When the Storm Breaks (Expectations): Reference Dependence and Demand for Flood Insurance

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November 1, 2025

Abstract

Households in hurricane-prone areas face rare but potentially devastating losses, yet flood insurance coverage remains low and unstable. This paper links hurricane forecasts to flood insurance uptake, introducing forecast errors as novel, exogenous reference points for household expectations. Using administrative records of NFIP policies in Florida merged with storm forecasts, I show that deviations between predicted and realized storm outcomes generate strong behavioral asymmetries: unanticipated impacts ("false misses") drive large increases in demand, often exceeding the response to correctly predicted strikes ("true hits"), while predicted threats that fail to materialize ("false hits") reduce uptake, suggesting that false alarms erode perceived risk. These patterns cannot be explained by actuarial risk alone and are consistent with reference-dependent preferences and loss aversion. Salience further amplifies these dynamics, as recent storms and hurricane-classified systems elicit the strongest responses, while near-miss "close calls" often depress demand. Together, the findings demonstrate that household insurance decisions are shaped as much by the psychological impact of forecast errors as by objective risk, with implications for forecast communication, policy timing, and disaster preparedness.

1 Introduction

The demand for flood insurance in the United States exhibits peculiar behavior. Even in highly flood-prone regions, take-up rates remain persistently low. When coverage does increases, it is typically caused by a major flooding event such as a hurricane (Gallagher, 2014). However, these increases often decline as memories of the event fade (?). Prior research has attributed this behavior to financial constraints (Grace et al., 2004), policy design (Zweifel and Eisen, 2012), and demographic characteristics (Kunreuther and Pauly, 2004), but little attention has been given to the psychological forces at play. In this paper, I argue that insurance demand depends not only on external factors but also on behavioral responses generated by expectations and on how expectations align with realized outcomes.

For example, consider the case of Hurricane Ian in 2022. As illustrated in Figure 1, early forecasts predicted that Ian would make landfall on Florida's Gulf Coast and then move northward toward Georgia within 72 hours. Homeowners along the western coast of Florida expected significant storm impacts, while residents on the Atlantic coast expected minimal effects. The forecast, however, proved inaccurate. Although Ian did indeed make landfall on the Gulf Coast (albeit earlier than predicted), it quickly shifted eastward, causing severe and unexpected damage in areas initially thought to be out of harm's way[1], while sparing much of northwest Florida entirely.

This misalignment between expected and realized storm impacts motivates the central idea of this paper. Homeowners in northwest Florida anticipated a direct hit that never occurred, a "False Hit", while homeowners on the Atlantic coast experienced a "False Miss", suffering impacts they had not expected. It is natural to predict that the residents who encountered the damaging effects of Ian would subsequently increase their demand for insurance. Yet those who were initially predicted to be affected also lived through a psychologically salient event: the expectation of being struck by a major hurricane. Even without physical damage, this expectation itself may raise subsequent demand.

This behavior is best understood through behavioral theories of decision-making under uncertainty. Prospect theory emphasizes that individuals evaluate outcomes relative to reference points and that losses loom larger than equivalent gains (Kahneman and Tversky, 1979). In this context, an expected storm hit produces a psychologically worse state than an expected miss. Expectation-based models of reference dependence formalize how anticipated outcomes generate utility shocks when violated (Kőszegi and Rabin, 2006, 2007, 2009), for example comparing an expected hit with an unexpected one. Salience theory further suggests that vivid, unexpected events – such as

[1]Hurricane Ian caused an estimated $112 billion in total damages, according to NOAA's National Centers for Environmental Information.

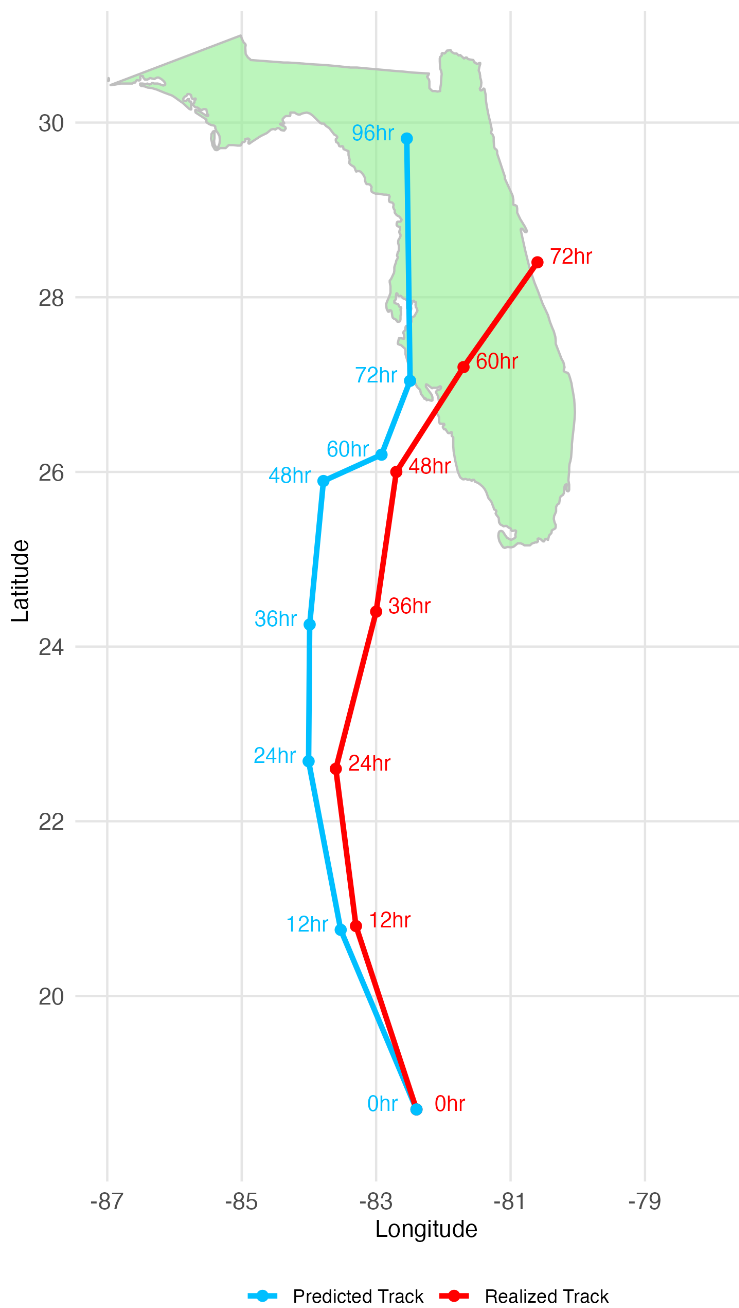


Figure 1: Hurricane Ian Predicted and Realized Tracks

Notes: The figure compares the predicted track of Hurricane Ian made at 12 PM on September 26, 2022 by The National Hurricane center with the storm's realized track. The red line shows the realized path, while the blue line indicates the predicted path at forecast horizons of 0 to 96 hours.

severe storms – generate disproportionate attention and influence subsequent behavior (Bordalo et al., 2012).

To test these theories, I combine data from the National Flood Insurance Program (NFIP) and the National Hurricane Center (NHC). As detailed in Section 4, the NFIP dataset documents flood insurance policies issued under the Federal Emergency Management Agency (FEMA) in the United States, including both homeowner and policy characteristics, while the NHC provides rich information on predicted and realized storm tracks.

In Section 5, I introduce a conceptual framework for understanding how homeowners interpret storm forecasts and outcomes and how these interpretations translate into insurance behavior. I outline four cases that represent distinct psychological mechanisms that influence behavior: experience-based responses, joint sensitivity to forecasts and realizations, asymmetric reactions to surprises, and reference-dependent behavior shaped by prior expectations.

Sections 6 and 7, develop a theoretical model and corresponding empirical identification strategy rooted in reference-dependence. The model characterizes how insurance decisions adjust when realized storm outcomes differ from expectations. Specifically, the model yields four unique behavioral categories–true hits, true misses, false hits, and false misses–that map directly to testable predictions for insurance demand. I estimate these relationships using a Poisson specification linking the behavioral categories to changes in insurance take-up.

The results presented in Section 8 and reinforced by robustness checks in Section 9 reveal three main findings. First, areas that experience false misses produce the largest increase in demand of 61-75%. In these cases, homeowners experience a double negative: they are hit by a storm they did not expect. The combination of a negative outcome and violated expectations generates a strong behavioral response that substantially raises demand. Second, true hits also increase demand, but to a lesser extent (25-31%). Correctly anticipating and experiencing a storm heightens perceived risk, yet the effect is more limited when compared to the influence of the misaligned expectations of false misses. Finally, false hits lead to declines in demand of 25-31%. This result is somewhat surprising, as one might expect the threat of a predicted storm to operate similarly to a false miss due to the violation of expectations. Instead, it appears that when a predicted storm fails to materialize, homeowners may update their beliefs about the overall likelihood or severity of storms and effectively downplay the risk, which reduces demand overall. Together, these findings show that insurance demand is shaped not only by storm outcomes but also by whether experiences align with prior expectations.

The policy implications, discussed in Section 10, are twofold. For insurers and regulators, understanding how households respond to forecast errors can improve the design of programs such as the NFIP. For forecasting agencies, the results highlight the behavioral consequences of forecast communication: even well-intentioned false alarms may erode demand for protection. Beyond flood insurance, forecast-based reference points can matter for agriculture, health, and other settings where ex ante risk expectations shape coverage decisions.

2 Related Literature

A large strand of literature details models on insurance behavior. Under standard expected-utility, risk-averse households should purchase actuarially fair coverage to smooth consumption across states of the world (Arrow, 1963; Mossin, 1968; Arrow, 1971). However, empirical evidence shows that actual behavior departs from this benchmark. Studies such as Browne et al. (2000) and Kunreuther and Pauly (2004) document persistent under-insurance in disaster-prone areas, even when the financial benefits of coverage are substantial, pointing to risk misperception and the under-weighting of low-probability events. A broad set of empirical studies further shows that disaster insurance markets exhibit low participation rates and pronounced cyclical patterns, with demand surging after major events but declining as memories fade (Kunreuther, 1978, 1996; Camerer and Kunreuther, 1989; Gallagher, 2014; Browne and Hoyt, 2000; Michel-Kerjan and Kousky, 2010; Hallstrom and Smith, 2005; Cai and Song, 2017; **?**).

A growing body of research identifies several frictions that help explain why observed insurance behavior departs from standard expected-utility predictions. Liquidity and credit constraints frequently limit households' ability to purchase coverage, even when premiums are actuarially favorable and potential losses are severe (Grace et al., 2004; Gollier, 2005). These financial barriers mean that households who are most exposed to risk are often the least equipped to protect against it. In addition to resource constraints, many consumers struggle to understand the complexity of insurance contracts. Deductibles, exclusions, and coverage limits are difficult to evaluate, and misunderstanding these policy features can distort perceived costs and benefits (**?**Zweifel and Eisen, 2012).

Distrust in insurers further suppresses demand. Field experiments show that households often question whether insurers will honor claims (Cole et al., 2013). This lack of trust can be particularly damaging in low-income or rural settings, where past negative experiences amplify skepticism. Moreover, lowering prices alone does not eliminate these barriers. Even when products are heavily subsidized or offered at steep discounts, take-up remains low (Giné et al., 2008; Cole et al., 2013).

A complementary strand of literature shows that small interventions can increase insurance participation. Simple reminders can counteract inertia, forgetfulness, and present-biased procrastination and increase renewal rates (Karlan et al., 2014). Framing devices, such as emphasizing losses rather than premiums or highlighting the protective role of insurance, have been shown to shift risk perceptions and willingness to insure (Johnson et al., 1993). In addition, default enrollment mechanisms exhibit even greater effects on consumer decisions (Ericson and Starc, 2012; Handel, 2013; Robinson et al., 2021). However, inertia from automatic renewals can lead to insufficient coverage rates (Barseghyan et al., 2011).

Behavioral models offer a natural framework to explain these irregularities in flood insurance demand. Prospect theory asserts that individuals evaluate outcomes relative to a reference point and place disproportionate weight on losses compared to gains (Kahneman and Tversky, 1979). In the context of flood risk, this implies that homeowners may respond more strongly to the threat of a potential loss than to equivalent reductions in premiums and that their reference point (shaped by recent storms or predicted paths) can shift over time. Expectation-based models extend this idea by predicting that anticipated outcomes help to determine the reference point itself and that deviations from those expectations generate utility shocks (Kőszegi and Rabin, 2006, 2007, 2009). For flood insurance, this means that households may react differently depending on whether a storm hits as predicted, misses unexpectedly, or causes damage in areas initially thought to be safe.

Empirical work supports these ideas in a range of settings. Households often over-insure small, routine risks in ways consistent with probability weighting and loss aversion (Sydnor, 2010). Distorted beliefs about likelihoods and sensitivity to losses have been shown not only in insurance choices but also in gambling environments, where individuals overweight small probabilities and react strongly to losses relative to gains (Wakker and Deneffe, 1996; Post et al., 2008). Similarly, in competitive health insurance markets, consumers show inertia when choosing deductibles and plans (Abaluck and Gruber, 2011; Handel, 2013). Experimental studies further show that reference points shape behavior in real-effort tasks (Abeler et al., 2011) and even professional sports performance (Pope and Schweitzer, 2011).

A closely related line of research utilizes forecast errors as exogenous shocks to reference points. Card and Dahl (2011) show that unexpected results from NFL games generate emotional and behavioral responses, demonstrating how deviations from anticipated results influence decision-making. Similar patterns appear in purchasing contexts: forecast surprises in weather lead households to adjust automobile purchases in ways consistent with reference-dependent preferences (Busse et al., 2015) and errors in earnings or market forecasts generate predictable shifts in stock returns (Allen et al., 2017). Related research in disaster settings shows that expectation formation itself shapes insurance demand: willingness to pay adjusts with perceived flood risk (Bin and Landry, 2013), households display myopia and misperceived probabilities (Kousky and Kunreuther, 2014), and expectations interact with adverse selection (Wagner, 2022).

This paper contributes to these literatures by introducing storm forecast errors as a novel, measurable reference points. Forecasts are salient, credible, and widely distributed, making them natural anchors for household expectations. Deviations from these forecasts create expectation shocks that are both psychologically meaningful and exogenous to individual households. By combining forecast data with detailed administrative records of flood insurance policies, this study provides direct evidence that forecast errors shape coverage decisions. In doing so, it advances the literature on insurance demand, enriches models of reference-dependence, and deepens the understanding of how salience and expectations influence protective investment in high-stakes markets.

3 Background

In this section, I outline the background information necessary to understand how homeowners interpret storm risk and make insurance decisions. I begin by describing the National Flood Insurance Program, which is the primary source of residential flood coverage in the United States. I then summarize how tropical cyclones are formed and classified and how their characteristics relate to potential damage. Finally, I review the forecasting process and the communication tools used to convey storm information to the public.

3.1 The National Flood Insurance Program

The National Flood Insurance Program was established by the U.S. Congress in 1968 through the National Flood Insurance Act (P.L. 90-448) in response to growing concerns over the widespread lack of private market coverage for flood risk[2]. At the time, repeated flood disasters had imposed heavy financial burdens on both affected households and the federal government, which frequently resulted in ad hoc disaster relief. The NFIP was designed to fill this gap by offering federally supported flood insurance to residents in flood-prone areas, thus shifting post-disaster assistance from reactive aid to proactive risk pooling (Michel-Kerjan and Kousky, 2010; Kousky, 2018).

By 2022, more than 22,000 communities in all 50 states and territories were enrolled in the NFIP, supporting nearly 5 million active policies and representing roughly \$1.3 trillion in total coverage (Congressional Research Service, 2023; Federal Emergency Management Agency (FEMA), 2023a). Policies are administered through the Write-Your-Own program, in which private insur-

[2]Prior to 1968, private flood insurance was virtually non-existent, While private coverage did exist between 1895 and 1927, it was later revoked due to major losses from the Mississippi River floods in 1927.

ers[3] sell and service policies on behalf of the federal government while the Federal Emergency Management Agency underwrites the risk and sets standardized premium rates. These premiums are calculated using FEMA's flood risk maps (known as Flood Insurance Rate Maps, or FIRMs), which incorporate factors such as property elevation, location within or outside special flood hazard areas, building age and type of structure, and more recently actuarial variables under the new Risk Rating 2.0 pricing methodology (Federal Emergency Management Agency (FEMA), 2023b; Kousky and Kunreuther, 2014).

Notably, NFIP policies must be paid in full for the entire year in advance and coverage typically does not begin until 30 days after purchase. This rule was explicitly designed to discourage last-minute purchases in anticipation of storms (Federal Emergency Management Agency (FEMA), 2023a). The delay introduces important temporal frictions into insurance decision-making: individuals must assess and act on risk in advance, often months before hurricane season peaks. In behavioral terms, this creates room for salience, risk perception, and recent weather experiences to disproportionately shape demand.

Although policyholders may cancel at any time, premiums are generally non-refundable, which further reduces the attractiveness of speculative or short-term enrollment. This reinforces the structure of the NFIP as a commitment device, which requires ex ante recognition of risk and sustained participation. These features contrast sharply with many forms of post-disaster aid or private short-term insurance markets.

3.2 Storm Classifications

Tropical cyclones, broadly referred to as storms in this paper, are organized atmospheric systems that originate over warm tropical or subtropical ocean waters. These systems develop when warm, moist air rises from the ocean surface, generating convection and releasing heat that fuels further development. A system is initially designated as a tropical disturbance when it exhibits sustained thunderstorm activity without well-defined circulation. If convection becomes organized and a center forms, the system is upgraded to a tropical cyclone (NOAA National Hurricane Center, 2019; Landsea and Franklin, 2013).

Storms are classified according to their maximum sustained one-minute surface wind speeds using the Saffir-Simpson Hurricane Wind Scale (SSHWS). A system with wind speeds of 38 mph

[3]It should be noted that private flood insurance is available in the United States, but it constitutes only a small share of the market. Such policies are rarely offered or chosen, largely because premiums tend to be higher than those of the NFIP and underwriting is more restrictive. Although precise counts are difficult to obtain, estimates from Resources for the Future indicate that the NFIP accounts for more than 90% of all residential flood insurance policies in force.

or less is classified as a (sub)tropical depression[4]. Once wind speeds reach between 39 and 73 mph, the storm becomes a (sub)tropical storm and receives an official name. When sustained winds exceed 74 mph, the system is classified as a hurricane. Hurricanes are further subdivided into five categories: Category 1 (74-95 mph), Category 2 (96-110 mph), Category 3 (111-129 mph), Category 4 (130-156 mph) and Category 5 (157 mph or greater). The National Hurricane Center designates storms in Category 1 and 2 as minor hurricanes, while storms in Categories 3 through 5 are considered major hurricanes, due to their increased potential for destruction (**?**). Although storms of any intensity can cause substantial damage through wind impact, storm surge, and inland flooding, major hurricanes account for a disproportionate share of economic losses[5]. These distinctions play an important role in the empirical analyses that follow, where I examine how variation in storm intensity shapes insurance behavior and policy uptake.

Geographically, storms form in both the Atlantic and eastern Pacific basins, but only a subset of these systems pose direct threats to the United States. Although the eastern Pacific sees a higher total number of tropical cyclones, prevailing wind patterns and cooler ocean temperatures often inhibit landfall. By contrast, the Atlantic basin, especially the Gulf of Mexico and the Caribbean Sea, provides ideal conditions for storm formation and intensification, with warmer waters and steering currents that frequently direct systems toward the U.S. mainland[6] (Emanuel, 2005).

To describe temporal patterns of risk, the NHC defines the Atlantic hurricane season as extending from June 1 to November 30, a window that captures nearly all historical U.S. landfall events[7]. On average, a typical season produces approximately 14 named storms, of which 7 become hurricanes and 3 escalate to major hurricanes (**?**). These storms generate a wide array of hazards, including high winds, torrential rainfall, coastal storm surge, and inland flooding, often affecting areas far beyond the immediate coastline.

3.3 Storm Forecasting and Risk Communication

Once a tropical cyclone forms, the NHC initiates a continuous cycle of forecast updates, typically issued at six-hour intervals (at 00, 06, 12, and 18 UTC) and continuing until the storm dissipates or

[4]Subtropical and tropical systems are defined by the same surface wind speeds, but tropical systems are characterized by a higher concentration of storm clouds and produce more torrential rainfall than that of subtropical systems.

[5]While exact averages by category are not widely published, major hurricanes commonly produce damages in the tens to hundreds of billions of dollars, whereas smaller storms (Category 1/2 hurricanes and tropical storms) typically cause damage in the lower-billions in the U.S.

[6]On average, the eastern Pacific generates roughly 15–17 named storms per year, compared to about 12–14 in the Atlantic. Yet a far smaller share affect the United States: historically, nearly one-third of Atlantic storms make landfall in the United States, whereas fewer than 10–15% of eastern Pacific storms do so, as most track westward or weaken over cooler waters (Emanuel, 2005).

[7]The NHC reports that roughly 97% of Atlantic produced storms form during hurricane season.

merges with another system. Each advisory includes predictions of the future trajectory, intensity and spatial extent of the storm, which serves as a critical input to emergency management, media coverage, and perception of risk at the home level (**?**).

These forecasts are generated using an array of weather prediction models that solve physical equations that govern atmospheric motion. The NHC synthesizes outputs from various global and regional models, each differing in spatial resolution, physical parameterizations, and initial condition schemes. By integrating multiple model outputs, human forecasters develop a consensus track[8] and intensity forecast for public release (Cangialosi et al., 2020; Tallapragada et al., 2014). Each forecast includes projected storm center coordinates and maximum sustained wind speeds at regular intervals: every 12 hours from 0 to 72 hours ahead and every 24 hours from 72 to 168 hours. This structure yields up to 11 discrete time point predictions per forecast cycle (**?**).

Central to public risk communication is the "cone of uncertainty", a graphical representation of the probable path of the center of the storm based on historical forecast errors over the past five years. The cone reflects only the uncertainty in the forecast track; it does not indicate the size of the storm or the range of potential hazards. As depicted in Figure 2, the cone widens with the forecast horizon, visually conveying the increasing uncertainty associated with longer lead times. Despite its technical limitations, the cone has become a widely recognized visual tool in media and public discourse, and plays a powerful role in shaping perceived risk and behavioral responses (Broad et al., 2007; Morss et al., 2010).

Forecast accuracy varies substantially with horizon. While 24- and 48-hour track forecasts are generally reliable, forecast errors increase sharply beyond 72 hours. This growing uncertainty at longer lead times can reduce confidence in forecasts and can delay protective actions by individuals who perceive the information as ambiguous or unreliable. As such, forecast credibility, timing, and clarity are essential not just for scientific accuracy but also for effective behavioral influence and insurance related decision-making.

4 Data Sources and Sample Construction

In this section, I describe the data sources and construction of the dataset used to examine how storm forecasts shape flood insurance decisions. I begin with administrative records from the NFIP, which provide detailed information on policy characteristics and household-level coverage decisions. I then outline the storm forecast and track data from the NHC, which allow for measure-

[8] Consensus forecasts are constructed from a weighted combination of dynamic and statistical model outputs, with weights dictated by each model's historical performance.

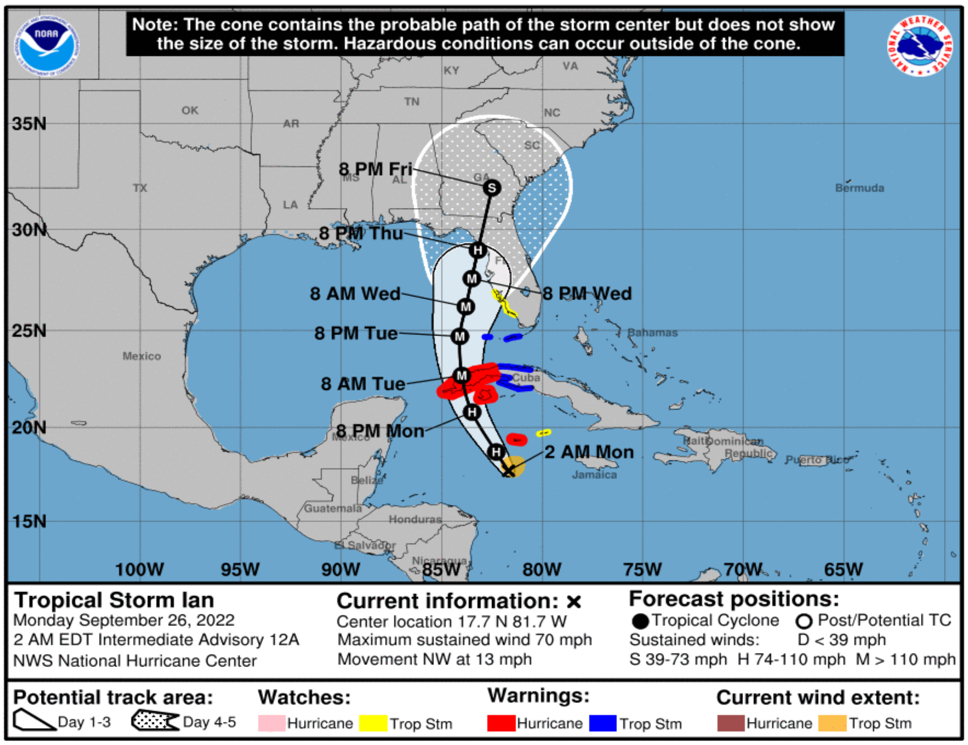


Figure 2: Cone of Uncertainty

Notes: The figure reproduces the National Hurricane Center's forecast cone for Tropical Storm Ian as of 2:00 AM EDT on Monday, September 26, 2022 **?**. The cone depicts the probable path of the storm's center, based on official forecasts, but does not represent the size of the storm or the full extent of hazardous conditions. Black dots mark forecast positions at 12-hour intervals, with the letter indicating storm intensity.

ment of predicted and realized storm exposure. Finally, I explain how these datasets are linked to create a panel that aligns household flood insurance decisions with forecast information available during the enrollment window.

4.1 Flood Insurance Policies

The empirical analysis draws on administrative records from the NFIP spanning 2009 to 2023. These data, maintained by FEMA, provide comprehensive information on all flood insurance policies nationwide, including newly issued and renewed contracts. Each policy record contains detailed property characteristics (e.g., structure type, geographic coordinates, estimated replacement cost), as well as policy-level attributes (e.g., coverage limits, deductibles, premiums, and effective dates).

For the purposes of this study, I focus on a homogeneous selection of policies. Specifically, the data set is restricted to policies issued for properties in Florida. The reason being that Florida consistently ranks among the most flood-prone states in the U.S. and has a high concentration of NFIP policies[9]. Additionally, focusing on a specific state allows for a consistent regulatory context and shared floodplain management practices, while Florida itself provides a direct link to Atlantic hurricane exposure. In order to study household-level decisions, I further restrict the data to only single-family residential homes and exclude commercial, condominium, and multifamily structures. Finally, to isolate initial purchase behavior, I retain only newly issued policies and exclude renewals. This ensures that the analysis captures responses to evolving risk perceptions, particularly those shaped by forecasts, rather than the inertia in ongoing coverage.

The resulting data set consists of more than 1.66 million policies over a 15-year period. Figure 3 presents the number of policies in effect for a given month between 2009 and 2023 broken down by type of policy. The graph reveals pronounced seasonality: policy activity rises sharply in late summer, coinciding with the Atlantic hurricane season, and falls during the winter months. This pattern holds for both new issuance and renewals. The cyclical pattern is consistent with the idea that salience and perceived storm risk strongly influence purchase decisions.

Beyond seasonality, the data reveal long-run trends. The total stock of active policies increased steadily until its peak around 2014-2015, followed by a gradual decline in subsequent years. This decline may reflect affordability concerns, growth in private-market alternatives, or changing perceptions of flood risk. Newly issued policies are smaller in magnitude but exhibit sharp, temporary

[9]As of 2023, the state of Florida had more than 1.7 million active policies under the NFIP, representing nearly 35% of all such policies nationwide.

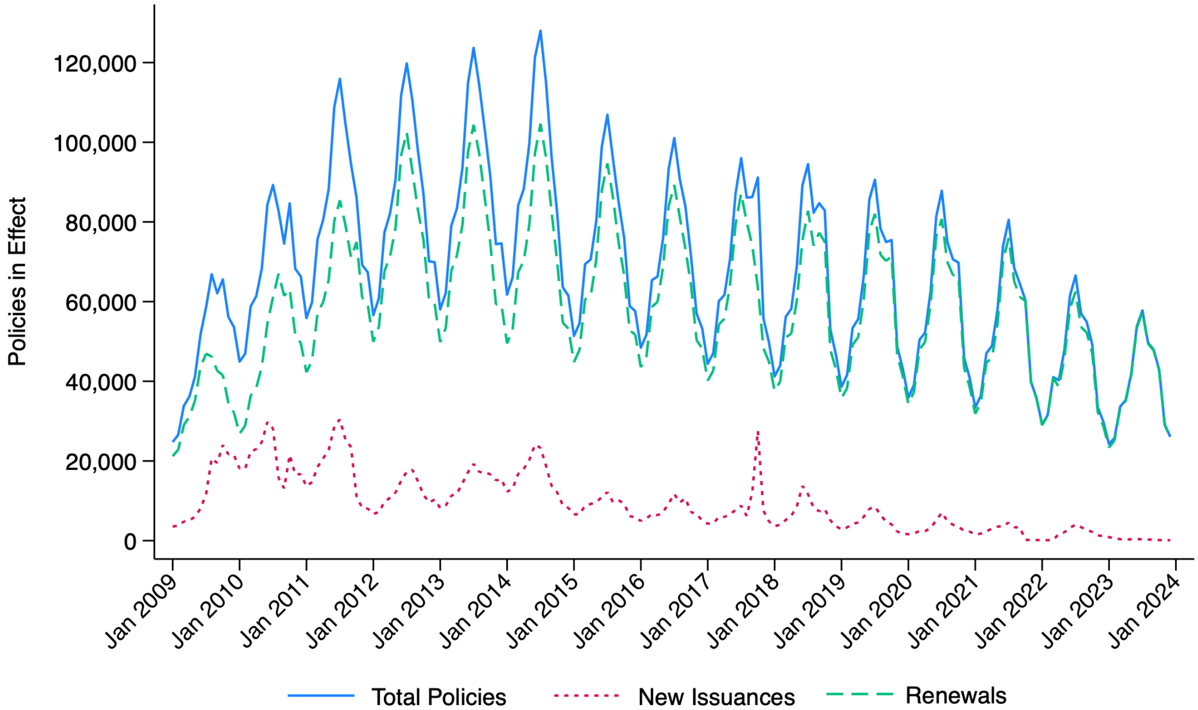


Figure 3: NFIP Policy Trends

Notes: The figure shows the distribution of NFIP policies in effect for each month from 2009 through 2023. The blue line represent the total number of policies (new and renewal). The green line indicates the number of renewals while the red line depicts the counts of new policies. All series exhibit strong seasonal patterns, with policy activity peaking prior to the June-November hurricane season and steadily declining there after.

spikes around major hurricanes that rapidly decay[10].

Table 1 reports the summary statistics for the corresponding sample. The typical policy covers a single-story primary residence with an average home age of 26 years. Roughly 83% of insured properties are primary residences, while only 6% are elevated structures. The average coverage amounts are $205,000 for buildings and $74,000 for contents, but these values vary widely, reflecting the heterogeneity of Florida's housing stock. Premiums average $493 annually, with total policy costs (including surcharges and fees) averaging $565, although some high-value homes pay substantially more. The deductibles remain modest, averaging around $1,450 for buildings and $1,260 for contents.

[10]The pronounced spike in 2017, for instance, occurred after the impact of Hurricane Irma.

Table 1: Summary Statistics for NFIP Policy Variables

Variable	Mean	Std. Dev.	Obs.
Building Deductible	1,449	1,202	1,655,539
Contents Deductible	1,262	929	1,546,265
Total Building Coverage	204,797	66,053	1,648,422
Total Contents Coverage	74,249	32,176	1,485,254
Total Premium	493	519	1,664,211
Total Policy Cost	565	557	1,664,208
Primary Residence (1 = Yes)	0.83	0.37	1,664,216
Elevated Building (1 = Yes)	0.06	0.24	1,664,216
Floors	1.35	0.70	1,664,207
Home Age (Years)	25.96	18.21	1,663,846
Observations			1,664,216

Notes: The table reports summary statistics for new residential flood insurance policies in Florida drawn from NFIP administrative data (2008-2023). All monetary values are expressed in U.S. dollars.

4.2 Storm Forecasts

Storm activity is measured using a storm-level panel constructed from forecast and track data provided by the National Hurricane Center. The dataset covers all tropical cyclones in the North Atlantic basin from 2008[11] to 2023 and includes both realized storm characteristics and the advance forecasts available to households prior to landfall.

Each storm is observed across multiple forecast cycles, which the NHC typically issues every six hours (00, 06, 12, and 18 UTC). At each issuance, the data set reports both the realized position and intensity of the storm at that moment, as well as a complete set of projected tracks, wind speeds, and storm radii at different lead times. Forecasts follow a standardized structure: for each cycle, the NHC provides predicted storm center coordinates and intensity at 0, 12, 24, 36, 48, 72, 96, and 120 hours ahead.

To illustrate, consider a forecast issued for Hurricane Ian at 12 UTC on September 25, 2022. When the forecast was distributed, the observed center of the storm was located near 14.7°N, 73.5°W with maximum sustained winds of 65 knots (tropical storm). The forecast then projected where the center would be 12 hours later (near Jamaica), 24 hours later (approaching the Cayman Islands), 48 hours later (south of Cuba), and so on. Alongside each projected location, the NHC provided predicted wind speeds such as 80 knots at 24 hours ahead (Category 1) and 110 knots at

[11]The storm data begin a year prior to that of the NFIP dataset to account for storms that occurred before the issuance of early 2009 policies.

72 hours ahead (Category 3) as well as estimates of storm size. This forecasting system was then repeated at the next issuance six hours later (18 UTC September 25, 2022), producing an updated set of observed conditions and a new sequence of predictions.

Using these data, Table 2 summarizes the annual storm counts by type and predicted intensity between 2008 and 2023. Tropical depressions and hurricanes are the most frequently predicted storm types, with occurrences varying between 2 and 14 per year. Category 1 hurricanes are the most commonly predicted outcome, while Category 4 and 5 storms are extremely rare. Several seasons (e.g. 2012 and 2013) did not have storms predicted above Category 2, highlighting the episodic nature of severe hurricanes. Overall, the total number of predicted storms fluctuates substantially over years, from as few as nine in 2014 to as many as 31 in 2020 (a year of unusually high activity), reflecting both climatological cycles and year-to-year variation in forecast severity. Subtropical systems also appear in the dataset, albeit at a much lower frequency than that of other storms.

Table 2: Annual Counts of Storm Types at Prediction

Category	Type	’08	’09	’10	’11	’12	’13	’14	’15	’16	’17	’18	’19	’20	’21	’22	’23
All Storms	Subtropical Dep.	0	0	0	0	0	0	0	0	0	1	2	0	2	1	0	0
	Subtropical Storm	0	0	0	0	0	1	0	0	0	0	0	2	0	0	0	1
	Tropical Dep.	8	6	8	11	9	9	3	7	7	6	5	8	14	10	6	10
	Tropical Storm	1	2	1	1	0	3	0	1	1	1	1	4	2	2	1	3
	Hurricane	8	3	12	7	10	2	6	4	7	10	8	6	13	7	9	7
Hurricanes	Category 1	3	1	7	3	8	2	4	2	3	4	6	3	7	3	6	4
	Category 2	1	1	1	2	2	0	1	1	2	2	0	1	1	2	1	1
	Category 3	4	1	3	2	0	0	1	0	1	1	0	0	2	0	1	0
	Category 4	0	0	1	0	0	0	0	1	1	3	2	1	3	2	1	2
	Category 5	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
All Storms		17	11	21	19	19	15	9	12	15	18	16	20	31	20	16	21

Notes: Storms are classified by type at the time of prediction and by Saffir-Simpson category for hurricanes. Counts include only storms that formed in the Atlantic and generated forecast tracks within the sample period.

4.3 Linking Insurance and Storm Forecast Data

The NFIP policy data are merged with the NHC storm forecast data along both temporal and spatial dimensions to construct a panel that links household insurance decisions with storm expectations. NFIP policies are first aggregated to the month-location level, recording the number of newly issued policies by effective date and geographic coordinates. This produces 1,227 distinct locations, which average 17.8 new policies per month. To ensure a complete panel structure, I generate the additional 270 geographical locations in Florida that do not appear in the NFIP records, as well as month-location combinations in which no new policies were issued. The resulting panel contains 1,497 unique locations observed over 180 months, with an average of 6.1 newly issued policies per month.

To illustrate the matching process, consider a location in Tallahassee with a policy effective date of October 2021. Under a forward-looking matching window, this observation is linked to all storms whose forecasts were issued between 31 and 120 days earlier, that is, storms that received forecasts between June and September 2021. Suppose a storm that falls within this period produces 2 forecasts. For each forecast, I compute the great-circle distance between the location's coordinates and the predicted storm center from the 72-hour projected location. If Forecast A's 72-hour prediction is located 310 nm from Tallahassee and Forecast B's prediction is 540 nm away, I record the closest distance (Forecast A) as the most relevant forecast and omit any others.

Finally, to account for the salience of more recent storm forecasts relative to those issued further in advance of the policy purchase date, all matched storms are ranked according to their temporal proximity to the effective month of the policy. Following the example above, if two storms occurred during the matching window with Storm A's retained forecast occurring 40 days before the policy date while Storm B's occurred 110 days earlier, Storm A is treated as the primary forecast exposure for that month-location observation.

4.4 Expected Outcomes

Using the method previously described, Figure 4 illustrates the relationship between predicted and realized storm distances for a coordinate in Tallahassee (30.4° N, 84.3° W). Each point corresponds to a unique storm that was predicted to pass within 600 nm of the area. The considerable dispersion around the 45-degree line reflects the error in forecasts: many storms deviate substantially from their predicted paths, with some missing entirely and others striking unexpectedly despite initial projections.

To categorize exposure, I classify storms using a binary "Predicted Hit" indicator that captures whether the predicted storm center fell within a specified distance of the policy location. The baseline threshold is set at 300 nautical miles, which approximates the average radial extent of tropical storm force winds in Atlantic hurricanes[12]. This threshold balances sensitivity to meaningful forecast exposure with the need to exclude distant storms unlikely to influence household

[12]This distance typically ranges between 200 and 400 nautical miles (Kimball and Mulekar, 2004)

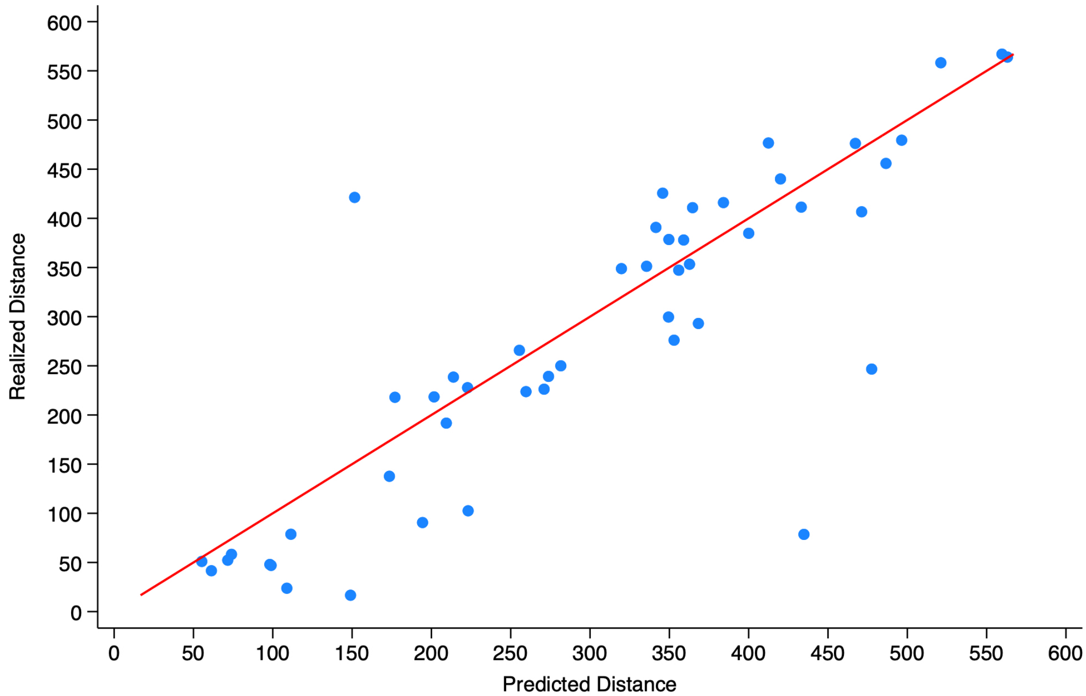


Figure 4: Predicted and Realized Storm Distances for Tallahassee

Notes: The figure plots the relationship between predicted and actual distances (in nautical miles) between the closest storm forecast point 72-hours out and realized locations across all storms that came within 600nm of the coordinate 30.4° N, 84.3 W.

perceptions. The same process is applied to the corresponding realized storm location to measure actual exposure, a ”Realized Hit”.

With these classifications, Figure 5 plots the probability of realized storm hits against the predicted distance at the 72-hour horizon. The vertical line marks the 300 nm threshold used to classify predicted hits (to the left) and predicted misses (to the right). The curve declines sharply as predicted distance increases: close predictions are associated with higher realized probabilities of impact, whereas distant predictions are rarely realized as strikes. However, even within the predicted hit zone, the accuracy of the forecasts is limited. When a storm is projected to pass within 300 nm, the realized probability of actual impact is only about 42%, which implies that the majority predicted hits do not materialize. Conversely, when storms are forecast to miss by more than 300 nm, the realized probability of an actual strike falls close to zero, but not entirely, and some storms still deviate from their projected paths.

This pattern highlights two important features of the forecast environment. First, forecasts are systematically informative. The predicted distance strongly correlates with realized exposure, confirming that households receive meaningful signals about risk. Second, forecasts are also noisy.

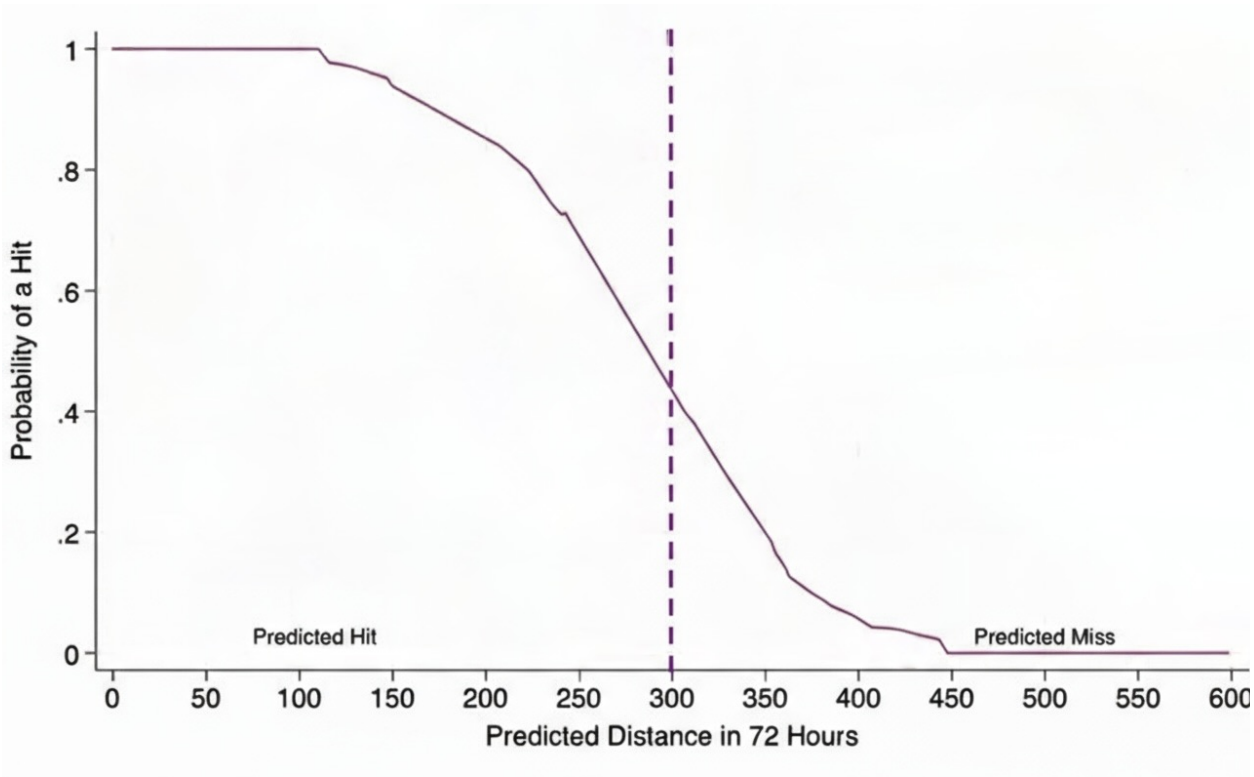


Figure 5: Probability of Realized Storm Impact

Notes: The figure plots the smoothed relationship between the predicted storm distance (in nautical miles) 72 hours before landfall and the realized probability that a location experiences a direct hit. The line represents a locally weighted regression (LOWESS) fit using a bandwidth of 0.5. The dashed vertical line marks the 300 nautical mile threshold used to classify predicted hits versus misses in the empirical analysis. The estimated probability declines sharply as the predicted distance increases beyond this cutoff, reflecting the nonlinear relationship between forecast proximity and realized storm exposure.

The gap between predicted hits and the realized hit generates expectation violations.

To further classify exposure, I combine the predicted and realized indicators into a four-category taxonomy of forecast accuracy. Specifically, I define a ”True Hit” as a storm for which both the predicted and realized distances fall within 300 nm, and a ”True Miss” when both fall outside 300 nm. A ”False Hit” occurs when the storm is predicted to come within 300 nm but the realized distance is greater, while a ”False Miss” occurs when the storm is predicted to remain beyond 300 nm but actually comes within 300 nm. Additionally, observations with no relevant storm activity during the 31-120 day exposure window are assigned a separate ”No Storm” indicator, which serves as the baseline category.

Table 3 reports the distribution of these classification across observations. True hits and true misses together account for more than 60% of cases, with tropical storms and hurricanes accounting for the majority of storm types. False hits and false misses are relatively rare and represent less than 3% of the sample. Roughly one-third of the observations fall into the no storm category, reflecting the frequency with which households faced no proximate storm activity during the decision window.

5 Behavioral Framework for Insurance Response

In this section, I describe how insurance decisions in the face of storm outcomes offer a unique window into how individuals perceive and respond to risk under uncertainty. Because storms are rare and highly variable in their impacts, households must often rely on imperfect forecasts when deciding whether to purchase flood insurance. The behavioral response to these forecasts is shaped not only by the eventual outcome of the storm, but also by the degree to which the realized conditions align with prior expectations. Specifically, I outline four conceptual cases that describe how individuals might interpret and react to different combinations of predicted and realized storm exposure. These cases draw on established theories of salience, availability bias, ambiguity aversion, and reference-dependent utility.

5.1 Case 1: Experience-Driven Updating

The most straightforward intuition is that individuals respond primarily to the realized impact of a storm, rather than its predicted trajectory. Because storms are rare and uncertain, homeowners can initially discount the risk and delay buying insurance. However, when a storm makes landfall nearby, the event becomes highly salient, prompting homeowners to update their beliefs and seek coverage in anticipation of future threats. If this prediction holds, I would expect insurance demand to increase similarly following both predicted hits and predicted misses, as long as the storm ultimately makes impact. In contrast, if the storm misses, individuals would perceive a lower threat and show little response.

This behavior is consistent with availability bias (Tversky and Kahneman, 1973), where recent or vivid events are more likely to influence decision-making than abstract probabilities. Empirical evidence supports this theory by showing that insurance uptake often increases after high-impact events (Gallagher, 2014; Kousky, 2018), consistent with reactive responses driven by experience. This may also reflect myopic risk assessment (Kunreuther and Pauly, 2004), in which individuals underweight low-probability future threats until risk becomes pronounced through direct exposure. However, this case contrasts with models of reference dependence in which individuals respond not only to outcomes, but also to how those outcomes compare to expectations.

Table 3: Distribution of Forecast Accuracy

Category	Frequency	Percent
True Hit	59,272	22.0%
Subtropical Storm	171	
Tropical Depression	7,347	
Tropical Storm	26,716	
Hurricane	25,038	
True Miss	113,778	42.2%
Subtropical Storm	86	
Tropical Depression	23,448	
Tropical Storm	43,619	
Hurricane	46,625	
False Hit	1,948	0.7%
Subtropical Storm	35	
Tropical Depression	862	
Tropical Storm	106	
Hurricane	945	
False Miss	4,850	1.8%
Subtropical Storm	0	
Tropical Depression	1,597	
Tropical Storm	3,223	
Hurricane	30	
No Storm	89,612	33.3%
Observations	269,460	

Notes: The table summarizes the distribution of forecast accuracy classifications across all predicted storm events within the analysis sample. Each observation represents a location-storm forecast instance classified as one of four categories: *True Hit*, *True Miss*, *False Hit*, and *False Miss*. Subcategories correspond to the storm type at the time of prediction.

5.2 Case 2: Dual Sensitivity to Forecasts and Outcomes

A second possible interpretation is that individuals respond not only to outcomes, but also to predictions themselves. Consider the two consistent cases: a predicted hit that results in a realized hit and a predicted miss that results in a realized miss. In this framework, I would expect the former to have the strongest effect on insurance demand, as the prediction reinforces the outcome and highlights risk (Bordalo et al., 2012). In contrast, the latter should have the weakest effect, as neither the prediction nor the outcome signals an elevated risk.

The remaining two cases, predicted hit but realized miss and predicted miss but realized hit, introduce conflicting information. In both cases, the homeowner becomes aware of the risk of a storm, either through a forecast warning or an unexpected impact. However, inconsistency between prediction and outcome can reduce trust in forecasts or increase ambiguity (Ellsberg, 1961; Kunreuther, 1996). Despite this, the salience of the event may still elevate perceived vulnerability. Consequently, insurance demand is expected to increase in these cases, albeit less than in the scenario where both the prediction and realization align to signal high risk.

5.3 Case 3: Asymmetric Salience of Surprise Events

A related interpretation builds upon Case 2, but places greater emphasis on the salience of realized outcomes. Individuals continue to respond to both predictions and actual storm outcomes, but realized hits (whether expected or not), heighten salience more than realized misses. As in Case 2, the implications for the consistent scenarios remain unchanged: a predicted hit that results in a realized hit is expected to generate the highest increase in demand, while a predicted miss that results in a realized miss elicits the least response.

However, this interpretation introduces an important distinction between the two conflicting cases. Specifically, a predicted miss that results in a realized hit is more salient than a predicted hit that results in a realized miss, as the former involves an unexpected impact and may prompt the updating of beliefs about both the risk of the storm and the reliability of the forecasts (Bordalo et al., 2012). In contrast, a false alarm may be discounted as noise. As a result, insurance uptake is likely to be higher after a surprise hit than after a false alarm, even though both involve inconsistencies between prediction and outcome.

5.4 Case 4: Reference Dependence and Forecast-Based Expectations

The final interpretation draws on the reference-dependent utility framework developed by Kőszegi and Rabin (2006, 2007, 2009), which incorporates expectation-based reference points and loss aversion. In this model, individuals assess outcomes relative to what they expect to happen, with losses weighted more heavily than gains. In the context of storm forecasts, the prediction establishes the reference point: a predicted hit sets the expectation of loss, while a predicted miss sets the expectation of safety or gain.

The psychological response depends not only on the realized outcome, but also on whether that outcome deviates from the prior expectation. A realized hit that was not predicted constitutes an unexpected loss and should therefore trigger the strongest increase in insurance demand. A predicted and realized hit is an expected loss and should still prompt insurance uptake, but to a lesser degree. In contrast, both types of misses represent gains. A predicted and realized miss (an expected gain) is the least likely to spur insurance behavior. A realized miss following a predicted hit is an unexpected gain; it may prompt modest demand due to residual salience, but loss aversion implies a muted response compared to the surprise hit.

6 Modeling the Effect of Forecasts and Insurance Demand

In this section, I develop a simplified model of the effect of storm outcomes on the decision to purchase flood insurance and establish the empirical framework for identifying the impact of storm forecasts. The main hypotheses are derived from Case 4 in the motivation section. Specifically, that storm forecasts shape expectations in a manner consistent with gain-loss utility evaluated relative to a rational, expectation-based reference point.

6.1 Insurance Demand Model

Consider a homeowner who, in each period, faces some risk of experiencing the effects of a storm. Let $d \geq 0$ denote the probability that the homeowner purchases flood insurance in a given period. This probability is influenced by the outcome of a storm present in the same period, indicated by $y \in \{0, 1\}$, where $y = 1$ indicates that the storm negatively impacts the homeowner (i.e., a "hit") and $y = 0$ indicates no impact (i.e., a "miss").

Let $p = E[y]$ denote the homeowner's prior belief about the likelihood of the storm impacting her area. The decision to purchase insurance is assumed to deviate from an initial level d^0 based on the psychological impact of the storm outcome, captured by the gain-loss utility. Specifically, I assume:

$$d = d^0 + \mu(y, p), \tag{1}$$

where $\mu > 0$ is a piece-wise linear function defined as:

$$\mu(y,p) = \begin{cases} \alpha(y-p), & y > p \quad \text{(False Miss)} \\ \beta(p-y), & y < p \quad \text{(False Hit)} \\ \gamma, & y = p = 1 \quad \text{(True Hit)} \\ 0, & y = p = 0 \quad \text{(True Miss)} \end{cases}$$

for positive constants α, β, and γ. The assumption $\alpha > \gamma > \beta$ captures behavioral asymmetries in response to storm outcomes. In other words, the marginal effect of a false miss exceeds that of a false hit, consistent with loss aversion. The parameter γ reflects a salience effect: when an anticipated storm strikes as expected, it reinforces perceived risk and increases insurance demand, even in the absence of surprise. In contrast, case $y = p = 0$ (true miss) does not have psychological salience and therefore does not affect insurance behavior.

Since storm outcomes are binary, the model implies four distinct expressions for insurance demand as a function of the probability of a hit, p:

$$\begin{aligned} d^{FM}(p) &= d^0 + \alpha(1-p) \\ d^{FH}(p) &= d^0 + \beta p \\ d^{TH}(p) &= d^0 + \gamma \\ d^{TM}(p) &= d^0 \end{aligned} \tag{2}$$

Figure 6 illustrates these cases. The upper, downward-sloping line corresponds to $d^{FM}(p)$. When $p = 0$, a storm hit is entirely unexpected, leading to the highest level of insurance demand at $d^0 + \alpha$. As p increases, expectations and outcomes gradually align and demand decreases until it converges with the true hit level d^{TH} at $p = 1$. Thus, d^{FM} decreases in p. The upward-sloping line represents $d^{FH}(p)$. When $p = 0$, a storm miss is fully anticipated, so demand aligns with the true miss level d^{TM}. As p increases, the miss becomes increasingly unexpected, reaching a maximum at $d^0 + \beta$, when $p = 1$. Unlike the other two cases, both $d^{TH}(p)$ and $d^{TM}(p)$ are constant with respect to p, as they reflect scenarios where the outcomes match prior expectations.

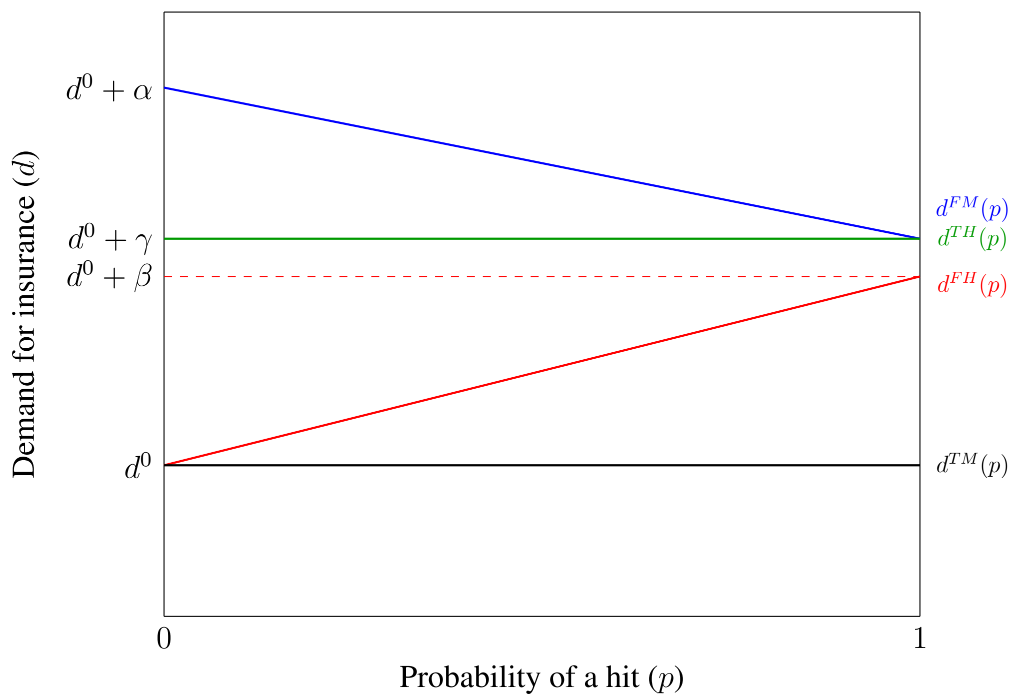


Figure 6: Stylized Model of Flood Insurance Demand Under Reference Dependence

Notes: The figure illustrates the four theoretical demand functions for flood insurance under reference-dependent preferences. Each line corresponds to a different combination of predicted and realized storm outcomes: False Miss ($d^{FM}(p)$), False Hit ($d^{FH}(p)$), True Hit ($d^{TH}(p)$), and True Miss ($d^{TM}(p)$). The horizontal axis represents the subjective probability of a storm hit (p), while the vertical axis measures insurance demand (d). When outcomes deviate from prior expectations, demand responds to the surprise of the event: $d^{FM}(p)$ declines with p as false misses become less misaligned, while $d^{FH}(p)$ increases with p as false hit become rarer. In contrast, $d^{TH}(p)$ and $d^{TM}(p)$ are constant, reflecting cases where realized outcomes match expectations.

6.2 Evaluating the Effect of Forecast Information

To assess how forecasts shape flood insurance demand, I estimate a Poisson count model of new policy issuance at the location-month level. A Poisson framework is appropriate given the count nature of the dependent variable. Storms are classified ex ante using the NHC's 72-hour forecasts, assigning each location-month to one of four categories: True Hit, True Miss, False Hit or False Miss, while observations without relevant storm activity form the omitted baseline. This structure facilitates direct comparisons of how forecast accuracy and expectation violations influence insurance uptake.

I next examine the robustness of these responses to alternative definitions of exposure. First, I vary the distance threshold used to define a predicted hit, testing cutoffs from 100 to 500 nautical miles, and introduce a ”close-call” category (250-350 nautical miles) to capture ambiguous events. Second, I vary the forecast horizon, using predictions 36, 48, 60, 96, and 120 hours in advance to determine whether shorter- or longer-range forecasts generate different behavioral patterns.

Additional robustness checks focus on storm salience. I restrict the forecast window to storms that occurred within 31-60 days (rather than 31-120) to test whether more recent forecasts exert a stronger influence. I also limit the sample to storms predicted to reach hurricane strength to evaluate whether expectations about event intensity amplify behavioral responses. Together, these extensions assess the durability and scope of the baseline results and examine whether temporal proximity and perceived severity magnify the effects of forecast information.

7 Empirical Methodology

Under the Poisson specification, the unit of observation is a location-month (i, t), where the dependent variable, Y_{it}, is the count of new NFIP policies issued in location i during month t. The model takes the following general form:

$$\log(E[\,Y_{it} \mid X_{it},\, p_{it},\, a_{it}]) = \theta + X_{it}\gamma + f(p_{it}, a_{it}; \lambda) \tag{3}$$

where X_{it} includes fixed effects for the month and year, regional trends, and location-level covariates; p_{it} represents the perceived probability of an impact from a storm; a_{it} indicates whether a storm actually occurred; and λ captures behavioral responses to expectation violations.

I assume that perceived hit probability p_{it} is a function of the predicted distance from the storm D_{it}, which operationalizes the forecast salience. Substituting this into the model produces:

$$\log(E[\,Y_{it} \mid X_{it},\, p_{it},\, a_{it}]) = \theta + X_{it}\gamma + g(D_{it}, a_{it}; \lambda) \tag{4}$$

This specification allows the effect of a realized storm a_{it} to depend on the proximity of the forecast storm, generating the four forecast-outcome categories of interest. The coefficients therefore identify the behavioral consequences of true hits, true misses, false hits, and false misses relative to periods without storm exposure.

The identification relies on two assumptions. First, households view NHC forecasts as informative and credible signals of risk. Second, conditional on forecast proximity, realized storm outcomes are exogenous to household insurance decisions. Under these conditions, variation across forecast-outcome pairs isolates the behavioral effects of expectation alignment and violation.

8 Baseline Empirical Results

The baseline regression model classifies storm exposure according to the following structure:

$$\begin{aligned} g(D_{it}, a_{it}, \lambda) = \quad & \lambda_1 \cdot \mathbb{1}(D_{it} \leq 300, a_{it} = 1) \\ & + \lambda_2 \cdot \mathbb{1}(D_{it} \leq 300, a_{it} = 0) \\ & + \lambda_3 \cdot \mathbb{1}(D_{it} > 300, a_{it} = 0) \\ & + \lambda_4 \cdot \mathbb{1}(D_{it} > 300, a_{it} = 1) \end{aligned} \tag{5}$$

which generates four mutually exclusive storm-forecast combinations: true hit (λ_1), false hit (λ_2), true miss (λ_3), and false miss (λ_4). A fifth category, no storm, captures observations with neither predicted nor realized storm activity within the 31-120 day window. This category is omitted from the specification and functions as a reference group, so all coefficient estimates are interpreted relative to periods without storm exposure.

The estimates presented in Table 4 reveal several patterns regarding how the precision of the forecast shapes the insurance decisions of the household. Column (1) provides the simplest specification with a set of fixed effects for location, year, and month that absorb spatial differences and seasonality. Column (2) incorporates random effects and detailed characteristics of the policy and property such as replacement cost, premiums, and structural attributes. The inclusion of these factors tests whether behavioral responses to storm information persist even after accounting for variables that traditionally influence insurance demand. Columns (3) and (4) sequentially add

Table 4: Baseline Regression Estimates

Storm Classification	(1)	(2)	(3)	(4)
Hit × Predicted Hit (True Hit)	0.14 (0.02)	0.25 (0.04)	0.31 (0.04)	0.50 (0.04)
Hit × Predicted Miss (False Miss)	0.72 (0.08)	0.61 (0.07)	0.75 (0.09)	1.05 (0.14)
Miss × Predicted Miss (True Miss)	0.03 (0.01)	0.02 (0.02)	0.04 (0.01)	0.04 (0.01)
Miss × Predicted Hit (False Hit)	-0.31 (0.05)	-0.31 (0.06)	-0.25 (0.05)	-0.18 (0.04)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.29	0.29	0.34	0.55
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	-0.32	-0.32	-0.32	-0.35
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	0.90	0.90	0.84	0.72
p-value	0.00	0.00	0.00	0.00

Notes: The table reports coefficient estimates from Poisson regression models of flood insurance demand using varying specifications. The omitted reference group is a ”No Storm” indicator for observations that had no storm exposure. The dependent variable is the percentage change of new flood insurance policies. Robust standard errors (in parentheses) are clustered at the location level.

storm-type indicators and a measure of storm activity that accounts for the number of storms within 600 nautical miles during the 90-day exposure window. These additional controls address the possibility that households respond differently to hurricane-strength systems than to weaker storms and that the salience of any individual forecast depends on the overall activity of the hurricane season.

In all specifications, true hits consistently increase the demand for new insurance policies, with effects ranging from 14% to 50%. The effect becomes larger as additional controls are introduced, particularly when storm activity is accounted for in Column (4). This pattern suggests that correct forecasts become more influential when households must process multiple competing storm signals. In busy hurricane seasons, a forecast that ultimately proves accurate appears to carry greater weight. Even so, true hits create modest increases in demand, which is consistent with reference-dependence, where anticipated outcomes generate smaller psychological adjustments. When a predicted hit actually materializes, the impact is less surprising and, therefore, the behavioral response, while positive, is limited.

In contrast, false misses generate substantially larger effects in insurance uptake with increases ranging from 61% to 105%. The estimates are robust across all specifications and consistently exceed those of true hits by a meaningful margin. The formal test in the lower panel confirms that the difference between false misses and true hits remains large and statistically significant throughout the specifications. This asymmetric pattern aligns closely with the predictions of expectation-based loss aversion: an unanticipated negative shock generates a sharper behavioral response than an anticipated one because the realized outcome lies well outside the household's forecast-based reference point. Put differently, being caught off guard by an unpredicted hit produces a heightened sense of vulnerability that strongly motivates insurance purchases. Importantly, this effect remains large even after controlling for storm severity and the density of storm activity, indicating that it reflects a genuine behavioral response rather than differences in underlying storm characteristics.

True misses show small, positive effects on new insurance uptake, with coefficients between 0.02 and 0.04. Relative to the omitted reference group, these estimates indicate that households purchase slightly more insurance during times when some storm activity occurs elsewhere, even if their own location is never predicted to be at risk. This suggests that general awareness of storms in the broader region can increase perceived vulnerability, leading to a slight increase in policy purchases. Importantly, these effects are very small compared to the responses observed for true hits and false misses, consistent with the idea that households do not significantly update behavior when nothing happens locally. Instead, true misses simply nudge demand upward relative to completely quiet periods.

False hits produce the opposite reaction. Their coefficients indicate decreases in insurance demand of roughly 18-31 percent, with similar magnitudes in all specifications. These negative responses violate standard reference-dependence predictions, which would not anticipate a reduction in demand following a harmless outcome. If anything, reference-dependence would suggest null effects or slight increases similar to true misses. Instead, the results suggest that false alarms erode trust in forecasts or lead households to reassess their personal risk downward, reinforcing the belief that threats are overstated or unlikely to materialize. In this sense, false hits act as "unexpected relief", reducing perceived vulnerability and consequently lowering the perceived value of insurance. The comparison between false hits and true misses supports this interpretation: while true misses generate only small positive effects on demand, false hits create substantial declines, implying that the act of warning, when not followed by an actual hit, plays a critical role in shaping subsequent risk perceptions.

The comparisons reported in the bottom panel of Table 4 synthesize these patterns. The difference between false misses and true hits is consistently positive and large, confirming that unexpected impacts generate far stronger behavioral adjustments than anticipated ones. Similarly, the comparison of false hits and true misses shows that false alarms reduce demand significantly more than non-events. Finally, the contrast of differences indicates an asymmetry in how households react to expectation violations: unexpected losses drive large increases in insurance purchasing, while unexpected non-losses drive reductions. These results show that households respond not only to storm impacts themselves but also to the alignment between expectation. Forecast errors– both under-predictions and over-predictions–carry powerful behavioral consequences, amplifying or dampening insurance demand in ways that cannot be explained by standard expected-utility.

9 Extensions and Robustness Checks

In this section, I evaluate how the main findings hold up when assumptions are relaxed. The baseline analysis relied on specific choices about how to define storm exposure, including the 300 nm hit threshold, the 72-hour forecast reference point, and the treatment of storms within the 90-day exposure period. Here, I vary each of these elements in turn by testing alternative distance thresholds, adding close-call classifications, shifting the forecast horizon, and examining the role of recency and storm severity. Across these robustness checks, the goal is to assess whether the behavioral patterns identified in the baseline, particularly the strong response to false misses, remain consistent when the underlying assumptions are modified.

9.1 Distance Threshold

Because storm impacts can vary widely in their reach, an important question is whether baseline patterns depend on how a ”hit” is defined. To examine this, I vary the hit threshold from the baseline 300 nm to four alternative distances: 100 nm, 200 nm, 400 nm, and 500 nm. These ranges span the typical spectrum of storm influence, from very narrow definitions that capture only direct landfall zones to broader thresholds that reflect the full range of large storms. For consistency and comparability, all regressions use the same specification as Column (3) in Table 4, which includes fixed effects, storm-type indicators, and policy-level covariates. Full specifications for each threshold are reported in the appendix.

Table 5 summarizes how the coefficient estimates change between these alternative thresholds. Overall, the results indicate that the baseline findings are highly robust. When the hit definition is tightened to 200 nm or expanded to 400 nm, the results remain closely aligned with those at 300 nm: true hits increase demand by 15-30%, false misses by 46-65%, true misses experience minimal effects, and false hits continue to yield negative responses. This consistency suggests that moderate adjustments to the hit threshold do not significantly alter the nature or magnitude of behavioral responses.

However, in extremes, the patterns weaken and become more difficult to interpret. Narrowing the definition to 100 nm leads to misclassifications, as storm effects routinely extend far beyond such distance. This generates distorted estimates: true hit effects increase sharply to 79%, while false misses decrease to 15%. This instability is consistent with the measurement error introduced by an overly restrictive distance cutoff that does not capture meaningful exposure. In the opposite direction, as the threshold increases, the classifications of the storms lose informative value because many storms are coded as “hits” despite posing limited risk. At 500 nm, the true hit effects drop to 12%, false misses to 68%, and false hits become only mildly negative at 9%. True misses even turn slightly negative, reinforcing that very distant storms do little to influence perceived vulnerability.

Despite these boundary issues, the loss aversion tests remain broadly consistent with the baseline at all reasonable thresholds. False misses continue to generate significantly stronger increases in demand than true hits, highlighting the robust and asymmetric behavioral response to unexpected impacts. Only at the 100 nm threshold does this contrast break down. In all, the results indicate that the key behavioral relationships are stable across a plausible range of distance thresholds.

Table 5: Regression Estimates by Hit Definition Threshold

Storm Classification	100 nm	200 nm	300 nm	400 nm	500 nm
Hit × Predicted Hit (True Hit)	0.79 (0.05)	0.30 (0.03)	0.31 (0.04)	0.15 (0.03)	0.12 (0.02)
Hit × Predicted Miss (False Miss)	0.15 (0.04)	0.46 (0.08)	0.75 (0.09)	0.65 (0.06)	0.68 (0.06)
Miss × Predicted Miss (True Miss)	0.02 (0.01)	0.02 (0.01)	0.04 (0.01)	-0.02 (0.01)	-0.03 (0.01)
Miss × Predicted Hit (False Hit)	0.59 (0.10)	-0.11 (0.04)	-0.25 (0.05)	-0.35 (0.03)	-0.09 (0.06)
Tests of Loss Aversion					
False Miss vs. True Hit (Hit Diff.)	-0.36	0.13	0.44	0.50	0.93
p-value	0.00	0.09	0.00	0.00	0.00
False Hit vs. True Miss (Miss Diff.)	0.44	-0.13	-0.32	-0.15	-0.06
p-value	0.00	0.00	0.00	0.00	0.08
Hit Difference vs. Miss Difference	-0.41	0.30	0.84	0.69	0.60
p-value	0.00	0.00	0.00	0.00	0.00

Notes: The table reports Poisson regression coefficients estimating percentage changes in flood insurance demand across alternative definitions of a storm ”hit”. Each column corresponds to a different distance threshold used to classify whether a location is considered hit by a storm Omitted variable is a ”No Storm” Indicator. The omitted reference group is a ”No Storm” indicator for observations that had no storm exposure. Robust standard errors (in parentheses) are clustered at the location level.

9.2 ”Close Calls”

Because many storms pass near a location without significant impacts and because these borderline cases may still influence behavior, I extend the classification scheme to include an additional ”close call” category. A storm is categorized a close call if its predicted or realized distance falls between 250 and 350 nautical miles. Under this expanded classification, storms within 250 nm are treated as hits, those beyond 350 nm as misses, and those in the bandwidth as close. This allows me to capture cases where households face a plausible but uncertain threat: situations likely to generate less clear expectations and more ambiguous risk perceptions.

Table 6 reports the results under this expanded classification. Consistent with baseline patterns, true hits continue to produce increases in insurance uptake, ranging from 19 to 66 percent across specifications. False misses generate even larger responses of 44 to 111 percent, reinforcing the finding that unexpected hits produce the strongest response. Unsurprisingly, false hits do not appear in this specification, as very few storms meet the criteria for being predicted as hits while also accounting for close calls, which is consistent with earlier evidence that such cases are relatively rare.

The introduction of the ”close” categories adds an interesting nuance to how households respond to ambiguous risk signals. True close storms are associated with modest declines in demand of

Table 6: Regression Estimates With "Close Call" Classifications

Storm Classification	(1)	(2)	(3)	(4)
Hit × Predicted Hit (True Hit)	0.19 (0.03)	0.37 (0.04)	0.41 (0.04)	0.66 (0.05)
Hit × Predicted Miss (False Miss)	0.46 (0.09)	0.44 (0.09)	0.62 (0.11)	1.11 (0.19)
Miss × Predicted Miss (True Miss)	0.03 (0.01)	0.01 (0.01)	0.03 (0.01)	0.04 (0.01)
Miss × Predicted Hit (False Hit)	-	-	-	-
Close × Predicted Close	-0.10 (0.03)	-0.16 (0.04)	-0.11 (0.04)	-0.07 (0.04)
Hit × Predicted Close	0.52 (0.08)	0.45 (0.07)	0.56 (0.09)	0.83 (0.13)
Miss × Predicted Close	-0.13 (0.03)	-0.17 (0.03)	-0.10 (0.04)	-0.07 (0.04)
Close × Predicted Hit	-0.02 (0.06)	-0.05 (0.06)	0.08 (0.08)	0.19 (0.09)
Close × Predicted Miss	0.24 (0.05)	0.24 (0.05)	0.23 (0.05)	0.21 (0.05)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X

Notes: The table presents Poisson regression estimates of flood insurance demand incorporating an expanded set of storm outcome classifications that account for "close call" events. The omitted reference group is a "No Storm" indicator for observations that had no storm exposure. The dependent variable is the percentage change of new flood insurance policies. Robust standard errors (in parentheses) are clustered at the location level.

roughly 10 to 16 percent. This suggests that accurate forecasts of benign near misses can reduce perceived vulnerability, reinforcing the idea that a storm can pass close by without causing harm. In contrast, storms predicted to pass nearby but that ultimately hit the location (Hit × Predicted Close) generate large increases in demand, between 45 and 83 percent. This case is extremely similar to that of false misses where the misalignment of expectations and subsequent negative outcome greatly increase demand. Additionally, storms that are predicted to be close but result in a miss (Miss × Predicted Close), consistently reduce in demand by 7-17% which is reminiscent of the behavior behind false hits.

Overall, incorporating close call classifications reinforces the baseline result: true hits and false misses remain the dominant drivers of flood insurance demand, producing the largest and most robust changes in policy uptake. The close call categories themselves paint a fuller picture by showing that ambiguous threats can influence behavior in systematic ways: decreasing demand when near misses reinforce safety and increasing demand when unexpected nearness or unexpected impact influences perceived vulnerability. These effects add nuance to the interpretation of forecast accuracy, but do not contradict the fundamental finding that expectation violations generate the most pronounced behavioral responses.

9.3 Forecast Horizons

Forecasts issued at different lead times may shape expectations differently, either because households place more trust in certain horizons or because some windows provide more time to prepare. To assess how the timing of storm information influences behavior, I re-estimate the baseline specification using alternative forecast-hour reference points. Table 7 reports results for horizons ranging from 36 to 120 hours, while retaining the hit threshold of 300 nm. This extension examines whether households respond more strongly to short-term, medium-range, or longer-term predictions. Once again, all regressions use the same specification as Column (3) in Table 4 to allow for comparability with full results presented in the appendix.

Across forecast horizons, true hits continue to increase demand, but the magnitude of this response varies with the timing of the forecast. The smallest effects appear on the very short (36-48 hour) and very long (120 hour) horizons, where estimates drop to around 20% or become statistically weak. By contrast, the 72- and 96-hour horizons produce the most stable positive responses, 31% and 35%, respectively. This pattern suggests that households respond the most to forecasts issued far enough in advance to allow action, but recent enough to be perceived as credible. The steady rise from the 48- to the 72-hour horizon reinforces the idea that medium-range forecasts balance urgency with reliability.

False misses show even greater sensitivity to forecast timing. The strongest effects occur at the 60-hour horizon with an increase of 46% and peaks at the 72-hour mark at 75% where the magnitude of the response more than doubles that of true hits. At 36, 48, 96, and 120 hours, the coefficients fluctuate in size and sign, reflecting the fact that very near forecasts leave little room for expectation formation and long-range forecasts are noisy enough that their violations may be less surprising.

True misses remain near zero across all horizons, consistent with their interpretation as conditions akin to the omitted no storm baseline. Their stability in forecast hours reinforces the idea that the absence of warning and impact has little informational value. However, false hits show substantial variation depending on the forecast timing. At the 60- and 72-hour horizons, false hits generate clear negative effects of 25%, reaffirming that false alarms reduce trust in warnings and dampen perceived risk. Yet at other horizons, particularly 48 and 120 hours, the coefficients turn positive. These reversals likely reflect that very early or very late forecast errors are interpreted differently: households may treat long-range over-predictions as volatile, and short-range over-predictions as evidence of uncertainty, sometimes reinforcing rather than undermining perceived threat.

Loss aversion tests highlight the horizons where expectation violations matter most. At 60, 72,

Table 7: Regression Estimates by Forecast Horizon

Storm Classification	36 hr	48 hr	60 hr
Hit × Predicted Hit (True Hit)	0.21 (0.02)	0.20 (0.02)	-0.20 (0.01)
Hit × Predicted Miss (False Miss)	-0.16 (0.07)	-0.13 (0.08)	0.46 (0.16)
Miss × Predicted Miss (True Miss)	-0.04 (0.01)	-0.03 (0.01)	-0.03 (0.01)
Miss × Predicted Hit (False Hit)	-0.03 (0.04)	0.26 (0.04)	-0.25 (0.06)
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	-0.31	-0.27	0.82
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.02	0.30	-0.22
p-value	0.71	0.00	0.00
Hit Difference vs. Miss Difference	-0.32	-0.54	1.35
p-value	0.00	0.00	0.00
Storm Classification	72 hr	96 hr	120 hr
Hit × Predicted Hit (True Hit)	0.31 (0.04)	0.35 (0.02)	0.02 (0.07)
Hit × Predicted Miss (False Miss)	0.75 (0.09)	-0.12 (0.09)	0.08 (0.05)
Miss × Predicted Miss (True Miss)	0.04 (0.01)	0.03 (0.01)	-0.01 (0.01)
Miss × Predicted Hit (False Hit)	-0.25 (0.05)	0.08 (0.03)	0.18 (0.07)
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.44	-0.38	0.06
p-value	0.00	0.00	0.13
False Hit vs. True Miss (Miss Difference)	-0.32	0.05	0.29
p-value	0.00	0.15	0.00
Hit Difference vs. Miss Difference	0.84	-0.41	-0.17
p-value	0.00	0.00	0.00

Notes: The table reports Poisson regression estimates of flood insurance demand using alternative forecast-hour reference points to define storm exposure. Each column corresponds to a different forecast hour used to define a homeowner's reference point. The omitted reference group is a "No Storm" indicator. Robust standard errors (in parentheses) are clustered at the location level.

and 96 hours, false misses consistently generate significantly larger responses than true hits, and false hits reduce demand more than true misses. The comparison of differences is particularly large at the 60- and 72-hour horizons (1.35 and 0.84), indicating that these windows are the most behaviorally meaningful.

These results suggest that the 72-hour forecast window offers the most informative anchor for household expectations. At this horizon, all four storm outcomes exhibit clear and interpretable effects that are consistent with reference-dependent models of decision making. Medium-range forecasts, issued roughly three days before a potential impact, appear to carry the right combination of credibility and reaction time to shape insurance demand most reliably.

9.4 Saliency

The baseline model assumes that all storms within the 90-day exposure window have the same influence on households, regardless of when they occurred. However, the behavioral impact of storms likely depends heavily on recency. More recent storms are easier to recall and more emotionally vivid, while older events may fade from memory or be discounted as less relevant. To test whether responsiveness varies with time, I re-estimate the model using 30-day bins to distinguish storms occurring 31-60, 61-90, and 91-120 days prior to the insurance decision.

The estimation strategy is formalized as:

$$\log(E[Y_{it}]) = \theta + Z_{it,31-60}\beta_1 + Z_{it,61-90}\beta_2 + Z_{it,91-120}\beta_3, \tag{6}$$

where θ includes the full set of location and time fixed effects, and each Z_{it} is an indicator equal to one if a storm passed within 300 nautical miles of location i during the designated window. Observations with no storms in the 31-120 day period serve as the omitted category.

Table 8 presents the results. The clearest pattern is that storms that occur 31-60 days before policy issuance have consistently large positive effects on demand. Across specifications, the coefficients range from 0.46 to 1.13, indicating that households significantly increase insurance purchases when a storm has occurred within the past month. These effects appear robust to additional controls, including random effects, home characteristics, storm type, and storm count. This suggests that recency significantly increases the relevance of storm exposure, making recent events more influential in shaping behavior than otherwise identical events that occurred further in the past.

In contrast, storms that occurred 61-90 days earlier produce small negative or near-zero effects in the first three specifications, with coefficients -0.08 and -0.09. In the full specification, the effect

Table 8: Regression Estimates by Timing of Storm Exposure

Exposure Window	(1)	(2)	(3)	(4)
31–60 Days	0.53 (0.03)	0.46 (0.03)	0.54 (0.03)	1.13 (0.11)
61–90 Days	-0.08 (0.02)	-0.08 (0.02)	-0.09 (0.02)	0.19 (0.04)
91–120 Days	-0.07 (0.02)	-0.27 (0.02)	-0.25 (0.02)	-0.04 (0.02)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X

Notes: The table reports Poisson regression estimates of flood insurance demand as a function of the time since the last storm exposure. Each row represents a window of time following the most recent storm event, capturing how the salience of recent storm experience decays over time. The omitted reference group is a ”No Storm” indicator for observations that had no storm exposure. Robust standard errors (in parentheses) are clustered at the location level.

turns positive (0.19), but remains much smaller than the 31-60 day responses. Furthermore, storms that occurred 91-120 days before the insurance decision have consistently negative effects in the first three columns, ranging from -0.07 to -0.27. Even in Column 4, the coefficient remains small (-0.04). Although the magnitudes are modest, the direction of the estimates aligns with a pattern of diminishing salience over time, consistent with the idea that households gradually discount or forget earlier events as they become less relevant.

However, not all storms carry the same psychological weight. Hurricanes are typically more memorable, more alarming, and more widely publicized than weaker systems, which may cause households to react more strongly to the former. To test whether the salience of storm type shapes behavioral responses, I re-estimate the model using a stricter exposure definition in which only storms officially classified as hurricanes are treated as predicted hits, while all weaker systems are recoded as equivalent to no storm. This allows a direct comparison between the baseline model, which treats all storm types uniformly, and models that focus only on high intensity events. Table 9 summarizes the results in four specifications: the baseline (Col. 1), hurricane only classification (Col. 2), recent storms only (Col. 3), and the intersection of recency and hurricanes (Col. 4).

Across all specifications, true hits and false misses remain associated with increased insurance uptake, though the magnitudes vary substantially depending on the type of storm and recency. In the baseline, true hits increase demand by 25% and false misses by 61%. When the type definition is restricted to hurricanes, both effects decrease in size: true hits fall to 11% and false misses to 31%. This decline reflects the fact that the hurricane only classification excludes many impactful but technically weaker storms; the narrower definition reduces the number of observed ”hit” and

”miss” events, leading to more muted results. In contrast, focusing on storms within the past 31-60 days amplifies the estimated effects. True hits increase uptake by 69%, while false misses increase by 36%.

The strongest responses occur when both filters, hurricanes and 31-60 day recency, are applied simultaneously. Under this narrow definition, true hits produce a 125% increase in uptake, and false misses yield an even larger 147% increase. These magnitudes far exceed those of the other specifications, suggesting that recent hurricane exposure is particularly salient. When storms are intense and recent, they generate large shifts in perceived risk and generate the highest levels of insurance demand.

The remaining two classifications also show consistent patterns. True misses switch from small positive effects in baseline (0.02) to negative values when limited to hurricanes (-0.15). Once recency is included, true misses again become positive (0.09 and 0.12), indicating that recent non strike conditions may still influence risk perceptions slightly. False hits are uniformly negative in Columns 1-3, ranging from -0.19 to -0.31, consistent with the interpretation that warnings that do not materialize reduce perceived risk. However, in Column 4 the estimate becomes statistically indistinguishable from zero, suggesting that when the sample is restricted to recent hurricanes only, the already rare false hit cases carry limited weight.

The loss aversion comparisons in the lower panel reveal how these patterns shift under the various filters. In the baseline, false misses exceed true hits, consistent with an asymmetric response to unexpected losses. This gap narrows under the hurricane only definition, indicating that storm severity alone does not amplify loss-aversion. When only recent storms are considered, the sign reverses: true hits exceed false misses, suggesting that recent predicted hits create larger behavioral responses than unexpected ones during this short window. Under the most restrictive definition, the difference between false misses and true hits is small and statistically insignificant, suggesting that when storms are both recent and severe, the difference between expected and unexpected hits diminishes.

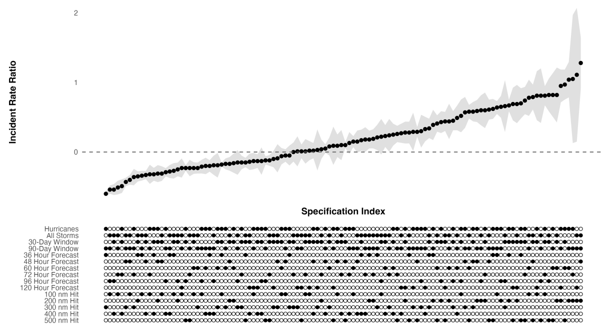
As a final test of robustness, I conduct a specification curve analysis that examines how sensitive the behavioral patterns are to modeling choices. Figure 7 plots the estimated effects for three key contrasts: True Hits vs. False Misses, True Misses vs. False Hits, and the difference between these two comparisons. Each point represents an estimate from a unique regression specification that varies the forecast horizon, hit-distance threshold, and sample restriction (hurricanes only vs. all storms; 30-day vs. 90-day windows).

Across a wide range of specifications, the results exhibit strong consistency. Panel A shows that the difference between true hits and false misses tends to be positive across nearly the full

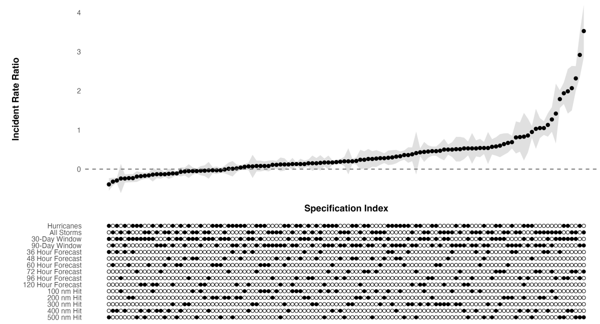
Table 9: Regression Estimates By Saliency Treatments

Storm Classification	(1)	(2)	(3)	(4)
Hit × Predicted Hit (True Hit)	0.25 (0.04)	0.11 (0.02)	0.69 (0.03)	1.25 (0.06)
Hit × Predicted Miss (False Miss)	0.61 (0.07)	0.31 (0.07)	0.36 (0.07)	1.47 (0.16)
Miss × Predicted Miss (True Miss)	0.02 (0.01)	-0.15 (0.01)	0.09 (0.01)	0.12 (0.02)
Miss × Predicted Hit (False Hit)	-0.31 (0.06)	-0.25 (0.01)	-0.19 (0.06)	0.00 (0.07)
Location & Time Fixed Effects	X	X	X	X
Random Effects	X	X	X	X
Home & Policy Variables	X	X	X	X
Hurricane Only		X		X
31–60 Day Exposure			X	X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.29	0.18	-0.20	0.10
p-value	0.00	0.00	0.00	0.18
False Hit vs. True Miss (Miss Difference)	-0.32	-0.12	-0.25	-0.11
p-value	0.00	0.04	0.00	0.10
Hit Difference vs. Miss Difference	0.90	0.34	0.07	0.24
p-value	0.00	0.00	0.52	0.04

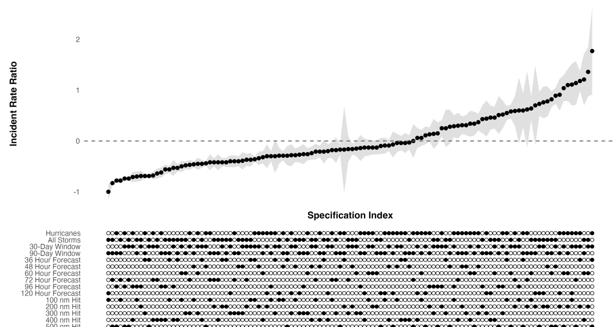
Notes: The table reports Poisson regression estimates of flood insurance demand under alternative saliency treatments designed to test how recent storm experience and event intensity shape behavioral responses. The omitted reference group is a ”No Storm” indicator for observations that had no storm exposure. Robust standard errors (in parentheses) are clustered at the location level.



Panel A: True Hit vs. False Miss



Panel B: True Miss vs. False Hit



Panel C: Hit Difference vs. Miss Difference

Figure 7: Specification Curve Analysis of Asymmetric Behavior

Notes: The three panels present specification curve analyses showing the robustness of estimated insurance responses across a full range of modeling choices. Each plotted point corresponds to an estimate from a separate Poisson regression using different combinations of samples (hurricanes vs. all storms; 30-day vs. 90-day windows), forecast horizons (36-120 hours), and hit-distance thresholds (100-500 nautical miles). Panel A, *True Hit vs. False Miss*, reports the estimated difference in insurance demand between expected hits and unexpected hits. Panel B, *True Miss vs. False Hit*, gives the contrast for expected vs. unexpected misses. Panel C, *Hit Difference vs. Miss Difference*, displays the differences between these two contrasts, which serves as the implied measure of loss aversion. Shaded regions denote 95% confidence intervals.

specification space, indicating that unexpected hits reliably generate higher insurance uptake than expected hits. The slope gradually increases along the specification index, with a pronounced rise among specifications using longer forecast horizons and wider hit thresholds.

Panel B presents the comparison between true misses and false hits. The pattern here is somewhat flatter, with many estimates clustering near zero and only turning strongly positive in the upper portion of the specification index. This suggests that households react far less consistently to false alarms and that only under certain conditions do false hits meaningfully depress demand relative to expected misses.

Panel C plots the difference contrasts that capture the asymmetry between behavioral responses to unexpected hits and unexpected misses. The curve begins negative, indicating that for many tightly defined specifications (narrow hit thresholds, short horizons, hurricane-only samples) the two contrasts are relatively similar in magnitude. However, as the specification expands, the estimates steadily rise toward zero and eventually become strongly positive. The right tail shows a sharp increase in the effects, reflecting specifications in which unexpected hits generate substantially larger demand responses than unexpected misses. The overall upward trajectory of the curve, despite some variability, indicates a persistent and robust asymmetry in behavior consistent with loss aversion.

10 Discussion

This paper provides new evidence on the behavioral drivers of flood insurance demand, showing that households respond not only to storm exposure, but also to the accuracy of the forecasts they rely on. By merging NFIP policy records with detailed hurricane predictions, the analysis illustrates that deviations between predicted and realized storm outcomes generate strong asymmetries in behavior. Unexpected storm impacts increase insurance uptake, often more than anticipated hits, while false alarms reduce demand, suggesting that unrealized threats erode trust and lower perceived risk. These patterns cannot be explained with standard expected-utility models alone; instead, they reveal that insurance decisions are fundamentally reference-dependent.

The results extend models of reference-dependent preferences and loss aversion in the context of natural disaster preparedness. Forecasts establish the expectations against which outcomes are evaluated and, when realized events depart from those expectations, households respond in ways consistent with gain-loss asymmetries. Importantly, this paper shows that these dynamics persist in a high-stakes, real-world environment where the financial consequences are substantial. This helps bridge the gap between experimental evidence on reference points and household investment behavior under disaster risk.

Salience also plays an important amplifying role. Recent storms and those classified as hurricanes generate especially strong responses, while accurate near miss forecasts often depress demand. These patterns align with theories of availability and salience, in which vivid, severe, or recently experienced events generate disproportionate attention. The interaction between salience and reference dependence is particularly noteworthy: when storms are both recent and severe, heightened attention appears to overpower loss-aversion effects, suggesting that salience can substitute for, or even override, the effects of expectations.

These findings have direct implications for risk communication and the design of the insurance market. First, they highlight the behavioral consequences of forecast errors. If households under-react to accurate warnings yet over-react to surprises, insurance demand will remain both volatile and low. Forecast communication strategies could be adapted to mitigate these responses, for example, by emphasizing uncertainty bands, probability distributions, or regret-framed messaging that encourages preparation for multiple plausible scenarios rather than a single projected path. Providing information on forecast confidence or historical accuracy can also temper expectations and reduce the sharp behavioral swings associated with surprises or false alarms.

Second, the results highlight the importance of timing. Salience peaks immediately after unexpected storm impacts. Targeted outreach, such as subsidies, reminders, or enrollment nudges during these windows, can be particularly effective in increasing coverage. Similarly, strengthening trust in forecasts by portraying false alarms as an inherent feature of prediction, rather than as errors, may help maintain compliance with warnings.

Third, the evidence suggests important considerations for the design of the NFIP program. The 30-day waiting period before coverage becomes effective creates a structural delay that can prevent increased post-storm salience from translating into actual enrollment. Aligning program rules with behavioral responses, perhaps by offering temporary waivers or expedited enrollment following major storms, could increase coverage at times when households are most motivated to insure.

The muted effect of true misses and the negative effect of false hits also raise behavioral questions. Non-events should produce little change in demand. Instead, repeated false alarms appear to generate ”forecast fatigue,” reducing trust in warnings and weakening protective behavior. This suggests that credibility is as crucial as accuracy in maintaining enrollment. Additional heterogeneity is also likely: responses may differ by income, geography, or previous experience. More vulnerable households may react differently to forecast errors than higher-income households.

Several limitations of this study should be acknowledged. First, the analysis focuses exclusively on new policy uptake, leaving unexamined renewals and adjustments in coverage levels, behaviors that may also respond to forecast accuracy but likely operate through different mechanisms, particularly when inertia or contractual frictions are involved. Second, although the observational design provides variation in storm exposure, it cannot fully disentangle the channels through which behavior responds, such as belief updating, shifts in attention, or changes in trust. Survey or experimental evidence could help directly measure expectations and more cleanly identify these mechanisms. Finally, the analysis varies the forecast horizons and distance thresholds independently. In reality, these dimensions may interact, for example, storms predicted far in advance may be treated differently depending on their distance, and close storms may carry different weight depending on the lead time of the forecast. Exploring the joint influence of these parameters would provide a more complete understanding of how households interpret storm information. Future research could also extend the analysis beyond Florida to other coastal states or private flood insurance markets, where behavioral responses can differ under different regulatory and pricing environments. Comparative work could also explore whether similar mechanisms operate in other domains where forecasts guide protective actions, such as agricultural insurance, epidemic preparedness, or financial risk management.

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A Hurricanes: 90-day Window

This section presents additional robustness checks that restrict the sample to hurricane events only. The analysis evaluates whether the main results hold when excluding weaker tropical systems and focusing on major storm events within the 90-day insurance response window. All specifications use Poisson regressions of new NFIP policy issuance and are estimated across varying forecast horizons (36–120 hours) and hit-distance thresholds (100–500 nautical miles).

Table 10: 36-Hour Window Across Distance Thresholds: Hurricanes Only

Panel A. 100 nm Threshold			
Storm Classification	(1)	(2)	(3)
Hit × Predicted Hit (True Hit)	0.40 (0.05)	0.35 (0.05)	0.36 (0.05)
Hit × Predicted Miss (False Miss)	1.57 (0.24)	1.45 (0.23)	1.42 (0.23)
Miss × Predicted Miss (True Miss)	-0.08 (0.02)	-0.09 (0.02)	-0.09 (0.02)
Miss × Predicted Hit (False Hit)	-0.23 (0.09)	-0.22 (0.09)	-0.21 (0.09)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.84	0.81	0.77
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	-0.16	-0.14	-0.14
p-value	0.09	0.16	0.16
Hit Difference vs. Miss Difference	1.19	1.11	1.06
p-value	0.00	0.00	0.00
Panel B. 200 nm Threshold			
Hit × Predicted Hit (True Hit)	0.01 (0.04)	-0.01 (0.04)	0.00 (0.04)
Hit × Predicted Miss (False Miss)	-0.12 (0.06)	-0.13 (0.06)	-0.11 (0.06)
Miss × Predicted Miss (True Miss)	-0.08 (0.02)	-0.09 (0.02)	-0.09 (0.02)
Miss × Predicted Hit (False Hit)	-0.15 (0.06)	-0.12 (0.06)	-0.12 (0.06)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	-0.13	-0.13	-0.11
p-value	0.03	0.03	0.07
False Hit vs. True Miss (Miss Difference)	-0.07	-0.04	-0.04
p-value	0.25	0.52	0.53
Hit Difference vs. Miss Difference	-0.06	-0.09	-0.07
p-value	0.51	0.30	0.41

Table 10 (cont'd)

Panel C. 300 nm Threshold			
Hit × Predicted Hit (True Hit)	-0.05 (0.03)	-0.05 (0.03)	-0.05 (0.03)
Hit × Predicted Miss (False Miss)	0.21 (0.08)	0.21 (0.07)	0.22 (0.07)
Miss × Predicted Miss (True Miss)	-0.08 (0.02)	-0.09 (0.01)	-0.09 (0.01)
Miss × Predicted Hit (False Hit)	0.78 (0.30)	0.67 (0.28)	0.67 (0.28)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.27	0.28	0.29
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.94	0.83	0.83
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.34	-0.30	-0.30
p-value	0.02	0.04	0.04
Panel D. 400 nm Threshold			
Hit × Predicted Hit (True Hit)	-0.07 (0.04)	-0.08 (0.04)	-0.08 (0.04)
Hit × Predicted Miss (False Miss)	0.82 (0.12)	0.79 (0.12)	0.79 (0.12)
Miss × Predicted Miss (True Miss)	-0.09 (0.01)	-0.09 (0.01)	-0.09 (0.01)
Miss × Predicted Hit (False Hit)	-0.01 (0.06)	-0.07 (0.05)	-0.07 (0.05)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.97	0.95	0.95
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.09	0.02	0.03
p-value	0.11	0.65	0.63
Hit Difference vs. Miss Difference	0.81	0.91	0.90
p-value	0.00	0.00	0.00

Table 10 (cont'd)

Panel E. 500 nm Threshold			
Hit × Predicted Hit (True Hit)	-0.05 (0.03)	-0.06 (0.03)	-0.06 (0.03)
Hit × Predicted Miss (False Miss)	-0.04 (0.14)	-0.04 (0.14)	-0.04 (0.14)
Miss × Predicted Miss (True Miss)	-0.10 (0.01)	-0.10 (0.01)	-0.10 (0.01)
Miss × Predicted Hit (False Hit)	0.29 (0.05)	0.28 (0.05)	0.28 (0.05)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.02	0.03	0.02
p-value	0.91	0.86	0.88
False Hit vs. True Miss (Miss Difference)	0.43	0.43	0.43
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.29	-0.28	-0.28
p-value	0.02	0.03	0.03

Table 11: 48-Hour Window Across Distance Thresholds: Hurricanes Only

Panel A. 100 nm Threshold			
Storm Classification	(1)	(2)	(3)
Hit × Predicted Hit (True Hit)	0.39 (0.04)	0.34 (0.04)	0.36 (0.04)
Hit × Predicted Miss (False Miss)	0.89 (0.20)	0.72 (0.18)	0.72 (0.18)
Miss × Predicted Miss (True Miss)	-0.09 (0.02)	-0.10 (0.01)	-0.10 (0.01)
Miss × Predicted Hit (False Hit)	-0.22 (0.05)	-0.20 (0.05)	-0.20 (0.05)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.36	0.29	0.27
p-value	0.01	0.02	0.03
False Hit vs. True Miss (Miss Difference)	-0.14	-0.11	-0.11
p-value	0.01	0.03	0.03
Hit Difference vs. Miss Difference	0.57	0.44	0.42
p-value	0.00	0.00	0.01

Table 11 (cont'd)

Panel B. 200 nm Threshold			
Hit × Predicted Hit (True Hit)	-0.03 (0.04)	-0.05 (0.03)	-0.04 (0.03)
Hit × Predicted Miss (False Miss)	-0.16 (0.06)	-0.17 (0.06)	-0.15 (0.06)
Miss × Predicted Miss (True Miss)	-0.10 (0.01)	-0.11 (0.01)	-0.11 (0.01)
Miss × Predicted Hit (False Hit)	-0.28 (0.05)	-0.27 (0.05)	-0.27 (0.05)
Location & Time Fixed Effects	X	X	X
Random Effects	X	X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	-0.13	-0.13	-0.11
p-value	0.02	0.03	0.06
False Hit vs. True Miss (Miss Difference)	-0.20	-0.18	-0.18
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	0.09	0.06	0.08
p-value	0.38	0.54	0.43
Panel C. 300 nm Threshold			
Hit × Predicted Hit (True Hit)	-0.07 (0.03)	-0.08 (0.03)	-0.08 (0.03)
Hit × Predicted Miss (False Miss)	0.26 (0.09)	0.22 (0.08)	0.23 (0.08)
Miss × Predicted Miss (True Miss)	-0.10 (0.01)	-0.11 (0.01)	-0.11 (0.01)
Miss × Predicted Hit (False Hit)	0.41 (0.12)	0.36 (0.12)	0.36 (0.12)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.35	0.33	0.34
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.57	0.53	0.53
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.14	-0.13	-0.12
p-value	0.16	0.19	0.21

Table 11 (cont'd)

Panel D. 400 nm Threshold			
Hit × Predicted Hit (True Hit)	-0.10 (0.04)	-0.11 (0.03)	-0.11 (0.03)
Hit × Predicted Miss (False Miss)	0.52 (0.11)	0.50 (0.11)	0.50 (0.11)
Miss × Predicted Miss (True Miss)	-0.11 (0.01)	-0.12 (0.01)	-0.12 (0.01)
Miss × Predicted Hit (False Hit)	0.38 (0.07)	0.35 (0.07)	0.35 (0.07)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.69	0.69	0.69
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.55	0.53	0.53
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	0.09	0.11	0.10
p-value	0.30	0.23	0.24
Panel E. 500 nm Threshold			
Hit × Predicted Hit (True Hit)	-0.08 (0.03)	-0.09 (0.03)	-0.09 (0.03)
Hit × Predicted Miss (False Miss)	0.02 (0.13)	-0.01 (0.13)	-0.01 (0.13)
Miss × Predicted Miss (True Miss)	-0.11 (0.01)	-0.12 (0.01)	-0.12 (0.01)
Miss × Predicted Hit (False Hit)	0.04 (0.05)	0.03 (0.05)	0.03 (0.05)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.10	0.09	0.08
p-value	0.47	0.53	0.55
False Hit vs. True Miss (Miss Difference)	0.17	0.17	0.17
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.06	-0.07	-0.08
p-value	0.67	0.60	0.57

Table 12: 60-Hour Window Across Distance Thresholds: Hurricanes Only

Panel A. 100 nm Threshold			
Storm Classification	(1)	(2)	(3)
Hit × Predicted Hit (True Hit)	0.08 (0.05)	0.05 (0.04)	0.05 (0.04)
Hit × Predicted Miss (False Miss)	0.17 (0.08)	0.07 (0.08)	0.08 (0.08)
Miss × Predicted Miss (True Miss)	-0.25 (0.01)	-0.22 (0.01)	-0.22 (0.01)
Miss × Predicted Hit (False Hit)	0.06 (0.10)	0.12 (0.09)	0.12 (0.09)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.08	0.02	0.03
p-value	0.24	0.78	0.64
False Hit vs. True Miss (Miss Difference)	0.41	0.44	0.44
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.23	-0.29	-0.28
p-value	0.03	0.00	0.00
Panel B. 200 nm Threshold			
Hit × Predicted Hit (True Hit)	-0.23 (0.01)	-0.24 (0.01)	-0.24 (0.01)
Hit × Predicted Miss (False Miss)	-0.46 (0.05)	-0.41 (0.05)	-0.42 (0.05)
Miss × Predicted Miss (True Miss)	-0.20 (0.01)	-0.16 (0.01)	-0.16 (0.01)
Miss × Predicted Hit (False Hit)	-0.06 (0.06)	-0.04 (0.06)	-0.04 (0.06)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	-0.30	-0.23	-0.24
p-value	0.00	0.01	0.01
False Hit vs. True Miss (Miss Difference)	0.18	0.13	0.14
p-value	0.02	0.07	0.07
Hit Difference vs. Miss Difference	-1.00	-1.00	-1.00

Table 12 (cont'd)

Panel C. 300 nm Threshold			
Hit × Predicted Hit (True Hit)	-0.23 (0.01)	-0.23 (0.01)	-0.23 (0.01)
Hit × Predicted Miss (False Miss)	0.28 (0.10)	0.30 (0.10)	0.32 (0.11)
Miss × Predicted Miss (True Miss)	-0.20 (0.01)	-0.12 (0.01)	-0.12 (0.01)
Miss × Predicted Hit (False Hit)	-0.15 (0.06)	-0.15 (0.06)	-0.15 (0.06)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.66	0.69	0.71
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.05	-0.04	-0.04
p-value	0.50	0.60	0.60
Hit Difference vs. Miss Difference	0.58	0.76	0.78
p-value	0.00	0.00	0.00
Panel D. 400 nm Threshold			
Hit × Predicted Hit (True Hit)	-0.23 (0.01)	-0.22 (0.01)	-0.22 (0.01)
Hit × Predicted Miss (False Miss)	0.76 (0.50)	0.65 (0.38)	0.65 (0.38)
Miss × Predicted Miss (True Miss)	-0.19 (0.01)	-0.11 (0.01)	-0.11 (0.01)
Miss × Predicted Hit (False Hit)	0.05 (0.11)	0.11 (0.11)	0.11 (0.11)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	1.28	1.11	1.12
p-value	0.01	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.30	0.24	0.24
p-value	0.01	0.04	0.04
Hit Difference vs. Miss Difference	0.75	0.70	0.70
p-value	0.05	0.02	0.02

Table 12 (cont'd)

Panel E. 500 nm Threshold			
Hit × Predicted Hit (True Hit)	-0.23 (0.01)	-0.22 (0.01)	-0.22 (0.01)
Hit × Predicted Miss (False Miss)	-0.22 (0.05)	-0.29 (0.04)	-0.29 (0.04)
Miss × Predicted Miss (True Miss)	-0.17 (0.01)	-0.10 (0.01)	-0.10 (0.01)
Miss × Predicted Hit (False Hit)	0.42 (0.12)	0.35 (0.12)	0.35 (0.12)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.02	-0.10	-0.10
p-value	0.71	0.10	0.11
False Hit vs. True Miss (Miss Difference)	0.70	0.50	0.50
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.40	-0.40	-0.40
p-value	0.00	0.00	0.00

Table 13: 72-Hour Window Across Distance Thresholds: Hurricanes Only

Panel A. 100 nm Threshold			
Storm Classification	(1)	(2)	(3)
Hit × Predicted Hit (True Hit)	0.31 (0.05)	0.26 (0.05)	0.26 (0.05)
Hit × Predicted Miss (False Miss)	0.40 (0.13)	0.27 (0.11)	0.27 (0.11)
Miss × Predicted Miss (True Miss)	-0.10 (0.02)	-0.11 (0.01)	-0.11 (0.01)
Miss × Predicted Hit (False Hit)	0.28 (0.09)	0.22 (0.07)	0.22 (0.07)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.07	0.01	0.01
p-value	0.11	0.11	0.11
False Hit vs. True Miss (Miss Difference)	0.42	0.38	0.38
p-value	0.12	0.09	0.09
Hit Difference vs. Miss Difference	-0.25	-0.27	-0.27
p-value	0.09	0.08	0.08

Table 13 (cont'd)

Panel B. 200 nm Threshold			
Hit × Predicted Hit (True Hit)	0.02 (0.04)	0.00 (0.03)	0.00 (0.03)
Hit × Predicted Miss (False Miss)	-0.13 (0.07)	-0.14 (0.06)	-0.14 (0.06)
Miss × Predicted Miss (True Miss)	-0.10 (0.02)	-0.11 (0.01)	-0.11 (0.01)
Miss × Predicted Hit (False Hit)	-0.04 (0.05)	-0.05 (0.05)	-0.05 (0.05)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	-0.15	-0.14	-0.14
p-value	0.02	0.04	0.00
False Hit vs. True Miss (Miss Difference)	0.07	0.07	0.07
p-value	0.18	0.15	0.01
Hit Difference vs. Miss Difference	-0.20	-0.20	-0.19
p-value	0.01	0.01	0.00
Panel C. 300 nm Threshold			
Hit × Predicted Hit (True Hit)	-0.01 (0.03)	-0.03 (0.03)	-0.03 (0.03)
Hit × Predicted Miss (False Miss)	0.29 (0.08)	0.24 (0.07)	0.23 (0.07)
Miss × Predicted Miss (True Miss)	-0.10 (0.02)	-0.11 (0.01)	-0.11 (0.01)
Miss × Predicted Hit (False Hit)	-0.23 (0.05)	-0.23 (0.05)	-0.23 (0.05)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.30	0.27	0.27
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	-0.14	-0.13	-0.13
p-value	0.01	0.02	0.02
Hit Difference vs. Miss Difference	0.51	0.46	0.46
p-value	0.00	0.00	0.00

Table 13 (cont'd)

Panel D. 400 nm Threshold			
Hit × Predicted Hit (True Hit)	-0.07 (0.04)	-0.09 (0.03)	-0.09 (0.03)
Hit × Predicted Miss (False Miss)	0.33 (0.06)	0.30 (0.06)	0.30 (0.06)
Miss × Predicted Miss (True Miss)	-0.12 (0.01)	-0.13 (0.01)	-0.13 (0.01)
Miss × Predicted Hit (False Hit)	-0.28 (0.04)	-0.28 (0.04)	-0.28 (0.04)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.44	0.44	0.44
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	-0.18	-0.17	-0.17
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	0.74	0.73	0.73
p-value	0.00	0.00	0.00
Panel E. 500 nm Threshold			
Hit × Predicted Hit (True Hit)	-0.08 (0.03)	-0.10 (0.03)	-0.10 (0.03)
Hit × Predicted Miss (False Miss)	-0.05 (0.05)	-0.09 (0.05)	-0.09 (0.05)
Miss × Predicted Miss (True Miss)	-0.10 (0.01)	-0.11 (0.01)	-0.11 (0.01)
Miss × Predicted Hit (False Hit)	0.00 (0.08)	0.00 (0.08)	0.00 (0.08)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.03	0.01	0.01
p-value	0.45	0.88	0.25
False Hit vs. True Miss (Miss Difference)	0.11	0.12	0.12
p-value	0.21	0.17	0.17
Hit Difference vs. Miss Difference	-0.07	-0.10	-0.10
p-value	0.42	0.24	0.25

Table 14: 96-Hour Window Across Distance Thresholds: Hurricanes Only

Panel A. 100 nm Threshold			
Storm Classification	(1)	(2)	(3)
Hit × Predicted Hit (True Hit)	0.57 (0.06)	0.52 (0.06)	0.52 (0.06)
Hit × Predicted Miss (False Miss)	1.55 (0.19)	1.32 (0.17)	1.32 (0.17)
Miss × Predicted Miss (True Miss)	-0.04 (0.02)	-0.05 (0.01)	-0.05 (0.01)
Miss × Predicted Hit (False Hit)	0.10 (0.03)	0.12 (0.03)	0.12 (0.03)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.63	0.52	0.52
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.15	0.18	0.18
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	0.42	0.29	0.29
p-value	0.00	0.00	0.00
Panel B. 200 nm Threshold			
Hit × Predicted Hit (True Hit)	0.15 (0.04)	0.13 (0.04)	0.13 (0.04)
Hit × Predicted Miss (False Miss)	-0.07 (0.06)	-0.10 (0.05)	-0.10 (0.06)
Miss × Predicted Miss (True Miss)	-0.04 (0.01)	-0.04 (0.01)	-0.04 (0.01)
Miss × Predicted Hit (False Hit)	0.09 (0.03)	0.08 (0.03)	0.08 (0.03)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	-0.20	-0.21	-0.20
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.13	0.13	0.13
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.29	-0.30	-0.29
p-value	0.00	0.00	0.00

Table 14 (cont'd)

Panel C. 300 nm Threshold			
Hit × Predicted Hit (True Hit)	0.03 (0.03)	0.01 (0.03)	0.02 (0.03)
Hit × Predicted Miss (False Miss)	0.52 (0.07)	0.45 (0.07)	0.45 (0.07)
Miss × Predicted Miss (True Miss)	-0.03 (0.01)	-0.04 (0.01)	-0.04 (0.01)
Miss × Predicted Hit (False Hit)	0.10 (0.04)	0.10 (0.04)	0.10 (0.04)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.48	0.43	0.43
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.13	0.15	0.14
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	0.30	0.25	0.25
p-value	0.00	0.00	0.00

Panel D. 400 nm Threshold			
Hit × Predicted Hit (True Hit)	0.02 (0.03)	0.00 (0.03)	0.00 (0.03)
Hit × Predicted Miss (False Miss)	0.69 (0.07)	0.66 (0.06)	0.66 (0.06)
Miss × Predicted Miss (True Miss)	-0.07 (0.01)	-0.08 (0.01)	-0.08 (0.01)
Miss × Predicted Hit (False Hit)	0.38 (0.06)	0.35 (0.06)	0.35 (0.06)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.65	0.65	0.65
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.48	0.46	0.46
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	0.12	0.13	0.13
p-value	0.06	0.04	0.04

Table 14 (cont'd)

Panel E. 500 nm Threshold			
Hit × Predicted Hit (True Hit)	-0.01 (0.04)	-0.02 (0.03)	-0.02 (0.03)
Hit × Predicted Miss (False Miss)	0.46 (0.04)	0.41 (0.04)	0.41 (0.04)
Miss × Predicted Miss (True Miss)	-0.05 (0.01)	-0.05 (0.01)	-0.05 (0.01)
Miss × Predicted Hit (False Hit)	-0.11 (0.08)	-0.10 (0.08)	-0.10 (0.08)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.48	0.45	0.45
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	-0.06	-0.05	-0.05
p-value	0.50	0.60	0.60
Hit Difference vs. Miss Difference	0.57	0.52	0.52
p-value	0.00	0.00	0.00

Table 15: 120-Hour Window Across Distance Thresholds: Hurricanes Only

Panel A. 100 nm Threshold			
Storm Classification	(1)	(2)	(3)
Hit × Predicted Hit (True Hit)	0.96 (0.12)	0.84 (0.11)	0.84 (0.11)
Miss × Predicted Miss (True Miss)	-0.26 (0.03)	-0.25 (0.03)	-0.25 (0.03)
Miss × Predicted Hit (False Hit)	0.08 (0.09)	0.13 (0.09)	0.13 (0.09)
Hit × Predicted Miss (False Miss)	1.56 (0.16)	1.40 (0.15)	1.40 (0.15)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.31	0.30	0.30
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.46	0.51	0.51
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.10	-0.14	-0.14
p-value	0.50	0.34	0.34

Table 15 (cont'd)

Panel B. 200 nm Threshold			
Hit × Predicted Hit (True Hit)	0.81 (0.07)	0.69 (0.06)	0.69 (0.06)
Hit × Predicted Miss (False Miss)	0.51 (0.18)	0.47 (0.17)	0.47 (0.17)
Miss × Predicted Miss (True Miss)	-0.28 (0.03)	-0.27 (0.03)	-0.27 (0.03)
Miss × Predicted Hit (False Hit)	1.41 (0.16)	1.18 (0.15)	1.18 (0.15)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	-0.17	-0.13	-0.13
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	2.34	1.99	1.99
p-value	0.10	0.20	0.20
Hit Difference vs. Miss Difference	-0.75	-0.71	-0.71
p-value	0.00	0.00	0.00

Panel C. 300 nm Threshold			
Hit × Predicted Hit (True Hit)	0.49 (0.07)	0.43 (0.06)	0.43 (0.06)
Hit × Predicted Miss (False Miss)	0.02 (0.06)	0.02 (0.06)	0.02 (0.06)
Miss × Predicted Miss (True Miss)	-0.30 (0.03)	-0.29 (0.03)	-0.29 (0.03)
Miss × Predicted Hit (False Hit)	0.41 (0.14)	0.32 (0.14)	0.32 (0.14)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	-0.32	-0.29	-0.29
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	1.02	0.86	0.86
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.66	-0.62	-0.62
p-value	0.00	0.00	0.00

Table 15 (cont'd)

Panel D. 400 nm Threshold			
Hit × Predicted Hit (True Hit)	0.30 (0.06)	0.25 (0.05)	0.25 (0.05)
Hit × Predicted Miss (False Miss)	-0.03 (0.05)	-0.04 (0.04)	-0.04 (0.04)
Miss × Predicted Miss (True Miss)	-0.31 (0.03)	-0.30 (0.03)	-0.30 (0.03)
Miss × Predicted Hit (False Hit)	1.14 (0.14)	1.05 (0.14)	1.05 (0.14)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	-0.25	-0.23	-0.23
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	2.11	1.94	1.94
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.76	-0.74	-0.74
p-value	0.00	0.00	0.00

Panel E. 500 nm Threshold			
Hit × Predicted Hit (True Hit)	0.08 (0.04)	0.06 (0.04)	0.06 (0.04)
Hit × Predicted Miss (False Miss)	-0.05 (0.06)	-0.07 (0.05)	-0.07 (0.05)
Miss × Predicted Miss (True Miss)	-0.31 (0.03)	-0.30 (0.03)	-0.30 (0.03)
Miss × Predicted Hit (False Hit)	1.89 (0.19)	1.73 (0.17)	1.73 (0.17)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	-0.12	-0.12	-0.12
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	3.22	2.92	2.92
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.79	-0.78	-0.78
p-value	0.00	0.00	0.00

B All Storms: 90-Day Window

This section relaxes the sample restriction to include all storm types within the 90-day insurance response window. All specifications estimate Poisson effects of new NFIP policy issuance across varying forecast horizons (36–120 hours) and hit-distance thresholds (100–500 nautical miles). This broader specification tests the robustness of the results to the inclusion of tropical storms and subtropical systems beyond hurricanes

Table 16: 36-Hour Window Across Distance Thresholds: All Storms

Panel A. 100 nm Threshold				
Storm Classification	(1)	(2)	(3)	(4)
Hit $\times$ Predicted Hit (True Hit)	0.37 (0.03)	0.34 (0.03)	0.39 (0.03)	0.39 (0.03)
Hit $\times$ Predicted Miss (False Miss)	0.29 (0.07)	0.27 (0.06)	0.35 (0.07)	0.37 (0.07)
Miss $\times$ Predicted Miss (True Miss)	0.02 (0.01)	0.02 (0.01)	0.07 (0.02)	0.06 (0.03)
Miss $\times$ Predicted Hit (False Hit)	0.09 (0.07)	0.10 (0.07)	0.19 (0.09)	0.16 (0.09)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	-0.06	-0.06	-0.03	-0.02
p-value	0.31	0.31	0.59	0.80
False Hit vs. True Miss (Miss Difference)	0.07	0.08	0.11	0.09
p-value	0.32	0.25	0.13	0.19
Hit Difference vs. Miss Difference	-0.12	-0.13	-0.12	-0.10
p-value	0.16	0.12	0.13	0.25

Table 16 (cont'd)

Panel B: 200 nm Threshold				
Storm Classification	(1)	(2)	(3)	(4)
Hit × Predicted Hit (True Hit)	0.11 (0.02)	0.10 (0.02)	0.17 (0.03)	0.17 (0.03)
Hit × Predicted Miss (False Miss)	0.29 (0.05)	0.27 (0.05)	0.25 (0.06)	0.23 (0.06)
Miss × Predicted Miss (True Miss)	0.01 (0.01)	0.01 (0.01)	0.08 (0.02)	0.07 (0.02)
Miss × Predicted Hit (False Hit)	0.08 (0.06)	0.09 (0.06)	0.18 (0.07)	0.16 (0.07)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.16	0.15	0.07	0.06
p-value	0.00	0.00	0.12	0.16
False Hit vs. True Miss (Miss Difference)	0.07	0.08	0.09	0.09
p-value	0.20	0.13	0.09	0.11
Hit Difference vs. Miss Difference	0.08	0.06	-0.02	-0.03
p-value	0.26	0.39	0.72	0.67

Panel C: 300 nm Threshold				
Storm Classification	(1)	(2)	(3)	(4)
Hit × Predicted Hit (True Hit)	0.09 (0.02)	0.08 (0.01)	0.16 (0.03)	0.16 (0.03)
Hit × Predicted Miss (False Miss)	-0.07 (0.07)	-0.09 (0.07)	0.02 (0.07)	0.01 (0.07)
Miss × Predicted Miss (True Miss)	0.01 (0.01)	0.01 (0.01)	0.10 (0.02)	0.08 (0.02)
Miss × Predicted Hit (False Hit)	-0.03 (0.03)	-0.02 (0.03)	0.06 (0.05)	0.04 (0.05)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	-0.14	-0.16	-0.12	-0.12
p-value	0.03	0.02	0.05	0.04
False Hit vs. True Miss (Miss Difference)	-0.04	-0.03	-0.04	-0.04
p-value	0.35	0.39	0.25	0.24
Hit Difference vs. Miss Difference	-0.11	-0.13	-0.09	-0.09
p-value	0.16	0.09	0.21	0.19

Table 16 (cont'd)

Panel D: 400 nm Threshold				
Storm Classification	(1)	(2)	(3)	(4)
Hit × Predicted Hit (True Hit)	0.03 (0.01)	0.03 (0.01)	0.02 (0.03)	0.01 (0.03)
Hit × Predicted Miss (False Miss)	1.12 (0.13)	1.10 (0.12)	1.12 (0.13)	1.11 (0.13)
Miss × Predicted Miss (True Miss)	-0.04 (0.01)	-0.03 (0.01)	-0.05 (0.02)	-0.06 (0.02)
Miss × Predicted Hit (False Hit)	-0.04 (0.04)	-0.06 (0.04)	-0.07 (0.05)	-0.07 (0.05)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	1.05	1.04	1.08	1.07
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.00	-0.03	-0.02	-0.02
p-value	0.96	0.54	0.55	0.70
Hit Difference vs. Miss Difference	1.06	1.10	1.13	1.11
p-value	0.00	0.00	0.00	0.00

Panel E: 500 nm Threshold				
Storm Classification	(1)	(2)	(3)	(4)
Hit × Predicted Hit (True Hit)	0.08 (0.01)	0.07 (0.01)	0.11 (0.03)	0.10 (0.03)
Hit × Predicted Miss (False Miss)	-0.14 (0.10)	-0.14 (0.10)	-0.15 (0.10)	-0.18 (0.09)
Miss × Predicted Miss (True Miss)	-0.06 (0.01)	-0.05 (0.01)	-0.03 (0.02)	-0.04 (0.02)
Miss × Predicted Hit (False Hit)	0.39 (0.04)	0.39 (0.05)	0.44 (0.04)	0.40 (0.04)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	-0.20	-0.19	-0.23	-0.26
p-value	0.05	0.05	0.04	0.01
False Hit vs. True Miss (Miss Difference)	0.48	0.46	0.48	0.47
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.46	-0.45	-0.48	-0.49
p-value	0.00	0.00	0.00	0.00

Table 17: 48-Hour Window Across Distance Thresholds: All Storms

Panel A. 100 nm Threshold				
Storm Classification	(1)	(2)	(3)	(4)
Hit × Predicted Hit (True Hit)	0.54 (0.03)	0.51 (0.03)	0.53 (0.03)	0.54 (0.03)
Hit × Predicted Miss (False Miss)	0.27 (0.05)	0.25 (0.05)	0.29 (0.05)	0.28 (0.05)
Miss × Predicted Miss (True Miss)	0.03 (0.01)	0.02 (0.01)	0.05 (0.02)	0.04 (0.02)
Miss × Predicted Hit (False Hit)	0.13 (0.08)	0.15 (0.08)	0.21 (0.08)	0.19 (0.09)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	-0.17	-0.17	-0.16	-0.17
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.11	0.12	0.15	0.15
p-value	0.16	0.11	0.04	0.05
Hit Difference vs. Miss Difference	-0.25	-0.26	-0.27	-0.27
p-value	0.00	0.00	0.00	0.00
Panel B. 200 nm Threshold				
Hit × Predicted Hit (True Hit)	0.15 (0.02)	0.14 (0.02)	0.15 (0.03)	0.15 (0.03)
Hit × Predicted Miss (False Miss)	0.44 (0.07)	0.42 (0.07)	0.41 (0.07)	0.40 (0.07)
Miss × Predicted Miss (True Miss)	0.02 (0.01)	0.01 (0.01)	0.03 (0.02)	0.02 (0.02)
Miss × Predicted Hit (False Hit)	-0.07 (0.07)	-0.06 (0.07)	-0.03 (0.08)	-0.04 (0.07)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.25	0.25	0.22	0.21
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	-0.08	-0.07	-0.06	-0.06
p-value	0.22	0.29	0.39	0.30
Hit Difference vs. Miss Difference	0.36	0.34	0.30	0.29
p-value	0.00	0.00	0.00	0.00

Table 17 (cont'd)

Panel C. 300 nm Threshold				
Hit × Predicted Hit (True Hit)	0.12 (0.02)	0.11 (0.01)	0.13 (0.03)	0.13 (0.03)
Hit × Predicted Miss (False Miss)	-0.11 (0.07)	-0.11 (0.07)	-0.15 (0.08)	-0.16 (0.08)
Miss × Predicted Miss (True Miss)	0.02 (0.01)	0.02 (0.01)	0.05 (0.02)	0.04 (0.02)
Miss × Predicted Hit (False Hit)	0.22 (0.03)	0.19 (0.03)	0.22 (0.03)	0.21 (0.03)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	-0.21	-0.20	-0.25	-0.26
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.20	0.17	0.16	0.16
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.34	-0.32	-0.36	-0.36
p-value	0.00	0.00	0.00	0.00
Panel D. 400 nm Threshold				
Hit × Predicted Hit (True Hit)	0.07 (0.02)	0.06 (0.02)	0.02 (0.03)	0.02 (0.03)
Hit × Predicted Miss (False Miss)	1.10 (0.11)	1.10 (0.11)	1.03 (0.12)	1.03 (0.12)
Miss × Predicted Miss (True Miss)	-0.03 (0.01)	-0.03 (0.01)	-0.08 (0.02)	-0.08 (0.02)
Miss × Predicted Hit (False Hit)	-0.06 (0.03)	-0.06 (0.03)	-0.10 (0.04)	-0.11 (0.04)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.96	0.97	0.99	0.99
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	-0.03	-0.03	-0.03	-0.03
p-value	0.38	0.26	0.34	0.41
Hit Difference vs. Miss Difference	1.02	1.04	1.05	1.04
p-value	0.00	0.00	0.00	0.00

Table 17 (cont'd)

Panel E. 500 nm Threshold				
Hit × Predicted Hit (True Hit)	0.09 (0.01)	0.08 (0.01)	0.11 (0.03)	0.11 (0.03)
Hit × Predicted Miss (False Miss)	1.03 (0.17)	0.97 (0.17)	0.95 (0.16)	0.98 (0.16)
Miss × Predicted Miss (True Miss)	-0.03 (0.01)	-0.03 (0.01)	-0.01 (0.02)	-0.02 (0.02)
Miss × Predicted Hit (False Hit)	0.33 (0.06)	0.32 (0.06)	0.36 (0.06)	0.34 (0.06)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.86	0.82	0.75	0.79
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.38	0.36	0.38	0.35
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	0.35	0.34	0.27	0.30
p-value	0.00	0.00	0.01	0.00

Table 18: 60-Hour Window Across Distance Thresholds: All Storms

Panel A. 100 nm Threshold				
Storm Classification	(1)	(2)	(3)	(4)
Hit × Predicted Hit (True Hit)	0.16 (0.05)	0.16 (0.05)	-0.01 (0.04)	-0.01 (0.04)
Hit × Predicted Miss (False Miss)	-0.11 (0.03)	-0.10 (0.03)	-0.28 (0.03)	-0.28 (0.03)
Miss × Predicted Miss (True Miss)	-0.20 (0.01)	-0.17 (0.01)	-0.29 (0.01)	-0.29 (0.01)
Miss × Predicted Hit (False Hit)	0.31 (0.10)	0.27 (0.09)	0.05 (0.08)	0.04 (0.08)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	-0.23	-0.23	-0.27	-0.27
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.65	0.54	0.49	0.48
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.53	-0.50	-0.51	-0.51
p-value	0.00	0.00	0.00	0.00

Table 18 (cont'd)

Panel B. 200 nm Threshold				
Hit × Predicted Hit (True Hit)	-0.21 (0.01)	-0.20 (0.01)	-0.34 (0.01)	-0.34 (0.01)
Hit × Predicted Miss (False Miss)	0.38 (0.10)	0.42 (0.10)	0.04 (0.07)	0.03 (0.07)
Miss × Predicted Miss (True Miss)	-0.12 (0.01)	-0.07 (0.01)	-0.22 (0.01)	-0.22 (0.01)
Miss × Predicted Hit (False Hit)	-0.03 (0.07)	0.00 (0.07)	-0.16 (0.06)	-0.17 (0.06)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.74	0.78	0.57	0.57
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.11	0.08	0.07	0.06
p-value	0.11	0.23	0.29	0.32
Hit Difference vs. Miss Difference	0.57	0.64	0.47	0.47
p-value	0.00	0.00	0.00	0.00
Panel C. 300 nm Threshold				
Hit × Predicted Hit (True Hit)	-0.21 (0.01)	-0.20 (0.01)	-0.31 (0.01)	-0.31 (0.01)
Hit × Predicted Miss (False Miss)	0.23 (0.17)	0.47 (0.16)	0.29 (0.15)	0.30 (0.15)
Miss × Predicted Miss (True Miss)	-0.07 (0.01)	-0.02 (0.01)	-0.18 (0.02)	-0.18 (0.02)
Miss × Predicted Hit (False Hit)	-0.24 (0.06)	-0.24 (0.06)	-0.33 (0.05)	-0.32 (0.05)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.57	0.82	0.88	0.89
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	-0.18	-0.23	-0.19	-0.18
p-value	0.00	0.00	0.00	0.01
Hit Difference vs. Miss Difference	0.92	1.36	1.32	1.29
p-value	0.00	0.00	0.00	0.00

Table 18 (cont'd)

Panel D. 400 nm Threshold				
Hit × Predicted Hit (True Hit)	-0.22 (0.01)	-0.20 (0.01)	-0.32 (0.01)	-0.32 (0.01)
Hit × Predicted Miss (False Miss)	0.08 (0.10)	0.15 (0.10)	-0.18 (0.06)	-0.18 (0.06)
Miss × Predicted Miss (True Miss)	-0.06 (0.01)	-0.01 (0.01)	-0.23 (0.02)	-0.24 (0.02)
Miss × Predicted Hit (False Hit)	0.77 (0.14)	0.65 (0.13)	0.22 (0.08)	0.21 (0.08)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.39	0.44	0.20	0.20
p-value	0.00	0.00	0.02	0.02
False Hit vs. True Miss (Miss Difference)	0.90	0.67	0.60	0.58
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.27	-0.13	-0.25	-0.24
p-value	0.00	0.07	0.00	0.00
Panel E. 500 nm Threshold				
Hit × Predicted Hit (True Hit)	-0.18 (0.01)	-0.16 (0.01)	-0.30 (0.01)	-0.30 (0.01)
Hit × Predicted Miss (False Miss)	-0.03 (0.06)	-0.09 (0.06)	-0.16 (0.04)	-0.16 (0.04)
Miss × Predicted Miss (True Miss)	-0.14 (0.01)	-0.08 (0.02)	-0.29 (0.02)	-0.29 (0.02)
Miss × Predicted Hit (False Hit)	0.30 (0.08)	0.17 (0.07)	-0.13 (0.05)	-0.15 (0.05)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.19	0.08	0.21	0.20
p-value	0.00	0.22	0.01	0.00
False Hit vs. True Miss (Miss Difference)	0.51	0.28	0.22	0.20
p-value	0.00	0.00	0.00	0.01
Hit Difference vs. Miss Difference	-0.21	-0.15	-0.01	0.00
p-value	0.01	0.06	0.90	0.98

Table 19: 72-Hour Window Across Distance Thresholds: All Storms

Panel A. 100 nm Threshold				
Storm Classification	(1)	(2)	(3)	(4)
Hit × Predicted Hit (True Hit)	0.56 (0.03)	0.52 (0.03)	0.59 (0.04)	0.60 (0.04)
Hit × Predicted Miss (False Miss)	0.19 (0.04)	0.18 (0.04)	0.30 (0.05)	0.30 (0.05)
Miss × Predicted Miss (True Miss)	0.04 (0.01)	0.03 (0.01)	0.10 (0.02)	0.10 (0.02)
Miss × Predicted Hit (False Hit)	0.64 (0.11)	0.52 (0.10)	0.62 (0.10)	0.60 (0.10)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	-0.24	-0.23	-0.18	-0.19
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.59	0.47	0.47	0.44
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.52	-0.48	-0.44	-0.44
p-value	0.00	0.00	0.00	0.00
Panel B. 200 nm Threshold				
Hit × Predicted Hit (True Hit)	0.15 (0.02)	0.14 (0.02)	0.21 (0.03)	0.21 (0.03)
Hit × Predicted Miss (False Miss)	0.42 (0.07)	0.40 (0.07)	0.55 (0.08)	0.55 (0.08)
Miss × Predicted Miss (True Miss)	0.04 (0.01)	0.04 (0.01)	0.10 (0.02)	0.10 (0.02)
Miss × Predicted Hit (False Hit)	-0.14 (0.04)	-0.13 (0.04)	-0.01 (0.05)	-0.01 (0.05)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.24	0.23	0.29	0.28
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	-0.17	-0.16	-0.10	-0.10
p-value	0.00	0.00	0.02	0.02
Hit Difference vs. Miss Difference	0.49	0.46	0.43	0.43
p-value	0.00	0.00	0.00	0.00

Table 19 (cont'd)

Panel C. 300 nm Threshold				
Hit × Predicted Hit (True Hit)	0.14 (0.02)	0.13 (0.02)	0.21 (0.03)	0.21 (0.03)
Hit × Predicted Miss (False Miss)	0.72 (0.08)	0.68 (0.08)	0.83 (0.08)	0.83 (0.08)
Miss × Predicted Miss (True Miss)	0.03 (0.01)	0.03 (0.01)	0.09 (0.02)	0.08 (0.02)
Miss × Predicted Hit (False Hit)	-0.31 (0.05)	-0.31 (0.05)	-0.22 (0.06)	-0.22 (0.06)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.51	0.49	0.52	0.51
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	-0.33	-0.32	-0.29	-0.29
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	1.26	1.21	1.13	1.11
p-value	0.00	0.00	0.00	0.00
Panel D. 400 nm Threshold				
Hit × Predicted Hit (True Hit)	0.08 (0.02)	0.08 (0.02)	0.11 (0.03)	0.11 (0.03)
Hit × Predicted Miss (False Miss)	0.52 (0.06)	0.51 (0.06)	0.54 (0.06)	0.54 (0.06)
Miss × Predicted Miss (True Miss)	0.01 (0.01)	0.01 (0.01)	0.03 (0.02)	0.03 (0.02)
Miss × Predicted Hit (False Hit)	-0.11 (0.02)	-0.10 (0.02)	-0.07 (0.03)	-0.05 (0.03)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.40	0.41	0.39	0.39
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	-0.12	-0.11	-0.09	-0.08
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	0.59	0.58	0.54	0.50
p-value	0.00	0.00	0.00	0.00

Table 19 (cont'd)

Panel E. 500 nm Threshold				
Hit × Predicted Hit (True Hit)	0.05 (0.02)	0.05 (0.02)	0.09 (0.03)	0.09 (0.03)
Hit × Predicted Miss (False Miss)	0.72 (0.06)	0.65 (0.06)	0.68 (0.06)	0.68 (0.06)
Miss × Predicted Miss (True Miss)	0.06 (0.01)	0.06 (0.01)	0.09 (0.02)	0.08 (0.02)
Miss × Predicted Hit (False Hit)	-0.09 (0.03)	-0.09 (0.03)	0.00 (0.04)	0.00 (0.04)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.64	0.58	0.55	0.54
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	-0.14	-0.13	-0.08	-0.08
p-value	0.00	0.00	0.01	0.01
Hit Difference vs. Miss Difference	0.90	0.82	0.69	0.68
p-value	0.00	0.00	0.00	0.00

Table 20: 96-Hour Window Across Distance Thresholds: All Storms

Panel A. 100 nm Threshold				
Storm Classification	(1)	(2)	(3)	(4)
Hit × Predicted Hit (True Hit)	0.75 (0.06)	0.72 (0.06)	0.75 (0.07)	0.79 (0.07)
Hit × Predicted Miss (False Miss)	0.97 (0.14)	0.87 (0.13)	0.93 (0.14)	0.93 (0.13)
Miss × Predicted Miss (True Miss)	0.05 (0.01)	0.04 (0.01)	0.08 (0.03)	0.08 (0.03)
Miss × Predicted Hit (False Hit)	0.17 (0.07)	0.18 (0.07)	0.22 (0.07)	0.22 (0.07)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.12	0.09	0.10	0.08
p-value	0.13	0.29	0.19	0.29
False Hit vs. True Miss (Miss Difference)	0.12	0.13	0.12	0.12
p-value	0.08	0.04	0.07	0.07
Hit Difference vs. Miss Difference	0.01	-0.04	-0.02	-0.04
p-value	0.96	0.65	0.85	0.70

Table 20 (cont'd)

Panel B. 200 nm Threshold				
Hit $\times$ Predicted Hit (True Hit)	0.27 (0.04)	0.25 (0.03)	0.29 (0.04)	0.30 (0.04)
Hit $\times$ Predicted Miss (False Miss)	0.23 (0.05)	0.19 (0.05)	0.27 (0.06)	0.26 (0.06)
Miss $\times$ Predicted Miss (True Miss)	0.04 (0.01)	0.04 (0.01)	0.09 (0.03)	0.08 (0.03)
Miss $\times$ Predicted Hit (False Hit)	0.40 (0.06)	0.38 (0.06)	0.46 (0.06)	0.45 (0.06)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	-0.03	-0.05	-0.02	-0.03
p-value	0.48	0.31	0.69	0.51
False Hit vs. True Miss (Miss Difference)	0.35	0.33	0.34	0.34
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.28	-0.29	-0.27	-0.28
p-value	0.00	0.00	0.00	0.00

Panel C. 300 nm Threshold				
Hit $\times$ Predicted Hit (True Hit)	0.17 (0.02)	0.16 (0.02)	0.20 (0.03)	0.20 (0.03)
Hit $\times$ Predicted Miss (False Miss)	-0.17 (0.08)	-0.20 (0.08)	-0.15 (0.09)	-0.15 (0.09)
Miss $\times$ Predicted Miss (True Miss)	0.05 (0.01)	0.04 (0.01)	0.09 (0.03)	0.09 (0.03)
Miss $\times$ Predicted Hit (False Hit)	0.12 (0.03)	0.08 (0.03)	0.14 (0.03)	0.13 (0.03)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	-0.29	-0.31	-0.29	-0.29
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.07	0.04	0.04	0.04
p-value	0.07	0.21	0.18	0.18
Hit Difference vs. Miss Difference	-0.33	-0.34	-0.32	-0.32
p-value	0.00	0.00	0.00	0.00

Table 20 (cont'd)

Panel D. 400 nm Threshold				
Hit × Predicted Hit (True Hit)	0.07 (0.03)	0.06 (0.03)	0.09 (0.04)	0.10 (0.04)
Hit × Predicted Miss (False Miss)	0.71 (0.06)	0.69 (0.06)	0.73 (0.06)	0.73 (0.06)
Miss × Predicted Miss (True Miss)	0.00 (0.01)	-0.01 (0.01)	0.02 (0.03)	0.02 (0.03)
Miss × Predicted Hit (False Hit)	0.24 (0.05)	0.21 (0.05)	0.23 (0.06)	0.22 (0.06)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.59	0.59	0.58	0.58
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.25	0.21	0.20	0.19
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	0.28	0.31	0.32	0.32
p-value	0.00	0.00	0.00	0.00
Panel E. 500 nm Threshold				
Hit × Predicted Hit (True Hit)	0.04 (0.03)	0.03 (0.03)	0.05 (0.04)	0.05 (0.04)
Hit × Predicted Miss (False Miss)	0.67 (0.04)	0.62 (0.04)	0.64 (0.04)	0.63 (0.04)
Miss × Predicted Miss (True Miss)	0.02 (0.01)	0.01 (0.01)	0.03 (0.02)	0.03 (0.02)
Miss × Predicted Hit (False Hit)	0.19 (0.07)	0.17 (0.07)	0.19 (0.07)	0.18 (0.07)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.60	0.58	0.56	0.56
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.17	0.15	0.15	0.14
p-value	0.00	0.01	0.02	0.02
Hit Difference vs. Miss Difference	0.37	0.37	0.36	0.36
p-value	0.00	0.00	0.00	0.00

Table 21: 120-Hour Window Across Distance Thresholds: All Storms

Panel A. 100 nm Threshold				
Storm Classification	(1)	(2)	(3)	(4)
Hit × Predicted Hit (True Hit)	0.46 (0.07)	0.41 (0.06)	0.43 (0.06)	0.46 (0.07)
Hit × Predicted Miss (False Miss)	1.33 (0.13)	1.21 (0.12)	1.27 (0.13)	1.28 (0.13)
Miss × Predicted Miss (True Miss)	-0.05 (0.02)	-0.05 (0.02)	-0.10 (0.02)	-0.10 (0.02)
Miss × Predicted Hit (False Hit)	0.11 (0.03)	0.13 (0.03)	0.12 (0.03)	0.12 (0.03)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.59	0.57	0.59	0.56
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.17	0.20	0.24	0.24
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	0.36	0.31	0.28	0.26
p-value	0.00	0.00	0.00	0.00
Panel B. 200 nm Threshold				
Hit × Predicted Hit (True Hit)	0.14 (0.04)	0.11 (0.04)	0.13 (0.04)	0.13 (0.04)
Hit × Predicted Miss (False Miss)	0.18 (0.08)	0.13 (0.07)	0.15 (0.07)	0.15 (0.07)
Miss × Predicted Miss (True Miss)	-0.04 (0.02)	-0.05 (0.01)	-0.09 (0.02)	-0.09 (0.02)
Miss × Predicted Hit (False Hit)	0.09 (0.03)	0.06 (0.03)	0.06 (0.04)	0.06 (0.04)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.04	0.02	0.02	0.02
p-value	0.53	0.78	0.71	0.72
False Hit vs. True Miss (Miss Difference)	0.14	0.12	0.16	0.16
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.09	-0.09	-0.12	-0.12
p-value	0.11	0.11	0.05	0.05

Table 21 (cont'd)

Panel C. 300 nm Threshold				
Hit × Predicted Hit (True Hit)	-0.02 (0.04)	-0.04 (0.04)	-0.03 (0.04)	-0.03 (0.04)
Hit × Predicted Miss (False Miss)	0.03 (0.05)	0.01 (0.04)	0.02 (0.04)	0.02 (0.04)
Miss × Predicted Miss (True Miss)	-0.04 (0.02)	-0.05 (0.01)	-0.09 (0.02)	-0.09 (0.02)
Miss × Predicted Hit (False Hit)	0.30 (0.07)	0.26 (0.07)	0.19 (0.06)	0.19 (0.06)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.05	0.05	0.05	0.05
p-value	0.09	0.10	0.10	0.11
False Hit vs. True Miss (Miss Difference)	0.35	0.32	0.31	0.31
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.22	-0.21	-0.20	-0.20
p-value	0.00	0.00	0.00	0.00

Panel D. 400 nm Threshold				
Hit × Predicted Hit (True Hit)	-0.08 (0.03)	-0.09 (0.03)	-0.09 (0.03)	-0.09 (0.03)
Hit × Predicted Miss (False Miss)	0.02 (0.04)	-0.01 (0.04)	0.00 (0.04)	0.00 (0.04)
Miss × Predicted Miss (True Miss)	-0.04 (0.01)	-0.05 (0.01)	-0.10 (0.02)	-0.10 (0.02)
Miss × Predicted Hit (False Hit)	0.94 (0.07)	0.85 (0.06)	0.81 (0.07)	0.81 (0.07)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.11	0.10	0.10	0.10
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	1.03	0.95	1.02	1.02
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.45	-0.44	-0.46	-0.46
p-value	0.00	0.00	0.00	0.00

Table 21 (cont'd)

Panel E. 500 nm Threshold				
Hit × Predicted Hit (True Hit)	-0.10 (0.03)	-0.11 (0.03)	-0.08 (0.02)	-0.08 (0.02)
Hit × Predicted Miss (False Miss)	0.17 (0.04)	0.15 (0.04)	0.18 (0.04)	0.18 (0.04)
Miss × Predicted Miss (True Miss)	-0.06 (0.01)	-0.07 (0.01)	-0.10 (0.02)	-0.10 (0.02)
Miss × Predicted Hit (False Hit)	0.48 (0.07)	0.44 (0.07)	0.41 (0.06)	0.41 (0.06)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.30	0.29	0.28	0.28
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.57	0.54	0.56	0.56
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.17	-0.17	-0.18	-0.18
p-value	0.00	0.00	0.00	0.00

C Hurricanes: 30-Day Window

This section further restricts the sample to hurricane events observed within a 30-day insurance response window. The shorter temporal window focuses on the most immediate behavioral reactions to storm exposure, when salience and perceived risk are likely to be strongest. All specifications estimate issuance across varying forecast horizons (36–120 hours) and hit-distance thresholds (100–500 nautical miles).

Table 22: 36-Hour Window Across Distance Thresholds: Hurricanes (Restricted)

Panel A. 100 nm Threshold			
Storm Classification	(1)	(2)	(3)
Hit × Predicted Hit (True Hit)	1.74 (0.14)	1.52 (0.12)	1.51 (0.12)
Hit × Predicted Miss (False Miss)	2.25 (0.30)	2.07 (0.28)	2.07 (0.28)
Miss × Predicted Miss (True Miss)	0.12 (0.01)	0.12 (0.01)	0.11 (0.01)
Miss × Predicted Hit (False Hit)	-0.14 (0.21)	-0.15 (0.21)	-0.15 (0.21)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.19	0.22	0.22
p-value	0.11	0.06	0.06
False Hit vs. True Miss (Miss Difference)	-0.23	-0.24	-0.24
p-value	0.28	0.28	0.28
Hit Difference vs. Miss Difference	0.55	0.60	0.60
p-value	0.03	0.02	0.02

Table 22 (cont'd)

Panel B. 200 nm Threshold			
Hit × Predicted Hit (True Hit)	1.26 (0.05)	1.10 (0.05)	1.09 (0.05)
Hit × Predicted Miss (False Miss)	-0.05 (0.06)	-0.03 (0.07)	-0.02 (0.07)
Miss × Predicted Miss (True Miss)	0.11 (0.01)	0.11 (0.01)	0.11 (0.01)
Miss × Predicted Hit (False Hit)	0.67 (0.23)	0.69 (0.23)	0.69 (0.23)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	-0.58	-0.54	-0.53
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.51	0.53	0.53
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.72	-0.70	-0.69
p-value	0.00	0.00	0.00
Panel C. 300 nm Threshold			
Hit × Predicted Hit (True Hit)	1.10 (0.04)	0.97 (0.04)	0.98 (0.04)
Hit × Predicted Miss (False Miss)	0.46 (0.11)	0.47 (0.11)	0.51 (0.11)
Miss × Predicted Miss (True Miss)	0.10 (0.01)	0.09 (0.01)	0.09 (0.01)
Miss × Predicted Hit (False Hit)	1.89 (0.48)	1.64 (0.43)	1.64 (0.43)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	-0.31	-0.25	-0.24
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	1.64	1.42	1.42
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.74	-0.69	-0.68
p-value	0.00	0.00	0.01

Table 22 (cont'd)

Panel D. 400 nm Threshold			
Hit × Predicted Hit (True Hit)	0.93 (0.03)	0.83 (0.03)	0.83 (0.03)
Hit × Predicted Miss (False Miss)	2.00 (0.20)	1.93 (0.20)	1.91 (0.20)
Miss × Predicted Miss (True Miss)	0.04 (0.01)	0.04 (0.01)	0.04 (0.01)
Miss × Predicted Hit (False Hit)	0.24 (0.07)	0.15 (0.06)	0.15 (0.06)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.56	0.60	0.59
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.20	0.11	0.12
p-value	0.00	0.05	0.04
Hit Difference vs. Miss Difference	0.30	0.43	0.42
p-value	0.01	0.00	0.00

Panel E. 500 nm Threshold			
Hit × Predicted Hit (True Hit)	0.81 (0.04)	0.74 (0.03)	0.74 (0.03)
Hit × Predicted Miss (False Miss)	1.90 (0.38)	1.89 (0.34)	1.87 (0.34)
Miss × Predicted Miss (True Miss)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)
Miss × Predicted Hit (False Hit)	0.48 (0.07)	0.47 (0.07)	0.46 (0.07)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.60	0.66	0.65
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.47	0.45	0.45
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	0.09	0.14	0.14
p-value	0.52	0.29	0.30

Table 23: 48-Hour Window Across Distance Thresholds: Hurricanes (Restricted)

Panel A. 100 nm Threshold			
Storm Classification	(1)	(2)	(3)
Hit × Predicted Hit (True Hit)	1.96 (0.12)	1.73 (0.10)	1.73 (0.10)
Hit × Predicted Miss (False Miss)	1.53 (0.28)	1.31 (0.25)	1.31 (0.25)
Miss × Predicted Miss (True Miss)	0.16 (0.01)	0.14 (0.01)	0.14 (0.01)
Miss × Predicted Hit (False Hit)	0.28 (0.12)	0.31 (0.12)	0.31 (0.12)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	-0.14	-0.15	-0.15
p-value	0.14	0.12	0.12
False Hit vs. True Miss (Miss Difference)	0.11	0.15	0.15
p-value	0.27	0.11	0.11
Hit Difference vs. Miss Difference	-0.23	-0.26	-0.26
p-value	0.07	0.03	0.03
Panel B. 200 nm Threshold			
Hit × Predicted Hit (True Hit)	1.34 (0.06)	1.16 (0.05)	1.16 (0.05)
Hit × Predicted Miss (False Miss)	-0.04 (0.07)	-0.02 (0.07)	0.00 (0.08)
Miss × Predicted Miss (True Miss)	0.14 (0.01)	0.13 (0.01)	0.13 (0.01)
Miss × Predicted Hit (False Hit)	0.10 (0.13)	0.10 (0.13)	0.10 (0.13)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	-0.59	-0.54	-0.54
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	-0.04	-0.03	-0.03
p-value	0.75	0.78	0.78
Hit Difference vs. Miss Difference	-0.57	-0.53	-0.52
p-value	0.00	0.00	0.00

Table 23 (cont'd)

Panel C. 300 nm Threshold			
Hit × Predicted Hit (True Hit)	1.13 (0.04)	1.01 (0.04)	1.01 (0.04)
Hit × Predicted Miss (False Miss)	0.64 (0.14)	0.62 (0.14)	0.66 (0.15)
Miss × Predicted Miss (True Miss)	0.13 (0.01)	0.12 (0.01)	0.12 (0.01)
Miss × Predicted Hit (False Hit)	1.13 (0.23)	1.04 (0.22)	1.03 (0.22)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	-0.23	-0.19	-0.17
p-value	0.00	0.01	0.03
False Hit vs. True Miss (Miss Difference)	0.89	0.82	0.82
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.59	-0.56	-0.54
p-value	0.00	0.00	0.00
Panel D. 400 nm Threshold			
Hit × Predicted Hit (True Hit)	1.00 (0.03)	0.89 (0.03)	0.89 (0.03)
Hit × Predicted Miss (False Miss)	2.49 (0.23)	2.44 (0.23)	2.42 (0.22)
Miss × Predicted Miss (True Miss)	0.04 (0.01)	0.03 (0.01)	0.03 (0.01)
Miss × Predicted Hit (False Hit)	0.64 (0.11)	0.62 (0.11)	0.62 (0.11)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.75	0.82	0.81
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.58	0.57	0.57
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	0.11	0.15	0.15
p-value	0.28	0.11	0.13

Table 23 (cont'd)

Panel E. 500 nm Threshold			
Hit × Predicted Hit (True Hit)	0.93 (0.05)	0.86 (0.05)	0.85 (0.04)
Hit × Predicted Miss (False Miss)	2.65 (0.40)	2.36 (0.36)	2.33 (0.36)
Miss × Predicted Miss (True Miss)	0.03 (0.01)	0.03 (0.01)	0.03 (0.01)
Miss × Predicted Hit (False Hit)	0.24 (0.05)	0.23 (0.05)	0.23 (0.05)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.89	0.81	0.80
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.20	0.20	0.19
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	0.57	0.51	0.51
p-value	0.00	0.00	0.00

Table 24: 60-Hour Window Across Distance Thresholds: Hurricanes (Restricted)

Panel A. 100 nm Threshold			
Storm Classification	(1)	(2)	(3)
Hit × Predicted Hit (True Hit)	0.26 (0.04)	0.15 (0.04)	0.15 (0.04)
Hit × Predicted Miss (False Miss)	0.29 (0.09)	0.16 (0.09)	0.18 (0.09)
Miss × Predicted Miss (True Miss)	-0.17 (0.01)	-0.15 (0.01)	-0.15 (0.01)
Miss × Predicted Hit (False Hit)	-0.01 (0.09)	0.05 (0.09)	0.05 (0.09)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.02	0.81	0.80
p-value	0.72	0.86	0.74
False Hit vs. True Miss (Miss Difference)	0.20	0.24	0.24
p-value	0.04	0.01	0.01
Hit Difference vs. Miss Difference	-0.15	-0.18	-0.18
p-value	0.12	0.04	0.05

Table 24 (cont'd)

Panel B. 200 nm Threshold			
Hit × Predicted Hit (True Hit)	0.00 (0.02)	-0.08 (0.02)	-0.08 (0.02)
Hit × Predicted Miss (False Miss)	-0.42 (0.05)	-0.37 (0.06)	-0.38 (0.06)
Miss × Predicted Miss (True Miss)	-0.17 (0.01)	-0.13 (0.01)	-0.13 (0.01)
Miss × Predicted Hit (False Hit)	0.00 (0.07)	0.02 (0.07)	0.02 (0.07)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	-0.42	-0.32	-0.33
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.20	0.17	0.17
p-value	0.01	0.03	0.03
Hit Difference vs. Miss Difference	-0.52	-0.42	-0.42
p-value	0.00	0.00	0.00

Panel C. 300 nm Threshold			
Hit × Predicted Hit (True Hit)	-0.09 (0.01)	-0.13 (0.01)	-0.13 (0.01)
Hit × Predicted Miss (False Miss)	0.39 (0.11)	0.40 (0.11)	0.42 (0.12)
Miss × Predicted Miss (True Miss)	-0.16 (0.01)	-0.11 (0.02)	-0.11 (0.02)
Miss × Predicted Hit (False Hit)	-0.09 (0.07)	-0.10 (0.07)	-0.10 (0.07)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.53	0.60	0.62
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.09	0.01	0.01
p-value	0.28	0.90	0.90
Hit Difference vs. Miss Difference	0.41	0.59	0.61
p-value	0.00	0.00	0.00

Table 24 (cont'd)

Panel D. 400 nm Threshold			
Hit × Predicted Hit (True Hit)	-0.11 (0.01)	-0.14 (0.01)	-0.14 (0.01)
Hit × Predicted Miss (False Miss)	0.90 (0.54)	0.76 (0.40)	0.76 (0.40)
Miss × Predicted Miss (True Miss)	-0.14 (0.01)	-0.07 (0.02)	-0.07 (0.02)
Miss × Predicted Hit (False Hit)	0.14 (0.12)	0.18 (0.12)	0.18 (0.12)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	1.13	1.05	1.05
p-value	0.01	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.32	0.26	0.26
p-value	0.01	0.02	0.02
Hit Difference vs. Miss Difference	0.61	0.62	0.62
p-value	0.10	0.04	0.04

Panel E. 500 nm Threshold			
Hit × Predicted Hit (True Hit)	-0.09 (0.01)	-0.12 (0.01)	-0.12 (0.01)
Hit × Predicted Miss (False Miss)	-0.15 (0.05)	-0.25 (0.05)	-0.25 (0.05)
Miss × Predicted Miss (True Miss)	-0.17 (0.01)	-0.09 (0.02)	-0.09 (0.02)
Miss × Predicted Hit (False Hit)	0.53 (0.14)	0.45 (0.13)	0.45 (0.13)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	-0.06	-0.15	-0.15
p-value	0.28	0.01	0.01
False Hit vs. True Miss (Miss Difference)	0.84	0.60	0.60
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.49	-0.47	-0.47
p-value	0.00	0.00	0.00

Table 25: 72-Hour Window Across Distance Thresholds: Hurricanes (Restricted)

Panel A. 100 nm Threshold			
Storm Classification	(1)	(2)	(3)
Hit × Predicted Hit (True Hit)	2.16 (0.12)	1.92 (0.10)	1.94 (0.11)
Hit × Predicted Miss (False Miss)	1.08 (0.18)	0.87 (0.16)	0.88 (0.17)
Miss × Predicted Miss (True Miss)	0.17 (0.02)	0.16 (0.02)	0.16 (0.02)
Miss × Predicted Hit (False Hit)	0.24 (0.09)	0.25 (0.09)	0.25 (0.09)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	-0.34	-0.36	-0.36
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.07	0.08	0.08
p-value	0.36	0.29	0.29
Hit Difference vs. Miss Difference	-0.38	-0.40	-0.41
p-value	0.00	0.00	0.00
Panel B. 200 nm Threshold			
Hit × Predicted Hit (True Hit)	1.54 (0.08)	1.35 (0.06)	1.36 (0.06)
Hit × Predicted Miss (False Miss)	0.18 (0.10)	0.20 (0.10)	0.21 (0.10)
Miss × Predicted Miss (True Miss)	0.13 (0.02)	0.13 (0.02)	0.13 (0.02)
Miss × Predicted Hit (False Hit)	0.90 (0.16)	0.79 (0.15)	0.79 (0.15)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	-0.54	-0.49	-0.49
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.67	0.58	0.58
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.72	-0.68	-0.68
p-value	0.00	0.00	0.00

Table 25 (cont'd)

Panel C. 300 nm Threshold			
Hit × Predicted Hit (True Hit)	1.32 (0.07)	1.17 (0.06)	1.18 (0.06)
Hit × Predicted Miss (False Miss)	1.46 (0.15)	1.44 (0.16)	1.43 (0.16)
Miss × Predicted Miss (True Miss)	0.11 (0.02)	0.11 (0.02)	0.11 (0.02)
Miss × Predicted Hit (False Hit)	-0.03 (0.07)	-0.03 (0.07)	-0.03 (0.07)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.06	0.13	0.11
p-value	0.38	0.08	0.13
False Hit vs. True Miss (Miss Difference)	-0.13	-0.13	-0.13
p-value	0.05	0.05	0.05
Hit Difference vs. Miss Difference	0.22	0.30	0.27
p-value	0.05	0.01	0.02
Panel D. 400 nm Threshold			
Hit × Predicted Hit (True Hit)	0.95 (0.04)	0.85 (0.04)	0.86 (0.04)
Hit × Predicted Miss (False Miss)	2.25 (0.18)	2.21 (0.18)	2.22 (0.18)
Miss × Predicted Miss (True Miss)	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)
Miss × Predicted Hit (False Hit)	-0.17 (0.07)	-0.19 (0.07)	-0.18 (0.07)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.67	0.74	0.73
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	-0.17	-0.19	-0.18
p-value	0.03	0.01	0.02
Hit Difference vs. Miss Difference	1.00	1.14	1.12
p-value	0.00	0.00	0.00

Table 25 (cont'd)

Panel E. 500 nm Threshold			
Hit × Predicted Hit (True Hit)	0.84 (0.06)	0.78 (0.06)	0.79 (0.06)
Hit × Predicted Miss (False Miss)	1.37 (0.07)	1.24 (0.07)	1.25 (0.07)
Miss × Predicted Miss (True Miss)	0.02 (0.01)	0.02 (0.01)	0.02 (0.01)
Miss × Predicted Hit (False Hit)	0.46 (0.30)	0.43 (0.29)	0.43 (0.29)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.29	0.26	0.26
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.44	0.41	0.41
p-value	0.07	0.09	0.09
Hit Difference vs. Miss Difference	0.00	0.00	0.00
p-value	0.57	0.57	0.57

Table 26: 96-Hour Window Across Distance Thresholds: Hurricanes (Restricted)

Panel A. 100 nm Threshold			
Storm Classification	(1)	(2)	(3)
Hit × Predicted Hit (True Hit)	1.90 (0.12)	1.71 (0.11)	1.71 (0.11)
Hit × Predicted Miss (False Miss)	2.02 (0.25)	1.73 (0.22)	1.73 (0.22)
Miss × Predicted Miss (True Miss)	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)
Miss × Predicted Hit (False Hit)	0.21 (0.11)	0.26 (0.11)	0.26 (0.11)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.04	0.01	0.01
p-value	0.64	0.93	0.93
False Hit vs. True Miss (Miss Difference)	0.22	0.27	0.27
p-value	0.02	0.01	0.01
Hit Difference vs. Miss Difference	-0.14	-0.21	-0.21
p-value	0.14	0.03	0.03

Table 26 (cont'd)

Panel B. 200 nm Threshold			
Hit × Predicted Hit (True Hit)	1.53 (0.08)	1.34 (0.07)	1.36 (0.07)
Hit × Predicted Miss (False Miss)	0.19 (0.11)	0.16 (0.10)	0.26 (0.11)
Miss × Predicted Miss (True Miss)	-0.05 (0.01)	-0.05 (0.01)	-0.05 (0.01)
Miss × Predicted Hit (False Hit)	1.17 (0.17)	1.15 (0.16)	1.20 (0.17)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	-0.53	-0.51	-0.51
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	1.29	1.27	1.27
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.79	-0.78	-0.78
p-value	0.00	0.00	0.00
Panel C. 300 nm Threshold			
Hit × Predicted Hit (True Hit)	1.32 (0.06)	1.16 (0.06)	1.31 (0.06)
Hit × Predicted Miss (False Miss)	1.31 (0.15)	1.25 (0.15)	1.25 (0.15)
Miss × Predicted Miss (True Miss)	-0.08 (0.01)	-0.07 (0.01)	-0.07 (0.01)
Miss × Predicted Hit (False Hit)	0.59 (0.14)	0.52 (0.14)	0.46 (0.13)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.00	0.04	-0.03
p-value	0.97	0.60	0.72
False Hit vs. True Miss (Miss Difference)	0.72	0.64	0.56
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.42	-0.37	-0.38
p-value	0.00	0.00	0.00

Table 26 (cont'd)

Panel D. 400 nm Threshold			
Hit × Predicted Hit (True Hit)	1.22 (0.07)	1.08 (0.06)	1.16 (0.07)
Hit × Predicted Miss (False Miss)	1.50 (0.13)	1.45 (0.13)	1.45 (0.13)
Miss × Predicted Miss (True Miss)	-0.22 (0.01)	-0.21 (0.01)	-0.21 (0.01)
Miss × Predicted Hit (False Hit)	0.68 (0.11)	0.61 (0.10)	0.64 (0.11)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.13	0.19	0.13
p-value	0.04	0.00	0.04
False Hit vs. True Miss (Miss Difference)	1.15	1.05	1.07
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.48	-0.42	-0.45
p-value	0.00	0.00	0.00
Panel E. 500 nm Threshold			
Hit × Predicted Hit (True Hit)	0.87 (0.08)	0.80 (0.08)	0.84 (0.09)
Hit × Predicted Miss (False Miss)	0.88 (0.05)	0.80 (0.05)	0.81 (0.05)
Miss × Predicted Miss (True Miss)	-0.19 (0.01)	-0.19 (0.01)	-0.18 (0.01)
Miss × Predicted Hit (False Hit)	-0.02 (0.15)	-0.03 (0.14)	-0.02 (0.14)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.01	0.00	-0.02
p-value	0.94	0.98	0.79
False Hit vs. True Miss (Miss Difference)	0.22	0.20	0.20
p-value	0.17	0.21	0.20
Hit Difference vs. Miss Difference	-0.18	-0.16	-0.18
p-value	0.24	0.27	0.22

Table 27: 120-Hour Window Across Distance Thresholds: Hurricanes (Restricted)

Panel A. 100 nm Threshold			
Storm Classification	(1)	(2)	(3)
Hit × Predicted Hit (True Hit)	1.30 (0.15)	1.14 (0.14)	1.14 (0.14)
Hit × Predicted Miss (False Miss)	1.85 (0.16)	1.65 (0.15)	1.65 (0.15)
Miss × Predicted Miss (True Miss)	-0.21 (0.02)	-0.20 (0.02)	-0.20 (0.02)
Miss × Predicted Hit (False Hit)	0.15 (0.10)	0.20 (0.10)	0.20 (0.10)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.24	0.24	0.24
p-value	0.03	0.02	0.02
False Hit vs. True Miss (Miss Difference)	0.46	0.51	0.51
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.15	-0.18	-0.18
p-value	0.29	0.21	0.21

Panel B. 200 nm Threshold			
Hit × Predicted Hit (True Hit)	1.13 (0.07)	0.98 (0.07)	0.98 (0.07)
Hit × Predicted Miss (False Miss)	1.25 (0.22)	1.19 (0.21)	1.19 (0.21)
Miss × Predicted Miss (True Miss)	-0.26 (0.02)	-0.25 (0.02)	-0.25 (0.02)
Miss × Predicted Hit (False Hit)	1.55 (0.18)	1.30 (0.17)	1.30 (0.17)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.06	0.10	0.10
p-value	0.60	0.32	0.32
False Hit vs. True Miss (Miss Difference)	2.44	2.07	2.07
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.69	-0.64	-0.64
p-value	0.00	0.00	0.00

Table 27 (cont'd)

Panel C. 300 nm Threshold			
Hit × Predicted Hit (True Hit)	1.08 (0.06)	0.95 (0.06)	0.95 (0.06)
Hit × Predicted Miss (False Miss)	1.39 (0.14)	1.30 (0.14)	1.30 (0.14)
Miss × Predicted Miss (True Miss)	-0.28 (0.02)	-0.27 (0.02)	-0.27 (0.02)
Miss × Predicted Hit (False Hit)	0.57 (0.19)	0.47 (0.17)	0.47 (0.17)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	0.15	0.18	0.18
p-value	0.05	0.03	0.03
False Hit vs. True Miss (Miss Difference)	1.20	1.03	1.03
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.48	-0.42	-0.42
p-value	0.00	0.00	0.00

Panel D. 400 nm Threshold			
Hit × Predicted Hit (True Hit)	0.92 (0.07)	0.80 (0.06)	0.80 (0.06)
Hit × Predicted Miss (False Miss)	0.61 (0.06)	0.58 (0.06)	0.58 (0.06)
Miss × Predicted Miss (True Miss)	-0.31 (0.02)	-0.30 (0.02)	-0.30 (0.02)
Miss × Predicted Hit (False Hit)	1.44 (0.14)	1.32 (0.14)	1.32 (0.14)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	-0.16	-0.12	-0.12
p-value	0.00	0.01	0.01
False Hit vs. True Miss (Miss Difference)	2.53	2.32	2.32
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.76	-0.74	-0.74
p-value	0.00	0.00	0.00

Table 27 (cont'd)

Panel E. 500 nm Threshold			
Hit × Predicted Hit (True Hit)	0.63 (0.04)	0.56 (0.04)	0.56 (0.04)
Hit × Predicted Miss (False Miss)	0.24 (0.09)	0.20 (0.08)	0.20 (0.08)
Miss × Predicted Miss (True Miss)	-0.31 (0.02)	-0.30 (0.02)	-0.30 (0.02)
Miss × Predicted Hit (False Hit)	2.40 (0.24)	2.19 (0.21)	2.19 (0.21)
Location & Time Fixed Effects	X	X	X
Random Effects		X	X
Home & Policy Variables		X	X
Storm Count			X
Tests of Loss Aversion			
False Miss vs. True Hit (Hit Difference)	-0.24	-0.23	-0.23
p-value	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	3.90	3.53	3.53
p-value	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.84	-0.83	-0.83
p-value	0.00	0.00	0.00

D All Storms: 30-Day Window

This section expands the 30-day analysis to include all storm types within the insurance response window. By relaxing the sample restriction to all storms, this specification tests whether short-run insurance demand responses are driven primarily by hurricane exposure or extend to less severe events. All models estimate Poisson regressions of NFIP policy issuances across forecast horizons (36–120 hours) and hit-distance thresholds (100–500 nautical miles).

Table 28: 36-Hour Window Across Distance Thresholds: All Storms (Restricted)

Panel A. 100 nm Threshold				
Storm Classification	(1)	(2)	(3)	(4)
Hit × Predicted Hit (True Hit)	0.97 (0.09)	0.89 (0.08)	1.26 (0.11)	1.29 (0.12)
Hit × Predicted Miss (False Miss)	0.31 (0.08)	0.30 (0.08)	0.67 (0.09)	0.74 (0.11)
Miss × Predicted Miss (True Miss)	0.03 (0.02)	0.03 (0.02)	0.29 (0.03)	0.29 (0.03)
Miss × Predicted Hit (False Hit)	-0.03 (0.04)	-0.02 (0.04)	0.29 (0.06)	0.29 (0.06)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	-0.33	-0.31	-0.26	-0.24
p-value	0.42	0.41	0.09	0.06
False Hit vs. True Miss (Miss Difference)	-0.06	-0.05	0.01	0.00
p-value	0.27	0.35	0.90	0.00
Hit Difference vs. Miss Difference	-0.29	-0.28	-0.26	-0.24
p-value	0.00	0.00	0.00	0.00

Table 28 (cont'd)

Panel B. 200 nm Threshold				
Hit × Predicted Hit (True Hit)	0.42 (0.04)	0.38 (0.03)	0.79 (0.06)	0.82 (0.06)
Hit × Predicted Miss (False Miss)	-0.16 (0.04)	-0.17 (0.04)	0.13 (0.05)	0.13 (0.05)
Miss × Predicted Miss (True Miss)	0.01 (0.02)	0.01 (0.02)	0.30 (0.03)	0.30 (0.03)
Miss × Predicted Hit (False Hit)	0.11 (0.05)	0.13 (0.05)	0.49 (0.06)	0.49 (0.06)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	-0.41	-0.40	-0.37	-0.38
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.10	0.11	0.15	0.15
p-value	0.05	0.03	0.00	0.00
Hit Difference vs. Miss Difference	-0.46	-0.46	-0.45	-0.46
p-value	0.00	0.00	0.00	0.00
Panel C. 300 nm Threshold				
Hit × Predicted Hit (True Hit)	0.29 (0.02)	0.27 (0.02)	0.73 (0.04)	0.75 (0.04)
Hit × Predicted Miss (False Miss)	0.07 (0.06)	0.04 (0.06)	0.45 (0.10)	0.46 (0.10)
Miss × Predicted Miss (True Miss)	0.00 (0.02)	0.00 (0.02)	0.34 (0.03)	0.34 (0.03)
Miss × Predicted Hit (False Hit)	-0.02 (0.04)	-0.01 (0.04)	0.34 (0.06)	0.34 (0.06)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	-0.17	-0.17	-0.16	-0.17
p-value	0.00	0.00	0.02	0.01
False Hit vs. True Miss (Miss Difference)	-0.02	-0.01	0.00	0.00
p-value	0.63	0.77	0.92	0.95
Hit Difference vs. Miss Difference	-0.15	-0.16	-0.16	-0.17
p-value	0.02	0.01	0.02	0.01

Table 28 (cont'd)

Panel D. 400 nm Threshold				
Hit × Predicted Hit (True Hit)	0.19 (0.01)	0.17 (0.01)	0.55 (0.03)	0.56 (0.03)
Hit × Predicted Miss (False Miss)	1.71 (0.22)	1.67 (0.22)	2.30 (0.25)	2.30 (0.25)
Miss × Predicted Miss (True Miss)	-0.04 (0.02)	-0.04 (0.01)	0.24 (0.02)	0.24 (0.02)
Miss × Predicted Hit (False Hit)	0.32 (0.07)	0.22 (0.07)	0.57 (0.09)	0.56 (0.09)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	1.28	1.28	1.13	1.11
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.38	0.28	0.27	0.27
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	0.65	0.78	0.67	0.67
p-value	0.00	0.00	0.00	0.00

Panel E. 500 nm Threshold				
Hit × Predicted Hit (True Hit)	0.22 (0.02)	0.20 (0.02)	0.69 (0.03)	0.69 (0.03)
Hit × Predicted Miss (False Miss)	0.10 (0.14)	0.09 (0.13)	0.35 (0.18)	0.33 (0.17)
Miss × Predicted Miss (True Miss)	-0.05 (0.02)	-0.05 (0.02)	0.32 (0.02)	0.32 (0.02)
Miss × Predicted Hit (False Hit)	0.44 (0.06)	0.42 (0.07)	0.71 (0.08)	0.69 (0.07)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	-0.10	-0.09	-0.20	-0.21
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.52	0.50	0.30	0.28
p-value	0.00	0.00	0.00	0.16
Hit Difference vs. Miss Difference	-0.40	-0.39	-0.38	-0.39
p-value	0.00	0.00	0.00	0.00

Table 29: 48-Hour Window Across Distance Thresholds: All Storms (Restricted)

Panel A. 100 nm Threshold				
Storm Classification	(1)	(2)	(3)	(4)
Hit × Predicted Hit (True Hit)	1.65 (0.10)	1.50 (0.09)	1.78 (0.11)	1.91 (0.14)
Hit × Predicted Miss (False Miss)	0.45 (0.07)	0.41 (0.07)	0.67 (0.08)	0.65 (0.08)
Miss × Predicted Miss (True Miss)	0.12 (0.02)	0.12 (0.02)	0.30 (0.03)	0.29 (0.03)
Miss × Predicted Hit (False Hit)	0.04 (0.05)	0.05 (0.05)	0.24 (0.06)	0.23 (0.06)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	-0.45	-0.43	-0.40	-0.43
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	-0.07	-0.06	-0.04	-0.04
p-value	0.16	0.23	0.45	0.43
Hit Difference vs. Miss Difference	-0.41	-0.40	-0.37	-0.41
p-value	0.00	0.00	0.00	0.00
Panel B. 200 nm Threshold				
Hit × Predicted Hit (True Hit)	0.79 (0.04)	0.71 (0.04)	0.99 (0.05)	1.01 (0.05)
Hit × Predicted Miss (False Miss)	0.15 (0.05)	0.15 (0.05)	0.41 (0.07)	0.41 (0.07)
Miss × Predicted Miss (True Miss)	0.11 (0.01)	0.10 (0.02)	0.29 (0.03)	0.29 (0.03)
Miss × Predicted Hit (False Hit)	-0.04 (0.07)	-0.03 (0.07)	0.21 (0.10)	0.21 (0.10)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	-0.36	-0.33	-0.29	-0.30
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	-0.13	-0.12	-0.06	-0.06
p-value	0.07	0.09	0.44	0.45
Hit Difference vs. Miss Difference	-0.26	-0.24	-0.24	-0.25
p-value	0.00	0.00	0.00	0.00

Table 29 (cont'd)

Panel C. 300 nm Threshold				
Hit × Predicted Hit (True Hit)	0.54 (0.02)	0.50 (0.02)	0.95 (0.04)	0.97 (0.04)
Hit × Predicted Miss (False Miss)	0.75 (0.13)	0.73 (0.13)	1.48 (0.20)	1.46 (0.19)
Miss × Predicted Miss (True Miss)	0.09 (0.01)	0.09 (0.02)	0.38 (0.03)	0.37 (0.03)
Miss × Predicted Hit (False Hit)	0.33 (0.04)	0.30 (0.04)	0.71 (0.06)	0.71 (0.06)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.13	0.15	0.27	0.25
p-value	0.08	0.04	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.22	0.19	0.25	0.25
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.07	-0.03	0.02	0.00
p-value	0.33	0.65	0.78	0.96
Panel D. 400 nm Threshold				
Hit × Predicted Hit (True Hit)	0.42 (0.01)	0.39 (0.01)	0.79 (0.04)	0.80 (0.04)
Hit × Predicted Miss (False Miss)	1.50 (0.18)	1.49 (0.18)	2.02 (0.19)	2.01 (0.19)
Miss × Predicted Miss (True Miss)	0.03 (0.01)	0.03 (0.01)	0.28 (0.02)	0.27 (0.02)
Miss × Predicted Hit (False Hit)	-0.01 (0.03)	-0.03 (0.03)	0.24 (0.06)	0.24 (0.06)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.77	0.79	0.69	0.67
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	-0.04	-0.05	-0.03	-0.02
p-value	0.26	0.10	0.40	0.49
Hit Difference vs. Miss Difference	0.83	0.89	0.74	0.71
p-value	0.00	0.00	0.00	0.00

Table 29 (cont'd)

Panel E. 500 nm Threshold				
Hit × Predicted Hit (True Hit)	0.41 (0.02)	0.38 (0.02)	0.88 (0.04)	0.89 (0.04)
Hit × Predicted Miss (False Miss)	1.32 (0.20)	1.23 (0.19)	1.81 (0.23)	1.89 (0.24)
Miss × Predicted Miss (True Miss)	0.01 (0.01)	0.01 (0.01)	0.32 (0.02)	0.32 (0.02)
Miss × Predicted Hit (False Hit)	0.30 (0.06)	0.28 (0.06)	0.82 (0.06)	0.81 (0.06)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.65	0.61	0.49	0.53
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.29	0.26	0.37	0.37
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	0.28	0.28	0.09	0.12
p-value	0.00	0.00	0.34	0.23

Table 30: 60-Hour Window Across Distance Thresholds: All Storms (Restricted)

Panel A. 100 nm Threshold				
Storm Classification	(1)	(2)	(3)	(4)
Hit × Predicted Hit (True Hit)	0.29 (0.05)	0.20 (0.04)	0.02 (0.04)	0.02 (0.04)
Hit × Predicted Miss (False Miss)	0.01 (0.04)	-0.01 (0.04)	-0.23 (0.03)	-0.23 (0.03)
Miss × Predicted Miss (True Miss)	-0.02 (0.01)	-0.02 (0.01)	-0.19 (0.01)	-0.18 (0.01)
Miss × Predicted Hit (False Hit)	0.31 (0.10)	0.26 (0.10)	0.01 (0.07)	0.01 (0.07)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	-0.22	-0.18	-0.24	-0.24
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.34	0.29	0.25	0.24
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.41	-0.36	-0.39	-0.39
p-value	0.00	0.00	0.00	0.00

Table 30 (cont'd)

Panel B. 200 nm Threshold				
Hit × Predicted Hit (True Hit)	0.01 (0.02)	-0.06 (0.02)	-0.22 (0.02)	-0.22 (0.02)
Hit × Predicted Miss (False Miss)	0.55 (0.11)	0.55 (0.11)	0.15 (0.08)	0.16 (0.08)
Miss × Predicted Miss (True Miss)	0.00 (0.01)	0.01 (0.01)	-0.15 (0.01)	-0.14 (0.02)
Miss × Predicted Hit (False Hit)	0.07 (0.07)	0.08 (0.07)	-0.07 (0.06)	-0.07 (0.06)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.54	0.64	0.48	0.49
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.06	0.06	0.09	0.08
p-value	0.35	0.36	0.21	0.24
Hit Difference vs. Miss Difference	0.45	0.55	0.36	0.38
p-value	0.00	0.00	0.00	0.00
Panel C. 300 nm Threshold				
Hit × Predicted Hit (True Hit)	-0.02 (0.02)	-0.06 (0.01)	-0.22 (0.01)	-0.22 (0.01)
Hit × Predicted Miss (False Miss)	0.35 (0.18)	0.57 (0.17)	0.39 (0.16)	0.41 (0.17)
Miss × Predicted Miss (True Miss)	0.05 (0.01)	0.06 (0.02)	-0.13 (0.02)	-0.12 (0.02)
Miss × Predicted Hit (False Hit)	-0.17 (0.06)	-0.19 (0.06)	-0.27 (0.05)	-0.26 (0.06)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.38	0.67	0.79	0.81
p-value	0.02	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	-0.21	-0.23	-0.17	-0.16
p-value	0.00	0.00	0.01	0.02
Hit Difference vs. Miss Difference	0.73	1.18	1.15	1.14
p-value	0.00	0.00	0.00	0.00

Table 30 (cont'd)

Panel D. 400 nm Threshold				
Hit × Predicted Hit (True Hit)	-0.07 (0.01)	-0.10 (0.01)	-0.22 (0.01)	-0.22 (0.01)
Hit × Predicted Miss (False Miss)	0.21 (0.11)	0.25 (0.11)	0.00 (0.09)	0.00 (0.09)
Miss × Predicted Miss (True Miss)	0.06 (0.02)	0.08 (0.02)	-0.09 (0.02)	-0.09 (0.02)
Miss × Predicted Hit (False Hit)	1.01 (0.16)	0.82 (0.15)	0.48 (0.11)	0.47 (0.11)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.30	0.39	0.29	0.29
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.89	0.69	0.64	0.62
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.31	-0.17	-0.21	-0.21
p-value	0.00	0.02	0.00	0.00
Panel E. 500 nm Threshold				
Hit × Predicted Hit (True Hit)	0.05 (0.02)	0.02 (0.02)	-0.12 (0.02)	-0.11 (0.02)
Hit × Predicted Miss (False Miss)	0.07 (0.06)	-0.03 (0.06)	-0.08 (0.05)	-0.08 (0.05)
Miss × Predicted Miss (True Miss)	-0.09 (0.02)	-0.05 (0.02)	-0.21 (0.02)	-0.21 (0.02)
Miss × Predicted Hit (False Hit)	0.46 (0.09)	0.29 (0.08)	0.04 (0.07)	0.03 (0.07)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.02	-0.05	0.05	0.04
p-value	0.72	0.44	0.45	0.51
False Hit vs. True Miss (Miss Difference)	0.59	0.36	0.32	0.30
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.36	-0.30	-0.21	-0.20
p-value	0.00	0.00	0.02	0.02

Table 31: 72-Hour Window Across Distance Thresholds: All Storms (Restricted)

Panel A. 100 nm Threshold				
Storm Classification	(1)	(2)	(3)	(4)
Hit × Predicted Hit (True Hit)	2.19 (0.11)	1.97 (0.09)	2.33 (0.12)	2.33 (0.12)
Hit × Predicted Miss (False Miss)	0.21 (0.04)	0.19 (0.04)	0.41 (0.07)	0.40 (0.07)
Miss × Predicted Miss (True Miss)	0.12 (0.01)	0.11 (0.01)	0.32 (0.03)	0.32 (0.03)
Miss × Predicted Hit (False Hit)	0.53 (0.11)	0.44 (0.11)	0.67 (0.14)	0.64 (0.13)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	-0.62	-0.60	-0.58	-0.58
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.37	0.30	0.27	0.25
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.72	-0.69	-0.66	-0.66
p-value	0.00	0.00	0.00	0.00

Panel B. 200 nm Threshold				
Hit × Predicted Hit (True Hit)	1.11 (0.09)	1.00 (0.08)	1.30 (0.10)	1.29 (0.10)
Hit × Predicted Miss (False Miss)	0.37 (0.07)	0.35 (0.06)	0.71 (0.11)	0.71 (0.11)
Miss × Predicted Miss (True Miss)	0.10 (0.01)	0.09 (0.01)	0.29 (0.04)	0.29 (0.04)
Miss × Predicted Hit (False Hit)	-0.24 (0.04)	-0.23 (0.04)	-0.03 (0.06)	-0.03 (0.06)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	-0.35	-0.32	-0.26	-0.25
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	-0.31	-0.29	-0.25	-0.25
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.06	-0.04	-0.01	-0.01
p-value	0.42	0.56	0.88	0.93

Table 31 (cont'd)

Panel C. 300 nm Threshold				
Hit × Predicted Hit (True Hit)	0.73 (0.03)	0.67 (0.03)	1.05 (0.05)	1.04 (0.05)
Hit × Predicted Miss (False Miss)	0.36 (0.07)	0.33 (0.06)	0.83 (0.11)	0.84 (0.11)
Miss × Predicted Miss (True Miss)	0.08 (0.01)	0.08 (0.01)	0.26 (0.03)	0.26 (0.03)
Miss × Predicted Hit (False Hit)	-0.19 (0.06)	-0.19 (0.06)	-0.06 (0.07)	-0.06 (0.07)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	-0.21	-0.20	-0.10	-0.10
p-value	0.00	0.00	0.05	0.08
False Hit vs. True Miss (Miss Difference)	-0.25	-0.24	-0.25	-0.26
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.05	-0.04	0.20	0.22
p-value	0.61	0.56	0.09	0.08
Panel D. 400 nm Threshold				
Hit × Predicted Hit (True Hit)	0.53 (0.02)	0.49 (0.02)	0.75 (0.03)	0.75 (0.03)
Hit × Predicted Miss (False Miss)	1.55 (0.16)	1.52 (0.16)	1.80 (0.17)	1.79 (0.17)
Miss × Predicted Miss (True Miss)	0.02 (0.01)	0.02 (0.01)	0.12 (0.02)	0.12 (0.02)
Miss × Predicted Hit (False Hit)	-0.36 (0.08)	-0.38 (0.08)	-0.34 (0.09)	-0.26 (0.10)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.67	0.70	0.60	0.59
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	-0.37	-0.39	-0.41	-0.34
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	1.66	1.77	1.73	1.40
p-value	0.00	0.00	0.00	0.00

Table 31 (cont'd)

Panel E. 500 nm Threshold				
Hit × Predicted Hit (True Hit)	0.42 (0.03)	0.40 (0.03)	0.78 (0.06)	0.78 (0.06)
Hit × Predicted Miss (False Miss)	1.41 (0.08)	1.27 (0.08)	1.47 (0.09)	1.48 (0.09)
Miss × Predicted Miss (True Miss)	0.03 (0.01)	0.03 (0.01)	0.23 (0.02)	0.24 (0.02)
Miss × Predicted Hit (False Hit)	0.06 (0.10)	0.04 (0.11)	1.01 (0.18)	1.04 (0.19)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.70	0.62	0.39	0.39
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.03	0.01	0.63	0.64
p-value	0.74	0.89	0.00	0.00
Hit Difference vs. Miss Difference	0.64	0.60	-0.15	-0.15
p-value	0.00	0.00	0.11	0.10

Table 32: 96-Hour Window Across Distance Thresholds: All Storms (Restricted)

Panel A. 100 nm Threshold				
Storm Classification	(1)	(2)	(3)	(4)
Hit × Predicted Hit (True Hit)	2.61 (0.14)	2.38 (0.13)	2.51 (0.13)	2.47 (0.14)
Hit × Predicted Miss (False Miss)	1.59 (0.17)	1.45 (0.15)	1.63 (0.17)	1.62 (0.17)
Miss × Predicted Miss (True Miss)	0.22 (0.02)	0.21 (0.02)	0.34 (0.03)	0.34 (0.03)
Miss × Predicted Hit (False Hit)	0.43 (0.14)	0.41 (0.13)	0.57 (0.14)	0.55 (0.14)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	-0.28	-0.27	-0.25	-0.24
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.17	0.16	0.17	0.16
p-value	0.09	0.09	0.07	0.08
Hit Difference vs. Miss Difference	-0.38	-0.37	-0.36	-0.35
p-value	0.00	0.00	0.00	0.00

Table 32 (cont'd)

Panel B. 200 nm Threshold				
Hit × Predicted Hit (True Hit)	1.84 (0.08)	1.65 (0.07)	1.84 (0.08)	1.81 (0.09)
Hit × Predicted Miss (False Miss)	0.81 (0.08)	0.74 (0.09)	0.98 (0.11)	0.97 (0.11)
Miss × Predicted Miss (True Miss)	0.19 (0.02)	0.19 (0.02)	0.33 (0.04)	0.32 (0.04)
Miss × Predicted Hit (False Hit)	0.78 (0.12)	0.77 (0.12)	1.05 (0.14)	1.04 (0.14)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	-0.36	-0.34	-0.30	-0.30
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.49	0.50	0.54	0.54
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.57	-0.56	-0.55	-0.55
p-value	0.00	0.00	0.00	0.00

Panel C. 300 nm Threshold				
Hit × Predicted Hit (True Hit)	1.66 (0.07)	1.50 (0.06)	1.71 (0.08)	1.69 (0.08)
Hit × Predicted Miss (False Miss)	0.65 (0.09)	0.63 (0.09)	0.87 (0.10)	0.86 (0.10)
Miss × Predicted Miss (True Miss)	0.19 (0.02)	0.18 (0.02)	0.34 (0.03)	0.34 (0.03)
Miss × Predicted Hit (False Hit)	0.43 (0.06)	0.34 (0.06)	0.58 (0.08)	0.57 (0.08)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	-0.38	-0.35	-0.31	-0.31
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.20	0.13	0.18	0.17
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.48	-0.42	-0.41	-0.41
p-value	0.00	0.00	0.00	0.00

Table 32 (cont'd)

Panel D. 400 nm Threshold				
Hit × Predicted Hit (True Hit)	1.28 (0.07)	1.16 (0.06)	1.29 (0.06)	1.27 (0.06)
Hit × Predicted Miss (False Miss)	1.58 (0.15)	1.54 (0.15)	1.65 (0.14)	1.64 (0.14)
Miss × Predicted Miss (True Miss)	0.08 (0.01)	0.08 (0.01)	0.16 (0.03)	0.16 (0.03)
Miss × Predicted Hit (False Hit)	0.90 (0.11)	0.82 (0.10)	0.88 (0.11)	0.86 (0.10)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.13	0.18	0.16	0.16
p-value	0.03	0.00	0.01	0.01
False Hit vs. True Miss (Miss Difference)	0.76	0.70	0.61	0.61
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.36	-0.30	-0.28	-0.28
p-value	0.00	0.00	0.00	0.00
Panel E. 500 nm Threshold				
Hit × Predicted Hit (True Hit)	0.89 (0.07)	0.82 (0.07)	0.95 (0.10)	0.94 (0.10)
Hit × Predicted Miss (False Miss)	1.56 (0.07)	1.44 (0.07)	1.48 (0.07)	1.47 (0.07)
Miss × Predicted Miss (True Miss)	0.10 (0.01)	0.10 (0.01)	0.20 (0.04)	0.20 (0.04)
Miss × Predicted Hit (False Hit)	0.20 (0.18)	0.18 (0.17)	0.21 (0.17)	0.20 (0.17)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.36	0.34	0.27	0.27
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.09	0.07	0.01	0.00
p-value	0.57	0.61	0.97	0.98
Hit Difference vs. Miss Difference	0.25	0.25	0.26	0.26
p-value	0.16	0.15	0.13	0.12

Table 33: 120-Hour Window Across Distance Thresholds: All Storms (Restricted)

Panel A. 100 nm Threshold				
Storm Classification	(1)	(2)	(3)	(4)
Hit × Predicted Hit (True Hit)	1.03 (0.11)	0.91 (0.10)	0.83 (0.10)	0.89 (0.10)
Hit × Predicted Miss (False Miss)	1.45 (0.11)	1.31 (0.10)	1.24 (0.10)	1.27 (0.10)
Miss × Predicted Miss (True Miss)	-0.24 (0.01)	-0.24 (0.01)	-0.29 (0.02)	-0.29 (0.02)
Miss × Predicted Hit (False Hit)	0.21 (0.16)	0.17 (0.15)	0.02 (0.13)	0.07 (0.12)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.21	0.21	0.22	0.20
p-value	0.02	0.01	0.01	0.02
False Hit vs. True Miss (Miss Difference)	0.60	0.54	0.43	0.50
p-value	0.00	0.00	0.01	0.00
Hit Difference vs. Miss Difference	-0.25	-0.21	-0.15	-0.20
p-value	0.07	0.12	0.28	0.11
Panel B. 200 nm Threshold				
Hit × Predicted Hit (True Hit)	1.09 (0.06)	0.97 (0.06)	0.90 (0.06)	0.96 (0.06)
Hit × Predicted Miss (False Miss)	1.45 (0.13)	1.31 (0.13)	1.05 (0.10)	1.08 (0.11)
Miss × Predicted Miss (True Miss)	-0.28 (0.01)	-0.28 (0.01)	-0.32 (0.02)	-0.32 (0.02)
Miss × Predicted Hit (False Hit)	0.57 (0.10)	0.54 (0.10)	0.37 (0.08)	0.36 (0.08)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.17	0.17	0.08	0.06
p-value	0.01	0.01	0.19	0.31
False Hit vs. True Miss (Miss Difference)	1.18	1.13	1.02	1.01
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.46	-0.45	-0.47	-0.47
p-value	0.00	0.00	0.00	0.00

Table 33 (cont'd)

Panel C. 300 nm Threshold				
Hit × Predicted Hit (True Hit)	1.11 (0.06)	0.99 (0.05)	0.93 (0.05)	0.98 (0.05)
Hit × Predicted Miss (False Miss)	0.45 (0.08)	0.44 (0.09)	0.32 (0.07)	0.29 (0.07)
Miss × Predicted Miss (True Miss)	-0.28 (0.01)	-0.27 (0.01)	-0.31 (0.02)	-0.31 (0.02)
Miss × Predicted Hit (False Hit)	0.13 (0.07)	0.11 (0.07)	0.01 (0.06)	0.01 (0.06)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	-0.32	-0.28	-0.32	-0.35
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.56	0.53	0.48	0.47
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.56	-0.53	-0.54	-0.56
p-value	0.00	0.00	0.00	0.00
Panel D. 400 nm Threshold				
Hit × Predicted Hit (True Hit)	0.75 (0.06)	0.66 (0.05)	0.75 (0.07)	0.78 (0.07)
Hit × Predicted Miss (False Miss)	0.46 (0.04)	0.42 (0.04)	0.47 (0.05)	0.46 (0.05)
Miss × Predicted Miss (True Miss)	-0.30 (0.01)	-0.30 (0.01)	-0.31 (0.02)	-0.31 (0.02)
Miss × Predicted Hit (False Hit)	1.04 (0.09)	0.95 (0.09)	1.02 (0.09)	1.05 (0.09)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	-0.17	-0.15	-0.16	-0.18
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	1.93	1.79	1.92	1.95
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.72	-0.69	-0.71	-0.72
p-value	0.00	0.00	0.00	0.00

Table 33 (cont'd)

Panel E. 500 nm Threshold				
Hit × Predicted Hit (True Hit)	0.34 (0.03)	0.29 (0.03)	0.60 (0.04)	0.61 (0.04)
Hit × Predicted Miss (False Miss)	0.70 (0.10)	0.64 (0.09)	1.11 (0.12)	1.10 (0.12)
Miss × Predicted Miss (True Miss)	-0.30 (0.01)	-0.30 (0.01)	-0.25 (0.02)	-0.25 (0.02)
Miss × Predicted Hit (False Hit)	0.29 (0.15)	0.27 (0.15)	0.65 (0.17)	0.65 (0.17)
Location & Time Fixed Effects	X	X	X	X
Random Effects		X	X	X
Home & Policy Variables		X	X	X
Storm Type Variables			X	X
Storm Count				X
Tests of Loss Aversion				
False Miss vs. True Hit (Hit Difference)	0.27	0.28	0.31	0.31
p-value	0.00	0.00	0.00	0.00
False Hit vs. True Miss (Miss Difference)	0.83	0.81	1.19	1.19
p-value	0.00	0.00	0.00	0.00
Hit Difference vs. Miss Difference	-0.31	-0.29	-0.40	-0.40
p-value	0.01	0.01	0.00	0.00