Evidence on Risk Preferences in E&P Operations: Examining the Decision to Evacuate

*By Christopher J. Jablonowski**

Introduction

Decisions to evacuate offshore oil and gas facilities in the path of hurricanes occur frequently in the Gulf of Mexico and are costly. There has been little empirical research on the variables that drive these decisions and the role of risk preferences in this decision-making context. This article summarizes some preliminary research on this high stakes decision. Econometric models provide support for the conclusion that location attributes, specifically water depth, increase the propensity to evacuate. There is also support for the conclusion that oil company experience increases the propensity to evacuate, that is, experience leads to caution. Initial results of a utility-based model suggest a high degree of risk aversion.

Offshore Drilling Operations Overview

In the Gulf of Mexico, oil companies lease oil and gas exploration and production rights from the U.S. government. Once a lease is acquired, the oil company drills exploration wells based on seismic data and geophysical and geological analysis. If economic quantities of hydrocarbons are discovered, the lease is developed with additional production wells. 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) that is installed on the platform. Oil companies engage the services of a drilling contractor who owns the drilling rig and employs and manages the drilling crew. Other subcontractors are typically coordinated by the oil company, and come to the drilling location as needed to perform specialty services. The number of people on board the rig on any day varies between drilling rig types, drilling contractors, oil companies, and is a function of current operations on the rig. Based on interviews with practitioners, an average of 55 persons on board is assumed for this analysis. While evacuation decisions are made for both production facilities and drilling units, it is the *drilling operations* that are the focus of this study.

Weather and Evacuation Criteria

When severe weather such as a hurricane threatens drilling operations, both the drilling contractor and the oil company make decisions regarding the immediate progress of the well, and whether or not to evacuate the drilling rig. Securing the well and rig equipment reduces the probability of drilling mud or oil spills and equipment damage. Evacuating the drilling rig of personnel eliminates the possibility of loss of life. In most oil company ethical and operating guidelines, it is stated that protection of workers is paramount. That is, the burden is clearly put on decision-makers to avert personal injuries and deaths. In addition to compelling ethical arguments, there exists a potential for direct economic consequences. 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. In fact, an average of one percent of the Gulf of Mexico drilling fleet is lost per year due to hurricanes.[1] Any personnel remaining on board during a hurricane would be subject to this catastrophic risk and the oil company would likely incur a large financial loss if all or part of the crew were lost due to a non evacuation.[2]

During the hurricane season, which typically spans 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 at their drilling locations. Some oil companies also retain private forecasters to develop additional storm development scenarios or customized forecasts. Prudent operators are always aware of the time required to safely secure the well and equipment and to evacuate the rig, which may take days. This time requirement, or safe evacuation time (SET), 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 before hurricane conditions would be present at the drilling location. The SET is continually updated based on drilling progress.

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. Decision-makers evaluate the raw data and the forecasts along with the SET to inform their optimization of drilling operations and their evacuation decisions. 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, partial evacuation of non-essential personnel). Longer duration operations are unlikely to be initiated. It is common for managers to meet several times per day to discuss the progress of the storm, drilling operations, and evacuation contingencies. It is a very complex and dynamic process.

Econometric Model of the Decision to Evacuate

The decision to evacuate for a particular hurricane is appropriately modeled as a discrete choice. Either the crew is

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*Christoher Jablonowski is with the Department of Petroleum and Geosystems Engineering, The University of Texas at Austin, 1 University Station CO300, Austin, TX 78712-0228. Telephone: 512-471-6262; email: cjablonowski@mail.utexas.edu. Thanks to Tim Considine and Barry Posner for helpful comments. All errors and omissions remain the responsibility of the author.
See footnotes at end of text.

released from the rig, or it stays on location and rides out the hurricane. In summary, an unobservable latent variable is defined, $Y_{it}*$, as the propensity to evacuate as follows:

$$Y_{it}* = X_{it}\beta + u_{it} \qquad (1)$$

where, X_{it} = Vector of independent variables, β = Vector of parameters to be estimated, and u_{it} = Random error term, $\sim N(0,\sigma^2)$. The subscript i represents the individual rig, and the subscript t represents the time index for the storm. The first observation is made when the hurricane (or tropical storm) enters the observation area,[3] 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. Y_{it}^* is not observed, but Y_{it} is according to the rule:

$$Y_{it} = 1 \text{ if } Y_{it}* > 0 \text{ (evacuate), 0 otherwise (not evacuate).} \qquad (2)$$

Development of a qualitative response model such as probit or logit is straightforward, and a probit model is employed here.

The ideal specification of Equations. (1) and (2) 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. Such a specification would allow a model of decision-makers' response to subtle changes in the forecasts and changes in raw hurricane position and strength. One would be modeling both the discrete decision to evacuate and the timing of that decision. There is a fundamental hurdle to such an analysis because the observations of the *decision* to evacuate (or not) are not precise. The evacuation observations are taken from drilling records that contain simple depth versus days plots that are loosely annotated with drilling information and other pieces of information regarding the overall progress of the well. Because of this, there is imprecise accounting of the timing of the decision to evacuate, although the start and overall duration of the evacuation is discernable. Given the quality of the data currently available on evacuations, a relaxed specification is proposed that models the discrete choice to evacuate, but does not incorporate the exact timing of the decision (deletion of time indexing).[4] As a result, it is not possible to obtain any information on which weather or forecast variables ultimately elicit the evacuation decision. For example, it will not be possible to comment on whether decision-makers are responding to 24 or 48-hour forecasts.

Independent Variables and the Data Set

Having described the decision-making process and base model, it is now appropriate to discuss the independent variables that belong in a model of evacuation decision-making.

<u>Location and Well Attributes.</u> It is reasonable to suspect that features of the well being drilled influence the decision to evacuate. Decision-makers on floating deepwater rigs are forced to make their evacuation decision earlier and under higher uncertainty than their counterparts on jackup or platform rigs due to a higher SET. A water depth variable, **WD400**, can be defined to represent this dichotomy. A binary variable is defined 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 sign expectation for this coefficient is positive. Similarly, other well attributes such as well depth in feet, **DEPTH**, and whether or not a well is being drilled over a production platform 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 temporarily abandon the well. Therefore, the sign expectation on the DEPTH coefficient is positive. When a well is being 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. Development wells are typically drilled over existing production platforms while exploration wells are drilled in open water. A binary variable, **EVD**, is constructed that takes on a value of one for exploration wells and zero for development wells. Based on these hypotheses, the expectation for the sign of this coefficient is negative. Another interpretation for EVD is independent of the time required to evacuate. 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, or even connected. For example, if the drilling rig's derrick were to collapse, it may fall on the production platform, increasing the damage and risk to the crew. A decision-maker may be more likely to evacuate in such circumstances.

<u>Evacuation Costs</u>. When evacuation costs are high, the likelihood of evacuation is decreased, *ceteris paribus*. For each storm and rig type, one can estimate the evacuation cost, **COST** = rig rate*evacuation duration.[6] This value varies between rig types and over the years as rig rates change. The expectation for the sign of this coefficient is negative.

<u>Decision-Maker Attributes</u>. It is possible that evacuation criteria vary among 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? One attribute that may affect the decision to evacuate is the decision-maker's offshore experience. More experienced operators who have made many such decisions may be more (less) likely to evacuate based on the accumulation of their experience making such decisions and living with the related outcomes. A variable **OPCUM** is defined that represents the cumulative number of wells drilled by the particular oil company as of the year prior to the evacuation decision. There is no hypothesis regarding the sign of this coefficient. That is, it is not clear whether experience should lead to caution, or confidence. A second hypothesis is to expect larger, well known companies that possess valuable brand names and accumulated goodwill to value evacuations differently. Such companies have more to lose in the case of a human catastrophe, and these losses would negatively impact the value of the brand name and

goodwill. To model this hypothesis, a variable **RET** is defined that takes on a value of 1 if the oil company possesses retail gasoline sales, and zero otherwise. The expectation is that the sign of the coefficient will be positive.[7]

Six storms were evaluated in this preliminary study. Correlation coefficients and basic descriptive statistics are available from the author. The sample is defined by storms where both evacuations and non-evacuations were observed. The sample used in this analysis includes the following named storms (year/#observations): Alicia (1983/13), Barry (1983/12), Chantal (1989/16), Elena (1985/13), Flo (1988/14), and Juan (1985/17).

Estimation of the Probit Model

A probit model for Equations. (1) and (2) is specified and estimated employing five of the six explanatory variables defined above and fixed effects for the individual storms. The COST variable is omitted due its high correlation ($\rho = 0.93$) with WD400. This specification appears 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 which exhibited a high proportion of evacuations which may be a result of the particular storm histories. Also, the results from a fixed effect model are significantly more robust than pooled estimates (not reported here). Since the error terms are i.i.d., the discrete nature of the dependent variable does not introduce any unusual estimation issues.[8] Results are presented in Table I.

Table I. Probit Model of Evacuation with Fixed Storm Effects

Variable	Coefficient Estimates (t-stats)	
ALICIA	-0.0533	(-.076)
BARRY	-0.2666	(-.381)
CHANTAL	1.5172	(2.145)
ELENA	1.1850	(1.526)
FLO	1.1050	(1.435)
JUAN	1.6382	(2.123)
RET	-0.2526	(-.550)
OPCUM	0.5148	(1.662)
DEPTH	-0.1613	(-.536)
WD400	0.5736	(1.397)
EVD	-0.5471	(-1.080)
LR (p-value)	21.7572	(0.016)
Log Likelihood	-38.7471	
LR Index	0.2192	
# Observations (Pos)	85 (62)	

The coefficient for WD400 is weakly significant and its sign is as expected. When in deep water, decision-makers are more likely to evacuate, likely due to the increased time to secure the well and rig, and the need to make an evacuation decision under greater uncertainty. Decision-makers on shallow water locations can defer their decision (relatively), and will, on average, evacuate less often. Recall that the expectation for the sign of the COST coefficient is negative, i.e., the higher the cost of evacuating the less likely to evacuate. Given that WD400 and COST are highly correlated (positively), one can conclude that COST does not appear to play a significant role in the decision to evacuate. This result is likely a manifestation of the scale of the costs and losses. Whatever the decision-making process is, the fact that the expected loss is orders of magnitude larger than the evacuation costs tends to mask the influence of slight variations in the cost.[9] The results suggest that whether or not the oil company has retail gasoline sales (valuable brand name)is not a significant factor in decision-making. Recall that if RET is construed as a proxy for risk preferences (see footnote 9), this result on RET could be due to a balancing of opposing forces on the decision-maker. OPCUM is significant at the 10 percent level, implying that experience leads to caution. Such a result may be due to bad experiences in the past that led to human and financial losses, and perhaps corporate policies that subsequently err on the cautious side. Although not statistically significant, the sign on EVD is negative as anticipated, providing some support for the idea that exploration wells are less likely to evacuate than development wells.

The differential evacuation rates between storms is observable in the scale and significance of the fixed effects. Alicia formed over the drilling area and quickly strengthened and evacuations may not have been possible in some cases. Barry was a weak storm that skirted the bottom of the Drilling Area, convincing some decision-makers to continue drilling operations. Chantal, Juan, and Flo display 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).

Risk Aversion, Utility, and the Decision to Evacuate

A test for the existence of risk aversion is possible via a richer specification of the model of the decision to evacuate that incorporates a utility function. A structural model of decision-making in a utility framework is developed along the lines of Cicchetti and Dubin (1994). A general form of utility function is defined, $U(W; s, e)$, where s represents attributes of the decision-maker, and e is a random component of utility. If one assumes additively separable errors, the utility function can be written as $U(W; s) + e$. Under the assumption of utility maximization, the decision-maker would evacuate when:

$$U(W-C;s)+e_1>(p)U(W-L;s)+(1-p)U(W;s)+e_2$$

where, W = Measure of wealth, C = Evacuation cost, p = Probability of a hit, and L = Expected loss given a hit. Finally, if one assumes that the e_i are independent and extreme value distributed (McFadden, 1974; Maddala, 1983), the probability of observing an evacuation is:

$$\Pr(evacuation) = 1/(1+e^{-\theta}), \qquad (3)$$

where

$$\theta = U(W-C;s) - [(p)U(W-L;s) + (1-p)U(W;s)].$$

There is no theoretical foundation to inform the specification of a utility function for offshore oil and gas decision-makers. Therefore, a flexible form from the family of hyperbolic absolute risk aversion functions (HARA) of the following form is specified:

$$U(W;s) = a_1(W+a_2)^k + e. \qquad (4)$$

A detailed discussion of the mathematical properties of this family of utility functions is available in Merton (1971). Given this utility function, utilities for each state are as follows:

Evacuate: $a_1(W\text{-}C+a_2)^k + e_1$ (5)

Do Not Evacuate: $(p)a_1(W\text{-}L+a_2)^k + (1\text{-}p)a_1(W+a_2)^k + e_2$.(6)

The exponent k is intended to capture differences in risk aversion across decision-makers and physical locations, and is a function of the variables previously defined in the discrete choice evacuation model. There are several ways to specify k here. Based on the results of the probit, k is specified as follows:

$$k = b_2WD400 + b_3OPCUM + c_1ALICIA + c_2BARRY + c_3CHANTAL + c_4ELENA + c_5FLO + c_6JUAN. \qquad (7)$$

This specification leads to the following likelihood function:

$$L = \Pi_i[1/(1+e^{-\theta_i})]^{y_i}[1-(1/(1+e^{-\theta_i}))]^{1-y_i} \qquad (8)$$

where y_i = observation of decision to evacuate (1) or not (0).[10]

Continuous wealth measures are not readily available for every decision-maker in the data set. Therefore, a proxy of annual drilling cost is used, based on the number of wells drilled by the oil company in the year of the observation and the average daily operating cost for the drilling rig. This approach defines the decision as one of *annual* utility maximization. This proxy should be sufficient to anchor the analysis on the appropriate part of the utility function. Note that rescaling of the wealth and cost figures in the context of numerical optimization must be proportional. The expected loss given a hit is computed assuming 55 people on board, and a value of statistical life of $2.275 million.[11] The historic climatological probability of a hit is taken from Considine *et al*. (2002). Parameters to be estimated are the a_i and b_i. The model of Equation (8) is estimated and the results presented in Table II.

Results are reported using the names of the explanatory variables, versus the b_i's, for clarity. As in the probit model, inclusion of fixed effects by storm significantly improves the overall fit of the model relative to pooled specifications. 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, although here their individual statistical significance is diminished. WD400 is significant at the 10 percent level, and OPCUM is now only marginally significant. But we are more interested here in the predicted values of the variable k. Predicted values of k can be interpreted as an indicator of the degree of risk aversion. As k decreases (increases), the level of risk aversion increases (decreases). The closer to one, the closer to risk neutrality. For these 85 observations, 74 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. While not all of the observations conform to the mathematical restriction on k, those that do indicate a high degree of risk aversion. Additional data would be valuable to further substantiate these initial findings.

Table II. Coefficient Estimates, Pooled Sample with Fixed Effects (k = b_2WD400 + b_3OPCUM + c_1ALICIA + c_2BARRY + c_3CHANTAL + c_4ELENA + c_5FLO + c_6JUAN)

Variable	Coefficient Estimates (t-stats)	
ALICIA	-0.306	(-1.0375)
BARRY	-0.225	(-.9614)
CHANTAL	0.062	(1.0423)
ELENA	0.017	(.3049)
FLO	0.006	(.0966)
JUAN	0.057	(1.1459)
A1	6476.678	(.4069)
A2	221.468	(.3469)
WD400	0.082	(1.7678)
OPCUM	0.092	(1.1321)
Log Likelihood	-37.965	
# Observations (Pos)	85 (62)	

Conclusion

These results provide support for the conclusion that both location attributes (water depth), and decision-maker experience increase the propensity to evacuate. The results on utility and risk preferences using a fixed effect model suggest a high degree of risk aversion in this setting. Issues that deserve additional study if additional data can be collected are the sensitivity to different specifications of the utility function, sensitivity to estimates of cost, and refining the proxy for wealth.

Footnotes

[1] Based on an analysis of the "Accident History of the Mobile Offshore Drilling Rig Fleet," Offshore Data Services, Houston, TX.

[2] Even when the oil company or drilling contractor carry general liability insurance, deductibles are often quite large (tens of millions of dollars), and a non-evacuation could be construed by the insurer as a lack of reasonable care, and refuse to pay for any losses.

[3] Based on interviews with decision-makers and historical track and speed information, the observation area is defined to begin west of 75 degrees longitude (about the eastern tip of Cuba) and north of 15 degrees latitude (about the southern tip of Mexico). This definition is intended to consistently capture the moment when decision-makers begin to pay attention to a storm's path insofar as it relates to management of their day-to-day operations and the potential decision to evacuate.

[4] In the current specification, time related (weather related) information is removed from the model. But previous research indicates there is consistent evacuation behavior across decision-makers for the primary categories of storm types (paths and intensities). Based on the relative similarity of the forecasts for each drilling location for those storms where evacuation rates do differ, the reasons for differences in the choice to evacuate are likely to reside in the decision-maker attributes, not weather or forecast information. 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.

[5] Because the evacuation decision is made earlier with less information, the probability window of a hit is larger and decision-makers are more likely to evacuate, ceteris paribus. Of course, this affect can work in the opposite direction if the earlier information indicates that a hurricane is not threatening, then waiting for later information that indicates a threat may actually increase the likelihood of evacuations (that is, jackup rigs would be more likely to evacuate). But previous research on hurricane forecast accuracy with respect to offshore operations indicated that the Pr(hit|forecasted miss) was only about 2 percent, so the opposite interpretation is not generally operative (see Considine et al. 2002).

[6] Decision-makers know their rig rate and develop an E(evacuation duration). To compute the COST here, the actual evacuation durations are used.

[7] Another plausible hypothesis posits that due to their larger accumulated wealth, large companies (RET=1) tend to be more risk neutral than smaller companies, and one could expect fewer evacuations, ceteris paribus. Under this hypothesis in the basic probit specification, the expectation of the sign of this variable coefficient is negative. A utility based model is estimated below that more fully investigates this issue.

[8] If the i.i.d. assumption is relaxed in this framework, the probit model is ill suited to the task. A random effects model is feasible, albeit quite complex (Greene, 2000; Baltagi, 2002).

[9] This issue is investigated via a valuation of hurricane forecasts in Considine et al. (2002).

[10] Maximization of Eqn. (8) is non-trivial given the complexity of the specification. The primary problem in this case is the nature of the utility function itself. Recall Eqn. (4): $U(W; s) = a1(W+a2)k + e$. Given that the goal is to estimate parameters comprising k and a2, no restrictions are placed on any parameters during the iterations. It is therefore possible for $-1<k<1$ and $(W+a2)<0$, causing a degeneration of the iterations. Techniques exist to overcome such obstacles, and involve ignoring degenerate observations during each iteration, rescaling of explanatory variables, and adjusting starting values.

[11] See Viscusi (2000) and Moore and Viscusi (1988) for additional context on value of life estimates.

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