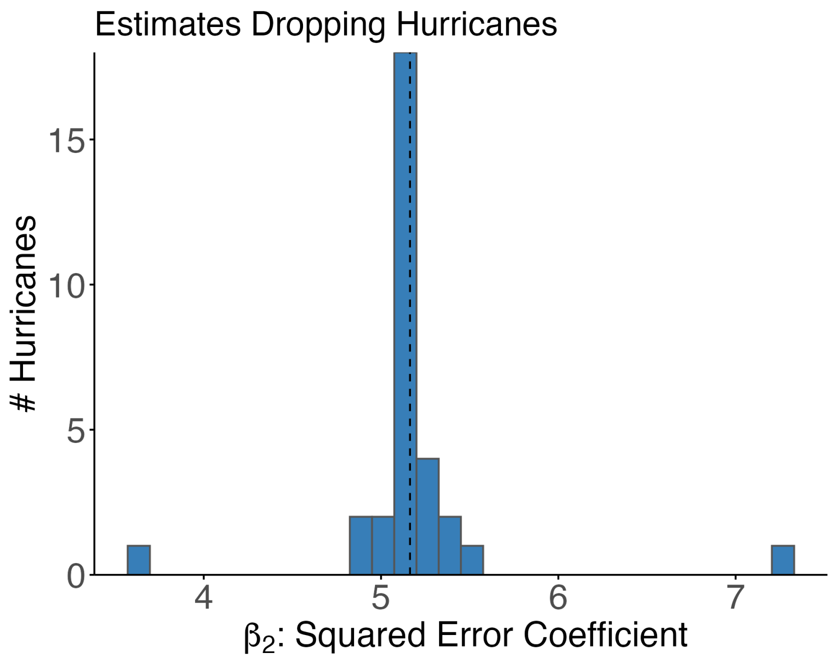
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Standard errors are Conley Spatial HAC with a distance radius of 400 km for spatial correlation and arbitrary autocorrelation within counties. e is the county-hurricane-specific forecast error, and μ is the hurricane-intensity bin-specific mean forecast error.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

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.

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.[32] 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 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

[32]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 while their wind speed error would always be near zero since they are not near the hurricane.

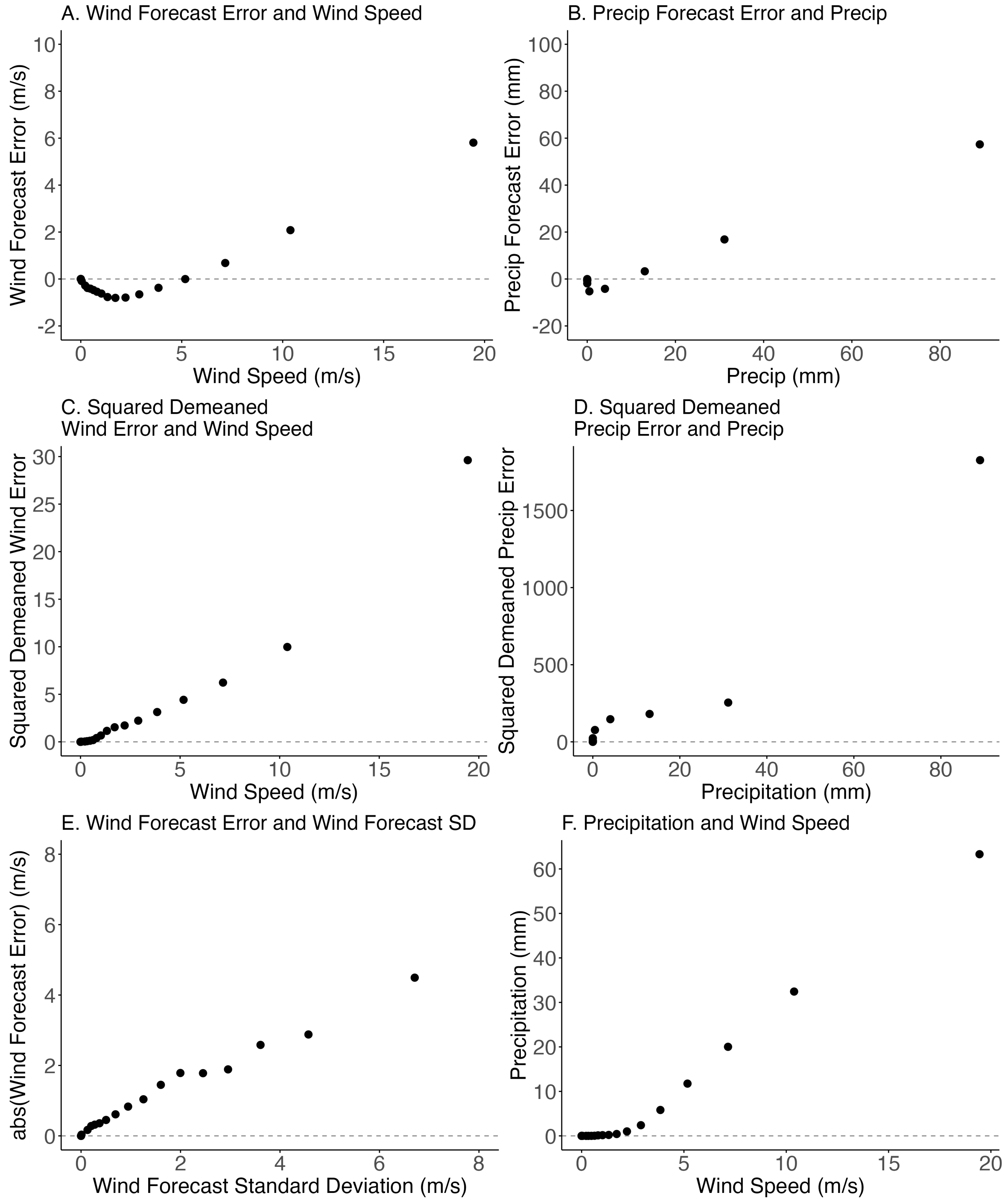
variation in wind speed errors not predicted by track errors. Panel D plots damages as a function of track errors and wind speed errors. The plot shows that there is a relatively clear correlation between damages and wind speed errors, but not with track errors.

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

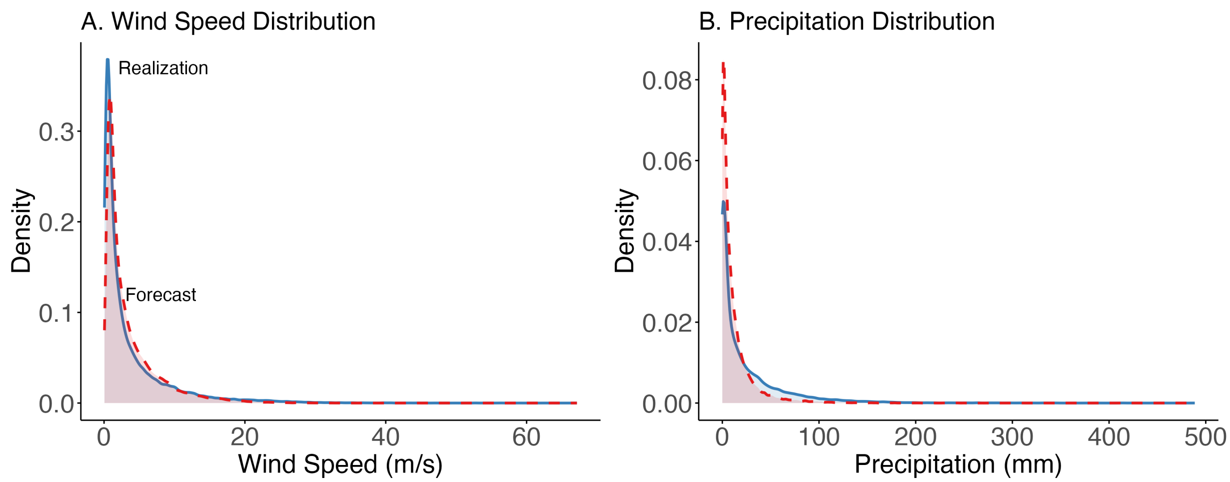
Note:
The table includes all Category 1 and greater hurricanes (maximum wind speeds greater than 33 m/s) that made landfall in the continental US between 2005–2022. Wind speed, precipitation, and their associated errors are averaged across counties to the hurricane level. Wind speed is the maximum sustained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



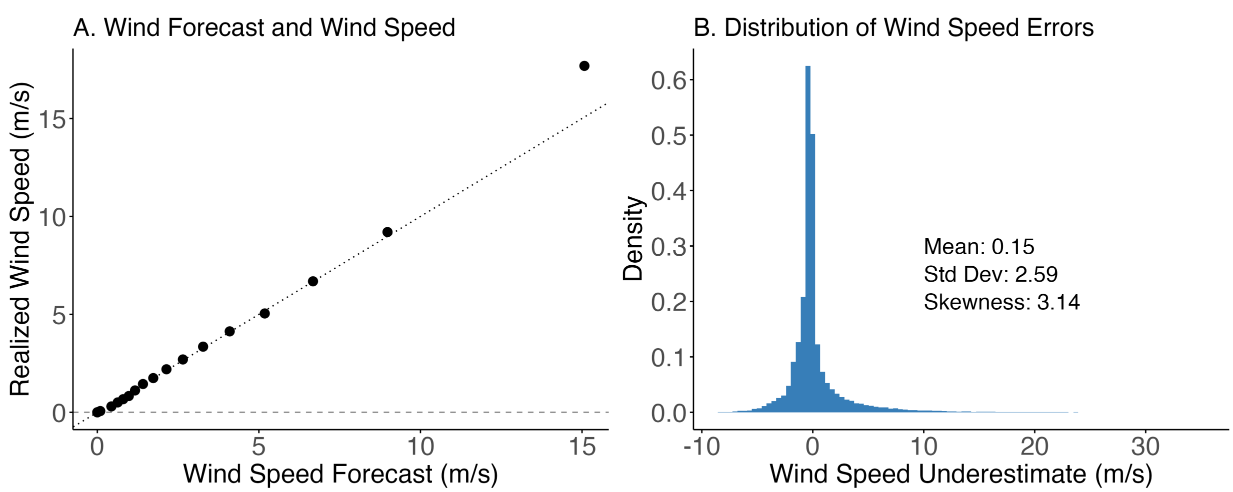
Note: Panel A plots the absolute error in the wind speed forecast (actual wind speed minus predicted wind speed) against the realized wind speed. Panel B plots the absolute error in the precipitation forecast against the realized precipitation. Panel C plots the squared demeaned error in the wind speed 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.



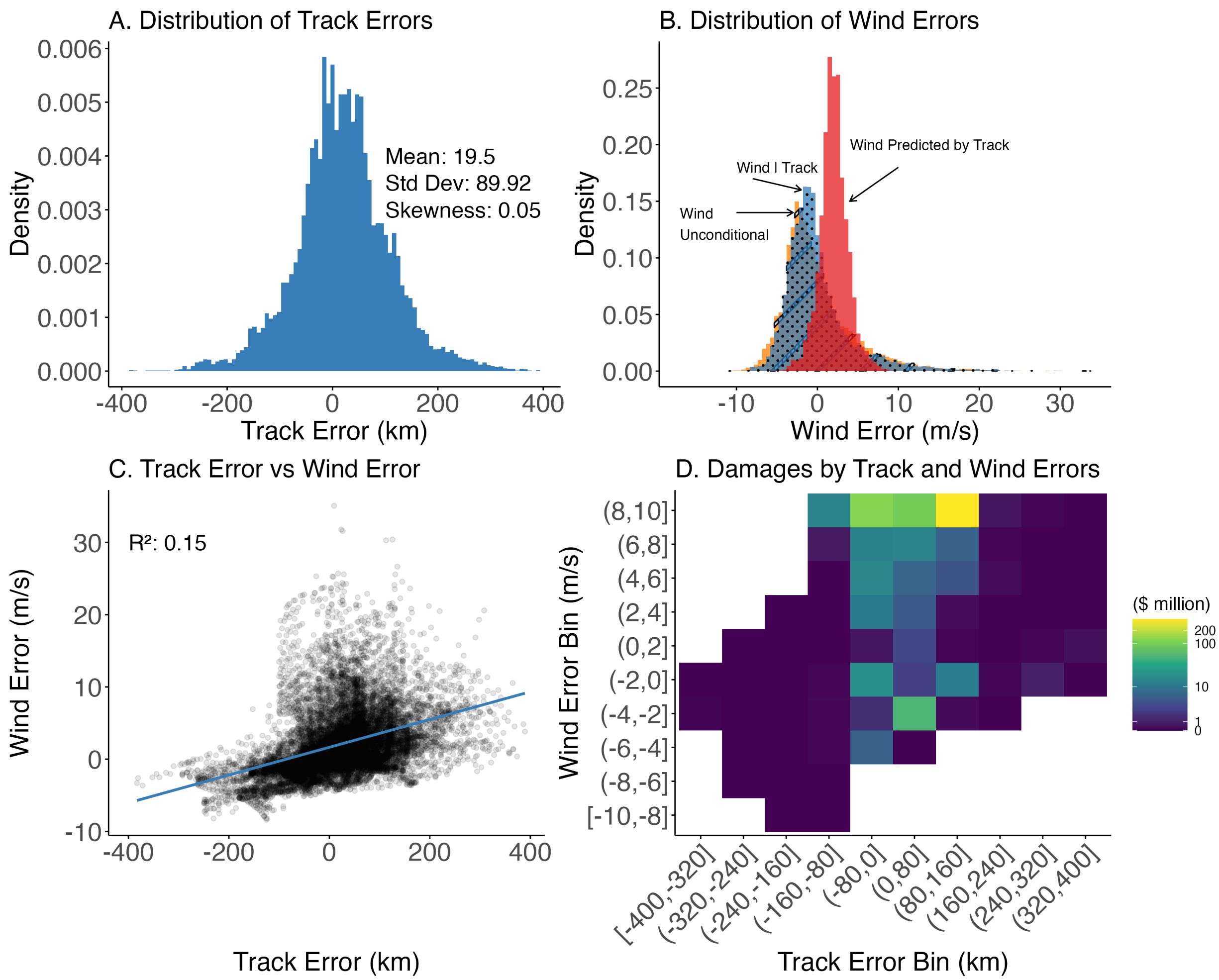
Note: Panel A shows the observed distribution of the realized and forecast wind speed by county-hurricane. Panel B shows the observed distribution of the realized and forecast precipitation by county-hurricane. The red dashed line is the distribution of the forecast and the blue line is the distribution 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 higher damage. Data are from counties within 400 km from the forecast and observed hurricane track. The number of observations is 15,018.

Our main approach approximates $\mathbb{E}_{\tilde{x}}[\beta_2(\tilde{x})]$ by estimating the model using a pooled dataset of different county-hurricane-forecast realizations. Here, we show that we can use our pooled dataset to estimate a weighted expectation of the $\beta_2(\tilde{x})$'s by regressing observed damages $D(\tilde{x}+e, a, \mathbf{i}, \mathbf{t})$ on $(e-\mu)^2 - \sigma^2$, which we call the *centered squared forecast error.*[33]

Denote a county-hurricane combination by z. Realized hurricane intensity will be drawn from some distribution $x_z \sim F_{x|z}$. A forecast $\tilde{x}_z$ for this draw is issued and the associated forecast error has distribution $e_z \sim \mathcal{N}_{e|z}(\mu_z, \sigma_z^2)$ with mean μ_z and variance σ_z^2. The relationship between the realization and forecast is defined by the forecast error $e_z = x_z - \tilde{x}_z$ and the distributions over the realization and the error imply some *ex ante* forecast distribution. To keep notation manageable, let D_z be total after-landfall costs for z and W_z be the centered squared forecast error for z:

$$D_z \equiv D(\tilde{x}_z + e_z, a_z^*, \mathbf{i_z}, \mathbf{t}) \qquad \text{and} \qquad W_z \equiv (e_z - \mu_z)^2 - \mathbb{E}_e[(e_z-\mu_z)^2 \mid z, \tilde{x}_z] = (e_z-\mu_z)^2 - \sigma_z^2.$$

Define the within-$(z, \tilde{x}_z)$ variance in the demeaned squared forecast error as:

$$\begin{aligned} V(z,\tilde{x}_z) &\equiv \text{Var}_e((e_z-\mu_z)^2 \mid z, \tilde{x}_z) \\ &= \text{Var}_e((e_z-\mu_z)^2 - \sigma_z^2 \mid z, \tilde{x}_z) \\ &= \text{Var}_e(W_z \mid z, \tilde{x}_z) \\ &= \mathbb{E}_e[W_z^2 \mid z, \tilde{x}_z] - \underbrace{\mathbb{E}_e[W_z \mid z, \tilde{x}_z]^2}_{=0} \\ &= \mathbb{E}_e[W_z^2 \mid z, \tilde{x}_z]. \end{aligned}$$

Define the county-hurricane-specific coefficient from a regression of D_z on W_z as:

$$\beta_{2,z}(\tilde{x}_z) = \frac{\text{Cov}_e(W_z, D_z \mid z, \tilde{x}_z)}{\text{Var}_e(W_z \mid z, \tilde{x}_z)} = \frac{\mathbb{E}_e[W_z\, D_z \mid z, \tilde{x}_z]}{\mathbb{E}_e[W_z^2 \mid z, \tilde{x}_z]},$$

where the covariance and variance are replaced by expectations because $\mathbb{E}_e[W_z \mid z, \tilde{x}_z] = 0$. Since we are holding z and $\tilde{x}_z$ fixed, this coefficient should formally be recovered from a regression where data are generated from a single county and forecast, but different realizations of hurricane intensity.

Define the county-hurricane-specific *ex ante* expected β_2 and its variance-weighted analogue as:

$$\beta_{2,z}^{\text{EA}} \equiv \mathbb{E}_{\tilde{x}|z}\big[\beta_{2,z}(\tilde{x}_z)\big] \qquad \text{and} \qquad \beta_{2,z}^{\text{EA,var}} \equiv \frac{\mathbb{E}_{\tilde{x}|z}\big[\beta_{2,z}(\tilde{x}_z)\, V(z,\tilde{x}_z)\big]}{\mathbb{E}_{\tilde{x}|z}\big[V(z,\tilde{x}_z)\big]}.$$

These *ex ante* coefficients are the expected relationship between damages and centered demeaned forecast error before observing any single forecast. Next, integrate the county-hurricane variance over forecasts in V_z and define a county-hurricane-specific weight parameter Ω_z as:

$$V_z \equiv \mathbb{E}_{\tilde{x}|z}[V(z,\tilde{x}_z)] \qquad \text{and} \qquad \Omega_z \equiv \frac{V_z}{\sum_{z'} V_{z'}}.$$

The following Lemma shows that the coefficient from a pooled regression of damages on the centered forecast error across county-hurricanes is the ratio of two expectations:

[33] We call $(e-\mu)^2 - \sigma^2$ the centered squared forecast error to avoid confusion with $(e-\mu)^2$, which is the squared demeaned forecast error.

LEMMA 1: *In the pooled regression of damages* $D_z = D(\tilde{x}_z + e_z, a_z^*, \mathbf{i_z}, \mathbf{t})$ *on the centered forecast error* $W_z = (e_z - \mu_z)^2 - \sigma_z^2$*, the estimated county-hurricane population coefficient,* $\hat{\beta}_{2,pooled}$*, is given by:*

$$\hat{\beta}_{2,pooled} \;=\; \frac{\mathrm{Cov}(W_z, D_z)}{\mathrm{Var}(W_z)} \;=\; \frac{\mathbb{E}[W_z\, D_z]}{\mathbb{E}[W_z^2]}.$$

PROOF:
The result follows because $\mathbb{E}[W_z] = 0$, as $\mathbb{E}[W_z \mid z, \tilde{x}_z] = \mathbb{E}\left[(e_z - \mu_z)^2 - \sigma_z^2 \mid z, \tilde{x}_z\right] = 0$ by construction.

The proposition below then shows that this ratio of expectations, and thus $\hat{\beta}_{2,pooled}$, can be expressed as a weighted average of the county-hurricane-specific, before-forecast ex ante coefficients.

PROPOSITION 3: *The pooled OLS coefficient* $\hat{\beta}_{2,pooled}$*, from regressing damages* $D_z = D(\tilde{x}_z + e_z, a_z^*, \mathbf{i_z}, \mathbf{t})$ *on the centered forecast error* $W_z = (e_z - \mu_z)^2 - \sigma_z^2$*, is a variance-weighted average of variance-weighted county-hurricane-specific ex ante coefficients:*

$$\hat{\beta}_{2,pooled} = \sum_z \Omega_z \cdot \beta_{2,z}^{\mathrm{EA,var}},$$

where $\beta_{2,z}^{\mathrm{EA,var}}$ *is the variance-weighted ex ante coefficient for county-hurricane* z*, defined as:*

$$\beta_{2,z}^{\mathrm{EA,var}} = \frac{\mathbb{E}_{\tilde{x}|z}\left[\beta_{2,z}(\tilde{x}_z) V(z, \tilde{x}_z)\right]}{\mathbb{E}_{\tilde{x}|z}\left[V(z, \tilde{x}_z)\right]},$$

where

$$\beta_{2,z}(\tilde{x}_z) \;=\; \frac{\mathrm{Cov}_e(W_z, D_z \mid z, \tilde{x}_z)}{\mathrm{Var}_e(W_z \mid z, \tilde{x}_z)} \;=\; \frac{\mathbb{E}_e[W_z D_z \mid z, \tilde{x}_z]}{\mathbb{E}_e[W_z^2 \mid z, \tilde{x}_z]}$$

is the county-hurricane-specific coefficient for forecast $\tilde{x}_z$ *in county-hurricane* z*, and* $V(z, \tilde{x}_z) = \mathrm{Var}_e(W_z \mid z, \tilde{x}_z)$ *is the variance of* W_z*. The weight* Ω_z *is:*

$$\Omega_z = \frac{V_z}{\sum_{z'} V_{z'}}, \qquad \textit{with} \qquad V_z = \mathbb{E}_{\tilde{x}|z}[V(z, \tilde{x}_z)],$$

where the summation over z' *includes all county-hurricanes in the sample.*

PROOF:
We want to show that the pooled OLS estimate, $\hat{\beta}_{2,pooled}$, is a variance-weighted average of county-hurricane-specific variance-weighted ex ante coefficients, $\beta_{2,z}^{\mathrm{EA,var}}$. Since $\mathbb{E}[W_z] = 0$, Lemma 1 indicates that the pooled OLS coefficient is given by:

$$\hat{\beta}_{2,pooled} = \frac{\mathbb{E}[W_z D_z]}{\mathbb{E}[W_z^2]}.$$

Using the law of iterated expectations and the covariance identity, the numerator can be expressed as:

$$\begin{aligned}\mathbb{E}[W_z\, D_z] &= \mathbb{E}_{z,\tilde{x}}\left[\mathbb{E}_e\left[W_z\, D_z \mid z, \tilde{x}_z\right]\right] \\ &= \mathbb{E}_{z,\tilde{x}}\left[\mathrm{Cov}_e\big(W_z, D_z \mid z, \tilde{x}_z\big) + \mathbb{E}_e[W_z \mid z, \tilde{x}_z] \cdot \mathbb{E}_e[D_z \mid z, \tilde{x}_z]\right].\end{aligned}$$

Because $\mathbb{E}_e[W_z \mid z, \tilde{x}_z] = 0$, this simplifies to:

$$\begin{aligned}
\mathbb{E}[W_z\, D_z] =& \mathbb{E}_{z,\tilde{x}}\left[\mathrm{Cov}_e\big(W_z, D_z \mid z, \tilde{x}_z\big)\right] \\
=& \mathbb{E}_{z,\tilde{x}}\left[\mathrm{Cov}_e\big(W_z, D_z \mid z, \tilde{x}_z\big) \cdot \frac{\mathrm{Var}_e\big(W_z \mid z, \tilde{x}_z\big)}{\mathrm{Var}_e\big(W_z \mid z, \tilde{x}_z\big)}\right] \\
=& \mathbb{E}_{z,\tilde{x}}\left[\beta_{2,z}(\tilde{x}_z) \cdot \mathrm{Var}_e\big(W_z \mid z, \tilde{x}_z\big)\right] \\
=& \mathbb{E}_{z,\tilde{x}}\left[\beta_{2,z}(\tilde{x}_z) \cdot V(z, \tilde{x}_z)\right].
\end{aligned}$$

We can then write this expectation as the sample average of the within-county-hurricane conditional expectations:

$$\text{(D.1)} \qquad \mathbb{E}[W_z\, D_z] = \mathbb{E}_{z,\tilde{x}}\big[\beta_{2,z}(\tilde{x}_z) \cdot V(z, \tilde{x}_z)\big] = \frac{1}{N}\sum_z \mathbb{E}_{\tilde{x}|z}\big[\beta_{2,z}(\tilde{x}_z) \cdot V(z, \tilde{x}_z)\big]$$

with N as the size of the sample. Similarly, we can express the denominator of the pooled coefficient as a sample average of a within-county-hurricane conditionally expected variance:

$$\text{(D.2)} \qquad \mathbb{E}[W_z^2] = \mathbb{E}_{z,\tilde{x}}\big[\mathbb{E}_e[W_z^2 \mid z, \tilde{x}_z]\big] = \mathbb{E}_{z,\tilde{x}}\big[V(z, \tilde{x}_z)\big] = \frac{1}{N}\sum_z \mathbb{E}_{\tilde{x}|z}\big[V(z, \tilde{x}_z)\big].$$

Combining (D.1) and (D.2):

$$\hat{\beta}_{2,pooled} = \frac{\frac{1}{N}\sum_z \mathbb{E}_{\tilde{x}|z}\left[\beta_{2,z}(\tilde{x}_z)V(z, \tilde{x}_z)\right]}{\frac{1}{N}\sum_{z'} \mathbb{E}_{\tilde{x}|z'}\left[V(z', \tilde{x}_{z'})\right]} = \sum_z \frac{\mathbb{E}_{\tilde{x}|z}\left[\beta_{2,z}(\tilde{x}_z)V(z, \tilde{x}_z)\right]}{\sum_{z'} \mathbb{E}_{\tilde{x}|z'}\left[V(z', \tilde{x}_{z'})\right]}.$$

We can then rewrite each term in the outer sum over z as:

$$\frac{\mathbb{E}_{\tilde{x}|z}\left[\beta_{2,z}(\tilde{x}_z) \cdot V(z, \tilde{x}_z)\right]}{\sum_{z'} \mathbb{E}_{\tilde{x}|z'}\left[V(z', \tilde{x}_{z'})\right]} = \frac{\mathbb{E}_{\tilde{x}|z}[V(z, \tilde{x}_z)]}{\sum_{z'} \mathbb{E}_{\tilde{x}|z'}[V(z', \tilde{x}_{z'})]} \cdot \frac{\mathbb{E}_{\tilde{x}|z}\left[\beta_{2,z}(\tilde{x}_z) \cdot V(z, \tilde{x}_z)\right]}{\mathbb{E}_{\tilde{x}|z}[V(z, \tilde{x}_z)]}.$$

The first term is just Ω_z, which is county-hurricane z's variance relative to the sum across all county-hurricanes. The second term is what we defined as $\beta_{2,z}^{\mathrm{EA,var}}$, which is the variance-weighted ex ante coefficient within county-hurricane z. This result implies that:

$$\begin{aligned}
\hat{\beta}_{2,pooled} &= \sum_z \frac{\mathbb{E}_{\tilde{x}|z}[V(z, \tilde{x}_z)]}{\sum_{z'} \mathbb{E}_{\tilde{x}|z'}[V(z', \tilde{x}_{z'})]} \cdot \frac{\mathbb{E}_{\tilde{x}|z}\left[\beta_{2,z}(\tilde{x}_z)V(z, \tilde{x}_z)\right]}{\mathbb{E}_{\tilde{x}|z}[V(z, \tilde{x}_z)]} \\
&= \sum_z \Omega_z \beta_{2,z}^{\mathrm{EA,var}}.
\end{aligned}$$

The weights Ω_z sum to 1, since:

$$\sum_z \Omega_z = \sum_z \frac{\mathbb{E}_{\tilde{x}|z}[V(z, \tilde{x}_z)]}{\sum_{z'} \mathbb{E}_{\tilde{x}|z'}[V(z', \tilde{x}_{z'})]} = \frac{\sum_z \mathbb{E}_{\tilde{x}|z}[V(z, \tilde{x}_z)]}{\sum_{z'} \mathbb{E}_{\tilde{x}|z'}[V(z', \tilde{x}_{z'})]} = 1.$$

Proposition 3 shows that $\hat{\beta}_{2,pooled}$ is a convex combination of the variance-weighted ex ante coefficients, $\beta_{2,z}^{\mathrm{EA,var}}$, from each county-hurricane. It did not impose any assumptions on how the variance might differ across county-hurricanes. Finally, we show that under the constant variance assumption in the main model, the pooled coefficient estimate is a convex combination of the unweighted, county-hurricane-specific before-forecast coefficients. This is formalized in the Lemma below:

LEMMA 2: *Under the constant variance assumption, the pooled OLS coefficient, $\hat{\beta}_{2,pooled}$, can be written as:*

$$\hat{\beta}_{2,pooled} \;=\; \sum_z \Omega_z \, \beta^{\text{EA}}_{2,z}.$$

with:

$$\beta^{\text{EA}}_{2,z} \;\equiv\; \mathbb{E}_{\tilde{x}|z}\big[\beta_{2,z}(\tilde{x})\big] \qquad \textit{and} \qquad \Omega_z \;\equiv\; \frac{V_z}{\sum_{z'} V_{z'}}.$$

PROOF:

Recall that:

$$\hat{\beta}_{2,pooled} = \frac{\sum_z \mathbb{E}_{\tilde{x}|z}\big[\beta_{2,z}(\tilde{x}_z) \cdot V(z,\tilde{x}_z)\big]}{\sum_z \mathbb{E}_{\tilde{x}|z}\big[V(z,\tilde{x}_z)\big]}.$$

Assuming the conditional variance $V(z, \tilde{x}_z)$ is constant for all forecasts $\tilde{x}_z$ within a given county-hurricane implies $V(z, \tilde{x}_z) = V_z$, so:

$$\mathbb{E}_{\tilde{x}|z}\big[\beta_{2,z}(\tilde{x}_z) \cdot V(z,\tilde{x}_z)\big] = V_z \, \mathbb{E}_{\tilde{x}|z}\big[\beta_{2,z}(\tilde{x}_z)\big] = V_z \, \beta^{\text{EA}}_{2,z} \qquad \text{and} \qquad \mathbb{E}_{\tilde{x}|z}\big[V(z,\tilde{x}_z)\big] = V_z.$$

Therefore:

$$\hat{\beta}_{2,pooled} = \frac{\sum_z V_z \cdot \beta^{\text{EA}}_{2,z}}{\sum_z V_z} = \sum_z \left(\frac{V_z}{\sum_{z'} V_{z'}} \right) \cdot \beta^{\text{EA}}_{2,z} = \sum_z \Omega_z \cdot \beta^{\text{EA}}_{2,z}.$$

In Table D.2 below, we reproduce our main results using the centered squared forecast error. The coefficients are approximately 10–60% smaller than those in the main text depending on the specification, but remain statistically significant.

Table D.2—The Before-Signal Value of a Wind Speed Forecast Improvement.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Damages + Recovery Expenditures (million \$)							
$\beta_2 : (e-\mu)^2 - \sigma^2$	2.75***	3.03***	2.10***	2.10***	2.48***	2.47***	
	(0.84)	(0.94)	(0.63)	(0.63)	(0.77)	(0.77)	
Hurricane $\beta_2 : (e-\mu)^2 - \sigma^2$							2.21*
							(1.16)
Sub-Hurricane $\beta_2 : (e-\mu)^2 - \sigma^2$							1.96
							(1.40)
(Damages + Recovery Expenditures) / GDP (%)							
$\beta_2 : (e-\mu)^2 - \sigma^2$	0.18***	0.19***	0.16***	0.16***	0.15***	0.16***	
	(0.07)	(0.07)	(0.06)	(0.05)	(0.06)	(0.05)	
Hurricane $\beta_2 : (e-\mu)^2 - \sigma^2$							0.25***
							(0.08)
Sub-Hurricane $\beta_2 : (e-\mu)^2 - \sigma^2$							0.05*
							(0.03)
Damages + Recovery Expenditures Per Capita (\$/person)							
$\beta_2 : (e-\mu)^2 - \sigma^2$	68.58***	73.32***	57.37***	59.06***	62.14***	68.16***	
	(19.93)	(20.77)	(15.16)	(15.02)	(17.86)	(17.26)	
Hurricane $\beta_2 : (e-\mu)^2 - \sigma^2$							80.72***
							(18.25)
Sub-Hurricane $\beta_2 : (e-\mu)^2 - \sigma^2$							29.77*
							(17.20)
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, and σ is the county-hurricane-specific ex ante forecast standard deviation. Hurricane wind speeds are those greater than 33 m/s (74 mph), while Sub-Hurricane wind speeds fall below that threshold.

This section extends the theoretical model in the main paper to explicitly account for the presence of irreducible physical uncertainty. Consider the case when the intensity of the hurricane is given by $x = \bar{x} + \epsilon_p$, where $\bar{x}$ is the predictable component and $\epsilon_p \sim \mathcal{N}(0, \sigma_p^2)$ is irreducible physical noise.[34] The agent receives a forecast $\tilde{x}$. The forecast error is $\epsilon_f = \bar{x} - \tilde{x} \sim \mathcal{N}(\mu_f, \sigma_f^2)$, where μ_f is the forecast bias, and σ_f^2 is the reducible variance of the forecast error. The total prediction error, e, is the sum of the reducible forecast error and the irreducible physical noise: $e = x - \tilde{x} = \epsilon_f + \epsilon_p \sim \mathcal{N}(\mu_f, \sigma_f^2 + \sigma_p^2)$, so the agent's conditional beliefs about hurricane intensity are given by: $x \mid \tilde{x} \sim \mathcal{N}(\tilde{x} + \mu_f, \sigma_f^2 + \sigma_p^2)$.

The timing of the model is as follows. First, the hurricane forms with predictable component $\bar{x}$. Second, the agent observes the noisy forecast $\tilde{x}$ and chooses adaptation $a(\tilde{x})$, incurring cost $C(a(\tilde{x}))$. Last, the unpredictable, physical noise component of the hurricane ϵ_p realizes, leading to damages $D(x, a(\tilde{x}))$.

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

$$\mathcal{C}(\tilde{x}; \mu_f, \sigma_f, \sigma_p) = \min_a \mathbb{E}[D(x, a(\tilde{x})) \mid \tilde{x}] + C(a(\tilde{x})).$$

In this case, the value of a forecast improvement is the reduction in minimized expected total cost from a marginal reduction in the forecast error, σ_f. Proposition 4 below provides the expression for this quantity.

PROPOSITION 4: *The value of a forecast improvement in the presence of irreducible physical noise, defined as the ex ante reduction in expected minimized total costs from a marginal decrease in reducible forecast error, σ_f, is:*

$$\begin{aligned}\frac{\mathrm{d}}{\mathrm{d}\sigma_f}\mathbb{E}_{\tilde{x}}\left[\mathcal{C}(\tilde{x})\right] &= \frac{\sigma_f}{(\sigma_f^2 + \sigma_p^2)^2}\mathbb{E}_{\tilde{x}}\left[\mathrm{Cov}\left(D(x, a^*(\tilde{x})), (e - \mu_f)^2 \mid \tilde{x}\right)\right] \\ &= 2\sigma_f \cdot \mathbb{E}_{\tilde{x}}[\beta_2(\tilde{x})],\end{aligned}$$

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

PROOF:

We seek to find the *ex ante* value of a forecast improvement, which is the reduction in expected minimized costs from a marginal decrease in σ_f:

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

By the envelope theorem, since $a^*(\tilde{x})$ minimizes $\mathcal{C}$, the effect of a change in σ_f on the minimized cost is given by the partial derivative:

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

To simplify notation, let $\sigma^2 = \sigma_f^2 + \sigma_p^2$. The conditional expectation of damages is then given by

[34]For example, see Landsea and Cangialosi (2018) for a discussion on the limits of hurricane forecastability.

integrating damages over the normal probability density function $\phi(x \mid \tilde{x}; \mu_f, \sigma^2)$:

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

Note that the derivative of σ with respect to σ_f is $\frac{\partial \sigma}{\partial \sigma_f} = \frac{\sigma_f}{\sigma}$, so differentiating the minimized total cost with respect to σ_f gives:

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

Next, we can use the chain rule to get:

$$\frac{\partial \phi(x \mid \tilde{x}; \mu_f, \sigma^2)}{\partial \sigma_f} = \frac{\partial \phi(x \mid \tilde{x}; \mu_f, \sigma^2)}{\partial \sigma} \frac{\partial \sigma}{\partial \sigma_f},$$

with

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

so it follows that the partial of the probability density function with respect to σ_f is given by:

$$\frac{\partial \phi(x \mid \tilde{x}; \mu_f, \sigma^2)}{\partial \sigma_f} = \phi(x \mid \tilde{x}; \mu_f, \sigma^2) \cdot \frac{\sigma_f}{\sigma^4}\left((e - \mu_f)^2 - \sigma^2\right).$$

Substituting back into the integral yields:

$$\frac{\partial \mathcal{C}}{\partial \sigma_f} = \frac{\sigma_f}{\sigma^4}\mathbb{E}\left[D(x, a^*(\tilde{x})) \cdot \left((e - \mu_f)^2 - \sigma^2\right) \mid \tilde{x}\right]. \tag{D.3}$$

As in the main paper, because $\mathbb{E}[(e - \mu_f)^2 - \sigma^2 \mid \tilde{x}] = 0$, we can use the covariance identity to get:

$$\mathbb{E}\left[D(x, a^*(\tilde{x})) \cdot \left((e - \mu_f)^2 - \sigma^2\right) \mid \tilde{x}\right] = \mathrm{Cov}\left(D(x, a^*(\tilde{x})), (e - \mu_f)^2 \mid \tilde{x}\right),$$

so, (D.3) becomes:

$$\frac{\partial \mathcal{C}}{\partial \sigma_f} = \frac{\sigma_f}{\sigma^4}\,\mathrm{Cov}\left(D(x, a^*(\tilde{x})), (e - \mu_f)^2 \mid \tilde{x}\right). \tag{D.4}$$

Taking the expectation over $\tilde{x}$ and rearranging the derivative and expectation gives the *ex ante* value and completes the first part of the proof:

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

For the second part of the proof, note that the variance of the squared demeaned error is:

$$\begin{aligned}\operatorname{Var}\left((e-\mu_f)^2 \mid \tilde{x}\right) &= \mathbb{E}\left[(e-\mu_f)^4 \mid \tilde{x}\right] - \left(\mathbb{E}\left[(e-\mu_f)^2 \mid \tilde{x}\right]\right)^2 \\ &= 3\sigma^4 - (\sigma^2)^2 \\ &= 2\sigma^4.\end{aligned}$$

The regression coefficient $\beta_2(\tilde{x})$ is then given by:

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

which we can rearrange to get:

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

Substituting this into (D.4) and taking the expectation over $\tilde{x}$ gives the final result of the proposition:

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