THE EFFICIENCY GAINS FROM PROBABILISTIC WEATHER FORECASTS: A CASE STUDY OF OIL AND GAS PRODUCERS IN THE GULF OF MEXICO

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BY

TIMOTHY J. CONSIDINE
CHRISTOPHER JABLONOWSKI
BARRY POSNER
CRAIG H. BISHOP

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125 HOSLER BUILDING
THE PENNSYLVANIA STATE UNIVERSITY
UNIVERSITY PARK, PA 16801
PHONE: (814) – 863-0810
FAX: (814) 863-7433
EMAIL: CPW@PSU.EDU

ABSTRACT

The threat of hurricanes often forces producers of crude oil and natural gas in the Gulf of Mexico to evacuate offshore drilling rigs and to temporarily cease production. More accurate hurricane forecasts would result in fewer false alarms, thereby, preventing these unnecessary evacuations and disruptions in production. This study estimates the value of existing and more accurate hurricane forecast information. Our empirical framework involves detailed computations of hurricane forecasting accuracy and actual observations on rig evacuations, costs, and potential losses. Our estimates indicate that the value of existing hurricane forecast information to oil and gas producers averaged roughly $8 million per year over the decade of the 1990s, which exceeds the operating budget of the National Hurricane Center. From an industry perspective, however, these values are a small fraction of production costs. Moreover, although recent hurricane forecast accuracy is improving, it has not been sufficient to create significant value to this industry. On the other hand, forecast value dramatically increases with improvements in accuracy, rising to more than $15 million per year with a 50% improvement in forecast accuracy. The results also suggest that higher potential losses substantially reduce forecast value. This study also develops and estimates several descriptive models of hurricane evacuation decisions with and without the assumption of expected utility maximization.

ACKNOWLEDGEMENTS

There is a necessary division of labor in any study and a sufficient degree of cooperation among team members required to achieve the goals. The nature and characteristics of this study emerged from extensive discussions between the two principal investigators, Tim Considine and Craig Bishop. The hard work and cooperation of two graduate students, Chris Jablonowski and Barry Posner, were instrumental in the successful completion of this research. Chris assisted in the early stages of the project proposal, data collection, and modeling. Barry computed the forecast probabilities and devised the methods used to value production delayed by hurricane threats. Much of this report is based upon their reports on various parts of this project. The last chapter that develops a model of hurricane evacuation decisions also appears in Chris Jablonowski's dissertation chapter written under the supervision of Professor Considine. The support of Dr. Stephen Nelson of the Atmospheric Sciences Division of the National Science Foundation, the National Oceanic and Atmospheric Administration, and the National Weather Service are gratefully acknowledged.

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CHAPTER I. INTRODUCTION

The loss of life and property from severe weather events can be considerable. While improved storm forecasts cannot avert most property damage, they can save lives. Moreover, more accurate forecasts enhance economic efficiency by reducing unnecessary disruptions in economic activity. As long as decision makers have the flexibility to respond to climate uncertainty, weather and climate information will have value.

Identifying and observing these options in many empirical settings, however, is often difficult. In addition, strategies for mitigating the adverse effects of an atmospheric event may be quite complex, involving the use the engineering, logistical, or financial strategies. This study examines a seemingly simple, clear-cut decision to evacuate offshore energy production facilities facing a threat of a hurricane strike. A direct hit could destroy the facility with considerable loss of life and environmental damage. On the other hand, disrupting production to avoid these losses is costly. Clearly, a weather forecast conceivably could have considerable value for this problem. The challenge for managers of these facilities is to balance these costs and losses based upon the actual or perceived likelihood of hurricanes strikes *given* forecast information.

This forecast information can be conveyed in several different ways. For instance, the National Hurricane Center (NHC) recently developed a method that computes forecast strike probabilities for a particular region or locality during storm events. Presumably this forecast information has more intrinsic value to those potentially affected by the storm because it conveys the degree of uncertainty surrounding a forecast. More accurate forecasts would involve fewer instances of false alarms and could be associated with higher levels of confidence in the forecasts. Forecasts with probabilities attached are a relatively recent development. Hence their historical track record is too short to estimate probabilistic forecast value. Moreover, as we demonstrate below, subjective probabilities developed on the basis of past operating experience with forecasts are in principle closely related to decisions made under probabilistic forecasts. Hence, the goal of this study is not to estimate the value of probabilistic forecasts per se but the value of existing forecasts and potential improvements in forecasting accuracy.

To accomplish this goal, this report develops a framework for estimating the incremental improvements in economic efficiency from more accurate hurricane forecasts. These gains would constitute the social benefits that would flow from any public investments to improve forecasting infrastructure, including observation and modeling systems and basic research. This study, therefore, could shed light upon the rate of return from these public investments. There is general public concern and interest in developing more accurate forecasts of hurricanes with a longer lead-time. Computational and observational systems to improve forecast accuracy are under development. Although this study represents only one sector affected by hurricane forecast information, establishing the general order of magnitude for the marginal benefits from improving forecast information could provide the basis for extensions to other sectors of the economy affected by hurricane hazards.

Like any good or service, the value of information reflects marginal utility. Since the value of weather forecast information is often difficult to observe, an indirect approach is necessary that involves calculation of an agent's utility with and without the forecast information. For example, baseline utility for a hurricane rig manager is the utility, measured in terms of net cost or profit, from using no forecast information. In this case, the rig manager could simply use historical probabilities of hurricane strikes at the rig location or simply ignore probabilities altogether. The utility from using a government or private sector forecast would presumably provide him with more information, which if reasonably more accurate than the baseline information, would allow him to make more timely and efficient decisions.[1]

Katz and Murphy (1997) note that most empirical estimates of the value of climate information utilize *prescriptive* rules on how decision makers ought to behave under uncertainty. Previous forecast valuation studies adopting this approach include harvest timing (Lave, 1963; Wilks et al., 1993), prevention of rain damage (Kolb and Rapp, 1962), orchard heating during frost conditions (Baquet et al., 1976; Katz et al., 1982), and irrigations decisions (Rogers and Elliot, 1988). While the paper by Epps (1997) establishes some rough estimates of the value of hurricane forecasts to energy producers, there are no studies that carefully measure forecast accuracy and the costs and losses associated with hurricane evacuation decisions with and without forecast information.

These prescriptive rules assume agents maximize expected utility with a linear utility function. For rather small changes in wealth, a linear utility function is a reasonable approximation. Estimates of forecast value also may change under alternatives to the expected utility hypothesis, such as those suggested by prospect theory. Schultze, et al. (1990), however, note that these departures are more likely for very low probability events and that for events with probabilities over 10% the expected utility hypothesis accurately describes decision-making.[2] Moreover, for our problem, the costs of rig evacuations and production disruptions are a small fraction of total industry costs. Nevertheless, the analysis below examines the effect of risk aversion in the form of higher expected losses on forecast value.

The lack of empirical verification of decision models used to estimate forecast value is a deficiency in the literature. Indeed, there are very few if any descriptive models of the real behavior of agents facing natural hazards. As a result, this study develops a discrete choice model of drilling rig evacuation decisions in Chapter VI.

[1] These forecasts could be multidimensional including forecasts of the track and intensity of a hurricane, derived from advanced numerical forecasting models using a sophisticated weather observation network.

[2] The findings in Chapter VI suggest that the expected utility hypothesis is consistent for more than 75% of evacuations.

ENERGY PRODUCTION AND HURRICANES

Offshore producers of crude oil and natural gas in the Gulf of Mexico (GOM) are literally on the frontlines of hurricane hazards. The impacts of hurricanes on oil and gas producers can be considerable. For example, Hurricane Andrew in 1992 destroyed 13 offshore oil and gas production platforms, four of which disappeared without a trace. Another 40 platforms were damaged and 5% of the natural gas supply in the United States was temporarily lost.

Once referred to as the "Dead Sea" by oil and gas drillers, the Gulf of Mexico is now one of the most promising prospects in North America. The GOM now produces about 5.1 trillion cubic feet of natural gas per year and more than 1.2 million barrels of crude oil per day, representing nearly 27 and 21 percent of total U.S. production respectively. The oil and gas infrastructure in the Gulf of Mexico is substantial with 6,400 producing wells, 4,000 active platforms, and 29,000 miles of pipelines.

Depending upon market prices, the consensus for future development is reasonably bright. Most of this optimism arises from the emergence of the Gulf of Mexico as a world-class deepwater exploration area. During the late 1990s several giant size fields with greater than 400 million barrels of oil were discovered. Moreover, the pace for discovery of significant fields over 100 million barrels of oil also increased. Contrary to expectations, substantial, high quality reserves have been discovered in deep water. As a result, the Minerals Management Service (1999) predicts significant increases in production over the next four years, almost entirely from deep water tracts that are particularly vulnerable to storm events. The value of hurricane forecast information; therefore, will likely rise in the future with this increased production activity.

Offshore energy producers must make two decisions when confronting the threat of a hurricane; one affecting the current flow of hydrocarbons from producing fields and the other involving drilling operations supporting exploration and development in new lease areas. Energy producers often shut-in or close wellhead valves during hurricanes. In this case, if the rig is destroyed, no hydrocarbons will escape from the well. For manned production platforms, evacuation also would occur with the shut-in decision, which would prevent any loss of life. Under these circumstances, production is not lost but simply deferred. These temporary reductions in energy production during hurricanes are illustrated for crude oil in Figure 1.1, which clearly indicates sharp reductions in crude oil production during the hurricanes.

In addition to current production, oil companies explore and develop new fields. Oil companies lease oil and gas exploration and production rights from the Minerals Management Service (MMS) of the U.S. federal government. A typical offshore lease block in the Gulf of Mexico is nine square miles. Once a lease is acquired, the oil company first drills exploration wells. If economic hydrocarbons are discovered, the lease is developed with additional so-called production wells. Production facilities needed to produce and manage the flow of hydrocarbons from the subsurface to the pipeline are typically installed on a platform. The size of the platform varies with the quantity and type of reserves discovered. Exploration and development drilling operations occur either on mobile offshore drilling units (MODUs) or directly on the production platform with a modular rig (platform rig), which is temporarily installed on the platform. Exploration wells are typically drilled in open water, while production

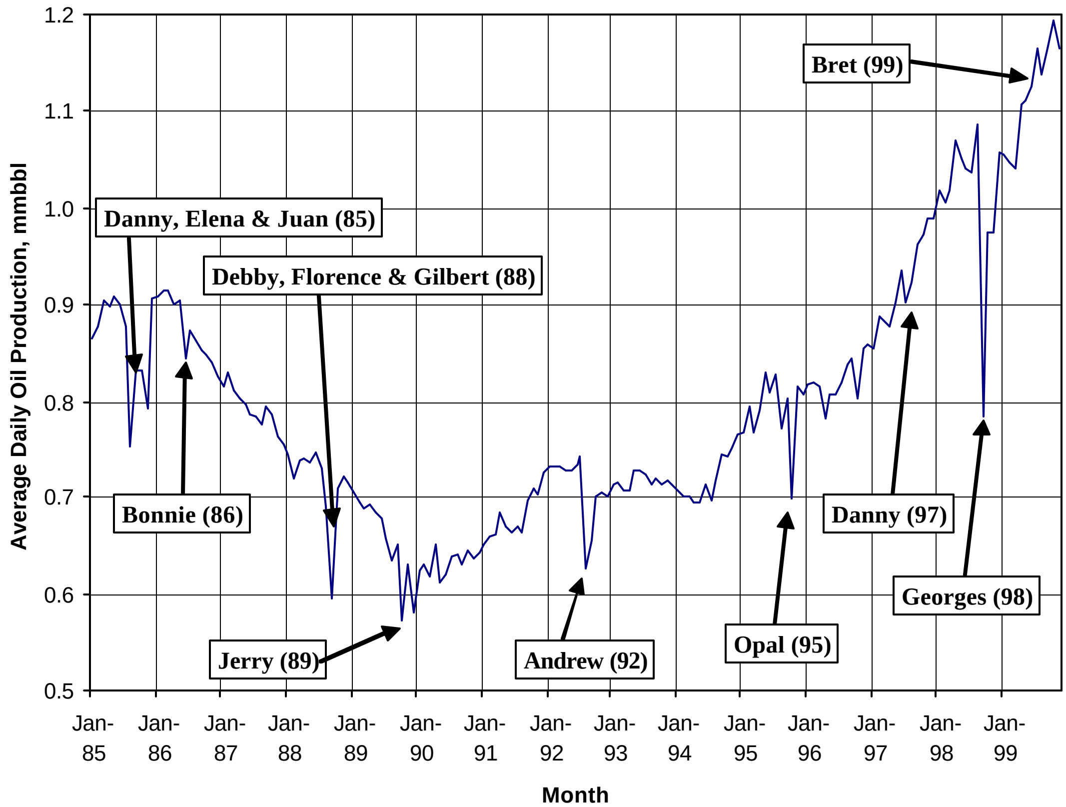


Figure 1.1: Average Daily Oil Production in the Gulf of Mexico, 1984-1999

wells are typically drilled over a platform. On average, 233 drilling rigs operate in the Gulf of Mexico in any given year between 1995 and 1998 (see Table 1.1).

Table 1.1: Number of active rigs by type

Rig Type	***1995***	***1996***	***1997***	***1998***
Jack-ups	110	115	115	74
Platform	18	19	25	16
Semi -submersible	28	34	33	39
Barge	45	54	46	27
Platform	35	41	36	21
Total	236	263	255	177

Source: *Offshore Data Services*

Oil companies engage the services of a drilling contractor who owns the drilling rig and employs and manages the drilling crew. These companies also coordinate other subcontractors who perform specialty services. When a hurricane threat looms, both the drilling contractor and the oil company jointly decide whether or not to evacuate the drilling rig. Most drilling rigs are rated to withstand approximately 100-knot winds. If winds exceed this rating, severe damage, complete loss, or both are possible. In fact, an average of one percent of the Gulf of Mexico drilling fleet is lost per year due to hurricanes. Any personnel remaining on board during a hurricane would be subject to this catastrophic risk. The oil company controls all modes of transportation to and from the rig and is, therefore, responsible for personnel safety and would likely incur a large financial loss if the entire crew were lost from failure to evacuate. Even if the oil company and/or drilling contractor carried general liability insurance, deductibles are often quite large, often in the tens of millions of dollars. Also, failure to evacuate could be construed by the insurer as negligence and grounds for refusal to pay for any losses. Beyond such direct economic considerations, the ethical and operating guidelines of oil companies mandate that protection of workers is paramount. These considerations strongly imply that the burden is clearly put on decision makers to avert personal injuries and deaths.

The oil and gas lease areas in the Gulf of Mexico and some selected hurricane tracks are displayed in Figure 1.2. The producing areas are extend from the western panhandle of Florida, around the coast of Alabama and Louisiana and to the barrier islands in southern Texas. Drilling is now occurring approximately 200 miles offshore.

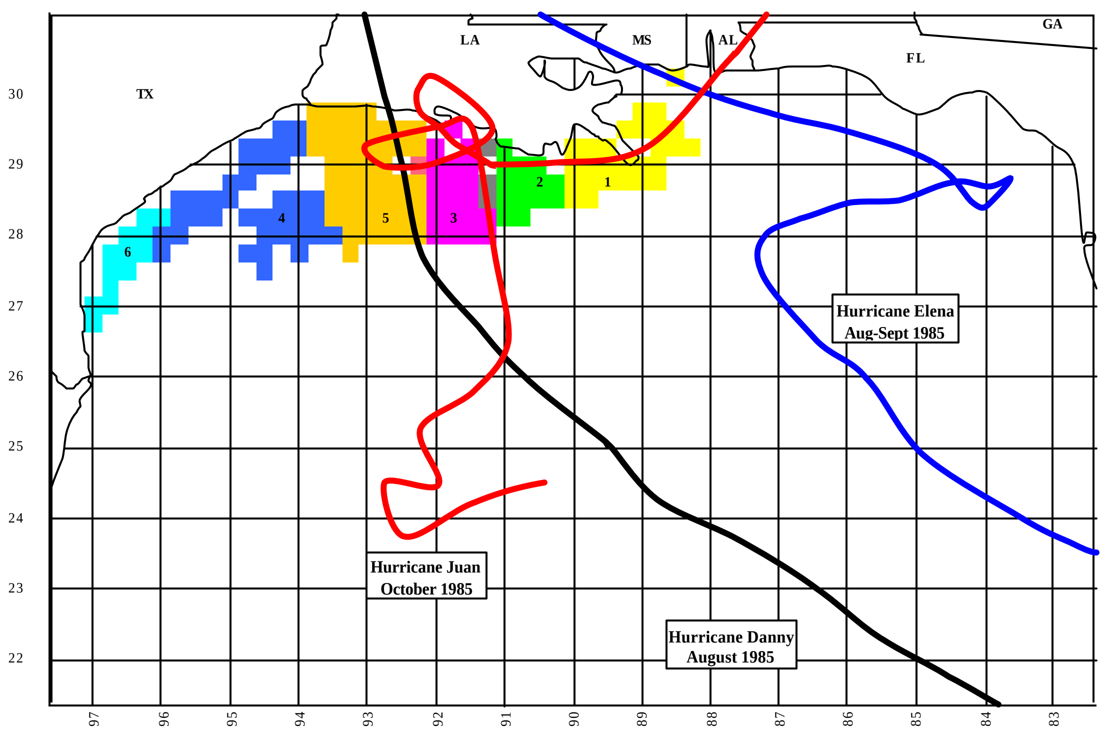


Figure 1.2: Oil and gas lease areas in the Gulf of Mexico and selected hurricane tracks

Oil and gas production by MMS region are plotted from 1990 to 1999 in the following two figures. MMS region 1 is the largest producer of crude oil with production reaching nearly 600,000 barrels per day in 1999 (see Figure 1.3). MMS region 2 is the next largest producer of crude oil with more than 300,000 barrels per day. The Texas Gulf coast region produces considerably smaller amounts of crude oil. In contrast, MMS region 5 off the mid Texas coast is the largest producer of natural gas until it was surpassed by MMS regions 1 and 3 in 1999 (see Figure 1.4).

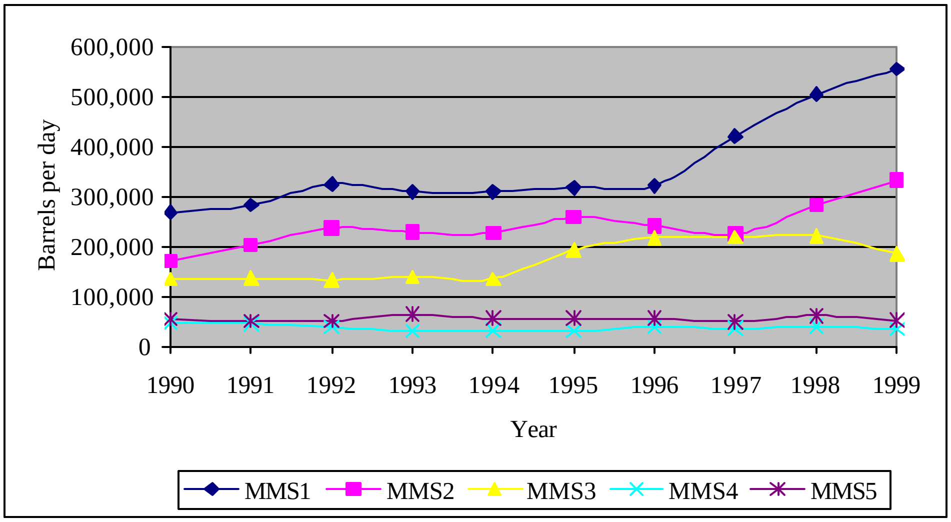


Figure 1.3: Crude oil production by MMS region in GoM

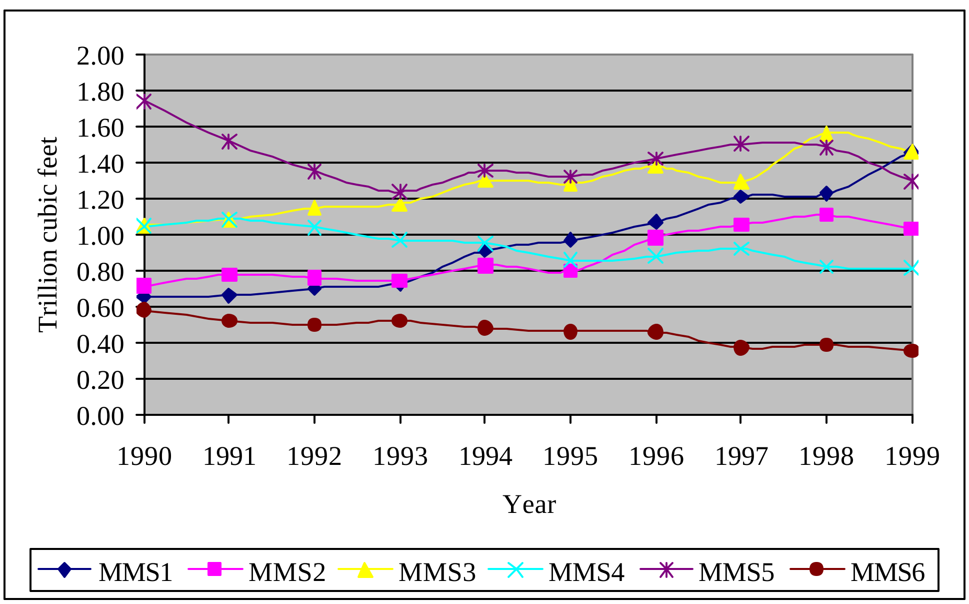


Figure 1.4: Natural gas production by MMS region in GoM

During the hurricane season from June through October, decision makers pay increased attention to weather developments. Drilling rig managers are normally equipped with sufficient technology to track hurricanes and to gather public forecast information. Some oil companies also retain private forecasters to develop additional storm development scenarios or customized forecasts. Prudent operators are keenly aware of the time required to safely secure the well and equipment, and to evacuate the rig, which may take days. We refer to this time requirement as the safe evacuation time (SET). The SET is a variable that is a function of the type of drilling rig, its location, features and progress of the well, and perhaps attributes of the decision makers. The fact that the SET is positive forces an evacuation decision to be made long before hurricane conditions would be present at the drilling location. Hence, if the hurricane changes course or does not intensify, an evacuation may be deemed a false alarm ex post. The SET is continually updated based on drilling progress and is ever present in the minds of decision makers.

Prior to evacuation, the well must be secured. This entails setting a cement plug over all open-hole sections bearing hydrocarbons. A plug also must be set at the base of the last installed casing string. At the surface, the procedures depend on the specific configuration of the wellhead and blowout prevention devices. Drilling and rig equipment must also be secured. Drill pipe must be laid down from the derrick, traveling equipment and crane booms must be tied down, hatches and windows must be closed, and the air gap (distance between the bottom of the drilling rig and the water line) may need to be adjusted. These procedures take time, and thus must be initiated many hours before the rig is evacuated. In deepwater locations where a drilling riser is in use, the retrieval of the riser itself may add as much as much as two to three days to the SET.

While the well is being secured, transportation must be arranged. This may be in the form of marine or air transportation. This process is complicated by two factors. First, other drilling rigs and production platforms are making similar arrangements, and there is a mild competition for limited transportation resources. Second, evacuation must occur before seas are too rough and/or wind speeds do not exceed safety margins for helicopters, about 50 knots for the largest helicopters typically used in the Gulf of Mexico. These two conditions occur well before hurricane conditions would be expected at the drilling location. These features of offshore logistics also affect the safe evacuation time.

When the rig is operating under a hurricane threat, weather becomes a critical component of the daily management routine. Current position coordinates, wind speed and pressure at the eye of the hurricane are available from the National Hurricane Center (NHC) every six hours. This raw data is valuable to decision makers, as it allows them to plot the track and speed of the storm, and thus to estimate the distance of the hurricane (in time) to the drilling rig. The NHC also generates 12, 24, 36, 48, and 72-hour forecasts. For each of these forecast types, the NHC provides iso-velocity contour lines for 50 knot and 64-knot winds in each quadrant (NE, SE, SW, and NW) relative to the eye of the hurricane. Decision makers evaluate the raw data and the forecasts along with the SET to optimize drilling operations and their evacuation decisions.

Plans for operations are continually evaluated against the likelihood that an evacuation will occur. The drilling contractor and the oil company managers work together to optimize rig operations under the weather constraint, and to structure operations to minimize the SET (*e.g.* maintaining a minimum of drill pipe in the derrick). Longer duration operations are unlikely to be initiated. Under a hurricane threat, managers often meet several times per day to discuss the progress of the storm, drilling operations, and evacuation contingencies.

AN OVERVIEW OF THE REPORT

This report provides a detailed description of the procedures used to quantify the uncertainties these energy company decision makers face and the estimation of costs and losses that their decisions entail. The report contains seven chapters. The decision model used to value forecast information then follows in the following Chapter. Our empirical analysis requires estimates of the probabilities of various combinations of forecasts and states of nature, which are developed in Chapter 3 with an analysis of hurricane-forecast accuracy for each oil and gas lease area in the Gulf of Mexico over the last 20 years. The costs and losses of preventive action, including evacuating drilling rigs and shutting in production and the losses from failure to act appear in Chapter 4. Chapter 5 of the report presents our estimates of forecast value under a range of different estimates of potential losses and forecast accuracy scenarios. A preliminary descriptive model of hurricane evacuation decisions is developed in Chapter 6. The report concludes with summary of our main findings and some suggestions for additional research.

CHAPTER II. CONCEPTUAL FRAMEWORK

Researchers using decision science have estimated the value of forecast information, in many cases for agricultural production. No studies have been completed estimating the value of weather forecast information to the energy sector. While the value of weather and climate forecasts to the natural gas and electric utility sectors probably dwarf the value of hurricane forecast information to the oil and gas industry, our focus on hurricanes is a good starting point because the decision is a seemingly simple, not encumbered by many possible actions with complex dynamic trade-offs.

The next section develops the traditional static cost-loss framework for our problem, assuming decision makers maximize expected utility with a linear utility function. This is the prescriptive approach referred to above. This approach requires estimates of the losses from the natural hazard with no preventive action taken, the costs of actions to prevent these losses, and the probabilities of various combinations of forecasts and states of nature. A descriptive model of actual evacuation decisions is developed in Chapter VI.

SOME GENERAL CONSIDERATIONS

Many classical market equilibrium models assume information is a free good with zero processing and assimilation costs. While there is considerable public information on weather and climate conditions and forecasts, the capability and incentives for assimilating this information to improve decision-making are not well established. Understanding how public officials and firms process climate information for decision-making has been the focus of several recent studies, many specifically directed to understanding the value of seasonal climate forecasts, such as the southern oscillation known as El Nino.

Most of these studies are based upon the economic theory of information developed by Marschak (1954) , Radner (1959), Lave (1963), and Nelson and Winter (1963) among others. The framework considers a single decision maker that must select one action, a, perhaps among several alternatives, A, to maximize utility, which depends in some known manner on the consequences, $c(a,w)$ associated with possible actions and an actual state of nature, w, among many possible states, W. This specification assumes that the decision maker's utility function provides a ranking of the possible consequences of each action. More formally, this problem can be stated as follows:

$$\max_a U\left[c\,(a,w)\right] \quad a\in A \,\&\, w\in W \tag{1}$$

The true state of the nature is not known prior to the decision; hence, the problem involves maximizing utility subject to the stochastic variable, w. This uncertainty is represented by subjective probabilities for realizing each of the various states of nature, denoted as p_w, that have a known prior probability distribution. These subjective probabilities could be formed on the basis of historical or climatological information that could be modified using forecast information. The utility maximization problem then becomes:

$$\max_a E_w\left\{U\left[c\left(a,\int_w f(w)\,dw\right)\right]\right\} \approx \max_a\left\{\sum_w p_w U\left[c\,(a,w)\right]\right\} \qquad (2)$$

If the decision maker is risk neutral, marginal utility is constant for any level of income or expenditure and this problem is equivalent to maximizing expected profit.

Observational or forecast information can modify the decision maker's subjective probability distribution. There are several ways of characterizing or quantifying the uncertainty around the event, including the use of climatological probabilities or Bayesian or subjective prior probabilities. The decision maker does not know in advance what the forecast will be For example, Nelson and Winter (1963) introduce a "message" or forecast, y, about a weather event among many possible messages, Y. They assume that the joint distribution of these messages and the possible events, $p\,(y,w)$, is known to the decision maker. So given this additional information, the decision maker will maximize expected utility conditional upon the message:

$$\max_a U\left[c\,\left(a, E_w\int p\,(w|\,y)\,dw\right)\right] \qquad (3)$$

This expected utility maximization problem simply says that the decision maker attempts to find an optimal action to maximize the utility of a consequence from that action given a forecast and the associated conditional expectation of weather conditions.

Responses to weather forecasts are often discrete decisions, such as evacuating or not. Now consider a different expression of the utility function in which utility is expressed as a function of wealth and re-define a general form of utility function, U(W; s, e), where s represents attributes of the decision maker, and e is a random component of utility. If we assume additively separable errors, we can write the utility function as U(W; s) + e. Under the assumption of utility maximization, the decision maker would undertake an evacuation if the utility from evacuating is greater than the expected utility of not acting to evacuate or:

$$\mathrm{U}(\text{W-C,s}) + e_1 > p\mathrm{U}(\text{W-L,s}) + (1-p)\,\mathrm{U}(\text{W,s}) + e_2 \qquad (4)$$

where, W is a measure of wealth, C is evacuation cost, p is the probability of a hit, and L is the loss given a hit. Finally, if we assume that the e_i are independent variates from an extreme value distributed (McFadden, 1974; Maddala, 1983), the probability of observing an evacuation, a, is:

$$\Pr(a) = 1\Big/\left(1+e^{-q}\right) \qquad (5)$$

where $q = \mathrm{U}(\text{W-C,s}) - \left[p\mathrm{U}(\text{W-L,s}) + (1-p)\,\mathrm{U}(\text{W,s}) \right]$. This simple model of evacuation probabilities forms the basis for the econometric model of evacuation decisions developed in Chapter VI. Given a mathematical approximation of the utility function and estimates of the costs, losses, and strike probabilities, the parameters of the utility function can be estimated with maximum likelihood estimation. These parameters allow one to estimate the marginal effect that characteristics of the decision maker may have on the probability of evacuation and his revealed degree of risk aversion.

Such a descriptive model while very appealing is not without complications, particularly the difficulty of observing evacuation decisions and measuring the factors – economic, engineering, and meteorological – that affect these decisions. The traditional cost-loss framework for forecast valuation, while assuming risk neutrality and a linear utility function does not require these stringent observational requirements and may be an appropriate approximation for many problems. Nevertheless, given the importance of understanding the utility of meteorological forecasts, we develop such a descriptive model below in Chapter VI.

THE TRADITIONAL COST-LOSS FRAMEWORK

A model of the hurricane hazard decision process can be developed from the cost-loss framework developed by Nelson and Winter (1964) and Katz and Murphy (1997). The decision process for shutting-in production and evacuating drilling rigs are conceptually the same, only the costs and potential losses differ. Hence, to simplify this section, we focus on the evacuation decision for a single rig manager at any arbitrary point in time.

In making this decision, the manager must balance the loss incurred if the rig is not evacuated, L, with the cost of evacuation, C. Following convention in the literature, our analysis assumes $C < L$ to avoid a trivial solution. In addition to the loss of the rig itself, a manned rig destroyed by a hurricane could entail considerable loss of human life. Oil and gas companies utilize both public and private information in making these decisions.

Consider that the manager receives a public probabilistic forecast of a hurricane, p, in which the rig is projected to be somewhere within a strike area identified by the National Hurricane Center forecast. Many companies purchase private weather services that translate this public information into a forecast of weather conditions important to the rig operator at the drilling location, such as wind speed and wave height, designated by z. Assume that private forecasts are based in part upon information provided by government forecasters. Hence, the expectation of z is conditional upon the probabilistic forecast of a hurricane strike made by the government and private information, f. Denote this private forecast as $E\left[z|p, f\right]$.

The decision rule for the manager is to evacuate if the expected weather conditions exceed some critical threshold, z_c. The use of a critical threshold is similar to the adaptation of this framework by Howe and Cochrane (1976) in their study of snowstorm hazards. This threshold would be a function of the design parameters of the rigs, such as its tolerance for wind speed and wave height. The decision to evacuate, $v = 1$, is discrete, dependent upon whether $E\{z|p, f\}$ exceeds z_c:

$$v = 1 \quad \text{if} \quad E\{z|p, f\} \geq z_c$$
$$v = 0 \quad \text{if} \quad E\{z|p, f\} < z_c.$$

The expected utility, in terms of minimizing cost or disutility, of the evacuation decision using only historical information is

$$V_0 = E\left\{U\left(\hat{v} \middle| E\left[z|p^1\right] \geq z_c\right)\right\} = \min\left(C, p^1 L\right), \tag{6}$$

where p^1 is the unconditional, historical probability of hurricane conditions exceeding the critical threshold. The value function, V_0, is the value of the evacuation decision based upon historical information alone. The above equation represents a set of simple decision rules in which the optimal action, $\hat{v}$, is equal to one (evacuate) if $C < p^1 L$ or the optimal action is to remain if the cost of evacuation is greater than the expected loss, or $\hat{v} = 0$ when $C > p^1 L$. The implicit assumption in equation (1) is that the decision maker is risk neutral and utility is linear, which may be a reasonable local approximation when costs and losses are a relatively small fraction of firm value or wealth.

Now consider the value of this decision under two possible forecasts. If the rig manager receives a forecast that weather conditions will equal or exceed rig tolerance, $E\{z|p, f\} \geq z_c$, his cost if he chooses to evacuate is C, while his expected loss if he chooses not to is $p_{11}L$, where p_{11} is the probability that weather conditions will exceed z_c given this forecast. This conditional probability can be calculated from the joint probability density function of forecasts and destructive weather conditions. Hence, the expected utility given this forecast is:

$$E\left\{U\left(\hat{v} \middle| E\left[z|p_{11}, f\right] \geq z_c\right)\right\} = \min\left(C, p_{11} L\right). \tag{7}$$

The second forecast is an all clear. In this case, he makes his decision depending on whether C or $p_{12}L$ is smaller, where p_{12} is the probability of this forecast being wrong, i.e., the odds of conditions exceeding z_c when the forecast suggests otherwise. In this case, expected utility is:

$$E\left\{U\left(\hat{v} \middle| E\left[z|p_{12}, f\right] < z_c\right)\right\} = \min\left(C, p_{12} L\right). \tag{8}$$

The expected utility of both possible types of forecasts is simply a weighted average of the two forecast:

$$V_1 = E\{U\} = p_1 \min(C, p_{11}L) + (1-p_1)\min(C, p_{12}L), \tag{9}$$

where the weight, p_1, is the probability of a forecast of destructive conditions. Katz and Murphy (1997) note that p_{11} and p_{12} are the Bayesian posterior probabilities, in this case, of destructive hurricane conditions.

As Nelson and Winter (1964) and Katz and Murphy (1997) demonstrate, the ratio of costs to losses is a critical parameter in determining the value of forecasts. In the absence of forecast information, evacuation occurs if $C < p^1L$ and evacuation does not occur when $C > p^1L$. In other words, if $C/L < p^1$ the rig manager would always evacuate because expected losses always exceed evacuation costs. Similarly, if expected losses are always less than evacuation costs, $C/L > p^1$ and the rig manager would never evacuate.

Similar rules apply when the decision maker uses subjective probabilities made on the basis of a weather forecast. If the decision maker knows the historical probabilities favor evacuation, or $C < p^1L$ and he receives an all-clear forecast such that evacuation costs remain less than expected losses, which in this case is the probability of the no strike forecast being incorrect, or $C < p_{12}L$, then his evacuation decision would not change. Only if evacuation costs were greater than expected losses under the all clear forecast, $C > p_{12}L$, would the rig manager reverse this decision to evacuate. For the other case, the rig manager does not evacuate if evacuation costs exceed expected losses under the storm forecast, $C > p_{11}L$. In this case, only if the conditional probability of a strike given a strike forecast, p_{11}, implies evacuation costs are less than expected losses given this forecast, $C < p_{11}L$, would the hit forecast change his decision. Therefore, forecasts only have value when $p_{12}L < C < p_{11}L$, or $p_{12} < C/L < p_{11}$. As Katz and Murphy observe, a forecast may have value for one decision but not for another decision depending upon the cost-loss ratio. If the cost-loss ratio falls in this range, then equation (9) simplifies to:

$$E\{V_1\} = p_1C + (1-p_1)p_{12}L, \tag{10}$$

which is the expected value of decisions using forecasts when they have value. This expected value is zero if the cost-loss ratio falls outside the value range given above.

To estimate the value of current hurricane forecasts we must compare the expected value given by (6) with the expected value using historical frequencies (9). Thus, the saving in expected cost that the forecast makes possible is given by:

$$V\{p, f\} = V_0 - V_1 = \min(C, p^1L) - p_1C - p_2p_{12}L, \tag{11}$$

Given the first minimum value function using historical information, this function implies:

$$V\{p,f\} = \begin{cases} p_2\left(C - p_{12}L\right) & if \quad \mathrm{C/L} \le p^1 \\ \\ p_1\left(p_{11}L - C\right) & if \quad \mathrm{C/L} > p^1 \end{cases}, \qquad (12)$$

where the expression associated with the second inequality uses the identity linking historical probabilities to the weighted average of conditional probabilities, $p^1 = p_1 p_{11} + p_2 p_{12}$. Improvements in forecasts would reduce the frequencies of incorrect forecasts. A perfect forecasting system would forecast favorable operating conditions $\left(1 - p^1\right)$ percent of the time and the forecasts would always be correct, i.e., $p_{12} = 0$.

This discussion clearly illustrates that estimation of the value of hurricane forecasts requires three key pieces of information, historical and conditional probabilities, costs of acting to evacuate drilling rigs and shut-in production, and the potential losses from inaction. The next chapter describes our analysis to estimate the relevant probabilities. Costs and losses of actions and inaction are discussed in Chapter V.

CHAPTER III. HURRICANE FORECAST ACCURACY

Estimating the value of hurricane forecasts and improvements in forecast accuracy requires the elucidation of the relationships between hurricane forecasts and actual storm events, which permits measurement of forecast accuracy. Previous studies of forecasting accuracy generally focus on hurricane landfalls. Our area of interest, however, is at sea, specifically for thousands of oil and gas leasing locations at six-hour intervals during the progression of many individual storm events. This level of spatial and temporal detail complicates our analysis considerably but provides a large and unique dataset to measure and evaluate hurricane forecasts.

The analysis presented in this chapter provides the basis for developing this database, calculating the probabilities of hurricane forecasts and the conditional probabilities of hurricane conditions given a forecast of a hurricane, or the Bayesian probabilities discussed above. With costs of taking preventative measures, and the losses associated with inaccurate forecasts, one is able to assign a value to the forecasts.

The next section of this chapter describes the basic features of our data on storm events and forecasts at oil and gas production and drilling locations in the Gulf of Mexico since 1980. A description of our procedures for comparing storm events with forecasts at specific production locations constitutes the second section of this chapter. The final section reports the results of applying these procedures to our database. Our study provides the basis for estimating the two-by-two probability matrix above for every oil and gas lease in the Gulf of Mexico from 1980 to 2000. Although the spatial level of detail is suppressed at this stage, our analysis provides summary measure of forecast accuracy over time, allowing us to estimate the improvement in forecast accuracy over time.

DATA TYPES

This study requires three principal inputs: data concerning the location, size and intensity of hurricanes and gale-force storms in the Gulf of Mexico (GoM); the records of all forecasts of storm location, extent and intensity; and geographical data concerning the location of oil and gas lease blocks in the GoM producing region.

Storm Data

A history of all North Atlantic tropical storms for the period 1980-2000 was obtained from the archives of the National Hurricane Center. The variables included in this data set are as follows:

- **Storm location**: the post-event best estimate of the center of the eye of the storm, in degrees of longitude and latitude.

- **Peak wind speed**: the top sustained wind speed at the wall of the eye of the storm, as observed by measurement from NOAA flights, satellite radar and ground and airborne sensor observations, measured in knots.

- **Size parameters**: The National Hurricane Center describes the size of a storm by using what are referred to as "size parameters". A storm is viewed from above as being composed of four 90^o circular segments, or "pie slices". A size parameter is simply the distance, in nautical miles, from the center of the storm to a line of constant wind velocity, in each of four different directions (NE, NW, SE, and SW).

Typically there were three sets of observations: the distances from the center to the line of 34 knot winds, signifying the extent of tropical-storm force winds, the distances to the line of 50 knot winds, specifying gale-force winds, and the distances to the arcs of 64 knot winds, signifying Category 1 hurricane force winds. The extent of a typical storm is shown in Figure 1, below. Each of the four arcs describes a line of constant wind velocity, or a wind speed contour. Assuming the storm in Figure 1 is a 50-knot (gale force) storm, then the four arcs each describes the line of 50-knot winds. At every location between one of the arcs and the storm center, the wind speed is greater than 50 knots. At all locations outside the arcs, the wind velocity is below 50 knots. On the four arcs the speed is assumed to be 50 knots.

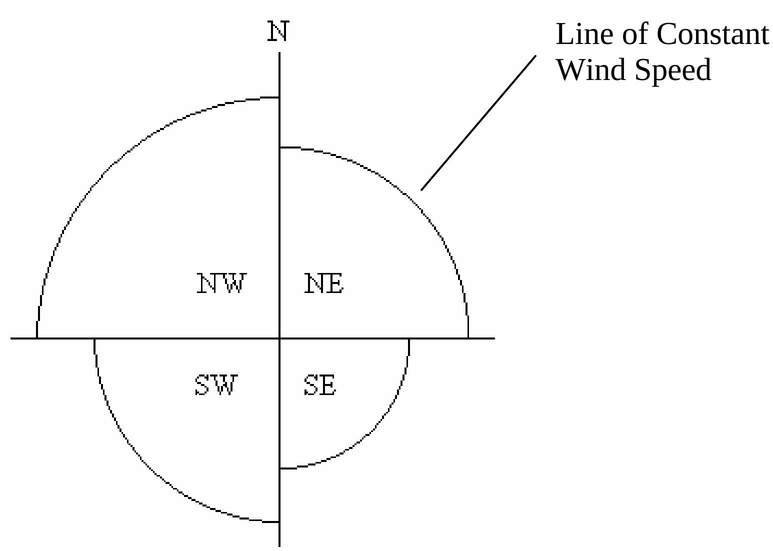


Figure 3.1: Idealized storm structure

As can be seen the storm illustrated in Figure 3.1 extends mostly to the northwest. Obviously, this is a simplification of the actual shape and size of a typical tropical storm, but it is an abstraction that is necessary to enable computation of storm extent.

Forecast Data

Forecast data for a similar period were obtained from archives located at the NHC FTP website. The forecast data contained similar data as described in the storm data section, as well as one other piece of information: the span of the forecast; that is, the time into the future for which the forecast is made. This study examines the five common forecast spans issued by the NHC: 12, 24, 36, 48 and 72 hours.

These forecasts are typically issued as parts of Marine Forecast Advisories (MFA). A sample MFA from 2000 is displayed in Appendix A of this report. MFA's are typically issued four times daily (at 0300, 0900, 1500 and 2100 UTC) at any time that a tropical storm is in existence in the North Atlantic basin. It contains descriptive warnings about coming storm conditions, as well as numerical forecasts.

Lease data

The GoM oil and gas production region is mapped into a set of blocks by the US Minerals Management Service (MMS). This has been done for the purpose of assigning oil and gas drilling and production rights for parts of the GoM to companies. Most of these blocks are approximately three by three mile squares. Boundaries and center-points of each of these lease blocks were downloaded from the MMS website.

The blocks extend from the Gulf coast of Florida in the east to the Texas barrier islands in the west. The southern boundary is delineated in the west by the extension of the US-Mexico border (26 degrees latitude), and extends southward to below 24 degrees latitude in the eastern Gulf. The blocks extend northward to the Gulf coasts of Texas, Louisiana, Alabama and the Florida panhandle. Currently, there are 29,544 defined blocks.

DATA SORTING AND MANIPULATION

A significant amount of data manipulation is required before commencing calculations. All of the storm events and forecasts had to be matched into pairs; that is, each forecast had to be matched up with the observed storm events at the times for which the forecasts were made. Eight sets of storm-forecast pairs were complied: 50 kt size parameter forecasts were compiled for 12, 24, 36, 48 and 72-hour forecasts. 64 kt size parameter forecasts were compiled for 12, 24 and 36-hour storms. The yearly availability of forecast types is summarized in Table 3.1.

Table 3.1: Annual availability of forecast types

Forecast Span	50 kt Forecasts	64 kt Forecasts
12 hour	1980-2000	1995-2000
24 hour	1980-2000	1995-2000
36 hour	1988-2000	1995-2000
48 hour	1985-2000	Never
72 hour	1985-2000	Never

To facilitate the computation of distance errors, we converted the position data to three-dimensional Cartesian coordinates at location $i, (x_i, y_i, z_i)$, where

$$x_i = radius * \cos(longitude_i)\cos(latitude_i)$$
$$y_i = radius * \sin(longitude_i)\cos(latitude_i)$$
$$z_i = radius * \sin(latitude_i)$$

The distance between these two points $i \,\&\, j$, $d_{i,j}$, in nautical miles, is calculated using the following formula:

$$d_{i,j} = \sqrt{\left\{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2\right\}}\,.$$

The definitions and conventions used in these calculations are summarized in Table 3.2.

Table 3.2: Definitions and conventions for location coordinates

Coordinate System Origins:

Origin for Cartesian co-ordinate system = center of Earth.
Origin for Lat/Long: intersection of Prime Meridian and equator, in the Gulf of Guinea in the South Atlantic.
Radius of Earth: 3960 miles
3441 nautical miles
(0.86898 miles/nm)

Latitude & Longitude Conventions:

Latitudes are increasingly positive as one moves north, starting at 0^o at the equator, increasing to 90^o at the North Pole
Longitudes are increasingly positive as one moves west from the Prime Meridian.

Axis convention:

Positive x-axis: from center of Earth through lat/long origin.
Positive y-axis: from center of Earth through 0^o lat / 90^o long point (near the Galapagos Islands, directly South of New Orleans)
Positive z-axis: from center of Earth through North-pole.

An initial filtering of storm and forecast data was performed to include only data that were pertinent to the region under study. The eastern boundary defined for this study is 75 degrees longitude. All event-forecast pairs that were completely to the east of this line, which is approximately 300 miles east of Miami, were excluded from the analysis. Similarly, pairs completely south of the 15-degree latitude and completely north of the 35-degree latitude lines were also excluded. These lines correspond approximately to the extreme southern tip of Mexico, about 600 miles south of the Florida Keys, and the Tennessee-Georgia border, about 300 miles north of the Gulf Coast near New Orleans.

Not all forecasts are included in this study, for a couple of reasons. First, some forecasts were made for storms that no longer existed when the forecast time passed, that is, the storm had died out in the time between the issuing of the forecast and its effective date/time. If the storm was dead, the NHC did not issue an MFA, and did not track the storm position or intensity. Secondly, not all forecasts (and in some cases, not all verified storm event reports) contained size parameters. Some forecasts only contained peak speed and storm position estimates, and as such were not considered in this analysis. After compiling all available event-forecast pairs it was necessary to exclude those that lacked size parameter specifications. Table 3.3 summarizes the completeness of storm event and forecast data. The term "E-F Pairs" refers to event-forecast pairs

Table 3.3: Completeness of storm-forecast pairs

Forecast Type	Total Event Forecast Pairs	Incomplete Specified Events	Incomplete Specified Forecasts	Fully Specified E-F Pairs	% Fully Specified
12 hr, 50 kt	1193	104	30	1049	87.9%
12 hr, 64 kt	531	14	0	517	97.4%
24 hr, 50 kt	1119	96	68	972	86.9%
24 hr, 64 kt	507	14	0	493	97.2%
36 hr, 50 kt	741	45	4	692	93.4%
36 hr, 64 kt	485	13	0	472	97.3%
48 hr, 50 kt	751	49	7	696	92.7%
72 hr, 50 kt	620	44	6	570	91.9%

The second-rightmost column in Table 3.3 contains the final, workable number of pairs used for analysis. After the event-forecast pairs were fully prepared and filtered, they were divided up into separate spreadsheets, one for each year of each available forecast type. Thus, a total of 105 storm data input files were compiled.

The amount of blocks associated with these definitions created insurmountable computational burden. That is, attempting to model whether each storm was present at each of nearly 30,000 blocks overloaded the available software. Thus, we decided to create an aggregated model of the GoM region, using a grid with a spacing of 0.25 degrees. This equates to a 15 nautical mile north-south spacing, and an east-west spacing which varies from 13.7 nautical miles in the south of the region in question to 13.0 nautical miles in the north of the region. The resultant grid contains 1060 nodes.

A program was written in Time Series Processor (TSP) 4.4 code to calculate the accuracy of the forecasts for each fully-specified event-forecast pair, at each of the 1060 nodes on the grid. For each node, the program examines the actual storm event and forecast storm, and reports whether the node was under actual and/or forecast storm conditions at each given point in time. The program examines the distance and direction from the node to the storm center, and reports whether the node is inside or outside the appropriate directional size parameter, for both actual and forecast storms. The result is a binary: 1 if node *i* falls under actual or forecast storm conditions at time *t*, 0 otherwise.

This yields a pair of the form (m,n) where m and n are either 1 or 0. Each pair corresponds to one of the quadrants of an event-forecast matrix in Table 3.4.

Table 3.4: Event-forecast matrix

		Forecast Event	
		Hurricane (•, 1)	No Hurricane (•, 0)
Actual	Hurricane (1, •)	(1,1)	(1,0)
Event	No Hurricane (0, •)	(0,1)	(0,0)

For purposes of data compilation, it is inconvenient to store data in these two-by-two matrices, so the data are stored in tabular form, with each quadrant in the event-forecast matrix assigned a sector code. These sector codes and their descriptions are defined in Table 3.5.

Table 3.5 Codes in the event-forecast matrix

Event Forecast Pair	**Sector Code**	**Event-Forecast Description**
(1,1)	"a"	Storm was forecasted and occurred
(1,0)	"b"	Storm was forecasted, did not occur
(0,1)	"c"	Storm occurred, but was not forecast
(0,0)	"d"	Storm was not forecast, and did not occur
n/a	"e"	Location in question outside scope of forecast

The sector codes are graphically depicted in Figure 3.2, in which the actual and forecast storms are modeled as circular storms for the sake of illustrative ease.

Additionally, if a node is some large distance from the location of the forecast storm center, then the lease is assumed to be unaffected by the storm in question, and the result is assumed to be in quadrant "e", which is simply a proxy for "non-events". A criterion had to be established for deciding on the critical cutoff distance. For each of the forecast spans, the distance between the center of the actual storm event and the forecast location for each event-forecast pair was calculated. This is referred to as the track error. The track errors for the previous five years were tabulated from which the 95th percentile of these data was established. The 95th percentile was assumed to be the maximum margin of error. This was added to the largest of the available storm size parameters, to define a critical distance cutoff. If the distance between node *i* and the forecast location was greater than this cutoff distance, the node was taken to be outside the range of influence of the forecast, and thus the event-forecast couple was assigned to quadrant "e", and thus, classified as a non-event.

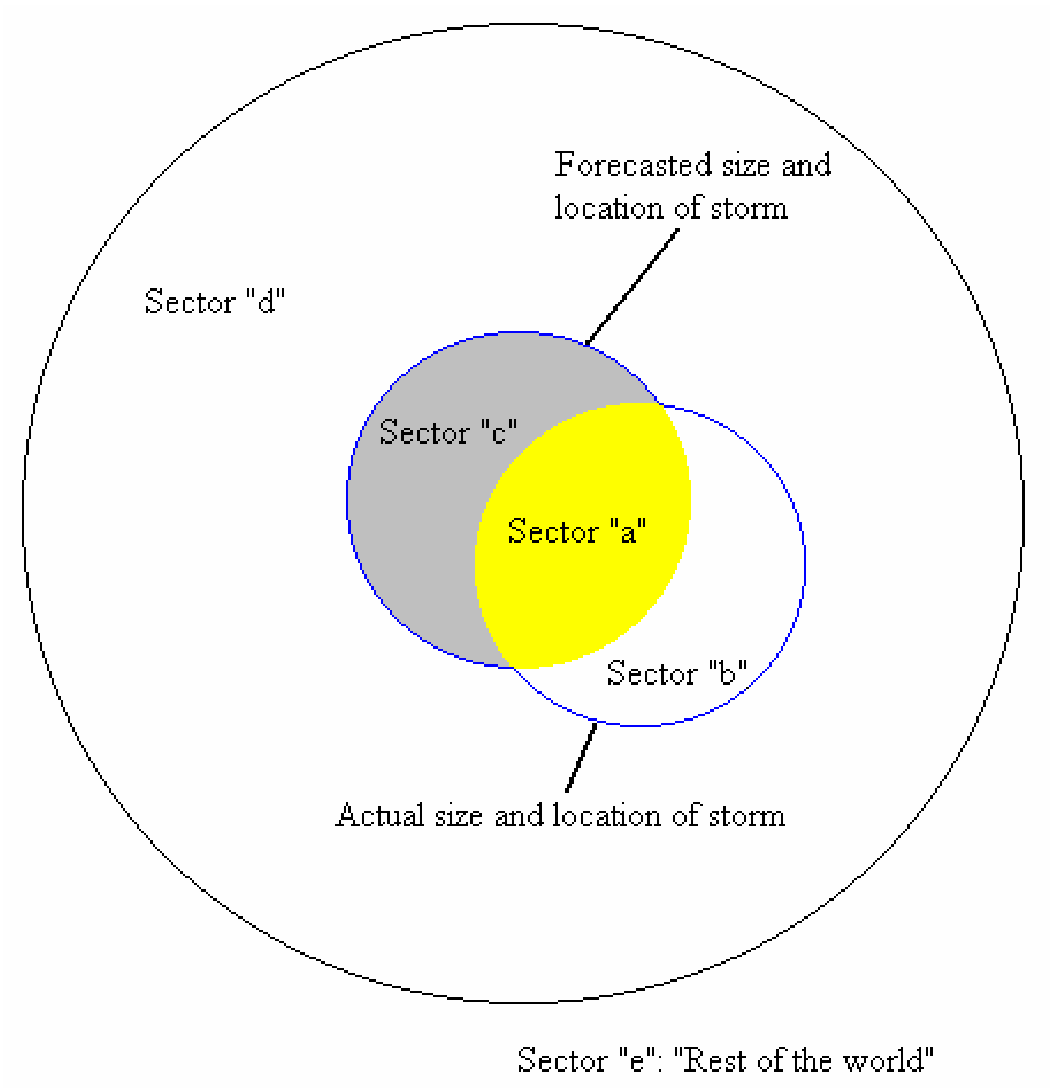


Figure 3.2: Definition of storm event-forecast sector codes

HURRICANE FORECAST ACCURACY

There are several different ways to measure hurricane forecast accuracy. This section provides several different measures for the105 output files that were generated, each containing six columns: the reference number of the node, and the five sector codes of the event-forecast matrix. A cumulative summary of these output files for the entire period in question is contained in Table 3.6, below. An annual breakdown of the distribution of sector codes can be found in the Appendix B of this report.

Table 3.6: Cumulative event-forecast matrix composition

Forecast Type	"a"	"b"	"c"	"d"	"e"
12 hr, 50 kt	6,241	3,814	3,687	57,170	1,041,028
12 hr, 64 kt	566	550	487	15,360	531,057
24 hr, 50 kt	3,413	6,667	4,870	137,767	1,032,363
24 hr, 64 kt	261	710	488	33,992	501,969
36 hr, 50 kt	1,209	2,761	2,321	128,589	598,640
36 hr, 64 kt	183	738	469	74,327	424,603
48 hr, 50 kt	1,631	6,019	4,388	251,255	474,467
72 hr, 50 kt	503	4,191	3,733	403,752	192,021

Binary Forecast Verification Measures

Several measures are used to measure the accuracy of binary forecasts. These are detailed as follows.

Critical Success Index (CSI)

This is defined as the correct number of "yes-yes", or quadrant "a" forecasts, divided by all forecasts except the correct "no-no", or quadrant "d" ones. This measure has values from zero to one, with higher values signifying greater accuracy. The observed CSI values are shown in Table 3.7. The CSI measures the accuracy of forecasts of low-

Table 3.7: Critical success index by forecast type, 1980 - 2000

	Forecast Type (Timespan - Windspeed)							
Year	**12-50**	**12-64**	**24-50**	**24-64**	**36-50**	**36-64**	**48-50**	**72-50**
1980	0.390		0.202					
1981	0.000		0.000					
1982	0.000		0.000					
1983	0.617		0.214					
1984	0.000		0.000					
1985	0.494		0.222				0.150	0.068
1986	0.141		0.045				0.000	0.000
1987	0.388		0.000				0.000	0.000
1988	0.471		0.185		0.144		0.115	0.041
1989	0.076		0.000		0.029		0.000	0.000
1990	0.114		0.000		0.000		0.000	
1991								
1992	0.453		0.334		0.209		0.038	0.008
1993							0.000	
1994	0.148		0.000		0.000		0.000	0.000
1995	0.456	0.392	0.215	0.020	0.118	0.000	0.074	0.017
1996	0.205	0.000	0.000	0.000	0.000		0.000	0.000
1997	0.218	0.071	0.069	0.000	0.000	0.000	0.000	0.000
1998	0.425	0.383	0.342	0.309	0.346	0.258	0.263	0.151
1999	0.320	0.029	0.100	0.023	0.025	0.000	0.000	0.000
2000	0.488	0.231	0.371	0.096	0.154	0.027	0.000	0.000

frequency events when said events are either forecast or occur, but ignores instances when they were neither forecasted or existing. It is symbolically defined as (a)/(a + b + c). It can be seen that while there are no discernable time trends, the CSI scores are higher in years when a large number of storms occur, such as 1985, 1988, 1992, 1995 and 1998

Probability of Detection (POD)

This is a measure of the likelihood that an event was forecasted, given that it occurred, or Probability(storm is forecast | storm occurred). Put in other words, it is the probability that a forecaster correctly foresaw the presence of a storm that occurred. Symbolically, this is calculated as a/(a + b). It also takes values between zero and one, and the more accurate the forecast the higher the value. The observed values are shown in Table 3.8. As can be seen, the POD decreases as the span of the forecast increases, and is smaller for 64-knot size parameters than for 50 knot. This is consistent, as the 64-knot contour will be smaller than the 50 knot one. Much like the CSI, the POD is greater in years with a larger number of hurricanes.

Table 3.8: Probability of detection by forecast type, 1980 - 2000

	Forecast Type (Timespan - Windspeed)							
Year	**12-50**	**12-64**	**24-50**	**24-64**	**36-50**	**36-64**	**48-50**	**72-50**
1980	0.600		0.328					
1981								
1982	0.000		0.000					
1983	0.701		0.236					
1984								
1985	0.649		0.316				0.218	0.117
1986	0.204		0.122					
1987	0.838		0.000				0.000	0.000
1988	0.659		0.341		0.297		0.273	0.159
1989	0.145		0.000		0.045		0.000	0.000
1990	0.211		0.000					
1991								
1992	0.592		0.448		0.313		0.062	0.011
1993								
1994	0.867		0.000		0.000		0.000	
1995	0.575	0.496	0.268	0.025	0.153	0.000	0.106	0.027
1996	0.243		0.000		0.000		0.000	0.000
1997	0.333	0.136	0.078	0.000	0.000	0.000	0.000	0.000
1998	0.625	0.563	0.527	0.497	0.520	0.420	0.379	0.205
1999	0.482	0.071	0.209	0.071	0.052	0.000	0.000	0.000
2000	0.693	0.293	0.604	0.171	0.308	0.042	0.000	0.000

False Alarm Rate (FAR)

This is the proportion of forecast events that fail to materialize, or the rate of "false positives", Pr (event did not occur | event was forecast to occur). It is calculated as c/(a + c). It takes values from zero to one, with a lower value accompanying a more accurate forecast. The detailed values are displayed in Table 3.9. False alarm rates are higher for 64-knot sized storms, as explained above. The rates increase as forecast range increases, and again are lower in busy hurricane years.

Table 3.9: False alarm rates by forecast type, 1980 - 2000

	Forecast Type (Timespan - Windspeed)							
Year	**12-50**	**12-64**	**24-50**	**24-64**	**36-50**	**36-64**	**48-50**	**72-50**
1980	0.474		0.655					
1981	1.000		1.000					
1982	1.000		1.000					
1983	0.164		0.306					
1984	1.000		1.000					
1985	0.326		0.572				0.677	0.860
1986	0.688		0.933				1.000	1.000
1987	0.581		1.000				1.000	
1988	0.378		0.711		0.780		0.833	0.948
1989	0.862		1.000		0.926		1.000	1.000
1990	0.800		1.000		1.000		1.000	
1991								
1992	0.340		0.433		0.614		0.911	0.974
1993							1.000	
1994	0.849		1.000		1.000		1.000	1.000
1995	0.311	0.349	0.478	0.905	0.658	1.000	0.803	0.954
1996	0.432	1.000	1.000	1.000	1.000		1.000	1.000
1997	0.614	0.870	0.625	1.000	1.000	1.000	1.000	1.000
1998	0.429	0.455	0.508	0.551	0.492	0.600	0.540	0.637
1999	0.512	0.955	0.839	0.968	0.955	1.000	1.000	1.000
2000	0.378	0.478	0.510	0.821	0.765	0.929	1.000	1.000

Forecast Bias (FB)

This is defined as the propensity for over- or under-forecasting of an event. It is defined as (a +c) / (a + b), which is equal to the total number of forecasts for a storm divided by the total number of storm occurrences. It can take any value between zero and positive infinity. If the measure is greater than one there is a bias towards over-forecasting of storms, whereas is it is less than one there is a tendency to under-forecasting. Forecast Bias is detailed in Table 3.10. Once again, it is important to look at busy hurricane years, such as 1980, 1983, 1985, 1988, 1995, 1998 and 2000 to get meaning from these results. In those later years where both size parameters are available we tend to see a lower bias for 64-knot storms. The bias tends to be lower than one in most of the busy years, with 1988 and 1998 being exceptions.

Table 3.10: Forecast bias by forecast type, 1980 – 2000

	Forecast Type (Timespan - Windspeed)							
Year	**12-50**	**12-64**	**24-50**	**24-64**	**36-50**	**36-64**	**48-50**	**72-50**
1980	1.140		0.950					
1981								
1982	6.000		13.000					
1983	0.839		0.340					
1984								
1985	0.963		0.738				0.674	0.835
1986	0.653		1.837					
1987	2.000		2.054				2.162	0.000
1988	1.059		1.180		1.351		1.636	3.047
1989	1.048		0.811		0.607		0.455	0.615
1990	1.053		1.222					
1991								
1992	0.896		0.790		0.812		0.693	0.428
1993								
1994	5.733		3.067		2.000		1.929	
1995	0.835	0.763	0.513	0.267	0.447	0.293	0.537	0.589
1996	0.427		0.519		0.759		1.329	0.820
1997	0.864	1.045	0.208	0.091	0.015	0.053	0.019	0.750
1998	1.096	1.031	1.071	1.107	1.023	1.051	0.825	0.565
1999	0.988	1.571	1.304	2.214	1.168	2.143	1.844	1.861
2000	1.114	0.561	1.232	0.951	1.308	0.583	0.556	2.468

Forecast Accuracy Statistics

Another method of assessing the accuracy of forecasts is to examine the errors contained in them. Two types of error exist for the forecasts in this study. The first, track error, is detailed above. It is simply the distance between the actual storm location and the forecast storm location, and is reported in nautical miles (nm). The other error is in the prediction of peak wind speeds. This means that some storms that are forecast to be sub-gale force may be of hurricane force, or vice-versa. This measure is reported as the forecast peak speed minus the observed peak speed. Therefore, a positive value means that the speed was over-forecasted, and a negative value means too low a speed was forecast. The reporting unit for this error is knots (kt).

Some summary statistics for the errors of the aggregate storm/forecast dataset are contained in Table 3.11. The track errors for each year and each forecast type are displayed in Figure 3.3. Additionally, the exponential best-fit curves for each type of track error are plotted along with the error data in Figure 3.4. This figure shows the extrapolated values of the track errors, and can be used to forecast the time at which each of the different forecast spans will converge to having the same accuracy. As can be seen from these figures, the track accuracy is increasing, and the accuracy of the forecasts is expected to converge at some time between 2030 and 2040 at the current rates of improvement.

Table 3.11: Aggregate forecast accuracy measures by forecast type, 1980 - 2000

		Forecast Span				
Error Type	**Statistic**	**12 hr**	**24 hr**	**36 hr**	**48 hr**	**72 hr**
Track	Mean, nm	49.3	92.0	132.4	180.5	286.4
Track	St. Dev., nm	34.4	54.7	73.0	105.0	183.0
Track	10^{th} %-ile, nm	16.5	31.9	50.0	67.1	103.8
Track	90^{th} %-ile, nm	91.2	167.2	232.4	319.9	508.4
Wind Speed	Mean, kt	0.6	0.2	0.0	-1.0	0.1
Wind Speed	St. Dev., kt	10.5	15.4	18.6	21.8	25.9

Figure 3.3: Track errors for all forecast types, 1980 - 2000

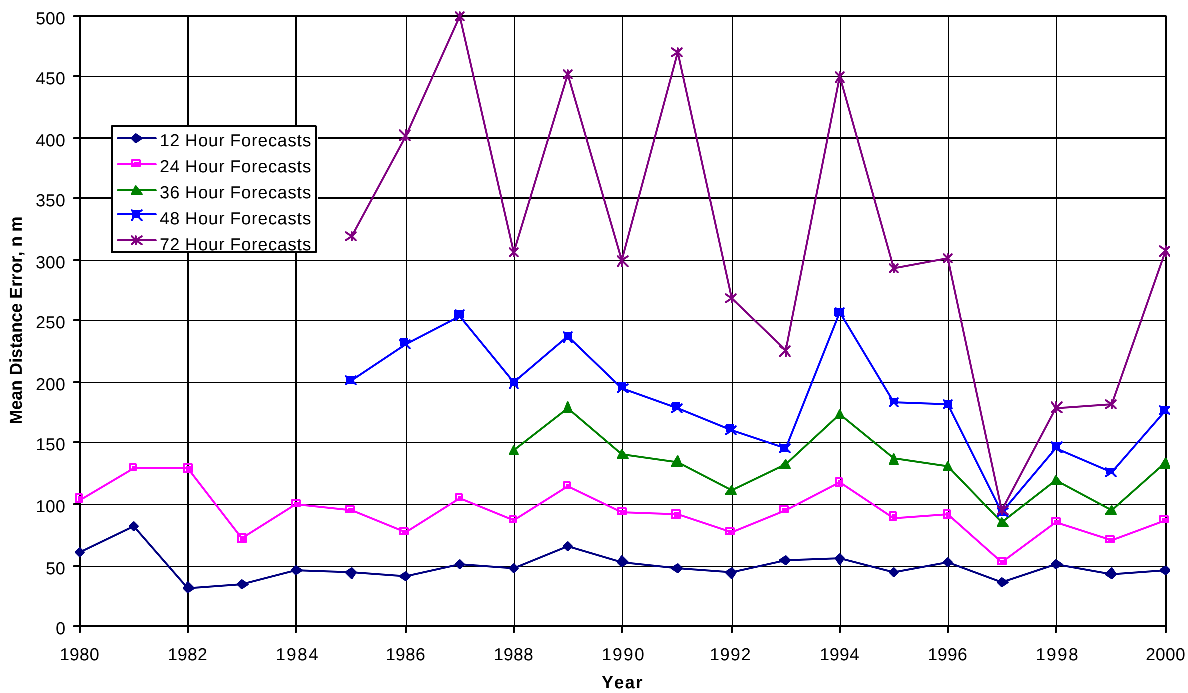
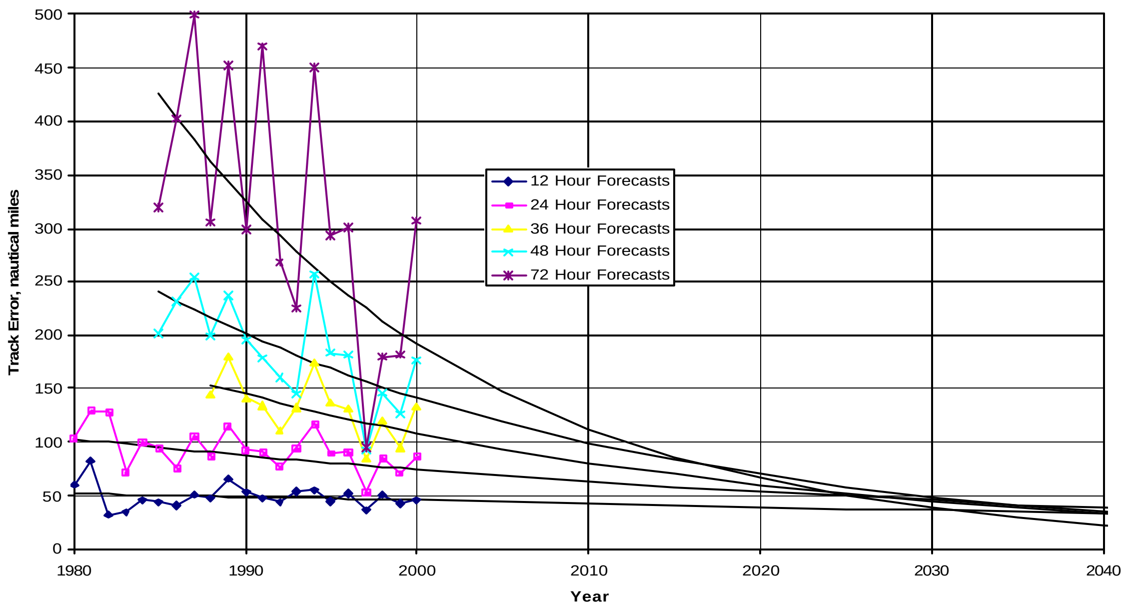


Figure 3.4: Projected track errors for all forecast types, 1980 – 2000



BAYESIAN PROBABILITIES

To approximate the Bayesian subjective probabilities, a moving average of probabilities is made to capture decision makers' accumulated knowledge of and changes to forecast accuracy. Our probabilities use a 10-year rolling moving average. That is, for 1990, we use the counts of observations from 1980-1989 to compute the probabilities. For 1991 we use 1981-1990 and so on. These cumulative probabilities appear in Table 3.12 for the 24 hour forecasts and Table 3.13 for the 48 hour forecasts. First of all notice that the 24 hour forecasts have approximately a 65% probability of a strike occurring when one is forecasted (Table 3:12) but that the 48 hour forecast has only a 24-27% strike probability when a strike is forecasted (see Table 3.13). On this basis, the 24 hour forecasts are much more accurate than the 48 hour forecasts, which is not surprising.

There is a gradual improvement in accuracy of no hit 48 hour forecasts (π_{22}), and the steady decline in accuracy of strike forecasts (π_{11}), with the exception of a reverse in course in 1999. This data indicates that forecasters are improving their ability to predict where hurricanes are not going, but have not improved their ability to predict where they are going. Another interesting result is that contrary to popular perceptions that hurricanes are more frequent with possible climate change, the historical strike probabilities, p^1, decline over the sample period.

Table 3.12: Cumulative probabilities of hurricanes and 24 hour forecasts, 1990-2000

	Strike Forecast		No Hit Forecast					
	Actual Event		Actual Event		Historical		Forecasts	
Year	Strike, p_{11}	No Hit, p_{12}	Strike, p_{21}	No Hit, p_{22}	Strike, p^1	No Hit, p^2	Strike, p_1	No Hit, p_2
1990	0.65	0.08	0.35	0.92	0.19	0.81	0.18	0.82
1991	0.65	0.08	0.35	0.92	0.18	0.82	0.18	0.82
1992	0.65	0.08	0.35	0.92	0.18	0.82	0.18	0.82
1993	0.65	0.08	0.35	0.92	0.18	0.82	0.17	0.83
1994	0.65	0.08	0.35	0.92	0.17	0.83	0.17	0.83
1995	0.64	0.07	0.36	0.93	0.16	0.84	0.16	0.84
1996	0.65	0.07	0.35	0.93	0.17	0.83	0.16	0.84
1997	0.64	0.08	0.35	0.92	0.17	0.83	0.16	0.84
1998	0.64	0.07	0.35	0.93	0.16	0.84	0.15	0.85
1999	0.63	0.08	0.37	0.92	0.17	0.83	0.16	0.84

Table 3.13: Cumulative probabilities of hurricanes and 48 hour forecasts, 1990-2000

	Strike Forecast		No Hit Forecast					
	Actual Event		Actual Event		Historical		Forecasts	
Year	Strike, p_{11}	No Hit, p_{12}	Strike, p_{21}	No Hit, p_{22}	Strike, p^1	No Hit, p^2	Strike, p_1	No Hit, p_2
1990	0.27	0.04	0.73	0.96	0.05	0.95	0.04	0.96
1991	0.27	0.04	0.73	0.96	0.05	0.95	0.04	0.96
1992	0.27	0.04	0.73	0.96	0.05	0.95	0.04	0.96
1993	0.25	0.04	0.75	0.96	0.04	0.96	0.04	0.96
1994	0.25	0.04	0.75	0.96	0.04	0.96	0.03	0.97
1995	0.25	0.03	0.75	0.97	0.04	0.96	0.03	0.97
1996	0.25	0.03	0.75	0.97	0.03	0.97	0.03	0.97
1997	0.24	0.03	0.76	0.97	0.03	0.97	0.02	0.98
1998	0.24	0.03	0.76	0.97	0.03	0.97	0.02	0.98
1999	0.28	0.03	0.72	0.97	0.03	0.97	0.02	0.98

CHAPTER IV. COSTS AND LOSSES

This chapter describes the methods used to estimate the costs associated with evacuating drilling rigs, the costs from shutting in production, and the potential losses from inaction.

DRILLING RIG EVACUATION COSTS

Evacuation costs for drilling rigs contain a fixed transportation component and the opportunity cost of foregone drilling time. The transportation cost is simply the product of the number of personnel to be evacuated and a per unit transport cost. Crews constantly move on and off rigs so measurement of the number of personnel at any point in time is extremely difficult. Based on personal experience and informal interviews with current industry practitioners, we assume 55 persons on board when the evacuation decision must be made.[3] Helicopters bring workers back to shore at a cost of $500 per head. Hence, the unit transportation cost per evacuation is $28,000.

The opportunity cost of lost drilling time is the daily standby cost for the drilling rig and ancillary services multiplied by the number of days off the rig. When a drilling rig is evacuated, the oil company is responsible to pay for most of the services while on standby, often at reduced *bad weather* rates. The most significant of these is the daily drilling rig rate (day-rate). Although contract terms vary from company to company, and vary based on market conditions when the contract is negotiated, we use the full day-rate for these computations. Using the full day-rate is intended to capture all ancillary services that would also be on a standby rate. Table 4.1 presents average day-rates in the Gulf of Mexico by rig type.

Table 4.1: Estimated 'bad weather' daily rig operating costs in thousands

Rig Type	1995	1996	1997	1998
Jack-ups	21.8	29.7	47.5	42.2
Platform	13.4	14.8	16.8	18.5
Semi-submersible	52.5	89.3	119.6	126.3
Barge & Platform	13.4	14.8	16.8	18.5

Source: *Offshore Data Services*

While the evacuation data do not indicate which rig type is employed at a given location, the water depth at the location is a good proxy for rig type. This proxy, however, cannot distinguish between a platform rig and a semi-submersible rig for wells in the relevant overlapping depths, or when semi-submersibles are inefficiently employed

[3] One of the authors, Christopher Jablonowski, was employed by Royal Dutch Shell as a drilling rig engineer and worked several years on offshore drilling rigs in the Gulf of Mexico.

to drill in shallow waters, or for platform rigs in shallow waters or on the tallest platforms. Assuming that the semi-submersible rigs are more likely employed to drill exploration wells (E) and platform rigs more likely to drill development wells (D), the assignment rules in Table 4.2 assign daily drilling rates to types of rigs stratified by water depth.

Table 4.2: Daily drilling rate assignments by water depth

Water depth in feet	Well Type	Rig Cost Applied
< 400	Exploration & development	Jackup
> 400 & < 1000	Exploration	Semi-submersible
> 400 & < 1000	Development	Average of platform & semi-submersible
> 1000	Exploration or development	Semi-submersible

Drilling rigs managers file daily logs with the Minerals Management Service, recording among other things, the time boarding and evacuating the rig. Our measure of total evacuation time is from evacuation to the resumption of normal drilling operations. Based upon a sample of storms presented in Table 4.3, the average evacuation over all

Table 4.3: Average days evacuated for offshore drilling rigs

Storm	Year	Count	Average	Standard Deviation
Bob	1979	8	2.69	1.60
Claudette	1979	7	6.20	1.86
Allen	1980	11	5.49	2.21
Jeanne	1980	18	4.81	3.77
Alicia	1983	6	5.08	4.84
Barry	1983	5	5.22	5.42
Danny	1985	22	4.89	2.29
Elena	1985	13	7.07	2.47
Juan	1985	15	7.32	4.68
Kate	1985	15	4.28	1.22
Flo	1988	11	7.97	6.60
Gilbert	1988	14	8.28	5.22
Chantal	1989	14	3.33	1.72
Jerry	1989	10	3.63	1.13

Source: Oil Drilling Services, Inc.

storms is 5.5 days. The null hypothesis that the average evacuation duration for each storm is equal to the grand mean of all storm evacuations is rejected for less than half the storms (see Table 4.4). Evacuation durations, however, do vary significantly between shallow and deep-water rigs. The mean evacuation time for shallow water rigs is 4.6 days and 7.5 days for deep-water rigs. Floating rigs over deep water require pulling the drilling riser that may take days, depending on the exact water depth. In this sense, a decision maker on a deep-water rig must act earlier than his counterpart on a shallow water rig to allow time for securing the rig and evacuating personnel. In the same vein, upon returning to a floating rig the riser must be rerun, incurring additional time.

Table 4.4: Test results for mean storm evacuation time

Storm	t-stat	Storm	t-stat
Bob	-4.97	Elena	2.30
Claudette	1.00	Juan	1.51
Allen	0.00	Kate	-3.86
Jeanne	-0.77	Flo	1.25
Alicia	-0.21	Gilbert	2.00
Barry	-0.11	Chantal	-4.71
Danny	-1.25	Jerry	-5.23

COSTS OF PRODUCTION DISRUPTIONS

The cost of evacuating production platforms and shutting in production includes the cost of removing personnel from the platforms, and the lost value of the oil and gas that is not produced due to the evacuation and shutdown. Similarly, the lost value of production can be broken down into a daily loss times the number of days shut down. The following section provides an analysis of the value of deferring oil and gas production. Procedures for estimating the impacts of hurricanes on oil and gas production are then described.

Value of Production Delays

Production from oil and gas wells is not generally considered to be a continuous function, but a discrete one. Since the marginal cost of producing from a well is very low compared to the capital cost of establishing the well, there is little economic incentive to vary production from any given well in response to price changes. Instead, if the marginal cost of producing is below the market price of oil, then the well will be produced at the maximum amount. If the marginal cost is above price, then the producer will shut in the well. Thus, production is a binary variable defined as $\left(0, q^{\max}\right)$.

Based upon petroleum engineering experience, maximum annual production from a field is typically about 10% of the proved reserves of the field. Thus, production in month t is

$$q_t = r R_0^{-rt}, \qquad (13)$$

where r is the monthly production rate, or 0.83% (10% / 12) and R_0 is initial reserves. Assuming production with constant marginal cost, c, sold at price, p, the net present value (NPV) of a net production revenues:

$$\Pi_0 = r R_0 \sum_{t=0}^{N} (p_t - c) e^{-rt} (1+r)^{-t/12} . \tag{14}$$

If production is deferred by one month, then the net present value is:

$$\Pi_1 = r R_0 \sum_{t=1}^{N+1} (p_t - c) e^{-r(t-1)} (1+r)^{-t/12} . \tag{15}$$

Hence, each month's net revenue is valued at a different price and at a slighter larger discount factor. If the second net present value were lower than the first, which is likely given the effects of discounting, the difference between the two net present values would represent the value of deferred production. Under the Hotelling rule, however, net revenue increases at the interest rate and these two net present values will be identical. On the other hand, abundant empirical evidence suggests that the Hotelling rule does not apply for many natural resource prices, particularly for oil and natural gas. As a result, the net present values are calculated using the empirical distribution of oil prices under a range of different discount rates and production periods.

Graphically, the two production streams are as detailed in Figure 4.1. We see two revenue streams, one running from t=0 to t=N, and another running from t=1 to t=N+1. The second stream has a lower revenue value for the same volume of production because it is deferred into the future, and thus discounted by an additional period. The net cost of deferring production is equal to the area of the black-shaded region in Figure 1 minus the grey-shaded region.

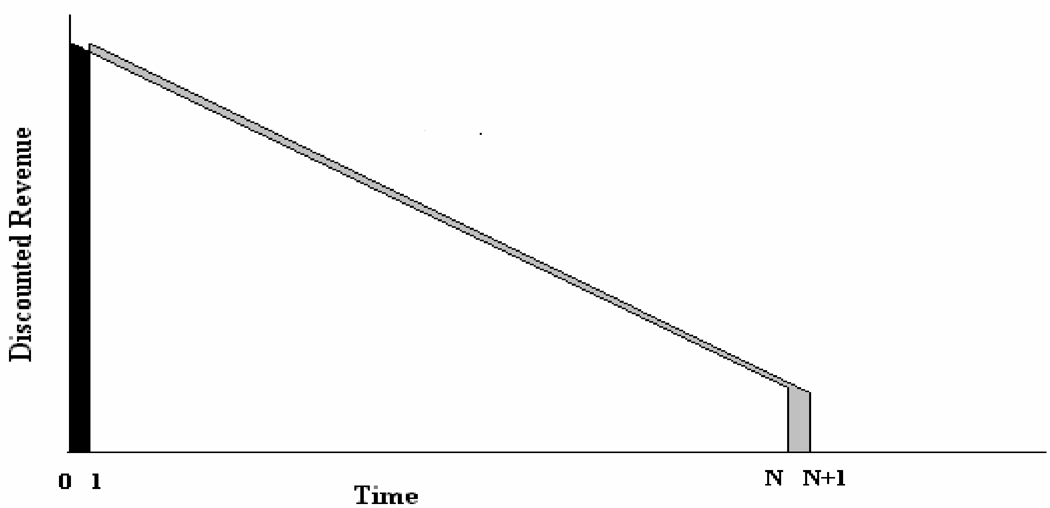


Figure 4.1: Graphical depiction of cash flows for current and delay production

As an illustration, these calculations were performed under three sets of assumptions for growth rates in unit profit, or price minus cost, for the hypothetical case summarized in Table 4.5 below. Under the constant unit profit assumption, deferring production by one month, the value of that deferred month's output was reduced to 52.1% of its non-deferred value. Put another way, the value of the reserves left in the ground for a month is 0.521 times their value if they were extracted in the first month. This fraction will henceforth be denoted as as the "one-month reserve value fraction". For 3% unit profit growth, the one month reserve value fraction is 0.617 (see Table 4.4).

Monthly prices changes for West Texas Intermediate crude oil from January 1986 to June 2002 averaged 0.4% with a standard deviation of 8.7%. Assuming normality and employing a random number generation process, 200 different price change trajectories were developed using $20 as the initial value in each case. The production horizon is assumed to be 233 months, based upon the estimated time for production from a given well to decline exponentially to the shutdown point. For each price path, using the same production profile, the above two NPV are calculated. Using this distribution for a 200-

Table 4.5: One month reserve values under different unit profit assumptions

Parameters		***Assumptions***	
Initial reserves:		2.5 million barrels	
First month production:		20,833 barrels	
Last month production:		2,990 barrels	
Number of months =		233	
Constant nominal price minus cost =		$20/bbl	
Constant discount rate of		10% per year.	
		Unit profit growth	
	Constant	3%	1%
NPV non-deferred	$25,142,699	$29,050,384	$24,032,787
NPV deferred	$24,943,154	$28,890,919	$23,822,272
NPV cost of deferring	$199,545	$159,465	$210,514
Cost as percent of first month revenue	47.90%	38.30%	50.50%
One-month reserve value fraction	0.521	0.617	0.495

trial using this distribution for a 200-trial Monte Carlo simulation of 233-month price change values created a set of corresponding price paths using $20 as the initial value in each case. The range of price paths varied widely, with values as low as $0.68 and as high as $1069 per barrel. For each of these price paths, using the same production profile, the NPV's of the cash-flows associated with uninterrupted production and with a one-month interruption in the first period were compared. From these calculations, 200 different values of the one-month reserve value fraction were found. Assuming a discount rate of 10%, the fractions are distributed as shown in Figure 4.2. As can be seen from Figure 4.2, the vast majority of outcomes are clustered between 0.25 and 0.75.Descriptive statistics for the one-month reserve value fraction calculated with an annual discount rate of 10% appear in Table 4.5.

Table 4.6: Statistics for one month reserve values under stochastic prices

Statistic	Value
Mean	0.698
Median	0.569
Minimum	0.229
Maximum	3.214
Standard deviation	0.456

The values calculated above exhibit significant sensitivity to changes in the discount rate. The aforementioned experiments were performed with constant annual discount rates ranging from 5% to 15%. Figure 4.3 displays the change in mean and median values versus annual discount rates.

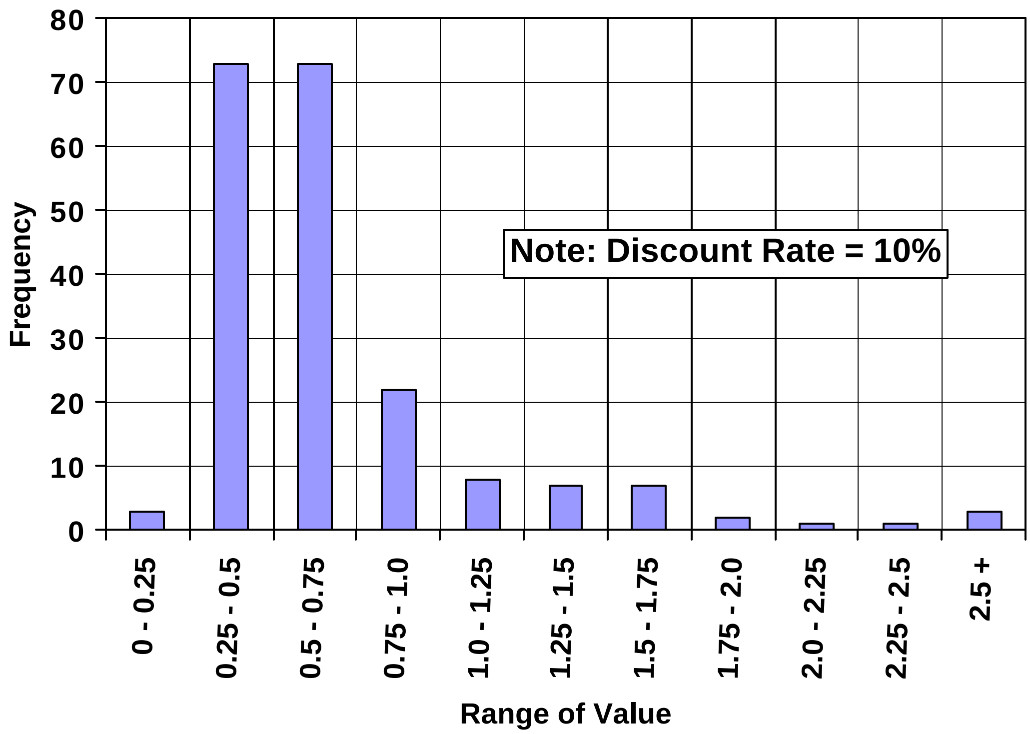


Figure 4.2: Frequency distribution of one-month reserve value fraction

As can be seen, the mean one-month RVF at low interest rates is close to one, which validates the classical Hotelling model. Given that the reference price sample has a mean monthly price rise of 0.4%, which translates to an annual price rise of 4.9%, this is not surprising. What is debatable is the discount rate that should be used. 5% is close to the current risk free rate, and is lower than most companies would be willing to accept from any venture. However, production of oil and gas from previously proven reserves and previously developed wells has a marginal cost of close to zero, and has relatively low risk when compared to the exploration and development functions of the integrated oil firm. As such, we should not be using the higher risk-premium rates that are typically associated with the mineral extraction industries. For this reason, a value of 10% may be a reasonable middle-ground.

Another point to be made is that even if a relatively low (and relatively constant) risk premium is used, the underlying "real" interest rate will fluctuate. It is an oversimplification to use a constant discount rate over a period of almost 20 years, as was used in these simulations. To gain a better model, one may wish to stochastically generate a discount rate price path for each of the oil price paths. This was currently beyond the scope of this study.

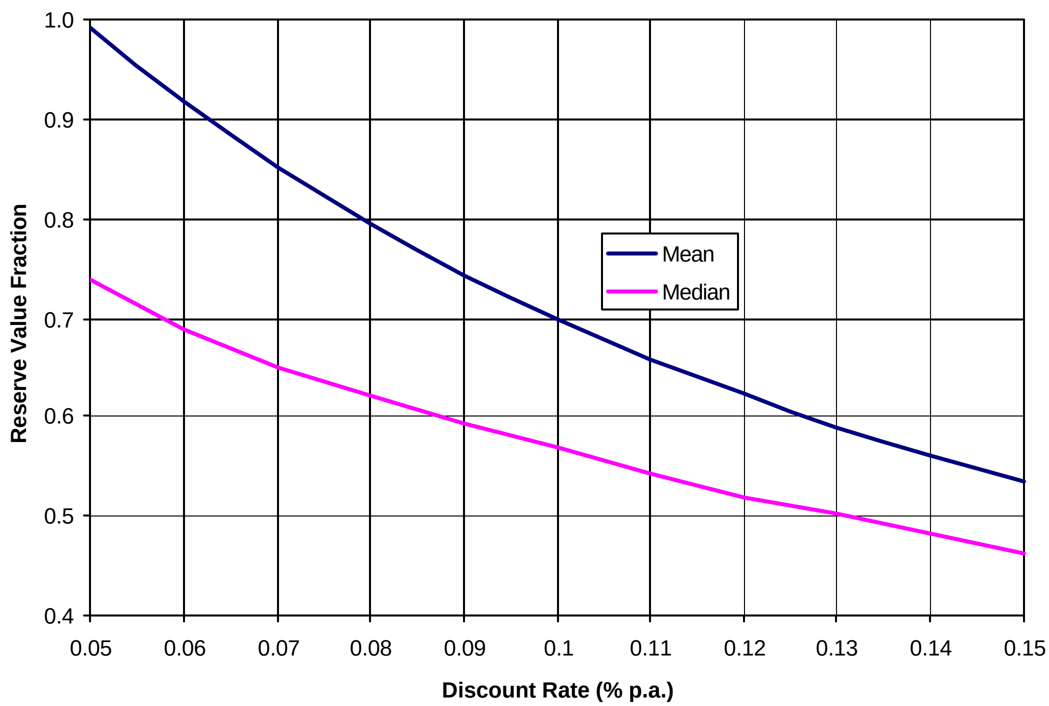


Figure 4.3: Sensitivity of one-month reserve value fraction to the discount rate

The length of the time path in consideration will have an effect on the cost of deferring production. If the time to abandonment is short, then there will be minimal mean weighted discounting of future revenue streams, as more of them are closer to the present. As the time to abandonment approaches infinity, we would assume the reserve value fraction would asymptotically decline to some value, given that the later (20 plus years into the future) revenue streams will be discounted to near zero at any reasonable discount rate. The mean and median values of the reserve value fraction for the 200 price paths were computed using values of abandonment times ranging from 2 months to 233 months into the future. The calculations were performed at a 10% p.a. discount rate. The results are shown in Figure 4.4.

Given the above considerations, an assumed average value must be used in the calculation of costs. This study assumes a mean RVF of 0.7, meaning that for every month out of production, or 30% of the value of the oil produced by a given platform will be lost. The authors further assumed that this fraction can be considered to be equivalent to 1% loss of value per day (30% per month divided by 30 days per month). Thus, for the analysis below, the value of lost production will be modeled thus:

$$c_x = RVL(t_{sd})(q_x p_x) \tag{16}$$

where x denotes the oil or natural gas commodity, $RVL = 0.01(t_{sd})$, t_{sd} is the length of the shutdown, q_x is daily production, and p_x is price.

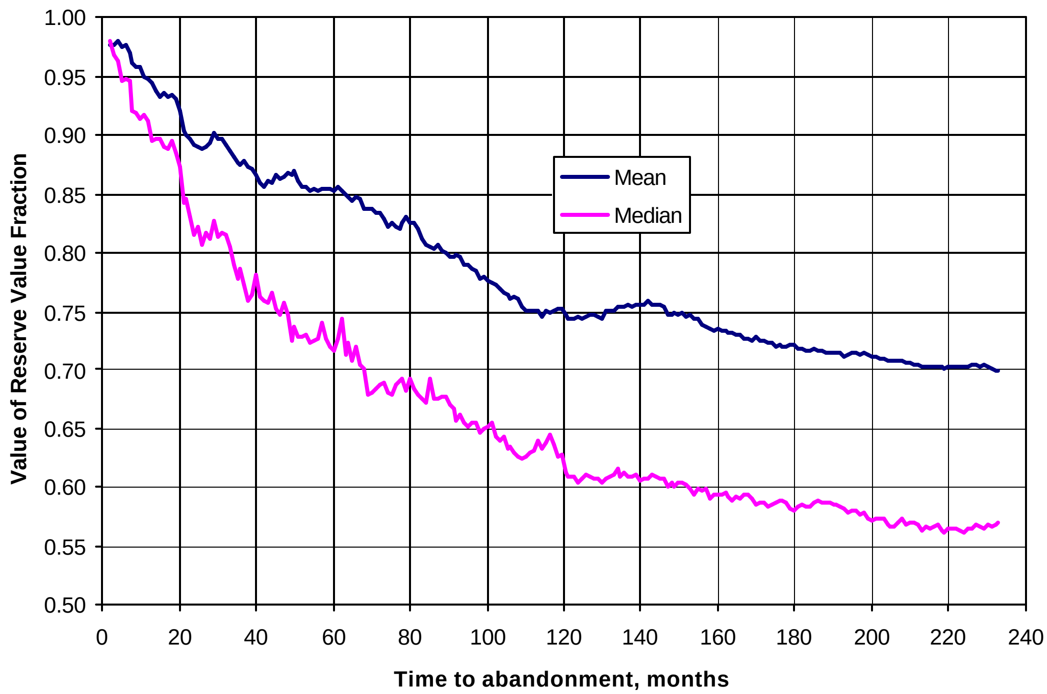


Figure 4.4: Sensitivity of one-month reserve value fraction to time to abandonment

Length of Shutdown

Given estimates of the lost revenue from a daily shutdown, the average length of shutdown must be determined. Unlike the drilling component of this study, which used actual shutdown data to develop an expected shutdown length, no empirical data are available for the typical length of a production shutdown. Two estimation methods are examined. The first method is a regression model that related aggregate monthly daily average production from oil and gas wells to a number of explanatory variables, including water depth, well hole depth, cumulative production, and a "storm-day" variable measuring the number of days experiencing storm conditions with 50-knot winds. For oil wells, the predicted drop in production was 221 barrels per “storm” day, and for gas wells it was 1916 thousand cubic feet per day per storm day. This method, however fails to measure false production shut-in decisions.

As a result, a second method is designed to solve this problem. This technique is less formal and involves inspection of the monthly changes in production for each 15 square mile grid block within the oil and gas production area. Time-series of production changes were generated for each grid-block, and the periods when storms were present in the Gulf were extracted. For each hurricane that entered the Gulf, the observed loss in production was converted to a "days of lost-time" variable. Thus, for each major storm (11 observed periods between 1985-1999), the production losses in each grid block in each Minerals Management Service (MMS) district were calculated. From each of these 11 data sets (for each MMS district), an expected shutdown length is needed. Since some grid blocks did not shutdown at all (i.e., exhibited an increase in production, or an insignificant decrease), merely taking an average would not suffice. Accordingly, our objective was to estimate the average length of shutdown observed over the set of all shutdowns, not over the set of all wells, be they shut down or not. For this reason, any grid-block that did not show a statistically significant decrease in production was eliminated from the analysis. The mean and standard deviation of shutdown days were then calculated for each MMS district. They are shown in Table 4.7. Note that oil production is minimal in MMS 6, and thus not considered in this analysis.

Table 4.7: Length and Standard Deviation of Shutdowns

	Oil platform shutdowns		Gas platform shutdowns	
MMS District	Mean	Standard Deviation	Mean	Standard Deviation
1	5.4	3.9	6.5	4.6
2	5.8	4.3	5.9	4.1
3	5.1	3.0	5.9	4.9
4	6.7	6.4	7.1	5.5
5	6.0	4.9	6.6	3.3
6	NA	NA	5.3	5.1

LOSSES FROM INACTION

While many rigs are built to withstand 100-knot winds, riding out a hurricane on these facilities places workers at considerable peril. Depending upon the location of the storm in relation to the rig, wave and wind interactions, especially Northeast of the center of the storm, can topple a rig even if winds are below this critical threshold. If a facility is toppled with workers on board, considerable loss of life is likely. Nevertheless, hurricanes often strike these facilities and escape destruction or major damage. This durability has not escaped the attention of rig managers. Indeed, there are some managers who decide to remain on rigs during some hurricanes. These features suggest that decision makers do not consider potential losses with complete certainty. Instead, this behavior suggests that they consider the conditional probability of complete loss given the probability of a hurricane strike.

This probability can be computed by counting the number of rigs lost and dividing by the number of rigs exposed to hurricane force winds. Unfortunately, estimating this probability is not possible because not all rigs operating during a hurricane will be exposed to hurricane force winds given the geographic extent of the drilling area. This precludes using an average rig count for entire Gulf of Mexico. Instead, our proxy for this probability is the probability of rig loss given that a hurricane exists. To estimate this probability, rig losses from strong hurricanes (category 2 or stronger) in the Gulf of Mexico were compiled from 1980 to 2000 (see Table 4.8). Of the

Table 4.8: Rig losses from hurricanes in the Gulf of Mexico, 1980-2000

Year	*Storm Count*	Storms Causing *Catastrophic Loss*
1980	3	1
1981	4	0
1982	4	0
1983	2	1
1984	2	1
1985	7	3
1986	2	0
1987	2	1
1988	5	0
1989	2	0
1990	4	0
1991	1	0
1992	2	1
1993	2	0
1994	2	0
1995	7	0
1996	8	0
1997	1	1
1998	7	1
1999	5	0
2000	4	0
Totals	76	10

Source: Accident History of the Mobile Offshore Drilling Fleet, © 2002 OneOffshore, Inc.

76 strong storms, 10 hurricanes resulted in rig losses. Our information does not reveal whether these rigs were manned or not. Based upon the data reported in Table 4.8, the probability of the potential for catastrophic losses is 10/76 = 0.1316.

Several judgments had to be made during the compilation of the data in Table 4.8. There are observations in the data set such as "rig found laying on side after hurricane Allen," which would most likely have resulted in 100% fatalities if persons were on board. There are far more observations such as "Thruster/Pontoon damage," and "Broke mooring lines and was adrift." While these two examples did not sink the rigs involved, the potential for a catastrophic outcome was high. This class of observations falls between rigs that are totally lost and those that are essentially unaffected by a storm. How to treat this class of observations in the context of computing the probability of loss of life is unclear. While the rigs were not lost *per se*, we could describe them as nearly lost (*e.g.* if rig was half submerged) and the threat of loss of life (or lawsuits) approaches that of a lost rig. Unfortunately, we do not observe many of the needed details to make such judgments on a case-by-case basis.

Another gray area is the fact that we do not know what the rig crew *would have been doing* if it had stayed on location. In the event that they were compelled to continue drilling, minor rig damage, which would not warrant inclusion as a lost rig, could have caused catastrophic loss of life due to complications with the drilling operation, namely a blowout if well control was lost. We would expect crews to continue working as long as possible; otherwise there is very little gain from remaining on the rig. There also may be an underreporting problem. Drilling contractors have a clear incentive not to publicize hurricane damage lest it reduce future marketability of the specific rig (damaged goods), or their reputation for hurricane readiness in general (warranted or not). In counting events, we erred on the side of including ambiguous cases as "lost rigs".

To compute an expected monetary loss, an estimate of the value of a statistical life (VSL), or the willingness to pay for a given reduction in mortality risk divided by that risk reduction (Krupnick, 2002) is needed. Estimation of VSL is a field unto itself. The economic and ethical issues have been debated, and empirical methods have been developed (Viscusi, 1991, 2000a, 2000b); Schwab-Christie and Soguel, 1995; Havrilesky, 1995). Moore and Viscusi (1988) argue that models of the wage-risk tradeoff based on Bureau of Labor Statistics (BLS) data systematically underestimate the value of human life. Their use of a more detailed data set published by the National Institute of Occupational Safety and Health (NIOSH) results in value of life estimates of \$5-7 million, versus estimates of \$2 million that commonly result from similar analysis of BLS data.

In a meta-analysis employing results from many VSL studies, Mrozek and Taylor (2002) present convincing evidence that the higher estimates for VSL are associated with studies that do not adequately control for industry effects on wages. They also note that the NIOSH data are aggregated to the 1-digit industry level. Their analysis also examines how VSL estimates vary with the level of risk (measured as lives lost per worker population), noting a nonlinear relation in which VSL rises up to a certain level of risk and then slightly falling at higher levels. This effect is particularly relevant for this study because individuals with low risk aversion may require less compensation for higher risk jobs. Given the likelihood that offshore oil and gas workers are likely to come from such a population and the specific industry focus of this study, which argues for using estimates studies using the BLS data controlling for industry effects; the VSL used in this study is $2.275 million, which is the average of two estimates for high risk occupations.[4] Given this estimate, the probability of rig destruction given a strong hurricane, and the average number of workers on a drilling rig, our potential loss estimate is $16.5 million. The estimate loss for production platforms is computed in a very similar fashion assuming 5 workers on board, which translates to a potential loss of $1.5 million per facility. For comparative purposes, the analysis below also uses a VSL of $6 million.

[4] Specifically, Mrozek and Taylor (2002) estimate two different models that each control for industry effects in slightly different ways, obtaining values $2.13 and $2.42 million at a risk of mortality of 2 out of 10,000 workers.

CHAPTER V. ESTIMATES OF FORECAST VALUE

This chapter presents our estimates of the value of hurricane forecasts to oil and gas producers in the Gulf of Mexico. The next two sections describe estimates of existing and perfect forecast value for drilling rig evacuation decisions and for decisions delaying production when faced with a hurricane strike threat. Within each section, the estimates of forecast value are made under different estimates for the value of statistical life and whether producers use expected or actual losses in their decisions. A sensitivity analysis is also presented for costs. The final section presents a summary and a comparison of the forecast value estimates with those from a partial improvement in forecast accuracy.

DRILLING RIG EVACUATIONS

For drilling rigs, the value of forecast information for any given rig at a specific location for a particular storm is computed as follows:

$$V_{rijt} = \begin{cases} p_{1it}\left[p_{11it}E(L) - C_{rt}\right], \dfrac{C_{rt}}{L} > p_{it}^{1} \\ \\ p_{2it}\left[C_{rt} - p_{12it}E(L)\right], \dfrac{C_{rt}}{L} \le p_{it}^{1} \end{cases} \tag{17}$$

where r is an individual drilling rig, i represents the production grid block, j is the specific storm event, and t is the year. Hence, the value of information varies by rig type, storm, production location (grid block), and over time. Note that the source of this variation comes from spatial and temporal variation in the conditional and unconditional probabilities as well as variation in evacuations costs across rig types over time. The aggregate value of information for drilling rig evacuations in any year is simply the sum of (17) over storms, grids, and drilling rigs. Recall that V_{rijk} is only computed when $\pi_{12ik} < C_{rk} / L < \pi_{11ik}$. Although the NHC produces a range of different forecasts from 12 to 72 hour and more recently 100-hour forecasts, the results presented below focus on the 24 and 48-hour forecasts, which are commonly employed by rig and production platform managers.

The value of the 24 and 48-hour forecasts are presented in Tables 5.1 and 5.2 respectively, each under two sets of VSL estimates. The evaluations use the 50 knot forecast because this is the maximum wind speed for helicopter departure from the rig, the common mode of transport for the last group of evacuees (typically the core management and operating personnel). For each forecast type, both the value of historical information and the value of perfect information are computed. In turn, for each of these cases, the computations are completed for an expected loss of $43,428,000 as computed above, and the complete loss value of $330 million using a VSL of $6 million. The computations using the VSL of $2.275 million yield an expected loss of $16,450,000 and a complete loss of $125 million. The value of perfect forecasts is computed by setting $p_{11} = p_{22} = 1, p_{12} = p_{21} = 0, p_1 = p^1, p_2 = p^2$.

The results illustrate the non-ordinal, discontinuous nature of the decision model. For example, the value of forecasts under the full loss assumption is identical to the value under the expected loss amount for both historical and perfect forecasts under with a value of statistical life estimate of $6 million (see Table 5.1). The C/L ratio is extremely small even under the expected loss case so that the same observations are used in each set of calculations. Recall that for a forecast to have any value $p_{12} < C/L < p_{11}$. Only in the cases where $p_{12} = 0$ is an observation likely to be included (note that there are such observations, and the value of forecasts is non-zero). And when $p_{12} = 0$, the scale of L is irrelevant based on our derivation of forecast value.

Table 5.1: Value of 24 hour forecasts for drilling in thousand 1999 dollars

	VSL = $6 million			
	Historical		Perfect	
Year	Expected loss	Full loss	Expected loss	Full loss
1990	366.8	366.8	48,577.5	48,577.5
1991	62.3	62.3	26,567.9	26,567.9
1992	0.0	0.0	11,584.8	11,584.8
1993	1,261.8	1,261.8	47,841.1	47,841.1
1994	552.6	552.6	44,645.0	44,645.0
1995	488.9	488.9	135,416.6	135,416.6
1996	928.9	928.9	404,871.7	404,871.7
1997	425.5	425.3	119,617.1	119,617.1
1998	929.2	929.2	401,570.1	403,920.0
1999	969.1	969.1	218,536.5	218,536.5
Total	5,985.0	5,984.8	1,459,228.4	1,461,578.3
Average	598.5	598.5	145,922.8	146,157.8
	VSL = $2.275 million			
1990	366.8	366.8	48,577.5	48,577.5
1991	62.3	62.3	26,567.9	26,567.9
1992	0.0	0.0	11,584.8	11,584.8
1993	1,261.8	1,261.8	47,841.1	47,841.1
1994	552.6	552.6	44,645.0	44,645.0
1995	1,030.8	488.9	135,416.6	135,416.6
1996	34,551.3	928.9	403,046.4	404,871.7
1997	14,392.3	425.3	111,252.1	119,617.1
1998	47,573.3	929.2	367,244.2	403,920.0
1999	5,036.4	969.1	212,503.3	218,536.5
Total	104,827.6	5,984.8	1,408,679.0	1,461,578.3
Average	10,482.8	598.5	140,867.9	146,157.8

The calculations using a VL of $2.275 million also appear Tables 5.1 and 5.2. Forecast values are dramatically higher than those using the $6 million VSL. For example, under the expected loss assumption, value rises from $0.60 to $10.5 million for the 24-hour forecast (see Table 5.1) and from $0.65 to $7.0 million for the 48-hour forecast (see Table 5.1). The cost-loss ratio increases considerably under a lower VSL and so more observations now meet the criterion $p_{12} < C/L < p_{11}$ and are included in the calculations. Also note the greater separation of values between the expected and full loss cases. Again, adjustments to the loss value in this range have an impact through the number of observations included in the calculations. The cost-loss ratio is extremely small even under the full loss case, and very few observations are relevant. But as the expected loss decreases from $43 to $16 million, the impact on historical forecast value is significant. Similar to the previous results, only in the cases where $\pi_{12} = 0$ is an observation likely to be included (note that there are such observations, and the value of forecasts is non-zero in 1999). When $\pi_{12} = 0$, the scale of L is irrelevant based on our derivation of forecast value.

Table 5.2: Value of 48 hour forecasts for drilling in thousand 1999 dollars

	VSL = $6 million			
	Historical		Perfect	
Year	Expected loss	Full loss	Expected loss	Full loss
1990	0.0	0.0	48,998.7	48,998.7
1991	0.0	0.0	27,009.3	27,009.3
1992	0.0	0.0	11,993.1	11,999.0
1993	0.0	0.0	47,516.3	47,516.3
1994	0.0	0.0	45,393.9	45,460.6
1995	0.0	0.0	138,505.4	138,505.4
1996	803.1	0.0	416,418.9	416,581.3
1997	1,259.4	0.0	121,034.4	122,771.4
1998	2,581.7	0.0	396,481.2	403,636.1
1999	1,855.6	0.0	209,911.1	216,298.1
Total	6,499.8	0.0	1,463,262.1	1,478,775.9
Average	650.0	0.0	146,326.2	147,877.6
	VSL = $2.275 million			
1990	0.0	0.0	48,998.7	48,998.7
1991	1,442.0	0.0	26,807.5	27,009.3
1992	0.0	0.0	11,851.5	11,999.0
1993	0.0	0.0	47,459.1	47,516.3
1994	158.6	0.0	45,001.7	45,460.6
1995	5,867.5	0.0	135,890.0	138,505.4
1996	19,537.6	0.0	353,793.8	416,581.3
1997	5,234.0	0.0	82,810.9	122,771.4
1998	28,133.7	0.0	273,514.0	403,636.1
1999	10,097.3	887.7	174,457.7	215,763.1
Total	70,470.8	887.7	1,200,584.7	1,478,241.0
Average	7,047.1	88.8	120,058.5	147,824.1

Also note the generally lower values and the presence of more zero values for the 48 hour forecasts, an indication of their inaccuracy (fewer instances of $\pi_{12} = 0$ means fewer observations included in the computation) relative to the 24 hour forecasts. In addition, for the value of perfect forecast information, the impact of full loss on the value of forecasts is modest. Finally, note that the value of the 48 hour forecasts under the full loss assumption with a VSL of $6 million is zero (see Table 5.2). The assumption of full loss can be construed as a proxy for risk aversion, which suggests the value of forecast decreases if the decision maker is risk averse.

The results in Tables 5.1 and 5.2 also display considerable variance in the annual forecast value estimates. In addition to costs, losses, and probabilities, the value of forecasts in any year depends upon the number of decisions to be made, which is a function of the number of storms and the number of rigs operating. For example, perfect forecasts are worthless if no decisions are necessary. Information on these data is presented in Figure 5.1 (along with daily drilling rig rates). Analysis of this data indicates the expected correlation, but of all three factors, it appears that the value of forecasts is most correlated with the number of storms, and to a lesser degree with the rig count.

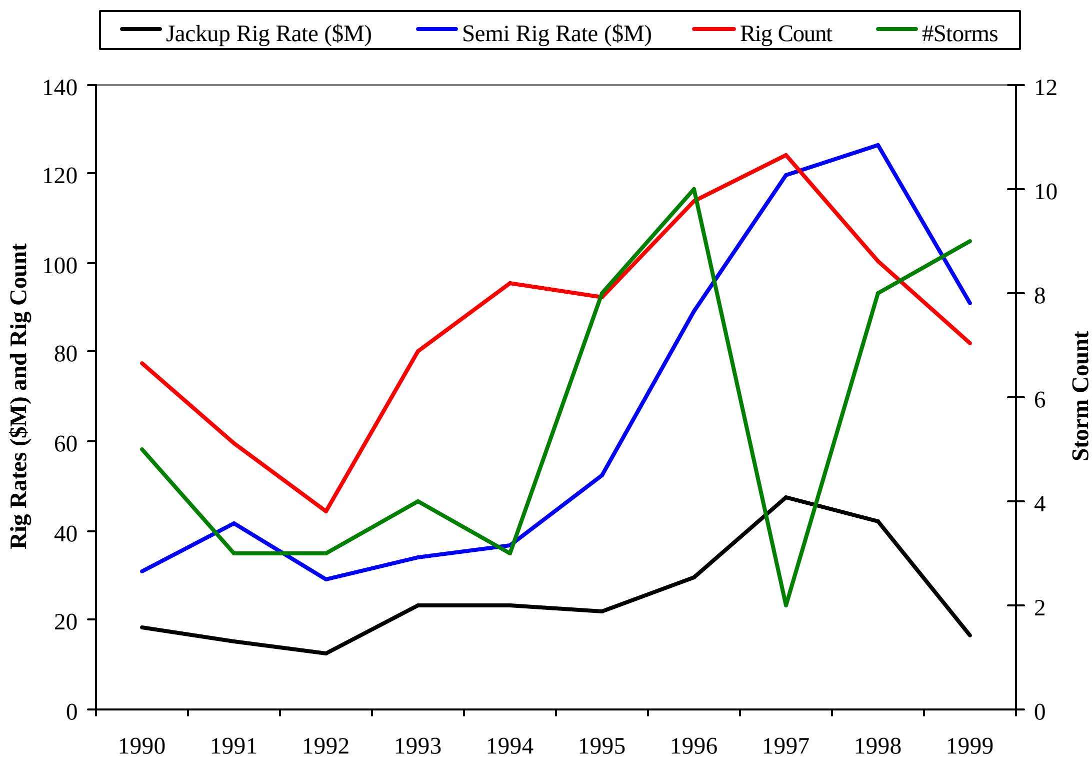


Figure 5.1: Number of storms, rig rates, and rig count, 1990-1999

To further examine the sensitivity of the results, the decision rules were computed for the following evacuation durations:

Deepwater rigs:	7.5 days – 1 std. dev. = 3.0 days
	7.5 days + 1 std. dev. = 12.0 days
Jackup rigs:	4.6 days – 1 std. dev. = 1.7 days
	4.6 days + 1 std. dev. = 7.5 days.

As expected, the value of forecasts decreases significantly with a decrease in evacuation costs. Therefore, the impact on the value of forecasts varies directly with C. The value of historical forecasts information under the low cost assumption is 2-4 percent of the value in the expected cost case. The value of perfect information also declined to 40-47 percent of expected loss values. Under higher evacuation costs, the value of historical forecasts increases by 57-70 percent and the value of perfect information by 26-40 percent.

Table 5.3: Sensitivity of 24 hour forecast values for drilling in thousand 1999 dollars

	VSL = $2.275 million			
	+1 standard deviation in costs			
	Historical		Perfect	
Year	Expected loss	Full loss	Expected loss	Full loss
1990	598.0	598.0	78,261.1	78,533.7
1991	364.9	101.6	42,733.3	42,775.2
1992	0.0	0.0	18,698.0	18,698.0
1993	1,955.0	2,057.3	77,261.6	77,391.9
1994	988.0	900.9	71,977.1	72,106.1
1995	5,425.1	797.1	216,319.9	218,243.8
1996	116,098.5	1,514.5	580,967.5	650,898.8
1997	23,145.6	693.5	139,753.1	192,345.7
1998	96,964.9	1,515.0	457,527.8	647,742.1
1999	38,193.2	1,580.0	306,154.6	350,513.2
Total	283,733.3	9,757.9	1,989,653.9	2,349,248.3
Average	28,373.3	975.8	198,965.4	234,924.8
	-1 standard deviation in costs			
1990	135.5	135.5	18,621.3	18,621.3
1991	23.0	23.0	10,360.7	10,360.7
1992	0.0	0.0	4,471.6	4,471.6
1993	466.3	466.3	18,290.4	18,290.4
1994	204.2	204.2	17,184.0	17,184.0
1995	180.7	180.7	52,589.3	52,589.3
1996	343.3	343.3	158,844.7	158,844.7
1997	175.8	157.2	46,888.6	46,888.6
1998	343.4	343.4	159,000.0	160,098.0
1999	358.1	358.1	86,559.9	86,559.9
Total	2,230.4	2,211.8	572,810.3	573,908.3
Average	223.0	221.2	57,281.0	57,390.8

The value of historical forecasts under the expected loss assumption and $2.275 million VSL ranges from $0.2 to $28.4 million per year for the 24 hour forecast, with a central estimate of $10.5 million per annum and from $0.3 to $11.1 million per year for the 48-hour forecast, which a mean of $7.1 million. Even though these estimates may seem sizeable, they are small compared to overall spending in the industry, where one well of medium complexity may cost over $5 million.

The value of perfect forecasts under the expected loss assumption ranges from $57 to $199 million per year for the 24 hour forecast, with a central estimate of $141 million per annum and from $57 to $151 million per year for the 48-hour forecast, which a mean of $120 million per year. These estimates suggest that perfect hurricane forecast information is quite valuable to the oil and gas industry. Naturally, such an ideal is unattainable. The last section of this chapter examines a more realistic case in which forecast accuracy increases half way to perfection.

Table 5.4: Sensitivity of 48 hour forecasts for drilling in thousand 1999 dollars

	VSL = $2.275 million			
	+1 standard deviation in costs			
	Historical		Perfect	
Year	Expected loss	Full loss	Expected loss	Full loss
1990	1,234.4	0.0	78,287.1	79,215.5
1991	3,449.5	0.0	37,901.7	43,475.4
1992	1,319.3	0.0	19,078.2	19,366.0
1993	3,533.7	0.0	75,382.2	76,840.1
1994	3,010.3	0.0	71,360.0	73,416.2
1995	10,182.6	0.0	182,796.6	223,213.7
1996	35,250.3	0.0	434,240.6	669,708.4
1997	4,075.0	819.9	98,277.3	197,412.5
1998	24,409.9	0.0	298,675.3	645,408.8
1999	24,225.7	4,098.9	212,102.6	343,467.6
Total	110,690.6	4,918.8	1,508,101.6	2,371,524.1
Average	11,069.1	491.9	150,810.2	237,152.4
	-1 standard deviation in costs			
1990	0.0	0.0	18,781.8	18,781.8
1991	0.0	0.0	10,543.1	10,543.1
1992	0.0	0.0	4,624.8	4,632.0
1993	0.0	0.0	18,192.4	18,192.4
1994	0.0	0.0	17,473.9	17,504.9
1995	0.0	0.0	53,797.1	53,797.1
1996	472.6	0.0	163,377.8	163,454.3
1997	685.2	0.0	47,187.0	48,130.2
1998	1,336.6	0.0	156,478.5	159,993.2
1999	698.8	0.0	82,870.0	85,665.2
Total	3,193.2	0.0	573,326.4	580,694.2
Average	319.3	0.0	57,332.6	58,069.4

Finally, these estimates should be viewed as minimum forecast valuations. In our selection of drilling rigs from the MMS database, only those rigs that are in a drilling mode could be observed. All rigs performing completions, work-over operations, abandonment, or in transit are not included. For these excluded rigs, location, or any of the other necessary criteria to perform a similar value of forecast calculation are unavailable. It is also true that the persons on board (POB) figure when rigs are in a non-drilling mode is less than it would be in a drilling mode. Our estimates indicate that approximately 60% of rigs are in a drilling mode at a given moment. Rigs performing these non-drilling operations are more likely to be platform work-over rigs (lower day-rates and POB), but this still leaves a significant number of rigs whose location, description (rig type), and POB at the time of the hurricane are unknown. Because of these gaps in the available data, a quantitative estimate for the value of forecasts for these rigs was not attempted.

PRODUCTION DELAYS

The computations for production are completed for each of the six MMS regions in the Gulf of Mexico as follows:

$$V_{it} = \begin{cases} p_{1it}\left[p_{11it}E\left(L_i\right)-C_i\right], \dfrac{C_{rk}}{L_i} > p_{it}^{1} \\ \\ p_{2it}\left[C_i - p_{12it}E\left(L_i\right)\right], \dfrac{C_i}{L_i} \le p_{it}^{1} \end{cases}, \quad (18)$$

where i is the MMS region. Note that in this case, losses vary by location based upon the number of manned platforms operating in each region. Total forecast value for production shut-in decisions in any year is the sum of (18) across all six MMS regions. The estimated values of the 24 and 48-hour forecasts appear in Tables 5.5 and 5.6, respectively.

Table 5.5: Value of 24 hour forecasts for production in thousand 1999 dollars

	VSL = $6 million			
	Historical		Perfect	
Year	Expected loss	Full loss	Expected loss	Full loss
1990	0.0	0.0	89,193.1	89,193.1
1991	0.0	0.0	48,694.3	48,694.3
1992	0.0	0.0	48,819.4	48,819.4
1993	0.0	0.0	66,826.3	66,826.3
1994	0.0	0.0	47,952.6	47,952.6
1995	0.0	0.0	115,943.5	115,943.5
1996	0.0	0.0	196,673.8	196,673.8
1997	0.0	0.0	41,979.7	41,979.7
1998	0.0	0.0	141,904.4	141,904.4
1999	0.0	0.0	179,666.8	179,666.8
Total	0.0	0.0	977,654.0	977,654.0
Average	0.0	0.0	97,765.4	97,765.4
	VSL = $2.275 million			
1990	0.0	0.0	89,193.1	89,193.1
1991	0.0	0.0	48,694.3	48,694.3
1992	0.0	0.0	48,819.4	48,819.4
1993	0.0	0.0	66,826.3	66,826.3
1994	0.0	0.0	47,952.6	47,952.6
1995	0.0	0.0	115,943.5	115,943.5
1996	0.0	0.0	196,673.8	196,673.8
1997	0.0	0.0	41,979.7	41,979.7
1998	0.0	0.0	141,904.4	141,904.4
1999	0.0	0.0	179,666.8	179,666.8
Total	0.0	0.0	977,654.0	977,654.0
Average	0.0	0.0	97,765.4	97,765.4

The value of 24-hour historical or current forecasts is zero under both VSL estimates (see Table 5.5). Moreover, the value of perfect 24-hour forecasts for production is much smaller than those for drilling. The reason again revolves around the relative value of the cost-loss ratio in relation to the critical conditional probabilities. Production decisions have a much lower cost-loss ratio. Even though drilling rigs have more lives at risk, their evacuation costs are relatively larger than production shut-in costs primarily due to the rather substantial opportunity costs from lost drilling time. This means that there a relatively fewer instances where the perceived quality of the hurricane forecast in production shut-in decisions justifies a reversal of decisions based upon historical information alone.

Unlike the drilling case, the value of the 24-hour forecast in production shut-in decisions is lower than the value of the 48-hour forecast (see Table 5.5 & Table 5.6). Again, forecasts only have value if the following condition is met $p_{12} < C/L < p_{11}$. In almost every case in our set of production decisions, the C/L ratio is below p_{12}. For every instance in the 24 hour case, this condition is violated. For *almost* every incidence in the

Table 5.6: Value of 48 hour forecasts for production in thousand 1999 dollars

	VSL = $6 million			
	Historical		Perfect	
Year	Expected loss	Full loss	Expected loss	Full loss
1990	5,133.7	5,155.1	91,826.4	102,539.7
1991	2,632.3	2,632.3	50,194.5	55,992.7
1992	2,614.0	2,614.0	50,522.7	56,261.2
1993	3,048.2	4,050.9	68,460.0	76,998.6
1994	2,131.9	2,567.6	49,618.4	55,169.2
1995	4,048.2	5,627.7	121,540.5	133,819.9
1996	4,430.6	9,146.3	202,038.3	227,252.1
1997	847.9	1,596.7	42,423.9	47,972.6
1998	2,711.1	5,606.3	148,685.1	163,264.7
1999	0.0	0.0	188,401.0	207,054.8
Total	27,597.9	38,996.9	1,013,710.7	1,126,325.6
Average	2,759.8	3,899.7	101,371.1	112,632.6
	VSL = $2.275 million			
1990	1,884.6	5,155.1	77,508.0	102,539.7
1991	1,151.9	2,632.3	44,287.1	55,992.7
1992	1,003.2	2,614.0	47,715.4	56,261.2
1993	1,118.3	4,050.9	63,470.9	76,998.6
1994	786.3	2,567.6	45,569.2	55,169.2
1995	1,501.4	5,627.7	110,265.2	133,819.9
1996	1,631.4	9,146.3	161,207.3	217,899.6
1997	313.1	1,596.7	33,466.5	45,472.5
1998	1,003.7	5,606.3	127,752.8	162,451.5
1999	1,030.7	0.0	162,587.7	203,181.7
Total	11,424.7	38,996.9	873,830.1	1,109,786.5
Average	1,142.5	3,899.7	87,383.0	110,978.7

48 hour case this is also the case, except for MMS region 6. In this case, the inequality conditions are met, but only for one reason. For this MMS district, there were no false negatives from 1985 to 1998. That is, under no instance did a hurricane strike a block when a no hurricane was forecasted. This is largely due to the small number of hurricanes that made it into the western Gulf in that period. Hence, p_{12} is zero for MMS 6, and this is what causes the inequality conditions to be met.

In this rare case, 48-hour forecasts were more valuable because they were more accurate than 24 hour ones. In 1988, in the 48-hour forecast for all grid blocks in MMS, there were 6 true positives and 16 false positives, but no false negatives. For the 24 hour forecasts for the same storm and same region, there were 4 true positives, 18 false positives, and (critically) 2 false negatives.

The sensitivity of the 24 and 48-hour forecast values to changes in costs are displayed in Tables 5.7 and 5.8. The 24-hour forecast value ranges from zero to $23.8 million per year, while the 48-hour forecast value is as low as $0.6 million per annum to more than $11 million per year.

Table 5.7: Sensitivity of 24 hour forecasts for production in thousand 1999 dollars

	VSL = $2.275 million			
	+1 standard deviation in costs			
	Historical		Perfect	
Year	Expected loss	Full loss	Expected loss	Full loss
1990	37,154.5	0.0	245,632.2	245,632.2
1991	15,179.1	0.0	133,961.4	133,961.4
1992	13,139.7	0.0	134,958.2	134,958.2
1993	22,149.7	0.0	185,513.8	185,513.8
1994	14,220.6	0.0	132,191.5	132,191.5
1995	5,566.9	0.0	316,416.3	316,416.3
1996	57,339.2	0.0	545,496.3	545,496.3
1997	15,786.5	0.0	116,061.7	116,061.7
1998	15,394.8	0.0	390,064.2	390,064.2
1999	42,155.4	0.0	498,955.1	498,955.1
Total	238,086.5	0.0	2,699,250.7	2,699,250.7
Average	23,808.6	0.0	269,925.1	269,925.1
	-1 standard deviation in costs			
1990	0.0	0.0	16,369.5	16,369.5
1991	0.0	0.0	9,120.2	9,120.2
1992	0.0	0.0	8,923.5	8,923.5
1993	0.0	0.0	11,980.1	11,980.1
1994	0.0	0.0	8,853.6	8,853.6
1995	0.0	0.0	22,597.7	22,597.7
1996	0.0	0.0	33,958.8	33,958.8
1997	0.0	0.0	7,179.5	7,179.5
1998	0.0	0.0	25,810.8	25,810.8
1999	0.0	0.0	30,509.9	30,509.9
Total	0.0	0.0	175,303.5	175,303.5
Average	0.0	0.0	17,530.3	17,530.3

The value of historical forecasts under the expected loss assumption and $2.275 million VSL ranges from $0to $23.8 million per year for the 24 hour forecast, with a central estimate of $0 million per annum and from $0.6 to $7.1 million per year for the 48-hour forecast, which a mean of $1.1 million. The value of perfect forecasts under the expected loss assumption ranges from $17 to $270 million per year for the 24 hour forecast, with a central estimate of $98 million per annum and from $20 to $129 million per year for the 48-hour forecast, which a mean of $87 million per year. These values are considerable lower than the value of forecast information for drilling rig evacuation decisions.

Table 5.8: Sensitivity of 48 hour forecasts for production in thousand 1999 dollars

VSL = $2.275 million				
+1 standard deviation in costs				
	Historical		Perfect	
Year	Expected loss	Full loss	Expected loss	Full loss
1990	1,640.0	14,919.5	149,399.7	247,047.7
1991	1,030.2	8,924.3	85,571.8	135,037.2
1992	894.9	7,911.3	88,359.6	136,991.9
1993	969.8	8,857.8	111,317.1	186,570.9
1994	701.1	6,200.9	79,897.3	134,532.9
1995	1,377.4	11,786.5	162,615.3	327,136.8
1996	6,462.7	12,883.2	193,235.7	550,926.1
1997	2,981.2	2,466.7	36,689.1	115,250.8
1998	27,077.7	7,891.0	183,904.8	403,611.5
1999	28,322.5	0.0	196,406.6	517,078.4
Total	71,457.7	81,841.2	1,287,396.9	2,754,184.3
Average	7,145.8	8,184.1	128,739.7	275,418.4
-1 standard deviation in costs				
1990	647.8	647.8	18,823.4	18,823.4
1991	391.4	391.4	10,488.8	10,488.8
1992	381.8	381.8	10,285.1	10,285.1
1993	499.6	499.6	13,811.3	13,811.3
1994	374.0	374.0	10,189.6	10,189.6
1995	1,018.0	1,018.0	26,091.3	26,091.3
1996	1,259.6	1,259.6	38,624.8	39,251.4
1997	242.3	242.3	8,033.7	8,207.1
1998	938.1	938.1	29,596.1	29,658.2
1999	0.0	0.0	34,802.8	35,109.0
Total	5,752.5	5,752.5	200,746.9	201,915.2
Average	575.3	575.3	20,074.7	20,191.5

PARTIAL FORECAST IMPROVEMENT

The next forecast scenario is a 50% improvement in forecast accuracy. In this case, our assumption is that the strike probability given a strike forecast, p_{11}, roughly doubles to 0.60. To maintain consistency with the other probabilities, p^1, p_{12}, and p_{22} are set to their historical means and p_1 is solved using, $p^1 = p_1 p_{11} + p_2 p_{12}$. The values for this forecast scenario appear in the middle of Table 5.9. In this case, a 50% improvement in the accuracy of the 48-hour forecast assuming a VSL of $2.275 million would increase value from $8.2 million to $23.7 million for an incremental value of more than $15 million. The incremental value is only $2.2 million with a VSL of $6 million. This diminishing marginal value of forecast information suggests that perceived losses, in this case approximated by VSL, or risk aversion may be an important factor in the value of hurricane forecast information. In other words, if losses are perceived to be very substantial, producers will always take preventive action regardless of evacuation costs. Finally, the non-linear nature of forecast value is illustrated by the perfect forecast scenarios, which suggest that potential marginal benefits from perfect information would be $200 million per year with a VSL of $2.275 million and roughly $240 million with a VSL of $6 million.

Table 5.9: Value of partial improvement in 48-hour forecast in thousand 1999 dollars

	VSL = $2.275 million					
	Existing Forecasts		50% Improvement		Perfect Forecasts	
Year	Drilling	Production	Drilling	Production	Drilling	Production
1990	0.0	1,884.6	0	2,167	48,998.7	77,508.0
1991	1,442.0	1,151.9	1,241	1,290	26,807.5	44,287.1
1992	0.0	1,003.2	0	1,115	11,851.5	47,715.4
1993	0.0	1,118.3	0	1,233	47,459.1	63,470.9
1994	158.6	786.3	0	856	45,001.7	45,569.2
1995	5,867.5	1,501.4	18,368	1,600	135,890.0	110,265.2
1996	19,537.6	1,631.4	69,294	1,699	353,793.8	161,207.3
1997	5,234.0	313.1	15,541	324	82,810.9	33,466.5
1998	28,133.7	1,003.7	68,728	1,042	273,514.0	127,752.8
1999	10,097.3	1,030.7	51,305	1,053	174,457.7	162,587.7
Average	7,047.1	1,142.5	22,448	1,238	120,058.5	87,383.0
Combined	8,189		23,685		207,441	
Year	VSL = $6 million					
1990	0.0	5,133.7	0	4,767	48,998.7	91,826.4
1991	0.0	2,632.3	0	2,470	27,009.3	50,194.5
1992	0.0	2,614.0	0	2,490	11,993.1	50,522.7
1993	0.0	3,048.2	0	3,905	47,516.3	68,460.0
1994	0.0	2,131.9	0	2,513	45,393.9	49,618.4
1995	0.0	4,048.2	0	5,530	138,505.4	121,540.5
1996	803.1	4,430.6	0	8,894	416,418.9	202,038.3
1997	1,259.4	847.9	6,495	1,572	121,034.4	42,423.9
1998	2,581.7	2,711.1	12,256	5,628	396,481.2	148,685.1
1999	1,855.6	0.0	0	0	209,911.1	188,401.0
Average	650.0	2,759.8	1,875	3,777	146,326.2	101,371.1
Combined	3,409		5,652		247,697	

CHAPTER VI: A DESCRIPTIVE DECISION MODEL

There has been considerable interest in whether or not prescriptive models of decisions made under uncertainty accord with actual behavior (Viscusi, 1985; Johnson and Holt, 1997). In this section, two descriptive methods of modeling the decision to evacuate are developed. The first section presents a qualitative analysis of hurricane evacuation decisions. This analysis sheds light on the overall propensity to evacuate, and permits a rough estimate of the costs of false evacuations to be made. Subsequent sections develop two econometric models of the decision to evacuate. These models allow an examination of the effects of several variables on the decision to evacuate. Limitations in the data prohibit estimation of the ideal specification. As a result, an alternative model is estimated.

A QUALITATIVE ASSESSMENT

This section develops simple decision rules for evacuation decisions to estimate the costs of false evacuations. This estimate can be compared to results from the decision analytic approach executed above, specifically the valuation of perfect information. This analysis also will provide a basis for the specification of an econometric model of evacuation decision making that follows. Table 6.1 provides a summary of the evacuation data for a sample of 15 storms occurring during the period 1979-1989. Each observation represents an individual drilling rig, *i.e.* a decision. Observations include on storms include decision counts, percent of rigs evacuated, and the *ex post* peak velocity in each storm near the drilling area appears in Table 6.1. The Drilling Area is west of 85

Table 6.1: Drilling rig evacuations during various hurricanes

Year	Storm	Number of Decisions	Percent Evacuated	Peak wind speed in drilling area
1979	Bob	9	89	65
1979	Claudette	10	70	45
1980	Allen	11	100	155
1980	Jeanne	18	100	60
1983	Alicia	13	46	100
1983	Barry	12	42	70
1985	Danny	22	100	75
1985	Elena	15	87	90
1985	Juan	18	83	75
1985	Kate	15	100	105
1988	Flo	14	79	70
1988	Gilbert	13	100	160
1988	Keith	12	0	60
1989	Chantal	16	88	55
1989	Jerry	10	100	64

degrees longitude (west of Tallahassee, Florida) and north of 25 degrees latitude (north of Tampa Bay, Florida). This captures the geographic extent of drilling operations.

The decisions include those made to evacuate or remain on the rig. Recall that in Chapter IV for the estimation of evacuation costs, only those observations where an evacuation occurred were included. After a careful examination of each storm path and the *ex post* peak wind speed, the following general conclusions regarding decision making behavior are proposed:

- If a storm that originated outside of the Drilling Area enters the Drilling Area, a high percentage of rigs are evacuated, almost regardless of the intensity of the storm.

- If a storm approaches but does not enter the drilling area, and is of high intensity, (e.g. Gilbert), a high percentage of rigs are evacuated. The opposite also appears to hold; if a storm approaches but does not enter the drilling area, and is of low intensity, (e.g. Keith), a low percentage of rigs are evacuated.

- If a storm forms within the drilling area, the evacuation decision is mixed (e.g. Alicia).

While these conclusions are qualitative, they provide some guidance to predict evacuation decisions for the majority of storms outside of the sample. For example, a weak storm in the Gulf of Campeche is unlikely to elicit an evacuation. Similarly, a strong storm that is on a clear path to enter the drilling area and, in fact, does is very likely to elicit an industry-wide evacuation. Fortunately, most storms are easily categorized. For those storms that do not fall into an easily defined category, an analog storm from the sample provides a guide.

Predicting Evacuation Decisions

In this section, the evacuation predictions are presented using our general rules and storm analogs where the state of evacuation is unclear (see Table 6.2). Those storms with a non-evacuation prediction are not included.

Decision criteria are needed to determine if an evacuation was warranted *ex post*. As mentioned above, most drilling rigs are rated to withstand ~100 knot winds in a worst case configuration (maximum variable load in the derrick). If winds exceed the rating, it is possible for the rig to be severely damaged or lost entirely. The following question was posed to decision makers in oil companies and drilling contractors, “If you had perfect information about the intensity of the storm at your location, what is the maximum allowable wind speed for which you would decide to remain on the rig?” Of course the answers to this question varied between companies and individuals, but a general consensus emerged that decision makers would be willing to "ride out” a Category 1 storm and would evacuate for anything stronger. Using this criterion, an *ex* *post* assessment of whether an evacuation was warranted or not for both our actual and predicted observation decisions is presented in Table 6.3.

Table 6.2: Evacuation predictions for out-of-sample, 1979-1999

Year	Storm	Percent evacuated, actual (predicted)	Peak wind speed in drilling area	Analogs
1979	Bob	89	65	
1979	Claudette	70	45	
1979	Frederic	(100)	115	
1979	Elena	(50)	35	Alicia (83)
1980	Jeanne	100	60	
1980	Allen	100	155	
1983	Alicia	46	100	
1983	Barry	42	70	
1985	Juan	83	75	
1985	Danny	100	75	
1985	Elena	87	90	
1985	Kate	100	105	
1986	Bonnie	(50)	75	Alicia (83)
1988	Flo	79	70	
1988	Gilbert	100	160	
1989	Jerry	100	64	
1989	Chantal	88	55	
1992	Andrew	(100)	120	Bob (79), Flo (88)
1994	Alberto	(85)	55	Chantal (89), Juan (85)
1995	Allison	(100)	65	
1995	Erin	(100)	80	
1995	Opal	(100)	130	
1996	Josephine	(50)	60	Alicia (83)
1997	Danny	(50)	70	Alicia (83)
1998	Georges	(100)	95	
1998	Earl	(100)	85	
1998	Charley	(50)	60	Alicia (83), Bob (79), Flo (88)
1998	Frances	(85)	55	
1998	Hermine	(50)	40	Alicia (83)
1999	Bret	(100)	125	
1999	Harvey	(50)	50	Alicia (83)

Our implicit assumption is that all rigs are exposed to the maximum wind speed, which may not, in fact, be true in all cases. Only one-third of evacuations are deemed appropriate *ex post*. These false alarms can be valued in a similar fashion to our rough estimates used to motivate the present question. Using the appropriate rig day-rates, the cost of these false alarms by year can be computed.

Table 6.3: Ex post assessments of decisions to evacuate, 1979-1999

Year	Storm	Percent evacuated, actual (predicted)	Peak wind speed in drilling area	Ex post (false alarm = 1)
1979	Bob	89	65	1
1979	Claudette	70	45	1
1979	Frederic	(100)	115	0
1979	Elena	(50)	35	1
1980	Jeanne	100	60	1
1980	Allen	100	155	0
1983	Alicia	46	100	0
1983	Barry	42	70	1
1985	Juan	83	75	1
1985	Danny	100	75	1
1985	Elena	87	90	0
1985	Kate	100	105	0
1986	Bonnie	(50)	75	1
1988	Flo	79	70	1
1988	Gilbert	100	160	1
1989	Jerry	100	64	1
1989	Chantal	88	55	1
1992	Andrew	(100)	120	0
1994	Alberto	(85)	55	1
1995	Allison	(100)	65	1
1995	Erin	(100)	80	1
1995	Opal	(100)	130	0
1996	Josephine	(50)	60	1
1997	Danny	(50)	70	1
1998	Georges	(100)	95	0
1998	Earl	(100)	85	0
1998	Charley	(50)	60	1
1998	Frances	(85)	55	1
1998	Hermine	(50)	40	1
1999	Bret	(100)	125	0
1999	Harvey	(50)	50	1

A SIMPLE EVACUATION DECISION MODEL

This section develops a discrete choice model of evacuation decisions. Of primary interest are those storms where both evacuations and non-evacuations are observed. Storms that meet this criterion include Alicia, Barry, Bob, Chantal, Claudette, Elena, Flo, and Juan. Bob (1979) and Claudette (1979) are not included in the present analysis due to incomplete data. Storms that cause either near complete or incomplete evacuations are less interesting because the decision to evacuate does not vary between decision makers. This leaves six storms for econometric modeling.

Decision makers elect to evacuate based on a complex set of variables, including specifics of the well in progress, the physical location of the rig, logistics, attributes of the decision maker, and forecast and actual storm positions and strength. The decision to evacuate for a particular hurricane is discrete; either the crew is released from the rig, or it stays on location and rides out the hurricane. This decision can be modeled with qualitative response models such as probit or logit. Define an unobservable latent variable, Y_{it}^{*}, as the propensity to evacuate as follows:

$$Y_{it}^{*} = X_{it} b + u_{it} \tag{19}$$

where Y_{it}^{*} is the unobserved latent variable for rig i in t time period during a storm, X_{it} is a vector of independent variables, b is a vector of parameters to be estimated, and u_{it} is a random error term, which is assumed to be normally distributed with zero mean and constant variance, $N\left(0, s^{2}\right)$

The first observation for a rig is made when the hurricane or tropical storm enters the Watch Area as defined above, and the last observation is made once the storm has made landfall (the typical end of life for most hurricanes) or once a particular rig has made a decision to evacuate. We do not observe Y_{i}^{*} but Y_{it} according to the rule:

$$Y_{it} = \begin{cases} 1 \; if \;\; Y_{it}^{*} > 0, \; (evacuate) \\ 0, \; otherwise \, (not \; evacuate) \end{cases} \tag{20}$$

Maximization of the likelihood function yields parameter estimates that are consistent and asymptotically normal and efficient. The function is globally concave, and it can be solved numerically with one of many optimizing techniques (Greene, 2000). Barring misspecification, the asymptotic covariance matrix can be computed as the inverse of the Hessian evaluated at the maximum likelihood estimates.

An Ideal Specification

The ideal specification of the model given by equations (19) and (20) would include observations every six hours (the frequency of new forecast and actual hurricane information) for each rig over the life of the hurricane, or until a decision to evacuate was made, at which point observations for that particular rig would cease (*i.e.* the decision is made, subsequent observations are meaningless). Such a specification would allow modeling a decision makers' response to subtle changes in the forecasts and changes in raw hurricane position and strength. In this case, the modeling would involve both the discrete decision to evacuate and the timing of that decision. Note that the structure of such a model will likely result in temporally unbalanced series, each rig may have a different number of observations based on its decisions. For example, a rig that evacuates early may have one or two "no evacuate" observations before an "evacuate" decision is observed, resulting in three observations for that rig. A second rig that evacuates later may have six or eight "no evacuate" observations before an "evacuate" decision is observed. Of course a rig may have all “no evacuate” decisions, which would represent the maximum number of observations for a rig per storm. A final comment is that for each series of observations for a rig, the only independent variables that change over time are the forecast and actual hurricane data.

Regardless of the merits and pitfalls of such a model, there is a more fundamental hurdle to such an analysis. Unfortunately, our observations of the evacuations decision are not precise in the temporal sense, we do not observe (in detail) the exact time that a rig is evacuated, we only know if it was evacuated or not, and the approximate duration of the evacuation. Our evacuation observations derive from drilling records that contain a simple depth versus days plot. This plot is loosely annotated with drilling information and other pieces of information regarding the overall progress of the well. The intended purpose of these records is to capture trouble spots for the given well, information that can be used as a reference for well planners if drilling is performed in the same area at a later date. As a result, there is imprecise accounting of weather related information regarding the exact dates and times of evacuations, although the overall duration of the evacuation can be approximated with some confidence.

A Relaxed Specification

Given the quality of the data on evacuations, a relaxed specification is undertaken that models the discrete choice to evacuate, but does not incorporate the exact timing of the decision. Again, the model to evacuate for a particular hurricane is discrete. Either the crew is released from the rig, or it stays on location and rides out the hurricane. This decision can be modeled using equations (19) and (20) as above, with the deletion of the subscript t.

In this specification, time and weather related information does not enter. Given the relative similarity of the forecasts for each drilling location, however, the reasons for differences in the discrete choice to evacuate are likely to reside in the other areas anyway. Recall that our qualitative analysis demonstrated consistent evacuation behavior observed for primary categories of storm types, in terms of paths and intensities. Therefore, it appears that dropping weather related information from the model of the evacuation decision does not result in a significant loss of information with regard to the ultimate decision to evacuate or not. Nevertheless, our specification below includes individual storm effects, which may reflect the unique meteorological attributes of each storm.

Having described the decision making process in detail, it is now appropriate to discuss the independent variables that belong in a model of evacuation decision making. The following variables are proposed for an initial specification. Subtleties of the econometric estimation will be addressed below.

Decision Maker Attributes.

It is possible that evacuation criteria vary among decision makers (oil companies). Some decision makers may be more conservative than others and hence more likely to evacuate under identical circumstances. But what attributes lead to different evacuation criteria? A reasonable hypothesis is to expect larger, well known companies that possess valuable brand names and accumulated goodwill to be more conservative in evacuation decisions. Such companies have more to lose in the case of a human catastrophe. These losses impact the value of the brand name and goodwill. Another plausible hypothesis argues that large companies, due to their superior accumulated wealth, tend to be more risk neutral than smaller companies, and one could expect fewer evacuations given the extremely low probabilities of a catastrophe actually occurring. To model both of these hypotheses, we define a variable (**RET**) that takes on a value of 1 if the oil company possesses retail gasoline sales (a brand name), and zero otherwise.

A second attribute that may affect the decision to evacuate is the decision maker's offshore experience. More experienced operators may be more (less) likely to evacuate based on the accumulation of their experience making such decisions. Define a variable **OPCUM** that represents the cumulative number of wells drilled by the particular decision maker as of the year prior to the evacuation decision. There is no prior hypothesis regarding the sign of this coefficient.

Location and Well Attributes.

Features of the well being drilled influence the decision to evacuate. As described above, whether or not the drilling rig is in deepwater (floating operations with drilling riser) influences the safe evacuation time (SET). Decision makers on a deepwater rig are forced to make their evacuation decision earlier than their counterparts on jackup or platform rigs. A water depth variable, **WD400**, can be defined to represent this dichotomy, with a binary variable that takes on a value of one when the water depth exceeds 400 feet (a proxy for the floating rig threshold). Based on this definition, the expectation is that the coefficient should be positive. Other well attributes such as well depth, **DEPTH**, and whether or not a well is being drilled over a production platform, **EVD**, may also affect the lead time required to secure the well. The deeper a well, the longer it takes to condition the drilling mud and hole, trip drill pipe, set cement plugs, and abandon the well. Therefore, the coefficient on the DEPTH variable should be positive.

When a well is drilled over an existing production platform, operational complexity increases. Securing the joint work site for a hurricane may require more time and precautions and, therefore, more lead time. As a result, define a binary variable EVD that takes on a value of one for exploration wells and zero for development wells. Development wells are typically drilled over existing production platforms. Based on our hypothesis, the coefficient for this variable should be negative. Another interpretation for EVD is independent of the SET effect. Since a production well is typically drilled over a platform, there is the opportunity for rig/platform interaction during a storm. Damage that may otherwise be uneventful when the rig or platform is isolated may be catastrophic when the structures are so close together. For example, if the drilling rig's derrick were to collapse, it may fall on the production platform, increasing the damage and perhaps initiating a blowout. A decision maker may be more likely to evacuate in such circumstances.

Evacuation Costs.

When evacuation costs are low, the likelihood of evacuation is increased, *ceteris paribus*. For each storm and rig type, evacuation cost is simply the rig rate multiplied by the evacuation duration. This value varies between rig types and over the years as rig rates change. If significant, the coefficient on this variable should be negative.

Descriptive Statistics

For the six storms modeled in this example, the correlation coefficients and basic descriptive statistics are summarized in Table 6.4. The continuous variables exhibit wide ranges, and the binary variables are not significantly unbalanced. In addition to the variables previously defined, Table 6.4 also includes information on the duration of evacuations for these storms, and the variable OPCY which represents the number of wells drilled by the decision maker (the oil company) in the year of the observation; the purpose of this variable is explained below.

Table 6.4: Descriptive Statistics for Discrete Choice Explanatory Variables

Variable	Mean	Standard deviation	Maximum	Minimum
Evacuate (Y_{it})	0.73	0.45	1.00	0
RET	0.69	0.46	1.00	0
OPCUM	808	726	3,068	2
DEPTH	9,852	5,585	22,000	360
WD	558	762	3,252	13
WD400 (binary)	0.35	0.48	1.00	0
EVD	0.82	0.38	1.00	0
COST ($1,000)	115	68	21	62
Days evacuated	4.5	4.8	23	0
OPCY	38	22	83	2

Analysis of the correlation coefficients, which is not included here, yields the anticipated conclusions. RET and OPCUM are somewhat correlated; large, integrated firms with retail operations typically have robust upstream operations. Similar logic holds for OPCUM and OPCY. The water depth variables (both the raw continuous variable and the binary variable) are highly correlated with COST. This is due to the fact that deepwater rigs are substantially more expensive to operate, and they are typically evacuated earlier, leading to longer duration evacuations. This last fact will affect the specification of the econometric model.

Estimation

Recall, we have a sample of six storms with the following observation counts by storm: Alicia, 13; Barry, 12; Chantal, 16; Elena, 13; Flo, 14; Juan, 17. Again, the sample is defined by those storms where both evacuations and non-evacuations were observed. Note that the number of observations is slightly less than the previously stated count for this sample of storms (by three). This is due to the fact that some evacuation observations occur on state leases where we have no borehole specific data, so the full vector of independent variables is unavailable.

Estimation of individual storm regressions is troubled by the low observations counts and poorly conditioned data. There are multiple instances where one or more independent variables perfectly predict the dependent variable. When all observation are pooled, the following results are obtained and presented in Table 6.5.

Table 6.5: Parameter estimates of probit model of drilling rig evacuation

Variable	Estimate	(t-statistic)
C	0.7109	(1.33)
RET	-0.1920	(-0.46)
OPCOM	-0.0076	(-0.29)
DEPTH	-0.0804	(-0.30)
WD400	0.7688	(2.18)
EVD	-0.1364	(0.34)
Likelihood ratio (LR)	5.2989	(0.381)
Log likelihood	-46.9772	
LR index	0.0534	
Observations (positive)	85 (62)	

Note that the COST variable is omitted due its high correlation with WD400. Only the coefficient for WD400 is significant, and it is signed as expected. When in deep water, decision makers are more likely to evacuate, reflecting the increased SET and the need to make an evacuation decision under greater uncertainty. Decision makers on shallow water locations can defer their decision (relatively), and avoid a greater share of evacuations, *ceteris paribus*.

Recall that our expectation of the sign of the COST variable was negative so that the higher the cost of evacuating, the less likely to evacuate. Given that WD400 and COST are highly positively correlated, the positive sign on WD400 implies that COST does not appear to play a significant role in the decision to evacuate. This may reflect the scale of the costs and losses. Whatever the nature of the decision making process, the fact that the expected loss is orders of magnitude larger than the evacuation costs would tend to mask the influence of slight variations in the cost.

The overall explanatory power of this model is low as indicated by the likelihood ratio test and index, and the fact that the model always predicts an evacuation. A second model of evacuation is specified based on one of the evacuation rules derived above in our qualitative analysis of evacuation decisions. Based on that analysis, define a new binary variable, ORIGIN, which takes on a value of one when the storm forms within the drilling area, and a value of zero otherwise. Additional variables based upon the other decision rules discussed above are not included because they would rely on *ex post* information that would not be available to decision makers. The results of this specification are given in Table 6.6.

Table 6.6: Parameter estimates of probit model with ORIGIN variable

Variable	Estimate	(t-statistic)
C	0.838	(1.529)
RET	-0.167	(-0.393)
OPCOM	-0.098	(-0.364)
DEPTH	-0.093	(-0.334)
WD400	0.735	(2.014)
EVD	-0.196	(-0.476)
ORIGIN	-0.842	(-2.086)
Likelihood ratio (LR)	9.705	(0.381)
Log likelihood	-44.774	
LR index	0.098	
Observations (positive)	85 (62)	

The results are similar to the previous specification, with only a slight improvement in overall explanatory power. The WD400 variable remains significant, and the newly introduced ORIGIN variable is negative and significant. This latter result implies that when a storm forms within the drilling area, decision makers either assume the storm will quickly move to land before strengthening and choose to remain on the rig, or that evacuation is complicated by deteriorating weather conditions (boats and helicopters cannot operate) and is simply not possible.

A third model is specified employing fixed effects for the individual storms. This would appear appropriate for this specific sample given that two of the storms (Alicia and Barry) exhibit more balanced proportions of evacuations and non-evacuations than the other storms that exhibited a high proportion of evacuations, which may be a result of the particular storm histories. Since the error terms are independent and identically distributed, the discrete nature of the dependent variable does not introduce any unusual estimation issues. These results are presented in Table 6.7.

The results from the fixed effect model are significantly more robust than the pooled estimates as indicated by the likelihood ratio test and index. A likelihood ratio test for the two models (pooled without ORIGIN variable versus fixed effect) yields a test statistic of 2(-38.75 + 46.98) = 16.46 which exceeds the critical value of 12.59 at the 95 percent significance level, indicating a significantly better fit for the fixed effect model.

The differential storm evacuation rates are detectable in the scale and significance of the fixed effects. Alicia formed over the drilling area and quickly strengthened. Evacuations may not have been possible, and this resulted in more non-evacuations. Barry was a weak storm that skirted the bottom of the Drilling Area, convincing some decision makers to continue drilling operations. Both of these peculiarities are reflected in the significance of the fixed effects. Chantal, Juan, and Flo display very similar storm histories to each other, so it is no surprise they yield similar fixed effects and significance. Elena was a strong storm that veered just east of the drilling area. This type of storm path is generally identified by high evacuation rates (for Elena evacuation rate was 87 percent). Given the results for Chantal, Juan, and Flo, the coefficient on Elena is difficult to explain.

Table 6.7: Parameter estimates of probit model with fixed storm effects

Variable	Estimate	(t-statistic)
ALICIA	-0.053	(-0.076)
BARRY	-0.267	(-0.381)
CHANTAL	1.517	(2.145)
ELENA	1.185	(1.526)
FLO	1.101	(1.435)
JUAN	1.638	(2.123)
RET	-0.256	(-0.550)
OPCOM	0.515	(1.662)
DEPTH	-0.161	(-0.536)
WD400	0.574	(1.397)
EVD	-0.547	(-1.080)
Likelihood ratio (LR)	21.757	(0.016)
Log likelihood	-38.747	
LR index	0.219	
Observations (positive)	85 (62)	

The estimates for decision maker attributes and location specific coefficients have changed from the pooled estimates. WD400, while still positive, is now insignificant. But the general consistency of the results on WD400 among the three specifications supports the conclusion that decision making is a function of this location attribute. Regarding the company attributes, OPCUM has taken on new significance. The positive sign on the coefficient implies that experience leads to caution. Such a result may be due to bad experiences in the past that led to human and financial losses.

We re-emphasize that the error terms in the fixed effect model are independent and identically distributed. If this assumption is relaxed in this discrete choice framework, the probit model is ill suited to the task. A random effects model is feasible, albeit quite complex (Greene, 2000; Baltagi, 2002). Based on the quality of both the data set and these initial results, such an investigation is possible in the future.

STRUCTURAL MODEL OF THE DECISION TO EVACUATE

This section examines the possibility that the decision maker is risk averse. If this is the case, the results of the Nelson-Winter analysis (where we posit a risk neutral decision maker) may be fundamentally flawed. Therefore, investigation into risk preferences is of some interest. Testing for risk aversion requires the specification of a utility function.

Our structural model of decision making is based upon the utility framework developed by Cicchetti and Dubin (1994), who studied the decision to self-insure in the context of home telephone maintenance. Define a general form of utility function, $U(W,s,e)$ where W is wealth or firm value, s represents attributes of the decision maker, and e is a random component of utility. With the assumption of additively separable errors the utility function is $U(W,s)+e$. Given utility maximization, the decision maker would evacuate when:

$$U(W-C,s)+e_1 > pU(W-L,s)+(1-p)U(W,s)+e_2 \tag{21}$$

where C is evacuation cost, p is the probability of a hurricane strike, and L is the loss given a hurricane strike.

If the e_i are independent and distributed as the extreme value distribution (McFadden, 1974; Maddala, 1983), the probability of observing an evacuation is:

$$\Pr(evacuation) = 1/(1+e^{-q}) \tag{22}$$

where $U(W-C,s)-\{pU(W-L,s)+(1-p)U(W,s)\}$. There is no information to inform the specification of a utility function for offshore oil and gas decision makers. Therefore, consider using the flexible form from the family of hyperbolic absolute risk aversion functions (HARA) of the following form:

$$U(W,s) = a_1(W+a_2)^k + e \tag{23}$$

A detailed discussion of the mathematical properties of this family of utility functions is available in Merton (1971). Given this utility function and the decision to evacuate, utility is $a_1(W+a_2)^k + e_1$. Given the decision to remain on the rig, utility is $pa_1(W+a_2)^k + (1-p)a_1(W+a_2)^k + e_2$.

The exponent k is intended to capture differences in risk aversion across decision makers and physical locations, and is a function of the variables defined above in the discrete choice evacuation model:

$$k = b_1 + b_2RET + b_3OPCUM + b_4WD400 + b_5EVD + b_6DEPTH \tag{24}$$

A simpler specification, $k = b_1 + b_2RET + b_3WD400$, employs one variable to describe the decision maker and one to describe the physical location. Recall that these two variables were the only ones to exhibit any statistical significance in the discrete choice modeling. This specification of k may be required if the full specification is poorly conditioned with respect to convergence.

Wealth is estimated based upon annual drilling cost, based on the number of wells drilled by the decision maker in the year of the observation, OPCY. For example, multiply OPCY by the average well duration in the Gulf of Mexico (about 25 days), and by an average daily operating cost for the drilling rig, services, and equipment (about $100,000) provides an estimated annual expenditure value. This approach puts the decision into one of *annual* utility maximization. Descriptive statistics for OPCY are given in Table 6.4. This proxy should be sufficient to anchor the analysis on the appropriate part of the utility function. Any rescaling of the wealth and cost figures in the context of numerical optimization must be proportional.

Evacuation cost is determined by the rig type and year of the observation. The expected loss given a hit, E(L), is $2.275 million as above. The historic climatological probability of a hurricane strike is used for p. This specification leads to the following likelihood function:

$$L = \prod_i \left[1 \big/ \left(1 + e^{-q_i}\right) \right]^{y_i} \left[1 - 1 \big/ \left(1 + e^{-q_i}\right) \right]^{1-y_i} \tag{25}$$

where $y_i =$ observation of decision to evacuate (1) or not (0).

Estimation Results

Maximization of equation (25) is accomplished numerically. The procedure is non-trivial given the complexity of the specification. The primary problem in this case is the nature of the utility function itself. There are no restrictions on any parameters during the iterations. It is therefore possible for $-1 < k < 1$ and $(W + a_2) < 0$, causing a degeneration of the iterations. Techniques exist to overcome such obstacles, and involve ignoring degenerate observations, rescaling of explanatory variables, and adjusting starting values. Use of all these methods was required for this data set.

The results for our pooled sample with the full specification of k are given in Table 6.8. All terms measured in dollars have been rescaled to millions of dollars. Standard errors are computed using the inverse of the Hessian evaluated at the maximum likelihood estimates. Of all the decision maker and location attributes, not one is significant. Nonetheless, we can compute predicted values of k as an indicator of the degree of risk aversion. The closer to k is to one, the closer it is to risk neutrality. For these 85 observations, the average value of k is 0.71 with a maximum of 0.93 and a minimum of 0.58. Note that when the model is estimated with the restriction that $b_i = 0$ (except for b_1), the log-likelihood value is –51.399, resulting in a likelihood ratio value of 8.164 which does not exceed the 95 percent critical value of 11.07.

In addition to the above specification, a simpler specification for k described above is estimated with the results presented in Table 6.9. The simplified model provides essentially the same fit as the fully specified model, thus this parsimonious approach hereafter. Again, the explanatory variables are not significant.

Table 6.8: Parameter estimates of HARA model of drilling rig evacuation

Variable	Estimate	(t-statistic)
a_1	18.313	(0.052)
a_2	248.219	(0.110)
b_1	0.677	(0.271)
WD400	0.229	(0.630)
OPCOM	0.016	(0.245)
RET	-0.025	(-0.169)
DEPTH	0.013	(0.159)
EVD	-0.070	(-0.444)
Likelihood ratio (LR)	-47.317	
Observations (positive)	85 (62)	

Finally, fixed effects of each storm are included in k as follows:

$$k = b_2 WD400 + b_3 OPCUM + \sum_{i=1}^{6} c_I STORM_I \qquad (26)$$

This controls for differences in behavior between storms. The results for this specification are in Table 6.10. As in the basic discrete choice model, inclusion of fixed effects by storm significantly improves the overall fit of the model versus the pooled specification (LR = 19.228 > 12.59) at the 95 percent significance level.

Table 6.9: Parameter estimates of restricted HARA model of drilling rig evacuation

Variable	Estimate	(t-statistic)
a_1	269.753	(0.045)
a_2	421.961	(0.164)
b_1	0.334	(0. 155)
WD400	0.168	(0.485)
OPCOM	0.005	(0.110)
Likelihood ratio (LR)	-47.579	
Observations (positive)	85 (62)	

The general structure of the results (signs and relative magnitudes) for the fixed effects coefficients is similar to those of the basic discrete choice model with fixed effects, except for the lack of statistical significance. Only WD400 is significant at the 10 percent level. Seventy-four percent of the observations yield positive k values, with those observations yielding an average value of k of 0.13 with a maximum of 0.28 and a minimum of 0.01. Note that our focus is on the positive values of k due to the definition of the degree of absolute risk aversion, R(W), for the utility function as,

Table 6.10: Parameter estimates of HARA model with fixed storm effects

Variable	Estimate	(t-statistic)
ALICIA	-0.306	(-1.037)
BARRY	-0.225	(-0.961)
CHANTAL	0.062	(1.042)
ELENA	0.017	(0.305)
FLO	0.006	(0.097)
JUAN	0.057	(1.146)
a_1	6,476.678	(0.407)
a_2	221.468	(0.347)
WD400	0.082	(1.768)
OPCUM	0.092	(1.132)
Log likelihood	-37.965	
Observations (positive)	85 (62)	

$R(W) = -R(W)'' / R(W)' = (1 - k) + a_2$. Monotonicity and concavity require that $0 < k < 1$ (Cicchetti and Dubin, 1994). The result for k is quite different to that obtained under the pooled specification. While not all of the observations conform to the mathematical restriction on k, those that do conform, indicate a higher degree of risk aversion.

The results from our pooled model indicate a slight degree of risk aversion, but the fact that none of the explanatory variables are statistically significant undermines any strong conclusions in this regard. The fixed effect model, while possibly indicating a higher degree of risk aversion, is similarly troubled by a lack of explanatory power. Other issues that may deserve additional study are the sensitivity to different specifications of the utility function, and defining a better proxy for wealth, although the latter effort is complicated by data availability for small or privately held companies.

Given all of this evidence, it is interesting to note that the WD400 variable is weakly significant in the fixed effect model. Based on this, it seems safe to conclude that water depth is a significant factor in evacuation decisions, and that other decision maker attributes are not.

CHAPTER VII: CONCLUSIONS AND POLICY IMPLICATIONS

More accurate forecasts of hurricanes are possible with improved observational accuracy of the conditions spawning storm development. These advances could be achieved with the application of new satellite observational systems and the development of better numerical weather prediction models. This study provides evidence from one industry on the potential benefits of these investments. The incremental value of benefits to the oil and gas industry from a 50% improvement in hurricane forecasting accuracy is approximately $15 million assuming a value of statistical life of $2.275 million. If weather forecasting technology could deliver such an improvement, then the question becomes whether the energy industry would be willing to support such an effort. Naturally, this raises a classic public goods problem since the benefits would flow to other industries, thus, creating potential free-rider problems and a lack of private investment. Similar benefits may exist for many other production activities affected by hurricanes, such as shipping and transportation. Naturally, local communities, specifically emergency management personnel, face similar evacuation decisions and also could benefit from improved forecast accuracy.

Identifying the possible actions agents can take with forecast information or more accurate forecasts is also a challenge for studies attempting to place a monetary value on this information. This case study focused on off-shore energy production with a clear delineation of possible actions in the event of a hurricane contributes to the literature on value of forecast information, using prescriptive decision rules for optimal actions with uncertain outcomes based upon the hypothesis of expected utility maximization under risk neutrality.

The second part of the descriptive methodology included the specification of several discrete choice econometric models. Interpreted jointly, these models provide some support for the conclusion that location attributes, specifically water depth, influence the propensity to evacuate. There is also limited support for the conclusion that decision maker experience increases the propensity to evacuate. These results support the notion that behavior changes as a result of the location of the drilling rig, not attributes of the decision maker or his company in general. While it is possible to use the econometric models in a predictive mode for storms outside of the sample, such an effort is compromised by several factors.

Finally, the results of our discrete choice model derived from a general utility function are mixed. The results from a pooled model indicate a slight degree of risk aversion, but the fact that none of the explanatory variables are statistically significant undermines any strong conclusions about decision maker behavior. The fixed effect model, while possibly indicating a higher degree of risk aversion, is similarly troubled by a lack of explanatory power. Issues that may deserve additional study are the sensitivity to different specifications of the utility function, and defining a better proxy for wealth.

Throughout we have noted two items regarding the domain of the investigation. Due to data availability, we focus only on drilling rigs and exclude production operations, workover operations, and construction activities. Each of these other functions faces the same type of evacuation decision, albeit with different parameters of cost and loss. Because of this, the present results should be viewed as only a portion of the total costs of false hurricane evacuations for the industry as a whole. Also, our analysis generally includes only those rigs in a drilling mode, and excludes those performing completions, workovers, abandonment, or that are in transit. Because of this, the results could be scaled up by a factor of 1.2-1.4 to account for these omitted rigs.

The preliminary descriptive model developed in this study could be applied to other decisions under natural hazards and to test whether these decisions are consistent with the expected utility hypothesis or alternatives, such as loss aversion and other behavioral hypotheses derived from prospect theory. Various hypotheses concerning the role of forecasts and forecast perception in these decisions could be tested. These descriptive models would provide alternative estimates for the value of forecast information.

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APPENDIX A: SAMPLE MARINE FORECAST/ADVISORY

132
WTNT22 KNHC 221446
TCMAT2
HURRICANE DEBBY FORECAST/ADVISORY NUMBER 12
NATIONAL WEATHER SERVICE MIAMI FL AL0700
1500Z TUE AUG 22 2000

AT 11 AM AST...1500Z...THE GOVERNMENT OF THE BAHAMAS HAS ISSUED A HURRICANE WARNING FOR THE SOUTHEAST BAHAMAS...INCLUDING ACKLINS...CROOKED...INAGUAS...MAYAGUANA AND THE RAGGED ISLANDS... AND ALSO FOR THE TURKS AND CAICOS ISLANDS.

A HURRICANE WARNING REMAINS IN EFFECT FOR ANGUILLA...THE BRITISH AND U.S. VIRGIN ISLANDS...PUERTO RICO AND ITS SURROUNDING ISLANDS...AND FOR THE NORTH COAST OF THE DOMINICAN REPUBLIC.

PRECAUTIONS TO PROTECT LIFE AND PROPERTY SHOULD BE RUSHED TO COMPLETION IN THE HURRICANE WARNING AREAS.

AT 11 AM AST...1500Z...THE GOVERNMENT OF THE BAHAMAS HAS ISSUED A HURRICANE WATCH FOR THE CENTRAL BAHAMAS...INCLUDING CAT...EXUMAS... LONG...RUM CAY...AND SAN SALVADOR.

A HURRICANE WATCH REMAINS IN EFFECT FOR HAITI NORTH OF PORT AUPRINCE.

AT 11 AM AST...1500Z...THE GOVERNMENT OF THE NETHERLANDS ANTILLES HAS DISCONTINUED THE HURRICANE WARNING FOR ST. MAARTEN...SABA... AND ST. EUSTATIUS.

HURRICANE CENTER LOCATED NEAR 18.5N 64.4W AT 22/1500Z
POSITION ACCURATE WITHIN 30 NM

PRESENT MOVEMENT TOWARD THE WEST-NORTHWEST OR 290 DEGREES AT 19 KT

ESTIMATED MINIMUM CENTRAL PRESSURE 999 MB
MAX SUSTAINED WINDS 65 KT WITH GUSTS TO 80 KT.
64 KT....... 20NE 0SE 0SW 20NW.
50 KT.......120NE 20SE 0SW 100NW.
34 KT.......150NE 25SE 25SW 120NW.
12 FT SEAS..300NE 150SE 100SW 200NW.
WINDS AND SEAS VARY GREATLY IN EACH QUADRANT. RADII IN NAUTICAL MILES ARE THE LARGEST RADII EXPECTED ANYWHERE IN THAT QUADRANT.

REPEAT...CENTER LOCATED NEAR 18.5N 64.4W AT 22/1500Z
AT 22/1200Z CENTER WAS LOCATED NEAR 18.2N 63.5W

FORECAST VALID 23/0000Z 19.2N 67.0W
MAX WIND 70 KT...GUSTS 85 KT.
64 KT... 60NE 10SE 10SW 60NW.
50 KT...120NE 30SE 30SW 120NW.
34 KT...150NE 50SE 50SW 150NW.

FORECAST VALID 23/1200Z 20.3N 70.3W
MAX WIND 75 KT...GUSTS 90 KT.
64 KT... 60NE 40SE 40SW 60NW.
50 KT...100NE 60SE 60SW 100NW.
34 KT...125NE 75SE 75SW 125NW.

FORECAST VALID 24/0000Z 21.5N 73.2W
MAX WIND 75 KT...GUSTS 90 KT.
64 KT... 60NE 40SE 40SW 60NW.
50 KT...100NE 60SE 60SW 100NW.
34 KT...125NE 75SE 75SW 125NW.

STORM SURGE FLOODING OF 1 TO 3 FEET ABOVE NORMAL TIDE LEVELS...
WITH DANGEROUS BATTERING WAVES...IS EXPECTED OVER PORTIONS OF
THE WARNED AREA.

REQUEST FOR 3 HOURLY SHIP REPORTS WITHIN 300 MILES OF 18.5N 64.4W

EXTENDED OUTLOOK...USE FOR GUIDANCE ONLY...ERRORS MAY BE LARGE

OUTLOOK VALID 24/1200Z 22.5N 75.5W
MAX WIND 80 KT...GUSTS 95 KT.
50 KT...100NE 60SE 60SW 100NW.

OUTLOOK VALID 25/1200Z 24.5N 78.5W
MAX WIND 85 KT...GUSTS 105 KT.
50 KT...100NE 60SE 60SW 100NW.

NEXT ADVISORY AT 22/2100Z

APPENDIX B: FORECAST SECTOR CODE COUNT DATA

Table B1: 12 hour, 50 knot Forecast Sector Code Counts

Year	a	b	c	d
1980	210	140	189	4,324
1981	0	0	11	798
1982	0	1	6	1,428
1983	291	124	57	4,163
1984	0	0	41	486
1985	3,072	1,663	1,489	14,890
1986	10	39	22	1,445
1987	31	6	43	647
1988	394	204	239	3,240
1989	12	71	75	2,088
1990	4	15	16	755
1991	0	0	0	24
1992	268	185	138	2,672
1993	0	0	0	422
1994	13	2	73	2,563
1995	640	473	289	4,130
1996	25	78	19	664
1997	27	54	43	1,856
1998	1,005	602	756	6,365
1999	81	87	85	2,080
2000	158	70	96	2,130

Table B2: 12 hour, 64 knot Forecast Sector Code Counts

Year	a	b	c	d
1995	207	210	111	3,303
1996	0	0	18	733
1997	3	19	20	1,644
1998	342	266	285	5,895
1999	2	26	42	2,148
2000	12	29	11	1,637

Table B3: 24 hour, 50 knot Forecast Sector Code Counts

Year	a	b	c	d
1980	124	254	235	8,460
1981	0	0	24	2,063
1982	0	1	13	4,346
1983	109	353	48	8,089
1984	0	0	100	2,594
1985	1,547	3,350	2,069	28,758
1986	6	43	84	3,425
1987	0	37	76	1,280
1988	201	389	495	10,493
1989	0	90	73	5,915
1990	0	9	11	1,618
1991	0	0	0	332
1992	203	250	155	5,404
1993	0	0	0	754
1994	0	15	46	6,443
1995	298	815	273	11,692
1996	0	81	42	3,079
1997	6	71	10	3,836
1998	754	676	777	16,124
1999	40	151	209	8,394
2000	125	82	130	4,668

Table B4: 24 hour, 64 knot Forecast Sector Code Counts

Year	a	b	c	d
1995	10	383	95	5,895
1996	0	0	2	1,960
1997	0	22	2	2,963
1998	242	245	297	12,419
1999	2	26	60	6,331
2000	7	34	32	4,424

Table B5: 36 hour, 50 knot Forecast Sector Code Counts

Year	a	b	c	d
1988	176	417	625	22,069
1989	4	85	50	9,033
1990	0	0	44	2,804
1991	0	0	0	959
1992	142	311	226	8,305
1993	0	0	0	1,785
1994	0	15	30	7,848
1995	168	931	323	24,125
1996	0	54	41	6,529
1997	0	65	1	4,636
1998	673	621	651	23,085
1999	10	181	213	10,412
2000	36	81	117	6,999

Table B6: 36 hour, 64 knot Forecast Sector Code Counts

Year	a	b	c	d
1995	0	417	122	22,581
1996	0	0	0	6,061
1997	0	19	1	4,689
1998	182	251	273	22,922
1999	0	28	60	12,066
2000	1	23	13	6,008

Table B7: 48 hour, 50 knot Forecast Sector Code Counts

Year	a	b	c	d
1985	801	2,874	1,676	35,212
1986	0	0	9	1,268
1987	0	37	80	4,413
1988	161	429	804	30,164
1989	0	88	40	12,473
1990	0	0	3	4,997
1991	0	0	0	1,694
1992	28	425	286	10,760
1993	0	0	2	4,279
1994	0	14	27	12,941
1995	109	919	443	42,977
1996	0	73	97	17,221
1997	0	54	1	6,161
1998	532	870	624	34,256
1999	0	128	236	19,036
2000	0	108	60	13,403

Table B8: 71 hour, 50 knot Forecast Sector Code Counts

Year	a	b	c	d
1985	189	1,425	1,158	21,149
1986	0	0	9	1,401
1987	0	37	0	6,260
1988	57	301	1,034	37,859
1989	0	26	16	11,829
1990	0	0	0	7,238
1991	0	0	0	2,962
1992	5	448	189	15,039
1993	0	0	0	9,147
1994	0	0	15	24,327
1995	23	822	475	73,395
1996	0	50	41	40,570
1997	0	16	12	4,212
1998	229	886	401	78,029
1999	0	101	188	43,018
2000	0	79	195	27,317

APPENDIX C: INDIVIDUAL STORM EFFECTS

The following is a brief description of each hurricane to enter the oil and gas production region of the Gulf of Mexico in the period 1985-1999. After the descriptions, a listing of the effects on production, along with an analysis of the statistical significance of those production effects, is included.

HURRICANE DANNY (AUGUST 1985)

This storm was first observed at Lat 18.5, Lon 80.7 (south of Cuba) on August 12. It slowly tracked northwest towards the Oil and Gas zone, picking up speed. It first attained hurricane-force winds at 0000UTZ, August 15, approximately 75 miles south of the MMS2-3 border.

It entered the Oil and gas region approximately six hours later, with peak winds of 75 knots, and took about 12 hours to pass across the drilling area and make landfall in central-western Louisiana. During its time in the drilling region, the peak speed was 80 knots, and 50-knot size parameters were approximately as follows:

NE: 100 nm NW: 50 nm SW: 50 nm SE: 125 nm.

Thus, the storm had a larger extent eastward from the eye. It spent about 12 hours in the drilling zone.

HURRICANE ELENA (SEPTEMBER 1985)

This storm started between Cuba and Haiti on August 28. It quickly moved northwest, attaining hurricane status at 1200, August 29 while due west of Key West. It followed this path towards the drilling zone until 1200 August 30, when it headed almost due east. After holding steady for 24 hours about 50 miles west of the Florida coast, with peak winds of 110 knots, it veered due west towards the drilling zone. At 1200, September [d] it barely clipped the northeast corner of MMS 1 before moving on to make landfall north of New Orleans. While near the drilling zone this storm had peak winds of 100 knots and the following 50-knot size parameters:

NE: 75 nm NW: 75 nm SW: 75 nm SE: 75 nm.

Note that this storm shrank quickly as it approached land. It was in the drilling zone for a maximum of 6 hours.

HURRICANE JUAN (OCTOBER 1985)

This storm had an unusual origin location: it was first observed in the central Gulf of Mexico, about halfway between New Orleans and the Yucatan Peninsula, on October 25. It meandered around that location for two days, not attaining hurricane force. On October 27 it started to head north towards the drilling zone, and finally reached peak wind speeds of 65 knots as it entered the zone at 0000, October 28, at the border of MMS

2 and 3. The storm rapidly moved due north through the drilling zone, but when it encountered land (near Morgan City, LA) it did not die down, but veered west back into the middle of MMS 5. At 0000 on the 29 it then reversed course, heading east through MMS 5 and 3.Once again, as this storm approached land it did another looping turn to the northwest, followed by another swing southeast through MMS 3. It crossed into MMS 2 at 0000, October 31, although it was now reduced to a gale-force storm with peak winds of 55 knots. In the following 15 hours is sped east, then northeast across MMS 2 and 1 before making landfall near Mobile. At its largest (on its first northward pass through the region) it had the following 50-knot size parameters:

NE: 100 nm NW: 100 nm SW: 100 nm SE: 100 nm.

By October 31 these had shrunk to:

NE: 0 nm NW: 0 nm SW: 50 nm SE: 50 nm.

This storm spent approximately 87 hours in or around the drilling zone. Juan resulted in two rigs overturning, and 11 deaths were associated with these rig collapses. According to the NHC archives, the rough seas and high winds caused by the storm made evacuation difficult.

HURRICANE BONNIE (JUNE, 1986)

This was also a storm with its origins in the Gulf, first observed at Lat 25.6, Lon 87.2, west of Key West and south of Mobile. It followed a WNW path for about 1.5 days, slowly gathering force. It entered the drilling zone at about 1500, June 25, with peak winds of 65 knots. It moved NW across MMS 5, and into the NE corner of MMS 4 before exiting the drilling zone and making landfall at about 1200, June 26 near the Texas-Louisiana border. This was a very compact storm, with 50-kt size parameters below 25 nm in each direction. Its winds peaked at 70-kt, and it was in the drilling zone approximately 18 hours.

HURRICANE FLORENCE (SEPTEMBER 1988)

This storm had its origins in the southwestern section of the Gulf of Mexico, south of Houston and west of the Yucatan. It was first observed at 0600, September 7. For one day it moved due east, making landfall on the west side of the Yucatan Peninsula. It then rebounded west, and then started to head north towards the drilling zone. By 1800 September 9 it had gained hurricane status, about 75 nm south of MMS 1. It entered the central portion of MMS 1 at about 0000 September 10, and quickly advanced northwest, making landfall over the Mississippi River Delta and rapidly losing steam. At its peak (as it entered MMS 1), the storm had the following size parameters:

NE: 100 nm NW: 50 nm SW: 50 nm SE: 100 nm.

However, in about 6 hours these shrank to:

NE: 0 nm NW: 00 nm SW: 25 nm SE: 25 nm.

This storm spent less than six hours in the drilling zone.

HURRICANE GILBERT (SEPTEMBER 1988)

The center of this storm did not enter the oil and gas region, only a small part of it affected the western Gulf. This storm had its origins in the central-west Atlantic, off the coast of Guyana on September 8. It slowly moved northwest, passing south of Cuba with peak winds of 155 knots. It crossed the Yucatan on September 15, the first category 5 hurricane to make landfall in the western hemisphere since Camille in 1969. This dropped its winds to 80 knots. Back over the western Gulf it picked up steam, increasing peak winds to 115 knots. It made landfall at La Pesca, Mexico at 2200 September 16, about 170 nm south of the most western part of MMS 6. This was a very large storm: when it was in the western gulf it had the following size parameters:

NE: 200 nm NW: 200 nm SW: 150 nm SE: 150 nm.

The large northward extent of this storm affected the western Gulf drilling region even though the eye was never within 175 nm of the region.

HURRICANE JERRY (OCTOBER, 1989)

Jerry started in the Bay of Campeche, of the north coast of southern Mexico. Between October 12 and 15 it moved northward, entering MMS 4 at about 1500 October 15. It barely made hurricane status, with winds picking up from 60 knots to 70 knots as it crossed MMS 4. It made landfall on Galveston Island at 0030 October 16 after spending about nine hours in MMS 4. At its peak, while in the center of MMS 4, the storm had the following size parameters:

NE: 50 nm NW: 30 nm SW: 30 nm SE: 50 nm.

HURRICANE ANDREW (AUGUST, 1992)

This hurricane was formed in the central Atlantic, 10 degrees north of the equator about halfway between Africa and South America, on August 16. It moved northwest until it reached Lat 25, Lon 65 (north of the Outer Antilles), and then headed due west. It passed over southern Florida in four hours on August 24, with peak winds of 120 knots, destroying the town of Homestead, 20 miles south of Miami. After dying down slightly, it picked up speeds as it moved WNW into the Gulf. It entered the southwest part of MMS 1 at about 2000 August 25, with speeds of 120 knots. After moving in a NW path across MMS 2 for another 10 hours, it made landfall over the central Louisiana coast. At its peak in the oil & gas region, the storm had the following size parameters:

NE: 90 nm NW: 60 nm SW: 60 nm SE: 60 nm.

The following is the record of damage to the offshore oil and gas industry: 13 toppled platforms, 5 leaning platforms, 21 toppled satellites, 23 leaning satellites, 104 other instances of structural damage, 7 pollution incidents, 2 fires and 5 drilling wells blown off location. Although Andrew caused 35 fatalities in the US, none of these were directly associated with offshore oil and gas.

HURRICANE OPAL (OCTOBER 1995)

This was another "near-miss" hurricane, in that its eye never quite entered the oil and gas-producing region. This storm formed over the Yucatan around September 29. After moving due west over the Bay of Campeche for about 150 nm, on October 2 it swung around to a north-northwest path, just is it gained Category I hurricane status. At 0600 October 4 its winds peaked at 130 knots, about 90 nm south of MMS 1. At 1800 October 4 the eye passed just over the southeastern tip of MMS 1 with peak winds of 100 knots. The following were the 50-kt size parameters as the hurricane touched the oil and gas region:

NE: 150 nm NW: 100 nm SW: 150 nm SE: 150 nm.

The storm made landfall near Pensacola, FL at 2200 October 4. It spent maybe 4 hours encroaching upon the drilling area. The storm was responsible for 9 deaths in the US, none related to oil and gas.

HURRICANE DANNY (JULY 1997)

Danny is the only storm in this study to have actually formed inside the oil and gas-producing region of the Gulf of Mexico. A weak non-tropical cyclonic wave in the northern gulf began to condense and organize into a tight circulation around 1200 July 16. This occurred at Lat 27.4, Lon 92.6, which is inside Grid Block 804 in the grid devised for analysis for this study. The peak winds at this time were 25-30 knots. It slowly moved east-northeast, crossing right through the middle of MMS districts 3, 2 and 1. It attained Category I status at 0600 July 18 as it moved into MMS 1, shortly after crossing over the Mississippi River delta. Storm winds peaked at 70 knots in the eastern portion of MMS 1 on July 19. The storm stalled over Mobile Bay on the 19th, and made landfall at the Alabama-Florida border on July 20. This was an extremely compact storm, with size parameters never getting above 30 nm in any direction. This storm spent approximately 42 hours inside the oil and gas region, although only about 20 of these hours were at hurricane force.

THE STORMS OF AUGUST-SEPTEMBER 1998

These storms included tropical Storm Charley, Hurricane Earl, Tropical Storm Frances, Hurricane Georges, Tropical Storm Hermine. An unprecedented period of storm activity gripped the Gulf in a six-week period in late August and September of 1998. Five storms of varying intensity blew through the region. First was **Hurricane Charley**, which had its origin in the center of the Gulf of Mexico. It was first observed at 0600 August 21. It moved quickly northwest, picking up intensity, until it entered MMS 6 at its peak of 60 knots at 0600 August 22. Within another four hours it had made landfall at Port Aransas, Texas, and dissipated to a tropical depression. There were no offshore deaths associated with this storm.

Hurricane Earl

This storm formed over the southwest Gulf, between Tampico and Merida, Mexico at 1200 August 31. It began to move east-northeast, and reached the edge of MMS 2 at about 0400 September 2. It attained Category I status eight hours later while located 125 nm SSE of New Orleans, on the south edge of MMS 1. It tracked along this edge for another eight hours, with peak winds of 85 knots (Cat. 2), and continued along out of the drilling area, making landfall at Panama City, FL at 0600 September 3. It spent about 14 hours near the edge of the drilling zone, with eight of those hours as a hurricane. It is unclear whether the eye ever entered the oil and gas producing regions, but a considerable part of the region was under the effect of this storm, as it had the following 50-kt size parameters at its peak:

NE: 100 nm NW: 60 nm SW: 0 nm SE: 120 nm.

Tropical Storm Frances

This was first observed in the western Gulf, about 120 nm east of the Texas-Mexico border at 1800 September 8. For the first 30 hours of its life, the storm moved SSW towards Mexico, directly away from the oil and gas zone. It then looped back upon itself and then headed straight north for one more day, with winds picking up to 45 knots. It then followed the same path as TS Charley, heading WNW over MMS 6. It entered the drilling region at about 0000 September 11, and passed over in about six hours, making landfall just north of Corpus Christi.

Hurricane Georges

This storm was first observed in the central Atlantic on September 16. Within a day it became a hurricane as it moved WNW across the Atlantic. Georges caused many deaths, mainly due to the fact that it passed directly over Puerto Rico, the Dominican Republic, Haiti and Cuba on its way to the Gulf. It hit land at Key West on September 25It passed across the 25th parallel about 300 nm due south of Pensacola at 0300 September 26, and headed northwest towards MMS 1. The eye entered the oil and gas region at about 1900 September 27, packing 95 knot winds. It then slowed in its path, taking 12 hours top move the 50 or so miles across MMS 1 to make landfall at Biloxi, MS. It meandered around this spot for 6-12 hours before moving eastward across Alabama and the Florida Panhandle. During its brief (8-10 hour) time in the oil and gas zone, the storm had 50-kt size parameters as follows:

NE: 75 nm NW: 60 nm SW: 60 nm SE: 100 nm.

While this storm is thought to have killed over 600 people, only one of those deaths was in the US. There was no record of damage to the offshore oil industry.

Tropical Storm Hermine

This storm formed as a tropical depression about 180 nm due south of New Orleans at 1200 September 17. It moved west and then south, away from the shore, for a day before looping back and heading due north. It entered MMS 2 as a tropical depression at 1400 September 19, with peak winds of 35 knots. It spent about 18 hours moving across MMS 2, becoming a tropical storm with peak winds of 40 knots while in the oil and gas zone. It made landfall at Cocodrie, LA at 0500 September 20. There were no reports of casualties or damage from this storm.

HURRICANE BRET (AUGUST, 1999)

Bret first formed as a tropical depression over the Bay of Campeche on August 18. After meandering in place for a day, it began to move due north toward the oil and gas zone. At 0000 August 22 it crossed the 25th parallel. Packing winds of 120 knots, it veered northwest. It passed over the southwestern tip of MMS 6 at 2000 August 22, and made landfall halfway between Brownsville and Corpus Christi four hours later. As it entered MMS 6 Bret had peak winds of 100 knots, and the following 50-kt size parameters:

NE: 75 nm NW: 30 nm SW: 25 nm SE: 40 nm.

APPENDIX D: EFFECTS OF HURRICANES ON PRODUCTION

To examine the effects on production of hurricanes, month-over-month changes in output from oil and gas wells during storm months were compared to the changes exhibited in non-storm months. The following procedure was employed.

An MS Access query of the complete production database was made. The following data were extracted in this query:

- Year
- Month
- Grid Number
- MMS District
- Monthly Oil Production
- Monthly Casing Gas Production
- Monthly Gas Production
- Monthly Condensate Production.
- Number of 50-knot storm factors.

Total oil well production was calculated in terms of BOE by dividing the casing gas amount by 26 and adding this to oil production.Total gas well production was calculated in terms of MSCF equivalent by multiplying condensate amount by 26 and adding this to gas production.Each total was divided by the number of days in each month, to yield daily average production figures.

The production figures were summed up for each MMS district. Our production database spans the months January 1985 – November 1999. This left us with a total of 179 monthly observations of daily average production for gas wells, for each of the six MMS districts, and for oil production in MMS districts 1-5. MMS 6 was not included in the oil analysis, due to the small and sporadic production of oil in this region. There has been no oil produce in MMS 6 since 1989.

The monthly changes in production were calculated. They were defined as follows:

$$\Delta q_i = \frac{q_i - q_{i-1}}{q_{i-1}}$$

where qi = daily average production in month i. This yielded a time series of 178 monthly changes for each type of rig in each MMS district.

The observations for those months that were deemed to be storm months were segregated, as were those months immediately following a storm month. A month was defined as a storm month if any of the grid blocks had been exposed to 50-knot or greater winds during that month. It was necessary to remove post-storm months, as they would show an abnormal increase over the previous month's production if the previous month was a storm month. I was striving to compare changes in production in any given storm month with the "normal" change in production in that month in a non-storm year.

After the storm and post-storm months had been segregated, the balance of the population of changes was examined. For each month of the year, and for each MMS district the mean and standard deviation of the month-over-month changes were calculated. For example, examining all 14 January observations, means and standard deviations were calculated for oil in MMS 1 through 5 and for gas in MMS 1-6. The final sample sizes, after removing storm and post-storm months, were:

Table D1: Monthly sample sizes

Month	Sample Size	Month	Sample Size
January	14	July	13
February	15	August	12
March	15	September	11
April	15	October	11
May	15	November	13
June	14	December	14

For each month coinciding with a storm described in the first part of this document, I examined the change in production in each MMS, and compare this value to the sample mean and standard deviation to decide whether the storm month's production was significantly different to the sample mean for all other observations for the month in question. For example, looking at Hurricane Opal, we see that change in MMS 1 oil production in October 1995 was 0.830, or that October 1995 oil production was 83% that of September 1995. For purposes of comparison, the mean change observed in all non-storm Octobers in our sample was 0.989, or 98.9% of September production. The standard deviation was 0.026.

A t-statistic was calculated using the standard formula:

$$t = \frac{q_i - \overline{q}_i}{s_i}$$

This t-statistic was compared to the critical t-statistic, that which corresponded to a 95% two-tailed confidence interval, and the significance of each result was noted. The test results are shown in the following tables. In the last column, if the difference from the mean was found to be statistically significant, the column is flagged "SIG." If not, it is flagged "ns"

Table D2: Tests for oil and gas production changes for Danny

				Crude Oil			
MMS	**SF**	**Change**	**Mean Ch.**	**Change SD**	**t-stat**	**Crit t-stat**	**Result**
1	3	0.867	0.990	0.039	-3.15	2.201	SIG
2	41	0.891	1.004	0.067	-1.68	2.201	ns
3	64	0.824	0.992	0.060	-2.78	2.201	SIG
4	0	0.719	0.982	0.076	-3.44	2.201	SIG
5	65	0.823	0.968	0.039	-3.76	2.201	SIG
				Natural Gas			
MMS	**SF**	**Change**	**Mean Ch.**	**Change SD**	**t-stat**	**Crit t-stat**	**Result**
1	3	0.996	1.007	0.053	-0.21	2.201	ns
2	41	0.926	1.015	0.043	-2.06	2.201	ns
3	64	0.868	0.996	0.036	-3.59	2.201	SIG
4	0	0.575	0.981	0.043	-9.39	2.201	SIG
5	65	0.994	0.989	0.036	0.14	2.201	ns
6	0	0.837	1.033	0.086	-2.28	2.201	SIG

Table D3: Tests for oil and gas production changes for Elena

				Crude Oil			
MMS	**SF**	**Change**	**Mean Ch.**	**Change SD**	**t-stat**	**Crit t-stat**	**Result**
1	14	0.935	1.030	0.036	-2.61	2.228	SIG
2	0	0.976	1.019	0.050	-0.87	2.228	ns
3	0	0.951	1.013	0.030	-2.07	2.228	ns
4	0	0.983	1.052	0.095	-0.72	2.228	ns
5	0	0.922	0.983	0.031	-1.99	2.228	ns
				Natural Gas			
MMS	**SF**	**Change**	**Mean Ch.**	**Change SD**	**t-stat**	**Crit t-stat**	**Result**
1	14	1.048	1.017	0.043	0.72	2.228	ns
2	0	0.951	1.012	0.060	-1.00	2.228	ns
3	0	0.952	1.002	0.044	-1.14	2.228	ns
4	0	0.976	0.988	0.046	-0.24	2.228	ns
5	0	1.060	1.002	0.047	1.24	2.228	ns
6	0	0.942	0.977	0.078	-0.45	2.228	ns

Table D4: Tests for oil and gas production changes for Juan

MMS	SF	Change	Mean Ch.	Change SD	t-stat	Crit t-stat	Result
				Crude Oil			
MMS	**SF**	**Change**	**Mean Ch.**	**Change SD**	**t-stat**	**Crit t-stat**	**Result**
1	66	0.936	0.989	0.026	-2.05	2.228	ns
2	128	0.962	1.052	0.092	-0.98	2.228	ns
3	157	0.981	0.993	0.029	-0.42	2.228	ns
4	9	0.952	0.986	0.049	-0.70	2.228	ns
5	181	0.899	1.000	0.042	-2.41	2.228	SIG
				Natural Gas			
MMS	**SF**	**Change**	**Mean Ch.**	**Change SD**	**t-stat**	**Crit t-stat**	**Result**
1	66	1.174	1.014	0.052	3.08	2.228	SIG
2	128	0.913	1.079	0.150	-1.10	2.228	ns
3	157	0.836	1.011	0.062	-2.81	2.228	SIG
4	9	0.954	1.047	0.083	-1.11	2.228	ns
5	181	0.981	1.003	0.054	-0.41	2.228	ns
6	0	1.198	1.060	0.115	1.21	2.228	ns

Table D5: Tests for oil and gas production changes for Bonnie

				Crude Oil			
MMS	**SF**	**Change**	**Mean Ch.**	**Change SD**	**t-stat**	**Crit t-stat**	**Result**
1	0	0.948	0.995	0.028	-1.71	2.16	ns
2	0	0.923	1.009	0.045	-1.89	2.16	ns
3	1	0.926	1.015	0.035	-2.54	2.16	SIG
4	3	0.953	0.988	0.062	-0.57	2.16	ns
5	15	0.912	1.016	0.077	-1.34	2.16	ns
				Natural Gas			
MMS	**SF**	**Change**	**Mean Ch.**	**Change SD**	**t-stat**	**Crit t-stat**	**Result**
1	0	0.917	0.993	0.042	-1.79	2.16	ns
2	0	0.997	0.982	0.040	0.38	2.16	ns
3	1	0.964	0.994	0.064	-0.46	2.16	ns
4	3	1.014	0.990	0.034	0.72	2.16	ns
5	15	0.851	0.969	0.030	-3.95	2.16	SIG
6	0	0.918	0.993	0.069	-1.09	2.16	ns

Table D6: Tests for oil and gas production changes for Gilbert

				Crude Oil			
MMS	**SF**	**Change**	**Mean Ch.**	**Change SD**	**t-stat**	**Crit t-stat**	**Result**
1	26	0.854	1.030	0.036	-4.84	2.228	SIG
2	0	0.862	1.019	0.050	-3.16	2.228	SIG
3	0	0.830	1.013	0.030	-6.16	2.228	SIG
4	0	0.981	1.052	0.095	-0.74	2.228	ns
5	0	0.878	0.983	0.031	-3.44	2.228	SIG
				Natural Gas			
MMS	**SF**	**Change**	**Mean Ch.**	**Change SD**	**t-stat**	**Crit t-stat**	**Result**
1	26	0.826	1.017	0.043	-4.45	2.228	SIG
2	0	0.852	1.012	0.060	-2.64	2.228	SIG
3	0	0.886	1.002	0.044	-2.65	2.228	SIG
4	0	0.907	0.988	0.046	-1.74	2.228	ns
5	0	0.929	1.002	0.047	-1.56	2.228	ns
6	3	0.810	0.977	0.078	-2.14	2.228	ns

Table D7: Tests for oil and gas production changes for Jerry

				Crude Oil			
MMS	**SF**	**Change**	**Mean Ch.**	**Change SD**	**t-stat**	**Crit t-stat**	**Result**
1	0	0.871	0.989	0.026	-4.52	2.228	SIG
2	0	0.853	1.052	0.092	-2.17	2.228	ns
3	0	0.880	0.993	0.029	-3.94	2.228	SIG
4	40	0.870	0.986	0.049	-2.37	2.228	SIG
5	3	0.943	1.000	0.042	-1.37	2.228	ns
				Natural Gas			
MMS	**SF**	**Change**	**Mean Ch.**	**Change SD**	**t-stat**	**Crit t-stat**	**Result**
1	0	1.002	1.014	0.052	-0.24	2.228	ns
2	0	0.985	1.079	0.150	-0.62	2.228	ns
3	0	1.071	1.011	0.062	0.97	2.228	ns
4	40	0.947	1.047	0.083	-1.21	2.228	ns
5	3	1.014	1.003	0.054	0.21	2.228	ns
6	0	0.958	1.060	0.115	-0.88	2.228	ns

Table D8: Tests for oil and gas production changes for Andrew

MMS	SF	Change	Mean Ch.	Change SD	t-stat	Crit t-stat	Result
				Crude Oil			
MMS	**SF**	**Change**	**Mean Ch.**	**Change SD**	**t-stat**	**Crit t-stat**	**Result**
1	33	0.871	0.990	0.039	-3.06	2.201	SIG
2	56	0.799	1.000	0.067	-2.99	2.201	SIG
3	35	0.837	0.991	0.060	-2.54	2.201	SIG
4	0	0.949	0.978	0.076	-0.39	2.201	ns
5	12	0.794	0.972	0.039	-4.61	2.201	SIG
				Natural Gas			
MMS	**SF**	**Change**	**Mean Ch.**	**Change SD**	**t-stat**	**Crit t-stat**	**Result**
1	33	0.865	1.007	0.053	-2.69	2.201	SIG
2	56	0.794	1.015	0.043	-5.11	2.201	SIG
3	35	0.897	0.996	0.036	-2.77	2.201	SIG
4	0	0.967	0.981	0.043	-0.33	2.201	ns
5	12	0.922	0.989	0.036	-1.88	2.201	ns
6	0	1.033	1.033	0.086	0.00	2.201	ns

Table D9: Tests for oil and gas production changes for Opal

MMS	SF	Change	Mean Ch.	Change SD	t-stat	Crit t-stat	Result
				Crude Oil			
MMS	**SF**	**Change**	**Mean Ch.**	**Change SD**	**t-stat**	**Crit t-stat**	**Result**
1	51	0.830	0.989	0.026	-6.09	2.228	SIG
2	7	0.842	1.052	0.092	-2.29	2.228	SIG
3	0	0.983	0.993	0.029	-0.33	2.228	ns
4	0	0.810	0.986	0.049	-3.60	2.228	SIG
5	0	0.804	1.000	0.042	-4.70	2.228	SIG
				Natural Gas			
MMS	**SF**	**Change**	**Mean Ch.**	**Change SD**	**t-stat**	**Crit t-stat**	**Result**
1	51	0.836	1.014	0.052	-3.45	2.228	SIG
2	7	0.915	1.079	0.150	-1.09	2.228	ns
3	0	0.891	1.011	0.062	-1.93	2.228	ns
4	0	0.954	1.047	0.083	-1.12	2.228	ns
5	0	0.899	1.003	0.054	-1.94	2.228	ns
6	0	0.993	1.060	0.115	-0.58	2.228	ns

Table D10: Tests for oil and gas production changes for Danny

Danny (1997)				*Crude Oil*			
MMS	**SF**	**Change**	**Mean Ch.**	**Change SD**	**t-stat**	**Crit t-stat**	**Result**
1	44	0.971	1.001	0.035	-0.85	2.179	ns
2	11	0.926	0.999	0.032	-2.29	2.179	SIG
3	0	0.947	1.000	0.037	-1.42	2.179	ns
4	0	1.023	0.997	0.098	0.27	2.179	ns
5	0	1.090	1.013	0.025	3.05	2.179	SIG
Danny (1997)				***Natural Gas***			
MMS	**SF**	**Change**	**Mean Ch.**	**Change SD**	**t-stat**	**Crit t-stat**	**Result**
1	44	0.972	0.976	0.058	-0.07	2.179	ns
2	11	0.926	0.995	0.053	-1.30	2.179	ns
3	0	0.995	0.974	0.057	0.36	2.179	ns
4	0	0.953	0.971	0.044	-0.41	2.179	ns
5	0	0.993	0.977	0.037	0.45	2.179	ns
6	0	1.075	0.958	0.059	1.99	2.179	ns

Table D11: Tests for oil and gas production changes for Georges, et al

)				*Crude Oil*			
MMS	**SF**	**Change**	**Mean Ch.**	**Change SD**	**t-stat**	**Crit t-stat**	**Result**
1	177	0.741	1.030	0.036	-7.94	2.228	SIG
2	10	0.671	1.019	0.050	-7.01	2.228	SIG
3	8	0.774	1.013	0.030	-8.01	2.228	SIG
4	43	0.808	1.052	0.095	-2.55	2.228	SIG
5	34	0.655	0.983	0.031	-10.69	2.228	SIG
				Natural Gas			
MMS	**SF**	**Change**	**Mean Ch.**	**Change SD**	**t-stat**	**Crit t-stat**	**Result**
1	177	0.748	1.017	0.043	-6.25	2.228	SIG
2	10	0.677	1.012	0.060	-5.55	2.228	SIG
3	8	0.734	1.002	0.044	-6.12	2.228	SIG
4	43	0.849	0.988	0.046	-3.01	2.228	SIG
5	34	0.811	1.002	0.047	-4.06	2.228	SIG
6	0	0.995	0.977	0.078	0.23	2.228	ns

Table D12: Tests for oil and gas production changes for Bret

				Crude Oil			
MMS	**SF**	**Change**	**Mean Ch.**	**Change SD**	**t-stat**	**Crit t-stat**	**Result**
1	0	0.987	0.990	0.039	-0.07	2.201	ns
2	0	0.952	1.000	0.067	-0.71	2.201	ns
3	0	0.976	0.991	0.060	-0.24	2.201	ns
4	0	0.942	0.978	0.076	-0.48	2.201	ns
5	0	1.009	0.972	0.039	0.96	2.201	ns
				Natural Gas			
MMS	**SF**	**Change**	**Mean Ch.**	**Change SD**	**t-stat**	**Crit t-stat**	**Result**
1	0	0.977	1.007	0.053	-0.56	2.201	ns
2	0	1.014	1.015	0.043	-0.01	2.201	ns
3	0	0.949	0.996	0.036	-1.33	2.201	ns
4	0	0.932	0.981	0.043	-1.13	2.201	ns
5	0	0.977	0.989	0.036	-0.35	2.201	ns
6	14	0.923	1.033	0.086	-1.29	2.201	ns

APPENDIX E: PROCEDURES IN DRILLING CALCULATIONS

This appendix describes the compilation of the probability information for the cost-loss calculations for drilling rig evacuations.

ORGANIZATION OF THE PROBABILITY INFORMATION

We now provide a brief summary of how the probability information is organized and defined in a Microsoft Access database. We also provide detailed information about each step in the computations as performed in our database. Posner (2002) has computed (summed) the number of observations for each entry in our 2x2 forecast/outcome notation. The data is summarized here for completeness.

Table E.1: Summary of forecast/outcome data availability, 1980-2000

Years	Forecast types	Wind speed (knots)
1980-1984	12,24	50
1985-1987	12,24,48,72	50
1988-2000	12,24,36,48,72	50
1995-2000	12,24,36	64

This leads to 105 year/forecast type/wind speed combinations. Multiplying by the 1,060 grid blocks leads to 111,300 2x2 tables which are stored in Access Table "NWProbs." We can use this raw data to compute probabilities in many ways. Of primary interest is a cumulative computation of probabilities to capture decision makers' accumulated knowledge of and changes (hopefully improvements) to forecast accuracy. We will compute our probabilities using a cumulative approach. That is, for value of forecast calculations in 1990, we will use the counts of observations from 1980-1989 to compute the probabilities. For 1991, we will add the counts of observations for 1990 and recompute the probabilities, and so on. This approach captures the accumulation of decision maker knowledge of forecast performance.

Using Query "NWProbsStep1", we can select the years to include for the cumulative probability computation. This forms the source for the next step. Using Query "NWProbs2," the observations of the 2x2 tables are summed across the selected years. Using Query "NWProbsStep3FINAL," we compute the unconditional forecast and storm probabilities, and the conditional probabilities for each record. Note that at this point, we are computing probabilities for each grid/forecast type/wind speed combination for the selected years. There is one important observation to be made at this point. Some grids have not had a storm forecast or a no-storm forecast for certain forecast type/wind speed combinations. In such cases, it is impossible to compute conditional probabilities (division by zero). To permit automation in the subsequent computations, we assign the

Gulf of Mexico average in these cases. This special step is accomplished in the query using the Table "ProbsForAllGOM," which was computed based on the entire 21 year set of observations. Note, this applies only in a small minority of cases.

MANAGING THE NELSON-WINTER COMPUTATIONS

In each year, we have identified a list of storms that are relevant in the context of evacuation decisions. Table "NWStorms" contains all of the forecast/outcome observations as reported by Posner (2002). A utility query was used to group the data into annual lists of storms. This list is given in Table "NWStormDatesForRigSelectionFINAL." There are 111 storms for the 1980-2000 time period. They are distributed over time as shown in Table C.2.1. Notice that this list includes storms not included in Table 3.16, since decision makers are unsure of the ultimate strength of the storm at the time of their evacuations.

Table E.2: Storm Count by Year, 1980-2000

Year	Number of storms	Year	Number of storms
1980	4	1991	3
1981	5	1992	3
1982	4	1993	4
1983	2	1994	3
1984	3	1995	8
1985	9	1996	10
1986	4	1997	2
1987	3	1998	8
1988	7	1999	9
1989	6	2000	9
1990	5		

This list defines the range of the index j for every year k.

The next step in data organization is to identify all of the drilling rigs that were operating during each storm given in Table C.2.1. To accomplish this, the Table "NWMaker" that contains information about every well ever drilled in the Gulf of Mexico was created. Using Query "Step1NW," all active drilling rigs and their locations are noted for each storm given in Table "NWStormDatesForRigSelectionFinal." This step defines ranges for both r and i for every storm j. These results are dumped into Table "NWStep1."

The next series of steps uses queries to build up the value of forecast computations. Our objective is to build a record for each rig r from Table "NWStep1" that contains fields defining C_{rk} and all of the needed π_{ik} data. First, we use a utility Query "Step2NW" on Table "NWStep1" to concatenate identification fields so that subsequent queries are possible. Query "Step3NW" is a critical step. In this query, we cross-query Query "Step2NW" with Table "RigRates" to add C_{rk}, with a series of mapping tables and Query "NWProbs1980-1985Step3FINAL" to add the π_{ik} data. Note that at this point, we are adding π_{ik} for all forecast types, so the number of records (rigs) for any given storm is multiplied by the number of forecast types available in that year. Also, we have made multiple definitions of C based on +/- one standard deviation of evacuation duration. These fields need only be retitled to accommodate subsequent queries.

Now that we have built Query "Step3NW," we use Query "Step4NW" to compute V_{rijk} per Eqn. (2). Note there are two versions of Query "Step4NW" to facilitate computations for both expected loss values. We also use this query to compute the value of perfect information by assigning π_{11}=π_{22}=1, π_{12}=π_{21}=0, π_1=π^1, and π_2=π^2. Query "Step5NW" simply sums across each forecast type for each year of the study for presentation purposes.