Oil Spills, Workplace Safety, and Firm Size: Evidence from the U.S. Gulf of Mexico – Revisited

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This Version Edited and Condensed for:

USAEE *Dialogue*
November Edition, 2001

(the uncondensed version of this paper is available from the author)

<u>*ABSTRACT*</u>

Health, safety, and environmental performance (HS&E) has always been a consideration of offshore exploration and production (E&P) operators, but since the Piper Alpha disaster in the North Sea in 1988, HS&E performance has become an industry priority. In the Gulf of Mexico (GOM), several changes are underway that are transforming the overall character of E&P operations. Shifts in the profile of operating companies (majors versus independents), deeper water operations, and more complex wells all contribute to this transformation. It is unknown what effect, if any, this transformation will have on HS&E outcomes in drilling and workover operations.

This research presents evidence to support the hypothesis that well complexity, specifically well depth and reach, increase the likelihood of HS&E incidents, while other well characteristics do not. Equally important is the evidence rejecting the hypothesis that company profiles have an effect on HS&E outcomes. The study period covers 1990-1998.

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1 Introduction

Health, safety, and environmental performance (HS&E) has always been a consideration of offshore exploration and production (E&P) operators, but since the Piper Alpha disaster in the North Sea in 1988, HS&E performance has become an industry priority. This shift has yielded much fruit. Incident rates on mobile offshore drilling units and platforms demonstrate a declining trend over time. In 1999, the global drilling industry posted its most dramatic decline in its lost time incidence rate in recent years (DC-1, 2000). While this trend is gratifying, leaders in industry continue to devote substantial resources to accelerate this performance improvement. As declared by a major oil company's Vice President of Technology, "Despite excellent safety management systems… we still injure too many people and this is unacceptable" (DC-2, 2000).

As the industry evolves with new technology and expansion into previously untested basins and horizons, the challenge for industry executives and policy makers is not only to maintain this motivation and continual performance improvement, but to prepare for changes in the operating environment that are fast approaching. This challenge is widely recognized, and key industry players have organized themselves around the world to address it (Dobson, 2000). Recognition and preparation are vital, but to succeed, the facts about risk factors must be rigorously investigated so that efforts are properly allocated.

In the Gulf of Mexico (GOM), several changes are underway that are transforming the overall character of E&P operations. Shifts in the profile of operating companies (majors versus independents), deeper water operations, and more complex wells all contribute to this transformation. Industry executives and policy makers are keenly interested in the effects that these changes may have on HS&E performance going forward. Fortunately, there exists a rich data set that can be used to test hypotheses. One such study, funded by the Minerals Management Service (MMS) by Iledare et al. (1997), served as the inspiration for the present research. Their analysis focused on *production operations*. The researchers tested for the first effect mentioned above, *i.e.* the changing profile of operating companies. But anecdotally important variables were not included, and therefore the conclusions about the effect of company profile are potentially inconclusive. The purpose of this paper is to test for the effect of company profile while controlling for these missing variables (and other control variables) to more fully explain the variables that affect HS&E outcomes. While this research is comparable in structure to Iledare et al. (1997), the focus here is on *drilling and workover operations*, and *downhole maintenance*. The study period covers 1990-1998.

2 Hypothesis

The offshore drilling process is an inherently dangerous activity. While random failures of equipment can cause HS&E incidents, the majority of incidents arise from unsafe procedures and worker behavior. Of course no one desires to be injured or to create environmental damage. This leads to the hypothesis of the present research, that HS&E incidents are a function of the environment created on site by the companies involved, the features of the well that increase risk and exposure, and the overall operating environment in industry. The goal is to examine which of these, if any, can explain the occurrence of HS&E incidents.

The first group of variables characterizes the companies involved in drilling operations. Both the drilling contractor and the oil company have a strong influence over HS&E performance. Some oil companies go to great expense to provide additional training prior to the start of a project, and some micromanage the drilling process to ensure safer operations.

The second group of variables that is hypothesized to influence HS&E outcomes are related to well complexity. As wells become more complex, the frequency of risky activities increases (discussed below). More generally, complexity is thought to dilute the focus on HS&E incident prevention.

Finally, the overall operating environment may influence HS&E outcomes. The drilling industry has been cyclical in the past. Rapid escalation in drilling activity brings less experienced workers into the field as drilling contractors staff previously idle rigs. Also, the regulatory environment may influence outcomes. If certain MMS Districts demonstrate less stringent enforcement, one could expect more HS&E incidents in that District, ceteris paribus.

3 Econometric Model and Variable Definitions

Based on the above hypothesis, an econometric model can be specified. In this section, I provide a general statement of the functional relationship, a description of the dependent variable and the set of independent variables, and a summary of the econometric model and its estimation.

The task is to test whether or not hypothesized variables have an impact on HS&E outcomes. The general structure of an econometric model to accomplish this task is straightforward. The dependent variable represents a discrete outcome, i.e. whether or not an incident occurred, and the independent variables are those hypothesized variables described below. This type of model, where the dependent variable takes on discrete values, is commonly referred to as a qualitative response (QR) model. In the ideal formulation, there is an observation for each well drilled in the study period, and the general model is written as:

$$Y = X\beta + u \,, \qquad (1)$$

Where Y is a vector of incident observations, X is a matrix of observations of the independent variables, β is a vector of estimated parameters, and u is a vector of disturbances ~N(0,σ^2).

The Dependent Variable

Minerals Management Service (MMS) regulations specify industry accident reporting requirements. They require lessees to notify the MMS of all serious accidents, any death or serious injury, and all fires, explosions, or blowouts connected with any activities or operations on the lease. All spills of oil or other liquid pollutants must also be reported to the MMS. These regulations also address the preparation of public accident reports and procedures used in conducting accident investigations (CFR, 1998). For this study, a HS&E incident is defined as any spill, injury, or well control incident associated with drilling or workover operations (including vessel interaction with same) and any *downhole* production operations.

The Independent Variables

Variables that characterize the companies involved in drilling operations are of interest not only in analyzing past performance as is done in this research, but also in painting a picture of the future. Most industry analysts expect the mix of operators working in the Gulf of Mexico to evolve in the coming years. For example, majors have been de-emphasizing their shallow water holdings in favor of larger deepwater prospects. While this is not the rule, it is a general trend (Furlow and DeLuca, 2000). An oil company operating a lease and the wells drilled on it has an influence over HS&E outcomes. If expectations on workers are high, if additional training is provided, and if enforcement is strong, a safety conscious workplace will result, reducing HS&E incidents. Previous research by Iledare et al. (1997) commented on the perception that *majors* (large, integrated companies) are typically better equipped to achieve these goals, although the results of that research did not support this perception. This perception will be tested again here. While the present specification proposes scope and scale binary variables comparable with Iledare et al. (1997), it adds an additional binary variable to account for downstream retail activities (gasoline sales) involving an established brand name. It seems reasonable to expect companies with valuable brand names to vigorously protect themselves from bad publicity generated by HS&E incidents such as the Piper Alpha or Exxon Valdez disasters than pure E&P companies whose only client is the pipeline. In summary, a company with a brand name has *more to lose* than its more anonymous counterpart. [See Notes for definitions of scope, scale, and brand variables].

The drilling or workover contractor is also an influential party in achieving desired HS&E outcomes. While this data is available for those wells that experienced an incident, it is not currently available from the MMS for all wells (in a tractable format), and unfortunately, is not included in the regression.

It is hypothesized that physical characteristics of the well being drilled have an impact on HS&E outcomes. Well complexity increases the frequency of *routine activities* that are known sources of HS&E incidents (pipe handling, etc.) (DC-1, 2000). Complexity also increases the incidence of *unusual operations* such as handling stuck drill pipe, casing, and logging tools. In addition, complexity in its most general sense increases the amount of individual tasks that need to be performed by workers, potentially diluting the focus on HS&E incident prevention. As is the case in the analysis of company variables, analyzing past performance is important, but equally important is the interpretation of the results in light of current trends indicating an increase in the technical complexity of well design.

The variables selected to represent well complexity are as follows:

Depth (DEPTH): This variable refers to the total measured depth (MD) plus the true vertical depth (TVD) of the well in feet. Increased MD means longer bit runs and wiper trips, increased pipe handling, and longer casing strings and casing job duration. Drill pipe and casing handling are a major source of injuries (DC-1, 2000). TVD is a proxy for maximum bottom hole pressure. MD and TVD are highly collinear, and an index combining the two variables effectively addresses this estimation problem, although individual variable coefficients are necessarily sacrificed. The expectation of the sign of this coefficient is positive.

Reach (REACH): This variable is defined as the horizontal distance between the surface location and the bottom hole location. It is measured in degrees of longitude and latitude. As reach increases, complexity increases, therefore the expectation of the sign of this coefficient is positive.

Water Depth (WD): This variable represents the water depth measured in feet. As water depth increases, the transition to floating operations is inevitable (except in the few cases of deeper water, fixed platform rigs). More complex operations such as mooring, stationkeeping, riser management (running and handling), and deepwater well control may increase the likelihood of injury and spills. The expectation of the sign of this coefficient is positive.

Duration (DUR): This variable captures the duration of a well in days. It is important to control for this variable as increased time on a well obviously increases the raw exposure time for injuries.

Well Type (TYPE): Whether a well is an exploration or production well affects the risk profile in may ways. TYPE is a binary variable representing whether or not a well is an exploration well. While exploration wells may contain more geologic uncertainty which tends to increase the likelihood of well control incidents, production wells are not immune to uncertainty. Production well paths may be less conservative in well design based on the increased quality and quantity of data available during well planning. The expectation of the sign of this coefficient is uncertain.

In addition to characteristics of the companies and the physical attributes of wells, a third component in the set of independent variables pertains to the overall operating environment. For example, the historic cyclicality of the drilling sector may influence HS&E outcomes. As one safety executive stated it during the ramp up in the mid 1990s, ”We need some help. We’re putting people out there that don’t have the experience” (DC-3, 1998). The variables selected to model the operating environment are as follows:

Crew experience (CREWEXP): This variable indirectly measures drilling crew experience using the year to year percentage change in the total number of wells drilled in the Gulf of Mexico. In the contract drilling industry, crews do not sit on standby in lean years, they are dismissed and move on to new jobs. When drilling activity increases, new crews must be recruited and trained. Anecdotally, these new recruits suffer a higher risk of injury than their more experienced counterparts. Research as reported in Dobson (1999) in part supported this belief. The expectation of the sign of this coefficient is positive.

MMS District (DISTRICT): This binary variable represents the MMS District in which the well is drilled. Although consistency in inspections and enforcement across all Districts is a goal, it may not be the case in fact. This variable will test whether or not the incidence of injuries and spills are affected by a more, or less strict enforcement environment. The expectation is that this variable will be insignificant.

Technology (TIME): This is a simple control variable entered as the calendar year to control for technological change over time.

Econometric Model Development

To estimate the general model as expressed in Eq. (1), a linear probability (LP) model is inadequate, as it does not constrain predicted values to lie between 0 and 1, and it can be shown that it is inherently heteroscedastic. A more sophisticated approach is required. Standard alternatives are the *probit* and *logit* probability models.

The development of a probability model is intuitively appealing. Note that one does not observe the actual probability of an incident occurring, one only observes whether or not an incident occurred. One can define this unobservable probability as Y^*, and the model can be expressed as:

$$Y^* = X\beta + u\,, \tag{2}$$

where the variables are as previously defined. But incident observations are made according to the rule:

$$Y_i = \begin{cases} 1, \text{ if } Y_i^* > 0 \\ 0, \text{ otherwise.} \end{cases} \tag{3}$$

Since the dependent variable is observed as either 0 or 1, it would appear to be appropriate to map $X_i\beta$ into a probability. One requires a function F such that:

$$prob(Y_i = 1) \quad = F(X_i\beta) \tag{4}$$

An obvious choice of a function F that maps $X\beta$ into [0,1] is a distribution function. If this function is the standard normal, Φ, one generates the normit or probit model (for the logit, the logistic distribution Λ is applied):

$$\text{prob}(Y_i = 1) = \Phi(X_i\beta) = \int_{-\infty}^{Xi\beta} \frac{1}{\sqrt{2\pi}} \exp\left(\frac{-z^2}{2}\right) dz \tag{5}$$

It is straightforward to show that the rule in Eq. (3) combined with Eq. (5) generates a likelihood function of the form:

$$L = \prod_{i=1}^{n} \Phi(X_i\beta)^{Y_i} (1-\Phi(X_i\beta))^{1-Y_i} \tag{6}$$

In the context of optimization, it is easier to maximize the log of the likelihood function:

$$\ln L = LL = \sum_{i=1}^{n} (Y_i * \ln(\Phi(X_i\beta)) + (1-Y_i) * \ln(1-\Phi(X_i\beta))). \tag{7}$$

This approach has several attractive properties. Maximization of the likelihood function yields parameter estimates that are consistent and asymptotically normal and efficient (given certain regularity conditions hold). The function is globally concave, simplifying the optimization, and it can be solved numerically.

4 Data Collection and Analysis

The study period for this analysis is 1990-1998, inclusive. A brief explanation of the data is important so that conclusions are viewed in the context of data quality. All of the data was collected from the MMS website (MMS-1, 2000), unless noted otherwise. The dependent variable, whether or not an incident occurred during the drilling of a particular well, is taken from MMS Accident Investigation Reports (MMS-2, 2000). Data for the independent variables originates from the MMS and industry publications. For each wellbore, observations are required of the operator of record, the technical complexity variables, and the operating environment variables.

There are two important points to make regarding the data collection and organization, especially with respect to the data aggregation issue to be discussed below. One, not all of the HS&E incidents in the MMS records are attached to a specific well, they are typically recorded by lease. In this data set, approximately one half of the drilling and workover incident reports contained a reference to the specific well, the remainder only contained the lease number. Two, if a lease had multiple operators in the study period, each was treated separately. For example, if a merger took place between *independent* A and *major* B (with different company profiles), and the designated operator changed in the MMS database, both periods of operatorship would be separately represented.

Data Aggregation

The fact that each observed incident could not be identified with a unique well required an adjustment to the model. The first attempt to address this problem was to aggregate the data by lease and by year, with independent variables being averaged for the year across wells, while other independent variables remained unaffected (except for the TYPE variable which is dropped due to the inappropriateness of averaging (a binary variable) across wells. While this aggregation permitted inclusion of all incidents, the dependent variable remained highly disproportionate, with a ratio of leases with incidents to all leases of ±2%. Initial regressions with this data set yielded negligible explanatory power by a variety of measures. As a final step, the data were aggregated for the entire study period by lease. This increased the proportion to ±6%. But by aggregating across time, the CREWEXP and YEAR were dropped from the specification. The estimation proceeds with this aggregated data set.

New Variable: COUNT

Previously, the DUR variable acted as a control for increased raw exposure time on a particular well. After data aggregation, an observation is made for a particular *lease* for the entire study period. It is possible that one field might contain 1 well in the study period while another may contain over 100. To control for this new feature of the data, I introduce a

COUNT variable that represents the number of wells drilled in each lease during the study period.

Correlation Coefficient Matrix

As a result of the data aggregation procedure, a few variables were lost, and a new variable was added. The final set of variables was used to construct a correlation coefficient matrix. This is shown in Table 1.

TABLE 1: Correlation Coefficient Matrix, All Variables

	Y	SCOPE	SCALE	BRAND	SS	SSB	DUR	DEPTH	REACH	WD	D1	D2	D3	D4	D5	COUNT
Y	1.00															
SCOPE	0.02	1.00														
SCALE	0.04	0.74	1.00													
BRAND	0.04	0.90	0.79	1.00												
SS	0.02	1.00	0.74	0.89	1.00											
SSB	0.02	1.00	0.74	0.89	1.00	1.00										
DUR	0.03	0.19	0.20	0.21	0.19	0.19	1.00									
DEPTH	0.04	0.18	0.19	0.22	0.18	0.18	0.50	1.00								
REACH	0.06	0.03	0.07	0.05	0.03	0.03	0.08	0.02	1.00							
WD	0.01	0.33	0.33	0.37	0.33	0.33	0.31	0.26	-0.01	1.00						
D1	0.01	0.17	0.16	0.19	0.16	0.16	0.08	0.04	0.08	0.22	1.00					
D2	0.00	0.10	0.06	0.08	0.10	0.10	0.03	0.13	-0.04	0.05	-0.23	1.00				
D3	0.02	-0.01	-0.01	-0.02	-0.01	-0.01	0.03	0.09	-0.03	-0.04	-0.22	-0.19	1.00			
D4	-0.05	-0.07	-0.07	-0.06	-0.07	-0.07	-0.06	-0.16	0.01	-0.05	-0.23	-0.20	-0.19	1.00		
D5	0.01	-0.15	-0.11	-0.15	-0.15	-0.15	-0.06	-0.06	-0.01	-0.15	-0.29	-0.26	-0.24	-0.25	1.00	
COUNT	0.22	0.04	0.06	0.05	0.04	0.04	-0.01	-0.09	0.09	-0.01	0.10	0.00	0.05	-0.07	-0.05	1.00

SS = SCOPE or SCALE (binary variable)
SSB = SCOPE or SCALE or BRAND (binary variable)
Di = MMS District
COUNT = Well Count

Included in the table are two new variables, SS and SSB. Due to the high correlation between the company profile variables, these binary variables were added to simplify the modeling process. SS takes on a value of 1 if either the SCOPE or SCALE variable is a 1. Similarly, SSB takes on a value of 1 if either the SCOPE or SCALE or BRAND variable is a 1. As noted the *Di* variables represent the MMS Districts.

Final Specification

As a result of the data analysis, subsequent aggregation process, and initial regression results, the final specification of the model is as follows:

$$Y_i = f\ (SSB_i, DUR_i, DEPTH_i, REACH_i, WD_i, D\#_i, COUNT_i),\ \forall (i = 1 \ldots n \text{ leases}) \qquad (8)$$

All subsequent discussion of results refers to this specification.

5 Results

Whether to use a probit or logit specification is a common empirical question. The two specifications typically yield very similar results. There are no economic or other arguments to favor one or the other on this data set. Both specifications were employed in initial regressions and verified this belief. As a result, only the probit results are presented here.

Results from the regression of the specification given in Eq. (8), maximizing Eq. (7) are shown in Table 2.

TABLE 2: Regression Results, Probit

Parameter	Estimate	Standard Error	t-statistic	P-value
C	-2.118033	.2121287	-9.984663	[.000]
SSB	.0260394	.0942392	.2763121	[.782]
DUR	.4434408E-01	.9078713	.0488440	[.961]
DEPTH	.0154875	.6581723E-02	2.353105	[.019]
REACH	.1574621	.5524873E-01	2.850058	[.004]
WD	.1252096	.4927506	.2541035	[.799]
D1	-.2318211	.1916296	-1.209735	[.226]
D2	-.1714641	.1928249	-.8892219	[.374]
D3	-.0829025	.1921361	-.4314781	[.666]
D4	-.3222668	.2022288	-1.593575	[.111]
D5	-.0429053	.1824580	-.2351518	[.814]
COUNT	.0414836	.4979688E-02	8.330571	[.000]

Number of observations = 2852.000
Number of positive obs. = 154.0000
Log likelihood = -553.0641

These results indicate three significant variables at the 5% level, each with the predicted sign: DEPTH, REACH, and COUNT. One MMS District, D4 (Lake Jackson), is nearly significant at the 10% level (under the logit, this t-statistic rises to 1.71). The SSB was used as the sole company variable in the final specification because each of the individual company variables (SCOPE, SCALE, and BRAND) was insignificant in initial regressions.

Chi-Squared and Overall Fit

General hypothesis testing for probability models is slightly different than OLS procedures. Instead of the typical F-test for all independent variables, the convention is to calculate a Likelihood Ratio (LR) test: LR = 2 ($L_u - L_r$), where L_u is the log-likelihood value from the unrestricted regression and L_r is the log-likelihood value from the restricted regression. This statistic is distributed asymptotically as χ^2 (r), where r equals the number of restrictions. For the base regression, the LR value of 92.4 (χ^2 critical [0.05] = 19.675) clearly rejects the null hypothesis that all coefficients are zero. Regarding the overall fit of the model, it is likely hampered by the disproportionate data set. While there are many means to qualify the overall fit of the model, I evaluated the Likelihood Ratio Index (LRI): LRI = 1 – (L_u / L_r). For the base regression this statistic equals ±0.08. Additional hypothesis testing regarding independent variable sub-groups (company variables, well complexity variables, operating environment variables) are available in the complete version of this paper.

6 Conclusions

This research presents evidence to support the hypothesis that well complexity, specifically DEPTH and REACH, increases the probability of HS&E incidents. The reasons for this are likely the increased exposure to pipe handling and similar high risk activities, and the dilution of focus on incident prevention due to the increased number of individual tasks associated with more complex wells. It was also found that water depth (WD) has not been a significant variable in influencing HS&E outcomes. Equally important is the evidence rejecting the hypothesis that company profiles have an effect on HS&E outcomes. These results can inform industry executives and policy makers of where to allocate HS&E incident prevention efforts. Also, the probit and logit specifications are consistent with each other with respect to coefficients, significance, and overall fit. Issues such as data aggregation (omitted variables), and the relatively low explanatory power of the model as elaborated above qualify these conclusions.

7 Future Analysis

There are at least two fronts for further analysis. First, a Poisson specification can address the effect of multiple incidents within one lease. Second, note that in this specification, it is taken as given that all incidents are reported. But this may not be the case in practice, and some incidents may go unreported for a variety of reasons. This hypothesis can be tested via *detection controlled estimation*. The interpretation of the dependent variable above changes from a vector of incidents to a vector of *reported* incidents. Two events must occur to generate an incident report. One, an incident must occur, and two, it must be reported. What we are interested in are the variables of these two underlying processes (an incident function and a reporting function). Fortunately, a likelihood function can be written to describe this joint process. Both of these fronts are being pursued by the author.

Notes:

1. The SCOPE variable is a binary variable indicating whether or not the operator is integrated into downstream activities. Companies with broader experience are likely to be more knowledgeable of HS&E and more capable of implementing successful prevention programs. For the purposes of this research, the determining factor of scope is whether or not an operator is integrated into *refining*. There are multiple sources for this data, including The National Petroleum News' Market Facts, the Energy Information Administration's Petroleum Supply Annual, and individual company websites (mainly for foreign-owned companies).

2. The SCALE variable is structured similarly to the SCOPE variable, except that here it represents the worldwide level of drilling activity. While the *number of wells drilled* might be the most appropriate variable, a reasonable proxy which is more readily available in the literature is the quantity of hydrocarbon reserves owned by a particularly company (based on the premise that there is a direct relationship between reserves and the number of exploration and development wells drilled). Companies with more drilling operations are likely to be more sophisticated (if only by accumulated experience) and should be more aware of HS&E pitfalls and prevention. A company is deemed to capture the benefits of scale if they possess more than 1 billion bbls of liquid reserves OR greater than 5 TCF of gas reserves. This is an arbitrary split, although there appears to be a natural break in the data around these thresholds. The source for this data is the Oil and Gas Journal's *OGJ200* (and its comparable predecessors).

3. The BRAND variable is an additional binary variable indicating whether or not a company possesses retail gasoline sales. As discussed above, a company with a brand name has more to lose in the case of a HS&E catastrophe. The source for this data is the National Petroleum News' Market Facts. The companies identified as retailers in this sample typically represent over 90% of U.S. retail sales during the study period.

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