EVOLUTION OF SUBJECTIVE HURRICANE RISK PERCEPTIONS: A BAYESIAN APPROACH*

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Abstract

This paper studies how individuals update subjective risk perceptions in response to hurricane track forecast information, using a unique data set from an event market, the Hurricane Futures Market (HFM). We derive a theoretical Bayesian framework which predicts how traders update their perceptions of the probability of a hurricane making landfall in a certain range of coastline. Our results suggest that traders behave in a way consistent with Bayesian updating but this behavior is based on the perceived quality of the information received.

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1. Introduction

Hurricanes have an enormous impact on the economic and environmental welfare of a region. Indeed, hurricanes are the most costly natural disaster in the U.S. Hurricanes adversely affect the economic development of a geographical area (Skoufias, 2003), local housing markets (Hallstrom and Smith, 2005), tourism (Meyer-Arendt, 1991), prices and supply of basic commodities (Park, 2009) and natural resource endowments (Yin et al., 2002). Hurricanes also clearly have other costs including human lives, evacuation, reconstruction, relocation, etc. (Whitehead, 2003). Further, increasing population and wealth over the last several decades are increasing the risk exposure of lives and property (Pielke and Landsea, 2008). In an effort to mitigate the costs of extreme weather events, federal agencies have financed weather research programs aiming to improve the accuracy of weather forecasting and to enhance the dissemination of usable weather information (NOAA, 2005).

The success of information dissemination programs, such as hurricane tracking forecasts, depends significantly on individual choices (e.g. whether or not to evacuate), and in turn, on our understanding of how risk perceptions, or subjective beliefs of the probability of an adverse event occurring, evolve over time. This study uses a unique data set from an event market to conduct an empirical analysis of how individuals update their risk perceptions about hurricane landfalls. In particular, we evaluate how much weight individuals place on specific information sources and measure the evolution of subjective uncertainty over time.

One standard method of assessing risk perceptions is the use of surveys. Survey research shows that prior perception of risk (Smith, et al. 2001), outside information (Viscusi, 1997; Cameron, 2005), credibility of the source of information (Cameron, 2005 and Viscusi and O'Connor, 1984), socio-economic characteristics (Dominitz and Manski, 1996; Flynn et al., 1994), among other factors, affect risk perceptions. For hurricanes, Baker (1995) uses surveys to study responses to hurricane track forecasts and evacuation notices and finds that updates of official warnings play a major role in shifting stated responses.

Surveys require well-designed monetary payments or other incentives to insure that survey responses accord with actual individual beliefs (see Fischhoff and Beyth-Marom, 1983 for a discussion). Still, surveys are typically designed with a single information event in mind. Researchers measure respondents' risk perceptions after presenting an information set and associated precision of the information set. Consequently, respondents do not get the opportunity to learn over time which forecasts perform better. Further, the information sources we study are correlated and so far research using survey methods examine only uncorrelated information. Similar to Viscousi and O'Conner (1984) and others, we find that the credibility of the source matters. However, unlike the previous literature which examines uncorrelated information, we find that traders give little weight to information that is less accurate but nonetheless valuable since it is relatively uncorrelated with other information sources.

The main alternative to surveys are hedonic methods, whereby researchers use changes in market prices to reveal changes in risk perceptions. Halstrom and Smith (2005) and Bin and Polasky (2004) are two prominent studies that use changes in housing prices to infer changes in hurricane risk perceptions subsequent to a hurricane event. Such studies must try to control for confounding influences on prices following an adverse event. First, individuals may take on adaptations to insulate themselves from future risk. Second, government regulatory policy changes may distort prices away from those which represent risk perceptions, by creating a moral hazard problem. Finally the econometrician may not observe individual heterogeneity in exposure to adverse events or in risk aversion. That is, individuals may be willing to pay different amounts to avoid an adverse event that occurs with a probability that all agree upon. For example, following a hurricane, owners may rebuild using hurricane proof windows and legislation may be passed to reimburse homeowners for hurricane damages. Thus, sale prices may not experience a large fall even though risk perceptions have increased. Some hedonic studies attempt to control for these factors. For example, Halstrom and Smith (2005) use a near miss hurricane to ensure that rebuilding will not be substantial and find a decrease in housing prices which they attribute to changes in risk perceptions. However, it is still possible that they underestimate changes in risk perceptions, since some homeowners undertake adaptations even if a hurricane is a near miss.

The present study proposes an alternative approach to study hurricane risk perceptions based on data from an event market. In an event market, researchers create securities whose payoffs depend on whether or not a certain event happens in the future. Traders then trade these securities in an online market. Payoffs are designed so that the price of the security represents the traders' subjective belief of the probability that the event occurs. Hence, the price of the security equals the traders' risk perception.

Events markets are well suited to reveal risk perceptions. Because traders win or lose real dollars, they have a strong incentive to reveal, through their trades, their true beliefs. Traders with uncertain beliefs receive less weight, because they give the trades of others more weight than prior beliefs when they update risk perceptions. Further, by design event markets are free of confounding influences from other aspects of risk.[1]

[1] One possible disadvantage is that our sample of traders is not random. In fact, most of the traders are meteorologists and all traders have some interest in hurricanes, while government information programs are typically aimed at the general population. Further, traders observe the trades of other traders and update their risk perceptions until at the end of trading all traders have an identical weight on new information. The general population, who do not have the benefit of observing changes in risk perceptions of other traders through trades, may react differently to new information. A second disadvantage may be a lack of liquidity in the market, but Tetlock (2007) argues that uninformed traders in thick markets inhibit information revelation.

The focus of our study is on perceptions of hurricane risk. Other studies focus on other environmental risk perceptions. Oberholzer and Mitsunari (2006) find that Toxic Release Inventory reports of toxic emissions a moderate distance from a home cause the price to fall, which they attribute to upward adjustments of risk perceptions. A series of papers by Viscusi (Viscusi and O'Connor, 1984; Viscusi and Magat, 1992; Viscusi, 1997; and others) study various environmental risks. For example, Viscusi (1997) studies air pollution and cancer and finds individuals give too much weight to high risk forecasts, which they call 'alarmist' learning. Cameron (2005) asks students to forecast future temperatures and studies how risk perceptions change after introducing new information. Students come close to Bayesian learning but place too much weight on priors when forecasts diverge. Flynn et al. (1994) asks survey respondents to rate various environmental hazards as low, medium, or high risk.

Fischhoff (1990), Davies et al. (1987), and others focus on developing ways of communicating expert information to the public for the case of climate risk perception. An important issue is how individuals weight competing information sources. Government information programs face increasing competition from alternative information sources. For example, a variety of non-official hurricane tracking forecasts now exist (Section 3 below gives a few examples).

It is unclear how much weight individuals place on competing hurricane tracking information sources, and how the government should respond. We find that traders in our event market put significant weight on a forecast other than the official National Hurricane Center (NHC) forecast. In general, we find traders behave in a way consistent with Bayesian updating with respect to two forecasts, but essentially ignore a third forecast. The third forecast is the least accurate forecast, and yet provides useful information because it is relatively uncorrelated with the other forecasts. Thus, our results indicate that it may be difficult for official sources to control the dissemination and interpretation of information if alternative forecasts are perceived as being credible.

Overall, traders are remarkably accurate forecasters. Indeed, traders correctly predict a hurricane will or will not make landfall in one of eight Gulf or Atlantic regions with 84% accuracy. The most accurate forecast, the NHC forecast, correctly predicts whether or not a hurricane will make landfall in one of eight regions with 81% accuracy. Traders are more accurate than the NHC for storms more than five days from landfall (69% to 54%), but less accurate for storms two days or less from landfall (90% versus 100%).

Finally, we conduct an *ex-post* test of rationality by grouping trade prices into bins and comparing the price with the average payoff. We find that although price and average payoff are close, a 'favorite-longshot' bias (see for example Tetlock, 2004) exists in that traders could mildly profit by buying securities with a price near one. The favorite-longshot bias is also evident from the relatively poor performance of the traders for storms close to landfall, which typically have a price very close to one. Jullien and Salanie (2000) and others find the favorite-longshot bias in sports wagering event markets but Tetlock (2004) finds no favorite-longshot bias in financial event markets and argues that one possible explanation is that those who bet on sports may be inexperienced with the double auction structure of event markets. Our results are consistent with this argument in that our traders, while experts in meteorology, have little experience with double auction event markets.

The rest of this article is organized as follows. The next Section gives an overview of the Bayesian approach in studying risk perception updating analysis, followed by a description of the data and the empirical model. Then, we present and discuss the empirical results. The last Section presents some concluding remarks along with some suggestions for further research.

2. Hurricane Risk Perception Updating Model: A Bayesian Approach

Although hurricane forecasting is an important public concern, this kind of information has an economic value only if it affects human behavior (Williamson et al., 2002). In this respect, hurricane tracking forecasts can be perceived as a support mechanism to reduce uncertainty within a decision making framework. Specifically, Hirschleifer (1973) argues that if we consider uncertainty as the dispersion of an economic agent's subjective probability distribution over potential economic and/or environmental conditions, then 'information' (hurricane forecasts in our case) may trigger changes on those probability distributions. That is, information can change individual perceptions of an economic and/or environmental problem and, consequently, alter behavior. Letson et al. (2007) reviews economic theory concerning individuals' utility-maximizing behavior accounting for hurricane forecasts and evacuation choices.

In the Bayesian framework, new information causes traders to update the probability that a certain hypothesis (hurricane landfall area in our case) is true.[2] Assume the true probability of hurricane h of type k making first landfall in coastline range j is P^*.[3] Note that all of the parameters below and P^* will depend on j and k, but we suppress this dependence where no confusion is possible. The true probability is unknown to traders. Since a hurricane of type k will either make landfall in range j or not,[4] traders can view this event as a Bernoulli distributed random variable. That is, each hurricane of type k is a draw from a Bernoulli urn in which P^* is

[2] Bolstad (2004) and Fischhoff and Beyth-Marom (1983) give detailed reviews of the Bayesian theory.

[3] Hurricane type characteristics may include Atlantic versus Gulf storm, wind speed, and/or the day of the year when the storm formed.

[4] Because storms may straddle more than one range, we define as our trigger event the location where the storm center makes its first U.S. landfall.

the probability of 'success,' in that the hurricane does make landfall in range *j*. Traders have prior beliefs that $P^* \sim \mathrm{BETA}(\alpha, \beta)$. The beta distribution is particularly advantageous since it allows for a wide variety of density function shapes. The mean of the beta distribution is $\alpha/(\alpha + \beta)$, meaning the prior distribution is equivalent to α out of $\alpha+\beta$ draws indicating success. If the prior was formed from previous similar hurricanes, then the prior indicates $\alpha/(\alpha + \beta)$ fraction of hurricanes of type *k* ended up making first landfall in range *j*.

Next, suppose traders receive hurricane track forecast information at time *t*. Each track forecast *i* contains a set of predicted latitude and longitude positions over time. Let $z_{it} = z(\Omega_{it})$ be the traders' belief of the probability of landfall in range *j* given the latitude and longitude information Ω_{it} of track forecast *i* at time *t*.[5] We can view z_{it} as the fraction of n_{it} draws from the Bernoulli urn which indicate success, where $n_{it}=q(\Omega_{it})z_{it}(1- z_{it})$ and $q(\Omega_{it})$ is the precision (or inverse of the variance) of z_{it}.[6] The precision varies by track and time since track forecasts vary in their accuracy, and all track forecasts become more accurate as hurricanes approach landfall. Given our distributional and information assumptions, it is well known (see for example DeGroot, 1970) the posterior distribution is also beta, with:

$$\alpha_t = \alpha + \sum_{i=1}^{I} z_{it} n_{it} \quad , \quad \beta_t = \beta + N_t - \sum_{i=1}^{I} z_{it} n_{it} \, , \tag{1}$$

$$P_t = \mathrm{E}[P^* \mid H] = \frac{\alpha + \sum_{i=1}^{I} z_{it} n_{it}}{\alpha + \beta + N_t} \, . \tag{2}$$

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[5] We specify $z(\Omega_{it})$ precisely in Section 3, but the theoretical model only requires that a function *z* exists.
[6] We are thus assuming the information content of each track forecast is known (indeed the only uncertain parameter is P^*). This assumption is standard in the literature (e.g. Viscusi, 1997), but of course the trader's actual environment is likely considerably more uncertain.

Here I is the total number of track forecasts and $N_t = \sum_{i=1}^{I} n_{it}$ represents the information contained within the track forecasts. Equation (2) may be decomposed into a linear weighted average of the priors and the information provided by each track forecast, with the weights being equal to the relative information content of each track forecast. Let $D_t = \alpha + \beta + N_t$ be the total precision of the prior and track forecast information. Then:

$$P_t = \frac{\alpha+\beta}{D_t} \cdot \frac{\alpha}{\alpha+\beta} + \frac{n_{1t}}{D_t} z_{1t} + \ldots + \frac{n_{It}}{D_t} z_{It} . \qquad (3)$$

Equation (3) shows that the information within each track forecast implies a predicted probability that the hurricane will make first landfall in range j, and that the posterior probability is a weighted average of the predicted probabilities. The weights equal the relative information content of each track forecast. Note that price levels (rather than price changes) are a function of the current information.

Equation (3) assumes the track forecasts are independent. In fact, the NHC forecast is an expert opinion forecast which explicitly considers other track information. Suppose a known fraction m_{ijt} of the draws tracks i and j make from the urn are common (which draws are common is unknown). We therefore have overlapping information sets (see for example Clemen, 1987 and Zeckhauser, 1971). We can interpret m_{ijt} as a correlation measure, since the correlation between z_{it} and z_{jt} is $m_{ijt} / \sqrt{n_{it}}\sqrt{n_{jt}}$. Following Viscusi (1997), we adapt the updating rule for the normal distribution to beta distribution used here.[7] Let $\hat{D}_t = e' V_t^{-1} e$, where e is a unit vector and is V_t the covariance matrix:

[7] Clemen (1987) shows the posterior distribution, when the prior is beta and the new information are outcomes of dependent binomial processes, is actually a mixture of beta distributions. However, the mixture is much more difficult to estimate, and differs little from the posterior distribution used here for large n.

$$V_t = \begin{bmatrix} 1/(\alpha+\beta) & 0 & 0 & 0 \\ 0 & 1/n_{1t} & m_{12t}/n_{1t}n_{2t} & m_{13t}/n_{1t}n_{3t} \\ 0 & m_{12t}/n_{1t}n_{2t} & 1/n_{2t} & m_{23t}/n_{2t}n_{3t} \\ 0 & m_{13t}/n_{1t}n_{3t} & m_{23t}/n_{2t}n_{3t} & 1/n_{3t} \end{bmatrix}, \quad e = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}.$$

We assume new track information is uncorrelated with the prior. Thus, if information sets are overlapping, equation (3) becomes:

$$P_t = \frac{1}{\hat{D}_t} e' V_t^{-1} \cdot \left[\alpha/(\alpha+\beta), z_{1t}, \ldots, z_{It}\right]'.$$

$$P_t = w_{0t} \cdot \alpha/(\alpha+\beta) + w_{1t} \cdot z_{1t} + \ldots + w_{It} \cdot z_{It} \tag{4}$$

Here $[w_{0t}, \ldots, w_{It}] = e' V_t^{-1} / \hat{D}_t$ are the weights on the prior and track information of security *j* for hurricane *h* at time *t*. The price remains a linear weighted average of the priors and track forecasts, but the weights account for the probability that information is redundant.

Equation (4) is closely related to Clemen (1987) and Viscusi (1997), who study beta-binomial models, and to Cameron (2005), who studies a Bayesian model which is not beta-binomial. In Section 4 we estimate a version of equation (4) using maximum likelihood.

3. Data

To analyze hurricane risk perceptions, we use data gathered from the Hurricane Futures Market (HFM) project at the University of Miami. When NOAA officially names a tropical storm, HFM creates a market for the storm. If the storm is north of a dividing line,[8] the storm is considered in the Atlantic region. Otherwise the storm is in the Gulf region. HFM issues ten securities for an Atlantic region storm. Eight securities pay one dollar if a hurricane makes first landfall within a

[8] Atlantic storms are those located north and east of the imaginary line extending from Key Largo, Florida (25.25°N, 80.30°W) through the Lesser Antilles (15°N, 65°W) and beyond. Specifically, a storm is designated an Atlantic storm if it forms east of 80.3°W and its latitude satisfies the inequality: latitude > 10.25 · (longitude - 65) / 15.3 + 15.0. Gulf storms are those forming west of 80.3°W or south of that same line when they are named.

particular range of U.S. coastline.[9] Securities have disjoint coastline ranges, and the union of ranges for all securities is the entire U.S. Atlantic coastline from Florida to Maine. Additionally, an ‘expires’ security pays one dollar if the storm expires without making U.S. landfall,[10] and a final security pays one dollar if the storm moves southwest into the Gulf region. For Gulf region storms, eight securities have coastline ranges which cover the U.S. Gulf coast from Florida to Texas. An expires security pays if the storm expires at sea or makes landfall in mainland Central America outside the U.S., and a final security pays if the storm moves North into the Atlantic region. Coastline ranges were computed so that since 1949 an equal number of hurricanes have made first landfall in each coastline range. Figure 1 is a map of the Eastern U.S. coastline which shows the landfall range of each security and the dividing line.

HFM creates multiple markets if more than one storm is present, and creates more than one market for an individual storm if the storm crosses the dividing line or returns to the ocean after making an initial landfall. For more details on HFM, see http://hurricanefutures.miami.edu/.

HFM data cover storms for later half of the 2005 season. Many storms elicited little or no trading activity. In such storms the price of a particular security is close or equal to one dollar, and the other securities have a price near zero. Traders put probability near or equal to one on a particular security paying off (typically the expires security). Since such storms apparently have no subjective risk, we exclude them from the sample. Our rule is to exclude storms with less than 20 trades. This leaves 4 usable storms, 13 securities, and 445 trades. Tables 1-3 present summary statistics for the 2005 Atlantic hurricane season and for security prices.

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[9] NOAA provides an exact latitude and longitude corresponding to the site where the hurricane first lands.

[10] A storm is defined to ‘expire’ if it has not made U.S. landfall or crossed the dividing line and the NHC issues its final advisory for that storm when it is still over the ocean, or over non-U.S. land.

Consider as an example the storm Ophelia, for which a market was created September 7, 2005 and which expired without making landfall on September 16, 2005. Figure 2 presents the evolution of the two securities most likely to payoff: A5 pays one dollar if first landfall occurs in a range of coastline which includes part of North and South Carolina (see Figure 1), and AX pays one dollar if Ophelia expires without making landfall. Initially, A5 traded at a price equal to $0.10, indicating that trader's subjective risk assessment was that Ophelia would make first landfall in A5 with probability equal to 0.1. New information from track forecasts then arrived, indicating that it was more likely Ophelia would make landfall in A5. Traders then revised their subjective beliefs upward, eventually to a peak of 0.85 on September 13, as Ophelia neared the Carolina coast. However, Ophelia then turned North and went out to sea, resulting in a decrease in the subjective risk of Ophelia making landfall in A5 to zero by September 15.

We collected latitude and longitude data for three standard track forecasts. The first track forecasts is NOAA's National Hurricane Center forecast, denoted NHC. As few as four NHC hurricane experts consider data from many separate track forecasts (including both of our other track forecasts), and through consensus create the NHC track forecast. Thus, the NHC forecast is a standard expert opinion-type forecast and is also the official government forecast that competes with private forecasts. NHC forecasts have become increasingly accurate over the years, due to computational advances, more data, and improved physical models (Franklin, et. al., 2003). A three day track forecast today is about as accurate as a two-day track forecast 20 years ago. The mean absolute error for a five day track forecast is 283.7 nautical miles, which improves to 108.6 nautical miles for a two day forecast, and 59.6 nautical miles for a one day forecast (60 nautical miles equals one degree latitude).

The second track forecast is the Geophysical Fluid Dynamics Lab (GFDL) forecast model (Bender, et. al., 1993). The GFDL model is a structural model (known as a 'dynamic model' in the hurricane literature). Structural models use numerical solutions to physics equations. GFDL forecasts are widely available on the web.

The third track forecast is the Climatology and Persistence (CLP5) forecast model (Aberson, 1998). CLP5 is a purely statistical regression model that forecasts using direction of motion, location, storm intensity, and day of the year information, using parameters estimated from data on previous hurricanes. CLP5 also proxies for basic information about a storm such as the storms current position and heading. CLP5 is widely available in tracking software and on the internet.

Consequently, our data contains three representative models, one expert forecast, one structural model, and one statistical model. Although other models are available (see http://www.nhc.noaa.gov/modelsummary.shtml for details), they are typically either structural, statistical, or a combination of both, and are thus unlikely to add much in the way of information not contained in the models we use. Interviews with the traders revealed that they were using GFDL and were aware of CLP5. Traders seemed to regard CLP5 as too inaccurate to pay much attention to, yet traders did claim to pay attention to the storms position, heading, speed, and other characteristics upon which CLP5 is based.

Each track forecast contains a set of predicted latitude and longitude positions over time. Each predicted latitude and longitude position is an l-hour ahead forecast. Tracks vary in the number of hour ahead forecasts they report (see Table 4), but no forecasts are greater than 126 hours ahead.

As noted in Section 2, traders must convert the point forecasts into probabilities of landfall, with associated precision. Appendix 1 shows how we calculate these probabilities. The probabilities depend closely on the accuracy of the point forecasts and the implied landfall locations. The probability z rises as the predicted landfall location nears the center of range j. If the predicted landfall location is in range j, then the probability rises with the accuracy of the point forecast. Similarly, precisions vary by track and time since track forecasts vary in their accuracy, and all track forecast become more accurate as hurricanes approach landfall. Table 5 gives summary statistics for the probability data.

As an example, Figures 3a-c plot the track forecasts for Hurricane Wilma, from October 17-23, 2005. In the graph, the most Northeast marker (square, circle, or plus) is the five day ahead forecast. From the graphs, on October 17 all three five day forecasts agreed that Wilma would still be in the Gulf of Mexico. However, the next day GFDL predicted Wilma would land in G7. NHC and CLP5 predicted Wilma would still be at sea, but CLP5 moved closer to the G8 coastline. The implied landfall probability of G7 for GFDL was only 0.24, however. For all tracks, five day ahead forecasts have large errors. Indeed, the standard deviation of the GFDL five day ahead forecast error is more than 4.5°, enough to move the landfall to nearly the border between Alabama and Florida. Traders were apparently considerably more confident than the historical accuracy of the GFDL forecast implies, however, since the trade price indicated Wilma would hit G7 with probability 0.40 and G8 with probability 0.45 (GFDL predicted G8 with probability 0.23). The next day, the NHC forecast predicted G8 (specifically, the probability of G8 rose from 0.28 to 0.37) and GFDL predicted the storm would be just off the G8 coastline. The price of G8 rose to 0.7, while the price of G7 dropped to 0.25. Again, traders were considerably more confident than the historical accuracy of the forecasts implied. The price eventually neared one as Wilma neared the G8 coastline, where it eventually made landfall. It is interesting to note that traders appeared overconfident, and yet their forecasts proved correct in this case. Interviews with traders subsequent to the 2005 season indicated traders did not view track forecasts of five days or more ahead as informative, yet their trades indicated surprising confidence. In Section 5 we estimate whether or not traders are systematically overconfident.

Figures 4a-c presents a second example, track forecasts for Hurricane Rita for the dates during which trades occurred (September 21-23, 2005). Rita is interesting because the three September 21, 12 pm forecasts predicted landfall in locations covered by three different securities (the orange lines). The NHC forecast predicted G1 ($z_{NHC,t}=0.49$), GFDL predicted G2 ($z_{GFDL,t}=0.41$), and CLP5 predicted G3 ($z_{CLP5,t}=0.40$). The forecasts predicted the storm was approximately three days from landfall, yet the landfall predictions are relatively close to borders between securities, and so the probabilities are relatively close to one half.

One hour subsequent to the release of these forecasts, the prices were P_{G1}=0.4, P_{G2}=0.6, and P_{G3}=0.03, indicating traders gave the GFDL forecast the highest weight. Traders apparently discounted CLP5, which predicted G3.[11] Indeed, all the forecasts had a higher probability of G3 than the traders. So traders were considerably more confident in G2 than the forecasts implied. Twelve hours later (green lines), the NHC forecast moved to G2 ($z_{NHC,t}=0.55$), GFDL continued to predicted G2 ($z_{GFDL,t}=0.46$), and CLP5 predicted G3 ($z_{CLP5,t}=0.49$). At this point, the price of G1 fell to 0.1, G2 increased to 0.85, and G3 was 0.05. Thus traders placed more weight on the forecasts (GFDL and NHC) that turned out to be correct, because the hurricane made landfall in

[11] The weights for CLP5 implied from equation (4) are all above 0.29.

G2.[12] Further, traders were more confident than the forecasts would suggest, given the forecasts predicted the storm was still more than two days from landfall.

These examples indicate traders can make sophisticated decisions and look at diverse information. They also indicate some possibility of overconfidence. Although these examples are suggestive, a formal statistical model is needed to ascertain exact weights placed on each forecast, and to test whether or not such weights are optimal in a Bayesian sense.

4. Empirical Model and Hypotheses

We estimate an empirical version of equation (4) with three track forecasts:

$$P_{hjt} = \beta_0 + \beta_{0h} \cdot s_{ht} + \beta_1 \left(w_{0,hjt} \frac{\alpha}{\alpha+\beta} \right) + \sum_{i=1}^{3} \beta_{i+1} \left(w_{i,hjt} z_{i,hjt} \right). \qquad (5)$$

Here $\beta = [\beta_0, \beta_{0k}, \beta_1, ..., \beta_4]$ is a vector of parameters to be estimated, and s_{ht} is a hurricane specific dummy.[13]

Equation (5) requires values for the priors α and β. We considered both the initial CLP5 forecast and a uniform prior (α=β=0). The results are virtually identical for these two cases, so we report results using the uniform prior.

As in equation (4), the data in equation (5) vary by hurricane, security, and over time. Our calculation of the probabilities accounts for security and time specific information. For example, if a hurricane is forecasted to make landfall at the border between securities, the security with the longer coastline will have a higher probability. In addition probabilities are relatively large if the forecast predicts landfall in a short period of time within the security range. However, it is possible that we have not considered hurricane specific information. For example,

[12] That the prices in a few cases sum to greater than one most likely occurs due to thinness in the market. In addition, the data is last trade data, and so trades do not occur at exactly the same time.
[13] Adding a dummy for the first day of trading had little effect on the results.

one track forecast may be more accurate in Gulf versus Atlantic storms, leading to different weights for different storms. Hence we use hurricane specific fixed effects, which controls for hurricane specific information we have not modeled.

Our dependent variable, P_{hjt}, is a continuous proportion observed on the [0,1] interval. Direct maximum likelihood estimation of equation (5) is generally not feasible since predicted values of P_{hjt} outside the unit interval have beta probability equal to zero. Thus, the likelihood function is not differentiable at 0 and 1, ruling out gradient based likelihood maximization algorithms. For this reason, we follow the literature (see for example, Ferrari and Cribari-Neto, 2004 or Paulino, 2001) and use a logit link function to transform the conditional mean to the unit interval. By using this approach, our beta distribution model can now be estimated by maximum likelihood. However, the transformation makes P_{hjt} a non-linear function of the regressors, which is inconsistent with the theoretical model outlined in Section 2. We therefore present a linear approximation of the regression results using first order Taylor series approximations of the nonlinear density functions (the logistic link is relatively linear in the unit interval, so the errors are small).

Equations (4) and (5) imply traders are Bayesian if $\beta_1 = ... = \beta_4 = 1$, so a test for Bayesian updating corresponds to a test of this restriction. If the constant term is positive and significant, then traders' probabilities exceed the Bayesian weighted average of forecasts. This signals either that traders have additional information, or that traders are overconfident. If the constant term is positive and significant but traders predictions are less accurate than the probabilities imply, then traders are overconfident (for example if, when the price is 0.8, hurricanes make landfall less than 80% of the time).

5. Results and Discussion

a. Bayesian Updating Test

Tables 6a-e summarize the regression results. From Table 6a, the coefficients for GFDL and NHC are highly significant and close to one, the theoretical value consistent with Bayesian updating. The CLP5 coefficient is nearly zero, indicating traders are ignoring CLP5 information, which is consistent with the statements from traders mentioned in Section 3 indicating their belief that CLP5 was too inaccurate to be useful. However, from a Bayesian perspective, traders are underweighting CLP5. Forecast CLP5 is indeed the least accurate forecast, but the low accuracy is somewhat offset by the low correlation CLP5 has with other forecasts. Thus, the information CLP5 does provide has relatively high marginal value. Thus our results using the entire data set reject strict Bayesian updating, but do not indicate in favor a specific behavioral hypothesis. Instead, the results are consistent with traders who are Bayesians but are unaware of the value of the CLP5 forecast.[14] The constant term is positive and significant, indicating either overconfidence or that traders are using other information besides the three track forecasts.

Hurricane Ophelia illustrates how traders ignored CLP5 information. Inspection of Figures 2 and 5 reveals the price of AX closely followed the NHC and CLP5 forecasts throughout much of the trading. However, during September 8-10, the price of AX fell while the CLP5 forecast was moving east (increasing the probability of AX) and the NHC forecast was moving northwest (increasing the probability of A5). Traders apparently put more weight on the NHC forecast during this period, and a trader would have earned more by assigning more weight to CLP5, since AX eventually paid off. Using data only for Ophelia and excluding trades from

[14] The hypothesis $\beta_2=\beta_3=\beta_4=1$ is rejected with $\chi^2=92.5$ ($prob>\chi^2=0.00$) and the hypothesis $\beta_2=\beta_3=1$ is not rejected with $\chi^2=2.43$ ($prob>\chi^2=0.22$).

September 9-10 results in the CLP5 coefficient being positive and not significantly different from one, confirming the idea that traders ignored CLP5 during these dates.

Subsequent to the trading season, we interviewed several traders. They indicated that CLP5 was a better predictor for Ophelia because Ophelia was a slow moving storm and CLP5 forecasts well for slow moving storms. Furthermore, in their opinion, the NHC did not maximize forecast accuracy, because it faces different penalties for type I (false positive) and type II (false negative) errors. In their opinion, the NHC predicts landfall too often and predicts storms will land near or on an urban center too often.[15] For Ophelia, traders we interviewed felt the NHC was predicting landfall because it feared the consequences of predicting that Ophelia would go out to sea, only to see it make landfall in the Carolinas.

To test this idea, in Table 6b we interact the Ophelia dummy with the NHC forecast. The coefficient is negative, indicating that the NHC forecast was given less weight for Ophelia, but not significant. Overall then, even though some traders felt the NHC forecast was biased for Ophelia and CLP5 was predicting AX, traders went with the NHC forecast (especially during September 8-10) because they did not view the CLP5 as providing valuable information.

Wilma provides another test case, this time between GFDL and the NHC. From Figure 3, the NHC consistently forecasted G8, whereas GFDL forecasted G7 on October 17-18, but switched to G8 on October 19, and then trended south towards GN.[16] The NHC forecast was very close to Tampa, a large urban center, whereas GFDL trended south to a less populated area. Prices appeared to closely follow GFDL. The price of G7 declined from \$0.44 to trade in the range of \$0.10 to \$0.25 after October 18, before declining to near zero as GFDL trended toward GN. Similarly, the price of GN increased briefly to \$0.35 at the end of the day on October 19 as

[15] Powell and Aberson (2001) examine NHC forecasts between 1976 and 2000 and find a bias to avoid type II errors, which they call a "least regret" forecast.
[16] Traders discounted CLP5, which predicted mainly G5 and G6, until the very end.

GFDL began to drift south of Tampa. From October 20-23, the probability of GN for GFDL declined because the effect of the standard error of the forecast narrowing as the storm approached the coast outweighed the effect of the forecast nearing the GN border. The price of GN also declined during the period from October 20-23. The prices are therefore consistent with traders' favoring GFDL over NHC. Interviews with the traders indicated they discounted the NHC forecast because the felt the NHC was compelled to predict landfall near Tampa.[17]

In Table 6c, we formally test this idea by including a term which interacts the Wilma dummy with the NHC forecast. The coefficient is negative and significant as expected, indicating that traders discounted the NHC forecast in favor of GFDL for Wilma.[18] Overall then, the results for Ophelia and Wilma indicate that traders discount the official forecast when they perceive bias and when they perceive the alternative information source is credible.

Turning next to Katrina, although CLP5 and GFDL briefly turned towards G4 very early on (Figure 6c), all three forecasts consistently predicted G3, the eventual winner. Traders also favored G3, whose probability never fell below 0.73. Nonetheless, traders seemed to favor G4, assigning G4 probabilities as high as 0.7 during trading,[19] despite the fact that no forecast had the probability of G4 above 0.07 during the period of trading. Katrina made landfall in G3, but extremely close to the border of G4. Close enough, in fact, that it took a couple of days to determine the winning security. The true probability of G4 is of course unobserved, but most likely greater than the probability indicated by the track forecasts. For consistency, in Table 6d we included a term which interacted the NHC forecast with the Katrina dummy. As expected the

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[17] Local weather patterns indicated there was almost no chance of a landfall near Tampa. Thus traders could effectively rule out model uncertainty as a reason for divergence of the forecasts.

[18] We can reject the hypothesis that the sum of the NHC coefficients equals one at the five percent level of significance.

[19] The sum of the probabilities was greater than one for about one day. This may reflect illiquidity in the market, but may also be because Katrina being the first hurricane with active trading. Therefore, there was probably quite a bit of learning during Katrina trading.

coefficient was not significant, since the forecasts were all in agreement that Katrina would make landfall near an urban area.

Turning next to Rita, from Figures 4a-c, GFDL and NHC generally predicted G2, whereas CLP5 generally predicted G3. Prices appeared to closely track GFDL and NHC, which was correct *ex post* since Rita eventually made landfall in G2. In Table 6e, we included a term which interacted the NHC forecast with the Rita dummy. As expected, the term was not significant. GFDL was generally closer than the NHC to the urban center Houston, so no perception of bias existed.

Overall then, our results indicate some support for Bayesian updating with respect to GFDL and NHC, but with CLP5 being generally underweighted. Furthermore, traders perceived the NHC forecast was biased in cases where the NHC predicted landfall near an urban center and when an alternative information source perceived to be credible predicted landfall elsewhere.

Government information dissemination faces difficult tradeoffs. If the information is unbiased, then the government agency may face a high penalty for not predicting an adverse event that occurs, while if the agency submits biased information it may be ignored. Here, the NHC apparently leans toward releasing biased information to ensure that type II errors will not occur. Alternatively, the NHC is minimizing expected losses and believes that information released with a small bias will minimize expected losses. Our results indicate that the NHC bias crept into the price of Ophelia AX, even though some traders were aware of it. However, the NHC bias did not affect Wilma security prices, as traders discounted the NHC forecast in favor of GFDL.

b. Accuracy

Consider as a measure of accuracy the fraction of trades for which $P_{hjt} \geq (<) 0.5$ and the hurricane made (did not make) landfall in range j. Table 7 indicates that, by this measure, traders forecast with an 84% success rate. When a hurricane is three days or less from landfall, the percentage rises to better than 90%. Traders are remarkably accurate in their forecasts. For forecasts, we similarly measure the fraction of forecasts for which $z_{hjt} \geq (<) 0.5$ and the hurricane made (did not make) landfall in range j. Table 7 indicates that, as expected, the official NHC forecast is the most accurate forecast, whereas CLP5 is the least accurate. Traders are more accurate than the NHC for storms greater than three days from landfall, whereas the NHC is more accurate for storms less than or equal to two days from landfall. Overall traders are slightly more accurate than the NHC.

One possible reason why traders are less accurate for storms near landfall is a 'favorite-longshot bias' (see for example Tetlock, 2004). The favorite-longshot bias occurs when expected returns from betting increase with the probability of winning. Traders could mildly profit by buying securities for which the hurricane is near landfall and forecasted to make landfall in the security range. Such securities have a high price and are thus 'favorites.' Additional evidence of a favorite-longshot bias is presented below.

In Table 7, each trade counts as one observation. Certain storms and securities are therefore over-sampled. In Table 8, we group trades by the nearest forecast release. In particular, since forecasts are released every six hours, each trade is matched to a set forecasts no more than plus or minus three hours from the trade. We then average all prices that are matched to the same set of forecasts. If a six hour period has no trades, we have no observation for that time interval. Table 8 reveals that the NHC forecast accuracy falls slightly, while the HFM forecast accuracy improves considerably to 94%. HFM over-sampled trades for which the traders were less accurate, but primarily averaging the trades reduces the impact of some less accurate trades that probably would not occur in a more liquid market.[20] HFM still outperforms all three track forecasts, however. Indeed, we computed HFM forecasts a number of ways and HFM outperformed all track forecasts with the exception of storms very close to landfall. The primary advantage of HFM is in Ophelia and Wilma, when the storms were more than five days from landfall. Thus, as noted in Section 5a, traders are more accurate in situations where the NHC faces a large penalty for type II error.

Still, Tables 7 and 8 do not provide a test of rationality. For example, it may be that 94% of storms of type *k* make first landfall in range *j*, but traders only assess a probability of 0.7. In that case Table 7 would indicate 94% accuracy, but traders would be consistently underestimating the probability of success. Therefore we grouped nearby trade prices into 20 bins,[21] and then for each bin compare the mid point of the range of prices in the bin with the percentage of actual successes for all trades in the bin's price range. Rationality implies the relationship between price and the percentage of actual successes is the 45 degree line.

Figure 7 shows that most observations are near the 45 degree line, but the slope is greater than one. Traders could mildly profit by betting on storms with a high price and selling securities with a low price.[22,23] Hence Figure 7 is consistent with a favorite-longshot bias. These results must be interpreted with caution because of the difficulty of estimating an event with a

[20] For example, 11 trades for Rita, security G3, occurred within three hours of the September 23, 12 noon. The average price was $0.32, while the forecasts ranged from 0.17 to 0.20. However, one trade was at $0.60. In a more liquid market with less price dispersion, trades would be closer to the mean trade, as the buyer would be able to find a seller for a price less than $0.60.

[21] The bins are of equal size and the results are not very sensitive to the number of bins used.

[22] Interestingly, one trader we interviewed noticed the bias and made significant profits selling securities with a low price. These trades apparently did not completely eliminate the bias, however.

[23] Jullien and Salanie (2000) and others find evidence of a favorite-longshot bias in horse racing, but Tetlock (2004) finds a reverse longshot bias for the case of sports event markets and no bias for financial event markets.

probability near one without a large data set. Even trade prices greater than or equal to 0.8, however, gives a slope greater than one.

6. Concluding Remarks

This study is the first to use event market data to study hurricane risk perceptions. Our regression model estimates how individuals update their subjective risk perceptions in response to hurricane track forecast information. The success of hurricane information dissemination programs depend on individual choices, and in turn on our understanding of how risk perceptions evolve over time. An important issue that we address is how much weight do individuals place on competing information sources, as well as their own prior beliefs, as they update their subjective beliefs about hurricane landfalls. We find traders behave in a manner consistent with Bayesian updating with respect to the official (NHC) forecast and a structural forecast model (GFDL), but underweight a statistical model (CLP5).

CLP5 is the least accurate forecast, but receives significant weight in the Bayesian forecast because it is relatively uncorrelated with the other forecasts. Since the value of CLP5 is subtle, it is perhaps not surprising that boundedly rational traders were unable to see the value of CLP5 information. Nonetheless, our results indicate differences between uncorrelated and (until now not examined in the literature) correlated information sources, since the value of correlated information sources is more difficult to ascertain.

Traders display remarkable skill. Traders correctly predict whether a hurricane will or will not make landfall in one of 8 regions for 84% of their trades. If the hurricane is 3 days or less from landfall, the percentage rises to over 90%. When comparing average forecasts made by traders with track forecasts on the same hurricane at roughly the same time, the traders forecast with 94% accuracy compared to 77% accuracy of the best track forecast (NHC).

Nonetheless, the NHC forecast outperformed traders for storms less than or equal to three days from landfall. Track forecasts are highly accurate when storms near landfall. Hence, security prices should be near one if the storm is projected to make landfall in the security range and near zero otherwise. But security prices tended to be too low when the landfall probability was near one and too high when the landfall probability was near zero. This is a favorite-longshot bias.

With regard to information dissemination, traders believed the NHC forecast was biased to avoid type II errors. For Wilma, traders discounted the NHC forecast in favor of GFDL (which turned out to be correct), but for Ophelia traders did not discount the NHC forecast in favor of CLP5 (which turned out to be correct). Traders perceived bias in both cases, but were only willing to discount the NHC forecast when the alternative forecast was perceived as credible. Our results indicate that it may be difficult for the NHC to control hurricane information dissemination in the face of credible alternatives.

Several caveats are in order. First, HFM at this time is a thin market. Due to the lack of trades, we cannot introduce other track forecasts traders may be watching, including official forecasts with different time lags. Our traders are mostly meteorologists, so it is unclear if the results generalize to the general population. An interesting test would be to examine if variation in compliance with evacuation orders and other decisions is related to differences in forecasts between the NHC and credible alternatives. We leave this question to future research.

Appendix 1: Computing the probabilities and precisions

Every six hours, institutions release track forecasts, which give point forecasts of the storm's position at various times in the future. Thus the information in track forecast i, Ω_{it}, consists of a set of L_i pairs of position coordinates, so $\Omega_{it} =\{Lat_{itl},Lon_{itl}\}$, $l=1...L_i$. Tracks vary in the number of point forecasts issued at each release. Each trader must at least implicitly convert the information Ω_{it} into a probability of first landfall in range j, z_{ijt}, upon which the price of the security is based. Here we explain how we compute the probability, based on the point forecasts and historical mean forecast errors.

The first step is to compute the standard deviation of the point forecast errors. NHC (2008) gives historical mean prediction errors by track and time to landfall. Hurricane track forecasts have become increasingly accurate, thus we consider only the 2000-06 mean absolute errors (2002-06 for CLP5). It is straightforward to show (proof available on request) that, if the latitude and longitude point forecast errors are normally distributed with mean zero and if the variance of the latitude error equals the variance of the longitude error, then the standard deviation in each direction, σ_{il}, is related to the mean absolute Euclidean distance error, MAE, according to: $\sigma_{il} \sim \sqrt{2/\pi} \cdot MAE_{il}$. For example, the third point on the black line of Figure 6c is the 36 hour ahead forecast of the August 28, 12 pm CLP5 Katrina forecast. Thirty six hour ahead CLP5 forecasts have a mean absolute distance error of 315.4 km, which corresponds to a standard deviation of the longitude error of 251.7 km.

We next compute the probability of landfall in range j via a Monte Carlo procedure. The simulated actual longitude position, $\tilde{c}_{itl}$, is a normally distributed random variable with mean equal to the point forecast Lon_{itl} and standard deviation σ_{il}. However, errors are positively serially correlated over point forecasts. That is, if the hurricane is west of the one day ahead forecast, the hurricane is likely to be west of the two day ahead forecast as well. We model the serial correlation as:

$$\tilde{c}_{it1} = \mathrm{N}(Lon_{it1}, \sigma_{il}^2)$$
$$\tilde{c}_{itl} = \tilde{c}_{it,l-1} + \mathrm{N}(Lon_{itl} - Lon_{it,l-1}, \sigma_{il}^2 - \sigma_{i-1,l}^2) \quad i = 2 \ldots L_i$$

Hence, $\tilde{c}_{itl} - Lon_{itl}$ is mean zero with standard deviation σ_{il}, but is positively serially correlated over *i*. A simulated actual latitude is computed in an identical manner.

Next, for each simulated actual track, $\tilde{c}_{it} = \{\tilde{c}_{it1}, \ldots, \tilde{c}_{itL}\}$ and the same for latitude, we compute the first landfall, by interpolating between the simulated actual positions, accounting for the curvature of the earth. The first landfall coordinate is the first intersection between the coastline (including the dividing line) and the line formed by interpolating the simulated actual positions. If all forecasts are at sea (over land), the track forecast is extrapolated forward (backward) using the last (first) two forecasts. If all simulated actual positions and the forward extrapolation are at sea, the simulated track is said to predict the storm will expire at sea. The probability is thus equal to the fraction of a large number (1000) of simulated actual tracks which make first landfall in range *j*.

To compute the precision of the probability, $q(\Omega_{it})$, we use a bootstrap procedure. For each track forecast, we have 1000 simulations which either made landfall in range *j* or did not. From this set, we draw a large number (1000) of samples with replacement of 1000 simulations each and compute the fraction which make landfall in range *j*. We then have a set of 1000 probabilities. The precision is the inverse of the variance of the set of probabilities.

Our methodology requires some fairly sophisticated computations. However, traders are at least aware of the various track forecasts, and how their error varies across tracks and as the hurricane approaches landfall. More straightforward methods of computing probabilities from track forecast information should produce similar regression results.

7. Appendix 2: Tables and Figures

Table 1: Summary statistics for the 2005 Atlantic hurricane season.

Number of Tropical and Subtropical Storms	28
Number of Hurricanes	15
Number of Major Hurricanes (Cat. 3-5)	7

Table 2. HFM Trade Data for year 2005: Summary Statistics. Hurricanes can potentially have multiple landfalls and thus multiple markets. Thirty two traders participated. All traders began with $100.

Summary Statistic	Number	Summary Statistic	mean	Std. Dev.	Max.	Min.
Storms with markets	11	Contracts	730.6	1,059.9	4,150.0	9.0
Securities with >20 trades	13	Ending Balance ($)	103.0	52.6	207.6	0.0
Storms with > 20 trades	5					

Table 3. Summary statistics for transaction prices by storm and security.

Storm (Intensity)	Trades	Mean	Std. Dev.	Maximum	Minimum
Katrina-Atlantic (Cat 1)					
Security A2	20	0.456	0.215	0.700	0.020
Katrina-Gulf (Cat 5)					
Security G3	22	0.894	0.063	0.980	0.730
Security G4	39	0.400	0.161	0.700	0.001
Ophelia (Cat 1)					
Security A5	29	0.235	0.218	0.750	0.001
Security AX	46	0.420	0.198	0.895	0.050
Rita (Cat 5)					
Security G1	36	0.379	0.162	0.700	0.015
Security G2	73	0.766	0.150	0.990	0.150
Security G3	63	0.168	0.145	0.600	0.001
Wilma (Cat 5)					
Security G7	26	0.247	0.148	0.440	0.010
Security G8	27	0.736	0.182	0.990	0.350
Security GN	32	0.176	0.079	0.350	0.010

Table 4. Standard deviation of longitude and latitude distance error in km by track and hours to landfall. Source: authors' calculations from data published by NHC (2008).

Track	Hours to Landfall							
	0	**12**	**24**	**36**	**48**	**72**	**96**	**120**
GFDL	64.6	112.1	177.1	257.7	353.6	486.9	552.1	896.3
NHC	17.8	89.6	156.1	219.0	284.4	422.2	558.9	743.1
CLP5	31.3	131.2	270.8	446.0	596.9	872.7	1088	1297

Table 5. Summary statistics for track forecasts. The top number in each cell is the mean and the bottom number is the standard deviation.

Storm	**Distance to security range**			**Probability of landfall in security range**			**Predicted hours to landfall**		
	CLP5	**GFDL**	**NHC**	**CLP5**	**GFDL**	**NHC**	**CLP5**	**GFDL**	**NHC**
Katrina-Atlantic									
Security A2	222.1 105.9	444.0 30.5	320.1 13.6	0.14 0.05	0.29 0.15	0.32 0.18	33.0 19.6	26.5 16.8	42.0 38.5
Katrina-Gulf									
Security G3	396.4 143.8	257.0 66.5	265.8 102.6	0.81 0.09	0.86 0.07	0.54 0.19	34.0 11.8	36.0 10.7	52.0 19.6
Security G4	422.0 45.1	322.1 53.5	343.7 72.7	0.08 0.02	0.09 0.03	0.06 0.02	34.0 11.8	36.0 10.7	52.0 19.6
Ophelia									
Security A5	957.1 392.0	884.3 601.8	653.0 712.6	0.23 0.18	0.20 0.18	0.19 0.17	54.0 32.7	52.8 39.3	43.4 27.2
Security AX	735.1 296.6	1,565.2 693.0	1,686.0 758.5	0.10 0.20	0.35 0.33	0.22 0.26	54.0 32.7	52.8 39.3	43.4 27.2
Rita									
Security G1	580.5 113.4	564.0 104.2	515.6 128.2	0.20 0.15	0.19 0.20	0.13 0.09	45.2 22.4	43.4 20.5	49.8 20.1
Security G2	370.6 171.0	358.0 174.1	338.6 197.7	0.54 0.18	0.60 0.18	0.30 0.19	45.2 22.4	43.4 20.5	49.8 20.1
Security G3	477.1 124.1	539.4 41.4	558.9 61.8	0.23 0.08	0.18 0.08	0.35 0.13	45.2 22.4	43.4 20.5	49.8 20.1
Wilma									
Security G7	800.2 179.3	960.4 809.9	812.1 797.6	0.21 0.08	0.21 0.09	0.13 0.07	85.5 36.9	77.1 34.5	109.3 30.9
Security G8	842.1 202.7	1,359.0 904.2	1,194.4 892.3	0.36 0.21	0.45 0.25	0.16 0.17	85.5 36.9	77.1 34.5	109.3 30.9
Security GN	837.3 128.9	921.5 431.8	643.3 461.0	0.28 0.13	0.21 0.13	0.18 0.11	85.5 36.9	77.1 34.5	109.3 30.9

Table 6a is maximum likelihood estimation using all securities with hurricane specific fixed effects. Tables 6b-e are maximum likelihood estimation results by storm and security. Independent variables equal z_{it}, i = *CLP5, GFDL, NHC*. **, *** indicates significance at the 5% and 1% level, respectively, and standard errors are in parenthesis. All coefficients and standard errors are computed using first order Taylor series approximations of the density function.

Table 6a. All storms (417 observations).

Method	Coefficient				Log Likelihood	χ^2
	Constant	GFDL	NHC	CLP5		
Fixed Effects	0.27^{***} (0.02)	1.13^{***} (0.13)	0.89^{***} (0.11)	0.00 (0.12)	98.11	155.90^{***}
Random Effects	0.27^{***} (0.05)	1.13^{***} (0.12)	0.90^{***} (0.10)	0.00 (0.12)	184.69	91.14^{***}

Table 6b. All storms, with interaction term between the Ophelia dummy and the NHC forecast. Fixed effects estimation (417 observations).

Method	Coefficient					Log Likelihood	χ^2
	Constant	GFDL	NHC	CLP5	OPHxNHC		
Fixed Effects	0.26^{***} (0.05)	1.17^{***} (0.13)	0.95^{***} (0.11)	0.00 (0.12)	-0.33 (0.27)	185.42	92.62^{***}

Table 6c. All storms, with interaction term between the Wilma dummy and the NHC forecast. Fixed effects estimation (417 observations).

Method	Coefficient					Log Likelihood	χ^2
	Constant	GFDL	NHC	CLP5	WILxNHC		
Fixed Effects	0.27^{***} (0.05)	1.12^{***} (0.12)	0.81^{***} (0.11)	-0.17 (0.13)	-0.57 (0.19)	188.99	99.74^{***}

Table 6d. All storms, with interaction term between the Katrina dummy and the NHC forecast. Fixed effects estimation (417 observations).

Method	Coefficient					Log Likelihood	χ^2
	Constant	GFDL	NHC	CLP5	KATxNHC		
Fixed Effects	0.27^{***} (0.06)	1.14^{***} (0.13)	0.92^{***} (0.11)	-0.02 (0.12)	-0.14 (0.36)	184.76	91.29^{***}

Table 6e. All storms, with interaction term between the Rita dummy and the NHC forecast. Fixed effects estimation (417 observations).

Method	Coefficient					Log Likelihood	χ^2
	Constant	GFDL	NHC	CLP5	RITAxNHC		
Fixed Effects	0.27^{***} (0.05)	1.06^{***} (0.13)	1.05^{***} (0.14)	-0.05 (0.12)	-0.26 (0.17)	184.88	95.53^{***}

Table 7. Forecast accuracy of HFM traders and track forecasts. A trade price or forecast is correct if the probability of a hurricane making landfall in j is greater than (less than) or equal to 0.5, and the hurricane makes (does not make) landfall in j.

Days from	HFM	Forecast Observations			Fraction Correct			
Landfall	Trades	GFDL	NHC	CLP5	HFM	GFDL	NHC	CLP5
All trades	433	418	431	431	0.84	0.79	0.81	0.62
>5 days	108	95	108	108	0.69	0.60	0.54	0.58
≤5 days	325	323	323	323	0.89	0.85	0.90	0.64
≤4 days	303	301	301	301	0.89	0.86	0.91	0.63
≤3 days	270	268	268	268	0.90	0.89	0.94	0.63
≤2 days	181	179	179	179	0.90	1.00	1.00	0.61
≤1 day	66	65	65	65	0.98	1.00	1.00	0.97

Table 8. Forecast accuracy of HFM traders and track forecasts, identical forecast times. For each track forecast release, we compute the average security prices during the next six hours. Six trades for which no forecasts are available are removed from the sample.

Days from	Observations	Fraction Correct			
Landfall		HFM	GFDL	NHC	CLP5
All trades	111	0.94	0.75	0.77	0.68
>5 days	39	0.92	0.56	0.56	0.62
≤5 days	72	0.94	0.85	0.89	0.71
≤4 days	65	0.94	0.88	0.92	0.72
≤3 days	52	0.96	0.94	0.96	0.71
≤2 days	38	0.95	1.00	1.00	0.68
≤1 day	19	1.00	1.00	1.00	0.95

Figure 1. Map of HFM landfall ranges.

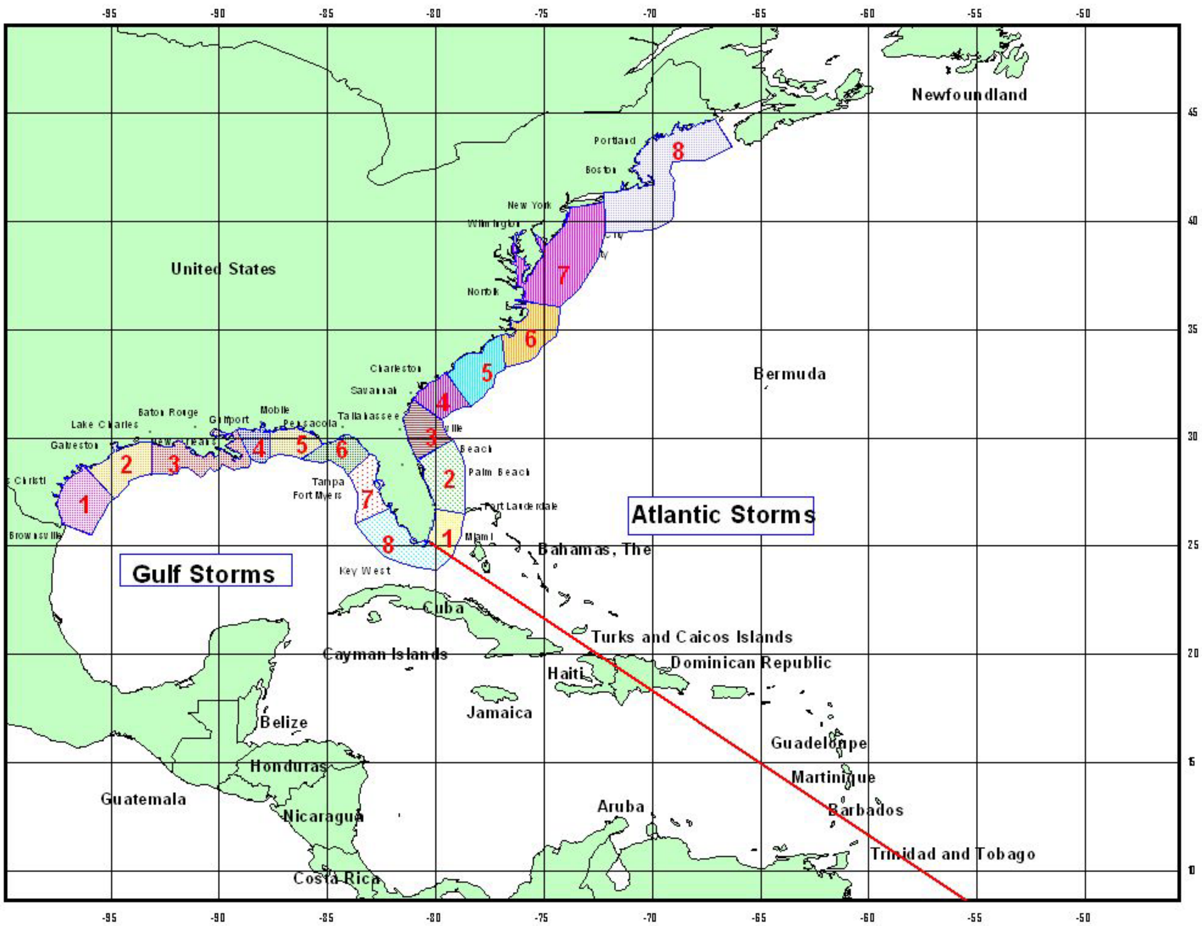


Figure 2. Trade-weighted average daily prices of Carolina (A5) and Expires (AX) Securities for Hurricane Oheilia, September 7-16, 2005.

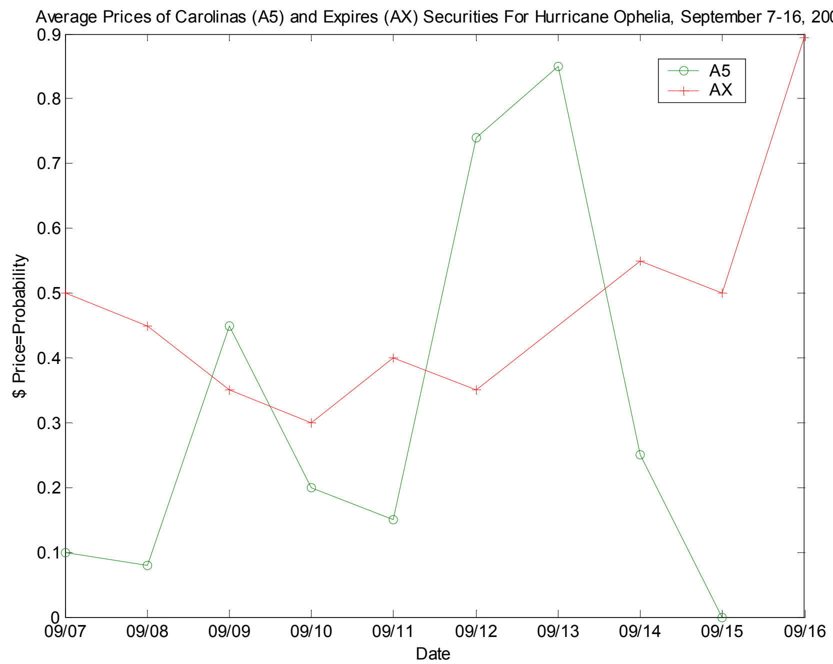


Figure 3a. GFDL track forecasts for Hurricane Wilma, October 17-24, 2005.

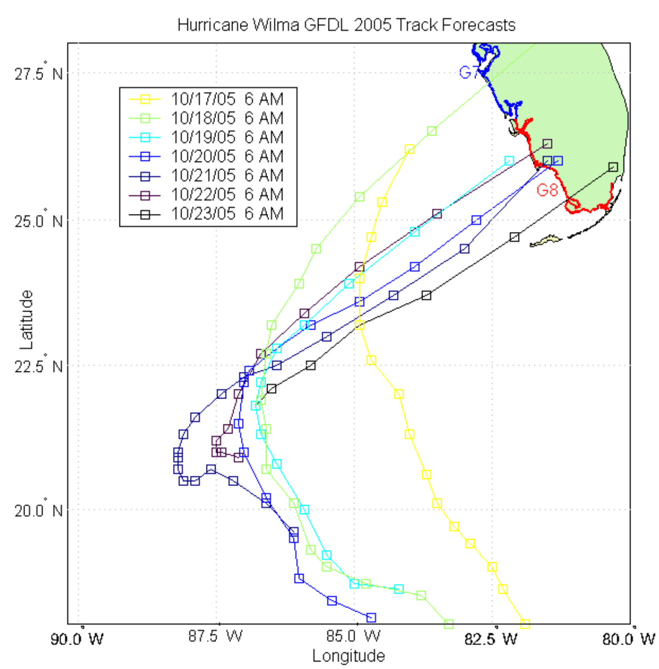


Figure 3b. NHC track forecasts for Hurricane Wilma, October 17-24, 2005.

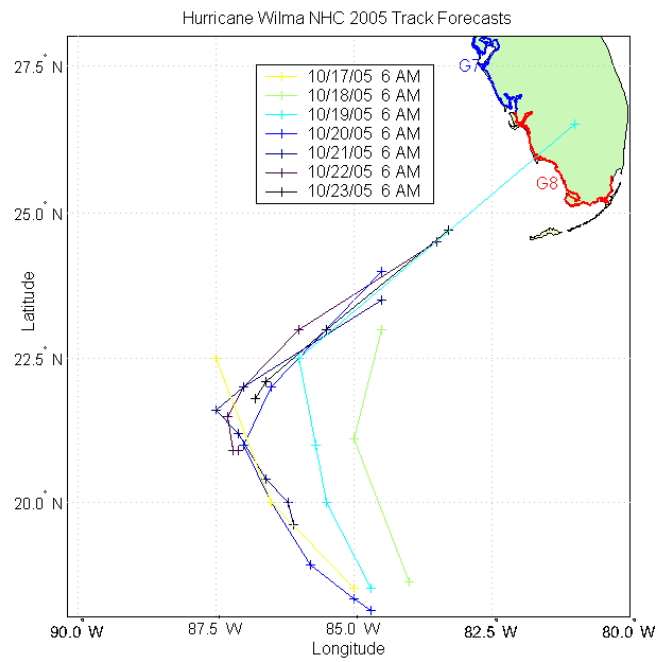


Figure 3c. CLP5 track forecasts for Hurricane Wilma, October 17-24, 2005.

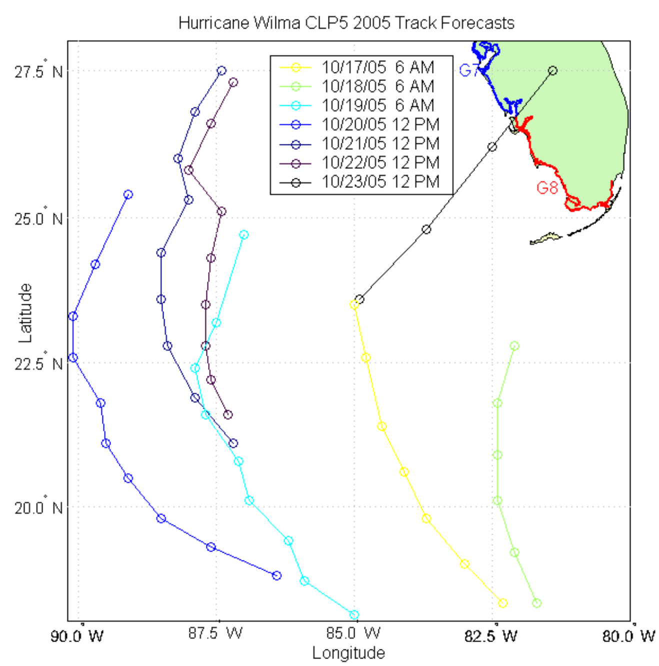


Figure 4a. GFDL track forecasts for Hurricane Rita, September 21-23, 2005.

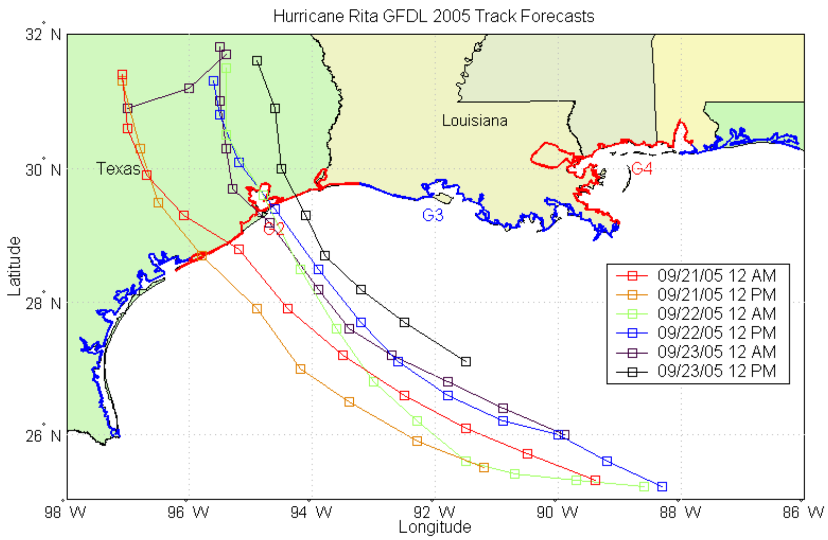


Figure 4b. NHC track forecasts for Hurricane Rita, September 21-23, 2005.

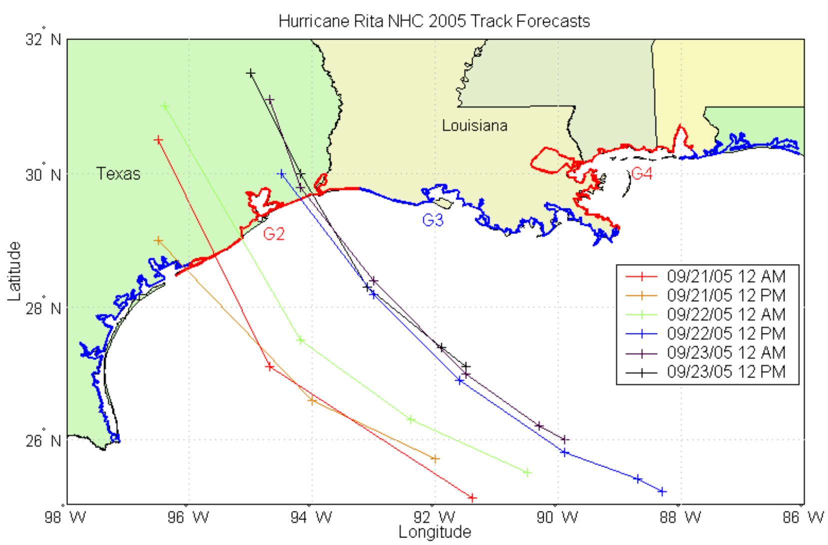


Figure 4c. CLP5 track forecasts for Hurricane Rita, September 21-23, 2005.

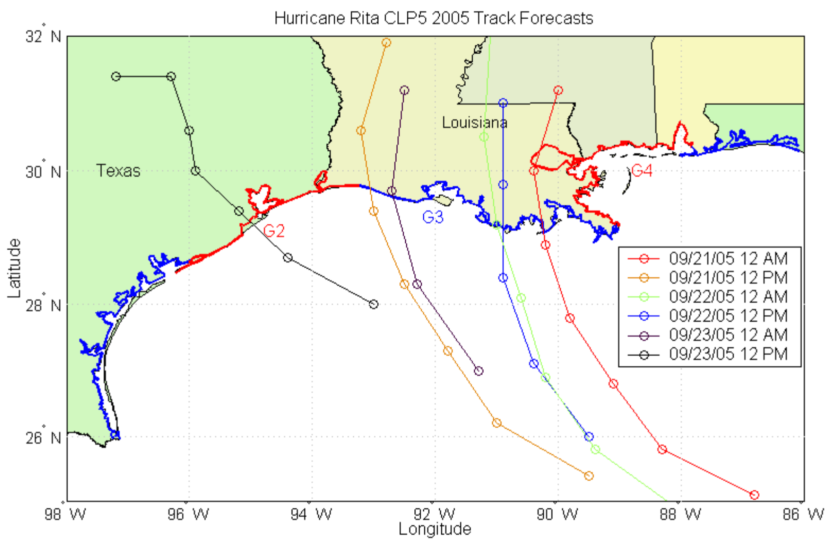


Figure 5a. GFDL track forecasts for Hurricane Ophelia, September 7-16, 2005.

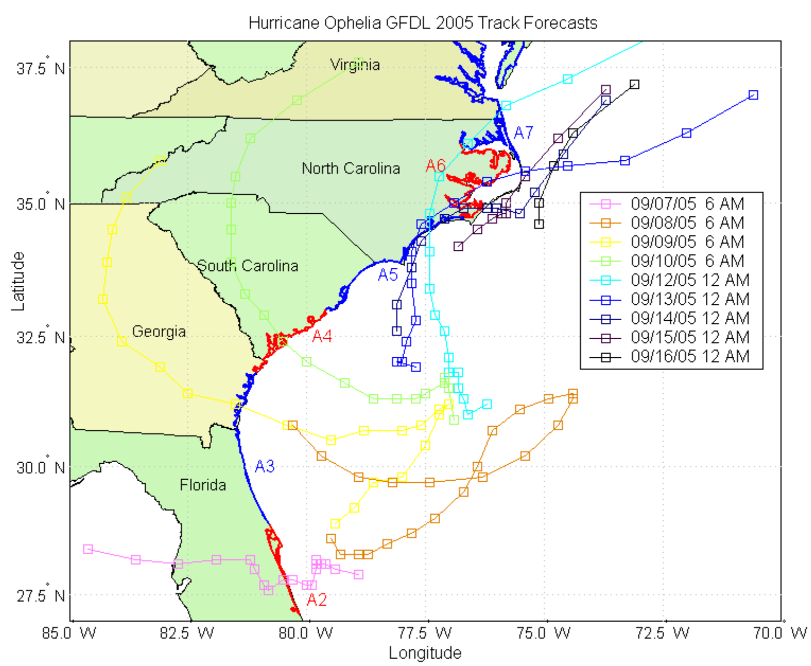


Figure 5b. NHC track forecasts for Hurricane Ophelia, September 7-16, 2005.

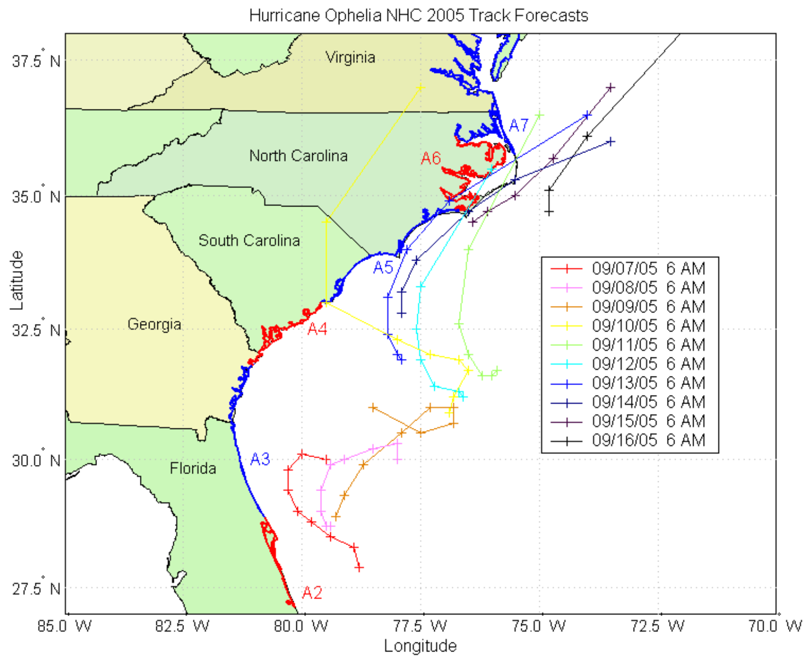


Figure 5c. CLP5 track forecasts for Hurricane Ophelia, September 7-16, 2005.

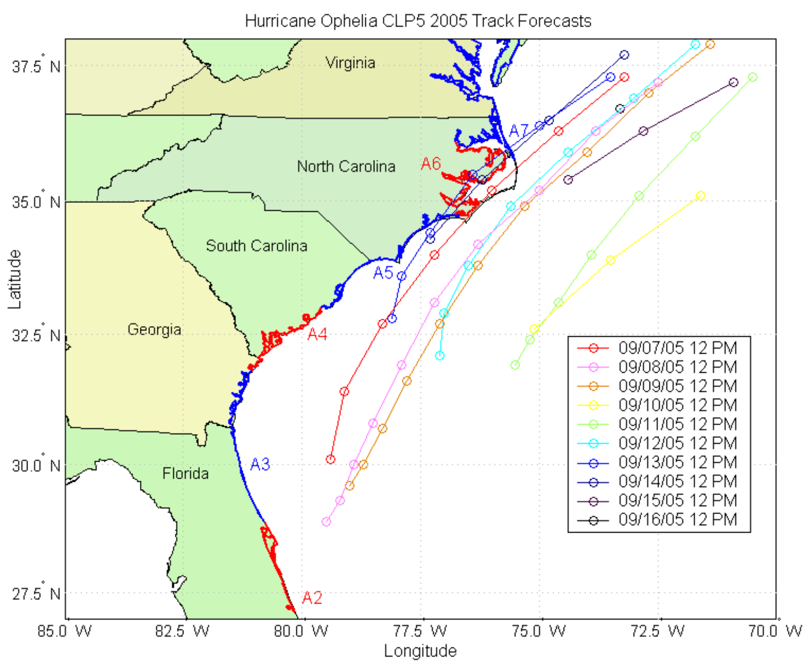


Figure 6a. GFDL track forecasts for Hurricane Katrina, August 27-28, 2005.

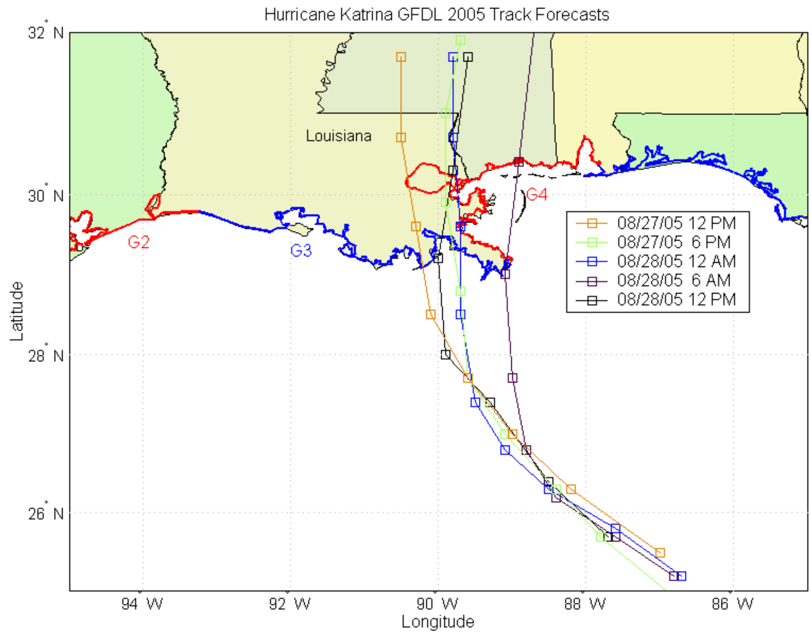


Figure 6b. NHC track forecasts for Hurricane Katrina, August 27-28, 2005.

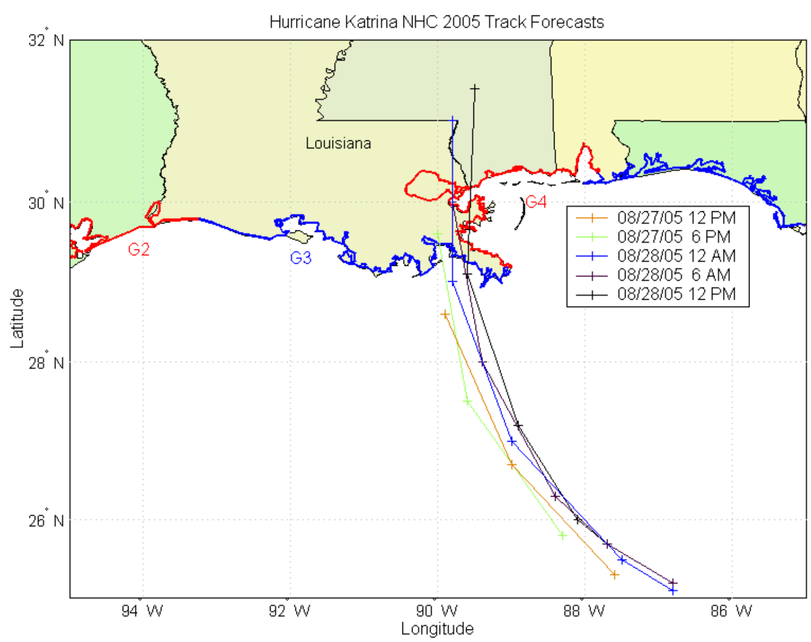


Figure 6c. CLP5 track forecasts for Hurricane Katrina, August 27-28, 2005.

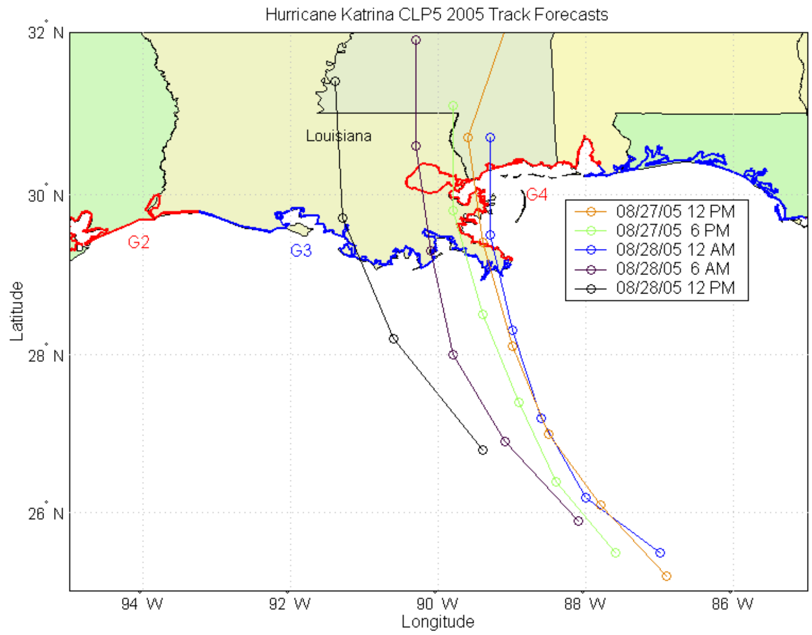
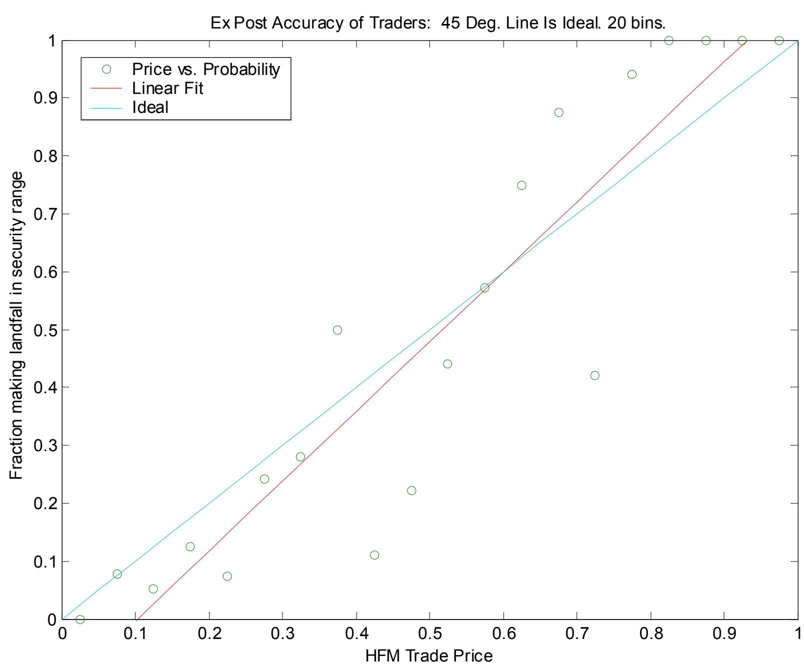


Figure 7. *Ex post* forecast accuracy, all storms.



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