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ORGANIZATIONAL, OPERATIONAL, AND NATURAL HAZARDS IN THE UPSTREAM OIL AND GAS INDUSTRY

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ABSTRACT

This research examines three aspects of upstream oil and gas management covering organizational choice, safety and environmental performance, and hurricane evacuation decision making. Each chapter is based on new and unique data sets compiled by the author over the course of four years. The inspiration for this work originates from the author's personal experience in the upstream oil and gas sector, primarily as an offshore drilling engineer in the Gulf of Mexico in the 1990's, but also as a contract manager responsible for turnkey and drilling rig contract design and risk allocation encompassing some $1.6 billion is contingent liability. Each chapter addresses critical issues facing today's oil and gas managers. The work applies current microeconomic and econometric methods to structure practical management questions within a formal analytic framework. The results provide insight into the complexities of modern day management decision making, and provide guidance to corporate and government policy makers.

The first chapter examines the decision of upstream oil companies to vertically integrate into the drilling function. In the Gulf of Mexico offshore oil and gas industry, there are some oil companies with relatively large, internal drilling organizations that plan and execute their drilling operations, some with small drilling organizations that opt to contract externally (turnkey) for almost all drilling operations, and a third group that employs a combination of internal and external resources. The chapter evaluates these organizational outcomes within the framework of *transaction cost economics.* The fundamental tenet of the theory of transaction cost economics is that surviving organizational forms are those that yield the lowest total cost of executing a transaction. Hence, the choice of organizational form for the drilling organization is determined by the expected costs of organizing drilling activities internally versus transacting with the market for the same services. Risk preference is also investigated as an explanation of these organizational outcomes. Econometric models are employed to model organizational choice and to estimate the underlying organizational cost functions. Estimation of the underlying cost functions permits isolation of the effects of transaction attributes to each form of organization, shedding light on the relative impact of internal

costs versus market hazards on organizational choice. The cost functions also enable estimation of organizational costs, permitting a calculation of the value of selective organizational choice. The results of this investigation provide joint support for the transaction cost paradigm and the risk preference hypothesis as determinants of organizational form. Estimates of organization costs indicate that the industry is not capturing all of the benefits of selective organizational choice, and that increased turnkey drilling is likely going forward.

The second chapter investigates health, safety, and environmental performance (HS&E) in offshore drilling. HS&E has always been a consideration of offshore exploration and production operators, but since the Piper Alpha disaster in the North Sea in 1988 resulted in 167 fatalities, HS&E performance has received considerably more attention from oil company decision makers and regulators worldwide. Significant investment has been made in risk assessment, process redesign, and advancing HS&E management techniques. In the Gulf of Mexico, the exploration and production sector continues to evolve in ways that may affect HS&E performance in years to come. Shifts in the demographics of the oil companies (majors versus independents) and where they operate, deeper water operations, and more complex wells all contribute to this transformation. The research investigates the determinants of HS&E incidents and reporting in offshore drilling. The results provide strong evidence to support the hypotheses that aspects of well complexity and site complexity increase the likelihood of HS&E incidents in drilling. Equally important is evidence generally rejecting the hypothesis that broader oil company attributes influence HS&E incidence. Models of incidence employ standard qualitative response models with binary and ordered dependent variable specifications, and a Poisson specification. Unlike previous studies, additional models are estimated by specifying a reporting function and employing detection control to account for the possibility of incomplete reporting. On whole, the results indicate that all firms exhibit similar performance in HS&E incidence and reporting, but this conclusion is somewhat sensitive to the specification of the model. Also, the evidence suggests that there is little difference in reporting behavior among regulatory districts. Analysis of time related variables provides insight into HS&E incidence and reporting over time, specifically in response to a 1996 regulatory policy change.

The third chapter examines the decision made by oil companies to evacuate offshore drilling rigs in the event of a hurricane. At its core, the problem is one of decision under uncertainty, a game of man against nature. The primary goals are to value existing forecast accuracy, to estimate the cost of false evacuations for the industry, to develop a behavioral model of the decision to evacuate, and to introduce the role of risk preferences in the decision to evacuate. The problem is examined from three unique perspectives. The first approach develops a prescriptive, decision analytic model. With this model, current forecast accuracy as demonstrated by the National Hurricane Center can be valued. Also estimated is the value of perfect forecast information. A second approach begins with a descriptive examination of actual drilling rig evacuation decisions for a sample of fifteen hurricanes in the Gulf of Mexico. From this data, and actual ex post storm paths and intensities, the costs of false hurricane evacuations from 1980-1999 is estimated. A discrete choice model of the evacuation decision is specified and estimated, identifying variables that influence the propensity to evacuate. The results of this descriptive analysis complement those of the decision analytic approach. The third approach examines the role of risk preferences in the decision to evacuate via specification of a utility function and a structural econometric model of the propensity to evacuate. The investigation reveals several key findings about the decision to evacuate in the offshore oil and gas industry. First, the prescriptive, decision analytic model indicates that over a range of value of life estimates, the value of current forecast information is insignificant when compared to overall industry expenditures, ranging from $5-103 million for the decade of the 1990's. Under the perfect information assumption, the value of forecasts is found to be about $1.1-1.4 billion for the decade. An analysis of imperfect improvement of forecast accuracy indicates that significant improvement in forecast accuracy over the status quo is required for forecasts to have meaningful value to industry. Based on the qualitative assessment of evacuation decisions, development of empirical evacuation rules, and application of these rules to estimate the cost of false evacuations, the value of perfect forecasts is estimated to be ~$267 million for the

1990's, about one-fifth of the value of perfect information estimated via the prescriptive approach. A second qualitative analysis, more directly comparable to the Nelson-Winter analysis, puts the value of perfect information in the $340-425 million range. These results provide support for an estimate of the value of perfect information in the range of $250-425 million for the decade, or $25-42 million per year. The discrete choice econometric 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. The results of the utility-based model, with respect to identifying the risk preferences, are mixed.

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1 Transaction Costs, Risk Preferences, and Organizational Outcomes: Modeling Governance In Gulf of Mexico Offshore Drilling

1.1 Introduction

In the Gulf of Mexico offshore oil and gas industry, some oil companies maintain relatively large, internal drilling organizations to plan and execute their drilling operations, some maintain small drilling organizations, opting to contract externally (turnkey) for almost all drilling activities, and others use some combination of internal and external resources. This paper examines these organizational outcomes within a framework of *transaction cost economics.* A fundamental tenet of the theory of transaction cost economics is that firms choose organizational forms to minimize the total cost of executing their transactions. Hence, the choice of organizational form for the drilling organization is theorized to be determined by the expected costs of organizing drilling activities internally versus transacting with the market for the same services. Risk preferences are commonly cited by decisions makers as contributing to this organizational choice, and this possibility is investigated also.

An econometric model is employed to model organizational choice and to estimate the underlying organizational cost functions. Estimation of the underlying cost functions permits isolation of the effects of transaction attributes to each form of organization, shedding light on the relative impact of internal costs versus market hazards on organizational choice. The cost functions also enable estimation of organizational costs, permitting a calculation of the value of selective organizational choice. The results of this investigation provide joint support for the transaction cost paradigm and the risk preference hypothesis as determinants of organizational form. Estimates of organization costs indicate that the industry is not capturing all of the benefits of selective organizational choice.

The chapter is organized as follows. Section 2 provides an introduction to the theory of transaction costs. The objective is to provide an adequate foundation in the theory for the present analysis. In Section 3 the details and nuances of organizational choice in offshore drilling are discussed. Section 4 provides an economic and technical literature review. Section 5 provides a general model of organizational choice, proposes independent variables and hypotheses, introduces alternative views of organizational choice, and motivates the estimation of the underlying organizational cost equations. Section 6 provides a brief introduction to the data set (a complete description is available in Appendix A). Section 7 details the econometric specification, estimation, and diagnostics. Section 8 discusses the econometric results, and Section 9 concludes.

1.2 The Theory of Transaction Costs

This section provides a brief introduction to the theory of transaction costs to develop a sufficient foundation for the present analysis. First, an overview of the origin and evolution of the field is given, emphasizing developments germane to the present research. This overview includes a broad discussion of the efficiencies and costs of different organizational forms. A comprehensive history of the theoretical and empirical development of the field is not provided; excellent contributions in this regard are available in the literature as cited below. A recent summary of the empirical literature is available in Shelanski and Klein (1999).

Origins and Milestones

The fundamental insights that inspired the development and evolution of the field of transaction cost economics are deservedly attributed to Ronald H. Coase. His seminal 1937 paper, *The Nature of the Firm*, proposed a new paradigm for explaining structural outcomes of markets and organizations. The core of this insight was a rather simple and unassuming question. He wondered, given the existence of an efficient, specialized exchange economy, why firms emerge at all as a form of organizing production (Coase, 1937). This query, and Coase's proposition that there must be some costs associated with accessing the price mechanism, initiated a new line of argument in the study of industrial organization. In his analysis of the market, Coase points outs the existence of positive transaction costs. He cites price discovery or information costs, contracting costs, and the costs of bounded rationality. In comparison, if transactions are organized under one authority by an entrepreneur-coordinator, such transaction costs are significantly reduced, and this latter form of organization is more attractive.

Coase framed the internal and market organization of production as alternatives, *i.e.* one either relies on the price mechanism or the entrepreneur-coordinator. The extent of the firm is therefore a conscious managerial choice based on a comparison of the respective institutional costs, or at the least a result of managerial trial and error over the long term.

Coase's framework contrasted with the prevailing wisdom of the day, that the extent of the firm was dictated primarily by production technology. In his exposition, Coase challenges his readers to discover whether it is possible to systematically study the forces (costs) which determine the extent of the firm.

Coase's propositions remained largely unattended until the 1960's (Coase, 1972; Williamson: 1985, 1986). Largely credited with reviving interest in the field, Oliver Williamson organized his views on vertical integration and the values of internal organization in an important 1971 article, *The Vertical Integration of Production: Market Failure Considerations*. In other works he integrated theories of contract with his views on organizational choice (Williamson: 1983, 1985, 1986). Williamson formalized the idea that firms economize on transaction costs. He advocated a broader analysis that would address organizational efficiencies in addition to technological efficiencies. Williamson explored the firm's organizational choices as a comparative institutional problem, and proposed a view of the firm as a governance structure rather than a production function (Williamson, 1999). A detailed assessment of Williamson's contribution to the field is available in Masten (1999).

Other important authors are too numerous to itemize here. However, work by Klein *et al.* (1978), Teece (1980), Monteverde and Teece (1982), Joskow (1985, 1987), and Masten (1984) are important to recognize as milestones in the development of a taxonomy of transaction costs, and in the development of empirical methods to test transaction cost hypotheses. Masten (1984) set off in an important direction, promoting the idea that internal coordination (transaction) costs deserve equal attention, versus the approach of focusing solely on the hazards of market exchange. This is the view adopted herein. To assume that costly behaviors such as opportunism do not occur, or are not significant within firms imposes an unrealistic reliance on the power of managerial fiat. Therefore, any complete study of organizational choice should identify not only those elements of a transaction that increase the hazards and costs of market exchange, but also those elements that increase the hazards and costs of internal organization.

Masten, Meehan, and Snyder (1991) present a study of organizational choice in shipbuilding. In the article the authors take up Masten's (1984) challenge to identify and then quantify a suite of both internal and market transaction costs. This work is especially important for its development and application of a complete econometric model of organizational decision making, and as such inspires the methodology used in the present analysis. Their framework is applied here, making the necessary modifications and expansions for this application.

Market Efficiency

A fundamental tenet of economic theory is that competitive markets and the price mechanism can be efficient means to allocate scarce resources. As such, prices are properly set through continuous exchange throughout the economy. Regardless of how producers of goods elect to organize themselves, they are in a state of competition with one another. Competition is a stern disciplinarian, rewarding efficient producers and punishing the inefficient. Producers are under constant pressure to minimize costs in order to compete for customers on price, and to satisfy their investor-owners who expect (at least normal) profits. In addition to price competition, producers strive to improve and differentiate current products from those of their competition. Innovation of new products is another outcome of competition. Additionally, producers may generate scale efficiencies. By aggregating demand, a producer can employ specialized production technology and achieve economies of scale, lowering cost.

It is this competitive market efficiency that led Coase to his oft paraphrased query. With such powerful incentives for efficient allocation and production efficiency in the marketplace, why would [vertically integrated] companies emerge at all as a form of organizing production? Williamson (1971) concurs with an added caveat, "… on account of bounded rationality and greater confidence in the objectivity of market exchange in comparison with bureaucratic processes, market intermediation is generally to be preferred over internal supply in circumstances in which markets may be said to 'work well.'"

The Market Caveat: Transaction Costs

In this section, the concept of transaction costs is discussed generally, highlighting some common market hazards and the resulting transaction costs. Only an overview is given here. Additional market hazards and more detailed analysis is reserved for the introduction and definition of topic specific independent variables in Section 5.

For discussion purposes, transaction costs can be placed into two categories. The first category of transaction cost includes costs actually realized during a transaction. Examples include screening costs, contracting costs, monitoring costs, coordination and scheduling costs, technology leakage, and production inefficiencies. The second category of cost includes expected costs that may or may not be realized in a given transaction. A common example is renegotiation costs. If a contingency arises that was not accounted for in the original contract, the parties must renegotiate. These renegotiations entail an opportunity cost. However, it is also possible that no such contingency arises and renegotiations are not required, therefore no renegotiation costs are incurred. *Ex ante*, a decision maker is forced to rely on an expectation of cost for this category of transaction cost. Note that it is possible for some types of transaction costs to display aspects of both of these categories.

<u>Asset Specificity</u>

The issue of asset specificity has received much attention in the transaction cost literature as both a source of increased *ex ante* contracting costs, and as a source of *ex post* renegotiation costs. Asset specificity refers to transaction specific investments for which there are few alternate applications. An example is an ore smelter designed for a specific application that cannot be costlessly reconfigured for another use. There are many types of asset specificity detailed in the literature (Besanko *et al.*, 1996), but the core of this issue is the existence of *quasi-rents.* A quasi-rent is the difference between the value of an asset in its best use and its second best use. Asset specificity can create quasi-rents which may be opportunistically appropriated by one of the parties to the transaction. Under these circumstances, internal organization is more likely, *ceteris paribus*. The important influence of asset specificity on organizational choice is well documented in Klein *et al.* (1978), Monteverde and Teece (1982), Williamson (1983), Masten (1984), Joskow (1987), and Lieberman (1991).

One may wonder why, if there are contracts in place, how can there be opportunistic behavior? First, recognize that contracts are negotiated and written by people with *bounded rationality.* That is, individuals have limits to their knowledge, and their ability to gather and process information. Bounded rationality prohibits a complete accounting of all contingencies that may arise during the life of a transaction, leaving some contingencies to be negotiated *ex post*. It is also difficult to perfectly define performance for some exchanges, *i.e.* performance may be subjective. Also, one party may have private information that can be used to craft the contract in its favor. With all of this said, even a complete contract can lead to opportunism, because enforcement is not free. The parties can always use the costs of enforcement as a lever to improve their *ex post* bargaining position. An important distinction for *ex post* transaction costs associated with asset specificity is that they may or not be realized, depending on whether or not one of the parties elects to act opportunistically. But it should be clear that as asset specificity increases, *ex ante* transaction costs are likely to be unavoidable as each party attempts to mitigate the likelihood of such behavior by writing a more complete contract. Intuitively, opportunistic behavior is constrained by the nature of the relationship of the parties. Reputation constraints can act to limit the likelihood of such behavior, and temper its impact (Joskow, 1985; Besanko *et al.*, 1996; Williamson, 1986).

Technology Transfer

Technology transfer can occur between the parties to a transaction. A firm may possess proprietary processes or knowledge that grants it a competitive advantage in its market. Research examining the concept of organizational knowledge as technology can be found in Teece (1983) and Oxley (1997). If proprietary knowledge exists, the firm may seek to minimize interaction with outside organizations to reduce the likelihood of technology transfer. A complementary view of the issue of technology transfer was explored by Monteverde and Teece (1982). They introduce the idea that if a particular transaction will *generate* valuable know how, it may be advantageous to organize it internally. Both of these issues are explored below in Section 5.

Monitoring Costs

Moral hazard is the term typically used to describe a case of asymmetric information in the form of hidden action, where one party can act in its own interest (to the detriment of the other) without the other party's knowledge (Brickley and Dark, 1987; Besanko *et al.*, 1996). In settings where moral hazards are present and are important because they may affect performance of the contract, either party may incur monitoring costs to deter detrimental hidden action. In cases where asset specificity is an important feature of the transaction, the party at risk of opportunistic behavior may have an increased incentive to shirk its contractual obligations, knowing that its investments are subject to appropriation, thus exacerbating the moral hazard problem. Again, reputation constraints play a role by limiting the payoff to bad behavior, and thus are important to account for in any analysis.

Information Costs

Adverse selection is the term typically used to describe a case of asymmetric information in the form of hidden information, where one party possesses information that it can use to craft a contract in its favor (Besanko *et al.*, 1996). For example, if a buyer is aware that a good is subject to manufacturing difficulties, but the seller is unsophisticated or unaware of the potential difficulties, the buyer can use this information to either constrain the buyer in some way, or in order not to hint at its information advantage, the buyer may elect to remain silent on certain contingencies. In the case where an information asymmetry exists, where this fact is known by the disadvantaged party, and is potentially costly, the uninformed party may choose to incur information collection costs to reduce the information asymmetry. Another facet to adverse selection is the case where the buyer only seeks market transactions for certain classes of products or projects. For example, a buyer may seek market transactions only for products or projects that contain great uncertainties. In this case, the potential sellers are again faced with the information asymmetry problem. Recent empirical work on the influence of information asymmetries on transaction costs can be found in Leffler and Rucker (1991) and Leffler *et al.* (2000).

Contracting Costs

When organizing a market exchange, a contract is typically written to document the terms of the transaction. These terms address items such as the definition of the good or service, price, inspection, delivery and acceptance criteria, suspension and termination provisions, liability, indemnity, insurance, assignment, and governing law. The costs of negotiating a bilateral contract are incurred by both parties, though not necessarily in equal proportions.

A *complete* contract would contain all the information required to govern a transaction under all contingencies. Intuitively, complete contracting does not appear possible because of bounded rationality. Information asymmetries also inhibit complete contracting. Even if bounded rationality did not exist, complete contracting would not appear to be economically feasible in most cases. The cost of identifying all contingencies, measuring performance, and agreeing on each party's responsibilities in each case would by itself appear to be prohibitive. The obvious implication is that contracts are *incomplete, i.e.* not all contingencies are itemized, or for some subset of itemized contingencies, there is no agreed on assignment of responsibilities. Because of this incompleteness, an opportunity exists for one or both parties to take advantage of gaps in the contract as they arise during the transaction. As others have observed, contracts reduce the risk of transactional opportunism, but do not eliminate it (Kronman, 1985).

As a good or service becomes more complex, or when uncertainty increases, the degree of contractual incompleteness would be expected to increase also. The parties would tend to devote additional resources in the writing of the contract to the identification of contingencies and to negotiation of the assignment of responsibilities in each case. As Masten (1984) concludes, the more complex a particular transaction, the greater the incentives to incur the costs of writing a more detailed contract.

An increase in complexity or uncertainty also increases the likelihood of renegotiations upon completion of the transaction (Williamson, 1985; Crocker and Reynolds, 1993). Whether these renegotiations are costly or not is important and is addressed below. These renegotiations may include interpretation of elements of the original contract, or new issues that were not captured in the original contract. Such renegotiation costs would decrease the likelihood of transacting with the market, *ceteris paribus* (Masten, 1984). Crocker and Reynolds (1993) examined the contracts that result under these circumstances (*i.e.* when expected renegotiation costs are high). An important feature of their work was the consideration of the effect of reputation as a remedy to increased contracting and renegotiating costs. They find that when reputations are good, less resources are required in contract writing *ex ante*, and renegotiations are more efficient.

Other issues also influence total contracting cost. Firms often incur screening costs to investigate the counterparty in order to assess the likelihood of satisfactory performance. These costs may be trivial if the counterparty has a good and public track record, and vice-versa. Also, contracts typically become more efficient as more transactions of a certain type are completed, as both parties learn where more and less detail is required, and learn the behaviors of the other party in instances of renegotiation. Thus, contracting experience should serve to reduce contracting costs.

Production Efficiency

One component of transaction costs is the difference in production efficiency. Some firms may be expected to be more efficient than others for a variety of reasons. A firm may have specific experience in a particular geographic area, it may be of sufficient size to capture economies of scale or scope, or it may have proprietary production or know-how technology. These issues have been explored in the transaction cost literature (Joskow, 1985; Teece: 1978, 1980). Differences in efficiency between internal production and a market provider are rightly considered a transaction cost (note, this cost can be positive or negative). Since production costs are often difficult to observe, many empirical studies assume no difference in production costs, and focus solely on other transaction costs (Masten *et al.*, 1991). However, recognizing that production efficiencies may exist and be significant calls for some form of inclusion in the analysis if possible.

In summary, it is clear that there are potential costs of accessing the price mechanism. These and other transaction costs will be discussed below in the specific context of oil and gas drilling.

Internal Organization

As Coase (1937) described, internal organization can be viewed as substitution of managerial control for the price mechanism. Organizing production internally certainly reduces or eliminates some transaction costs. Consider contracting costs for example. Internal agreements between departments, divisions, and affiliates are often required in some form, but since the typical hazards of exchange are significantly reduced, the costs of making these agreements is likely to be trivial. If required, the dispute resolution mechanism is management authority, not the court system. Such a resolution will be more efficient (less costly, more timely, etc.) as more information is typically available to the management authority, and controls are more sensitive and refined. These facts act to reduce the cost of resolution vis-à-vis adjudication in the courts (Williamson, 1971; Besanko *et al.*, 1996). It follows that contractual incompleteness is not as important for internally organized transactions. Other facets of internal organization are also important. Aligning the interests of the two parties through integration is a form of union, serving to increase transactional security (Kronman, 1985). Organizing production internally reduces the risk of opportunism, as both parties to the exchange are in a relationship with no defined end date and hence, there is an expectation of repeated transactions (Besanko *et al.*, 1996; Williamson, 1986).

Given the transaction cost reducing nature of internal organization, it is obvious to question, as Coase did, why all production is not carried out by one large firm? He surmised that there must be some form of internal coordination cost function that is increasing in the level of internally organized activities. He also applied the concept of bounded rationality to the coordinator, that is, the increasing difficulty to allocate resources effectively as the scale of activities grows (Coase, 1937). To summarize, internal organization is not immune to transaction costs, it carries its own set of potential hazards and inefficiencies. A thorough history of economic thought regarding the limits to organizational growth is given in Williamson (1986). The prevailing phraseology used to describe this phenomenon is *diseconomies of scale in management*, that is, there is an incremental loss of control between hierarchical layers and this loss of control entails a cost.

The Agency Problem

While organizing production internally reduces or eliminates some transaction costs, internal production faces several impediments to efficiency. Internal producers typically do not have to compete for their customers (assuming no external sales). Regardless of their cost or quality, the internal producer is not at risk of losing sales in the short run, and perhaps can survive in the long run if information on performance is poor. This structure does little to drive cost reduction and innovation. There are also simple administrative concerns. For example, overhead costs are sometimes allocated to production units, complicating cost accounting by production management. How can a manager evaluate costs and make improvements if he cannot easily obtain accurate figures? Also, the internal producer's costs may not be readily observable by senior management, especially if the production unit's costs are consolidated in financial statements. This means that performance shortfalls are less likely to be observed and corrected. These notable features of internal production: captive customers, reduced efficacy of management cost control, and an information gap between production and senior management creates an environment susceptible to inappropriate behavior, otherwise known as an *agency problem*. Agency problems and the resulting costs are quite real. If any of the above mentioned conditions exist, individuals may elect to shirk their fiduciary responsibilities, knowing that their behavior is difficult to observe, or that if observed, will have little impact on their employment status.

Another important element of the agency problem is influence costs. These are costs incurred by the firm due to individuals who lobby for resource allocations that lead to misappropriation of the firm's resources. These individuals take advantage of the information gap described above to perpetuate personal goals, without regard for the effect on the firm. This may create and sustain a bias to procure internally and may support inefficient organizational structures (Williamson, 1985; Besanko *et al.*, 1996). Influence costs also include the costs of reconciling poor past decisions that were a result of influence peddling. Globerman and Schwindt (1986) conclude, "As the size of an organization increases, the agency-principal relationship becomes increasingly attenuated. As a result, the risks of intraorganizational opportunism increase relative to interorganizational opportunism." If one contrasts this discussion of the agency problem with the market efficiencies discussed above, it should be expected that absent of transaction costs, minimal levels of vertical integration would be expected.

Although it is not investigated in depth herein, it is interesting to consider the possibility that some internal drilling organizations survive in part as a result of influence peddling. For example, managers of inefficient internal drilling organizations can reduce the likelihood of revealing this fact by limiting direct comparison with other drilling organizations, or by controlling information about mistakes and failures. Overcoming this problem is not easy. One solution would be to isolate the poor-performing organization so it could not compete for company resources. But this is not easy, as any connection to the company as a whole will permit influence activities to take place. Meyer *et al.* (1992) conclude that true isolation necessitates divestiture, the implication being that agency costs cannot be totally eliminated if the function remains integrated.

An Alternative: Risk Preferences

An alternative to the transaction cost paradigm of organizational choice is rooted in the decision maker's risk preferences. Consider an internally organized transaction. The firm retains control and makes all decisions regarding the progress of the transaction.

The firm assumes all costs associated with overruns and benefits associated with savings. In cases where the cost variance is high, the firm is directly exposed to this variance. Compare this structure to organizing production with the market where a fixed price is negotiated for the product. The seller is paid upon delivery, and the buyer's price variance is essentially eliminated. In this case, the seller is the residual claimant to all costs associated with overruns and benefits associated with savings. In those cases where the cost variance is high and the buyer is risk averse, there is value to the buyer of a fixed price alternative. In oil and gas offshore drilling, there are some transactions with high costs and high variances in actual performance, so if significant risk aversion is present among oil companies, it is likely to be observable in organizational choices.

In empirical investigations of this sort, there appear to be two main approaches to test for the influence of risk preferences. One method is to model the decision maker, that is, to identify variables that may indicate risk preference, and test whether these variables explain observed organizational or contracting choices. The other method is to model the transaction in terms of its uncertainty, and to test whether or not uncertainty variables influence organizational choices. If decision makers are risk averse, then uncertainty variables should be statistically significant. The issue of how the seller's risk preferences may influence organizational outcomes is an important subtlety, and is addressed below.

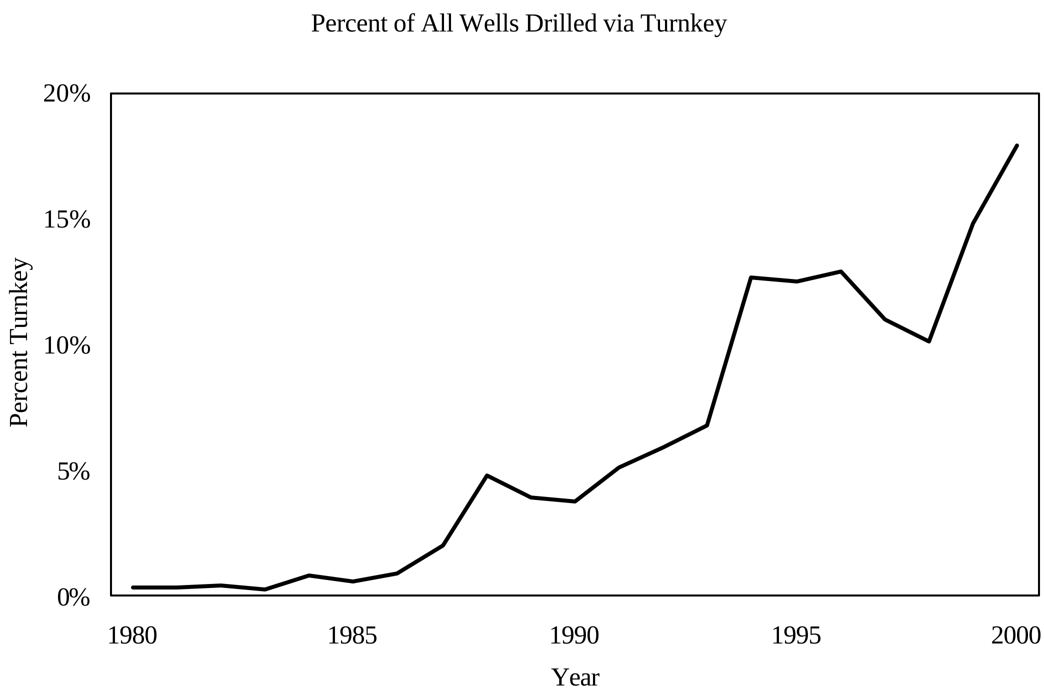
1.3 Organizational Choice in Offshore Drilling

There are a variety of organizational arrangements employed by oil companies in the execution of their offshore drilling programs. While these are multiattribute arrangements, a spectrum, indexed by risk and control, can be defined for discussion purposes. At one end of this spectrum is the internally drilled well where the oil company retains control and holds the risk. At the other end is the turnkey drilled well where the oil company relinquishes control and sheds much of the risk. There are other organizational arrangements along this spectrum. Examples of these are footage contracts, incentive based contracts, shared risk, and integrated services (Day *et al.*, 1997; Hart, 1998). Overall, these organizational forms are more like internal or turnkey drilling than they are different. For example, an oil company may drill a well internally and employ a form of shared risk contract with its subcontractors, but the risks shared in such an agreement are typically modest, and are only intended as incentive instruments, not risk shedding instruments. Therefore, the present research focuses on the more dramatic choice between internal drilling and the turnkey approach.

For internally drilled wells, the oil company has total control over all aspects of the planning of the well, coordination of service contractors, and makes all decisions regarding the progress of the well during the drilling phase. The oil company assumes all risks associated with drilling and incurs all of the costs. This is the predominant form of drilling organization in the Gulf of Mexico. In the 1990's, 80-90 percent of all wells were drilled in this manner (see Figure 1.1).

Under a turnkey drilling approach, the oil company transfers the majority of detailed planning to the turnkey driller. The turnkey driller coordinates the service contractors, and makes (almost) all decisions regarding the progress of the well during drilling phase. The turnkey driller assumes most risks (although this is a function of the details of the contract), and offers a fixed price to the oil company. Payment is made upon successful completion of the contract terms. Typical contract terms for exploration drilling include reaching a specified true vertical depth, running a specified suite of electric logs, or collecting rock and fluid samples. Typical contract terms for development drilling include a successful production casing cement job, evidenced by a successful pressure test or cement bond log.

Figure 1.1: Percent of Wells Drilled Under Turnkey, 1980-2000



If an oil company maintains the staff to execute drilling projects internally, then the organizational choice can be modeled on a well to well basis. For those oil companies with no such staff, or those companies with small staffs, the decision can still be modeled as if it did. Such an oil company can contract for a drilling engineer and execute a quasi-internal organization (*i.e.* assuming all the risk and costs), or the turnkey option can be selected. In fact, this latter approach is used in the Gulf of Mexico.

A transaction cost model prescribes that the decision maker chooses the organizational form with the lower total costs. These costs can be categorized as differences in productive efficiency, realized transaction costs, and expected transaction costs that may or may not be realized. The risk preference hypothesis introduced above addresses the possibility that oil company decision makers may be risk averse, and that the cost of holding the risk may be an important element of the organizational choice.

What do practitioners say about this organizational choice? Turnkey drillers market their services primarily as a risk management tool. An oil company's cost risk originates primarily from the geometry of the well design, geologic risk, and the level of drilling experience in the area (a means to reduce risk through informed planning). A fixed cost turnkey option is meant to eliminate this risk (ADTI, 2001; Diamond, 2001; Hart, 1998; Furlow and DeLuca, 1999). Other reasons often promoted by turnkey drillers as reasons for employing the turnkey option are handling peaks in the drilling workload (for companies with small permanent staffs mentioned above) and benchmarking internal performance in well design, procurement, and operations. Oil companies most often cite both workload and risk management as the primary motives for turnkey. Senior oil company decision makers have been quoted on their choice to use turnkey, "[I] let those guys drill the first well in the area," "…you know your costs are going to be capped, it's a good trade-off," and "[We] limit our risk to geological and exploration risks. Using turnkey helps mitigate the drilling risks" (Hart, 1998). Based on these comments, an analysis of organizational choice in offshore drilling should address the presence and impact of risk.

The model developed here proposes to explain this organizational choice by examining, on a well by well basis, the impact of variables thought to influence the transaction costs of both internal and turnkey organizations. Specific variables are included to test the strength of a transaction cost explanation versus a risk preference explanation of observed organizational outcomes. It is of course possible that some combination of these hypotheses will explain the observations best, rather than one dominating the other. As the literature search below demonstrates, this approach to analysis of organizational choice in offshore drilling is an original line of research in the oil and gas literature.

1.4 The Offshore Drilling Literature

In this section, the technical and economic literature concerning organizational choice in offshore drilling is reviewed.

Technical Perspectives

There is a limited technical literature on the subject of organizational design with respect to drilling organizations (internal versus turnkey). Much of the analysis of organizational choice in drilling can be found in technical trade journals or technical conference proceedings, and focuses on case studies, activity summaries, market trends, and matters of practical interest (bidding methods, risk management, contracting, negotiation, and dispute resolution). Noteworthy contributions on turnkey related matters include Oeffner (1988) on shared risk contracts, Erickson (1989) and Baum *et al.* (1998) on risk allocation and transfer, De Wardt (1990) on organizational efficiency and flexibility, Day *et al.* (1997) on implementation, and Hart (1998) which provides a broad overview of the issues involved in employing turnkey drilling. A broader family of articles examines the details of oil company-service company contracting strategies; examples of this type of work include Torsvoll and Grotmol (1999) and Flatt *et al.* (2000). None of these works addresses the drilling organizational choice in the context of transaction cost economics. Also, there does not appear to be any quantitative research that examined the issue of risk preferences and drilling organizational choice.

Relevant Economic Literature on Oil and Gas

Teece's (1978) analysis of oil company integration discussed the rationale for integration between major components of the oil and gas industry, *i.e.* production and refining, refining and marketing, etc., but did not quantitatively address integration issues within these components in a transaction cost framework. Hallwood (1990) addresses the level of integration within the exploration and production (E&P) sector. The focus is on the disintegration of oil companies from the production of intermediate inputs, and provides some important insight regarding the organizational structure of oil companies. Hallwood finds that 91 percent of intermediate inputs (by value) are provided by external sources. The main exceptions to the bias toward disintegration are the reservoir and production engineering consultancy. Hallwood does not distinguish nor discuss the drilling engineering consultancy which is the subject of this research. This important omission (important because drilling constitutes a large portion of exploration and development costs, and is inherently uncertain) left open the question of disintegration of the drilling engineering consultancy. A second article by Hallwood (1991) addresses the transaction cost paradigm in the context of oil and gas, and investigates some integration decisions in the petroleum industry. However, the analysis is qualitative only, and does not address the organizational choice of drilling internally versus turnkey. While Hallwood's two articles are the most focused analysis of integration decisions within E&P, his studies are qualitative and do not evaluate the drilling organization choice as is envisioned here.

In many ways, the detailed, quantitative analysis proposed here follows the typical evolution of economic inquiry from the broad (Teece, 1978) to an intermediate level of detail (Hallwood: 1990, 1991). The present analysis also provides a capstone to the qualitative body of articles in the technical oil and gas literature. Therefore, in addition to adding to the growing body of empirical research on transaction costs, risk preferences, and organizational design, this paper makes its primary contribution to the oil and gas economics and management literature. It provides specific insight into the determinants of organizational design for drilling organizations, and a framework and demonstration of an econometric methodology that can be applied to similar organizational choices.

1.5 A General Model of Transaction Costs in Offshore Drilling

This section has several objectives. A model of organizational choice is presented, and transaction costs in the context of offshore oil and gas drilling are introduced and discussed. Hypotheses and expectations are developed, and risk preferences are discussed. This model of organizational choice follows the work of Masten *et al.* (1991). Deviations from their model are addressed in Section 7.

Modeling Organizational Choice

The broad hypothesis is that transaction costs and risk preferences affect organizational choice. Specific hypotheses about what the appropriate transaction costs are, and how risk preferences will be modeled is discussed below. First, a simple view of organizational choice is presented to motivate the discussion. If the decision maker is viewed as selecting organization type on a well to well basis, a latent variable can be defined indicating the propensity to employ turnkey drilling, y_i^*, such that:

$$y_i^* = Z_i\gamma + u_i \,. \qquad \text{(a)}$$

However, y_i^* is not observable, instead one observes y_i, which takes on values of 0 (internal) or 1 (turnkey) according to the rule:

$$y_i = \begin{cases} 1 \text{ if } y_i^* > 0 \\ 0 \text{ otherwise,} \end{cases} \qquad \text{(b)}$$

where:

Z_i = vector of transaction attributes
γ = coefficients for transaction attributes
u_i = random error term $\sim N(0,\sigma^2)$.

This model sufficiently motivates the next step, identification and discussion of specific transaction costs that should be included in the vector Z. In Section 7, this econometric model is fully derived and expanded to more accurately depict the decision making process.

Independent Variables – Transaction Costs

In Section 1.2, several types of transaction costs were introduced. In this section, these definitions are revisited, and additional transaction costs specific to offshore oil and gas drilling are introduced.

<u>Technology Transfer</u>

Oil companies that drill wells internally accumulate drilling expertise. This expertise resides formally in written drilling practices and procedures and informally in the minds of the drilling staff. This latter type of knowledge is typically acquired through the teachings of senior personnel or through personal experience, and can be thought of as the *tricks of the trade*. Oil and gas wells are costly investments. The accumulated expertise of a drilling organization represents a tremendous asset, and can be considered a form of know-how technology (Oligney and Economides, 1998; Duey, 1999). Some oil companies consider this in-house drilling expertise to be a source of competitive advantage, and to share proprietary knowledge with another oil company or a turnkey driller would dissipate this advantage. In fact, one major oil company's proprietary well planning guidelines advise managers to consider turnkey drilling only for those wells with "low-tech drilling techniques."

When an oil company executes a project with a turnkey driller, there is a high level of interaction between the respective professional staffs during well planning and drilling, and the opportunity arises for technology transfer from the oil company to the turnkey driller. For example, if an oil company has drilled several wells with an unusual, complex characteristic, and the turnkey driller is relatively inexperienced in that respect, it may be in the oil company's interest to share some technical information with the turnkey driller to optimize design of the well. Such an incentive is strengthened if the turnkey option is chosen and operations begin. If the turnkey driller encounters problems during drilling, it is in the best interest of the oil company to assist the turnkey driller (even though it is not required to do so) to increase the chances for a quality wellbore and timely completion. While the oil company does not have to pay for an unfinished project, there is an opportunity cost associated with a delay or potential problems with the wellbore in the long term. It is anticipated that in this context, there exists some optimal level of technology transfer that balances the cost of the technology transfer against the value of a lower bid or the costs of delays or long term problems with a substandard wellbore. As a result of the high level of interaction and these incentives, there exists a potential for technology transfer from the oil company to the turnkey driller.

The value of drilling know-how is difficult to quantify. A simple proxy can serve the purpose. Drilling know-how is very likely to be positively correlated with the cumulative drilling experience of the drilling organization. While some proprietary know-how dissipates over time via personnel departures, the written practices and procedures survive, as does the know-how that was successfully passed on to remaining coworkers. A reasonable means to model cumulative drilling experience is to calculate a cumulative total by year of the number of wells drilled by each oil company (**OPCUM**). For a particular observation of organizational choice, the cumulative drilling experience can be observed (calculated up to the previous year to avoid any endogeneity problem). Additional detail about the construction of this variable is included in Appendix A. The expectation is that as the level of cumulative drilling experience increases, the likelihood of turnkey drilling decreases.

Monteverde and Teece (1982) introduce the possibility that a firm may choose to organize internally based on the potential that a transaction will generate valuable know-how. Similar to the firm's concern with the costs of technology transfer above, here the firm values the benefits of potential technology acquisition through direct experience. If this value is high, turnkey drilling is less likely, *ceteris paribus*. In this sense, any of the independent variables that describe situations where important technology may be generated could be viewed as influencing the organizational choice. For example, deep water drilling has been the undisputed drilling frontier of the 1990's. Firms that establish a capability to operate in deep water have an advantage as a preferred partner, and will be more competitive in lease acquisition. Therefore, firms would be strongly inclined to drill deep water wells internally in this period.

Monitoring Cost

When contracting with a turnkey driller, there is a moral hazard in the form of hidden action. The turnkey driller receives payment only when the well is successfully drilled per the contract terms, and is not a residual claimant to any oil and gas revenue. Therefore the turnkey driller does not have incentives that promote optimal investment in the well (optimal is defined to represent the level of investment which provides the highest net present value of the well accounting for future hydrocarbon production and well interventions). The turnkey driller's objective is profit maximization, *i.e.* completion of the well in compliance with specifications at the lowest cost possible. If a circumstance should arise during drilling where the optimal response requires additional expenditure, the turnkey driller's incentives are to conceal this fact and not to make the expenditure where possible (where it is not patently obvious, and where it would not hinder completion of the drilling of the well and receiving payment, and where there would be no damage to the turnkey driller's reputation). An example of such an operation could be the setting of a liner hanger, a common procedure in offshore drilling. Perhaps the liner hanger does not perform as designed. The turnkey driller can either retrieve the hanger for inspection, redressing, and re-running, or set the liner on bottom and cement it in place. The least costly option for the turnkey driller is to set the liner on bottom. For the duration of the drilling operation, this is unlikely to cause a problem, but in the long run, the liner may buckle and increase costs for the oil company (note that the oil company may make the same choice to set the liner on bottom, but it is the concealment that is the issue here). Unless the oil company observes the original failure of the liner hanger, it would be difficult to know exactly what happened downhole, and subsequent failure of the liner would be difficult to trace to the turnkey driller's actions during drilling.

As mentioned above, asset specificity can exacerbate the moral hazard problem. An oil well is the ultimate transaction specific investment. It is a custom designed product that meets very specific geologic objectives. It cannot be moved or sold to others; it has no alternate value. Once the turnkey driller has invested any sum in a project, all of its investment is subject to post contractual opportunism on the part of the oil company (subject to contract and reputation constraints). If a dispute arises, the turnkey driller is in an extremely weak bargaining position, since payment is typically made in a lump sum upon completion of the drilling. Although the turnkey driller could hold the well hostage by threatening to plug it with cement or otherwise make it unusable, this strategy is obviously of little value, considering the oil company knows the well has no alternate use. In light of this, the turnkey driller faces a constant incentive to underinvest in the project, knowing that all investments are subject to appropriation (or renegotiation) by the oil company.

Physical Monitoring

The moral hazard creates an incentive for the oil company to monitor turnkey drilling practices. The method commonly employed by an oil company to monitor the turnkey driller is to send representatives to the well site for 24-hour surveillance of operations, and to send representatives to off-site facilities to observe equipment inspections or other critical procedures. The more expensive it is to monitor turnkey driller behavior, the less likely to choose turnkey. Since actual monitoring costs are not available, a proxy must be employed. If one (reasonably) assumes a positive correlation between the measured depth (**MD**) of the well (downhole costs) and the water depth (**WD**) of the well (rig costs) with future intervention costs, the oil company will invest more resources in monitoring on deep and deepwater wells to reduce the probability of a future intervention. It is proper to view the monitoring cost in this way, because one should not expect the turnkey driller to engage in behaviors that will compromise the behavior of the well during drilling, so a view of possible future costs is appropriate. As measured depth and water depth increase, it is less likely to observe turnkey drilling. In the same vein, it is possible to relate the value of oil and gas production to the incentive to monitor, but since this does not make sense for exploration wells where production is not known *ex ante*, this approach is not pursued.

Reputation as Monitor

Reputation has been mentioned in numerous places above as an important element of contractual relations. Empirical evidence has shown that reputation is important when information about behaviors is good, when a long term relationship is desired, or when there is an expectation of repeated interaction (Allen and Lueck, 1992; Joskow, 1985; Besanko *et al.*, 1996). These conditions hold in the offshore oil industry. The industry, while consisting of thousands of individuals, is a close-knit community of professionals. Detailed information about the history of behaviors of companies and specific people is commonplace. Since turnkey contracts are written for the value of the well, the potential loss in trade to the turnkey drillers due to bad behavior is great. When reputations are important and behavior is self-regulating, less resources are required in contracting (screening, itemizing contingencies and uncertainties) and in monitoring (Crocker and Reynolds, 1993; Allen and Lueck, 1992).

As a contracting partner, turnkey drillers began with a blank slate at the origin of the industry in 1980 (see Figure 1.1 above). It is reasonable to assume that in the early years of the industry when there was no track record of performance, many oil companies appraised the potential for moral hazards and the resulting monitoring cost as too high, and avoided turnkey drilling as an organizational choice (either by not bidding at all, or due to prohibitively high expected monitoring costs). However, as the turnkey industry gained experience, and its percentage of all wells drilled increased, a reputation was established in these respects. If this reputation is good, then monitoring costs are low, and turnkey drilling is more likely, *ceteris paribus*. This hypothesis can be tested by including a variable that proxies for this reputation, a *reputation index* of sorts. This index should be inversely related to (expected) monitoring costs. To this end, the percent of wells drilled under turnkey for each year in the study period (**TKPCT**) is employed.

As TKPCT increases, the likelihood of turnkey drilling increases. Note that this variable is lagged to avoid any endogeneity problems.

Information Costs

For a typical drilling project, the oil company possesses superior knowledge regarding the subsurface environment relative to a turnkey driller. Although the turnkey driller is an experienced player, it cannot acquire (except at prohibitive cost) the depth of knowledge of the subsurface environment accumulated by the oil company throughout its entire pre-drilling geologic evaluation, which may have spanned several years. Since the oil company desires a low bid price, it has an incentive to conceal information that indicates geologic uncertainty (which may lead to increased expected drilling costs). Another hurdle facing the prospective turnkey driller is the possibility that the oil company may bid only those wells where there is increased uncertainty or a firm expectation of drilling difficulty. The leading turnkey driller, commenting on these circumstances, stated that "the contractor and the client need to work together and share all the relevant information and develop a sense of trust between each other" (Baum *et al.*, 1998). But in the cases where this objective is unmet, the turnkey driller has an incentive to inform itself on the drilling prospect, and thus incurs information collection costs. The general result is described by Leffler and Rucker (1991). In this context, an oil company indirectly incurs these information collection costs in higher bids (the exact proportion depends on the exact model of bidding behavior). Since the oil company cannot prevent the turnkey driller from incurring such costs, there is an incentive to provide disclosure of the subsurface knowledge. Which of these two incentives is stronger is likely to vary on a case by case basis. That is, is the oil company better off if it withholds information and incurs the information collection costs through higher bids, or if it shares all information, lowers information collection costs, but receives potentially higher bids as a result of the information shared?

For the present model of transaction costs, some measure of these information collection costs is required. For a drilling prospect in locations where there have been many other wells drilled, information costs are lower, as much of the important drilling information eventually enters the public domain, or can be purchased at reasonable costs from market data providers. In those cases where there are few or no offset wells, information costs are higher. The information seeker will have to purchase or trade private information (information not available from a market data provider), or perform additional technical research. A variable can be defined to model this information cost, the cumulative number of wells drilled in the lease block to date (**BLKCUM**). This variable represents the cumulative number of wells drilled in the subject lease block at the time of the organizational choice. Information collection costs are reduced if many wells have been drilled nearby. As BLKCUM increases, information collection costs decline, and the likelihood of turnkey drilling increases.

Contracting Costs

The contracting process can be described as a series of steps. These include: research and screening of potential suppliers, bidding and negotiation, writing the contract, monitoring performance, renegotiation, and enforcement. Each of these steps involves some opportunity cost. For some transactions, the contracting process represents an enormous expense over months or years of negotiation. Offshore oil and gas wells conform to this model of a contracting process. Four sources of contracting costs are examined: writing costs, renegotiation costs, contracting expertise, and screening costs.

Writing Costs

The assignment of mechanical and geologic risk between the oil company and the turnkey driller in a turnkey contract is an important and sensitive issue. For an accounting and discussion of some major risks in turnkey drilling, see Erickson (1989). If a well is physically complex, there are a greater number of mechanical contingencies, the contract will be more detailed, and therefore more costly to construct. Geologic complexity introduces additional dimensions of contingencies and uncertainties, and similarly adds to the cost of contracting. As measures of mechanical complexity and geologic uncertainty increase, one expects contract writing costs to increase as the parties attempt to identify, define, and assign risk in a mutually agreeable way. These issues (and the subsequent impact on contracting costs) were recognized early in the formation of the turnkey industry, and attempts have been made to agree on a standard offshore turnkey drilling contract (IADC, 2001). A standard contract has been drafted and is used as a base by some operators, while others elect to customize their contracts.

Contracting costs cannot be observed directly, and one must rely on proxies. An important factor in selecting complexity and uncertainty proxies is to avoid independent variable endogeneity. That is, if an attribute is not known prior to the organizational choice, it should be used to explain the choice. The following mechanical complexity and geologic uncertainty variables meet this requirement:

Mechanical Complexity

True Vertical Depth (**TVD**): This is the vertical distance from mean sea level to the bottom of the well measured in feet. Fluid pressure in the formations being drilled increases with depth, and this pressure increases complexity of the well design and execution. TVD is largely known prior to the organizational choice, and in the cases where it changes during the drilling process, the *ex post* TVD can be used as an unbiased estimate for the planned TVD.

Reach (**RCH**): This is the horizontal distance (map view) from the surface location to the bottom hole location measured in feet. Increasing reach implies increased hole angles and/or long deviated (non-vertical) sections, both of which add to the complexity of the well design and execution.

Water Depth (**WD**): This is the depth of the water at the drilling location measured in feet. Water depth generally increases operational complexity. Examples include the move from legged jackup drilling rigs to floating operations with attendant mooring, stationkeeping, remote vehicle operations, and the change from surface to subsea equipment configurations. Drilling issues in deep water include shallow water flow and unconsolidated formations, both adding to complexity in design and execution. Binary variables corresponding to water depth thresholds of rig type are investigated. These include WD400 which captures the change from jackup rigs to platform or floating rigs, and WD1000 which captures only the change to floating rigs.

As each of these variables increases, contracting costs increase, and the likelihood of turnkey drilling decreases.

Geologic Complexity

Exploration versus Development Well (**EVD**): This is a binary variable indicating whether or not a well is an exploration well (1) or development well (0). By definition, the targets of an exploration well are untested, therefore an exploration wells contains more geologic uncertainty than a development well, *ceteris paribus*. Because of this increased uncertainty, exploration wells are expected to have higher contracting costs and thus decrease the likelihood of turnkey drilling, making the expectation of the sign of this coefficient negative.

Cumulative Drilling in Block to Date (**BLKCUM**): This variable represents the cumulative number of wells drilled in the same lease block as the well to be drilled at the time of the organizational choice. A typical lease block is nine square miles. Geologic uncertainty is reduced if there are nearby wells available for reference. Note that wells in the same block typically penetrate the same geologic cross section. As the number of wells drilled increases, contracting costs decline, and therefore the likelihood of turnkey drilling increases, making the sign of this coefficient positive. Note, this is the second appearance of BLKCUM, but the coefficient expectation is identical.

Renegotiation Costs

Under the above described circumstances of mechanical complexity and geologic uncertainty, the number of contingencies that are overlooked is expected to increase, increasing the potential for *ex post* renegotiation costs, *ceteris paribus.* In the sense that the contracting cost proxies above account for mechanical complexity and geologic uncertainty in the contract writing phase, they also can be construed to proxy expected *ex post* renegotiation (with the same coefficient expectations). Note that such costs are random variables and realizations depend on actual outcomes in the field, therefore the decision maker acts on some expectation of *ex post* costs. This view of complexity and uncertainty leading to increased renegotiation costs has been addressed by Williamson (1985) and Joskow (1985). While this view does not introduce any new independent variables, it provides an additional justification for the variables already defined, thus adding to the overall strength of the test of the transaction cost hypothesis.

Reputation as Remedy

These contract writing and renegotiation costs may be tempered if reputations are good, permitting a less complete contract. In an empirical analysis of contract choice in Air Force engine procurement, Crocker and Reynolds (1993) address the issue of optimally incomplete contracts. They argue that a tradeoff exists between *ex ante* contract writing costs and *ex post* renegotiation costs. They present evidence to support the conclusion that the degree of contractual incompleteness is (at least) a function of the complexity and uncertainty associated with the transaction, and the reputation of the seller. Baum *et al.* (1998) briefly discuss this concept in the context of turnkey drilling, but provide no empirical analysis of its effect on organizational choice.

As the turnkey drilling industry has matured, both oil companies and turnkey drillers have accumulated direct experience in contracting and renegotiation, are likely to have learned of other companies' experiences, and have developed and refined their expectations of these costs. If turnkey driller reputations are good, this fact will temper the increase in contract writing and renegotiation costs anticipated due to complexity and uncertainty. To model reputation, the previously defined TKPCT is employed as a reputation index.

Contracting Experience

It has been discussed above how know-how is a form of technology. Since turnkey drilling was introduced as an organizational option in the 1980's, both the turnkey drillers and the oil companies have accumulated contracting experience (assuredly some good and bad). This experience promotes efficient contract writing by enabling the parties to better identify contingencies and to incorporate the appropriate elements in the contract *ex ante.* Contracting experience should also promote efficient renegotiation as norms and relationships develop, even if good reputations do not. The following proxy is employed to model contracting experience:

Cumulative Turnkey Wells Drilled (**TKCUM**): This is a continuous variable and represents the cumulative number of wells drilled under turnkey on an annual basis. As contracting experience increases, contracting costs should decline, increasing the likelihood of turnkey drilling.

Screening Costs

Screening refers to the process a buyer engages to investigate the competency of a potential supplier. This competency has many components, but most important in this context are operational competence and financial solvency. The oil company needs to be assured that the turnkey driller possesses the personnel and capital to execute complex and expensive offshore drilling projects. If the potential supplier has little experience, the screening process is more costly, as the buyer must conduct a complete investigation. If the potential supplier presents a resume of many successfully completed projects and references, then the screening process is less costly. As the turnkey industry has grown and accumulated experience, performance under a variety of conditions has been observed. This accumulation of experience has likely served to reduce screening costs, thus making turnkey drilling more likely. This hypothesis can be tested by using the TKCUM variable previously defined.

Internal Costs / Production Efficiency

One may observe vertical integration in an industry or for a specific transaction where there are few hazards of exchange and low transaction costs. At first glance, this result appears to contradict the general line of argument herein. However, such a result can obtain if by organizing production internally, the firm captures production efficiencies that are not available to the typical market provider (Walker and Weber, 1987; John and Weitz, 1988). Thus, the term *transaction costs* should be carefully interpreted and applied. While any loss or gain in production efficiency due to organizational choice can be classified as a transaction specific cost (because the actual value of the production efficiency will vary by transaction), it should be recognized that the majority of this production efficiency accrues to all potential transactions, and in this way is not transaction specific (Masten *et al.*, 1991). The purpose of this section is to describe some of the factors that may lead to low internal production costs.

Economies of Scope

Operating offshore oil and gas operations is a challenging task. There is a tremendous amount of expertise required for drilling and production operations, air and marine logistics, weather response, and communications. In addition to this know-how, inputs such as labor, and air and marine transportation can be shared across different segments of offshore operations. If an oil company possesses a high level of expertise and activity in offshore operations (acquired through non-drilling activities such as production, construction, and pipelining), it can capture economies of scope. An appropriate proxy for offshore expertise and activity is the number of active production platforms operated by the oil company (**PLAT**). The expectation is that as the number of active platforms increases, an oil company captures economies of scope, and internal organization of production is more likely.

Economies of Scale

In broad terms, economies of scale are achieved when production volume is large enough to support specialization, that is, a low cost production technology can be employed. In offshore drilling, this translates to specialization in engineering expertise (equipment design, drilling mud, directional drilling, well design, operations), purchasing leverage, logistics, and economies of scale in management. By aggregating demand for drilling and reaching relatively high output levels, a turnkey driller may capture economies of scale. If by itself an oil company has sufficient demand from within, its drilling organization also may capture economies of scale. On the other hand, smaller oil companies with fewer wells to drill may incur a production inefficiency by organizing their drilling internally. There is empirical evidence that supports this view (Forbes and Zampelli, 2000). A proxy for economies of scale in the oil company is the number of wells drilled per year (**OPCY**). There is a potential variable endogeneity problem here, but if one assumes that the choice of internal versus turnkey is independent of whether or not a well is drilled (decision to drill a well is made prior to decision to drill internally or turnkey, in reality a fair assumption), the same year well count is appropriate. The expectation is that as the well count increases, an oil company captures economies of scale, and the likelihood of turnkey drilling decreases. Note that it would be appropriate to construct a similar proxy for turnkey drillers (TKCY), because as is described below, cost functions for each type of organization are to be estimated. But generating a similar proxy is not possible because reliable data (well counts) at the turnkey driller level are not available.

<u>Asset Specificity</u>

The concept of asset specificity was introduced above. It has also been described how an oil well is the ultimate transaction specific investment. It is a custom designed product that meets very specific geologic objectives. It cannot be moved or sold to others; it has no alternate value. This extreme asset specificity implies that the entire well cost can be interpreted as a quasi-rent. Therefore, one well is not more or less asset specific than another, but one well may have a higher quasi-rent than another, based on the level of investment. In this sense, one can model organizational choice as a function of the quasi-rent. Note, the importance of reputation in this context has already been established. The fact that market transactions occur in this situation of extremely unbalanced leverage reinforces the role that reputation plays.

Two implications of asset specificity and quasi-rents on organizational choice have been recognized. One was described above in the discussion of monitoring costs. A second was noted regarding the effect on contracting costs. Due to the weak bargaining position of the turnkey driller, there is an incentive for significant investment in more complete contracting. But in these cases, only the exacerbation of the moral hazard, and a general increase in contracting costs was addressed. There was no mention of the degree of the effect. If one assumes that the degree of the effect is a positive function of the quasi-rent, then variables indicative of cost can be used to model these effects with the obvious expectations. As the level of investment rises, monitoring costs and contracting costs are expected to rise. Fortunately, variables indicative of costs have already been defined and are as follows: MD, TVD, RCH, WD, and EVD. The expectations for these coefficients in this context are the same as previously defined. Therefore, these variables add to the overall strength of the test of the transaction cost paradigm.

<u>Regulatory Factors</u>

Oil companies operate under a variety of regulatory authorities. The Minerals Management Service (MMS) is the Federal regulator, and is of prime importance in offshore drilling. An important part of the law sets forth that oil companies retain ultimate liability for all regulatory non-compliance on the leases they operate (including all reporting and fines) regardless of the choice of drilling organization. When an oil company employs turnkey drilling, almost all control over day to day rig operations is transferred to the turnkey driller, reducing some of an oil company's control over regulatory performance. While most operators employ monitors at the drilling location, many "comply/no comply" choices will be made by the turnkey driller.

While consistency in inspections and enforcement across all MMS Districts is a goal, it may not be the case in fact. A district may be more vigorous in enforcement, less flexible in its interpretation of the regulations, and slower to approve deviations from the original drilling permit. In such a district, the oil company may need to devote more resources to the compliance function, and may be instructed to implement changes to ongoing operations. The introduction of a third party (turnkey driller) who is contractually in charge of operations into the regulator-oil company relationship may increase oil company-turnkey driller coordination costs. In such a district, turnkey drilling would be less likely. To account for the possibility of different coordination costs by MMS District, binary variables are included to represent the MMS Districts. There are no hypotheses for individual districts. The variables are as follows: Houma (**HO**), New Orleans (**NO**), Lafayette (**LA**), Lake Jackson (**JX**), and Corpus Christi (**CC**). Lake Charles is the omitted region.

Transaction versus Company Attributes

Oxley (1997) has argued that broad company attributes such as R&D spending and firm size should not have a material affect on organizational outcomes. It seems inappropriate to draw blanket conclusions about these types of company attributes. For example, based on such reasoning, one might conclude that international scale is a company attribute, not related to organizational decisions on drilling wells in the Gulf of Mexico. But if the international operations serve to accumulate know-how that is shared across business units, it seems appropriate that they could be considered a transaction attribute vis-à-vis technology transfer. In fact, it would seem difficult in most cases to disentangle such broader company attributes from individual transactions. While one strong test of this hypothesis is included here, and the issue is recognized in some of the independent variables, a distinction is not made for each of the independent variables. It is left to the reader to judge the present definitions of transaction costs, and whether or not they are better classified as transaction specific, generic company attributes, or some combination of the two.

A Strong Test – Retailing

A variable that would fit Oxley's definition in this context is the level of downstream vertical integration; whether or not an oil company sells gasoline should not materially affect the choice of drilling organization. A variable representing gasoline sales should then be insignificant in a properly specified organizational choice model for drilling. But there is an alternative hypothesis based on the existence of valuable retail brands among some oil companies. For the most part, retail gasoline outlets sell a commodity; well developed and maintained brands help to increase profits. It is in these oil companies' interest to maintain the value of their brands. An alternate hypothesis is that the potential for negative publicity in the E&P sector through health, safety, or environmental incidents (HS&E) that may damage the downstream brand name and hurt retail sales influences organizational choice in E&P.

When an oil company employs turnkey drilling, it transfers much of the control for operations to the turnkey driller. Although the turnkey driller has incentives to act prudently with respect to HS&E issues, it is possible that due to differences in the payoff functions of each party that the turnkey driller may be less careful in preventing HS&E incidents than a company with a valuable retail brand name. To test this hypothesis, a binary variable indicating whether or not the oil company is integrated into retail gasoline sales (**RET**) is defined. The scale of such sales is not addressed. The hypothesis is that turnkey drilling is less likely for those oil companies with retail sales.

Firm Size - Global E&P Scale

It has been described above how accumulated drilling experience is its own form of technology. If an oil company has worldwide experience, and one assumes some level of information sharing between divisions, such a firm would have greater accumulated experience and know-how, and be at greater risk of technology transfer (greater than the technology proxy defined above which is Gulf of Mexico only). Is this an irrelevant company attribute variable per Oxley, or can it be interpreted as a transaction specific variable? Again, this distinction is not clear. To model worldwide drilling experience, the best variable would be actual well counts, but the cost of collecting such data is prohibitive. Instead, one can rely on reserves as a proxy. There is a positive relationship between the amount of reserves and the number of wells drilled to develop those reserves. One can define a critical level of scale in worldwide reserves as greater than ±750MM bbls liquids or greater than ±5 TCF gas. More information on this definition is available in Appendix A. Firms with reserves exceeding one or both of these thresholds were marked as such in the appropriate year using a binary variable (**RES**).

The preceding discussion of transaction costs, independent variables, and expectations is summarized in Table 1. Note that several variables appear more than once, being justified as proxies for different facets of transaction costs. The content of Table 1 is consolidated in Table 3.

Table 1.1: Summary of Transaction Cost Variables

Transaction Cost	(Coefficient Expectation) / Cost or Proxy	Variable
A. Technology Transfer	(-) / Cumulative Well Count of Opco in GOM	**OPCUM**
A1. Technology Acquisition	(-) / Water Depth (2)	**WD**
B. Monitoring	(-) / Measured Depth (1) (2)	**DEPTH**
	(-) / Water Depth (2)	**WD**
	(+) / Percent wells under turnkey (2)	**TKPCT**
B1. Information	(+) / Cumulative well count in lease block (2)	**BLKCUM**
C. Contracting		
Writing		
Mechanical Complexity	(-) / True Vertical Depth (1) (2)	**DEPTH**
	(-) / Reach	**RCH**
	(-) / Water Depth (2)	**WD**
Geologic Uncertainty	(-) / Exploration or Development? (E=1, D=0)	**EVD**
	(+) / Cumulative well count in lease block (2)	**BLKCUM**
Renegotiation [same variables and expectations as *Writing*]		
Reputation	(+) / Percent wells under turnkey (2)	**TKPCT**
Contracting Experience	(+) / Cumulative turnkey wells drilled (2)	**TKCUM**
Screening	(+) / Cumulative turnkey wells drilled (2)	**TKCUM**
D. Internal Costs / Production Efficiency		
Value of Scale	(-) / Current Year Well Count of Opco	**OPCY**
Value of Scope	(-) / Current number of active platforms	**PLAT**
E. Asset Specificity (**DEPTH, WD, RCH, EVD**), same expectations		
F. Regulatory Regime	(n/a) / MMS District (binary variables) (Lake Charles excluded)	**NO, HO, LA, JX, CC**
G. Company Characteristics (3)		
Brand protection	(-) / Retail brand name (Y=1, N=0) (3)	**RET**
Global E&P scale	(-) / Reserves Threshold (Y=1, N=0) (3)	**RES**

NOTES:

(1) MD and TVD are highly collinear; the sum of the two generates a DEPTH index variable which is employed instead. (2) Appears more than once. (3) These variables are typically correlated, the magnitude depends on the definitions used. The definitions used for all cases here are those detailed in Appendix A.

A Risk Preference Approach

The alternative of a risk preference approach to the transaction cost approach to organizational choice was introduced above. In the offshore drilling context, the distribution of risk is a distinguishing feature of the organizational choice. Under internal drilling, the oil company holds the risk, while under turnkey drilling, the turnkey driller holds the risk. Practitioners confirm that risk plays a role in organizational choice. In empirical investigations of this sort, there appear to be two main approaches to test for the influence of risk preferences. One method is to model the decision maker, that is, to identify variables that may indicate risk preference, and test whether these variables explain observed organizational or contracting choices. The other method is to model the decision or transaction in terms of its uncertainty, and test whether or not uncertainty variables influence organizational choices. If decision makers are risk averse, then uncertainty variables should be statistically significant.

In this section, a test of the risk preference hypothesis is described using the independent variables already introduced. The work of Leffler and Rucker (1991) and Leffler *et al.* (2000) provides additional insight into these methods, and empirical results for the timber industry. The model developed therein is loosely analogous to the turnkey versus internal organization choice studied here.

Modeling the Transaction

A transaction cost argument for variables representing pre-bid information collection costs has been presented. Again, the potential for adverse selection makes historical drilling information valuable, and turnkey bidders will incur pre-bid information collection costs to improve the accuracy of their bid (one does not need to impose risk aversion on the turnkey driller to expect this behavior, it can be motivated by a desire to improve the accuracy or competitiveness of the bid). Similar to the model detailed in Leffler and Rucker (1991), the oil company would observe this information collection cost in the form of higher turnkey bids. The higher the uncertainty, the higher the information collection costs, and less likely (on average) that the turnkey bids will be competitive with an internal organization cost estimate. This information feature of offshore drilling led the leading turnkey driller to observe that prospects whose risks are hard to price are unlikely to be good candidates for turnkey drilling (Baum *et al.*, 1998). This argument represents the received transaction cost paradigm. Risk neutral oil company agents ignore cost variance, and select organizational form based on: Min[E(internal cost), E(turnkey cost)]. For prospects where uncertainty is high, turnkey drilling is less likely.

If oil company risk preferences matter, a different line of argument and expectations result. Consider a risk averse oil company facing a drilling prospect where cost variance is high and pre-bid information collection costs are included in the submitted bids. Per the above, the resulting turnkey bids will be higher than the expected internal organization cost for the same well, *ceteris paribus*. However, if the value of risk reduction (from the *fixed* price turnkey alternative) outweighs the value of the increase in bids due to information collection costs, one is more likely to observe turnkey drilling. This expectation is the opposite of the transaction cost expectation, thus the results can provide information as to which model is more likely in play in this context.

In offshore drilling, cost variance increases with the number of unknown parameters associated with the well under consideration. This includes items such as downhole pressure, composition of the strata to be drilled, the general stability of formations during drilling, and response of formations to different types of drilling mud. As wells are drilled in an area, the number of these unknown parameters decreases. In this sense, the cumulative drilling experience in a block (BLKCUM) is a proxy for these unknowns. If BLKCUM is low, cost variance is high, and bidders will incur pre-bid information costs in the form of additional research. As BLKCUM increases, cost variance decreases, and the expectations for each of the above approaches is as described. Note that the expectation for the sign of the coefficient of this variable under the transaction cost approach and the risk preference approach are opposite. As was described in the discussion of contract writing costs, other variables also introduce uncertainty. From that list, obvious variables are DEPTH, RCH, WD, and EVD. Again, in a risk preference framework, the expectations for the signs of these coefficients are reversed. Thus, there are five variables that can be employed to examine the independent power of the risk preference alternative.

Modeling the Decision Maker

A second approach to examine risk preferences is to observe attributes of the decision maker that may indicate risk preferences. Examples in the literature include Chisholm (1997), where the author investigated similar issues (risk-sharing and liquidity constraints) for the motion pictures industry. The peculiarities of that industry permit some reasonable assumptions regarding the risk preferences of the contracting parties. But the subsequent analysis did not support the hypothesis that risk preferences affected the choice of contract structure. A notable article by Smith (1982) found significant risk aversion among oil companies in the pursuit of offshore leases, with decreasing risk aversion as firms grew in size (net worth). In Gulf of Mexico drilling, there is a wide variety of company sizes: (1) large, widely held public companies, (2) small, closely held public companies, and (3) small, privately held companies.

Similar to Smith (1982), the present analysis proposes a measure of net worth to proxy for risk aversion. The higher the net worth, the more likely to be risk neutral. The measure is market capitalization. An important observation here is that all oil companies face the same scale of drilling costs and variance on a per well basis. As market capitalization increases, an oil company is better equipped to absorb variance in drilling costs; smaller oil companies are less so equipped. The common example of gambler's ruin is instructive (Newendorp, 1975). Ideally, market capitalization is a continuous variable, but to collect such data for all of the companies in this study on an annual basis is prohibitive. Instead, a market capitalization (**CAP**) of $1 billion is used as a threshold to distinguish *large* companies (a binary variable that takes a value of 1 for large companies). While this number is of course arbitrary, this appears to be a natural break in a market capitalization ranking of companies, and hence may be a *de facto* indicator of significant differences in decision making criteria. Note that the expectation of the sign for this variable is negative, which is also the expectation for the RET variable under the transaction cost hypothesis. Because of this, the variable has limited value in informing on the transaction cost versus risk preference hypotheses, except to the degree that one coefficient has a significantly larger value, perhaps indicating relative impact.

It is interesting to consider the potential influence of the seller's risk preferences. It is important to recognize that turnkey drillers are larger (market capitalization) than some oil companies, but smaller than others. Therefore, if one suspects that some oil companies may be risk averse based on size, there is no reason to exclude the possibility that turnkey drillers may be risk averse. If one expects a risk averse oil company to value a fixed price alternative, one would expect a risk averse turnkey driller to increase its bid such that the certainty equivalent value meets expectations for the risks taken. As the bid increases, it diminishes the attractiveness of the turnkey option, *ceteris paribus*. The greater the risk aversion, the higher the adjustment to the bid. If one allows the possibility of risk averse turnkey drillers, the impact on the analysis is in the interpretation of results. For example, if it is found that as uncertainty increases, the likelihood of turnkey drilling increases, one could conclude that the value of a fixed price alternative to the oil company outweighs the bid adjustment of the turnkey driller, *ceteris paribus*. In other words, the oil company is relatively more risk averse. Note that the seller's risk preferences are only relevant in the analysis of transaction uncertainty, not in the analysis of oil company size.

Table 1.2: Summary of Risk Preference Variables
(All other variables from Table 1.1 still apply)

Variable Type	(Coefficient Expectation) / Cost or Proxy	Variable
Transaction Uncertainty		
A. Information	(-) / Cumulative well count in lease block	**BLKCUM**
B. Mechanical	(+) / True Vertical Depth	**DEPTH**
	(+) / Water Depth	**WD**
	(+) / Reach	**RCH**
C. Geologic	(+) / Exploration or Development? (E=1, D=0)	**EVD**

* Note: these five coefficient expectations are opposite of the transaction cost expectations.

Decision Maker Attributes		
D. Risk Preferences	(-) / Market Capitalization (Y=1, N=0) (1)	**CAP**

NOTES:
(1) See Appendix A for additional information.

Organizational Cost Estimates

In addition to estimating the organizational choice model with the variables introduced above, a second objective is to estimate the underlying cost functions for each organization. Estimation of the underlying cost functions permits isolation of the effects of transaction attributes to each form of organization, shedding light on the relative impact of internal costs versus market hazards on organizational choice. The cost functions also enable estimation of organizational costs, permitting a calculation of the value of selective organizational choice. The detailed econometric model is developed below.

1.6 Data Set Overview

The study area is the Gulf of Mexico Outer Continental Shelf (OCS). The OCS was selected as a subset of all Gulf of Mexico offshore wells (*i.e.* state waters are not included) due to the availability of detailed individual well data from the MMS. Detailed information regarding wells in state waters is not readily available. While data was collected for 1980-2000, the final data set represents 1990-2000, and consists of 6,135 observations. During the 1980's, the percentage of wells drilled under turnkey was extremely low, and it is very likely that econometric estimation in that time period would add little value to the analysis. The 1994-2000 period was examined (contains a higher proportion of turnkey drilled wells) and initial estimations did not reveal any significant differences from 1990-2000 estimates. Therefore, all analysis hereafter assesses the 1990-2000 time period.

Each observation represents a unique wellbore. Per Equations (a) and (b), the dependent variable is whether or not the well is internally or turnkey drilled, and the independent variables are those described in Tables 1.1 and 1.2. Table 1.3 presents basic statistical information on the data set. Detailed information on the dependent variable and each independent variable is available in Appendix A.

Table 1.3: Basic Statistical Information for Dependent and Independent Variable(s)

	Mean	Standard Deviation (s)	+2s	-2s	Maximum	Minimum
TK (Dep Var)	0.14	0.35	1	0	1	0
DEPTH	20,334	7,985	36,305	4,364	50,950	1,146
WD	382	811	2,003	7	7,716	7
WD400	0.15	0.36	1	0	1	0
WD1000	0.08	0.29	1	0	1	0
RCH	3,667	2,919	9,505	0	19,866	0
EVD	0.48	0.50	1	0	1	0
BLKCUM	16	30	76	0	407	0
OPCY	29	33	95	1	173	1
OPCUM	730	1,135	3,000	1	4,537	1
TKCUM	467	288	1,043	140	1,095	140
TKPCT	0.08	0.039	0.160	0.004	0.140	0.030
PLAT	78	112	302	0	509	0
NO	0.23	0.42	1	0	1	0
HO	0.18	0.38	1	0	1	0
LA	0.17	0.37	1	0	1	0
JAX	0.15	0.35	1	0	1	0
CC	0.04	0.42	1	0	1	0
RET	0.42	0.49	1	0	1	0
RES	0.43	0.49	1	0	1	0
CAP	0.62	0.48	1	0	1	0

Notes:
1. "-2s" adjusted to zero or minimum value if technically inappropriate (i.e. negative).
2. Binary variables set to limits for "+/- 2s."

One technical subtlety warrants a comment here. Only *original* wellbores are included. Offshore wells are commonly bypassed or sidetracked due to drilling trouble, or due to changing geologic objectives. The likelihood of sidetracking may or may not be known prior to the organizational choice, but this detail cannot be determined from the available data. Also, sidetracking occurs after the original wellbore has been drilled and is typically done on the spot, that is, there is not an additional organizational choice made at that point in time, the form chosen for the original wellbore is typically maintained through completion of the project. Therefore, the focus is only on the original organizational choice and sidetrack wells are not included.

Independent Variable Correlation

A correlation matrix was calculated for the entire set of independent variables to check for collinearity and is included in Appendix A. Potential problems among the following variables exist (correlation coefficient noted in parentheses): MD and TVD (~1), TKCUM and TKPCT (0.83), OPCY and OPCUM (0.84), RET and RES (0.86), RET and CAP (0.64), and RES and CAP (0.68).

Initial econometric estimations demonstrate the anticipated problems when including both correlated variables in a specification. Therefore, MD and TVD have been added together to create a depth index, DEPTH. TKPCT and TKCUM share the same coefficient expectation in all cases; based on econometric analysis to be described below, TKPCT is employed and the results are used to infer the effects of TKCUM. Similarly, OPCY is omitted in certain places but again its effects are inferred via OPCUM. Regarding the company attributes, the use of two of these variables in the same specification is avoided. This is not problematic as there is another (albeit local) measure of scale in OPCY. Results of initial specifications presented below demonstrate the impact of different combinations of these variables.

Collecting variables that appear more than once in Tables 1.1 and 1.2, a consolidated list of variables and expectations results and is given in Table 1.4.

Table 1.4: Consolidated Transaction Cost Variables

Variable	(Coefficient Expectation) / Cost or Proxy
DEPTH	(-) / MD+TVD Index
WD (WD400, WD1000)	(-) / Water Depth
RCH	(-) / Reach
EVD	(-) / Exploration or Development? (E=1, D=0)
BLKCUM	(+) / Cumulative well count in lease block
OPCUM	(-) / Cumulative Well Count of Opco in GOM
OPCY	(-) / Current Year Well Count of Opco
TKCUM	(+) / Cumulative turnkey wells drilled
TKPCT	(+) / Percent wells under turnkey
PLAT	(-) / Current number of active platforms
NO, HO, LA, JX, CC	(n/a) / MMS District (binary variables) (Lake Charles excluded)
RET	(-) / Retail brand name (Y=1, N=0)
RES	(-) / Reserves Threshold (Y=1, N=0)
CAP	(-) / Market Capitalization (Y=1, N=0)

Note:
Under risk preference hypotheses, the variables BLKCUM, DEPTH, WD, RCH, and EVD have the opposite expectation.

1.7 The Econometric Model, Estimation, and Results

In this section, a complete econometric model of organizational choice that accounts for the underlying organizational cost functions is specified. A discussion of the estimation methods and the initial and base case results is given. A detailed narrative of the evolution of mathematical methods employed in transaction cost studies in available in Masten (1996).

The Econometric Model

The model of Eqns. (a) and (b) was used to motivate a discussion of organizational choice, transaction cost identification, and independent variable selection. That model is now modified to fully account for the underlying structure of the decision maker's choice and the availability of data. A *two stage* model is employed to this end. The first stage models the discrete organizational choice as described in Eqns. (a) and (b). The second stage uses the first stage results to estimate the underlying organizational costs. This family of models is generally attributed to Heckman (1979), and is well developed in texts such as Maddala (1983) and Johnston and DiNardo (1997), and in applied research such as Gronau (1974) and Masten *et al.* (1991).

The decision maker faces a choice between two organizational forms on a well by well basis, internal or turnkey drilling. Each of these forms entails a total cost, and based on observable attributes of the transaction, the decision maker develops expectations of these costs *ex ante.* This can be represented as follows:

$$I_i = \text{cost of Internal organization} \quad = X_{1i}\beta_1 + e_{1i} \qquad (1)$$

$$M_i = \text{cost of Turnkey organization} \quad = X_{2i}\beta_2 + e_{2i} \qquad (2)$$

where X_i is a vector of transaction attributes for well i, β is a vector of coefficients, and e_i is a random error term. To structure the problem in this way grants insight not only into the variables that affect the hazards of market exchange, but also into the variables that influence internal organization cost, which is equally interesting. In the most general case, the costs I and M include the cost of the product (the well), realized transaction costs, and expected transaction costs that may or may not be realized. The independent variables defined above reflect each of these components. If the decision-maker is a risk-neutral, expected utility maximizer, he chooses the lower expected cost option. But all that is typically observed due to data availability (the present case is no exception) is the choice of organizational form, y_i:

$$y_i = \begin{cases} 1, \text{ if } M_i < I_i \\ \\ 0 \text{ otherwise.} \end{cases} \qquad (3)$$

Recall the variables of the function for the unobserved latent variable, $y_i^* = Z_i\gamma + u_i$. A discrete choice model, such as probit, based only on the observed organizational choice is straightforward, but such a model only informs about the relative difference in the coefficients of the underlying cost equations. That is,

$$\begin{aligned} \Pr(y_i = 1) = \Pr(M_i < I_i) &= \Pr(X_{2i}\beta_2 + e_{2i} < X_{1i}\beta_1 + e_{1i}) \\ &= \Pr(e_{2i} - e_{1i} < X_{1i}\beta_1 - X_{2i}\beta_2). \end{aligned} \qquad (4)$$

A discrete choice model for Eqn. (3) only informs on $(\beta_1 - \beta_2)/\sigma_{(e2-e1)}$. This is problematic for interpretation if X_1 and X_2 have common elements, because the magnitude of the individual effects on I and M is obscured. As Masten *et al.* (1991) observe, if X_1 and X_2 have common elements and if there is uncertainty of the effect of a specific independent variable, even a very general interpretation is compromised. For example, consider a hypothesis that well depth increases turnkey contracting costs faster than internal contracting costs, *i.e.*, $\beta^M_{Depth} > \beta^I_{Depth} > 0$. Based on the simple discrete choice model, one would expect the well depth coefficient, $\beta^I_{Depth} - \beta^M_{Depth}$, to be negative. But finding the coefficient to be negative does not refute the possibility that β^I_{Depth} and β^M_{Depth} are both negative, and that well depth actually lowers transaction costs. In this example, this is a distinct possibility since the present model includes several independent variables in the risk preference context where sign expectations are opposite of the transaction cost expectations. Therefore, a different approach is required if one is to properly estimate coefficients for Eqns. (1) and (2).

As stated above, costs for each organizational form are not observable. If one could observe costs, Equations (1) and (2) could be estimated directly. However, such estimates suffer from selectivity bias because one does not observe costs for organizational forms not chosen. To show this, examine the expectation of the error term of Equation (1):

$$E(e_{1i} \mid u_i < -Z_i\gamma) = E(\sigma_{e1,u}\, u_i \mid u_i < -Z_i\gamma)$$
$$= -\sigma_{e1,u}\, (\phi(-Z_i\gamma)/\Phi(-Z_i\gamma)) = \lambda_i, \qquad (5)$$

where ϕ and Φ are the pdf and cdf of the standard normal distribution, respectively. In a likewise fashion, $E(e_{2i} \mid u_i > -Z_i\gamma) = \sigma_{e2,u}\, (\phi(Z_i\gamma)/\Phi(Z_i\gamma))$. Note, it is assumed e_1, e_2, and u are trivariate normal, with a mean vector zero, and $\sigma_u^2 = 1$. A summary of these results and of the underlying statistics is available in Maddala (1983). The most important of these results are the conditions for identification of the model. These are as follows:

a. $\sigma_{e1,e2} = 0$, or
b. One variable in X_1 is not included in X_2.

The second condition is less restrictive here because the present hypotheses suggest that $X_2 \neq X_1$.

Results from the first stage organizational choice estimation (γ) can be used to compute the expected bias for each observation, λ_i, as described in Eq. (5). This new variable is added as a regressor to Equations (1) and (2), its coefficient simply being an estimate of $\sigma_{e1,u}$ and $\sigma_{e2,u}$ (which are of no economic interest). Again, if one observes costs or a proxy for costs, estimation of Equations (1) and (2) proceeds in this manner, hence the *two stage* designation. Parameter estimates from the regressions will be unbiased.

Estimation of the Organizational Choice Model

Based on the summary of independent variables in Table 1.4, and the discussion of the collinearity problem in Section 1.6, initial regressions were made to investigate the differences between specifications, and to select a specification to serve as a base case for discussion. First, the discrete organizational choice model introduced in Eqns (a) and (b) is estimated as a probit. Recall Eqns (a) and (b) where a latent variable was defined indicating the propensity to employ turnkey drilling, y_i^*, such that:

$$y_i^* = Z_i\gamma + u_i \,. \qquad \text{(a)}$$

But y_i^* is not observable, instead one observes y_i, which takes on values of 0 (internal) or 1 (turnkey) according to the rule:

$$y_i = \begin{cases} 1 \text{ if } y_i^* > 0 \\ 0 \text{ otherwise,} \end{cases} \qquad \text{(b)}$$

where:

Z_i = vector of transaction attributes
γ = coefficients for transaction attributes
u_i = random error term $\sim N(0,\sigma^2)$.

Therefore, prob ($y_i = 1$) = prob ($y_i^* > 0$) = prob ($Z_i\gamma + u_i > 0$) = prob ($u_i > - Z_i\gamma$). If both sides of this expression are divided by the standard deviation of u_i, u_i / σ_u is observed to be distributed as a standard normal variable. Since γ and σ_u always appear together, σ_u can be normalized to one to simplify the notation. Finally, since the distribution is symmetric, prob ($y_i = 1$) = prob ($u_i < Z_i\gamma$) = $\Phi(Z_i\gamma)$, where Φ is the cdf of the standard normal distribution. In a binary model, prob ($y_i = 0$) is simply $1 - \Phi(Z_i\gamma)$. This derivation leads to the following likelihood function:

$$L = [\ \Pi_{yi=0}\ (1 - \Phi(Z_i\gamma))\ ]\ [\ \Pi_{yi=1}\ \Phi(Z_i\gamma)\ ]$$
$$L = \Pi_n\ (1 - \Phi(Z_i\gamma))^{(1-yi)}\ (\Phi(Z_i\gamma))^{yi}.$$

The log-likelihood for all n observations is given as follows:

$$\ln L = \Sigma_n\ (1- y_i)\ \ln\ (1 - \Phi(Z_i\gamma) + (y_i)\ \ln\ (\Phi(Z_i\gamma)). \qquad \text{(c)}$$

The log-likelihood is maximized numerically, typically in an iterative fashion using one of many available algorithms such as the steepest gradient or Newton's method. The asymptotic covariance matrix is computed by evaluating the negative inverse of the Hessian at the maximum likelihood estimates. Other methods for computing the covariance matrix were examined, but differences were trivial and are not presented.

Table 1.5 presents results from three specifications intended to probe the impact of different specifications of the water depth variable. Equation 1 employs a continuous variable for water depth, while Equations 2 and 3 employ binary variable to model rig type thresholds based on water depths of 400 and 1000 feet, *i.e.* jackup/platform drilling rigs to floating drilling rigs. The results indicate that the choice of specification for the water depth variable is unlikely to have a major impact on inferences. Each of these definitions is viable, but since the hypothesis regarding water depth is based primarily on the discrete jump to floating operations, the WD400 binary variable is employed hereafter.

Table 1.5: Probit Model of Organizational Choice (Stage 1) – Analysis of Water Depth Specifications

Variable	Coefficient Estimates (t-statistics)					
	(1)		(2)		(3)	
CONSTANT	-1.5899	(-17.167)	-1.6225	(-17.715)	-1.6572	(-18.097)
DEPTH	0.2486	(8.261)	0.2413	(8.099)	0.2535	(8.490)
WD	**-0.0006**	**(-7.977)**				
WD400			**-0.8264**	**(-9.308)**		
WD1000					**-0.9131**	**(-7.406)**
RCH	-0.3674	(-4.505)	-0.3643	(-4.453)	-0.4055	(-5.013)
EVD	0.1093	(2.234)	0.0973	(1.990)	0.0939	(1.931)
BLKCUM	-0.7198	(-5.042)	-0.7163	(-5.033)	-0.6165	(-4.486)
TKCUM	0.1052	(13.977)	0.1027	(13.642)	0.1032	(13.800)
TKPCT						
OPCY						
OPCUM	-0.0002	(-5.833)	-0.0002	(-6.097)	-0.0002	(-6.136)
PLAT	-0.8464	(-2.874)	-0.7718	(-2.636)	-0.6758	(-2.323)
RET	-0.1213	(-1.919)	-0.1272	(-2.012)	-0.1675	(-2.683)
RES						
CAP						
NO	-0.0019	(-.028)	-0.0336	(-.496)	-0.0565	(-.839)
HO	0.1182	(1.807)	0.1414	(2.149)	0.0774	(1.195)
LA	-0.0812	(-1.182)	-0.0710	(-1.033)	-0.0919	(-1.345)
JAX	-0.1652	(-2.351)	-0.1784	(-2.545)	-0.1709	(-2.445)
CC	-0.2718	(-2.296)	-0.2909	(-2.462)	-0.2668	(-2.257)
LR (p-value)	713.669	(.000)	697.583	(.000)	663.557	(.000)
Log Likelihood	-2111.407		-2119.450		-2136.463	
# of Observations	6135		6135		6135	

Table 1.6 presents specifications that examine different combinations of OPCY/OPCUM and TKPCT/TKCUM. As anticipated, the impact on overall inferences is minor due to the high level or correlation between these variables. Based on these results, OPCUM and TKPCT are employed hereafter, and results for OPCY and TKCUM are inferred accordingly.

Table 1.6: Probit Model of Organizational Choice (Stage 1) – Analysis of TKPCT/TKCUM and OPCY/OPCUM Specifications

Variable	Coefficient Estimates (t-statistics)							
	(4)		(5)		(6)		(7)	
CONSTANT	-1.6225	(-17.715)	-1.5788	(-17.318)	-1.7599	(-17.898)	-1.8113	(-18.305)
DEPTH	0.2413	(8.099)	0.2291	(7.745)	0.2292	(7.747)	0.2415	(8.100)
WD400	-0.8264	(-9.308)	-0.8447	(-9.567)	-0.8383	(-9.423)	-0.8261	(-9.217)
RCH	-0.3643	(-4.453)	-0.3590	(-4.407)	-0.3851	(-4.713)	-0.3899	(-4.749)
EVD	0.0973	(1.990)	0.1062	(2.177)	0.0985	(2.020)	0.0909	(1.858)
BLKCUM	-0.7163	(-5.033)	-0.7098	(-4.991)	-0.6636	(-4.750)	-0.6669	(-4.760)
TKCUM	**0.1027**	**(13.642)**	**0.1054**	**(13.997)**				
TKPCT					**8.2162**	**(13.577)**	**8.1395**	**(13.434)**
OPCY			**-0.4456**	**(-4.056)**	**-0.4282**	**(-4.061)**		
OPCUM	**-0.0002**	**(-6.097)**					**-0.0003**	**(-6.472)**
PLAT	-0.7718	(-2.636)	-0.8095	(-2.694)	-0.7660	(-2.616)	-0.6630	(-2.293)
RET	-0.1272	(-2.012)	-0.2505	(-4.221)	-0.2713	(-4.566)	-0.1311	(-2.066)
RES								
CAP								
NO	-0.0336	(-.496)	-0.0456	(-.675)	-0.0434	(-.643)	-0.0283	(-.418)
HO	0.1414	(2.149)	0.1292	(1.970)	0.1294	(1.975)	0.1417	(2.153)
LA	-0.0710	(-1.033)	-0.0758	(-1.109)	-0.0820	(-1.200)	-0.0787	(-1.146)
JAX	-0.1784	(-2.545)	-0.1825	(-2.608)	-0.1858	(-2.653)	-0.1804	(-2.570)
CC	-0.2909	(-2.462)	-0.2836	(-2.413)	-0.2874	(-2.429)	-0.2979	(-2.502)
LR (p-value)	697.583	(.000)	671.114	(.000)	667.167	(.000)	699.504	(.000)
Log Likelihood	-2119.450		-2132.684		-2134.658		-2118.489	
# of Observations	6135		6135		6135		6135	

Finally, specifications for the company attribute variables, RET, CAP, and RES are investigated. These are presented in Table 1.7.

Table 1.7: Probit Model of Organizational Choice (Stage 1) – Analysis of RET, RES, and CAP Specifications

Variable	Coefficient Estimates (t-statistics)					
	(8)		(9)		(10)	
CONSTANT	-1.8113	(-18.305)	-1.8067	(-18.305)	-1.7022	(-17.009)
DEPTH	0.2415	(8.100)	0.2452	(8.212)	0.2585	(8.570)
WD400	-0.8261	(-9.217)	-0.8036	(-8.979)	-0.7353	(-8.244)
RCH	-0.3899	(-4.749)	-0.3854	(-4.689)	-0.4072	(-4.905)
EVD	0.0909	(1.858)	0.0820	(1.673)	0.0630	(1.274)
BLKCUM	-0.6669	(-4.760)	-0.6780	(-4.841)	-0.7238	(-5.127)
TKPCT	8.1395	(13.434)	8.1980	(13.559)	8.3447	(13.652)
OPCUM	-0.0003	(-6.472)	-0.0002	(-6.202)	-0.0002	(-5.468)
PLAT	-0.6630	(-2.293)	-0.5443	(-1.876)	-0.2454	(-.850)
RET	**-0.1311**	**(-2.066)**				
RES			**-0.2335**	**(-3.864)**		
CAP					**-0.5247**	**(-10.377)**
NO	-0.0283	(-.418)	-0.0204	(-.299)	-0.0117	(-.170)
HO	0.1417	(2.153)	0.1346	(2.042)	0.1662	(2.496)
LA	-0.0787	(-1.146)	-0.0852	(-1.239)	-0.0713	(-1.027)
JAX	-0.1804	(-2.570)	-0.1777	(-2.527)	-0.1047	(-1.464)
CC	-0.2979	(-2.502)	-0.2599	(-2.173)	-0.1358	(-1.125)
LR (p-value)	699.504	(.000)	710.424	(.000)	805.651	(.000)
Log Likelihood	-2118.489		-2113.029		-2065.416	
# of Observations	6135		6135		6135	

All three of these specifications are viable based on hypotheses, and each offers insight into the impacts of the specification on inferences. While there is a fair degree of correlation between each of the company attribute variables, there are interesting differences in the results. Most notably, the significance of EVD and PLAT decreases from (8) to (10). The regulatory variables are also different in (10).

Overall, the first stage results provide support for the hypothesis that both transaction costs and risk preferences influence organizational choice. The coefficient estimates for WD400, RCH, TKPCT (and TKCUM), and OPCUM (and OPCY) support a transaction cost view, while the coefficients for DEPTH and BLKCUM support a risk preference view. If one were to judge based on this evidence alone (number of variables in support), it would appear that the transaction cost hypothesis provides a stronger explanation of organizational choice. Note that the coefficients for RET and CAP support the transaction cost and risk preference view, respectively. However, also note that the magnitude of CAP is nearly four times as great, perhaps indicating that while both effects are present, risk aversion is a more powerful influence on organizational choice (a simple impact analysis can shed some light on this difference).

Impact Analysis

Another means to examine the individual influence independent variables have on the dependent variable is to compute a range of each independent variable X_i and compute the effect on the mean probability for the sample as if every observation for X_i was at one end or the other of this range. These computations provide additional information about the relative strength of the competing hypotheses. Tables 1.8 and 1.9 present the results of this analysis using both a +/- 2 standard deviation (s) definition for the range as given in Table 1.3. The impact is defined as the difference between the two mean values.

Table 1.8: Independent Variable Impact Analysis for Specification (8)

Variable	Coefficient Estimate	t-statistic	Mean of Predicted Values +2s	-2s	Impact
DEPTH	0.2415	(8.100)	0.2926	0.1099	0.1827
WD400	-0.8261	(-9.217)	0.0217	0.1038	-0.0821
RCH	-0.3899	(-4.749)	0.0491	0.0933	-0.0442
EVD	0.0909	(1.858)	0.1000	0.0865	0.0135
BLKCUM	-0.6669	(-4.760)	0.0378	0.0934	-0.0556
TKPCT	8.1395	(13.434)	0.2152	0.0240	0.1912
OPCUM	-0.0003	(-6.472)	0.0209	0.1154	-0.0945
PLAT	-0.6630	(-2.293)	0.0667	0.0933	-0.0266
RET	-0.1311	(-2.066)	0.0792	0.0982	-0.0190
NO	-0.0283	(-.418)	0.0898	0.0940	-0.0042
HO	0.1417	(2.153)	0.1116	0.0894	0.0222
LA	-0.0787	(-1.146)	0.0838	0.0952	-0.0114
JX	-0.1804	(-2.570)	0.0725	0.0975	-0.0250
CC	-0.2979	(-2.502)	0.0572	0.0949	-0.0377

The four most important variables in terms of impact are TKPCT, DEPTH, OPCUM, and WD400. As noted above, three of these variables support the transaction cost hypothesis, adding credence to the argument that transaction costs are more influential than risk preferences.

In Table 1.9, the same analysis is done for Spec. (10). Here, two of the four most influential variables support the transaction cost hypothesis. The notable difference between the two specifications is the impact of the company attribute variable. In Spec. (8), RET, while statistically significant, has relatively little impact on the average predicted probability. In Spec. (10), CAP is the third most influential variable. Again, these specifications and results provide support for both organizational hypotheses.

Table 1.9: Independent Variable Impact Analysis for Specification (10)

Variable	Coefficient Estimate	t-statistic	Mean of Predicted Values +2s	-2s	Impact
DEPTH	0.2585	(8.570)	0.2970	0.1064	0.1906
WD400	-0.7353	(-8.244)	0.0253	0.0977	-0.0724
RCH	-0.4072	(-4.905)	0.0461	0.0894	-0.0433
EVD	0.0630	(1.274)	0.0938	0.0849	0.0089
BLKCUM	-0.7238	(-5.127)	0.0338	0.0895	-0.0557
TKPCT	8.3447	(13.652)	0.2088	0.0229	0.1859
OPCUM	-0.0002	(-5.468)	0.0349	0.1017	-0.0668
PLAT	-0.2454	(-.850)	0.0794	0.0894	-0.0100
CAP	-0.5247	(-10.377)	0.0541	0.1304	-0.0763
NO	-0.0117	(-.170)	0.0880	0.0897	-0.0017
HO	0.1662	(2.496)	0.1101	0.0852	0.0249
LA	-0.0713	(-1.027)	0.0812	0.0910	-0.0098
JX	-0.1047	(-1.464)	0.0774	0.0916	-0.0142
CC	-0.1358	(-1.125)	0.0722	0.0900	-0.0178

For discussion purposes hereafter, Specification (8) will be examined. As described above, the construction of the CAP variable is somewhat subjective, as compared to the RET variable which is well defined.

Diagnostics and Analysis

In a discrete choice model such as this, specification and significance tests are different than the typical suite of tests for models estimated with ordinary least squares (OLS). For example, the typical R^2 statistic has no analytic counterpart in probit, and one must rely on other, more ad hoc approaches.

Overall Fit

An intuitive means to examine the fit of the model is to compute McFadden's Likelihood Ratio Index: LRI = 1 – [L (c,β) / L (c,0)], where L (c,β) is the optimal log likelihood value and L (c,0) is the same but under the restriction that all coefficients are equal to zero. Obviously, this must lie between 0 and 1. However, this ratio is only informative to the effect that *higher is better*, and there is no analytical foundation in the same vein as R^2 in the OLS context.

To address this weakness, other approaches have been proposed. One approach is to examine the percentage of correct predictions, which in the present case is quite high. However, note that this data set is disproportionate in the dependent variable, and the common result of this feature is that the dominant choice (here, internal organization = 0) is predicted almost all the time. This can be seen by examining the mean of the dependent variable which is 0.139, which is approximately equal to 1 minus the fraction of correct predictions of 0.8605. One may also review the prediction rule itself. That is, if the model predicts a value greater than 0.5, predict a 1, and vice versa. Obviously, it is very unlikely that the model will ever predict a 1. The solution of course is to lower the cutoff point. But this approach increases the likelihood that the model will assign a 1 when it is not appropriate. In fact, lower cutoff points were tested but had the effect of decreasing prediction accuracy. There is no easy solution to this problem. These and other methods in this regard are described in Greene (2000).

However, it is possible to construct a test based on a null hypothesis similar to the typical F-test in OLS that all coefficients are zero. The intuition is clear, one calculates the difference between the restricted and unrestricted regression, if this difference is *large* the null hypothesis is rejected. The appropriate test statistic is the likelihood ratio (LR) as follows: LR = 2[L (c,β) – L (c,0)] ~ χ^2(k-1), and is noted as such in the reporting of results above.

Coefficients in a Probability Model

Unlike OLS, the coefficients of a probability model such as probit do not have a user-friendly interpretation. In the probit, the derivative of the probability with respect to a specific independent variable is:

$$\partial E(y) / \partial X_k = \phi\, (\mathbf{Xb})\beta_k \,,$$

where ϕ is the standard normal density. The marginal probability varies with the level of X and with the other variables in the model, hence the coefficients are somewhat lacking in straightforward interpretation. To remedy this, one can examine the derivatives at the mean values of all the independent variables. The interpretation here is intuitive, such a vector of derivatives represents the typical observation. More appealing is a method advocated by Greene (2000). The marginal effects are computed for each variable at each observation and these results are averaged for the sample. These results are closer in form to the probit analysis itself. These calculations are shown in Tables 1.10 and 1.11.

Table 1.10: Marginal Impacts, Computed at Mean of X_i (the "typical" observation)

Variable	Average Marginal Effect
C	0.316460
DEPTH	-0.048051
WD400	0.136694
RCH	0.075706
EVD	-0.011704
BLKCUM	0.134570
TKPCT	-1.551384
OPCUM	0.000035
PLAT	0.045625
CAP	0.097544
NO	0.002171
HO	-0.030892
LA	0.013250
JX	0.019467
CC	0.025241

Table 1.11: Average of Marginal Impacts, Computed at Each Observation

Variable	Average Marginal Effect
C	-0.152155
DEPTH	0.023107
WD400	-0.065726
RCH	-0.036398
EVD	0.005631
BLKCUM	-0.064698
TKPCT	0.745910
OPCUM	-0.000018
PLAT	-0.021936
CAP	-0.046901
NO	-0.001046
HO	0.014856
LA	-0.006373
JX	-0.009359
CC	-0.012139

Estimation of the Underlying Cost Functions

As described above, estimation of the underlying cost functions in Eqns. (1) and (2) permits isolation of the effects of transaction attributes to each form of organization, shedding light on the relative impact of internal costs versus market hazards on organizational choice. The cost functions also enable estimation of organizational costs, permitting a calculation of the value of selective organizational choice. In this section, two issues regarding estimation of the underlying cost equations are discussed. The first issue is the selection of a proxy for costs. Since production costs and transaction costs are not observable, an appropriate proxy must be selected to serve as the dependent variable. The second issue is the specification and estimation of the underlying cost equations. The dependent variable, as will be explained, is truncated at zero. A linear specification may be inappropriate, given that nothing constrains predicted values to be greater than zero. A semilog specification is estimated, and a more flexible *duration* model is specified and estimated.

A Proxy for Total Costs

Actual total cost data are not available for this analysis. While oil companies may collect and retain individual well cost information, it is not commonly made available to the public. In addition, transaction costs such as contracting costs are rarely documented. Therefore, This study employs a proxy for these costs, the *duration* of the well measured in days. Duration is observable for all observations, so censoring is not an issue. A significant portion of the cost of drilling a well is variable cost, due mainly to the drilling rig dayrate and professional services that are typically priced per diem. In this sense, duration clearly accounts for the direct cost of the well (the potential differences in productive efficiency), is highly correlated with total cost and the proxy is suitable.

Choice of Independent Variables

Recall that for identification of the model (without imposing independence of the two error terms), at least one element in X_1 must not be in X_2, or vice versa (Maddala, 1983; Masten *et al*., 1991). In this context, different specification of the independent variables makes economic sense. For example, the cumulative number of turnkey wells drilled to date should not affect the internal transaction cost function, and the active platform count should not affect the turnkey cost function. The relevant independent variables for each organizational form are given in Table 1.12.

Table 1.12: Independent Variables for Individual Organization Cost Functions

Internal Organization (X1)	Turnkey Organization (X2)
DEPTH	DEPTH
WD400	WD400
RCH	RCH
EVD	EVD
BLKCUM	BLKCUM
	TKPCT (TKCUM)
OPCUM (OPCY)	OPCUM
PLAT	
RET	RET
NO	NO
HO	HO
LA	LA
JAX	JAX
CC	CC
LAMBDA	LAMBDA

RET is included in both functions because there may be differences in costs within oil companies for the same reasons one expects differences between oil companies and turnkey drillers. Recall that LAMBDA is the expected selection bias, computed from the results of the organizational choice model.

A Simple Specification

The dependent variable is duration in days, t, and is therefore truncated at zero. Given this, a starting point for the analysis is a simple semilog specification for each organizational cost function (these will continue to be referred to as cost functions, recognizing that the dependent variable is in fact only a proxy for cost):

Internal organization: $\ln(t_i) = X_{1i}\beta_1 + e_{1i}$ (6a)

Turnkey organization: $\ln(t_i) = X_{2i}\beta_2 + e_{2i}$. (6b)

The results of the estimation of Eqns. (6a) and (6b) are given in Table 1.13.

Table 1.13: Underlying Cost (Duration) Functions, Semilog Estimation

Variable	Coefficient Estimates (t-statistics)					
	Internal Organization		Turnkey Organization		Recall: Probit Results	
CONSTANT	1.38613	(38.974)	3.27237	(3.423)	-1.8113	(-18.305)
DEPTH	0.74763	(58.571)	0.71643	(8.425)	0.2415	(8.100)
WD400	0.17849	(6.455)	0.94128	(3.153)	-0.8261	(-9.217)
RCH	0.28455	(9.179)	0.65285	(4.512)	-0.3899	(-4.749)
EVD	0.03890	(2.121)	-0.08426	(-1.665)	0.0909	(1.858)
BLKCUM	0.29545	(9.597)	0.17515	(.648)	-0.6669	(-4.760)
TKPCT			-7.43240	(-2.653)	8.1395	(13.434)
OPCUM	-0.00001	(-1.470)	0.00016	(1.420)	-0.0003	(-6.472)
PLAT	0.03115	(.384)			-0.6630	(-2.293)
RET	0.04450	(1.903)	0.19703	(2.845)	-0.1311	(-2.066)
NO	-0.15558	(-6.091)	-0.24357	(-4.489)	-0.0283	(-.418)
HO	-0.10989	(-4.124)	-0.24779	(-3.800)	0.1417	(2.153)
LA	-0.03273	(-1.230)	-0.07810	(-1.274)	-0.0787	(-1.146)
JAX	0.13046	(4.701)	0.30682	(3.746)	-0.1804	(-2.570)
CC	0.24614	(5.619)	0.63186	(4.249)	-0.2979	(-2.502)
LAMBDA	-0.02212	(-.282)	-1.00376	(-2.288)		
R-squared	0.53		0.66			
F-stat (p-value)	430.0161	(.000)	115.8266	(.000)		
Log Likelihood	-4667.688		-586.515			
# of Observations	5285		850			

Note that for this specification, the coefficient estimates represent the proportional change in the dependent variable per unit change in the independent variable. Basic diagnostics are included in the table. The probit results are included to highlight the relationship between the organizational choice model and the underlying cost equations. For example, WD400 and RCH increase costs for both forms of organization, but turnkey costs rise at a faster rate (presumably due to transaction costs), making the coefficient in the organizational choice model negative, supporting the transaction cost hypothesis. In fact, all but one variable (NO) conform to this relationship between the two cost functions and the probit. The additional information from the cost functions adds a measure of robustness to the results that are unavailable from the probit alone. Other interesting results involve EVD, where internal costs rise and turnkey costs decrease as a function of this variable, providing dual support for the risk preference view. Overall, these results support the mixed results of the probit, that both transaction costs and risk preferences play a role in organizational outcomes. Of additional note in Table 1.13 is the fact that BLKCUM is positive and significant, contrary to expectations. It was expected that for internal drilling, increasing BLKCUM would be cost reducing. OPCUM (OPCY) and PLAT are insignificant in the internal organization cost functions, indicating no gains from scale or scope. But note that when combined with the effects of OPCUM as a technology transfer proxy in the turnkey function, the joint impact on the probit coefficient for OPCUM is significant.

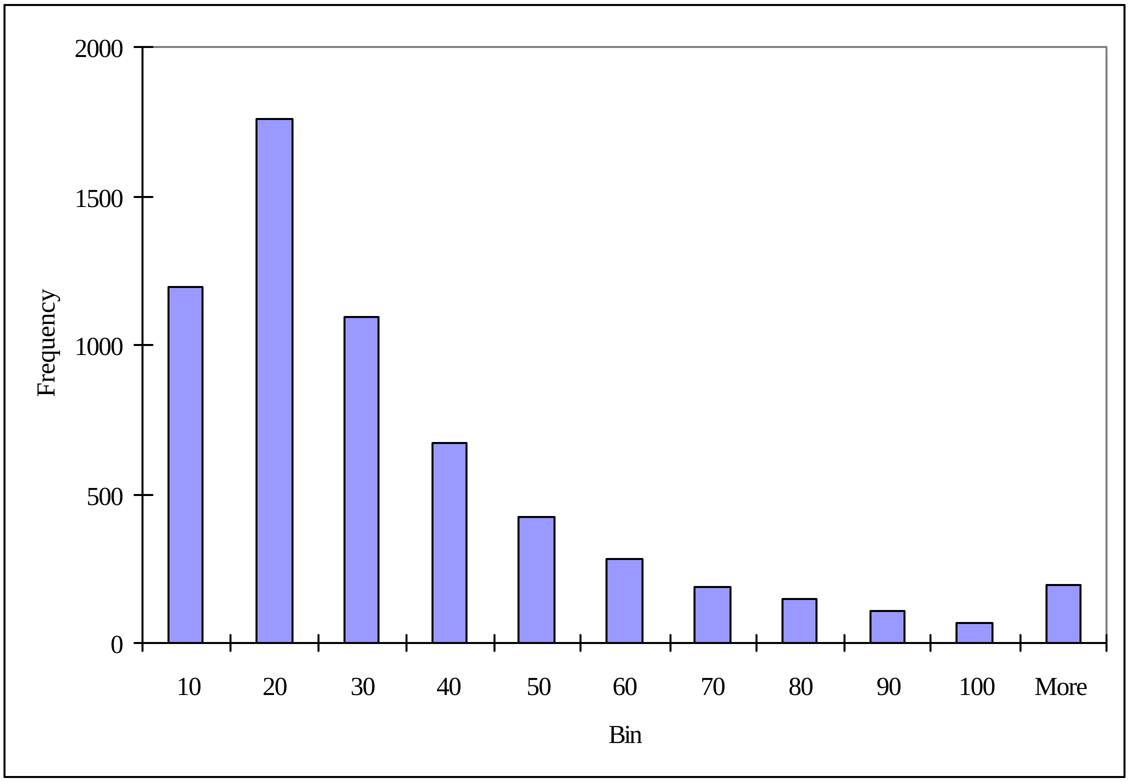
The semilog specification estimated above is meant to account for the truncated nature of the dependent variable. While it does so, the simple specification is somewhat restrictive. To provide a more flexible specification, a more general model of duration is needed. This is investigated in the next section.

Duration Models

Duration analysis is encountered in many contexts. In the natural sciences it is commonly called *survival* analysis due to the application of the methodology to study living subjects' response to control variables of interest (Cox and Oakes, 1984). Engineers, more interested in the failure behavior of machines or processes use the phrases *reliability* or *failure time* analysis (Cohen and Whitten, 1988) (Kalbfleisch and Prentice, 1980). Sociologists and political scientists use the term *event history* analysis (Blossfeld *et al.*, 1989). In economics, duration analysis can be used to study unemployment, labor strikes, business survival, insurance claims, *i.e.* any phenomenon where the variable of interest is the duration of some condition or state.

In short, the general approach in duration modeling is to specify a probability density function (pdf) for the dependent variable, and employ maximum likelihood techniques to estimate parameter coefficients. Specifying a pdf allows greater flexibility in model specification. A common sense starting point in duration analysis is to visually inspect the distribution of the dependent variable so that an appropriate density function may be specified. In cases where there is no economic theory to inform the choice of density function (as is the case here), this approach must suffice. Figure 1.2 displays a histogram for the dependent variable placed into bins of 10 day multiples of duration.

Figure 1.2: Histogram of Duration



Modeling of duration data involves specifying a hazard function, $\theta(X_iB)$, and employing a single or multiple parameter pdf for the dependent variable. There is no restriction on the selection of the pdf.

Exponential Specification

A common initial specification is the one parameter exponential pdf:

$$f(t) = \theta \exp(-\theta t). \tag{7}$$

Covariates are introduced through the specification of θ. As suggested by Terza (1998) and Greene (2000), the sample selection can be modeled as a form of unobserved heterogeneity. This accomplished by specifying θ as follows:

$\theta = \exp(-X\beta + e)$. (8)

This specification prohibits negative values. The introduction of the error term, e, sufficiently generalizes the model and will allow a straightforward treatment for sample selection. The same assumptions about u, e_1, and e_2 are made as above: trivariate normal, mean vector zero, and $\sigma_u^2 = 1$. Therefore, (8) can be re-written as:

$$\theta = \exp(-X\beta + \delta u), \tag{9}$$

where δ is an estimate of $\sigma_{e,u}$. The unconditional pdf for the internal organization is (reintroducing a complete notation): $f(t_{1i} \mid X_{1i}, \delta u_i)$. To generate an unconditional pdf, one must integrate out the error term as follows:

$$f(t_{1i} \mid X_{1i}) = \int_{-\infty}^{-Z_i g} f(t_{1i} \mid X_{1i}, du_i)\, g(u_i)\, du_i \tag{10}$$

where, for an exponential pdf for t_{1i},

a.) $f(t_{1i} \mid X_{1i}, \delta u_i) = \theta_{1i} \exp(-\theta_{1i}\, t_{1i}) = [\exp(-X_{1i}\beta_1 + \delta u_i] \exp(-[\exp(-X_{1i}\beta_1 + \delta u_i]\, t_{1i})$, and
b.) $g(u_i) = g(u_i \mid u_i < -Z_i\gamma) = \phi(u_i) / \Phi(-Z_i\gamma))$ (pdf of truncated normal).

The log-likelihood function for the internal organization, L^I, is derived as follows:

$$L^I = \Pi \int_{-\infty}^{-Z_i g} \{ [\exp(-X_{1i}\beta_1 + \delta u_i] \exp(-[\exp(-X_{1i}\beta_1 + \delta u_i]\, t_{1i}) \} [\phi(u_i) / \Phi(-Z_i\gamma)]\, du_i.$$

$$\ln(L^I) = \Sigma \int_{-\infty}^{-Z_i g} -X_{1i}\beta_1 + \delta u_i - [\exp(-X_{1i}\beta_1 + \delta u_i]\, t_{1i} + \ln(\phi(u_i)) - \ln(\Phi(-Z_i\gamma))\, du_i. \tag{11}$$

Symmetrical development for the turnkey organization generates the following log-likelihood function, L^M:

$$\ln (L^M) = \Sigma \int_{-Z_i g}^{\infty} -X_{2i}\beta_2 + \delta u_i - [\exp(-X_{2i}\beta_2 + \delta u_i] t_{2i} + \ln (\phi(u_i)) - \ln (\Phi(Z_i\gamma)) du_i. \quad (12)$$

Integration and optimization is performed numerically via maximum likelihood, generating estimates for β and δ simultaneously. Table 1.14 contains the results from the estimation of Eqns. (11) and (12). The organizational choice coefficients are presented again for reference.

Table 1.14: Underlying Cost (Duration) Functions, Exponential Specification

Variable	Coefficient Estimates (t-statistics)					
	Internal Organization		Turnkey Organization		Recall: Probit Results	
CONSTANT	1.6253	(73.973)	1.1617	(11.638)	-1.8113	(-18.305)
DEPTH	6.9832	(91.958)	8.9563	(38.267)	0.2415	(8.100)
WD400	0.3025	(18.853)	0.2570	(2.858)	-0.8261	(-9.217)
RCH	0.2257	(11.022)	0.3597	(5.640)	-0.3899	(-4.749)
EVD	0.0206	(1.684)	0.0240	(.633)	0.0909	(1.858)
BLKCUM	0.2633	(14.144)	-0.2444	(-1.835)	-0.6669	(-4.760)
TKPCT			-1.1273	(-2.133)	8.1395	(13.434)
OPCUM	0.0118	(1.973)	-0.1022	(-2.754)	-0.0003	(-6.472)
PLAT	0.0853	(1.624)			-0.6630	(-2.293)
RET	0.0273	(1.849)	0.1842	(3.381)	-0.1311	(-2.066)
NO	-0.0461	(-2.649)	-0.1919	(-3.637)	-0.0283	(-.418)
HO	-0.0948	(-5.220)	-0.1148	(-2.417)	0.1417	(2.153)
LA	-0.0256	(-1.425)	-0.0943	(-1.766)	-0.0787	(-1.146)
JAX	0.1291	(6.957)	0.1488	(2.692)	-0.1804	(-2.570)
CC	0.2369	(8.219)	0.3675	(3.501)	-0.2979	(-2.502)
Delta	-0.0002	(.075)	-0.0006	(.044)		
Mean Log Likelihood	-53.7479		-35.4429			
# of Observations	5285		850			

An appropriate test statistic is the likelihood ratio, LR = 2[L (c,β) – L (c,0)] ~ χ^2(k-1), and in each case the null hypothesis that all coefficients are zero is rejected.

On the whole, the exponential specification generates similar results to the simple semilog specification estimated above in terms of coefficient signs and significance. Key differences are as follows. The DEPTH variable now indicates that turnkey costs rise faster than internal costs, yet the probit coefficient is positive. This strengthens the risk preference argument. On the other hand, the WD400 variable indicates the opposite result, further strengthening the transaction cost argument. EVD is now insignificant in both functions, and BLKCUM indicates the same contrary result. The results for OPCUM (OPCY) are now contrary to expectations, indicating that scale increases internal costs, and lowers turnkey costs. In summary, this analysis provides support for both the transaction cost and risk preference hypotheses. As in the semilog specification, the relationship between the organizational choice model and the underlying cost functions is evident for most variables.

Estimation of the organization cost functions under the imposition that $\sigma_{e1,e2} = 0$ (alternate criterion for identification), using the full vector of independent variables ($X_1 = X_2$) from the organizational choice equation, does not yield any additional insight and is not presented here.

1.8 Valuing Selective Organizational Choice

While the results for the cost functions isolate the effects of transaction attributes to each form of organization, it is interesting to examine the value of selective organizational choice. That is, if decision makers are optimizing on total costs, the expectation is that status quo organizational choices are cost minimizing. Exclusive adoption of one form of organization or the other should be inefficient. Other empirical studies have examined this same question in shipbuilding (Masten *et al.*, 1991) and R&D alliances (Sampson, 2001).

First, the expected costs (durations) for the status quo using the parameters from the exponential model are computed. The exponential model is used because it demonstrates far better predictive performance than the semilog specification. Using these parameter estimates again, the values of exclusive internal and turnkey organization are computed. That is, if all wells were drilled via one governance mode, what is the expected cost? Recall that this approach estimates duration, which is the proxy for total costs. In this context it is best viewed as a cost index. These computations are performed for the entire data set (all firms) for both cost specifications, and present the results in Table 1.15.

Table 1.15: Organization Costs (Durations), Industry – Exponential Specification

	Current Internal Wells	Current Turnkey Wells	TOTAL
Estimated Durations	162,440	24,002	186,442
Durations if All Wells Drilled Internally	162,440	26,300	188,740
Durations if All Wells Drilled Turnkey	141,670	24,002	165,672

The first row of Table 1.15 gives the estimated duration for the status quo governance structure. The estimated total duration increases if all wells were to be drilled internally (row two), implying that the current governance structure is cost minimizing vis-à-vis an all-internal governance approach. But when examining an all-turnkey governance approach, total costs actually decline by 13 percent, indicating that a portion of the internally drilled wells *should have been* drilled via turnkey. These computations indicate that 86% of the wells drilled internally actually demonstrate lower estimated durations under a turnkey governance approach.

There are a few plausible explanations for these results, and they are not necessarily mutually exclusive. One, early in the study period, oil companies may have overestimated the transaction costs associated with turnkey drilling due to their collective inexperience with turnkey. Given this, they elected to continue to drill the majority of their wells internally. Such conservatism in estimating costs seems natural in the early stages of industry growth. Two, factors such as regret avoidance, a desire for consistency, and misunderstood sunk costs may have supported the inefficient status quo. Results of many studies of exit decisions indicate a general reluctance of management to terminate unprofitable products and loss-making divisions, making exit slower and less frequent than would otherwise be predicted (Samuelson and Zeckhauser, 1988). Three, some firms (those with large internal drilling departments) may have been subject to considerable internal influence peddling, as entrenched decision makers sought to preserve their status versus lowering costs. Turnkey drilling is a direct threat to the scope of administration of drilling decision makers. Under turnkey drilling, internal drilling staffs would undoubtedly shrink, and administration of many of the ancillary services would be passed on to other parts of the organization. Influence peddling can sustain a bias to procure internally (Williamson, 1985; Besanko *et al*., 1996; Meyer *et al*., 1992). As was discussed above, information on poor internal drilling performance can be easily obscured by drilling management. It appears that these factors, and possibly others, were quite costly to the industry as whole. Since the figures in Table 1.15 represent durations, one can estimate the scale of this inefficiency. If one assumes a daily drilling spread cost of $75,000, the inappropriate governance cost the industry ($75,000/day) * (20,770 days) = $1.558 billion in this study period.

While influence peddling can be a successful short term tactic, it is unlikely to sustain an inefficient organization indefinitely. The fact that the turnkey market share continued to grow through the study period provides some evidence that the true value of turnkey drilling was being recognized. Also, this trend appears to be continuing based on the most recent market data. The industry appears to be moving to a new structural equilibrium.

1.9 Discussion

Some basic observations regarding the results are made above, but a more detailed analysis that links these results with the original hypotheses is valuable. To accomplish this, each of the transaction cost hypotheses is evaluated using the outline of Table 1.1 as a guide. When just the variable name is mentioned, the reference is of course to the coefficient on the variable. When discussing the underlying cost functions, the reference is to the exponential specification of Eqns. (11) and (12).

OPCUM was devised to model the likelihood of technology transfer. The higher the accumulated experience of the drilling organization, the greater the likelihood that valuable know-how exists. In all of the organizational choice models (choice models), OPCUM is negative and significant which is consistent with the transaction cost hypothesis. In estimation of the underlying cost functions, OPCUM is relevant in the turnkey function only, and the results are contrary to expectations, perhaps reflecting a shortcoming in the proxy for costs. An alternative explanation is that OPCUM is picking up the effects of increased contracting experience in general.

With respect to monitoring cost, DEPTH, WD, and TKPCT were employed to model those forces that serve to increase and decrease monitoring costs. The coefficient on DEPTH is consistently positive and significant in the choice models, contradicting the transaction cost expectation and supporting the risk preference hypothesis. In the cost functions, DEPTH is significantly positive in both functions as expected, and the coefficient is larger for turnkey. Such coefficients would argue for a negative coefficient in the choice model. The fact that it is not indicates that the value of shedding the risk on deeper, more complex wells outweighs the increased cost of turnkey drilling, *ceteris paribus*. WD400 is negative and significant in the choice models, supporting the transaction cost hypothesis. TKPCT was devised to proxy for turnkey industry reputation. If reputation is good, monitoring costs are thought to decline, *ceteris paribus*. In the choice model, TKPCT is positive and significant, implying that as reputation improves, monitoring costs decline. In the turnkey cost function, the coefficient is negative as expected.

BLKCUM was defined to model information costs. As information costs decline with increasing experience and available data in an area, total costs (to both organizational forms) decline. In the choice model, the coefficient is negative, supporting the risk preference hypothesis. As more offset information becomes available, the value of risk shedding decreases, and turnkey drilling is less likely. The results of the cost function estimation are mixed. While the coefficient for turnkey drilling is negative, the coefficient for internal drilling is positive, indicating an increase in costs with experience. There is not an obvious explanation for this result.

Contract writing and renegotiation costs are modeled by DEPTH, RCH, WD400, EVD, and BLKCUM. Results for three of these variables have been discussed already. Again, the results on DEPTH and BLKCUM support the risk preference hypothesis, while the result for WD400 supports the transaction cost hypothesis. RCH is negative and significant in the choice model, supporting the transaction cost hypothesis. As expected, RCH is positive and significant in both of the cost functions, indicating increased costs with complexity. Here, the results conform to expectations in that the coefficient for turnkey is larger than the coefficient for internal drilling. The results are mixed on EVD. Its significance varies between specifications of the choice model, but it is always positive, supporting the risk preference hypothesis. EVD is positive for the internal function (significant at the 10% level), indicating an increased cost of exploration drilling, or the cost of holding the exploration risk, or both. The coefficient is insignificant in the turnkey function. This result is an example of how the estimation of the underlying cost functions provides insight into the nature of the contracting decision. Here, one sees the choice of organizational form is not a function of a market hazard, but instead a function of internal costs, a point that would be missed in interpreting the choice model alone.

Other variables employed to model contracting costs are TKPCT and TKCUM that represent the influence of reputation and experience in moderating contracting hazards. Again, TKPCT is interpreted directly and as a proxy for TKCUM. All transaction cost expectations are met in the cost functions and the choice model, providing strong evidence for the relevance of reputation in influencing organizational choice.

To account for the potential of differences in productive efficiency due to scale or scope economies, OPCY (recall OPCUM is used as a proxy) and PLAT were defined. Both variables are negative and significant in the choice models, indicating that scale and scope play a role in organizational choice, and supporting the transaction cost hypothesis. Strangely, both variables are positive and significant in the internal cost function (PLAT at 10%).

The issue of asset specificity has appeared throughout as an important component of costs and organizational choice. It has been mentioned in the discussion of monitoring costs and contracting costs, and the scale of quasi-rents has been hypothesized to influence organizational choice. The results are mixed. The variables selected to model the effects of asset specificity are: DEPTH, WD, RCH, and EVD. As described above, some of these variables conform to the transaction cost hypothesis (WD and RCH), while others support the risk preference hypothesis (DEPTH and EVD).

Controlling for the regulatory regime was done to control for potential differences in enforcement practice across districts. Such differences may influence the decision to introduce a third party (turnkey driller) to the regulatory relationship between the oil company and the regulator. In the choice models, it appears that turnkey drilling is more likely in Houma, and less likely in Lake Jackson and Corpus Christi (relative to the excluded District of Lake Charles). Results of the cost functions also support these conclusions.

The RET variable is negative and significant in the organizational choice model, indicating that those companies with branded gasoline sales are less likely to turnkey.

This result is also found in the underlying cost functions. This result runs against the admonitions of Oxley (1997) that broader company attributes do not influence organizational choice. Insofar as CAP may indicate risk preferences, there is support for the notion that larger companies act in a more risk-neutral manner than small companies, verifying earlier results of Smith (1982) for E&P decision-makers. This provides support for the risk preference hypothesis.

To summarize the findings on the risk preference hypothesis, note that of the five variables defined to test this hypothesis, three of those variables support the risk preference hypothesis over the transaction cost hypothesis. This is significant because these particular variables represent multiple dimensions of transaction costs. For example, DEPTH was hypothesized to increase monitoring costs, contracting costs, and add to hazards associated with asset specificity (quasi-rents). Given this, the fact that the results on DEPTH support the risk preference hypothesis are more persuasive. This also holds for WD400 and BLKCUM, which were also justified on more than one account.

Thus, while not all of the results can be satisfactorily explained, the results of the organizational choice model do provide robust support for the conclusion that both transaction costs and risk preferences influence organizational choice in offshore drilling. The estimates of the cost functions reveal that sometimes internal costs, not market hazards, are more important in organizational choice. Estimates of the value of selective organizational choice indicate that the current industry structure is suboptimal, but continues to move in the direction of increased efficiency (more turnkey drilling).

The No-Bid Phenomenon

The possibility that a company may choose not to turnkey those prospects where there is a possibility of technology acquisition through direct experience was introduced above. The example of water depth being such a frontier drilling area. The results of the organizational choice models provide support for this view. While the primary testing purposes of the WD400 variable are summarized in Table 1.1, the regression results conform to this additional transaction cost interpretation. None of the other technical features described by the independent variable set can be construed as frontier technology in the study period, except perhaps at their extreme limits.

It should be noted that some companies do not consider turnkey drilling at all (Baum *et al.*, 1998). Executing a bidding process is not costless, as such its cost must be weighed against the likelihood that a competitive bid will be received. If this likelihood is low due to high estimates of transaction costs, high internal efficiencies, or other strategic reasons, turnkey bidding may not occur. From a strategic viewpoint, some companies consider the drilling process as core to the oil and gas development process, and that the in-field know-how generated during drilling helps to optimize exploitation of the field over the long term. Such a company does not turnkey, regardless of transaction specific attributes. Modeling such behavior using company attributes is problematic, because both large and small companies may hold this view. Regardless, it is interesting to consider which of the independent variables might account for non-bidding behavior. Of primary interest is the CAP variable, because if firms are risk neutral, there is no additional value to the fixed price alternative of turnkey. Such a firm's internal estimates are therefore on a level playing field with a turnkey bid. Second, firms with scale and scope generate a cost advantage over all prospects, and as has been described, this effect is not transaction specific *per se*. This view of the problem is generally supported by the results in Table 1.7, specifically Spec. (10). These results can therefore be construed as outcomes of non-bidding, not selective organizational choice.

1.10 Conclusions

The results of this analysis provide support for the conclusion that both transaction costs and risk preferences influence organizational choice in offshore drilling. The coefficient estimates for WD, RCH, TKCUM (and TKPCT), OPCUM (and OPCY), and PLAT support a transaction cost view, while the coefficients for DEPTH, EVD, and BLKCUM support a risk preference view. Note that the coefficients for RET and CAP are expected to be negative under both hypotheses which they are. By justifying certain independent variables on multiple theoretical grounds, there is some uncertainty into which contributing component of transaction cost has the most influence. However, what this approach gives up in terms of specificity, it gives back in the power of the test. For example, if DEPTH can be modeled as an indicator of transaction cost on several accounts, then the test of both hypotheses is that much stronger.

The results advise a view of transaction costs and risk preferences as complementary theories of organizational choice, not substitutes. In offshore drilling, where uncertainty is high, and the one-sided risk bearing of turnkey drilling is a notable feature of the transaction, it seems quite plausible that risk preferences should influence organizational choice. The results confirm this view. The cost functions indicate that decision makers have been slow to take advantage of the turnkey option, perhaps due to institutional momentum or influence peddling. But the turkey market share continues to grow, as the industry appears to be moving to a new equilibrium. The optimal industry structure still calls for a mix of internal and turnkey drilling.

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2 The Determinants of Safety and Environmental Incidents in Offshore Drilling: Employing Detection Controlled Estimation to Model Incidence and Reporting Rates

2.1 Introduction

Health, safety, and environmental performance (HS&E) has always been a consideration of offshore exploration and production operators, but since the Piper Alpha disaster in the North Sea in 1988 resulted in 167 fatalities, HS&E performance has received considerably more attention from oil company decision makers and regulators worldwide (DC-2, 2000). Significant investment has been made in risk assessment, process redesign, and advancing HS&E management techniques. This paradigm shift has generated results. Accidents on mobile offshore drilling units (MODUs) demonstrate a declining trend through the 1990's. Figure 2.1 presents the lost time incidence rate for the U.S. offshore drilling sector. The lost time incidence rate (LTIR) is computed as follows: LTIR = [(#incidents * 200,000) / total hours worked].

Figure 2.1: Lost Time Incidence Rate, U.S. Offshore, 1990-2000
(Source: International Association of Drilling Contractors, Accident Statistics Program)

In the Gulf of Mexico, the exploration and production (E&P) sector continues to evolve in ways that may affect HS&E performance in years to come. Shifts in the demographics of the oil companies (majors versus independents) and where they operate, deeper water operations, and more complex wells all contribute to this transformation. It is unknown what effect, if any, this evolution will have on HS&E performance in drilling operations. This uncertainty is widely recognized, and oil companies and regulators are keen to identify those areas where investment in prevention, policy, and enforcement will yield the greatest benefits, and hence inform efficient resource allocation. A thorough literature search indicates an absence of any quantitative analysis of HS&E performance in drilling operations as is presented here.

Fortunately, there exists a rich data set on Gulf of Mexico HS&E incidents that can be used to address this information gap. A database of all reported HS&E incidents is maintained by the U.S. Minerals Management Service (MMS), which is the regulatory authority for all Gulf of Mexico oil and gas activities. Previous studies such as Iledare *et al.* (1997) and Shultz (1999) have used this data set to examine HS&E incidence, but focused primarily on production operations. These previous studies examined the significance of oil company attributes, MMS enforcement practices, platform characteristics, and accident history on HS&E performance. But potentially important variables such as the oil company’s offshore experience, physical well characteristics, water depth, number of wells producing, and regulatory differences by district were not fully specified, therefore those results must be qualified by these omissions.

The present research is most comparable in structure to Iledare *et al.* (1997), but the subject here is drilling operations. The model also includes variables omitted in previous studies. The results provide robust support for the hypothesis that aspects of well complexity and site complexity increase the likelihood of HS&E incidents. Equally important is evidence rejecting the hypothesis that broader oil company attributes influence HS&E incidence. Models of incidence employ standard qualitative response models with binary and ordered dependent variable specifications, and a Poisson specification. Unlike previous studies, models are estimated employing detection control to account for the possibility of incomplete reporting. The results from this latter approach indicate that while broader company attributes may not affect HS&E incidence, they may affect reporting behavior. Also, the evidence suggests that there is little difference in reporting behavior among MMS districts. Analysis of time related variables provides insight into HS&E incidence and reporting over time, specifically in response to a 1996 policy change. The study period covers 1990-1998.

The chapter is organized as follows. Section 2 provides a brief introduction to offshore operations, regulation, and reporting. Section 3 provides an economic motivation for the subject, and Section 4 provides an economic and technical literature review. Section 5 provides general models of HS&E incidence and reporting, and proposes independent variables and hypotheses. Section 6 provides an overview of the data set (additional detail is given in Appendix A). Section 7 details the econometric specification, estimation, and diagnostics. Section 8 presents the econometric results, and Section 9 provides a discussion of the results and their implications. Section 10 concludes.

2.2 Offshore Operations, Regulation, and Reporting

In this section, an overview of offshore operations is provided. First, a brief introduction to the offshore working environment is given, and a discussion of the fundamental differences between drilling and production operations follows. Next, the role of the MMS as regulator is discussed, followed by descriptions of reporting requirements, enforcement, and incident data collection procedures.

Offshore Operations

The offshore drilling process is inherently dangerous. The combination of personnel performing a variety of simultaneous operations with heavy equipment, immense physical forces and pressures, and geologic uncertainty create an environment where the risk of HS&E incidents is high and ever-present. Because the fundamental nature of offshore operations is unlikely to change in the short term, and some aspects like geologic uncertainty will always be present (DC-4, 1998), the focus of HS&E prevention has typically been placed on automation and worker behavior. Regarding worker behavior, recent studies indicate that the majority of incidents stem from procedural mistakes or lack of communication regarding the work to be done (Dykes *et al.*, 2000). Therefore, an analysis of HS&E incidents should be concerned with identifying factors that tend to aggravate or mitigate these circumstances. A summary of the psychological aspects of HS&E incidence is available in Flin and Slaven (1996).

Drilling versus Production

Drilling and production operations are two distinct processes in upstream E&P. Drilling involves the use of a drilling rig. Drilling rigs are large, mobile units (unless built into the production platform) and move from lease to lease drilling both exploration and development wells. Rigs such as jackups, submersibles, semisubmersibles, and drillships are typically referred to as mobile offshore drilling units (MODUs), while modular rigs that are temporarily installed on the platform are referred to as platform rigs. Exploration wells are most often drilled in open water where no platform exists. Production wells are typically drilled over a platform, either by a MODU or a platform rig. As a result, the drilling of a production well is more likely to involve interaction with a production platform and the existing wells on the platform. These features of the operations are important and are addressed below in development of hypotheses.

The production process, which has been studied more heavily, is fundamentally different than drilling. After wells are drilled, the production facility enters an initial production phase. There is limited entry into the wellbore in this phase, and the bulk of activity revolves around production equipment on the surface such as maintenance of separators, compressors, and flow and control piping. Because one process is focused on downhole operations and the other on surface operations, the nature of HS&E risks is quite different. An analogy can be made to the construction industry, where the risks faced by workers during construction of a building are quite different than the risks faced by maintenance workers once the facility is put into use. Previous studies have focused primarily on HS&E performance in the production process, while this study focuses on performance in the drilling process.

Overview of MMS Regulation

The MMS is responsible for administering more than 7,000 active offshore leases covering more than 39 million acres, where on average, 35,000 personnel are involved in drilling and production activities. Of the MMS' many administrative functions, the regulatory program is of most interest here. The regulatory scope includes approval of exploration and development plans, facilities, operations, routine inspection, and HS&E incident investigation. Incidents reported to the MMS may trigger an investigation by the MMS district office in which the incident occurred. In the case of a major incident, the MMS may create an investigative panel of district, regional, and headquarters personnel, as well as representatives of the U.S. Coast Guard and other federal agencies including the National Transportation Safety Board. Findings from both types of investigations may lead to the issuance of safety alerts, technology assessment and research, changes in training programs, or improvements in the MMS regulatory program.

Reporting

MMS regulations at 30 CFR 250.19 (a) 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, well control incident, fire or explosion associated with drilling operations. Incidents associated with production (*e.g.* compressor fire) are not included unless they were somehow related to the presence of a drilling rig or simultaneous activity (drilling and production). This definition is intended to capture the fundamental difference between typical drilling and production operations discussed above.

In this study, the possibility of incomplete HS&E reporting on the part of oil companies is explicitly addressed. Notwithstanding reporting requirements in the law, it is possible that an individual installation manager, or a company in general, will not comply with the reporting guidelines in every instance. This behavior can be motivated by pressures to deliver better HS&E performance statistics within the company or to the MMS, or by the fear of civil penalties if the oil company was at fault in an incident. In fact, there is evidence of incidents in the MMS database that were only discovered and reported after a MMS site inspection. As Iledare *et al.* (1997) observe, offshore installations (drilling rigs or production platforms) are geographically isolated, and reporting may vary among operators. Underreporting has also been mentioned as an issue in recent trends in North Sea accident statistics (DC-2, 2000). An econometric model is specified to test for the presence of incomplete reporting.

Enforcement

In 1992, the MMS codified its existing policy for collecting accident data and conducting accident investigations. Under that policy, MMS investigated all major accidents, some minor accidents, and all blowouts. The degree of investigation was left to the discretion of the relevant MMS District Supervisor. Major accidents are fires and explosions that resulted in damage of $1 million or more, liquid hydrocarbon spills of 200 barrels or more during a period of 30 days, or accidents involving a fatality or serious injury that caused substantial impairment of any bodily unit or function.

The districts followed this policy until 1996 when the Gulf of Mexico (GOM) Region implemented a more stringent policy. Since that date, the GOM Region investigates all fires and explosions, all blowouts, all spills greater than one barrel, all accident related fatalities, all collisions involving structural damage to facilities, and injuries and accidents requiring repairs on a case by case basis. The degree of investigation is still left to the discretion of the district Supervisor.

Incident Data Collection

The source for Gulf of Mexico HS&E incident data is the set of MMS Accident Investigation Reports (multi-year) (MMS, 2000). As pointed out by previous authors (Iledare *et al.*, 1997; Shultz, 1999), the incident database presents a challenge to researchers. Incidents are often difficult to match up with specific locations or wells, the type of activity that caused the incident is not always discernible, and often there is very little information on the nature of the incident. Considerable effort is required to construct a quality data set for quantitative analysis. Also, changes in reporting requirements and investigation criteria have changed over time as discussed above. Based on the advice of senior MMS officials, this study is limited to the most recent data (1990-1998) which has been identified as the highest quality and most consistent in form. As one moves farther back in time, the overall quality of the incident database degrades, and inferences would tend to be less reliable.

2.3 Motivation

Analysis of HS&E performance can be motivated in many ways. While many would agree that employers have a moral duty to provide a safe workplace and to enact measures to ensure their employees are not injured, a focus on the direct economic incentives is more appropriate in this context. Two issues will be discussed in this section. First, an argument is made that it is in the oil companies' best economic interest to reduce HS&E incidents, both at the individual company level and at the industry level. Second, for operators and regulators to improve HS&E performance and regulation thereof, the parties must be informed as to the processes that cause incidents, and any factors that may lead to incomplete reporting. With limited resources, efforts must be applied in the areas where the highest benefits are available.

Economic Incentives and the License to Operate

In addition to the costs of personal suffering of injured individuals, there are direct economic consequences of personal injuries for the oil company. Costs for the drilling sector vary, but the range of estimates indicates that it costs between $50,000 and $100,000 to simply administer a lost time injury (Buchan, 1999). This does not include other costs such as lost productivity, sick pay, equipment damage, increased insurance premiums, or costs of legal action should a claim arise, which could be several times as much (Flin and Slaven, 1996; Sumrow, 2002). For smaller companies, such costs could be a significant percentage of total administrative costs. Reducing the number of incidents represents a direct savings of these costs. The managerial problem is then to balance investment in incident prevention with cost savings at the margin. The difficulty lies in determining the optimal balance, since the costs and benefits may vary from year to year, and in general are hard to quantify. Therefore, incident prevention investments are less able to compete for limited company resources against more tangible investment opportunities. This feature of the problem will often lead to sub-optimal levels of investment in HS&E prevention.

On a larger scale, oil companies are increasingly concerned with their overall license to operate. The industry faces political opponents in most of the locations where it operates. These parties often cite HS&E performance as a reason to limit E&P activities, *e.g.* leasing of E&P acreage (Brinded, 1998; O'Leary, 2001; Gidley and Hall, 2002). The Gulf of Mexico is no exception. The MMS has become increasingly aggressive in its assessment of individual operators, and has the power to disqualify oil companies from operation, and to impose civil penalties of up to $25,000 per day. The maximum civil penalty is also expected to increase in the coming years (DC-4, 1998). Regarding incentives, the MMS plans to reward compliant operators with fewer inspections and less oversight. Carolita Kallaur, Associate Director for Offshore Minerals Management MMS has stated that "[HS&E] performance will drive regulatory decision making" (DC-4, 1998). Therefore, oil companies with good performance should incur lower compliance costs. As an industry, good performance may drive broader reform that reduces compliance costs more generally.

Clearly, operators benefit both individually and collectively from improved HS&E performance. Recognizing the increasing economic importance of HS&E performance at the industry level, a collection of 23 leading operators and contractors issued the following declaration at an industry conference (Buchan, 1999):

> "We pledge our commitment to work together to achieve a step change in safety performance in all the areas where we have activity. We believe that a step change in safety can be achieved through personal commitment, leadership, the ways we behave and the ways we work together."
>
> Houston Declaration, January 29, 1998

Efficient Resource Allocation

Qualitative risk assessments and incident investigations are valuable, but tend to yield diverse recommendations. Incidents are often the result of complex interactions among different risk factors. Without a systematic approach, limited resources are likely to be misallocated (Robnett, 1998). A detailed quantitative model can address this shortcoming.

Oil companies are keen to learn where to focus their HS&E prevention efforts for the economic reasons cited above. Regulators are also interested in improving HS&E performance, but also have the added responsibility of setting regulatory, inspection, investigation, and enforcement policy. With limited resources, both parties will value information on HS&E performance to improve resource allocation.

To be an effective regulator, the MMS must set policy and practice based on experience, but also plan for anticipated changes in industry. As trends in oil company demographics, well complexity, site complexity, and regulatory influence play out, the MMS is interested to know the expected influence on HS&E performance so that policy and practice are efficiently administered. Some of these trends inform the selection of explanatory variables below, and are briefly summarized here:

- The deepwater Gulf of Mexico holds high potential, as recent deepwater activity in drilling and production demonstrates (Nixon *et al.*, 2000; LeBlanc and Murillo, 2000; Thomas, 2000). Therefore, risks unique to deepwater (floating) operations such as well control, mooring, and stationkeeping are important to account for.

- In shallow water, there is also a possibility for ever increasing well depths as shallower reserves are exhausted and as drilling technology permits exploitation of deeper reserves (Dodson *et al.*, 2000). Also, horizontal reach (the distance in plan view form the surface location to the bottom of the well) has increased over time (Lingner *et al.*, 2000). More complex well paths and the attendant operations add complexity to the overall drilling process.

- As the Gulf of Mexico matures, an increasing number of redevelopment programs will be executed on platforms with existing wells and production. These features of operations tend to increase complexity of drilling operations.

- Market variables such as changes in rig utilization draw less experienced workers into the field, possibly increasing the likelihood of HS&E incidents.

- MMS reporting and enforcement policies evolve over time, as do oil company efforts in HS&E incident prevention. Both of these facts potentially affect the likelihood of HS&E incidence and the reporting behaviors of oil companies.

The MMS should also be interested in any information regarding the reporting behavior of oil companies. Information on incomplete reporting can guide the formulation of efficient inspection policy.

In summary, there is significant value to a quantitative analysis of HS&E incidence. In addition to a general moral argument for HS&E incident prevention, there are direct economic incentives at the individual company and industry levels. From the regulator's perspective, the results assist in the formulation and administration of policy in many areas.

2.4 Literature Review

The topic of offshore HS&E performance has received most discussion among practitioners. The majority of work can be found in drilling literature such as industry technical journals, trade journals, and conference proceedings. Recent contributions focus primarily on statistics and root cause analysis (OGP, 2000; Dobson, 1999; Dykes *et al.*, 2000), assessing performance (Rozendal, 2000), and safety awareness and management (Buchan, 1999; Lane and Watkiss, 1999; Richardson and Watkiss, 2000; Allwright, 2000). None of these studies addresses the topic in a rigorous, quantitative fashion. Any statistical analysis is quite general, and meaningful inferences are limited.

In the economic literature, the topic has received little coverage. One notable investigation was made by Iledare *et al.* (1997). The study, sponsored by the MMS, focused strictly on production operations, not drilling operations. The primary objectives were to test for company attribute impacts and MMS enforcement on HS&E performance. A hypothesis was tested that independents (smaller, non-integrated companies) are less safe than majors (larger, integrated companies) due to the latter's increased technical and regulatory experience, and overall staffing and skills in the area of HS&E. The study found no support for this hypothesis. However, potentially important variables such as offshore experience, physical well characteristics, water depth, number of wells producing, and regulatory differences among MMS districts were not included in the econometric specifications, and therefore the conclusions about the effect of company attributes are potentially inconclusive. Finally, the authors employed a weighting scheme to the incident vector based on incident severity. Based on discussions with practitioners and MMS officials, this may not be appropriate. The difference between a minor injury and a fatality may have been an inch in distance, or a second in time. In this way, the distinction between the two types of incidents unduly diminishes the seriousness of minor injuries.

A second notable investigation was made by Shultz (1999). In that study, the focus was also on production operations, not drilling operations. The research investigated similar explanatory variables to Iledare *et al.* (1997). A more refined variable for platform complexity was employed, and a platform-specific experience variable for the oil company was added. Some results confirmed earlier findings, while others were contradictory. For example, while Iledare *et al*. (1997) find platform age to be significant, Shultz (1999) finds the same variable to be insignificant. But Shultz (1999) did not include any qualitative variables for oil company attributes, and for this reason, inferences may be biased.

Nothing in the existing literature estimates the potential impact of incomplete reporting of HS&E incidents. If incomplete reporting is introduced, a non-standard econometric approach is required. Similar phenomena (violation detection) have been addressed elsewhere, and methodologies have been derived (Epple and Visscher, 1984; Feinstein: 1989, 1990). It is straightforward to employ these methodologies in the context of reporting. An analysis that incorporates a separate reporting function in addition to an incidence function provides valuable information to the regulator. The factors that lead to incomplete reporting are isolated, and an estimate of current reporting behavior can be made. Such information is sure to be influential in policy making.

In summary, the literature review reveals several gaps in the knowledge base. First, there is no econometric analysis of drilling HS&E incidents in either the drilling literature or the economic literature. Second, there is no application of detection controlled estimation for HS&E incidents in drilling or production. The present research proposes to fill these gaps with a comprehensive econometric model of HS&E incidence and reporting in offshore drilling. It fills the quantitative gap in the drilling literature, the drilling gap in the economic literature, and provides evidence on the possibility of incomplete reporting by employing a model of detection controlled estimation.

2.5 Models and Determinants of Safety and Environmental Incidence and Reporting

In this section, basic functional relationships of HS&E incidence and reporting are introduced, primarily to motivate a discussion and specification of dependent and independent variables. Completely specified models of incidence and reporting are presented in Section 2.7. As stated in the discussion of offshore operations, recent studies indicate that HS&E incidents stem primarily from procedural mistakes or lack of communication regarding the work to be done. Therefore, an analysis of HS&E incidents should investigate factors that aggravate or mitigate these circumstances.

The broad hypothesis of this research is that HS&E performance is a function of three sets of factors. The first of these is the working environment developed on site by the oil company. This category is intended to capture training efforts, procedural completeness, and safety management and awareness. The second set of factors relates to the physical features of the operations that increase complexity. This includes attributes of the wells being drilled, and features of the location. The third set of factors describe the general operating environment in industry, and include regulatory variables and market variables. The objective is to test specific hypotheses about each of these factors to discover which, if any, can explain HS&E performance. Unlike previous studies in this context, the possibility that not all incidents are reported is explicitly addressed. That is, there are two distinct processes underlying the set of incident observations. To observe an incident in the reported data set, two events must occur in succession. First, an incident must occur. Second, the incident must be reported.

HS&E Incidence

A basic functional relationship for HS&E incidence can be represented as follows:

$$Y_{1i} = X_{1i}\beta_1 + u_{1i} \quad (1)$$

where,

Y_{1i} = Incident observations
X_{1i} = Vector of independent variables
β_1 = Vector of parameters (to be estimated)
u_{1i} = Random error term, $\sim N(0,\sigma^2)$.

In the primary formulation, there is an observation of HS&E incidence for each lease i in every year where drilling activity occurred. In this section, the objective is to identify suitable specifications for Y_1, and the independent variables that belong in X_1. Note, the subscript "1" is used for all models of HS&E incidence. The subscript "2" will be used for all models of HS&E reporting.

The Dependent Variable, HS&E Incidence

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, well control incident, fire or explosion associated with drilling operations. This definition is intended to capture the fundamental difference between typical drilling and production operations discussed above.

There are many ways to specify the incident vector, Y_1. In this study, several approaches are employed, including qualitative models using binary and ordered categories, and a Poisson count specification. The econometric details for each of these specifications and an explanation of how incident observations are organized for each of specifications is discussed in Section 2.7.

Independent Variables, HS&E Incidence

Oil Company Attributes

The oil company involved in drilling a well has 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. If expectations on workers are high, if additional training is provided, and if enforcement is strong, a safety conscious workplace will result, improving HS&E performance, *ceteris paribus* (Flin and Slaven, 1996). Previous research by Iledare *et al.* (1997) commented on the perception that majors are typically better equipped than independents to achieve these goals, although the results of that research did not support this perception. Nonetheless, an impression remains among some regulators that the majors are more concerned with HS&E, are better equipped to manage HS&E performance, and make more investments in HS&E incident prevention.

Any view of the majors that presupposes increased HS&E awareness and prevention efforts should be founded in economic theory. What is the difference between majors and independents that could motivate increased investment in HS&E performance? One view is that majors have more to lose in the event of a HS&E catastrophe. Most majors possess valuable brand names and significant accumulated goodwill. In the event of a serious HS&E incident, it is possible that these assets would be negatively impacted. Therefore, majors could be expected to invest more heavily in HS&E prevention than their somewhat anonymous counterparts whose only customer is the pipeline. To model this behavior, a binary variable is defined that indicates whether or not the oil company has retail gasoline sales, **RET**. As described, such a company will have a different payoff function with respect to HS&E performance. The expectation on the sign of the coefficient is negative (*i.e.* a company with a brand name is represented by a 1).

The retail variable is of interest not only in analyzing past performance as is done in this research, but also in providing guidance for the future, as most observers expect the demography of oil companies working in the Gulf of Mexico to evolve in the coming years. In recent years, 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).

Other company attributes relevant in this context are the company's accumulated offshore drilling experience, and its overall offshore experience. A variable is defined that represents the oil company's accumulated drilling experience to date, **OPCUM**. Companies with more drilling experience should be more skilled in HS&E management, and have fewer incidents, *ceteris paribus*. The expectation for the sign of this coefficient is negative. To model overall offshore experience, knowledge of working in and around platforms, and managing simultaneous operations (production while drilling), the variable **PLAT** is defined. This variable represents the average number of active platforms operated by the oil company in the year of the observation. The expectation for the sign of this coefficient is negative.

It is important to note that the drilling contractor is also an influential party in determining HS&E performance. While drilling contractor data is typically available for those wells that experienced an incident, it is not currently available from the MMS for all wells (in a tractable format), and is not included in the analysis.

Technical Variables

The second set of factors that are hypothesized to influence HS&E performance are the physical characteristics of the well being drilled or features of the location itself. Well complexity increases the frequency of routine activities that are known sources of HS&E incidents (pipe handling, running casing, etc.) (DC-1, 2000). Complexity also increases the incidence of unusual operations such as well control, stationkeeping, and 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 on a well, complicating procedures and communication, and potentially diluting the focus on HS&E incident prevention among workers and supervisors. The following set of independent variables is defined, and expectations about their significance are established.

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. Tripping is the process of pulling drill pipe in or out of the well. Drill pipe and casing handling are a major source of injuries (DC-1, 2000). TVD is a proxy for maximum bottom hole pressure. Increased pressure increases the risk of well control incidents, *ceteris paribus*. Since MD and TVD are nearly collinear, an index (their sum) is used to model for these effects. The expectation of the sign of this coefficient is positive.

REACH. This variable is defined as the horizontal distance (plan view) between the surface location and the bottom hole location measured in feet. As reach increases, operational complexity increases in many respects, therefore the expectation of the sign of this coefficient is positive.

WD400. This is a binary variable that assumes a value of one when the water depth exceeds 400 feet, and zero otherwise. This depth threshold represents an approximate break over to floating operations which is the point of interest. While imperfect, *i.e.* it incorrectly captures wells drilled with platform rigs in water depths greater than 400 feet, it is a reasonable proxy for the floating rig threshold. On a floating rig, more complex operations such as mooring, stationkeeping, riser management (running and handling), remote vehicle operations, and deepwater well control may increase the likelihood of injury and spills as described above. The expectation of the sign of this coefficient is positive.

EVD. Whether a well is an exploration or production well affects the risk profile in may ways. EVD is a binary variable that assumes a value of one for explorations wells, and zero otherwise. While exploration wells may contain more geologic uncertainty which tends to increase the likelihood of well control incidents, production wells are not immune to geologic or mechanical uncertainty. Production wells may be less conservative in well design based on the increased quality and quantity of data available during well planning. Due to the geologic uncertainty of exploration drilling, it is also possible that operations are conducted in a more conservative fashion, reducing HS&E risks. In addition, exploration wells typically do not run production casing, eliminating a long and arduous operation. Finally, production wells are typically drilled over a platform or other structure, while exploration wells are likely to be drilled in open water. Therefore, some platform interaction issues are also captured by this variable. Based on the complex interplay of all these factors, there is no a priori expectation for the sign of this coefficient.

NOWELLS. If a well is drilled over an existing platform with producing wells, drilling operations are more complicated on at least two counts. One, the added congestion in the well bay area reduces the space available for wellhead work during drilling. Such space constraints may lead to suboptimal procedures. Two, the presence of simultaneous operations (drilling and production) creates unique hazards for both operations. Also, the two different crews and supervision adds to managerial complexity. The variable NOWELLS represents the sum of active producing oil, gas, and service wells on the platform when the well is drilled. It is thought that this variable will control for both the congestion and the complexity effects. The expectation for the coefficient of this variable is positive.

COUNT. The incident observations in the data set are for each lease in each year of the study period where a well was drilled. If ten wells were drilled in a lease versus one, it would be more likely to observe an incident in the more active lease, *ceteris paribus*. The COUNT variable is a simple count of the number of wells drilled in the lease per year to control for this activity effect. The expectation of the sign of this coefficient is positive. Note that while the sum of the durations in days might be a more precise variable to control for this effect, limitations in the data set prevent its use in this context.

Operating Environment Variables

The last set of factors thought to influence HS&E performance are a function of the overall operating environment. These factors include the regulatory climate in general, potential differences in regulatory practice between MMS districts, the drilling labor and equipment markets, and overall industry progress in HS&E performance.

As discussed above, MMS investigation guidelines have changed within the study period, the notable change (more stringent investigations) occurring at the beginning of 1996. Such policy changes may influence HS&E performance and reporting. It is possible that certain MMS districts demonstrate more or less stringent enforcement, and one could expect more or less HS&E incidents in that district as oil companies respond to the particular environment, *ceteris paribus*. It seems likely though that oil companies promote one HS&E management policy for the entire Gulf of Mexico on the basis of operational efficiency. Guidelines are drawn up, training occurs, and operations are monitored. Maintaining six distinct HS&E policies seems quite unlikely. Also, employees are often shifted around the Gulf at short notice. Based on this, MMS district variables are not included in models of HS&E incidence. This view becomes important below when issues of identification in the econometric model are addressed.

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. While evidence on the frequency of injury among these workers is mixed (Dobson, 1999; OGP, 2000; DC-3, 1998), it is an issue that should be accounted for in the model. Finally, a cursory view of incident statistics indicates a strong trend to safety improvement over time (see Figure 2.1 above). This may be explained in part by increased efforts by oil companies in incident prevention.

To account for all of these effects, a set of annual binary variables to model operating environment effects is specified. This approach captures the three relevant effects listed above: the regulatory climate in general, changes in the drilling markets, and progress in

HS&E prevention over time. The excluded year is 1990 (the first year of the study), so coefficients have a convenient interpretation as relative to this base year.

HS&E Reporting

Allowing for incomplete reporting requires the introduction of a separate reporting function. Here, a simple function is defined to motivate the discussion of the variables that may influence the likelihood to report a HS&E incident. An unobservable latent variable, Y_2^*, is defined as the propensity to report an incident as follows:

$$Y_{2i}^* = X_{2i}\beta_2 + u_{2i} \qquad (2a)$$

where,

Y_{2i}^* = Unobserved latent variable
X_{2i} = Vector of independent variables
β_2 = Vector of parameters (to be estimated)
u_{2i} = Random error term, $\sim N(0,\sigma^2)$.

One does not observe Y_{2i}^*, but Y_{2i} according to the rule:

$$Y_{2i} = \begin{cases} 1 \text{ if } Y_{2i}^* > 0 \\ 0 \text{ otherwise.} \end{cases} \qquad (2b)$$

Given an incident occurs, a report is either made or not made. This discrete view of reporting lends itself to qualitative response models such as probit or logit. The probit is employed throughout this analysis. This function can be viewed as the probability of a report given an incident occurs, and can be shown in a probit to be $\Phi(X_{2i}\beta_2)$ (ref. Chapter 1 derivation). This model of reporting sufficiently motivates the identification and discussion of the variables to be included in X_2. More detail on the reporting function and the joint process of incidence and reporting is presented below.

Independent Variables, HS&E Reporting

Of primary interest are oil company attributes. Is one type of company more likely to report than another, and why? Smaller firms may be reluctant to report incidents due to the potential for civil penalties. The smaller the oil company, the larger a penalty would be in percentage terms of costs. Larger firms (typically RET=1) may be more likely to report incidents based on the reputation and goodwill arguments presented above. The costs of brand name degradation and loss of goodwill that would result if a firm was found to have concealed an incident are likely to outweigh the expected civil penalties resulting from an investigation. In practice, it is also true that these larger firms are more likely to have established reporting norms and processes for verification. Due to these more formal structures within the company, consistent reporting is more likely. To test these hypotheses, the previously defined **RET** variable is employed. The expectation is that companies with brand names are more likely to report incidents.

Another variable that may influence the propensity to report an incident is the MMS district where the well is drilled. If certain districts are more or less stringent in enforcement, *i.e.* if they differ in the frequency or thoroughness of inspections, then reporting may vary by district. A set of binary variables is defined to model for this effect. There are six districts, so five variables are required. The districts and variables are: New Orleans (**NO**), Houma (**HO**), Lafayette (**LAF**), Lake Jackson (**JAX**), and Corpus Christi (**CC**). The excluded district is Lake Charles.

Insofar as MMS inspection and investigation policy has changed over time, there may have been a reporting response to these changes. Therefore, the annual binary variables are appropriate to include in the reporting function. Finally, one would not expect technical variables to influence the reporting decision. Table 2.1 summarizes the elements of X_1 and X_2 and expectations.

Table 2.1: Summary of Independent Variables

Variable	Coefficient Expectation (+/-)
HS&E Incidence (X_1)	
OPCUM	**-**
PLAT	**-**
RET	**-**
DEPTH	**+**
RCH	**+**
WD400	**+**
EVD	**?**
NOWELLS	**+**
Time Effects (8)	**?**
COUNT	**+**
HS&E Incident Reporting (X_2)	
RET	**+**
MMS districts (5)	**?**
Time Effects (8)	**?**

2.6 Data Set Origins, Overview and Basic Statistics

The study area is the Gulf of Mexico Outer Continental Shelf (OCS). Based on the advice of senior MMS officials, only the most recent data, 1990-1998, which has been identified as the highest quality and most consistent in form is included.

Incident Observations – The Dependent Variable

The source for Gulf of Mexico HS&E incident data is the set of MMS Accident Investigation Reports (multi-year) (MMS, 2000). As pointed out by previous authors (Iledare *et al.*, 1997; Shultz, 1999), the incident database presents a formidable challenge to researchers. Incidents are often difficult to match up with specific locations or wells, the type of activity that caused the incident is not always discernible, and often there is no information on the nature of the incident. Considerable verification effort for each data point is required to construct a quality data set for quantitative analysis.

The first step in organizing the incident data was to identify all those leases in the study period that experienced drilling activity by year (drilling activity is defined as at least one well drilled). Since it is proposed to test hypothesis about company attributes, it is important to capture different operatorship periods for the same lease. This can result in multiple entries for a lease in one year (if multiple companies drilled a well in the same year). Eliminating records with incomplete information, this analysis results in 5,076 observations distributed over the study period as depicted in Table 2.2.

Table 2.2: Distribution of Drilling Activity Over Time, 1990-1998

Year	Count of Leases with Drilling Activity
1990	617
1991	418
1992	307
1993	506
1994	590
1995	572
1996	700
1997	760
1998	606

There is variety in these observations. Some leases had one well drilled in the entire study period, some leases had wells drilled in every year, and others has multiple wells drilled in more than one, but not all of the years. From the MMS incident database, drilling related incidents were noted for the appropriate lease and year. For this study, a HS&E incident is defined as any spill, injury, well control incident, fire or explosion associated with drilling operations. Incidents associated with production (*e.g.* compressor fire) are not included unless they were somehow related to the presence of a drilling rig or simultaneous activity. There were 220 leases that experienced at least one incident. The distribution of these 220 observations over time is presented in Table 2.3, along with a calculation of the percent of active leases that reported at least one incident.

Table 2.3: Distribution of Reported Incident Observations Over Time, 1990-1998

Year	Count of Leases With At Least One Reported Incident	Percent of Active Leases With At Least One Reported Incident
1990	15	2.43%
1991	15	3.59%
1992	3	0.98%
1993	6	1.19%
1994	13	2.20%
1995	16	2.80%
1996	36	5.14%
1997	70	9.21%
1998	46	7.59%

Casual inspection of Table 2.3 implies that some form of regime change occurred in 1996. This could be the manifestation of the increase in drilling activity shown in Table 2.2. That is, as activity ramped up, less experienced workers are brought into the field, increasing the risk of incidents (the evidence on this effect is mixed as noted above). It is also possible that changes in MMS enforcement and investigation policy influenced the incidence and the reporting of HS&E incidents. Based on this, it may be appropriate to evaluate this subset of observations (1996-1998) without concern for fixed time effects as proposed above. This will be investigated below.

The HS&E incident information is organized in categories as follows:

- Well control, blowouts
- Fires and explosions, and miscellaneous (*e.g.* dropped object)
- Spills
- Individual injuries (and a flag for fatalities)
- Multiple person injury events, and number of persons injured (and number of fatalities).

This approach permits flexibility in the specification of the dependent variable. For example, it is straightforward to construct a binary variable indicating whether or not an incident occurred in each lease in each year. Incidents can also be summed to create a count variable. Distribution of the incidents by type is presented in Table 2.4. Note that the sum of all incidents is greater than 220 (total is 272) because some leases experienced more than one incident in a year.

Table 2.4: Distribution of Incidents by Type, 1990-1998

SpudYear	Blowouts	Fire, Explosion, Misc.	Spills	Individual Injuries	Multiple Injury Events
1990	7	4	4	5	3
1991	6	2	1	7	1
1992	1	1	1	2	0
1993	2	2	0	2	0
1994	1	5	0	6	3
1995	3	8	1	6	1
1996	1	22	2	20	2
1997	4	41	1	36	4
1998	6	20	4	19	5

Independent Variables

Data for the independent variables originates from a variety of sources, but the majority originates from databases maintained by the MMS. A description of the independent variable is available in Appendix A. The process of organizing the data is informative. First, a lease table was constructed that contains every lease within the study period that had at least one well drilled. Information is then attached to the records in the lease table from a variety of other tables describing physical features of the well(s) drilled, the lease, the number of producing wells, and company attributes. If more than one well was drilled in a lease in a year, then the appropriate attributes are averaged.

Table 2.5 presents basic statistics for the set of independent variables. Note that the dependent variable as shown represents a binary specification of incidence. Details on the other specifications are given in section 2.7.

Table 2.5: Basic Statistical Information for Dependent and Independent Variable(s)

	Mean	Standard Deviation (s)	+2s	-2s	Minimum	Maximum
Y	0.0433	0.2036	0.4505	0.0000	0	1
OPCUM	813.5218	1177.7586	3169.0390	1.0000	1	4422
PLAT	77.4976	111.8696	301.2368	0.0000	0	502
RET	0.4632	0.4987	1.0000	0.0000	0	1
DEPTH	20940.3632	7515.0333	35970.4297	5910.2966	1146	50950
RCH	3773.5701	2752.9483	9279.4668	0.0000	0	16950.5
WD400	0.1455	0.3521	1.0000	0.0000	0	1
EVD	0.4782	0.4824	1.0000	0.0000	0	1
NOWELLS	4.2573	9.2760	22.8093	0.0000	0	88
NO	0.2313	0.4217	1.0000	0.0000	0	1
HO	0.1785	0.3830	1.0000	0.0000	0	1
LAF	0.1718	0.3772	1.0000	0.0000	0	1
JAX	0.1466	0.3537	1.0000	0.0000	0	1
CC	0.0449	0.2071	1.0000	0.0000	0	1
DV98	0.1194	0.3243	1.0000	0.0000	0	1
DV97	0.1497	0.3568	1.0000	0.0000	0	1
DV96	0.1379	0.3448	1.0000	0.0000	0	1
DV95	0.1127	0.3162	1.0000	0.0000	0	1
DV94	0.1162	0.3205	1.0000	0.0000	0	1
DV93	0.0997	0.2996	1.0000	0.0000	0	1
DV92	0.0605	0.2384	1.0000	0.0000	0	1
DV91	0.0823	0.2749	1.0000	0.0000	0	1
count	1.6720	1.6485	4.9689	1.0000	1	37

Notes:
1. "-2s" adjusted to zero or minimum value if technically inappropriate (i.e. negative).

Correlation Coefficients

The set of independent variables was used to construct a correlation coefficient matrix to detect potential collinearity problems. This is presented in Appendix B. Analysis of the data indicates moderate correlation among OPCUM and RET: $\rho = 0.64$. All other correlation coefficients are below 0.50.

2.7 Econometric Models, Specification, and Estimation Methods

In this section, several models of HS&E incidence are specified, both with and without controlling for the possibility of incomplete reporting. First, three forms of the incidence function are specified assuming complete reporting. Estimation of these models permits basic comparison of parameter coefficients and significance, overall comparison of the specifications, goodness of fit and other diagnostics, and should reveal any pathologies in the data set. Results from these specifications also establish a benchmark for evaluating efficiency gains from the subsequent detection controlled models. Second, two detection controlled models are developed. One employs a binary incident function and the other a Poisson distributed incident function. As defined above, the reporting behavior is binary, a firm either reports or does not report an incident (or set of incidents), and the decision is independent of the number of incidents. Discussion of potential misspecification, interpretation of the parameter estimates, and the robustness of the models is reserved for Section 2.8.

Complete Reporting

Binary Probit

To construct a binary dependent variable, each lease is examined to determine if at least one incident occurred. The dependent variable for leases that meet this criterion is one, otherwise it is zero. With this definition, there are 220 positive observations. A probit model identical to that proposed for the reporting function above in Eqns (2a) and (2b) is specified. Recall the result of a probit specification is that: Prob (Incident)$_i$ = Prob(Y_{1i} = 1) = $\Phi(X_{1i}\beta_1)$. Also note that the log-likelihood function is given by:

$$\ln L = LL = \sum_{i=1}^{n} Y_{1i} * \ln\left(\Phi\left(X_{1i}\boldsymbol{b}_1\right)\right) + (1 - Y_{1i}) * \ln\left(1 - \Phi\left(X_{1i}\boldsymbol{b}_1\right)\right). \qquad (3)$$

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

Ordered Probit and Poisson Specifications

It is often the case that a binary dependent variable is insufficiently descriptive of the process being modeled. By lumping outcomes into just two categories, important information may be lost. This argument is applicable here. There are leases in the data set that experience different types of HS&E incidents (fire versus a fatality), and sometimes more than one incident in a year. To accommodate for this reality, two additional models of incidence are specified: an ordered probit and a Poisson specification.

In an ordered probit, dependent variable outcomes are classified into categories. To apply, these categories should form an ordered continuum in some aspect. In this case, the severity of the incident is appropriate. If multiple incidents occurred on one lease, the worst incident is used to define the category. Again, weighting fatalities more than injuries is avoided for the reasons given above. This assignment process yields the following distribution of incidents among the categories.

Y_i	Number of Observations	Conditions
3	19	Multiple injury event
2	99	Individual injury event
1	102	Blowout, fire, explosion, spill, or miscellaneous
0	4856	No reported incident

Similar to the probit model, an unobserved latent variable is defined:

$$Y_{1i}^{*} = X_{1i}\beta_1 + u_{1i} \,, \tag{4a}$$

where the right hand side variables are defined as above. Incident observations are made according to the rule:

$$
Y_{1i} = \begin{cases} 0, & \text{if } Y_{1i}^* \le 0 \\ 1, & \text{if } 0 < Y_{1i}^* \le \mu_1 \\ 2, & \text{if } \mu_1 < Y_{1i}^* \le \mu_2 \\ \ldots & \\ G, & \text{if } \mu_{G-1} \le Y_{1i}^*, \end{cases} \tag{4b}
$$

where $\mu_i > \mu_{i-1}\ \forall\ i$. The μ_i's are unknown parameters and are estimated simultaneously with β_1. Development of the probabilities and likelihood function follow in a similar fashion to the binary probit. Similar to the binary probit, it is helpful to normalize the variance of the error term to one. For the first interval, the probability is derived as follows:

$$\text{Prob}(Y_{1i} = 0) = \text{Prob}(X_{1i}\beta_1 + u_{1i} \le 0) = \text{Prob}(u_{1i} \le -X_{1i}\beta_1) = \Phi(-X_{1i}\beta_1).$$

For the second and third interval:

$$\text{Prob}(Y_{1i} = 1) = \text{Prob}(X_{1i}\beta_1 + u_{1i} \le \mu_1) - \Phi(-X_{1i}\beta_1) = \text{Prob}(u_{1i} \le \mu_1 - X_{1i}\beta_1) - \Phi(-X_{1i}\beta_1)$$
$$= \Phi(\mu_1 - X_{1i}\beta_1) - \Phi(- X_{1i}\beta_1).$$

$$\text{Prob}(Y_{1i} = 2) = \text{Prob}(X_{1i}\beta_1 + u_{1i} \le \mu_2) - \Phi(\mu_1 - X_{1i}\beta_1)$$
$$= \text{Prob}(u_{1i} \le \mu_2 - X_{1i}\beta_1) - \Phi(\mu_1 - X_{1i}\beta_1) = \Phi(\mu_2 - X_{1i}\beta_1) - \Phi(\mu_1 - X_{1i}\beta_1).$$

This derivation is repeated until the last category, yielding:

$$\text{Prob}(Y_{1i} = G) = 1 - \Phi(\mu_{G-1} - X_{1i}\beta_1).$$

The likelihood function follows:

$$L = [\ \Pi_{y1i=0}\ \Phi(-X_{1i}\beta_1)\ ]\ [\ \Pi_{y1i=1}\Phi(\mu_1 - X_{1i}\beta_1) - \Phi(- X_{1i}\beta_1)\ ]\ [\ \Pi_{y1i=2}\ \Phi(\mu_2 - X_{1i}\beta_1) - \Phi(\mu_1 - X_{1i}\beta_1)\ ] \ldots [\ \Pi_{y1i=G}\ (1 - \Phi(\mu_{G-1} - X_{1i}\beta_1)\ ].$$

Barring misspecification, the asymptotic covariance matrix can be computed as the negative inverse of the Hessian evaluated at the maximum likelihood estimates.

Another means to model HS&E incidence is with a Poisson specification, which is appropriate for count data. In the present context, some leases experience more than one incident per year. Accounting for this fact offers a richer specification than the simple binary approach. Count models are common in the empirical literature (Feinstein, 1989; Michener and Tighe, 1992). A Poisson specification assumes that each observation is drawn from a Poisson distribution. To construct the dependent variable, the following categories of events are added: blowouts + fires/explosions/miscellaneous + spills + individual injuries + multiple injury events. This summation yields the following distribution of counts.

Incident Count	Number of Observations
5	1
4	0
3	4
2	40
1	175
0	4856

The Poisson distribution has the following probability density function (pdf), given that the time interval of the observation is set to unity:

$$\text{Prob}\,(Y_{1i} = y_{1i}) = \exp\,(-\lambda_{1i})\,\lambda_{1i}^{y_{1i}} / y_{1i}! \qquad (5a)$$

where λ_{1i} is the sole parameter of the distribution. Note that for the Poisson, both the mean and variance of Y_{1i} equal λ_{1i}. Covariates are typically introduced by defining $\ln \lambda_{1i} = X_{1i}\beta_1$. This specification assumes that observations are independent, and that all stochastic variation is captured by the independent variables. It is straightforward to estimate the model using maximum likelihood techniques.

The likelihood equation is derived as follows:

$$L = \prod_{i=1}^{n} \exp(-\lambda_{1i})\, \lambda_{1i}^{\,y_{1i}} / y_{1i}! \qquad (5b)$$

$$\ln L = LL = \sum_{i=1}^{n} -\lambda_{1i} + y_{1i} X_{1i} \beta_1 - \ln(y_{1i}!). \qquad (5c)$$

There are several ways to proceed in computing the standard errors for the estimate of β_1. Barring misspecification, the asymptotic covariance matrix can be computed as the negative inverse of the Hessian evaluated at the maximum likelihood estimates. Other methods are described by Cameron and Trivedi (1998), most notably the Huber or Eicker-White method which is robust to certain forms of misspecification. The Hessian-based standard errors are used in the presentation of results below, given that an alternative means to address the most common form of misspecification in the Poisson, overdispersion, will be investigated.

An important issue when dealing with a Poisson distributed random variable is the unusual restriction that the variance equals the mean, a property commonly referred to as equidispersion. In the common case where the variance exceeds the mean, the sample is said to be overdispersed, and the Poisson model may be overly restrictive and produce inefficient standard errors. Cameron and Trivedi (1990, 1998) propose several tests for overdispersion in the Poisson. If overdispersion exists, more flexible models of the mean-variance relationship can be specified. To this end, the negative binomial approach is commonly employed. Specification of negative binomial models also generates the simplest test (albeit *ex post*) for overdispersion in the basic Poisson.

Negative Binomial

The parameter of the Poisson distribution can be redefined as $\lambda_{1i} = \exp(X_{1i}\beta_1 + u_i)$, where the random error term u_i has the normal function of capturing unobserved randomness of the incident generating process. Substituting this expression into (5a) above yields the conditional pdf:

$$\text{Prob } (Y_{1i} = y_{1i} \mid X_{1i}, u_i) = e^{-e^{X_{1i}b_1+u_i}} (e^{X_{1i}b_1+u_i})^{y_{1i}} /(y_{1i})! \tag{5d}$$

which is expressed hereafter with the notation $f(Y_{1i} \mid X_{1i}, u_i)$. To develop the expression for the unconditional pdf, $f(Y_{1i} \mid X_{1i})$, the random error term must be integrated out:

$$f(Y_{1i} \mid X_{1i}) = \int_0^\infty e^{-e^{X_{1i}b_1+u_i}} (e^{X_{1i}b_1+u_i})^{y_{1i}} /(y_{1i})! \, [g(u_i)] \, du_i \, , \tag{5e}$$

where $g(u_i)$ is the pdf of the error term. For certain choices of $g(u_i)$, such as the standard normal, no closed form exists. For mathematical convenience only, a common choice of pdf for u_i is the gamma distribution. Specifically, specify $u_i^* = \exp(u_i)$ to be gamma distributed. The pure gamma distribution is a two parameter distribution. For purposes of identification, a normalization reduces the gamma to a one parameter distribution as follows:

$$\gamma(u_i^* \mid \theta) = [\theta^\theta/\Gamma(\theta)] \exp(-\theta u_i^*) \, u_i^{*\theta-1} \tag{5f}$$

where $\Gamma(\theta) = \int_0^\infty t^{q-1} e^{-t} \, dt$.

This specification of the error component permits closed form integration of Eq. (5e), generating the following result:

$$\frac{\Gamma(Y_{1i}+q)}{\Gamma(q)\Gamma(Y_{1i}+1)} \left[\frac{e^{X_{1i}b_1}}{e^{X_{1i}b_1}+q}\right]^{y_{1i}} \left[\frac{q}{e^{X_{1i}b_1}+q}\right]^{q} . \tag{5g}$$

Additional information about the negative binomial model and the gamma distribution is available in Cameron and Trivedi (1998), Lancaster (1990), Blossfeld *et al*. (1989), Hausman *et al*. (1984) and Vermunt (1996). Unlike the basic Poisson, the variance can now be modeled, via specifications of θ. This approach introduces the needed flexibility to account for overdispersion. If one defines $\theta = (1/a)\ (\exp(X_{1i}\beta))^k$ for a>0, the variance of $Y_{1i} = \exp(X_{1i}\beta) + a(\exp(X_{1i}\beta))^{2-k}$. Two common models are estimated for k=0 (Negbin II) and k=1 (Negbin I). The value of the parameter a is estimated simultaneously with β_1. This flexible specification of the variance may yield a better fit of the data in the case of overdispersion than the basic Poisson.

Detection Control

The possibility of incomplete reporting was introduced above. Such a possibility casts doubt on any inferences made from the simple models of HS&E incidence specified above. That is, all that is estimated with a model of incidence is the relationship between *reported* incidents and the independent variables, and reported incidents may not be representative of all incidents. If underreporting is significant, it may lead to biased parameter estimates. To incorporate the possibility of incomplete reporting, a model of *detection controlled estimation* (DCE) is developed (Feinstein, 1990). To be clear, a better phrase in this context would be *reporting* controlled estimation, since the reporting function is the responsibility of the oil company, not the regulator.

It is instructive to think of observations falling into one of three categories. One, no incident occurs, therefore no report is made. Two, an incident occurs, and no report is made. Three, an incident occurs and a report is made. It is only this last category of incidents that is observable in the data set, *i.e.* the unconditional probability of a report. More formally, the following terms are defined:

P(R) = unconditional probability of a report (observable)
P(A) = unconditional probability of an incident (unobservable)

Employing Bayes' Law, the result is that P(R) = P(A) P(R|A), given the constraint P(A|R) = 1 (no false reports). The objective then is to model P(A) and P(R|A), the two components of real interest.

Accounting for the joint nature of the processes in the econometric model yields consistent parameter estimates. It also isolates the effects of the independent variables of each process, generating valuable insight into the differences between the two processes. Also, parameter estimates can be used to compute the probability of an incident given no report was made, P(A|NR).

Binomial Specification of Detection Control

Recall the binary probit HS&E incidence model in Eqn. (3). The probability of an incident for a particular observation is $\Phi(X_{1i}\beta_1)$, which can be viewed as P(A). Recall the reporting function of Eqns. (2a) and (2b), and the probability of a report given an incident occurs is $\Phi(X_{2i}\beta_2)$, which can be viewed as P(R|A). Note that these functions are unobservable in isolation. If one assumes the u_i's are independent (additional identification requirements will be discussed below), the probability of observing a reported incident for observation i is Prob $(Y_i = 1) = \Phi(X_{1i}\beta_1)\Phi(X_{2i}\beta_2)$. The probability of not observing a report is simply $1 - \Phi(X_{1i}\beta_1)\Phi(X_{2i}\beta_2)$. This approach captures the possibility of incidents going unreported. The likelihood function is easily derived from these two equations, and estimation is done numerically using maximum likelihood. The log likelihood is as follows:

$$\ln L = LL = \sum_{i=1}^{n} Y_i * \ln\left(\Phi\left(X_{1i}\boldsymbol{b}_1\right)\Phi\left(X_{2i}\boldsymbol{b}_2\right)\right) + (1 - Y_i) * \ln\left(1 - \Phi\left(X_{1i}\boldsymbol{b}_1\right)\Phi\left(X_{2i}\boldsymbol{b}_2\right)\right). \qquad (6)$$

Note that Y_i now has the interpretation of *reported* incidents.

Poisson Specification of Detection Control

There is no theoretical restriction on the specification of the incident function. Based on the models already defined, a detection controlled Poisson specification is developed (Feinstein, 1989). To account for the possibility of incomplete reporting, the oil company's reporting choice is defined as above, *i.e.* the company either reports or does not, and the number of incidents does not affect the reporting choice. It is straightforward to construct a likelihood function and to use maximum likelihood to estimate this model. It is best explained in terms of subsets of observations. For all non-zero observations, m, the log-likelihood function is derived as follows (note, ln λ_{1i} = $X_{1i}\beta_1$):

$$L_m = \prod_{i=1}^{m} [\exp(-\lambda_{1i})\,\lambda_{1i}^{y_{1i}} / y_i!][\Phi(X_{2i}\beta_2)] \qquad (7a)$$

$$\ln L_m = LL_m = \sum_{i=1}^{m} -\lambda_{1i} + y_{1i}X_{1i}\beta_1 - \ln(y_{1i}!) + \ln[\Phi(X_{2i}\beta_2)] \qquad (7b)$$

For all zero observations, m-n, the probability of each observation is the sum of two terms as follows:

$$\begin{aligned} \text{Prob}(Y_i = 0) &= P(Y_{1i} = 0) + [1 - P(Y_{1i} = 0)]\,[1 - \Phi(X_{2i}\beta_2)]. \\ &= 1 - \Phi(X_{2i}\beta_2) + P(Y_{1i} = 0)\,\Phi(X_{2i}\beta_2), \qquad (8a) \end{aligned}$$

where P(•) is the Poisson probability density function. It is simply the sum of the probability that no incident occurred plus the probability that an incident occurred but was not reported. The log-likelihood for Eqn. (8a) is as follows:

$$\ln L_{n-m} = LL_{n-m} = \sum_{i=n-m}^{n} \ln[1 - \Phi(X_{2i}\beta_2) + \exp(-\lambda_{1i})\,\Phi(X_{2i}\beta_2)] \qquad (8b)$$

The likelihood for the entire sample is $L_s = LL_m + LL_{n-m}$ (8c).

Identification in the Detection Controlled Framework

The detection controlled framework introduces important issues in identification which are investigated in Feinstein (1990). The derivations and discussion are substantial, and as such are not reproduced here. In brief, there are two relevant issues in this context. The first issue is the assumption of independence of the error terms in the incidence and reporting functions. While this assumption is not required for identification, it simplifies the model a great deal. Given the discussion above regarding operating environment variables and the operational efficiency for oil companies of maintaining one Gulf-wide HS&E policy, this assumption seems reasonable in this context. A second condition on the elements of X_1 and X_2 is that each must contain at least one unique variable. This requirement is met by including the MMS variables only in the reporting function(s), and the technical variables only in the incidence function(s). Again, as described above, there are sound economic justifications for these specifications.

2.8 Results and Diagnostics

In this section, all of the previously defined models are estimated. First, the three incidence functions without detection control are estimated. Estimation of these models permits basic comparison of parameter coefficients and significance, overall comparison of the specifications, goodness of fit and other diagnostics, and should reveal any pathologies in the data set. The dispersion condition of the Poisson model is investigated via the estimation of two negative binomial models. Results from these specifications establish a benchmark for evaluating any efficiency gains from the detection controlled models. Second, the two detection controlled models are estimated. One employs a binary incident function and the other a Poisson distributed incident function. As defined above, the reporting behavior is binary in both cases, a firm either reports or does not report an incident (or set of incidents), and the decision is independent of the number of incidents.

Binary Probit, Poisson, and Ordered Probit

The three simple models of HS&E incidence assuming complete reporting defined above are estimated. These models are the binary probit, the ordered probit, and the Poisson, and are represented above in Eqns. (3), (4a, 4b), and (5a, 5b, 5c) respectively. The results are presented in Table 2.6. Note that only the variables hypothesized to influence incidence are included since complete reporting is assumed (*i.e.* no MMS binary variables). Variables significant at the 10% level or higher are highlighted.

Table 2.6: Regression Results (Complete Reporting), 1990-1998

Variable	Sign Expectation	Coefficient Estimates (t-statistics)					
		PROBIT		POISSON		ORDERED PROBIT	
C		-2.35784	(-14.130)	-3.96333	(-10.795)	-2.31757	(-14.190)
OPCUM	-	-0.52935	(-1.473)	-0.00012	(-1.556)	-0.00005	(-1.423)
PLAT	-	**0.56875**	**(1.854)**	**0.00107**	**(1.695)**	**0.00056**	**(1.861)**
RET	-	0.08622	(.958)	0.17952	(.922)	0.07010	(.791)
DEPTH	+	**0.14138**	**(2.870)**	**0.00003**	**(3.215)**	**0.00002**	**(3.150)**
RCH	+	0.09835	(.738)	0.00002	(.702)	0.00001	(.522)
WD400	+	0.01056	(.105)	0.05525	(.262)	-0.00074	(-.008)
EVD	?	**-0.35224**	**(-4.078)**	**-0.79983**	**(-4.749)**	**-0.36321**	**(-4.267)**
NOWELLS	+	**0.09207**	**(3.017)**	**0.01847**	**(4.825)**	**0.00913**	**(3.052)**
DV98	?	**0.47916**	**(3.466)**	**0.69260**	**(1.989)**	**0.45505**	**(3.366)**
DV97	?	**0.58379**	**(4.445)**	**0.94076**	**(2.788)**	**0.53984**	**(4.202)**
DV96	?	**0.27803**	**(1.978)**	0.43734	(1.215)	**0.25367**	**(1.844)**
DV95	?	0.01510	(.096)	-0.25282	(-.615)	-0.01175	(-.076)
DV94	?	-0.09284	(-.567)	-0.51613	(-1.207)	-0.08002	(-.503)
DV93	?	**-0.39895**	**(-1.995)**	**-1.33909**	**(-2.626)**	**-0.43049**	**(-2.173)**
DV92	?	**-0.44724**	**(-1.775)**	-0.96263	(-1.432)	**-0.46108**	**(-1.861)**
DV91	?	0.14109	(.852)	-0.00601	(-.015)	0.11975	(.737)
COUNT	+	**0.06927**	**(4.979)**	**0.11284**	**(5.420)**	**0.06086**	**(4.624)**
Mu1						0.30192	(10.455)
Mu2						1.02668	(13.182)
LR (p-value)		179.1166	(.000)	215.2556	(.000)	171.8512	(.000)
Log Likelihood		-816.1070		-1000.0540		-1023.7290	
LR Index		0.0989		0.0972		0.0774	
# Observations		5076		5076		5076	

The same three models of HS&E incidence are now re-estimated, but now loosely allow for incomplete reporting by including the MMS binary variables. The results are presented in Table 2.7. Note that these are not the detection controlled models. The results are presented in Tables 2.6 and 2.7 to establish a reference point for later comparison with the detection controlled models. Variables significant at the 10% level or higher are highlighted.

Table 2.7: Regression Results ("Incomplete" Reporting), 1990-1998

Variable	Sign Expectation	Coefficient Estimates (t-statistics)					
		PROBIT		POISSON		ORDERED PROBIT	
C		-2.3512	(-13.110)	-3.9962	(-10.300)	-2.3045	(-13.130)
OPCUM	-	-0.4711	(-1.310)	-1.1235	(-1.467)	-0.4479	(-1.266)
PLAT	-	**0.6012**	**(1.934)**	**1.1138**	**(1.737)**	**0.6031**	**(1.973)**
RET	-	0.0885	(.977)	0.1872	(.955)	0.0678	(.759)
DEPTH	+	**0.1481**	**(2.904)**	**0.3010**	**(3.230)**	**0.1603**	**(3.200)**
RCH	+	0.1018	(.756)	0.1888	(.707)	0.0675	(.508)
WD400	+	0.0657	(.633)	0.1287	(.587)	0.0510	(.497)
EVD	?	**-0.3522**	**(-4.053)**	**-0.8083**	**(-4.793)**	**-0.3650**	**(-4.264)**
NOWELLS	+	**0.1107**	**(3.523)**	**0.2089**	**(5.261)**	**0.1069**	**(3.465)**
NO	?	**-0.1882**	**(-1.773)**	-0.2356	(-1.096)	-0.1499	(-1.446)
HO	?	-0.0817	(-.758)	-0.1121	(-.513)	-0.1031	(-.968)
LAF	?	-0.0958	(-.883)	-0.1928	(-.814)	-0.0965	(-.904)
JAX	?	-0.0662	(-.556)	-0.0597	(-.224)	-0.0792	(-.672)
CC	?	**0.3353**	**(2.090)**	**0.6377**	**(2.064)**	**0.3418**	**(2.185)**
DV98	?	**0.4931**	**(3.563)**	**0.7220**	**(2.045)**	**0.4657**	**(3.441)**
DV97	?	**0.5970**	**(4.542)**	**0.9775**	**(2.848)**	**0.5502**	**(4.281)**
DV96	?	**0.2927**	**(2.079)**	0.4765	(1.306)	**0.2656**	**(1.928)**
DV95	?	0.0167	(.106)	-0.2283	(-.550)	-0.0124	(-.080)
DV94	?	-0.1101	(-.667)	-0.5125	(-1.197)	-0.0999	(-.623)
DV93	?	**-0.4162**	**(-2.069)**	**-1.3507**	**(-2.641)**	**-0.4514**	**(-2.265)**
DV92	?	**-0.4258**	**(-1.695)**	-0.9234	(-1.367)	**-0.4435**	**(-1.795)**
DV91	?	0.1513	(.915)	0.0188	(.046)	0.1276	(.787)
COUNT	+	**0.7420**	**(5.249)**	**0.1195**	**(5.640)**	**0.0648**	**(4.853)**
Mu1						0.3040	(10.457)
Mu2						1.0313	(13.209)
LR (p-value)		189.1125	(0.00)	223.1408	(0.00)	181.3905	(0.00)
Log Likelihood		-811.1091		-996.1117		-1018.9600	
LR Index		0.1044		0.1007		0.0817	
# Observations		5076		5076		5076	

All three specifications yield similar results with respect to individual coefficient signs and significance. There is also very little difference between the set of specifications that include the MMS binary variables and those that do not. Among the company attributes, the PLAT variable is significant and positive, opposite of expectations. OPCUM and RET are statistically insignificant. At this stage, these results fail to support the hypothesis that broader company attributes influence HS&E performance. Technical variables DEPTH and NOWELLS are significant and have the expected sign. There were no sign expectations for EVD, but the negative sign indicates support for the hypothesis that drillers are more conservative during exploration drilling, and their behavior counteracts any increased operational risks due to the exploratory nature of the project. Recall that EVD also captures site complexity features, and this result indicates significant hazards in drilling rig/platform interaction. The annual binary variables DV96, DV97, and DV98 are significant and positive, indicating increased incidence and/or reporting in these years vis-à-vis 1990. These results may be indicative of the structural change hypothesized above. DV92 and DV93 are significant and negative. The COUNT variable, which controls for raw exposure time is significant and positive as expected. Of the MMS binary variables in Table 2.7, only CC (Corpus Christi) is consistently significant. This provides general support for the hypothesis that there is no significant difference between districts in HS&E incidence and/or reporting. This result is qualified by the fact that these models do not fully account for incomplete reporting.

Next, a brief analysis of the dispersion condition of the Poisson model is presented. The overall effect of mild overdispersion on inferences may be insignificant and not require additional treatment (Michener and Tighe, 1992). One way to determine the degree of the effect is to specify and estimate an alternate model for the mean-variance relationship. The negative binomial model was derived above for this purpose. The Negbin I and Negbin II (with MMS binary variables) are estimated and the results presented in Table 2.8. The Poisson results from Table 2.7 are included for comparison.

Table 6.8: Poisson and Negative Binomial Regression Results

Variable	Sign Expectation	Coefficient Estimates (t-statistics)					
		POISSON		Negbin I		Negbin II	
C		-3.9962	(-10.300)	-4.1695	(-11.111)	-4.1883	(-10.821)
OPCUM	-	-1.1235	(-1.467)	-0.9771	(-1.345)	-1.0539	(-1.351)
PLAT	-	**1.1138**	**(1.737)**	**1.2416**	**(2.036)**	0.9656	(1.449)
RET	-	0.1872	(.955)	0.2091	(1.138)	0.1372	(.704)
DEPTH	+	**0.3010**	**(3.230)**	**0.2842**	**(2.782)**	**0.3549**	**(3.134)**
RCH	+	0.1888	(.707)	0.2084	(.772)	0.1921	(.654)
WD400	+	0.1287	(.587)	0.1618	(.775)	0.1216	(.546)
EVD	?	**-0.8083**	**(-4.793)**	**-0.7491**	**(-4.134)**	**-0.8618**	**(-4.456)**
NOWELLS	+	**0.2089**	**(5.261)**	**0.2009**	**(3.938)**	**0.2440**	**(3.452)**
NO	?	-0.2356	(-1.096)	**-0.3619**	**(-1.705)**	-0.2536	(-1.101)
HO	?	-0.1121	(-.513)	-0.1815	(-.834)	-0.0889	(-.380)
LAF	?	-0.1928	(-.814)	-0.2461	(-1.107)	-0.1168	(-.492)
JAX	?	-0.0597	(-.224)	-0.2056	(-.811)	0.0464	(.180)
CC	?	**0.6377**	**(2.064)**	**0.6465**	**(2.069)**	**0.7109**	**(2.022)**
DV98	?	**0.7220**	**(2.045)**	**0.9749**	**(3.253)**	**0.7986**	**(2.765)**
DV97	?	**0.9775**	**(2.848)**	**1.2126**	**(4.247)**	**1.0093**	**(3.729)**
DV96	?	0.4765	(1.306)	**0.6426**	**(2.082)**	**0.5036**	**(1.736)**
DV95	?	-0.2283	(-.550)	-0.0033	(-.009)	-0.1677	(-.489)
DV94	?	-0.5125	(-1.197)	-0.2605	(-.687)	-0.4907	(-1.351)
DV93	?	**-1.3507**	**(-2.641)**	**-0.9709**	**(-2.007)**	**-1.3858**	**(-2.801)**
DV92	?	-0.9234	(-1.367)	**-1.0124**	**(-1.601)**	**-0.9178**	**(-1.748)**
DV91	?	0.0188	(.046)	0.3256	(.897)	0.0116	(.032)
COUNT	+	**0.1195**	**(5.640)**	**0.1204**	**(6.711)**	**0.1402**	**(4.925)**
a				0.3881	(4.839)	4.0565	(4.919)
LR (p-value)		223.1408	(0.00)	185.9658	(.000)	168.1512	
Log Likelihood		-996.1117		-946.3241		-955.2314	
LR Index		0.1007		0.0895		0.0809	
# Observations		5076		5076		5076	

Note that for both Negbin models, estimates for the parameter *a* are positive and significant, indicating that the basic Poisson is overdispersed. But overall, there is no compelling difference among the models in regard to individual coefficient signs and significance. The only variables with noteworthy differences are DV92 and DV96. Therefore, for the detection controlled models that follow, the basic Poisson specification as derived above is employed.

In summary, the results for the probit, ordered probit, and Poisson specifications do not provide clear guidance on which specification is to be preferred. Each yields similar results with respect to coefficient signs and significance. A Likelihood Ratio Index (*LR Index* as reported in Tables above) has been computed as LR Index = 1- L_u/L_r, where L_u is the unrestricted log-likelihood value and L_r is the restricted value. The probit and Poisson appear slightly better than the ordered probit, notwithstanding the statistical significance of the estimates for the μ_i's. Thus, detection controlled models are estimated for the binary and Poisson incidence specifications below. A detection controlled model for the ordered probit is feasible, but is reserved for later work.

Structural Change

Recall the regulatory change that occurred in 1996 discussed above. The change lowered the bar for initiating investigations, and made investigations more thorough. Such a change may have influenced HS&E incidence and/or reporting. A series of tests can be made on the annual binary variables to examine their influence. For the probit, the hypothesis that all of the annual binary variable coefficients are jointly zero can be tested. To execute this, a likelihood ratio test is employed. If a restricted regression is estimated where a subset of coefficients is hypothesized to be jointly zero (β^*), one obtains a restricted log-likelihood value. The difference between the restricted and unrestricted regressions is examined, and if this difference is large, the null hypothesis is rejected. The appropriate test statistic is computed as follows: $LR = 2[\, L(c,\beta) - L(c, \beta^*)] \sim \chi^2(q)$, where q equals the number of restrictions. For this null hypothesis in the probit of Table 6.7, LR = 2[-811.1091 - -855.6362] = 89.05, which clearly exceeds the 95 percent critical value of 15.507. Thus the null hypothesis that the annual binary variables are jointly zero is rejected. If the same test is run with a null hypothesis that the 1991-1995 coefficients are jointly zero, LR = 2[-811.1091 - -817.3030] = 12.39, which exceeds the 95 percent critical value of 11.07. The null hypothesis is again rejected. Finally, a test of the null hypothesis that the 1996-1998 coefficients are jointly zero rejects this hypothesis.

These tests and results on the annual binary variables are not clearly informative of any structural change. A better test of structural change at 1996 can be made as follows. Divide the data into two subsets, 1990-1995 and 1996-1998. The model is estimated (again, the probit of Table 2.7) and this yields two, unrestricted log likelihood values. The log likelihood for the model as a whole is the sum of these two values. Next, if all of the observations are pooled a restricted regression is estimated, the restriction being that the coefficients for each subset are equal. The likelihood ratio test is constructed as above. For this data, the sum of the log likelihoods for the two unrestricted regressions is –304.4003 + -506.7792 = -811.1795. For the restricted model, the log likelihood is -855.6362. The LR = 88.91 which exceeds the 95 percent critical value of 25.00 and the null hypothesis of no structural change is rejected. This approach allows both the constant term and the coefficient vector to change between the two regimes.

The results of the two subset regressions for the probit specification are presented in Table 2.9. Differences between the separate regressions and the pooled regression are noteworthy. PLAT is significant in only one regime. While DEPTH and EVD display similar features to the pooled regression, NOWELLS is now only significant in one regime. The COUNT coefficient is unchanged. Within the suite of MMS variables there are interesting changes. The effects of NO and CC are each isolated to one of the regimes, and JAX has taken on new significance.

The general implication of these results is that the 1996 policy change did influence HS&E outcomes. This implication is most interesting with respect to the MMS districts. In New Orleans, Lake Jackson, and Corpus Christi, the policy change affected the significance or sign of the coefficient, implying differential responses to the policy change. Note that these conclusions are all relative to the omitted district of Lake Charles, which itself could have been affected.

Table 2.9: Unrestricted Estimates for 1990-1995 and 1996-1998 Subsets, Probit

Variable	Coefficient Estimates (t-statistics)			
	PROBIT (1990-1995)		PROBIT (1996-1998)	
C	-2.4874	(-10.475)	-1.9069	(-10.263)
OPCUM	-1.0109	(-1.436)	-0.1934	(-.449)
PLAT	1.0389	(2.186)	0.2584	(.625)
RET	0.0561	(.399)	0.1280	(1.086)
DEPTH	0.1342	(1.685)	0.1673	(2.517)
RCH	0.0228	(.102)	0.1773	(1.052)
WD400	0.0525	(.293)	0.1121	(.859)
EVD	-0.3359	(-2.524)	-0.3345	(-2.930)
NOWELLS	0.0241	(.439)	0.1792	(4.250)
NO	-0.0193	(-.106)	-0.3348	(-2.510)
HO	0.0939	(.523)	-0.2140	(-1.568)
LAF	-0.0020	(-.010)	-0.1581	(-1.180)
JAX	0.3158	(1.781)	-0.3779	(-2.243)
CC	0.4985	(2.338)	0.1058	(.401)
COUNT	0.0861	(4.192)	0.0692	(3.337)
LR (p-value)	41.1170	(0.00)	72.2585	(0.00)
Log Likelihood	-304.4003		-506.7792	
LR Index	0.0633		0.0665	
# Observations	3010		2066	

An identical analysis for the Poisson was performed, and the results are presented in Table 2.10. OPCUM has taken on new significance in the 1990-1995 interval. PLAT is now insignificant along with RET. DEPTH is only significant in the 1996-1998 interval. RCH, WD400, and EVD are unchanged, and NOWELLS is now only significant in the 1996-1998 interval. Within the suite of MMS variables there are again interesting changes. The effect of CC is isolated to one of the regimes, and NO and JAX have taken on new significance. Again, the general implication of these results is that the 1996 policy change did influence HS&E outcomes.

Table 2.10: Unrestricted Estimates for 1990-1995 and 1996-1998 Subsets, Poisson

Variable	Coefficient Estimates (t-statistics)			
	POISSON (1990-1995)		POISSON (1996-1998)	
C	-4.6714	(-8.834)	-3.1352	(-9.174)
OPCUM	-2.7137	(-1.780)	-0.5804	(-.683)
PLAT	1.5441	(1.273)	0.8595	(1.107)
RET	0.1960	(.572)	0.2029	(.853)
DEPTH	0.2523	(1.292)	0.3112	(2.979)
RCH	0.3148	(.575)	0.1777	(.577)
WD400	-0.1580	(-.365)	0.2511	(.932)
EVD	-0.8649	(-3.413)	-0.7664	(-3.517)
NOWELLS	0.1321	(1.577)	0.2555	(5.331)
NO	0.2628	(.574)	-0.4630	(-1.885)
HO	0.2958	(.687)	-0.2592	(-1.000)
LAF	0.2392	(.445)	-0.3322	(-1.295)
JAX	0.8075	(1.866)	-0.4958	(-1.293)
CC	1.1568	(2.401)	0.2503	(.538)
COUNT	0.1497	(9.771)	0.0909	(3.392)
LR (p-value)	57.6250	(0.00)	72.7523	(0.00)
Log Likelihood	-373.5901		-625.3232	
LR Index	0.0716		0.0550	
# Observations	3010		2066	

A final specification to test for structural change can be made by constructing a binary variable that takes on a value of 1 when an observation is in the 1996-1998 regime. The results of this regression for the probit and Poisson are presented in Table 2.11. The binary variable REGIME is significant and positive, indicating an increase in incidence, reporting, or both in the 1996-1998 period.

Table 2.11: Test of Structural Change Using a Binary Variable

Variable	Sign Expectation	Coefficient Estimates (t-statistics)			
		PROBIT		POISSON	
C		-2.437	(-16.409)	-4.3681	(-14.369)
OPCUM	**-**	-0.440	(-1.238)	-0.1013	(-1.350)
PLAT	**-**	**0.551**	**(1.795)**	0.1014	(1.566)
RET	**-**	0.094	(1.049)	0.1870	(.948)
DEPTH	+	**1.480**	**(2.931)**	**0.0296**	**(3.173)**
RCH	+	0.102	(.766)	0.1762	(.660)
WD400	+	0.072	(.699)	0.1413	(.644)
EVD	**?**	**-0.335**	**(-3.902)**	**-0.7894**	**(-4.697)**
NOWELLS	+	**0.107**	**(3.432)**	**0.0204**	**(5.078)**
NO	**?**	**-0.193**	**(-1.835)**	-0.2435	(-1.142)
HO	**?**	-0.083	(-.778)	-0.1031	(-.471)
LAF	**?**	-0.099	(-.914)	-0.1885	(-.802)
JAX	**?**	-0.050	(-.425)	-0.0328	(-.123)
CC	**?**	**0.316**	**(1.986)**	**0.6128**	**(1.973)**
REGIME	**?**	**0.555**	**(8.051)**	**1.1362**	**(7.212)**
COUNT	+	**0.076**	**(5.392)**	**0.1205**	**(5.574)**
LR (p-value)		168.1222	(0.00)	199.4471	
Log Likelihood		-821.6042		-1007.9590	
LR Index		0.0928		0.0900	
# Observations		5076		5076	

The issue of structural change and its implications will be revisited below in the estimation and discussion of the detection controlled models.

Detection Controlled Estimation

Two detection controlled models as defined in Eqns. (6), (7), and (8) are now estimated. One employs a binary incident function, and the other a Poisson distribution for the incident function. As defined above, the reporting behavior is binary in both cases, a firm either reports or does not report an incident (or set of incidents), and the decision is independent of the number of incidents. The results of the estimation are presented in Table 2.12.

Table 2.12: Detection Controlled Estimates (1990-1998)

Variable	Sign Expectation	Coefficient Estimates (t-statistics)			
		PROBIT	t-stat	POISSON	t-stat
Incident Function					
C		-2.2523	(-5.043)	-1.2211	(-2.503)
OPCUM	-	-0.1020	(-.144)	-0.0727	(-.974)
PLAT	-	-0.0061	(-.006)	0.0747	(1.178)
RET	-	0.0227	(.083)	-0.3809	(-1.422)
DEPTH	+	3.5030	(2.651)	0.0311	(2.906)
RCH	+	0.1471	(.586)	0.2272	(.794)
WD400	+	0.1778	(.903)	0.1472	(.698)
EVD	?	-0.4342	(-2.400)	-0.8310	(-4.399)
NOWELLS	+	0.7869	(1.750)	0.0222	(3.629)
DV98	?	0.2987	(.675)	-0.9372	(-1.994)
DV97	?	0.4132	(.980)	-0.6883	(-1.656)
DV96	?	0.2589	(.524)	-0.4093	(-.904)
DV95	?	1.5635	(1.825)	-0.0968	(-.165)
DV94	?	1.0155	(1.427)	-0.6860	(-.958)
DV93	?	0.1714	(.217)	-3.9620	(-7.290)
DV92	?	-0.1934	(-.167)	-0.0699	(-.087)
DV91	?	0.3201	(.589)	-2.6639	(-4.701)
COUNT	+	0.1834	(2.582)	0.1319	(6.725)
Reporting Function					
C		-0.8205	(-1.508)	-1.6367	(-6.813)
RET	+	-0.0007	(-.004)	0.4243	(2.428)
NO	?	-0.3355	(-1.889)	-0.2425	(-1.448)
HO	?	-0.2113	(-1.367)	-0.1470	(-.860)
LAF	?	-0.2224	(-1.432)	-0.0467	(-.263)
JAX	?	-0.1079	(-.614)	-0.1005	(-.535)
CC	?	0.6613	(1.904)	0.5442	(1.933)
DV98	?	0.4082	(1.044)	1.2298	(3.393)
DV97	?	0.4425	(1.207)	1.1739	(4.121)
DV96	?	0.1316	(.320)	0.5557	(2.084)
DV95	?	-0.7820	(-1.599)	0.0141	(.048)
DV94	?	-0.7726	(-1.503)	0.1294	(.338)
DV93	?	-0.6890	(-1.352)	5.8230	(.161)
DV92	?	-0.5003	(-.652)	-0.4427	(-1.141)
DV91	?	-0.0394	(-.088)	3.8880	(.284)
Log Likelihood		-799.6966		-939.6682	
# Observations		5076		5076	
Actual Positives		220		220	
Estimated False Negatives		1396		1141	

Unlike the results from the non-detection controlled estimations, the two specifications here do not march in perfect lockstep. There are several instances where individual variable significance is different.

Evaluation of the company attribute variables indicates that none of these variables are individually significant in the incidence function. Recall that PLAT was significant above. In the reporting function, RET is now significant in the Poisson specification, indicating that there may be a difference in reporting behavior among firms given an incident occurs. Such a result may explain conclusions such as those in Iledare *et al.* (1997) that independent oil companies tend to have lower accident rates than majors. The observed performance difference could be due in part to incomplete reporting, not better HS&E performance.

Analysis of the technical variables indicates that DEPTH, EVD, and NOWELLS are again significant in the incidence function, and they hold the same signs as in the non-DCE models. This result was anticipated since they were not included in the reporting function. These results indicate that well and site complexity increase the likelihood of a HS&E incident. Especially noteworthy are the complementary results on EVD and NOWELLS which indicate that site complexity is composed of two parts. One part is the basic drilling rig/platform interaction, and the second is the density of production activity on the platform. The COUNT variable remains significant in both models. Noteworthy is the fact that WD400 is consistently insignificant. This result should be well received by regulators, as the relentless push into deeper waters by the oil companies does not appear to be a cause for concern vis-à-vis HS&E performance.

The MMS binary variables display slightly different results here. In the probit model, both NO and CC are significant in the probit specification, while only CC is significant in the Poisson specification. These results provide some support for the hypothesis that differences in reporting exist between districts.

The largest difference in inference comes in the analysis of the time trend binary variables. In the probit specification, only one of the annual binary variables is significant (DV95), and only in the incidence function, whereas in the previous specifications several of these variables were significant. In the Poisson specification, the situation is quite different. DV93, DV91, DV98, and DV97 are significant in the incidence function. Note that all of these coefficients are negatively signed, indicating that incidence is decreased relative to 1990. DV98, DV97, and DV96 are significant and positive in the reporting function, indicating that reporting in these years is increased relative to 1990. These results seems to support the regime change hypothesis, and that the increase in reported incidents in the 1996-1998 period is due primarily to increased reporting, not increased incidence. This result clearly demonstrates the value of detection controlled estimation. These results contradict the conclusions one might draw from examining models that assume complete reporting. More incidents are observed not because more are occurring (actually, less may be occurring), but because more are being reported.

Evidence on Incomplete Reporting - *"False Negatives"*

It is interesting to estimate HS&E incidence in those cases where no report was made. Again, this can be viewed in terms of Bayes' Law. The statistic of interest is P(A|NR), where NR represents a non report, essentially a false negative. This can be viewed in the context of the current definitions (given the joint probit specification of incidence and reporting) as follows:

$$
\begin{aligned}
P(A|NR) &= [P(A)\, P(NR|A)] / P(NR) \\
&= [\Phi(X_{1i}\beta_1)\, (1-\Phi(X_{2i}\beta_2)] / (1- \Phi(X_{1i}\beta_1)\Phi(X_{2i}\beta_2)).
\end{aligned}
$$

Using the estimates of β_1 and β_2, this computation can be made directly for all observations where no incident is reported. In the case of the joint probit specification as represented in Table 2.12, the mean P(A|NR) is 28.7 percent (σ = 26 percent). That is, 28.7 percent of the non reports are likely to have actually incurred an incident.

For the Poisson specification, the method is identical, although the computation is slightly more cumbersome:

$$
\begin{aligned}
P(A|NR) &= [Pr(A)\ Pr(NR|A)] / Pr(NR) \\
&= \{[1 - P(0)][1 - \Phi(X_{2i}\beta_2)] / [1 - \Phi(X_{2i}\beta_2) + P(0)\Phi(X_{2i}\beta_2)] \\
&= [1 - P(0) - \Phi(X_{2i}\beta_2) + P(0)\Phi(X_{2i}\beta_2)] / [1 - \Phi(X_{2i}\beta_2) + P(0)\Phi(X_{2i}\beta_2)] \\
&= 1 - P(0)/(1 - \Phi(X_{2i}\beta_2) + P(0)\Phi(X_{2i}\beta_2)),
\end{aligned}
$$

where $P(\bullet)$ is the Poisson pdf. The average P(A|NR) is 23.5 percent (σ = 17 percent). That is, 23.5 percent of the non reports are likely to have actually incurred an incident. These results are also presented in Table 2.12. The number of false negatives estimated under each specification are comparable in scale, indicating some robustness in this computation. The degree of underreporting is severe, these estimates indicate that only 14-16 percent of incidents are reported.

Impact Analysis

While analysis of individual coefficients and estimates of false negatives is informative, it can be difficult to disentangle all of the information contained in the regression results, *e.g.* there are false negatives, but it is difficult to ascertain in what years they are concentrated. A more intuitive analysis of reporting behavior is available. The mean of P(R|A) can be computed, *i.e.* $\Phi(X_{2i}\beta_2)$, by evaluating each observation in the data set *as if* it occurred in a particular year or MMS district. This analysis illuminates changes over time and among MMS districts, *ceteris paribus*. The results of this analysis for the probit specification are given in Table 2.13.

Table 2.13: Impact Analysis for P(R|A), MMS Districts and Annual Variables, Probit

	1990	1991	1992	1993	1994	1995	1996	1997	1998
New Orleans	0.12	0.12	0.05	0.03	0.03	0.03	0.15	0.24	0.23
Houma	0.15	0.14	0.06	0.04	0.04	0.03	0.18	0.28	0.27
Lafayette	0.15	0.14	0.06	0.04	0.03	0.03	0.18	0.27	0.26
Lake Jackson	0.18	0.17	0.08	0.05	0.04	0.04	0.21	0.31	0.30
Corpus Christi	0.44	0.42	0.25	0.20	0.18	0.17	0.49	0.61	0.60
Lake Charles	0.21	0.19	0.09	0.07	0.06	0.05	0.25	0.35	0.34

This analysis supports the conclusions above, that part of the increase in reported incidents in the 1996-1998 period is due to an improvement in reporting behavior. Note that the P(R|A) fluctuates over time, and was elevated in 1990-1991 before declining to extremely low levels in 1992-1995. But in 1996 there is a marked increase, followed by an additional increase and leveling off in 1997-1998. A plausible explanation for this increase is the MMS policy change described above. As the level of regulator scrutiny increases, oil companies face a increased risk of unreported incidents being discovered ex post and fines levied. Therefore, the incentive to report increased. Also noteworthy in this analysis is the fact that Corpus Christi displays considerably higher mean P(R|A) values than the other MMS districts. There is no anecdotal information to explain this result. Otherwise, there does not appear to be a significant difference between districts in the probability of reporting incidents. This result bolsters a similar conclusion drawn from inspection of the MMS variables' t-statistics reported in Table 2.12.

A similar analysis could be done for the RET variable to investigate the differences in P(R|A) between firm types. But since the RET is small and insignificant in the probit, this is not presented. While the results in Table 2.13 yield insights into reporting behavior, changes in incidence over time are also interesting. Similar to the above, one can compute the mean of P(A), *i.e.* $\Phi(X_{1i}\beta_1)$, by evaluating each observation in the data set *as if* it occurred in a particular year. The results of this analysis are presented in Table 2.14.

Table 2.14: Impact Analysis for P(A), Incidence Variables, Probit

Year	P(A)
1990	0.20
1991	0.27
1992	0.15
1993	0.23
1994	0.47
1995	0.65
1996	0.25
1997	0.29
1998	0.26

Casual inspection of these results indicate that the mean P(A) was relatively constant over the study period, except for substantial increases in 1994-1995. The 1996-1998 period demonstrates slightly higher levels of incidence than the 1990-1993 period. The decrease in 1996 relative to 1995 can be interpreted as a response to the MMS policy change, as oil companies responded to the potential for increased scrutiny with renewed attention to HS&E incident prevention.

In addition to the fully specified detection controlled models and results as presented in Table 2.12, it is possible to estimate a more parsimonious specification of the detection controlled models. Instead of employing a full suite of annual binary variables, the models can be estimated using the previously defined REGIME binary variable to capture and focus on the most important time effect - the regulatory policy change in 1996. Table 2.15 presents the result of such a specification. Differences between these results and the fully specified models above provide insight into the impacts of the choice of specification on inferences.

Table 2.15: Detection Controlled Estimates With Structural Change (1990-1998)

Variable	Sign Expectation	Coefficient Estimates (t-statistics)			
		PROBIT	t-stat	POISSON	t-stat
Incident Function					
C		-1.9450	(-2.972)	-1.7887	(-4.488)
OPCUM	-	0.4831	(.360)	-0.0556	(-.736)
PLAT	-	-2.9411	(-1.716)	0.0500	(.776)
RET	-	0.2729	(.667)	-0.1975	(-.650)
DEPTH	+	6.3560	(2.994)	0.0325	(3.028)
RCH	+	0.1565	(.327)	0.1985	(.698)
WD400	+	0.1651	(.444)	0.1495	(.707)
EVD	?	-0.6778	(-1.791)	-0.8644	(-4.616)
NOWELLS	+	7.9749	(2.453)	0.0253	(3.877)
REGIME	?	-0.5907	(-1.566)	-0.1029	(-.343)
COUNT	+	0.4015	(1.927)	0.0823	(4.741)
Reporting Function					
C		-1.7782	(-14.772)	-1.4153	(-7.662)
RET	+	0.0399	(.419)	0.2432	(1.333)
NO	?	-0.0829	(-.750)	-0.1997	(-1.346)
HO	?	-0.0655	(-.568)	-0.1045	(-.677)
LAF	?	-0.1078	(-.939)	-0.1454	(-.941)
JAX	?	-0.0511	(-.387)	-0.0780	(-.452)
CC	?	0.3454	(1.935)	0.4442	(1.764)
REGIME	?	0.6628	(7.389)	0.8277	(4.466)
Log Likelihood		-809.6622		-959.8659	
# Observations		5076		5076	
Actual Positives		220		220	
Estimated False Negatives		2834		1084	

Evaluation of the company attribute variables in the incidence function indicates that PLAT is significant at the 10 percent level in the probit specification with the expected sign, but all other company attribute variables are unchanged. On whole, this evidence does not support a view of companies as differing in their incident rates. In the reporting function, RET is not significant in either specification, whereas in the fully specified model, RET is significant in the Poisson specification. Thus, only one of four detection controlled specifications indicates a difference in reporting between firms.

Analysis of the technical variables again indicates that DEPTH, EVD, and NOWELLS are significant in the incidence function with the anticipated signs. These results further support the conclusion that well and site complexity increase the likelihood of a HS&E incident. The COUNT variable remains significant in both models. Also noteworthy is the fact that WD400 is consistently insignificant, a result which should be well received by regulators, as activity shifts to deeper waters in the years ahead.

The MMS binary variables display slightly different results, but conform generally to the results of the fully specified model. In the probit model, only CC is significant, and in the Poisson, the results are almost identical. These results provide some support for the hypothesis that differences in reporting exist between districts, at least for Corpus Christi.

Analysis of the results for the REGIME variable are interesting. In the incidence function, the variable is shown to be statistically insignificant in both specifications, indicating no difference in incidence between the two periods. In the reporting function though, the variable is highly significant and positive, indicating an increase in the propensity to report an incident in the post-1996 time period. This result seems to support the regime change hypothesis, and that the increase in reported incidents in the 1996-1998 period is due primarily to increased reporting, not increased incidence. This result again demonstrates the value of detection controlled estimation in isolating various effects on the variable of interest.

Evidence on Incomplete Reporting - "False Negatives"

As before, it is interesting to estimate HS&E incidence in those cases where no report was made. Again, the statistic of interest is P(A|NR), where NR represents a non report, essentially a false negative. In the case of the joint probit specification as represented in Table 2.15, the mean P(A|NR) has increased from 28.7 to 58.4 percent (σ = 37 percent). That is, 58.4 percent of the non reports are likely to have actually incurred an incident. While the results with respect to variable sign and significance are quite similar between the two specifications, the change has a marked, and admittedly counterintuitive effect on this statistic.

For the Poisson specification, the average P(A|NR) has decreased only slightly to 22.3 from 23.5 percent (σ = 12 percent). That is, 22.3 percent of the non reports are likely to have actually incurred an incident. For the Poisson, the change in specification had little effect on this statistic. In sum, the degree of underreporting is now estimated to be more severe, these estimates indicate that only 7-17 percent of incidents are reported.

Impact Analysis

As was done previously, a more intuitive analysis of reporting behavior is provided. The mean of P(R|A) can be computed, *i.e.* $\Phi(X_{2i}\beta_2)$, by evaluating each observation in the data set *as if* it occurred in one of the particular regimes or MMS districts. The results of this analysis for the probit specification are given in Table 2.16.

Table 2.16: Impact Analysis for P(R|A), REGIME and MMS District Variables, Probit

	1990-1995	1996-1998
New Orleans	0.12	0.31
Houma	0.15	0.36
Lafayette	0.15	0.35
Lake Jackson	0.18	0.40
Corpus Christi	0.44	0.69
Lake Charles	0.21	0.44

This analysis supports the conclusions above, that part of the increase in reported incidents in the 1996-1998 period is due to an improvement in reporting behavior. All MMS Districts show an improvement after the 1996 policy change. Again noteworthy in this analysis is the fact that Corpus Christi displays considerably higher mean P(R|A) values than the other MMS districts.

While the results in Table 2.16 yield insights into reporting behavior, changes in incidence over time are also interesting. Similar to the above, one can compute the mean of P(A), *i.e.* $\Phi(X_{1i}\beta_1)$, by evaluating each observation in the data set *as if* it occurred in a particular year. The results of this analysis are presented in Table 2.17.

Table 2.17: Impact Analysis for P(A), Incidence and REGIME Variables, Probit

Year	P(A)
1990-1995	0.64
1996-1998	0.54

Inspection of these results indicates that the mean P(A) declined in the 1996-1998 time period, but not by a large amount. The decrease may be tied to the MMS policy change as argued above.

2.9 Discussion

This investigation employs a variety of methods to examine HS&E incidence and reporting, and generates a considerable volume of results. In this section, the major findings of this research are summarized, and a list of key results most relevant to policy makers is presented.

Company Attributes

The objective in specifying company attribute variables was to examine the influence of drilling experience, offshore experience, and reputation constraints in determining HS&E outcomes. In the non-DCE analyses, the PLAT variable is generally significant and positive, opposite of expectations. OPCUM and RET are generally insignificant. In the DCE models, all of the company attribute variables are insignificant in the incidence function, with the exception of PLAT in one specification of the probit DCE. RET is positive and significant in the reporting function (Poisson) of one of four DCE specifications. On whole, these results indicate that all firms exhibit similar performance in HS&E incidence and reporting, but this conclusion is somewhat sensitive to the specification of the model. Regardless, these results clearly demonstrate the value of DCE. The specification isolates the effects on incidence and reporting, revealing the influence of the independent variables in each context. In one case, this result is especially important, as it conflicts with previous research that reports that smaller companies (typically, those where RET = 0 in this data set) demonstrate slightly better HS&E performance (Iledare *et al*., 1997). This research suggests that this previous result may be due to better reporting of the larger companies, not increased incidence.

Technical Variables

There were five technical variables defined to investigate the influence of well and site complexity on HS&E incidence: DEPTH, RCH, WD400, EVD, and NOWELLS. The results indicate that well and site complexity do increase the likelihood of a HS&E

incident. DEPTH is consistently positive and significant across specifications. Especially noteworthy are the complementary results on EVD and NOWELLS which support the hypothesis that site complexity is composed of two parts. The first part is the basic drilling rig/platform interaction (modeled by EVD), and the second is the density of production activity on the platform (modeled by NOWELLS). The COUNT variable remains significant and positive throughout as expected. Finally, the fact that WD400 is consistently insignificant is an important finding. This result should be well received by regulators, as the continuing push into deeper waters by oil companies does not appear to be a cause for concern vis-à-vis HS&E incidence. Overall, the results for the technical variables are robust to different specifications. The results regarding complexity also confirm the findings of others (Iledare *et al.*, 1997; Shultz, 1999), who find that site complexity is a significant source of HS&E incidence.

MMS Districts

With the exception of Corpus Christi (CC), reporting behavior is generally consistent across MMS districts. This is also reflected in the insignificance of the individual MMS binary variables in the DCE regression. This result is bolstered by the impact analysis depicted in Table 2.13, which also indicates that reporting behavior among the districts has tended to move together over time.

Annual Binary and REGIME Variables

The analysis of HS&E incidence and reporting over time provides needed insight into trends in both areas. With respect to incidence, the results indicate that the probability of incidents is relatively steady over time, except for two extremely poor years (high incidence) in 1994-1995. The policy change in 1996 appears to have reversed this trend. This conclusion is based on the complementary results in the analysis of MMS districts. With respect to reporting, there appears to be a policy response by oil companies in 1996 where the mean P(R|A) increases markedly over a low, four year trend.

The results on underreporting are surprising. The DCE analysis indicates severe underreporting of HS&E incidents. Based on the results depicted in Tables 2.12 and 2.15, only 7-17 percent of incidents were reported in the study period.

Policy Implications

Certain results are highlighted here for the corporate and government policy maker. Initiatives in HS&E prevention and regulation should focus on the following results:

1. There does not appear to be significant differences between MMS districts in the reporting behavior of oil companies. The exception to this is Corpus Christi, where reporting appears to be slightly higher. The MMS may wish to examine Corpus Christi's specific operational practices to identify any major differences in its execution of the regulations.

2. MMS inspection resources should be biased to smaller companies where the likelihood of reporting is possibly lower. Increased scrutiny changes the payoff function for non-reporting by increasing the probability of getting caught, and should inspire better reporting over time.

3. Prevention and regulatory resources (planning, inspection, research) should be allocated to high complexity sites, *i.e.* where drilling rigs are on or over platforms, and sites with higher numbers of active wells. This recommendation applies to oil company resources also.

4. A primary purpose of reporting incidents is to learn from mistakes, and to establish procedures to prevent similar incidents from happening in the future. The indication that a large percentage of incidents go unreported represents a tremendous loss of information and efficiency. To increase the probability of reporting, the MMS should consider increasing the penalty for non-reporting. Such a change would alter the payoff function, and should inspire better reporting over time.

2.10 Conclusions

This research examines the determinants of HS&E incidence and reporting in offshore drilling. The detection controlled methodology isolates the effect of independent variables on the propensity for incidents and the propensity to report incidents. There is strong evidence to support the hypothesis that aspects of well complexity and site complexity increase the likelihood of HS&E incidents in drilling. There is also evidence that rejects the hypothesis that water depth (floating operations) increases the likelihood of HS&E incidence. Equally important is evidence rejecting the hypothesis that broader oil company attributes influence HS&E incidence. An analysis of reporting behavior provides mixed support for the hypothesis that larger firms (those with established brands) are more likely to report an incident than their more anonymous counterparts; this result is dependent on the specific model of incidence employed. The evidence does not support the existence of differential reporting behavior between MMS districts, the exception being Corpus Christi which appears to garner higher reporting rates. Also, reporting behavior in MMS district tends to move together over time. Finally, the analysis provides consistent support for the conclusion that the 1996 policy change reduced HS&E incidence and increased HS&E reporting.

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3 Valuing Hurricane Forecasts and Evacuation Decisions in the Offshore Oil and Gas Industry

3.1 Introduction

This research examines the decision made by oil companies to evacuate offshore drilling rigs in the event of a hurricane. At its core, the problem is one of decision under uncertainty, a game of man against nature (Milnor, 1954). The primary goals are to value existing forecast accuracy, to estimate the cost of false evacuations for the industry, to develop a behavioral model of the decision to evacuate, and to introduce the role of risk preferences in the decision to evacuate. The problem is examined from three unique perspectives. The first approach develops a prescriptive, decision analytic model along the lines of Nelson and Winter (1964). With this model, the value of current forecast accuracy as demonstrated by NOAA's National Hurricane Center is estimated. An estimate is also made for the value of perfect forecast information. A second approach begins with a descriptive examination of actual drilling rig evacuation decisions for a sample of fifteen hurricanes in the Gulf of Mexico. From this data, and actual ex post storm paths and intensities, an estimate is made of the costs of false hurricane evacuations from 1980-1999. A discrete choice model of the evacuation decision is also specified and estimated, identifying variables that influence the propensity to evacuate. The results of this descriptive analysis complement those of the decision analytic approach. The third approach examines the role of risk preferences in the decision to evacuate via specification of a utility function and a structural econometric model (logit) of the propensity to evacuate. This model is of similar construction to Cicchetti and Dubin (1994) who examined the decision to self insure for home telephone maintenance.

The investigation reveals several key findings about the decision to evacuate in the offshore oil and gas industry. First, the prescriptive, decision analytic model indicates that over a range of value of life estimates (VL), the value of current forecast information is insignificant when compared to overall industry expenditures, ranging from $5-103 million for the decade of the 1990s. Under the perfect information assumption, the value of forecasts is estimated to be about $1.1-1.4 billion for the decade. The analysis of imperfect improvement of forecast accuracy indicates that significant improvement in forecast accuracy over the status quo is required for forecasts to have meaningful value to industry. Based on the qualitative assessment of evacuation decisions, development of empirical evacuation rules, and application of these rules to estimate the cost of false evacuations, the value of perfect forecasts is estimated to be $270 million for the 1990s, about one-fifth of the value of perfect information estimated via the prescriptive approach. A second qualitative analysis, more comparable to the Nelson-Winter analysis, puts the value of perfect information in the $340-425 million range. This result provides support for an estimate of the value of perfect information in the range of $250-425 million for the decade, or $25-42 million per year. The discrete choice econometric 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. The results of the utility-based model, with respect to determining risk preferences, are mixed.

Due to data availability, the focus is only on drilling rigs and excludes production operations, workover operations, and construction activities. Because of this, the results can be viewed as only a portion of the total costs of false hurricane evacuations for the industry as a whole. Some anecdotal market information is provided to gauge the relative size of the drilling portion vis-à-vis these other offshore activities.

3.2 Offshore Operations, Weather, and Hurricane Evacuation Decision Making

In this section, an overview is provided of offshore operations, the impact of weather on day to day decision-making, and the structure of the decision to evacuate. Detailed knowledge of operations and decision-making is necessary to motivate the structure of the models that follow.

Drilling Operations Overview

Oil companies lease oil and gas exploration and production rights from the U.S. government. A typical offshore lease block in the Gulf of Mexico is nine square miles in area. Once a lease is acquired, the oil company first drills exploration wells based on previously acquired seismic data and geophysical and geological analysis. If economic quantities of hydrocarbons are discovered, the lease is developed with additional productions wells. Production facilities needed to produce and manage the flow of hydrocarbons from the subsurface to the pipeline grid are typically installed on a platform. The size of the platform varies with the quantity and type of reserves discovered. Not all projects are developed with surface facilities, some projects are entirely subsea, consisting solely of wellheads and flowlines on the seafloor. It is the *drilling operations* that are the focus of this study. The impact of hurricanes on *production operations* has been addressed by others (Considine *et al.*, 2002). Other operations such as well servicing and construction are addressed here only in broad terms.

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 temporarily installed on the platform. Exploration wells are typically drilled in open water, while production wells are typically drilled over a platform. Oil companies engage the services of a drilling contractor who owns the drilling rig and employs and manages the drilling crew. Note that in the past, some oil companies owned and operated their own drilling rigs, but within this study period, this is generally not the case. 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 personal experience and informal interviews with practitioners, an average of 55 persons on board is assumed for all analysis herein.

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 of 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. Note that the rig is left on location (with the possible exception of drillships), and its survivability is not a function of the state of personnel evacuation.

There are two primary reasons to secure the well and to evacuate the drilling rig. First, 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 (as shown below). Any personnel remaining on board during a hurricane would be subject to this catastrophic risk. Since the oil company controls all modes of transportation to and from the rig, it therefore bears responsibility for personnel safety. The oil company would likely incur a large financial loss if the entire crew were lost due to a non evacuation. Even when the oil company or drilling contractor carry general liability insurance, deductibles are often quite large (tens of millions of dollars). Also, a non-evacuation could be construed by the insurer as a lack of reasonable care, argue that the decision to not evacuate was negligent, and refuse to pay for any losses.

Beyond such direct economic considerations, a second important component to the evacuation decision (while less tangible) is also influential. There are compelling ethical issues in such cases involving human life. In fact, it is stated explicitly in many oil company ethical and operating guidelines that protection of workers is paramount. That is, the burden is clearly put on decision-makers to avert personal injuries and deaths. This is a complex feature of the evacuation decision, and an attempt is made to model and value this behavior below.

A final note regarding the economic incentives of evacuation involves the long-term worker response to companies who tend to evacuate only in the most severe of storms, and to remain for all others. Research indicates that offshore workers' perceptions of job risk are a function of management's commitment to safety issues (Fleming *et al*., 1998). In theory, workers demand a compensating wage differential to account for the increased hazard when working for such a company.

Information and Decision-Making

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 keenly aware of the time required to safely secure the well and equipment, and to evacuate the rig, which may take days. This time requirement is hereafter referred to 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 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 uncased sections of the well bearing hydrocarbons. A plug must also 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 preventers. 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. When a MODU is drilling over a production platform, it is important to isolate the two structures, disconnecting service lines and walkways. These procedures take time, and thus must be initiated many hours before the rig is evacuated. In deepwater locations where drilling riser is in use, the retrieval of the riser itself adds considerable time 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 aggravated 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 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 features of offshore logistics are part and parcel of computing the SET. The critical wind speed is likely to occur well before hurricane conditions would be expected at the drilling location and as such, is generally viewed as the *ex ante* criteria for evacuation under uncertainty. That is, forecasts may be updated after the decision to evacuate is foregone, making use of a higher threshold impractical.

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 isovelocity contour lines for 50 knot and 64 knot winds in each quadrant (NE, SE, SW, and NW) relative to the eye of the hurricane. The availability of each of these forecasts varies over time. The 50 knot forecast coincides with the logistics constraints noted above, and will be employed as the criterion to define a hit herein. Decision-makers evaluate the raw data and the forecasts along with the SET to inform their optimization of 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, 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.

3.3 Motivation

Valuing weather information is a topic of concern to many parties. Both producers and consumers of forecasts have a vested interest in knowing the value of the information that is changing hands. A well done valuation can inform on the quality of forecasts, guide investment in new forecasting technology, support (refute) arguments for increased public financing, and shed light on decision-making processes.

A collection of articles on the subject of the economic value of forecasts has been compiled by Katz and Murphy (1997). The several authors therein provide an overview of decision under uncertainty, forecast verification, and the general structure of value of information models. The work also documents a variety of previous forecast valuation studies in 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). A study of the oil and gas industry is a unique contribution to this body of knowledge. For the oil and gas industry, relatively little is known about the value of forecasts, the costs of false evacuations, or the specific factors or conditions that influence the propensity to evacuate. The only study that was found is Epps (1997), which provides only a brief overview and casual estimate of the costs of evacuations.

The drilling rig evacuation decision in the oil and gas industry is an ideal subject for valuation modeling. The decision-maker has but two actions to take (evacuate or not), and there are only two states (each) of forecasts and nature that are possible at the rig (hit or not, given a strict definition of a hit). As a result, the scale of the model is manageable and amenable to empirical analysis. Probability information is available, and definitions for the payoffs are straightforward.

The primary goals are to value existing forecast accuracy, to estimate the cost of false evacuations for the industry, and to develop a behavioral model of the decision to evacuate. The problem is examined from three perspectives. The first approach develops a prescriptive, decision analytic model along the lines of Nelson and Winter (1964). With this model, an attempt is made to value current forecast accuracy as demonstrated by NOAA's National Hurricane Center. An estimate of the value of perfect forecast information is also made. The second approach begins with a descriptive examination of actual drilling rig evacuation decisions for a sample of fifteen hurricanes in the Gulf of Mexico spanning 1979-1989. From this data, and actual ex post storm paths and intensities, an estimate is made of the costs of false hurricane evacuations from 1980-1999. A discrete choice model of the evacuation decision is also specified and estimated. The results of this descriptive analysis complement those of the decision analytic approach, and highlight differences between the structure and execution of the two approaches. A description of the relative merits of prescriptive and descriptive methods is available in Johnson and Holt (1997). The third approach examines the role of risk preferences in the decision to evacuate via specification of a utility function and a structural econometric model (logit) of the propensity to evacuate.

In the remainder of this section, a rough estimate of the costs of hurricane evacuations for the 1995-1998 period is provided to provide a preliminary economic motivation. A detailed empirical estimate based on actual evacuation decisions is reserved for Section 3.5. The objective here is to assess the magnitude of the costs.

Estimate of the Costs of Evacuation

To estimate the costs of evacuation for the industry as a whole, one requires two pieces of information. First, the costs incurred by oil companies given the decision to evacuate. Second, the number of rigs, on average, that are operating in the Gulf of Mexico.

There are three main components to the cost of evacuation. One is the fixed transportation cost. Based on conversations with practitioners, and an analysis of marine and air transportation costs, this fixed cost is estimated to be $28,000 per rig. A second component is the standby cost for the drilling rig and ancillary services. 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 (dayrate). Although contract terms vary from company to company, and vary based on market conditions when the contract is negotiated, the full dayrate is assumed here for these computations. Using the full dayrate is intended to capture all ancillary services that would also be on a standby rate (cementing, MWD/LWD, casing crews, drilling mud, etc.). The third component is the time required to resume normal operations once the rig is remanned. In the Gulf of Mexico, the geologic formations can be unstable, and it is often the case that significant time must be spent to reclaim or redrill portions of the wellbore that were left uncased when the rig was evacuated. An analysis of the duration of evacuations across all rig types yields an average evacuation of 5.5 days (a more detailed analysis of evacuation durations by rig type will be done below). This includes the time spent reclaiming the wellbore to its pre-evacuation condition.

Table 3.1 presents average dayrates in the Gulf of Mexico by rig type. Table 3.2 presents the average rig count. Note that not all of these rigs are drilling all of the time. Some are engaged in completions, workovers, abandonment operations, and rig moves. The data indicate that only ~60% of these rigs are engaged in drilling at any moment. This fact will be important in the analysis below, because only the data for rigs that are in a drilling mode are typically observed. The results must therefore be scaled (up) to reflect that evacuation decisions are made for all offshore rigs, regardless of their current activity. All data in the tables that follow is from *Offshore Data Services*, Houston TX.

Table 3.1: Average Daily Drilling Rig Rates ($000), Gulf of Mexico, 1995-1998

Rig Type	1995	1996	1997	1998
Jackups	21.833	29.708	47.479	42.192
Platform	13.375	14.800	16.800	18.531
Semisubmersibles/Ships	52.500	89.292	119.583	126.250
Barge Drilling*	13.375	14.800	16.800	18.531
Platform Workover*	13.375	14.800	16.800	18.531

* Daily rates for barge rigs and workover rigs are not readily available; we set the rate equal to platform drilling rigs, the closest counterpart.

Table 3.2: Rig Count by Rig Type, Gulf of Mexico, 1995-1998

Rig Type	1995	1996	1997	1998
Jackups	110	115	115	74
Platform	18	19	25	16
Semisubmersibles/Ships	28	34	33	39
Barge Drilling	45	54	46	27
Platform Workover	35	41	36	21

With these data in hand, estimates are made for evacuation costs by rig type for an evacuation event where *all* rigs are evacuated. Table 3.3 presents these results. The figures include the $28,000 lump sum transportation costs. For example, to compute the cost for jackup rigs in 1995, the computation is as follows:

[($21,833/day)*(5.5 days) + $28,000]*110 = $16,288,965.

Table 3.3: Estimated Evacuation Costs by Rig Type ($000), Gulf of Mexico, 1995-1998

Rig Type	1995	1996	1997	1998	TOTALS
Jackups	16,289	22,011	33,251	19,244	90,794
Platform	1,828	2,079	3,010	2,079	8,995
Semisubmersibles/Ships	8,869	17,650	22,628	28,173	77,320
Barge Drilling	4,570	5,908	5,538	3,508	19,524
Platform Workover	3,555	4,485	4,334	2,728	15,103
TOTALS	35,111	52,132	68,762	55,732	211,736

The average annual cost over the four year period is $53 million. The final step in estimating the costs of evacuation is to multiply this figure by the number of full evacuations per year. This number is not observed directly, but based on an actual sample of evacuation decisions for 15 storms, it was observed that the industry as a whole is quick to evacuate once a storm enters the Gulf of Mexico. Based on actual storm counts in the 1995-1998 period, it is estimated that there were at least eight evacuation events, *i.e.* an average of two per year. Multiplying the estimated evacuation cost by two yields the average cost of evacuations per year, $106 million. If an evacuation is deemed unwarranted ex post (based on a change in storm track or the lack of storm intensity), the entire cost can be viewed as a loss in efficiency. Such a loss can also be viewed as the value of perfect information; if perfect information were available, the evacuation would not have occurred. These cost estimates are significant, and warrant a more detailed analysis.

3.4 Valuing Forecast Information – A Prescriptive, Decision Analytic Approach

In this section, a decision analytic model is developed to value forecast information. The general structure of the model is common as described in Murphy (1997) and Johnson and Holt (1997). The approach of Nelson and Winter (1964) is mirrored here. The model is prescriptive in that it specifies how decision-makers respond to costs of evacuations, losses, and forecast and climatological information. This approach has only one empirical component, the historic joint distribution of forecasts and outcomes. A descriptive model is developed in the next section.

First, an overview of the model is provided, defining its variables and parameters generally, and then the model is expanded to account for the nature of the drilling rig evacuation decision and the structure of the data set. Second, a detailed analysis for three critical components of the model, their origin and organization is provided. Third, the results of the calculations are presented and discussed.

The Nelson-Winter Framework

In this model of decision under uncertainty, actions that the decision-maker can take are defined, along with the possible outcomes, the probabilities of these outcomes, and the associated payoffs. A risk neutral, cost minimizing decision-maker is assumed. In the event of a hurricane approaching the drilling rig, the decision-maker faces a discrete choice between evacuation or remaining on the drilling rig.

If no forecasts are available, his decision and resulting cost V_c would be based on:

$$V_c = \text{Min}\ (C, \pi^1 L), \tag{1a}$$

where,

V_c = Cost based on climatological information alone
C = Total cost of evacuation
π^1 = Unconditional probability of hurricane force winds at the drilling rig
L = Cost of losses (human life) if the rig is not evacuated and hurricane force winds are experienced.

The assumption is made that the evacuation is completely effective and eliminates the possibility of loss of life. Damage to the drilling rig is not included in L, which will occur whether or not the rig is evacuated. π^1 would be available to the decision-maker based on historical data. Note, at this stage L is deterministic. The complication when L is not deterministic is accounted for below.

In the presence of discrete forecast information (forecast hit or miss), the decision-maker faces a similar choice structure. In the case where a forecast (f) of a hit (h) is made, the decision and resulting cost V_{fh} is based on:

$$V_{fh} = \text{Min}\ (C, \pi_{11} L + \pi_{21} (0)) = \text{Min}\ (C, \pi_{11} L), \tag{1b}$$

where,

π_{11} = Conditional probability of a hit given a hit is forecast
π_{21} = Conditional probability of a miss given a hit is forecast.

In the case where a forecast of a miss (m) is made, the decision and resulting cost V_{fm} is based on:

$$V_{fm} = \text{Min}\,(C, \pi_{12} L + \pi_{22}\,(0)) = \text{Min}\,(C, \pi_{12} L), \qquad (1c)$$

where,

π_{12} = Conditional probability of a hit given a miss is forecast
π_{22} = Conditional probability of a miss given a miss is forecast.

Therefore, the expected cost for the decision-maker in the presence of discrete forecasts is a weighted value as follows:

$$V_f = \pi_1\, \text{Min}\,(C, \pi_{11} L) + \pi_2\, \text{Min}\,(C, \pi_{12} L), \qquad (1d)$$

where π_1 is the unconditional probability of a forecast of a hit ($\pi_2 = 1 - \pi_1$). π_1 would be available based on historical data.

As Nelson and Winter demonstrate, forecasts can only have value when $\pi_{12} < C/L < \pi_{11}$. This condition results from the following observations. In the absence of forecast information, note from Eqn. (1a) that if $C/L < \pi^1$ evacuation occurs and vice versa. Eqns. (1b) and (1c) yield the following results: if $C/L < \pi_{11}$ and $C/L < \pi_{12}$, the decision-maker would always evacuate. Likewise, if $C/L > \pi_{11}$ and $C/L > \pi_{12}$, the decision-maker would always remain on the rig. It is reasonably assumed that $\pi_{11} > \pi_{12}$ (this is later shown to be true in the empirical data). Finally, observe that $\pi^1 = \pi_1\, \pi_{11} + \pi_2\, \pi_{12}$, so π^1 always falls between π_{11} and π_{12}. Consider a decision-maker who observes $C/L < \pi^1$ (evacuate), learning that $C/L < \pi_{12}$ (evacuate) does not change his decision. Likewise, if he observes $C/L > \pi^1$ (remain), learning that $C/L > \pi_{11}$ (remain) does not change his decision. Therefore, it is only in cases where $\pi_{12} < C/L < \pi_{11}$ can the conditional probabilities change an evacuation decision vis-à-vis a decision based on climatological information alone.

This observation allows a simplification of Eqn. (1d) to the following:

$$V_f = \pi_1 C + \pi_2 \pi_{12} L. \tag{1e}$$

The value of forecasts V is simply the difference between V_c (cost based on historical climatological information alone) and V_f (cost based on forecast information). That is:

$$V = \text{Min}\,(C, \pi^1 L) - [\pi_1 C + \pi_2 \pi_{12} L]. \tag{1f}$$

This result is the core of the Nelson-Winter analysis.

A Fully Specified Model for Drilling

The objective is to operationalize Eqn. (1f) using actual data on forecasts, costs, and losses. But this equation only represents the value of information for one decision-maker. In the present context of drilling rig evacuations, this result must be generalized to account for the nature of the data set. To this end, the following subscripts are defined:

r: represents an individual drilling rig.
i : represents a geographical grid block as defined by Posner (2002); there are 1,060 grid blocks defined for the Gulf of Mexico.
j : represents a particular storm event.
k : represents the year of the computation; when used to index weather/forecast probability information (π's), it denotes the *currently defined* π's. The definition of the π's is detailed below.

The index r is required because there can be more than one drilling rig on a grid block. Given this, Eqn. (1f) can be modified as follows:

$$V_{rijk} = [\min(C_{rk}, \pi^1{}_{ik} L) - \pi_{1ik} C_{rk} - (1 - \pi_{1ik}) \pi_{12ik} L]_j. \tag{1g}$$

Such a specification introduces needed flexibility into the definition of C which varies across rig types and over time, and into definition of the π's which vary by grid block and over time as defined below. The Min operator is eliminated for computational ease:

$$V_{rijk} = \begin{cases} [\pi_{1ik} (\pi_{11ik} L - C_{rk})]_j, \text{ when } C_{rk} / L > \pi^1_{ik} \\ [\pi_{2ik} (C_{rk} - \pi_{12ik} L)]_j, \text{ when } C_{rk} / L \leq \pi^1_{ik}. \end{cases} \qquad (2)$$

The value of information for any year is then given by:

$$V_k = \Sigma_j \, \Sigma_i \, \Sigma_r \, [\, V_{rijk} \,]. \qquad (3)$$

Recall that V_{rijk} is only computed when $\pi_{12ik} < C_{rk} / L < \pi_{11ik}$. Also, this calculation is valid for each forecast type. That is, Eqn. (3) can be computed for a 12 hour forecast, a 48 hour forecast, etc. Note that each forecast type valuation is discrete, they are not additive. It is assumed that decision-makers observe all forecasts to develop an understanding of the particular storm, but for the evacuation decision, it is expected that one forecast dominates based on the SET for the particular rig. Based on conversations with practitioners, forecast values for the 24 and 48 hour forecasts are computed, as those were commonly identified as the most relevant to the evacuation decision.

A Numerical Example

To demonstrate how these computations are executed, a simple numerical example is provided for Eqn. (2) based in part on empirically derived parameters. Recall Eqn. (2):

$$V_{rijk} = \begin{cases} [\pi_{1ik} (\pi_{11ik} L - C_{rk})]_j, \text{ when } C_{rk} / L > \pi^1_{ik} \\ [\pi_{2ik} (C_{rk} - \pi_{12ik} L)]_j, \text{ when } C_{rk} / L \leq \pi^1_{ik}. \end{cases}$$

In this example, the focus is on the value of the 48-hour forecast, V^{48}_{rijk}. To compute this value, estimates of C_{rk}, L are needed, along with the unconditional and conditional probability information, the π_{ik}'s.

The costs of evacuation C_{rk} depend on the rig type (jackup versus platform versus floating rig) and the year of the computation because the drilling market is cyclical and dayrates fluctuate in a wide band. For the present example, it is assumed that C is constant at $500,000. The loss L incurred if the rig is not evacuated and hurricane force winds hit the rig is arbitrarily assigned a cost of $10 million. In practice, L is not deterministic. That is, even when hurricane force winds are experienced at the rig, the loss is not assured. This nuance is addressed below. Lastly, based on historical forecast and actual outcome information, the needed probabilities are computed. These probabilities are computed by grid block, and updated over time as they are done in practice. For the present example however, Gulf-wide statistics are employed for the 48-hour forecast for 1980-2000. This data is shown in Tables 3.4 to 3.6 below.

Table 3.4: Forecast / Outcome Observations Counts, Gulf of Mexico, 48-hour Forecast, 1980-2000

		Forecast	
		Hit	Miss
Outcome	Hit	1,631	6,019
	Miss	4,388	251,255

Table 3.5: Unconditional Probabilities, Gulf of Mexico, 48-hour Forecast, 1980-2000

$\pi_1 = 0.023; \pi_2 = 0.977$

$\pi^1 = 0.029; \pi^2 = 0.971$

Table 3.6: Conditional Probabilities, Gulf of Mexico, 48-hour Forecast, 1980-2000

		Forecast Hit	Miss
Outcome	Hit	0.271	0.023
	Miss	0.729	0.977

For reference, the average conditional probabilities are presented in Table 3.7. These figures represent the average of the conditional probabilities computed at the grid level for 1980-2000. Note that these differ slightly from the probabilities of Table 3.6 because those results are based on total observation counts. The standard deviations are given in parentheses. The difference between the methods is trivial.

Table 3.7: Average of Conditional Probabilities Across Grids, Gulf of Mexico, 48-hour Forecast, 1980-2000 (standard deviations in parentheses)

		Forecast Hit	Miss
Outcome	Hit	0.259 (0.24)	0.023 (0.01)
	Miss	0.741 (0.24)	0.977 (0.01)

Once this data is in hand, the computations, while cumbersome in scale, are straightforward. In this case, C / L = \$500,000 / \$10 million = 0.05, which is greater than π^1 which invokes the top half of Eqn. (2). Note here that this C / L value also satisfies the needed condition $\pi_{12} < C / L < \pi_{11}$ for the forecast to have any value. Now, compute as follows:

$$\pi_1 (\pi_{11} L - C) = 0.02 (0.27 * \$10x10^6 - \$500,000) = \$44,000.$$

This calculation represents the value of forecast information to one decision-maker. It is only for one rig, in one grid block, in one hurricane, in one particular year. If a rig count of 100 rigs is assumed across all of the grid blocks during a particular hurricane (and if all rigs were identical), the above number would be multiplied by 100 (= $4.4 million) and this would be the value of forecast information to the industry for that particular hurricane. Continuing, if there were four hurricanes in a given year, the individual hurricane amount would be multiplied by four.

What is proposed here is to execute the model as fully specified in Eqn. (2). Costs (C) are allowed to vary across rig types and time based on actual rig dayrates, and probability information is computed at the grid block level, and updated over time to account for new observations of forecasting performance. Since C and the probabilities vary, both parts of Eqn. (2) may come into play. Also, the condition $\pi_{12} < C / L < \pi_{11}$ is not always satisfied, and as such, not all observations will be included.

Assessing the Probability Information

A detailed summary of how the probability information is organized and how the computations are performed in Appendix C. Posner (2002) has computed (summed) the number of observations for each entry in the 2x2 forecast/outcome notation. The data is summarized in Table 3.8.

Table 3.8: Summary of Forecast/Outcome Data Availability, 1980-2000

Years	Forecast Types	Wind Speeds (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. This raw data can be used 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. The computations here will be made with a cumulative approach. That is, for value of forecast calculations in 1990, the counts of observations from 1980-1989 will be used to compute the probabilities. For 1991, the counts of observations for 1990 will be added and the probabilities recomputed, and so on. This approach captures the accumulation of decision-maker knowledge of forecast performance.

It is observed that 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, the Gulf of Mexico average is assigned in these cases. Note, this applies only in a small minority of cases.

The impact of the probability information over time can be assessed by constructing a simple valuation example. If the same C and L figures given in the previous example are used, but the cumulative computation results for the probability information are employed, the impact of the probability information can be isolated. The cumulative (entire Gulf of Mexico) probability information for the 48-hour forecast for the 1990-1999 period has been computed. The raw counts by year are given in Table 3.9 using the counting convention defined by Posner (2002), and the cumulative probabilities are given in Table 3.10. Note that 48-hour forecasts were not available prior to 1985.

Table 3.9: Observation Counts by Year, Gulf of Mexico, 48-hour Forecast, 1985-2000

Year	a	b	c	d
1985	801	2874	1676	35212
1986	0	0	9	1268
1987	0	37	80	4413
1988	161	429	804	30164
1989	0	88	40	12473
1990	0	0	3	4997
1991	0	0	0	1694
1992	28	425	286	10760
1993	0	0	2	4279
1994	0	14	27	12941
1995	109	919	443	42977
1996	0	73	97	17221
1997	0	54	1	6161
1998	532	870	624	34256
1999	0	128	236	19036
2000	0	108	60	13403

The definitions for the observation counts in Table 3.9 are as follows:

	Forecast	Actual
a:	Hit	Hit
b:	Miss	Hit
c:	Hit	Miss
d:	Miss	Miss

A Note on Relevant Hurricane Forecasts

There is an important distinction to be made between relevant and irrelevant forecasts and current hurricane parameters. The only forecasts and parameters to be concerned with are those that elicit an evacuation decision to be made (evacuate or not). For example, if a hurricane is in the mid-Atlantic area, it is of no immediate interest to decision-makers vis-à-vis an evacuation decision. Only when the hurricane enters a certain perimeter of interest do forecasts and hurricane parameters become important in the context of decision-making. The size of this perimeter depends on many factors. For example, a deepwater drilling rig has a longer SET than a jackup drilling rig, therefore a deepwater drilling rig would have a larger perimeter of interest, *ceteris paribus*. Based on personal experience, interviews, and historical track and speed information, a Watch Area has been defined that begins west of 75 degrees longitude (about the eastern tip of Cuba) and north of 15 degrees latitude (about the southern tip of Mexico). Only storms that entered, or were forecasted to enter this zone are examined. This definition is generous in the sense that it is likely to include hurricanes that may not have been relevant, but shrinking this zone poses a bigger error of excluding storms that were relevant. As this definition is made primarily to reduce data volumes and manipulation, it was thought to be better to err on the side of inclusion.

The definition of relevance using historical forecast errors is refined further. That is, even when a storm is in the Watch Area, the forecasts may be irrelevant for a given drilling location. For example, if the historical 48 hour forecast exhibits an average track error of 100 miles with a standard deviation of 50 miles, a 48 forecast that puts the storm 500 miles from a rig is unlikely to be of any interest to that decision-maker. Only when the rig is within the forecast error (+/- two standard deviations) is the forecast relevant. Controlling for this feature of the forecast verification problem is important to avoid what has been termed the *Finley Effect*. Including irrelevant observations (as defined here) would bias measures of accuracy and make the forecasts appear more accurate than they truly are (Murphy, 1997). That is, one would be overloaded with successful “no hit” forecasts. Additional details of the methodology and computations are detailed in Posner (2002).

Table 3.10: Cumulative Probability Calculations by Year, Gulf of Mexico, 48-hour Forecast, 1990-1999

Year	π_{11}	π_{12}	π_{21}	π_{22}	π^1	π^2	π_1	π_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

Noteworthy is the gradual improvement in accuracy of no hit forecasts (π_{22}), and the steady decline in accuracy of hit 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. Using the figures of Table 3.10, the value of information to the example rig for a storm in each of these years is computed and given in Table 3.11.

Table 3.11: Value of Forecast Information as a Function of Variable p ’s, ($), 1990-1999

Year	Value
1990	86,541
1991	81,996
1992	80,567
1993	73,177
1994	70,396
1995	63,035
1996	51,372
1997	46,357
1998	44,870
1999	58,390

The impact of the structure of the probability information for this example is evident. The steady decline in forecast value (with the exception of 1999) is seen to be more sensitive to the degradation of the conditional probability figure π_{11} than to the gradual improvement of $\pi_{12.}$ Recall that the computation is also sensitive to the value of π^1 which dictates which of these probabilities is incorporated into the computation.

For comparison, one can perform the same set of computations for the 24-hour forecasts. Similarly constructed probability information is given in Table 3.12.

Table 3.12: Cumulative Probability Calculations by Year, Gulf of Mexico, 24-hour Forecast, 1990-1999

Year	π_{11}	π_{12}	π_{21}	π_{22}	π^1	π^2	π_1	π_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	0.65	0.08	0.35	0.92	0.17	0.83	0.16	0.84
1998	0.65	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

The 24-hour forecasts demonstrate good accuracy when predicting both hits and misses. About two-thirds of the time a hit is forecast, it actually occurs (π_{11}). For the no hit forecasts and outcomes, forecasters are correct over ninety percent of the time. It is expected that the accuracy is better here than the 48-hour forecasts which it is for π_{11}, but it is also noted that the π_{22} values demonstrate slightly less accuracy. Note the difference between the π^1 values for the two forecast types. The climatological probability of a hit for the leases included in the 24-hour forecasts (and computations) is three to four times higher than that for the 48-hour forecasts. Also note that the C/L ratio does not satisfy the condition $\pi_{11} > C/L > \pi_{12}$, rendering the forecasts valueless in this example. The intuition behind this result is clear. Once a location meets the criterion for a 24-hour forecast *to be relevant* as was defined above, the probabilities are such that the forecast itself has little value – it will always be cost minimizing to evacuate. Note that this result is not generalizable because the probabilities used in the example are for the entire Gulf of Mexico, the costs are constant across decision-makers, and costs are constant over time. All three of these constraints are relaxed in the detailed forecast valuation to be performed below.

Estimates for Costs of Evacuation

Data was collected on actual evacuation decisions from Gulf of Mexico drilling operations. It is reasonable to suspect that there are differences in the SET between shallow water rigs (jackups) and deepwater rigs (floaters). This hypothesis is based on the nature of deep water drilling operations where more lead time is needed to secure the rig for a hurricane, mainly due to the time to retrieve the drilling riser. Differences in the SET should lead to differences in the average duration of evacuations. The data set therefore includes a broad sample of both types of rigs.

Table 3.13 presents summary data for the evacuation observations. Note, this table only includes those observations where evacuations occurred, that is, the concern here is in estimating E(duration | evacuation). Note, there are observations of non-evacuations in the data set which will be important for the subsequent evaluation of the evacuation decision. The data in Table 3.13 is pooled across rig types. Significantly more data was available in the 1980s and the observations are restricted to that time frame.

Table 3.13: Evacuation Observations

StormName	Year	#Obs	Average Evacuation Duration By Storm, Days	Standard Deviation of Evacuation Duration By Storm, Days
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	13	8.28	5.22
Chantal	1989	14	3.33	1.72
Jerry	1989	10	3.63	1.13
Total #Obs		168		

Evacuation Duration Uniqueness By Storm

Before investigating for differences between rig types, it is interesting to test whether or not the average evacuation duration can be modeled as a random variable originating from one probability density function (pdf) of evacuation durations, or if each evacuation duration originates from a unique pdf. If the latter case holds, one would ideally want to model average evacuation duration as a function of some quantitative or qualitative storm attributes. If not unique, one can simply focus on potential differences between rig types.

If one assumes that evacuation duration is a random variable originating from a normal pdf, a null hypothesis can be formed about the average evacuation duration for a particular storm. That is:

H_O: duration for storm i = μ,
H_A: duration for storm i $\neq \mu$.

At the 0.05 significance level, the null hypothesis is rejected for less than half of the storms. Based on this result, and the complexity of quantitatively or qualitatively classifying storms for this purpose, average evacuation durations are used. This analysis is summarized in Table 3.14.

Table 3.14: Hypothesis Testing for Evacuation Uniqueness

Storm Name	Year	#Obs	Average Evac Time By Storm, Days	Standard Dev of Evac Time By Storm, Days	t-stat
Bob	1979	8	2.69	1.60	-4.97
Claudette	1979	7	6.20	1.86	1.00
Allen	1980	11	5.49	2.21	0.00
Jeanne	1980	18	4.81	3.77	-0.77
Alicia	1983	6	5.08	4.84	-0.21
Barry	1983	5	5.22	5.42	-0.11
Danny	1985	22	4.89	2.29	-1.25
Elena	1985	13	7.07	2.47	2.30
Juan	1985	15	7.32	4.68	1.51
Kate	1985	15	4.28	1.22	-3.86
Flo	1988	11	7.97	6.60	1.25
Gilbert	1988	13	8.28	5.22	1.92
Chantal	1989	14	3.33	1.72	-4.71
Jerry	1989	10	3.63	1.13	-5.23

Note: The t-statistic is calculated as follows: t-stat = $(x-\mu)$ / (s/sqrt(n)), x = sample (storm) mean, s = estimate of population standard deviation, n = # of sample observations. The t-statistic is preferred to account for the small sample sizes.

Do Floating Rigs Demonstrate Longer Evacuation Durations?

It is reasonable to suspect that there may be a difference between the average evacuation duration for a jackup rig or platform rig and a floating rig. Floating rigs incur the extra step of pulling the drilling riser which may take days, depending on the exact water depth. In this sense, a decision-maker on a floating rig must act earlier than his counterpart on a jackup 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. Note that in the measure of total evacuation time, the time spent upon returning to the rig to resume operations where they were suspended is included. This also may include the redrilling of lost portions of the wellbore.

It is easy to compare jackup rig versus floating rig evacuation durations if one looks at the two subsets of the whole sample and computes a t-statistic.

Pooled Sample:	Mean = 5.5	Standard Dev. = 3.7	n = 169*
Shallow Subset (SH):	Mean = 4.6	Standard Dev. = 2.9	n = 103
Deep Water Subset (DW):	Mean = 7.5	Standard Dev. = 4.5	n = 54

* Some observations in the pooled sample do not have water depths recorded, this is why the subsets do not add to 169.

t_{SH} = 4.6 – 5.5 / (2.9/sqrt(103)) = -3.15.

t_{DW} = 7.5 – 5.5 / (4.5/sqrt(54)) = 3.27

These computations suggest that there are two distinct evacuation processes and that different expected evacuation durations are appropriate in the value of forecast calculations. This is the course followed in the computations. Also, sensitivity to +/- one standard deviation for these duration estimates is examined.

Daily Drilling Rates

The duration of evacuations has been analyzed above. The other component to the total cost of evacuations is the daily drilling rate. The primary daily cost lies in the drilling rig dayrate. While terms and conditions vary by contract, the operator is typically liable for a large portion of the drilling dayrate during a hurricane evacuation. The operator is also typically responsible for standby rates for ancillary service contractors. Given that dayrates vary over time and between rig type, the model accounts for changes in daily drilling rates.

Data has been collected on monthly drilling rig dayrates in the Gulf of Mexico for different rig types (platform, jackups, submersibles, and semisubmersibles) for 1980-1999. While the evacuation data does not consistently indicate which rig type is being employed on a given location, the water depth at the location can be used as a proxy for rig type. It is recognized that such a proxy cannot distinguish between a platform rig and a semisubmersible rig for wells in the relevant overlapping depths, or when semisubmersibles are inefficiently employed to drill in shallow waters, or for platform rigs in shallow waters or on the tallest platforms. One can make the assumption that exploration wells (E) are more likely to be drilled by the semisubmersible and development wells (D) by the platform rig in the relevant overlapping depths. While the dayrate proxy is imperfect and will misassign costs on occasion, it is thought to be better than not addressing the issue at all, or just using duration multiplied by some average rig rate index. Therefore, the assignment rules as given in Table 3.15 are used.

Table 3.15: Daily Drilling Rate Assignments by Water Depth

Water depth	Well Type	Rig Cost Applied
0-400’	E or D	Jackup
>400’ and <1000’	E	Semi
>400’ and <1000’	D	Platform/Semi Avg.
>1000’	E or D	Semi

Estimates for Catastrophic Losses

An estimate is required of the losses (L) incurred given a decision not to evacuate. As mentioned above, it is important to recognize that losses are not deterministic, but random in nature. That is, even when a hurricane does hit a rig, the rig may be totally undamaged. Decision-makers know this, and therefore are hypothesized to base their decisions on an expectation of L, E(L). To estimate E(L), an estimate of L given a catastrophic loss is required, and an estimate of the probability of loss given the rig is hit by hurricane force winds. To this end, drilling rig casualty information from 1957-present was collected. The 1980-2000 data is presented in Table 3.16. The analysis is restricted to these years to model the current drilling rig fleet survivability (*i.e.* current technology in rig design).

Table 3.16: Drilling Rig Casualty Data, 1980-2000

Storm Year	Storm Count	Count of Rigs Suffering Catastrophic Loss	Count of Storms Causing Catastrophic Loss
1980	3	4	1
1981	4	0	0
1982	4	0	0
1983	2	4	1
1984	2	1	1
1985	7	4	3
1986	2	0	0
1987	2	1	1
1988	5	0	0
1989	2	0	0
1990	4	0	0
1991	1	0	0
1992	2	3	1
1993	2	0	0
1994	2	0	0
1995	7	0	0
1996	8	0	0
1997	1	1	1
1998	7	1	1
1999	5	0	0
2000	4	0	0
Sums	76	19	10

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

The Storm Count only includes those storms where hurricane force winds were observed. There are three critical issues regarding the construction of Table 3.16:

1. There are observations in the data set such as "Found laying on side after hurricane Allen," which would most likely have resulted in 100 percent fatalities if persons were on board. But 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*, they could be described 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, one cannot observe many of the needed details to make such judgments on a case by case basis.

2. Another gray area is the fact that one does 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. One would expect crews to continue working as long as possible, otherwise there is minor value to remaining on the rig.

3. The data set is likely subject to underreporting. Drilling contractors have a clear economic 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, ambiguous cases as described in #1 and #2 were included as "lost rigs."

Estimate of Loss Given a Catastrophic Event

Based on personal experience and informal interviews with current industry practitioners, 55 persons on board (POB) is assumed if the decision is made not to evacuate. The actual POB is a function of the operations underway at the time of the decision. To compute an expected loss, one requires an estimate of the economic value of human life. Estimation of the value of human life (VL) in this context 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).

In an influential article, Moore and Viscusi (1988) argue that models of the wage-risk tradeoff based on Bureau of Labor Statistics (BLS) data systematically underestimate VL. Their use of a more detailed data set published by the National Institute of Occupational Safety and Health (NIOSH) results in VL of $5-7 million, versus estimates of $2 million that commonly result from similar analysis of BLS data.

In a meta-analysis of results from 33 VL studies, Mrozek and Taylor (2002) find the mean to be $6 million, and to vary within a wide range of $15,863 to $30.7 million. They also present convincing evidence to suggest that more risk neutral workers may self-select into riskier occupations. This would result in lower wage differentials (than expected) and yield lower VL estimates, *ceteris paribus*. If offshore drilling is assumed to be a risky profession that attracts such risk neutral individuals, a $6 million VL may be too high. It is possible that offshore oil and gas workers come from such a population. But given the better relative safety performance of the offshore industry relative to private industry overall (according to BLS statistics, it is safer to work in the oil and gas industry than to work in a furniture factory), it is not clear that offshore work would be perceived as risky by a well informed worker. Whether such counter-intuitive statistics are known to the average worker is debatable.

To examine the sensitivity of forecast value to different estimates of VL, two cases are examined. First, a VL of $6 million is assumed. The loss given a catastrophic event occurs is then (55 persons)($6 million/person) = $330 million. Second, the forecast value is computed for a VL of $2.275 million, which is the average of two estimates for high risk occupations. In this case, the loss given a catastrophic event occurs is then (55 persons)($2.275 million/person) = $125 million.

Probability of Loss

The ideal probability of loss statistic would be computed by counting the number of rigs lost and dividing by the number of rigs exposed to hurricane force winds for the entire study period. This would be the independent probability of catastrophic loss facing each decision-maker given hurricane force winds. Unfortunately, this statistic cannot be computed, primarily because not all rigs operating during a hurricane will actually be exposed to hurricane force winds given the geographic extent of the drilling area. This precludes using an average rig count for this purpose. Also, as has been mentioned in several places, one can only observe those rigs in a drilling mode, and thus one cannot properly account for all rigs for the duration a hurricane. A proxy is proposed that will indicate the probability of catastrophic damage for a particular hurricane. This proxy is defined as:

Pr (L) = Pr (Hurricane imposing catastrophic loss | Hurricane exists).

From Table 3.16, this can be computed as 10/76 = 0.1316. This excludes all weak storms that are included in other calculations, such as those made in computing the probability information. Therefore, the expected loss in any storm would be computed as:

E(L) = L * Pr(L) = ($330 million) (0.1316) = $43,428,000 for the higher VL;
= ($125 million) (0.1316) = $16,450,000 for the lower VL.

Do Decision-Makers Employ An Expected Loss Approach?

It is possible that decision-makers are risk averse. Anecdotally, one observes that decision-makers are quick to evacuate when a storm appears as if it will enter the Drilling Area, almost regardless of its intensity. Decision-makers may be acting (computing) on the assumption that if the rig is hit and has not been evacuated, a large or complete loss will be incurred, not an expected loss as was presented above. The value of forecasts in the context of a complete loss assumption below will be explored below.

Managing the Nelson-Winter Computations

The goal is to compute V_k per Eqn. (3). The steps taken to build up and automate this computation are detailed in Appendix C. Here, an overview is provided.

In each year, storms have been identified that are relevant in the context of evacuation decisions. There are 111 storms for the 1980-2000 time period. They are distributed over time as shown in Table 3.17. 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 3.17: 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 3.17. To accomplish this, a table was created that contains information about every well ever drilled in the Gulf of Mexico with data provided from the Minerals Management Service (MMS). This step allows definition of ranges for both r and i for every storm j. The last series of steps collects and organizes other variables such as C_{rk} and all of the needed π_{ik} data.

Results and Discussion

In this section, the results of the value of forecast calculations are presented. In Tables 3.18 and 3.19, the value of forecast results for two forecast types, the 24- and 48-hour 50 knot forecasts assuming a VL of \$6 million are reported. The focus is on 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 presented. For each of these cases, the results assuming an expected loss of \$43,428,000 as computed above, and the complete loss value of \$330 million are presented. Following these results and discussion, a second set of results is presented based on a VL of \$2.275 million, giving an expected loss of \$16,450,000 based on the complete loss of \$125 million.

Table 3.18: Value of 24-hour, 50 knot Forecasts, VL = \$6 million, 1990-1999

	Historical Value of Forecasts (\$)		Value of Perfect Forecasts (\$)	
Year	E(L) = \$43,428,000	E(L) = \$330,000,000	E(L) = \$43,428,000	E(L) = \$330,000,000
1990	303,964	303,964	40,258,167	40,258,167
1991	53,515	53,515	22,808,581	22,808,581
1992	0	0	10,220,208	10,220,208
1993	1,140,544	1,140,544	43,243,933	43,243,933
1994	510,397	510,397	41,237,849	41,237,849
1995	461,995	461,995	127,967,801	127,967,801
1996	891,695	891,695	388,664,432	388,664,432
1997	415,204	415,018	116,711,954	116,711,954
1998	916,602	916,602	396,134,617	398,452,763
1999	969,056	969,056	218,536,542	218,536,542
Totals	5,662,973	5,662,786	1,405,784,082	1,408,102,229
Average	566,297	566,279	140,578,408	140,810,223

Table 3.19: Value of 48-hour, 50 knot Forecasts, VL = $6 million, 1990-1999

	Historical Value of Forecasts ($)		Value of Perfect Forecasts ($)	
Year	E(L) = $43,428,000	E(L) = $330,000,000	E(L) = $43,428,000	E(L) = $330,000,000
1990	0	0	40,607,217	40,607,217
1991	0	0	23,187,469	23,187,469
1992	0	0	10,580,438	10,585,633
1993	0	0	42,950,307	42,950,307
1994	0	0	41,929,505	41,991,113
1995	0	0	130,886,731	130,886,731
1996	770,945	0	399,749,334	399,905,275
1997	1,228,826	0	118,094,802	119,789,600
1998	2,546,732	0	391,114,592	398,172,614
1999	1,855,628	0	209,911,071	216,298,069
Totals	6,402,132	0	1,409,011,467	1,424,374,028
Average	640,213	0	140,901,147	142,437,403

The value of perfect forecasts is computed by setting $\pi_{11}=\pi_{22}=1$, $\pi_{12}=\pi_{21}=0$, $\pi_1=\pi^1$, and $\pi_2=\pi^2$. These results highlight the complexity of the impacts of the specification of C, L, and the π's on the value of forecasts. First, in examining the left hand side of the 24-hour results where the historical value of forecasts is computed for both an expected loss and a full loss amount, it is seen that the value of forecasts under the full loss assumption is almost identical to the value under the expected loss amount. The C/L ratio is extremely small even under the expected loss case, and the same set of observations are generally relevant. Recall that for a forecast to have any value, $\pi_{12} < C/L < \pi_{11}$. 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). And when $\pi_{12} = 0$, the scale of L is irrelevant based on the derivation of forecast value. In the 48-hour results, note the presence of zero values for many years, an indication of their inaccuracy (fewer instances of $\pi_{12} = 0$ means fewer observations included in the computation) relative to the 24 hour forecasts. Finally, note that the value of the 48 hour forecasts under the full loss assumption is zero. The assumption of full loss can be construed as a proxy for risk aversion, and one obtains the expected result, that the value of forecasts decreases if the decision-maker is risk averse.

Second, in examining the right hand side of each table where the value of perfect information is computed, one observes that the impact of L on the value of forecasts is modest. This is again explained by the structure of the derivation. To value perfect information, one sets π_{12} =0 and π_{11} =1. Because of this, even when L is large, all observations will be included, because C/L will always meet the relevance criterion. The fact that C/L is small will typically invoke the bottom half of Eqn. (2). Recall the structure of Eqn. (2):

$$
V_{rijk} = \begin{cases} \pi_{1ik}(\pi_{11ik} L - C_{rk}), \text{ when } C_{rk} / L > \pi^1_{ik} \\ \pi_{2ik}(C_{rk} - \pi_{12ik} L), \text{ when } C_{rk} / L \leq \pi^1_{ik}. \end{cases}
$$

Therefore, since π_{12} = 0, the magnitude of L will in most cases be irrelevant. Also note that in the context of perfect information, risk aversion (proxied by the scale of L) is irrelevant, because forecasts are deterministic.

The value of historical forecasts under the expected loss assumption ranges from $5-7 million for the decade. This figure is small when compared to overall spending in the industry, where one well of medium complexity may cost as much. <u>Based on this, one can conclude that the overall accuracy of forecasts in the 1990's has not been good enough to be of much use to decision-makers</u>.

In the context of valuing forecast improvements, computation of the value of perfect information defines the maximum possible benefit. Here it can be seen see that the average value of forecasts for the decade to be about $1.4 billion, or $140 million per year. With reliable forecasts, decision-makers could avoid costly false evacuations. This result conforms (in magnitude) to the rough estimate of the costs of evacuations presented above in the general motivation of the problem. There, the conclusion was that if there were two evacuations per year, the cost would be $106 million. If these evacuations were unwarranted *ex post* (which they often are), this cost can be construed as the value of perfect information. The fact that these estimates are of the same magnitude provides some empirical support for the integrity of the decision analytic approach. An empirically based estimate of the cost of false evacuations is performed below and will shed additional light on these estimates.

The calculations are repeated using a VL of $2.275 million and the results are given in Tables 3.20 and 3.21. The results shed light on the sensitivity of forecast value to VL.

Table 3.20: Value of 24-hour, 50 knot Forecasts, VL = $2.275 million, 1990-1999

	Historical Value of Forecasts ($)		Value of Perfect Forecasts ($)	
Year	E(L) = $16,450,000	E(L) = $125,000,000	E(L) = $16,450,000	E(L) = $125,000,000
1990	303,964	303,964	40,258,167	40,258,167
1991	53,515	53,515	22,808,581	22,808,581
1992	0	0	10,220,208	10,220,208
1993	1,140,544	1,140,544	43,243,933	43,243,933
1994	510,397	510,397	41,237,849	41,237,849
1995	974,093	461,995	127,967,801	127,967,801
1996	33,168,202	891,695	386,912,192	388,664,432
1997	14,042,740	415,018	108,550,088	116,711,954
1998	46,929,324	916,602	362,273,390	398,452,763
1999	5,036,433	969,056	212,503,319	218,536,542
Totals	102,159,211	5,662,786	1,355,975,527	1,408,102,229
Average	10,215,921	566,279	135,597,553	140,810,223

Table 3.21: Value of 48-hour, 50 knot Forecasts, VL = $2.275 million, 1990-1999

	Historical Value of Forecasts ($)		Value of Perfect Forecasts ($)	
Year	E(L) = $16,450,000	E(L) = $125,000,000	E(L) = $16,450,000	E(L) = $125,000,000
1990	0	0	40,607,217	40,607,217
1991	1,237,962	0	23,014,241	23,187,469
1992	0	0	10,455,540	10,585,633
1993	0	0	42,898,581	42,950,307
1994	146,515	0	41,567,240	41,991,113
1995	5,544,761	0	128,415,232	130,886,731
1996	18,755,495	0	339,631,161	399,905,275
1997	5,106,913	0	80,799,627	119,789,600
1998	27,752,892	0	269,811,870	398,172,614
1999	10,097,328	887,679	174,457,656	215,763,081
Totals	68,641,865	887,679	1,151,658,366	1,423,839,040
Average	6,864,187	88,768	115,165,837	142,383,904

These results highlight the sensitivity of forecast value to assumptions of VL. The value of historical forecasts under the expected loss cases increases by an order of magnitude or more. This is a result of the change in the C/L ratio. It has increased considerably and more observations now meet the criterion $\pi_{12} < C/L < \pi_{11}$ 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 C/L ratio is extremely small even under the full loss case, and very few observations are relevant. But as the E(L) 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 the derivation of forecast value. 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. Second, in examining the right hand side of each table where the value of perfect information is presented, one observes that the impact of L on the value of forecasts is modest. This result was discussed above.

For a VL of $2.275 million, the value of historical forecasts under the expected loss assumption ranges from $68-103 million for the decade. This figure is still small when compared to overall spending in the industry. Based on this, one can again conclude that the overall accuracy of forecasts in the 1990's has not been good enough to be of much use to decision-makers.

Again, in the context of valuing forecast improvements, computation of the value of perfect information defines the maximum possible benefit. Here, the range of forecast values is $1.1-1.4 billion for the decade, or $110 to $140 million per year. The change in VL did have a modest impact on the historical valuations. But overall, these estimates are close to the previous results, again because the scale of L is often made irrelevant because $\pi_{12} = 0$ under the perfect information assumption.

The results for the 48 hour, 50 knot forecasts are summarized in Table 3.22 to highlight the shared structure of all of the results.

Table 3.22: 48 hour, 50 knot Forecast, Average Annual Forecast Value ($million) for the 1990's

VL = $ 6 million

	Historical Forecasts	Perfect Information
E(L)	0.6	140.9
Full Loss	0	142.4

VL = $ 2.275 million

	Historical Forecasts	Perfect Information
E(L)	6.8	115.2
Full Loss	0.1	142.4

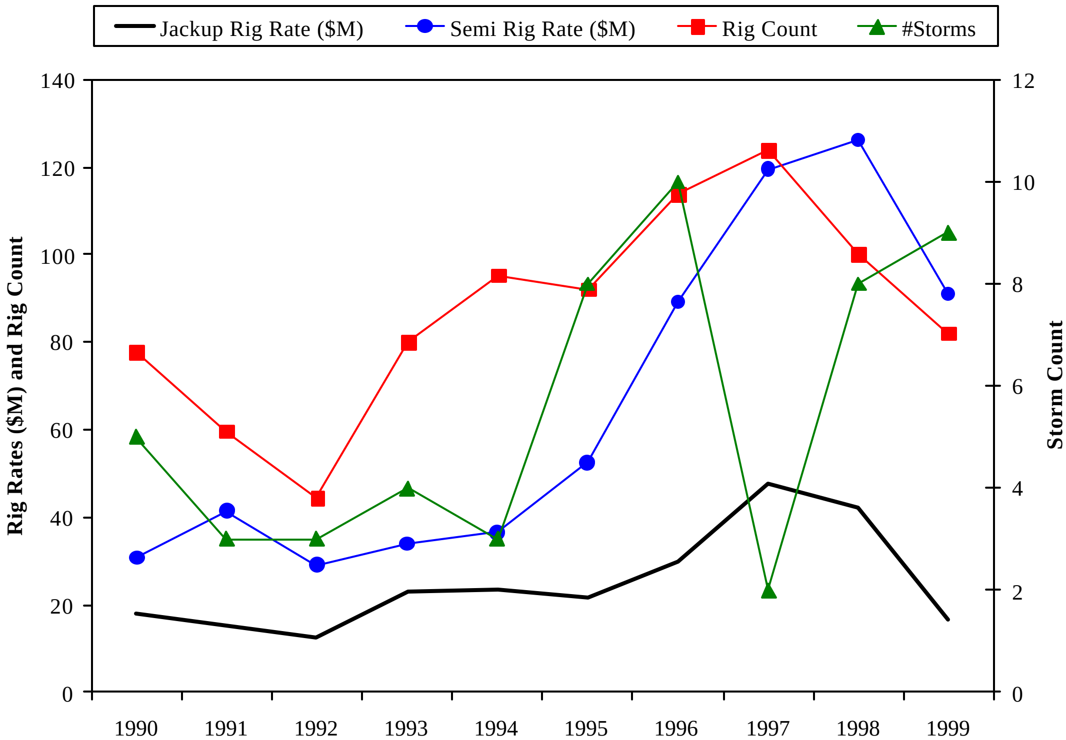
In sum, while the assumption of VL impacts the estimate for the value of historical forecasts, the difference is minor given the overall character of the results, *i.e.* relative to overall industry spending. Given this, the lack of a detailed VL estimate for offshore workers, and the variance of VL estimates in the literature, subsequent sensitivity analyses are limited to cases with the VL = $ 2.275 million assumption.

Finally, it is important to recognize that these estimates should be viewed as minimum forecast valuations. In the selection of drilling rigs from the MMS database, one is only able to observe those rigs that are in a drilling mode. That is, all rigs that are performing completions, workovers, abandonment, or are in transit are not included. For these unincluded rigs, one cannot know their location, or any of the other necessary criteria to perform a similar value of forecast calculation. It is also true that the POB figure when rigs are in a non-drilling mode is less than it would be in a drilling mode. A casual analysis of the data indicate that only ~60% of rigs are in a drilling mode at a given moment. It is likely that the rigs that are performing these non-drilling operations are more likely to be platform workover rigs (lower dayrates 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 is not attempted. Nevertheless, it does not seem inappropriate to multiply the results above by a factor of 1.2-1.4 to account for these *missing* rigs.

Additional Variables Influencing the Value of Forecasts

In Tables 3.18 – 3.21, considerable variance is observed in the annual forecast value estimates. At this point, it is important to note that in addition to C, L, and probability information, the value of forecasts in any year depends on the number of storms and the number of rigs operating (*i.e.* the number of decisions to be made). That is, perfect forecasts are valueless if no decisions depend upon them. Information on these data is presented in Figure 3.1 (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 3.1: Storm Count, Rig Count, and Rig Rates, 1990-1999



Sensitivity of Results to Estimates of Evacuation Duration

It is straightforward to alter the expected evacuation durations and recompute the value of information. Here, +/- one standard deviation for each of the rig types is examined:

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.

Tables 3.23 to 3.26 present this analysis for the VL of $2,275 million.

Table 3.23: Value of 24-hour, 50 knot Forecasts, Minus 1 s.d. of Costs, 1990-1999

Year	Historical Value of Forecasts ($)		Value of Perfect Forecasts ($)	
	E(L) = $16,450,000	E(L) = $125,000,000	E(L) = $16,450,000	E(L) = $125,000,000
1990	112,335	112,335	15,432,222	15,432,222
1991	19,777	19,777	8,894,671	8,894,671
1992	0	0	3,944,862	3,944,862
1993	421,505	421,505	16,532,796	16,532,796
1994	188,625	188,625	15,872,523	15,872,523
1995	170,737	170,737	49,696,555	49,696,555
1996	329,539	329,539	152,486,059	152,486,059
1997	171,513	153,376	45,749,795	45,749,795
1998	338,744	338,744	156,847,804	157,930,957
1999	358,129	358,129	86,559,896	86,559,896
Totals	2,110,906	2,092,769	552,017,181	553,100,335
Average	211,091	209,277	55,201,718	55,310,034

Table 3.24: Value of 48-hour, 50 knot Forecasts, Minus 1 s.d. of Costs, 1990-1999

Year	Historical Value of Forecasts ($)		Value of Perfect Forecasts ($)	
	E(L) = $16,450,000	E(L) = $125,000,000	E(L) = $16,450,000	E(L) = $125,000,000
1990	0	0	15,565,244	15,565,244
1991	0	0	9,051,298	9,051,298
1992	0	0	4,080,040	4,086,383
1993	0	0	16,444,273	16,444,273
1994	0	0	16,140,291	16,168,957
1995	0	0	50,837,890	50,837,890
1996	453,688	0	156,837,708	156,911,095
1997	668,580	0	46,040,919	46,961,297
1998	1,318,470	0	154,360,451	157,827,600
1999	698,763	0	82,870,001	85,665,211
Totals	3,139,500	0	552,228,117	559,519,248
Average	313,950	0	55,222,812	55,951,925

The value of forecasts decreases significantly with a decrease in evacuation costs. This is the expected result given that for most of the computations ($C / L \leq \pi^1$) the bottom half of Eqn (2) is computed:

$$V_{rijk} = \begin{cases} \pi_{1ik}(\pi_{11ik} L - C_{rk}), \text{ when } C_{rk} / L > \pi^1{}_{ik} \\ \pi_{2ik}(C_{rk} - \pi_{12ik} L), \text{ when } C_{rk} / L \leq \pi^1{}_{ik}. \end{cases}$$

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.

Table 3.25: Value of 24-hour, 50 knot Forecasts, Plus 1 s.d. of Costs, 1990-1999

	Historical Value of Forecasts ($)		Value of Perfect Forecasts ($)	
Year	E(L) = $16,450,000	E(L) = $125,000,000	E(L) = $16,450,000	E(L) = $125,000,000
1990	495,594	495,594	64,858,222	65,084,112
1991	313,261	87,252	36,686,581	36,722,490
1992	0	0	16,495,553	16,495,553
1993	1,767,158	1,859,582	69,837,297	69,955,070
1994	912,602	832,169	66,483,955	66,603,175
1995	5,126,653	753,253	204,420,921	206,239,047
1996	111,451,026	1,453,850	557,710,964	624,842,805
1997	22,583,500	676,660	136,358,909	187,674,114
1998	95,652,417	1,494,460	451,334,898	638,974,568
1999	38,193,240	1,579,983	306,154,565	350,513,188
Totals	276,495,451	9,232,804	1,910,341,864	2,263,104,122
Average	27,649,545	923,280	191,034,186	226,310,412

Table 3.26: Value of 48-hour, 50 knot Forecasts, Plus 1 s.d. of Costs, 1990-1999

	Historical Value of Forecasts ($)		Value of Perfect Forecasts ($)	
Year	E(L) = $16,450,000	E(L) = $125,000,000	E(L) = $16,450,000	E(L) = $125,000,000
1990	1,023,011	0	64,879,751	65,649,189
1991	2,961,362	0	32,538,597	37,323,640
1992	1,163,884	0	16,831,041	17,084,883
1993	3,194,151	0	68,138,494	69,456,341
1994	2,780,548	0	65,914,014	67,813,270
1995	9,622,454	0	172,741,686	210,935,572
1996	33,839,196	0	416,857,631	642,899,454
1997	3,976,014	800,000	95,890,402	192,617,903
1998	24,079,503	0	294,632,530	636,672,800
1999	24,225,684	4,098,857	212,102,614	343,467,564
Totals	106,865,808	4,898,857	1,440,526,759	2,283,920,617
Average	10,686,581	489,886	144,052,676	228,392,062

Under higher evacuation costs, one observes the expected result in the value of forecasts. Again, the C/L ratio generally dictates the computation of the bottom half of Eqn. (2), and the relationship between C and the value of forecasts is direct. Here, the value of historical forecasts increases by 57-70 percent, and the value of perfect information by 26-40 percent.

The Value of Partial Improvements in Forecast Accuracy

The value of historical and perfect information was computed above. The structure of those computations permits a straightforward assignment of probability values. Note that when performing the computations for perfect information, $\pi_{11}=\pi_{22}=1$ and $\pi_{12}=\pi_{21}=0$, π_1 must equal π^1 and π_2 must equal π^2. It is then assumed that π^1 and π^2 are given by the historical data for each grid block. Computations then proceed as described. But if one is interested to know the value of a partial improvement in forecast accuracy, say π_{11} = 0.60 for the 48-hour, 50 knot forecast (versus current average of 0.27), an expression for π_1 must be derived. Knowing that $\pi^1 = \pi_1 \pi_{11} + \pi_2 \pi_{12}$, it is clear that $\pi_1 = (\pi^1 - \pi_{12})/(\pi_{11} - \pi_{12})$. A problem arises if one uses historical values for π^1 which is often zero at the grid level. This will result in a negative value for π_1 which is of course inappropriate. Therefore, π^1, π_{12}, and π_{22} are set to their average values over the study period, and π_1 = (0.03-0.02)/(0.60-0.02) = 0.0172 ($\pi_2 = 1 - \pi_1 = 0.9828$). With these definitions, computations proceed normally. Computing the value of *imperfect improvement* in forecast accuracy allows a mapping of the value of forecasts as a function of improvement, informing any cost-benefit analysis in the context of public financing.

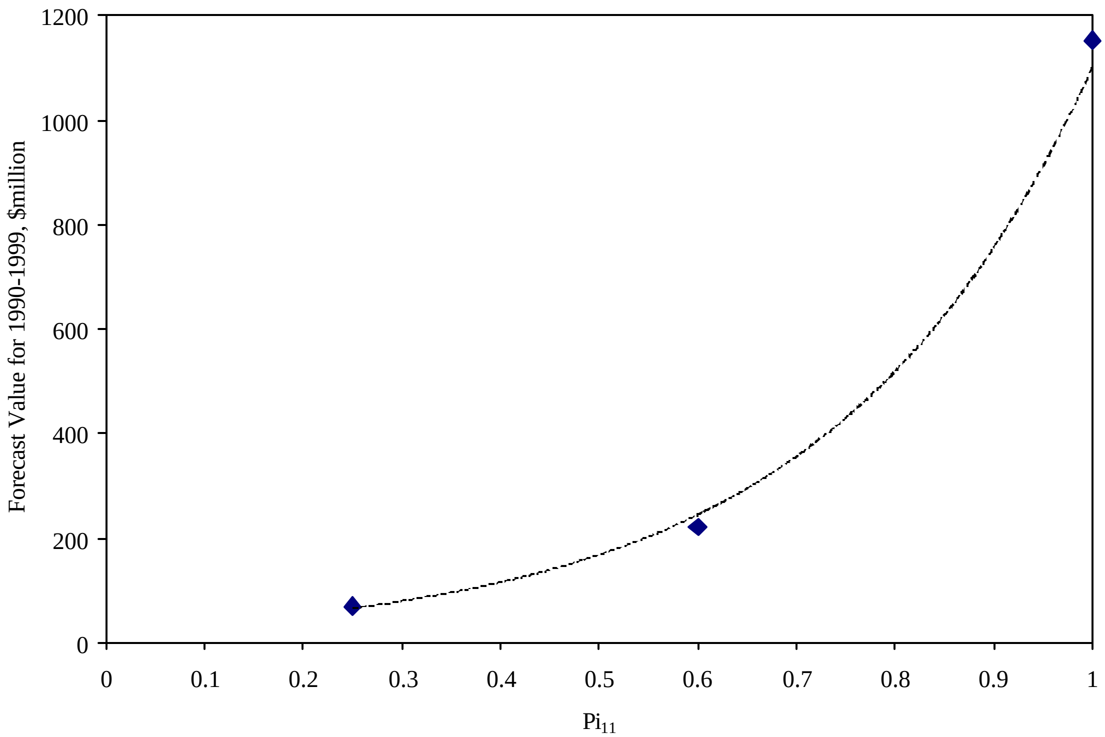
Table 3.27 presents the results for the 48-hour, 50 knot forecasts. Note, in these calculations, all grids face the same probabilities.

Table 3.27: Value of Imperfect Improvement (π_{11} = 0.60), 48-hour, 50 knot, VL = $2.275 million, 1990-1999

	Value of Imperfect Improvement ($)	
Year	E(L) = $16,450,000	E(L) = $125,000,000
1990	0	0
1991	1,135,871	0
1992	0	0
1993	0	0
1994	0	0
1995	17,664,356	0
1996	68,406,868	0
1997	15,400,781	0
1998	67,538,700	0
1999	51,304,500	0
Totals	221,451,076	0

The appropriate comparison for this result is Table 3.21. This limited analysis yields the expected result, the value of partial improvement falls between the status quo value of $69 million and value of perfect information of $1152 million for the expected loss of $16.45 million. For the full loss amount, C/L < π_{12} for all observations (by construction), so no values are relevant. While the construction of the computation required some strong assumptions and is not perfectly comparable to the structure of the previous computations, it is interesting to note that a doubling of π_{11} to equal 0.60, while increasing the value of forecasts by three, does not drive forecast value close to the value of perfect forecasts. This result is depicted in Figure 3.2 under the expected cost and loss assumptions.

Figure 3.2: Value of Forecast Improvement, 48-hour, 50 knot



Such a result implies that significant improvement in forecast accuracy over the status quo will be needed for forecasts to have meaningful value when compared to the overall scale of industry spending.

In summary, the value of current forecast information is insignificant when compared to overall industry expenditures, ranging from $5-7 million for the decade under expected costs and losses and a VL of $6 million. Under the perfect information assumption, the value of forecasts is estimated to be about $1.4 billion for the decade. This perfect information valuation is significant when compared to overall industry expenditures. When the VL is assumed to be $2.275 million, the value of current forecast information ranges from $68-103 million for the decade under expected costs and losses. Under the perfect information assumption, the value of forecasts is estimated to range from $1.1-1.4 billion for the decade. There is also a strong sensitivity in both directions to variation in the costs of evacuation. Again, note that all of these figures could be scaled up to account for (unobservable) rigs that are not in a drilling mode. The analysis of imperfect improvement of forecast accuracy indicates that significant improvement in forecast accuracy over the status quo will be needed for forecasts to have meaningful value to industry.

3.5 Modeling the Decision to Evacuate – A Descriptive Approach

There has been considerable interest in whether or not prescriptive models of decision 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 examined. First, a qualitative analysis of the evacuation data set is made. This analysis sheds light on the overall propensity to evacuate, and permits a rough estimate of the costs of false evacuations to be made. Second, two econometric models of the decision to evacuate are specified. 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, and a more general model is estimated instead. A catalog of descriptive studies is available in Johnson and Holt (1997).

A Qualitative Assessment

In this section, a qualitative assessment of a sample of actual evacuation observations is made. This assessment is used 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 will also inform the specification of an econometric model of evacuation decision-making that follows. Evacuation data was collected for a sample of 15 storms spanning 1979-1989 (this time period yielded significantly more observations than the 1990's from the commercial data provider). Each observation represents an individual drilling rig, *i.e.* a decision. The storms, observation counts, percent of rigs evacuated, and the *ex post* peak wind speed of the storm (in/near the drilling area) are given in Table 3.28. The Drilling Area is defined to be west of 85 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.

Table 3.28: Evacuation Data Set, Basic Statistics

Year	Storm Name	#Obs	Percent Evacuated	Peak Wind Speed in Drilling Area
1979	Bob	9	0.89	65
1979	Claudette	10	0.70	45
1980	Allen	11	1.00	155
1980	Jeanne	18	1.00	60
1983	Alicia	13	0.46	100
1983	Barry	12	0.42	70
1985	Danny	22	1.00	75
1985	Elena	15	0.87	90
1985	Juan	18	0.83	75
1985	Kate	15	1.00	105
1988	Flo	14	0.79	70
1988	Gilbert	13	1.00	160
1988	Keith	12	0.00	60
1989	Chantal	16	0.88	55
1989	Jerry	10	1.00	64
	Total #Obs	208		

The observation count includes all decisions to evacuate or to remain on the rig. Recall that in Table 3.13 above, only those observations where an evacuation occurred are included, thus the increase here in the total number of observations. Each storm path was carefully examined, and the *ex post* peak wind speed and draw the following general conclusions regarding decision-making behavior:

1. 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.

2. 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 following 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.

3. If a storm forms <u>within</u> the drilling area, the evacuation decision is mixed (*e.g.* Alicia).

While these conclusions are quite general, they provide sufficient guidance to predict evacuation decisions for the majority of storms outside of the sample. For example, one can predict with confidence that 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 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, analog storm from the actual sample can be employed as a guide.

Ad Hoc Prediction of Evacuation Decisions

In this section, ad hoc evacuation predictions are made using the general conclusions above, and analogs are employed for cases where the state of evacuation is unclear. For the latter instances, Alicia and Barry are relied on as analogs, and evacuation rates of 50 percent are assigned. These results are presented in Table 3.29. Not included in this list are those storms where a complete non evacuation is predicted, because in such cases the value of forecast information is likely to be zero given the non-threatening nature of such storms (*e.g.* a mid-Atlantic storm).

Table 3.29: Evacuation Predictions for Out-of-Sample Storms, 1979-1999

Year	Storm Name	Actual (Predicted) Percent Evacuated	Peak Wind Speed in Drilling Area	Analog(s)
1979	Bob	0.89	65	
1979	Claudette	0.7	45	
1979	Frederic	(1.00)	115	
1979	Elena	(0.50)	35	Alicia (1983)
1980	Jeanne	1	60	
1980	Allen	1	155	
1983	Alicia	0.46	100	
1983	Barry	0.42	70	
1985	Juan	0.83	75	
1985	Danny	1	75	
1985	Elena	0.87	90	
1985	Kate	1	105	
1986	Bonnie	(0.50)	75	Alicia (1983)
1988	Flo	0.79	70	
1988	Gilbert	1	160	
1989	Jerry	1	64	
1989	Chantal	0.88	55	
1992	Andrew	(1.00)	120	
1994	Alberto	(0.85)	55	Bob (1979), Flo (1988), Chantal (1989), Juan (1985)
1995	Allison	(1.00)	65	
1995	Erin	(1.00)	80	
1995	Opal	(1.00)	130	
1996	Josephine	(0.50)	60	Alicia (1983)
1997	Danny	(0.50)	70	Alicia (1983)
1998	Georges	(1.00)	95	
1998	Earl	(1.00)	85	
1998	Charley	(0.50)	60	Alicia (1983)
1998	Frances	(0.85)	55	Bob (1979), Flo (1988), Chantal (1989), Juan (1985)
1998	Hermine	(0.50)	40	Alicia (1983)
1999	Bret	(1.00)	125	
1999	Harvey	(0.50)	50	Alicia (1983)

Valuing Forecast Information

Criteria are required to determine if an evacuation was warranted *ex post*. Above it was discussed that 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 also 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 (maximum sustained wind speeds of 82 knots, gusts higher), and would evacuate for anything stronger. Using this criterion, one can make an *ex post* assessment of whether an evacuation was warranted or not for both the actual and predicted observation decisions. This assessment is presented in Table 3.30.

Table 3.30: Ex Post Assessments of Decision to Evacuate, 1979-1999

Year	Storm Name	Actual (Predicted) Percent Evacuated	Peak Wind Speed in Drilling Area	Ex Post? (FALSE ALARM = 1)
1979	Bob	0.89	65	1
1979	Claudette	0.7	45	1
1979	Frederic	(1.00)	115	0
1979	Elena	(0.50)	35	1
1980	Jeanne	1	60	1
1980	Allen	1	155	0
1983	Alicia	0.46	100	0
1983	Barry	0.42	70	1
1985	Juan	0.83	75	1
1985	Danny	1	75	1
1985	Elena	0.87	90	0
1985	Kate	1	105	0
1986	Bonnie	(0.50)	75	1
1988	Flo	0.79	70	1
1988	Gilbert	1	160	1
1989	Jerry	1	64	1
1989	Chantal	0.88	55	1
1992	Andrew	(1.00)	120	0
1994	Alberto	(0.85)	55	1
1995	Allison	(1.00)	65	1
1995	Erin	(1.00)	80	1
1995	Opal	(1.00)	130	0
1996	Josephine	(0.50)	60	1
1997	Danny	(0.50)	70	1
1998	Georges	(1.00)	95	0
1998	Earl	(1.00)	85	0
1998	Charley	(0.50)	60	1
1998	Frances	(0.85)	55	1
1998	Hermine	(0.50)	40	1
1999	Bret	(1.00)	125	0
1999	Harvey	(0.50)	50	1

Note it is assumed 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 the rough estimates used to motivate the present question. Using the appropriate rig dayrates, the cost of these false alarms by year can be computed. The results are presented in Table 3.31.

Table 3.31: The Cost of False Evacuations

Year	Estimated Total Cost of False Evacuations
1979	87,624,346
1980	29,208,115
1981	0
1982	0
1983	9,711,992
1984	0
1985	24,525,717
1986	3,643,744
1987	0
1988	16,809,146
1989	17,264,256
1990	0
1991	0
1992	0
1994	14,657,848
1995	33,002,246
1996	31,674,878
1997	49,592,056
1998	118,455,337
1999	19,167,244
Sum	455,336,924
Average	22,766,846
Standard Dev.	31,304,941

The estimated average annual cost of false hurricane evacuations over this study period is $23 million. While costs in one year may be as high as $118 million, the fact that several years do not experience an evacuation pushes the average down considerably. Note that these figures are computed only for the rigs observed in a drilling mode. As was discussed above, these figures can be scaled up, perhaps by a factor of 1.2-1.4 to account for unobserved rigs. The resulting values are of course a function of the joint distribution of hurricanes, rig counts and rig rates (recall Figure 3.1).

To compare these results with those of the Nelson-Winter analysis, note the sum of annual costs for 1990-1999 is $270 million (from Table 3.31). As was argued above, this cost can be viewed as the value of perfect information, *i.e.* avoidable costs. This sum is about one-fifth of the value of perfect information estimated via the Nelson-Winter analysis. The sources of this difference are several. First, the ad hoc analysis uses a higher wind speed criterion (82 knots) to determine whether or not an evacuation was warranted *ex post*. Recall that the Nelson-Winter analysis uses the 50 knot criterion throughout. Second, the domain of the ad hoc analysis is restricted to those storms that were judged likely to elicit an evacuation decision, while the domain of the Nelson-Winter analysis includes all storms that entered the large Watch Area. Thus, the Nelson-Winter approach may have valued forecasts for storms that were irrelevant from a decision-making perspective, and the ad hoc approach may have overlooked some storms that were in fact relevant. Third, the ad hoc approach is not indexed at the grid level as is the Nelson-Winter approach, and thus is based on less detailed information. Given these differences, it is unclear what weight to attach to the ad hoc estimate, but the results do provide some information on the sensitivity of the Nelson-Winter results to alternate assumptions. The results provide a bracket for the value of perfect information for the decade in the $250-1400 million range. It is probable that the true value is closer to the low end given the more accurate selection of relevant storms, and the fully empirical nature of the qualitative estimate, albeit with an ad hoc approach for predicting evacuation rates.

In an attempt to reconcile some of this difference in valuations, examine the Nelson-Winter perfect forecast valuations only for the storms in Table 3.30, *i.e.* Andrew to Harvey. This eliminates one source of error in the definition of the domain of the analysis. Summing perfect forecast values for these storms yields the results shown in Table 3.32 for both forecast types. These values are closer to the $270 million qualitative estimate, and a more appropriate comparison of the two methods.

Table 3.32: Perfect Forecast Values for Subset of Relevant Storms

	24-hour	48-hour
1990	0	0
1991	0	0
1992	3,475,000	3,468,000
1993	0	0
1994	12,783,000	13,033,000
1995	48,469,000	48,542,000
1996	37,218,000	32,336,000
1997	53,426,000	40,343,000
1998	226,292,000	170,018,000
1999	43,696,000	36,232,000
Totals	425,359,000	343,972,000
Average	42,535,900	34,397,200

Note that lowering the wind speed criterion in the ad hoc analysis would only lower the values in Table 3.32. These results provide support for a value of perfect information in the lower end of the range stated above. Relative to the overall scale of industry spending, this is small, and may not warrant significant public finance of initiatives to improve hurricane forecasts.

Discrete Choice Models

In this section, the descriptive analysis of evacuation decision-making is formalized via a discrete choice model. Of primary interest are those storms where a variety of decisions are observed (*i.e*. evacuation percentage >0.00 or <1.00). Storms that meet this criterion are: Alicia, Barry, Bob, Chantal, Claudette, Elena, Flo, and Juan. Bob (1979) and Claudette (1979) are not included in the present analysis due to incompleteness of other data sets constructed by the author, which begin in only 1980. 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.

The Criteria for Evacuation

Offshore operations and the decision to evacuate have been described in some detail. As a result of the qualitative analysis, it is expected that decision-makers elect to evacuate based on a complex set of variables. These include specifics of the well in progress, the physical location of the rig, logistics, attributes of the decision-maker, forecast and actual storm positions and strength. Therefore, an econometric model of decision-making should capture as many of these components as possible.

Econometric Model of the Decision to Evacuate

The decision to evacuate for a particular hurricane is modeled as a discrete choice. 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. The probit is employed here, and its development has been described previously. In summary, an unobservable latent variable is defined, Y_i^*, as the propensity to evacuate as follows:

$$Y_{it}^* = X_{it}\beta + u_{it} \qquad (4)$$

where,

Y_{it}^* = Unobserved latent variable
X_{it} = Vector of independent variables
β = Vector of parameters, to be estimated
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 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.

Y_{it}^* is not observed, but Y_{it} is according to the rule:

$$Y_{it} = \begin{cases} 1 \text{ if } Y_{it}^* > 0 \text{ (evacuate)} \\ 0 \text{ otherwise (not evacuate).} \end{cases} \qquad (5)$$

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 negative inverse of the Hessian evaluated at the maximum likelihood estimates.

i. An Ideal Specification

The ideal specification of Eqns. (4) and (5) 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 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. Note that temporally unbalanced series are likely, as 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. The observations of the exact time of the evacuation are not precise. All that is readily observable is whether the rig was evacuated, and the approximate duration of the evacuation. The evacuation observations are taken 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. Because of this, 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. Finally, for those rigs that did not evacuate, one cannot observe *when* that decision was made, regardless of the quality of the present data set.

ii. A Relaxed Specification

Given the quality of the data on evacuations, a relaxed specification is proposed that models the discrete choice to evacuate, but does not incorporate the exact timing of the decision. The decision to evacuate for a particular hurricane is modeled as a discrete choice. Either the crew is released from the rig, or it stays on location and rides out the hurricane. This decision can be modeled per Eqns. (4) and (5) as above, with the deletion of the subscript t. All that is modeled is the ultimate decision to evacuate or not, and the timing of the evacuation is not incorporated. 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 more likely to respond to the 24 or 48-hour forecasts.

In this specification, time related (weather related) information is removed from the model. But recall that the qualitative analysis demonstrated consistent evacuation behavior across decision-makers for the primary categories of storm types (paths and intensities) observed. Based on the relative similarity of the forecasts for each drilling location for those storms where evacuation rates differ (*e.g.* when the storm originates in the Drilling Area), the reasons for *differences* in the discrete 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. Also note that models will be specified that include individual storm effects, and this addresses in part the unique attributes of each storm.

Independent Variables

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.

<u>Decision-Maker Attributes</u>. 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, a variable **RET** is defined 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. A variable **OPCUM** is defined 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 hypothesis regarding the sign of this coefficient. That is, it is not clear whether experience should lead to caution, or confidence.

<u>Location and Well Attributes.</u> It is reasonable to suspect that 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 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. 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. 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 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. A binary variable, **EVD**, is constructed 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 these hypothesis, the expectation for the sign of this coefficient is 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.

<u>Evacuation Costs</u>.

When evacuation costs are low, the likelihood of evacuation is increased, *ceteris paribus*. For each storm and rig type, one can estimate the evacuation cost (**COST** = rig rate*evacuation duration). This value varies between rig types and over the years as rig rates change. If significant, the expectation for the sign of this coefficient is negative.

Descriptive Statistics

For the six storms modeled here, correlation coefficients and basic descriptive statistics are computed. These are summarized in Tables 3.33 and 3.34.

Table 3.33: Descriptive Statistics for Discrete Choice Explanatory Variables

	Mean	Standard Deviation	High	Low
Y (Evacuate? Yes=1)	0.73	0.45	1.00	0.00
RET	0.69	0.46	1.00	0.00
OPCUM	808.94	726.44	3068.00	2.00
DEPTH	9852.32	5585.10	22000.00	360.00
WD (raw)	558.48	762.21	3252.00	13.00
WD400 (binary)	0.35	0.48	1.00	0.00
EVD	0.82	0.38	1.00	0.00
COST ($'000)	115.29	67.92	219.06	61.90
Evacuation Days	4.51	4.77	23.00	0.00
OPCY	37.93	21.81	83.00	2.00

Observations: 85 (6 storms)

The continuous variables exhibit wide ranges, and the binary variables are not significantly unbalanced. In addition to the variables previously defined, Table 3.33 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 3.34: Correlation Coefficients for Discrete Choice Explanatory Variables

	Y	RET	OPCUM	DEPTH	WD	WD400	EVD	COST	DAYS	OPCY
Y	1.00									
RET	-0.04	1.00								
OPCUM	-0.12	**0.57**	1.00							
DEPTH	-0.09	0.10	-0.01	1.00						
WD	0.07	0.25	0.08	0.04	1.00					
WD400	0.08	0.25	0.12	0.01	0.77	1.00				
EVD	-0.01	0.04	0.01	-0.03	0.16	0.12	1.00			
COST	0.17	0.28	0.05	-0.02	**0.72**	**0.93**	0.07	1.00		
DAYS	0.55	0.02	0.06	0.07	0.31	0.32	0.01	0.32	1.00	
OPCY	-0.02	0.62	**0.76**	0.06	0.02	0.00	0.02	0.00	0.03	1.00

Significant results are highlighted. Analysis of the correlation coefficients 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.

Further information about the source and construction of company and well data variables can be found in Appendix A.

Estimation

Recall, the sample is defined with 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 in Table 3.13 for this sample of storms (by three). This is due to the fact that some evacuation observations occur on state leases where no borehole specific data is available, so the full vector of independent variables is unavailable. These observations have been retained in other calculations herein where possible.

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. These results are not presented. When all observation are pooled, the following results are generated as presented in Table 3.35.

Table 3.35: Probit Model of Evacuation, Pooled Sample

Variable	Coefficient Estimates (t-stats)	
C	0.7109	(1.331)
RET	-0.1920	(-.456)
OPCUM	-0.0076	(-.029)
DEPTH	-0.0804	(-.296)
WD400	0.7688	(2.184)
EVD	-0.1364	(-.338)
LR (p-value)	5.2989	(0.381)
Log Likelihood	-46.9772	
LR Index	0.0534	
# Observations (Pos)	85 (62)	

Note that COST variable is omitted due its high correlation (ρ = 0.93) 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, likely due to 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 the expectation of the sign of the COST variable was negative, the higher the cost of evacuating, the less likely to evacuate. Given that WD400 and COST are highly correlated (positively), one can conclude from the positive sign on WD400 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 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 can be specified based on one of the evacuation rules derived above in the qualitative analysis of evacuation decisions. Based on that analysis, a new binary variable is defined, ORIGIN, which takes on a value of one when the storm forms within the Drilling Area, and a value of zero otherwise. Additional specifications based on the other of the above rules would rely on *ex post* information that would not be available to decision-makers, and this approach is avoided. The results of this specification are given in Table 3.36.

Table 3.36: Probit Model of Evacuation with ORIGIN Variable, Pooled Sample

Variable	Coefficient Estimates (t-stats)	
C	0.838	(1.529)
RET	-0.167	(-.393)
OPCUM	0.098	(.364)
DEPTH	-0.093	(-.334)
WD400	0.735	(2.014)
EVD	-0.196	(-.476)
ORIGIN	-0.842	(-2.086)
LR (p-value)	9.705	(.138)
Log Likelihood	-44.774	
LR Index	0.098	
# Observations (Pos)	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 can be 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 which exhibited a high proportion of evacuations which may be a result of the particular storm histories. Since the error terms are i.i.d., the discrete nature of the dependent variable does not introduce any unusual estimation issues. These results are presented in Table 3.37.

Table 3.37: 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 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 evacuation rates between storms is observable 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.

Note how the decision-maker attribute 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.

Recall that the error terms in the fixed effect model are i.i.d. 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 deferred for follow-up work.

Discussion

In this section the decision to evacuate has been examined from two perspectives. The first involved a qualitative assessment of evacuation decisions, development of empirical evacuation rules, and application of these rules (and analogs) to estimate the cost of false evacuations. The initial estimate of $270 million for 1990-1999 is about one-fifth of the value of perfect information estimated via the full blown Nelson-Winter analysis. The probable sources of this difference are differences in the wind speed criterion and in the domain of the analyses. In the Nelson-Winter approach, forecasts were valued for all storms that entered the large Watch Area, not just those that entered or came close to entering the Drilling Area as was done in the analog/rules-based approach. The Nelson-Winter approach may have wrongly valued forecasts for storms that were in fact irrelevant from a decision-maker's standpoint. Given this large difference, the Nelson-Winter results were examined only for the subset of storms used in the qualitative estimate, controlling for the domain. These results put the value of perfect information in the $340-425 million range. This result provides support for an estimate of the value of perfect information in the range of $250-425 million for the decade, or $25-42 million per year. Relative to the overall scale of industry spending, this is small, and may not warrant significant public finance of initiatives to improve hurricane forecasts for offshore drilling.

The second part of the qualitative investigation involved 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. 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. The pooled models are of limited use due to their low explanatory power and the fact that the pooled model always predicts an evacuation (note that the pooled model with the ORIGIN variable does vary in its predictions, but such storms are rare). The fixed effect model, while offering slightly better explanatory power, is of no use for predicting evacuations for storms outside of the sample. Even if analogs could be identified, they would not be available to decision-makers *ex ante*, hence such an approach would not be valid. Finally, if these barriers did not exist, it is unlikely that the results of such an exercise would diverge greatly from the results of the Nelson-Winter and analog/rules-based approach.

3.6 Risk Aversion, Utility, and the Decision to Evacuate

In this section, risk preferences of the decision-maker are explicitly introduced. If the decision-maker is risk averse, the results of the Nelson-Winter analysis (where a risk neutral decision-maker was assumed) may be fundamentally flawed. Therefore, investigation into risk preferences is of some interest. 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. In this section, such a model is specified and estimated.

Structural Model of the Decision to Evacuate

A structural model of decision-making in a utility framework is developed along the lines of Cicchetti and Dubin (1994), who studied the decision to self-insure in the context of home telephone maintenance. 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:

$$U(W\text{-}C;\, s) + e_1 > (p)U(W\text{-}L;\, s) + (1\text{-}p)U(W;\, s) + e_2, \qquad (6)$$

where,

W = a measure of wealth
C = evacuation cost
p = probability of a hit
L = 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:

$$\Pr(\text{evacuation}) = 1 / (1+ e^{-\theta}), \quad (7)$$

$$\text{where } \theta = U(W\text{-}C; s) - [(p)U(W\text{-}L; s) + (1\text{-}p)U(W; s)]. \quad (8)$$

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:

$$U(W; s) = a_1(W+a_2)^k + e. \quad (9)$$

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 $a_1(W\text{-}C+a_2)^k + e_1$. Given the decision to remain on the rig, utility is $(p)a_1(W\text{-}L+a_2)^k + (1\text{-}p)a_1(W+a_2)^k + e_2$.

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:

$$k = b_1 + b_2RET + b_3OPCUM + b_4WD400 + b_5EVD + b_6DEPTH. \quad (10)$$

A simpler specification of $k = b_1 + b_2OPCUM + b_3WD400$ 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 necessitated if the full specification is poorly conditioned with respect to convergence.

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 decision-maker in the year of the observation, OPCY. For example, one can 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) to get an annual expenditure value. This approach puts the decision into one of *annual* utility maximization. Descriptive statistics for OPCY are given in Table 3.33. 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.

Regarding other variables of the model:

C = evacuation cost, determined by the rig type and year of the observation. Descriptive statistics are given in Table 3.33.

L = the expected loss given a hit, E(L). 55 POB and a VL of $2.275 million is assumed as was done in the Nelson-Winter analysis.

p = the historic climatological probability of a hit,

and parameters to be estimated are the a_i and b_i.

This specification leads to the following likelihood function:

$$L = \Pi_i \left[1 / (1 + e^{-\theta i}) \right]^{yi} \left[1 - \{1 / (1 + e^{-\theta i})\} \right]^{1-yi}, \qquad (11)$$

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

Estimation

Maximization of Eqn. (11) 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. Recall for example Eqn. (9): $U(W; s) = a_1(W+a_2)^k + e$. Given that the goal is to estimate parameters comprising k and a_2 itself, no restrictions are placed 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 during each iteration, rescaling of explanatory variables, and adjusting starting values. Use of all these methods was required for this data set.

The results for the pooled sample with the full specification of k are given in Table 3.38. All terms measured in dollars have been rescaled to millions of dollars, and standard errors are computed using the negative inverse of the Hessian evaluated at the maximum-likelihood estimates.

Table 3.38: Coefficient Estimates, Pooled Sample

Variable	Coefficient Estimates (t-stats)	
A1	18.313	(.0521)
A2	248.219	(.1105)
B1	0.677	(.2708)
WD400	0.229	(.6300)
OPCUM	0.016	(.2452)
RET	-0.025	(-.1687)
DEPTH	0.013	(.1593)
EVD	-0.070	(-.4438)
Log Likelihood	-47.317	
# Observations (Pos)	85 (62)	

Results are reported using the names of the explanatory variables, versus the b_i's, for clarity. Standard errors are computed using the negative inverse of the Hessian evaluated at the maximum likelihood estimates. Of most interest are the parameters comprising the variable k defined above. Of all the decision-maker and location attributes, not one is significant. Nonetheless, 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). 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. Also, the scale of the a_2 coefficient could be viewed as a red flag that the numerical optimization had gone off course. But given the form of the underlying utility function, this is not problematic. Recall that the wealth, cost and loss values are raised to a small power, so this type of result might be expected.

In addition to the above specification, one can specify and estimate the model with a simpler specification of k as described above. This is helpful in the numerical optimization as complexity is added to the specification (below), so long as the sacrifices in explanatory power are insignificant. The model was estimated with the simpler specification of k, and the results are given in Table 3.39.

Table 3.39: Coefficient Estimates, Pooled Sample ($k = b_1 + b_2$OPCUM + b_3WD400)

Variable	Coefficient Estimates (t-stats)	
A1	269.753	(.0451)
A2	421.961	(.1637)
B1	0.334	(.1550)
WD400	0.168	(.4854)
OPCUM	0.005	(.1096)
Log Likelihood	-47.579	
# Observations (Pos)	85 (62)	

The simplified model provides essentially the same fit as the fully specified model, thus the parsimonious approach is employed hereafter. Again, none of the explanatory variables is significant.

Finally, k is respecified to test for fixed effects of each storm as follows:

$$k = b_2\text{WD400} + b_3\text{OPCUM} + c_1\text{ALICIA} + c_2\text{BARRY} + c_3\text{CHANTAL} + c_4\text{ELENA} + c_5\text{FLO} + c_6\text{JUAN}.$$

This controls for differences in behavior between storms. The model is estimated and the results presented in Table 3.40.

Table 3.40: Coefficient Estimates, Pooled Sample with Fixed Effects

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)	

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. 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. Again, the predicted values of k can be interpreted as an indicator of the degree of risk aversion. 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. Note the focus only on the positive values of k due to the definition of the degree of absolute risk aversion, R(W), for the utility function as it is defined. Note that $R(W) = - R(W)'' / R(W)' = (1-k) / W + a_2$. 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 indicate a higher degree of risk aversion.

Discussion

The results from the 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, and by several nonconforming (negative) estimates of k. 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. This is the only variable in the models, basic discrete choice included, that is consistently in line with hypotheses. 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.

3.7 Conclusions

The investigation reveals several key findings about the decision to evacuate in the offshore oil and gas industry. First, the prescriptive, decision analytic model indicates that over a range of value of life estimates (VL), the value of current forecast information is insignificant when compared to overall industry expenditures, ranging from $5-103 million for the decade of the 1990s. Under the perfect information assumption, the value of forecasts is estimated to be about $1.1-1.4 billion for the decade. This perfect information valuation is more significant when compared to overall industry expenditures. There is also a strong sensitivity in both directions to variation in the costs of evacuation. The analysis of imperfect improvement of forecast accuracy indicates that significant improvement in forecast accuracy over the status quo is required for forecasts to have meaningful value to industry. This result provides little ammunition for those parties arguing for increased public financing of weather research.

A descriptive methodology was also exercised. Based on a qualitative assessment of evacuation decisions, development of empirical evacuation rules, and application of these rules to estimate the cost of false evacuations, the value of perfect forecasts is estimated to be $270 million for the 1990s, about one-fifth of the value of perfect information estimated via the prescriptive approach. The probable sources of this difference are differences in the wind speed criterion and in the domain of the analyses. The Nelson-Winter approach may have wrongly valued forecasts for storms that were in fact irrelevant from a decision-maker's standpoint. Given this large difference, the Nelson-Winter results were examined only for the subset of storms used in the qualitative estimate, *i.e.* those judged to be relevant from a decision-making standpoint. This controls for error due to the domain definition. These results put the value of perfect information in the $340-425 million range, much closer to the qualitative estimate of $270 million. This result provides support for an estimate of the value of perfect information in the range of $250-425 million for the decade, or $25-42 million per year.

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. Regardless of the barriers, it is unlikely that the results of such an exercise would diverge greatly from the results of the Nelson-Winter and analog/rules-based approach.

Finally, the results of the utility based model 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 this discussion two items regarding the domain of the investigation have been noted. Due to data availability, the focus is only on drilling rigs and excludes 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, the analysis generally includes only those rigs in a drilling mode, and excludes those performing completions, workovers, abandonment, or that are in transit. To account for this latter factor, the results could be scaled up by a factor of 1.2-1.4 to account for these omitted rigs.

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APPENDIX A

Description of Origin and Organization of Independent Variables for Organizational Choice Data Set

This data appendix describes the data collection and manipulation procedures for most of the independent variables employed in this research, including some which were originally proposed but subsequently dropped from the analysis. While some attention is given to relating these procedures and the resulting variable vectors to the economic theory contained in the body of the paper, the focus here is on the nuts-and-bolts details of how the data was collected and organized into usable formats, primarily for record-keeping and reference.

A basic understanding of database terminology is assumed.

The appendix is organized as follows:

A.1 Description of Source Data Tables

This section of the Appendix describes the basic data tables and the most important fields contained therein. Together, these tables form the raw data source(s) for queries that (in part) generate the matrices of explanatory variables.

The Borehole Table

The borehole table captures technical information about each well drilled in the Gulf of Mexico OCS since drilling began in 1947. The raw data was downloaded from the MMS website on 6/12/2001. There are 40,165 unique records. These records include all boreholes regardless of purpose of the well, including original holes, bypasses, and sidetracks. In addition, incomplete records (*e.g.* measured depth field is null) are included in this count. The steps to reduce this large data set to the final data set to be used in the regression analysis are detailed in the appropriate sections below.

A quick analysis of incomplete records resulted in 1870 records with null entries for MD, TVD, BotNSDist, BotEWDist, BotLong, and BotLat, the majority of these occurring in 1999-2001, with an increase in the frequency of null values observed as one moves forward in time to the present day. A reporting lag is the likely source of these null entries. In addition, there are 324 records with missing SpudDate entries (all of which are missing their TdDate entries also). These wells almost exclusively have a status of APD, CNL, or AST, which are Permit Approved, Permit Cancelled, and ST Approved, respectively. Such wells have not yet been spudded or have been cancelled by the operator.

The key fields in this table are as follows:

API#: This is a unique identifier for each well drilled, and contains information about the location of the well. It is a 12 digit number:

2 digits- state code
3 - county code
5 - unique well code
2 - sidetrack code
---
12 digits

BotLse: This is the bottom lease designation, and is an important field to link tables together. Leases are tracked as text because while some are pure numbers, others contain a G or S in the field.

BotFld and BotBlkNo and WellName: These fields identify the well's area name and block number and well number. These fields are used for well area well counts.

SpudDate and TdDate: These dates determine the duration of the well, a proxy for transaction costs. Unfortunately, it cannot be determined whether or not operations were suspended for long period of time prior to completion (TD) of the well. Discussion of the decision to eliminate outliers in this field is discussed below.

Md, Tvd, and Wd: Measured depth, true vertical depth, and water depth, respectively. These are used directly to create the respective explanatory variables. Note that for water depth (WD), binary variables are also defined indicating whether or not a well is drilled in deeper than 400’ of water (WD400) (the maximum depth of jackup rigs), and deeper than 1000’ of water (WD1000), the approximate maximum depth of fixed platform rigs (indicating the use of semisubmersible, floating drilling rigs).

TypeCode: This indicates the purpose of the well: exploration, development, core (geology), or relief. Only exploration and development wells are considered here. Note that only 140 wells in the entire 40,000+ data set are not E&D.

MMSDistrict: The MMS district; these entries are converted to a set of five binary variables. The legend is as follows:

01 - New Orleans
02 - Houma
03 - Lafayette
04 - Lake Jackson
05 - Lake Charles
06 - Corpus Christi

StatusCode and StatusDate: A field indicating the status of the well, or of the permit if the well has not been spudded. Used mainly for determining history of a well when needed due to other missing data. The codes that are included in the study are:

COM - Borehole Completed
PA - Permanently Abandoned
ST - Borehole Side Tracked
TA - Temporarily Abandoned

The codes that are not included in the study are:

APD - Application for Permit to Drill
AST - Approved Sidetrack
BP - Bypass
CNL - Borehole is cancelled. The request to drill the well is cancelled after the APD or sundry has been approved. The status date of the borehole was cancelled.
CT - Core Test Well
DRL - Drilling Active
DSI - Drilling Suspended
VCW - Volume Chamber Well

Note that 99 percent of all wells fall in the included category.

Individual Turnkey Company Dummy Variables: These dummy variables indicate which TK company drilled a specific turnkey-drilled well. The four major companies are ADTI (Global Marine), Triton (Noble Drilling), DOTS (Diamond), and Cliffs (now Transocean Sedco Forex).

These data were obtained directly from the four companies, although reporting appears somewhat inconsistent over time.

ODS Dummy Variable: This dummy variable is a master list of turnkey wells obtained from Offshore Data Services (ODS - a Gulf of Mexico Oil and Gas Consulting Firm). The list contains wells as early as 1987, but no tracking was done by ODS prior to that date. After 1987, the ODS vector and turnkey company provided data are a close match (note the exception below). In those cases where wells are identified as being turnkey-drilled from the turnkey company-provided data and the ODS vector did not show the same (because the well was drilled prior to 1987, or other unspecified reasons), the ODS vector was updated to reflect the turnkey-drilled well. This updating procedure assumes that if a turnkey company reports that it drilled a well, it did, a fair assumption. These procedures transform the ODS vector into the dependent variable in the discrete organizational choice model.

A fifth category "Other" is used to capture the subset of wells that appear on the ODS list but not on any of the turnkey company lists. This difference reflects a group of smaller turnkey companies and their combinations that have drilled wells through the years such as Transocean Offshore Turnkey Drilling, Offshore Turnkey Ventures, Sonat Offshore Drilling, Petroleum Engineers Inc., Rowan Drilling, Francis W. Brown, Reading and Bates, W&T Offshore, SBM, and Petroleum Professionals Inc.

Note: For both the turnkey company provided data and the ODS data, matching of the identified wells to the MMS data set is not 100 percent perfect. Wells change names (*e.g.* an exploration well “#1” might be changed to well “#A-1” when a platform is set), and during the matching process, some wells as named were not found in the MMS data set. To reconcile these differences, other data such as well depth, operator, and spud date were used to identify the appropriate well when available. In the majority of these cases, wells were satisfactorily identified. In the cases where the identity could not be unequivocally reconciled, no action was taken, *i.e.* no well was marked as being turnkey drilled. This last category represents a small portion of wells, less than 2 percent.

CurrOperNo: This field contains the MMS Company number for the CURRENT leaseholder. Note that this is not necessarily the company that drilled a particular well. There are several possible histories for a lease and for a block. Consider the case where an operator farms-out a prospect to a third party operator. In this case, the choice of drilling organization is made by the farm-in company. Also, an active lease may change hands, and the MMS database updates all existing wells in that lease to the new owner, so wells drilled by the prior owner(s) will appear as drilled by the new owner. This of course is unacceptable since explanatory variables describing company characteristics are supposed to reflect features of the company that DRILLED the well (*i.e.* made the organizational choice). Hence, additional data collection was needed, and this data appears in the following two fields:

> ***OrigOperManualUpdate***: A vector of original operator (the company that DRILLED a specific well) was partly available from Lexco, an oil and gas data company. While Lexco provided the data for 36,246 of the observations, about 4,000 null entries remained. To update the null entries, a two step process was used. In the first step, each null value was analyzed and obvious updates were made manually based on dates, API chronology, drilling history, and other available reference data on the well and lease. Most of the null entries were updated in this step, leaving only about 600 nulls. In the second step, these remaining nulls were updated to the operator currently listed in the MMS database. These 600 nulls were mainly leases that only had one owner and have since expired, or newly issued leases that are unlikely to have had an ownership change. While this does not eliminate a farm-in discrepancy, it is an unbiased method and is probably accurate. This vector is used to match company characteristic variables from the company tables (discussed below) to individual wells.
>
> ***OrigOperAutoUpdate*:** To create this vector, a one-step update procedure was used for the null entries. Here, all nulls were updated to the operator currently listed in the MMS database. While unbiased, this is an arbitrary approach and does not take advantage of other information in the data, as such it is expected to contain more inaccuracies.

Surface and Bottom Longitude and Latitude: These coordinates allow the calculation of horizontal distance (reach) between the surface location and the bottom location.

Miscellaneous fields are as defined in the database itself.

The Turnkey Well Count and Percentage Table

This table records the number of turnkey wells drilled each year from 1980 to the present, the cumulative turnkey wells drilled by year, and the percent of wells drilled under turnkey in each year. This variable proxies for the turnkey industry's experience and reputation. This variable is attached to each well record based on the spud year of the well. Unless otherwise noted in the text, turnkey data is lagged to avoid any endogeneity problem.

The Cumulative Well Count By Block and Year

These tables record the total number of wells drilled in each block each year for the block's history, and the cumulative number of wells drilled in each block by year. This information is also used to construct a binary variable indicating whether or not a well is the first well in the field. These are all proxies for specific in-field experience. Note that this knowledge typically survives an ownership change. While experienced geology and drilling staff may not be associated with subsequent drilling, much of the drilling history and in-field drilling know-how will be transferred in the form of written morning reports which are typically part of the data package transfer. Increased knowledge of a block's geology and drilling history reduces uncertainty, which can lower transaction costs and increase the likelihood of turnkey drilling, or the increased knowledge can be viewed as risk-reducing, lowering the desire for risk transfer that turnkey drilling offers, ceteris paribus.

The Company Profile Tables

The company profile tables capture a wide variety of individual company information such as number of wells drilled by year (used as a proxy for current year coordination costs, and cumulative wells drilled used as a proxy for know-how), and other more general descriptors such as a company's worldwide reserves (scale), its refining capability (scope), its retail operation and brand name possession (reputation), its overall market capitalization (risk preferences), and a variable distinguishing Majors and International Integrateds from smaller firms according to a variety of measures of a leading oil company consulting firm.

The starting point for these tables is the MMS' data on all lease owners. In this data set, all companies that have operated or are operating in the Gulf of Mexico are assigned a MMS Company Number. The idiosyncrasies of this table forced a meticulous analysis to create a usable data set; these idiosyncrasies are discussed below.

Drilling Organization Well Counts

A table that accounts for all wells drilled by an oil company in each year (OPCY) and the cumulative experience by year (OPCUM) is desired. One complicating factor with the MMS data set is that one oil company may be listed under several different names and company numbers. For example, Shell Oil Company has drilled wells under Shell Offshore Inc., Shell Deepwater Production Inc., and Shell Deepwater Development Inc., each with its own MMS company number. But these three entities are in fact one drilling organization, or technical community, and should be treated as such. This situation exists for many other companies also. While it is trivial to count wells for each of these entities, it is more complicated to devise a procedure to sum their activities. This procedure is further complicated by the scale of the problem, almost 500 organizational entities have drilled at least one well since 1980. Nonetheless, some form of organizational mapping was required to correctly account for *organizational* drilling activity and experience.

Continuing with the Shell example is instructive. A table was created that attached a unique company number (one of the entity's regular MMS company numbers) to each of the entity's MMS company numbers. This table can be interpreted as an organizational mapping of related drilling entities into a common organization. It should be noted that not all of the mapping is unambiguous. For example, companies have merged with others, companies have changed names but retained their MMS company number, and other complicated company histories introduced some judgment into the mapping process. In any ambiguous case, every effort was made to properly assign entities into organizations that reflected the evolution of the organization over time. In defense of these individual judgments, note that most of the mapping was straightforward, so the result is believed to be a very good representation of oil company drilling organizations. With this mapping in hand, a series of queries yielded a table containing all companies that have drilled a well since 1980 (these are the company numbers that appear in the Borehole table) with the appropriate *organizational* well counts by year attached. With this, a subsequent query could attach these numbers to each borehole record.

Retail Operations

This binary variable captures information about a company's retail operations over time. Each unique drilling organization was examined for the presence of a retail brand name in the 1980-present time period, and those with retail operations were noted as such in the appropriate year. The primary sources for this data are the annual Market Facts publication of the National Petroleum News, and company websites. In recent years, the retail market has consolidated, and the Market Facts reports firms representing over 90% of retail sales, with the remainder comprised of companies with less than 1% national market share. In earlier years, the percentage is lower at about 80%, but again, the remainder is comprised of companies with less than 1% national market share. The great majority of these smaller retailers are <u>not</u> integrated into E&P, hence this vector is a very accurate representation of those GOM E&P firms with brand name retail operations over time.

Refining

This binary variable captures information about a company's refining operations over time. Each unique drilling organization was examined for the presence of forward integration in refining for the 1980-present time period, and those with refining operations were noted as such in the appropriate year. The primary sources for this data are the annual Market Facts publication of the National Petroleum News, and company websites (websites mainly for foreign companies that have no U.S. refinery presence). As the Market Facts reporting is very detailed, including refineries down to 10,000 bbls/day output, this vector is a very accurate representation of those GOM E&P firms integrated in refining over time.

Worldwide E&P Scale

Overall E&P scale can be an indicator of several economic variables, and some measure was desired for investigation. Any measure is necessarily arbitrary, since no one can know if/where a discrete threshold value for significant gains to scale exists. But there appears to be a reasonable break in the data. Based on information collected from the OGJ200 and its predecessors, the threshold for scale applied here is worldwide reserves greater than ±750MM bbls liquids OR greater than ±5 TCF gas. Firms with reserves exceeding one or both of these thresholds were marked as such using a binary variable (SCALE=1) in the data set.

Market Capitalization

A common proxy for a risk preference variable is net worth. In the context of firms, net worth can be equated to market capitalization, the market value of equity. Here, the objective is to define those firms that possess a significant market capitalization such that their risk preferences and their resulting behaviors (organizational choices) may be significantly different from smaller, hypothetically more risk averse firms. The assignment marks those firms with greater than $1B in market capitalization as "large" firms (CAP=1).

A General, Major / Independents Classification

Industry analysts often divide the industry into peer groups to investigate differences in behaviors and performance indicators. A binary variable has been defined using the system employed by a well reputed, oil and gas strategic management consulting firm to create an additional dummy variable representing Majors and Independents. This system employs a variety of company attributes to make the assignment, including market capitalization, scale, scope, international diversification, etc.

Active Platform Count

A variable was desired to represent scope of offshore operations. It was decided to use the number of active platforms as a proxy for scope in offshore operations. This is a continuous variable.

A.2 Analysis of Variables in the Final Data Set

This section provides a brief analysis of the dependent and independent variables. Unless otherwise noted, all data analysis below is restricted to the 1990-present time frame.

The Dependent Variable

This research models a managerial decision by an oil company on the means to drill an offshore oil and gas well. The decision maker chooses to plan and drill a well with internal resources, in which case he absorbs all of the actual costs, or he chooses the turnkey option where the well is planned and drilled by external resources for a fixed price. The turnkey company absorbs actual costs, and is constrained to charge the agreed on fixed price to the oil company. The turnkey option only became available in 1980, but the attraction of a fixed price alternative has helped the industry to grow considerably since then. Figure A.1 depicts the percentage of all wells drilled under the turnkey option from 1980 to the present. Note that in 2001, much of the data set is incomplete.

Figure A.1: Percent of Wells Drilled Under Turnkey, 1980-2001

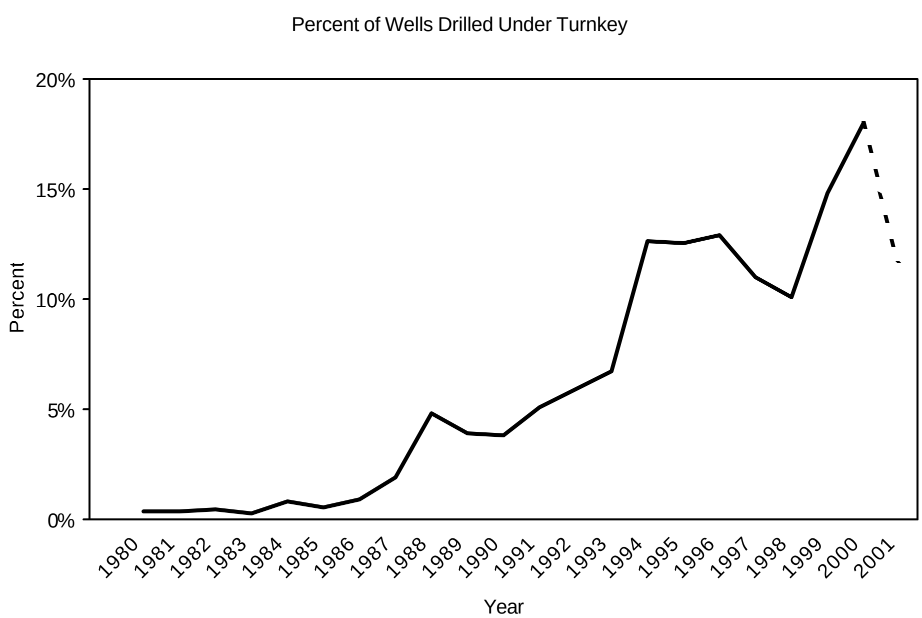
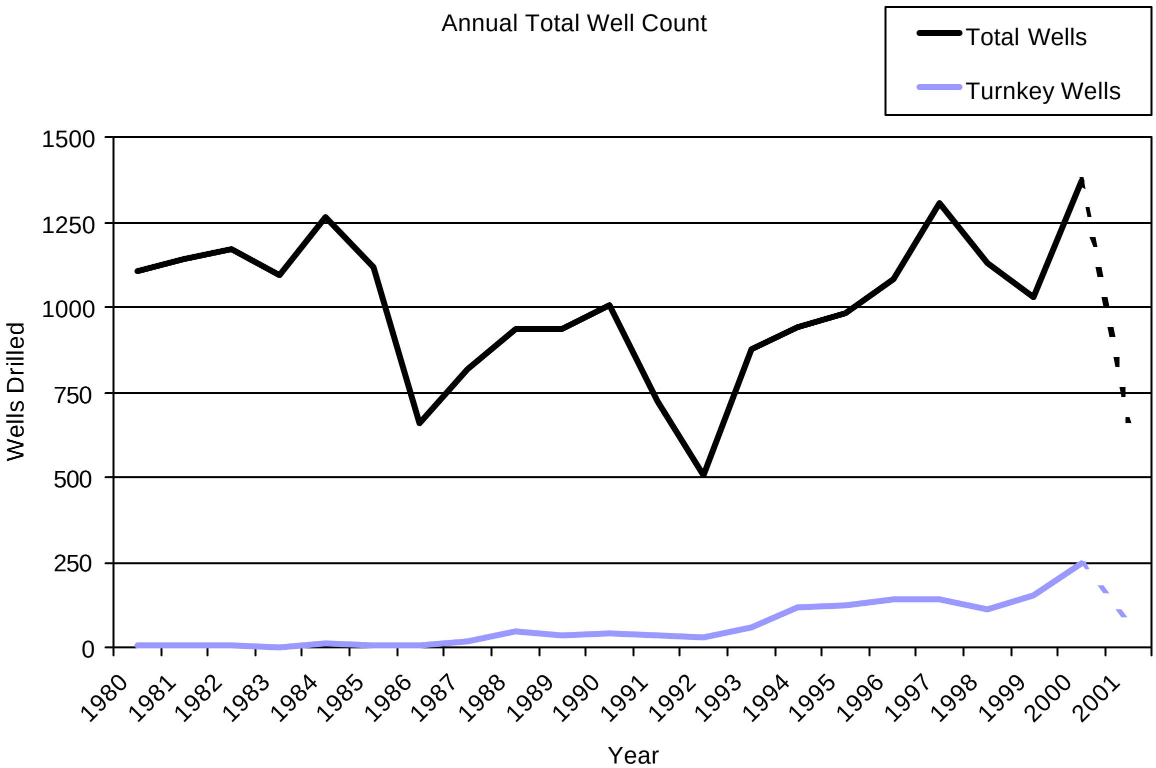


Figure A.2 depicts the annual total well count and the turnkey well count for the Gulf of Mexico.

Figure A.2: Annual Well Count, 1980-2001



Note: Due to the small subset of turnkey wells in the early years of the industry (1980s), regression results are unlikely to be robust in this period. If all of the data is pooled (1980-present), this feature of the data may compromise results. Initial specifications and results support this concern. Therefore, the body of this research is focused on the 1990-2000 subset where the proportion of turnkey drilled wells averages about 10 percent.

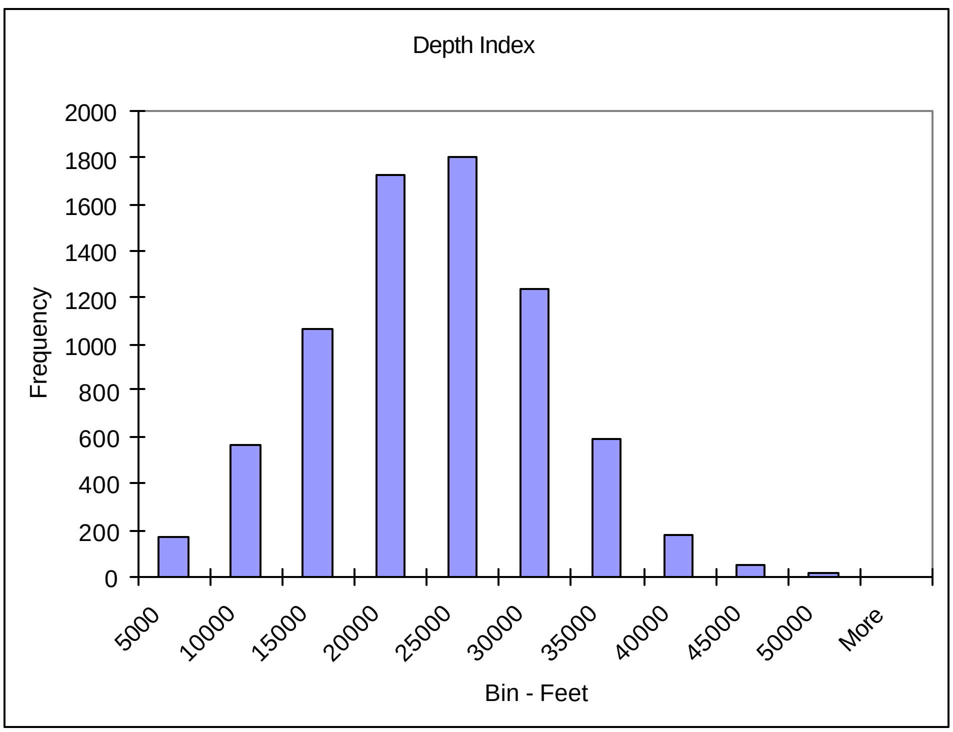
Explanatory Variables

The body of the paper introduces the explanatory variables in detail, and that discussion is not repeated here. Unless otherwise noted, all data is for the 1990-2000 study period.

Depth Index

In Figure A.3, a histogram of the Depth Index data is presented. The Depth Index is the sum of measured depth and true vertical depth. This is a means to deal with a collinearity problem between these two variables.

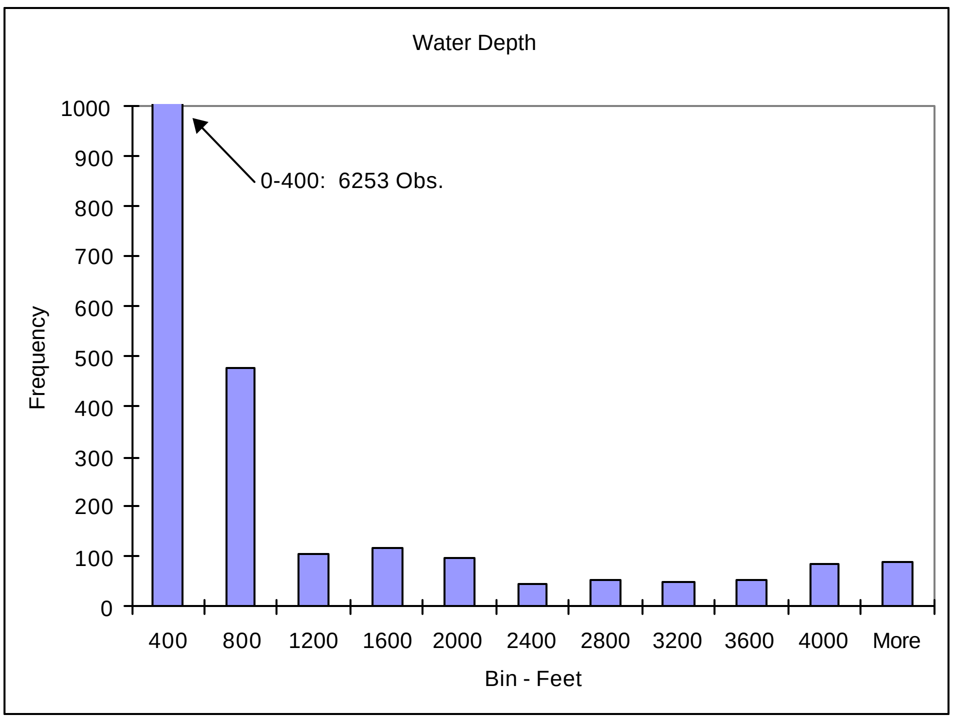
Figure A.3: Depth Index Histogram



Water Depth

Increasing water depth eventually leads to the use of platform drilling rigs or floating operations. The distribution of wells by water depth is shown in Figure A.4. Based on this distribution, binary variables have been defined to indicate wells drilled in greater than 400’ of water (WD400) and 1000’ of water (WD1000). Note that 400’ is a good proxy for the maximum water depth of jackup drilling rigs, and that the tallest fixed structures are about 1000’.

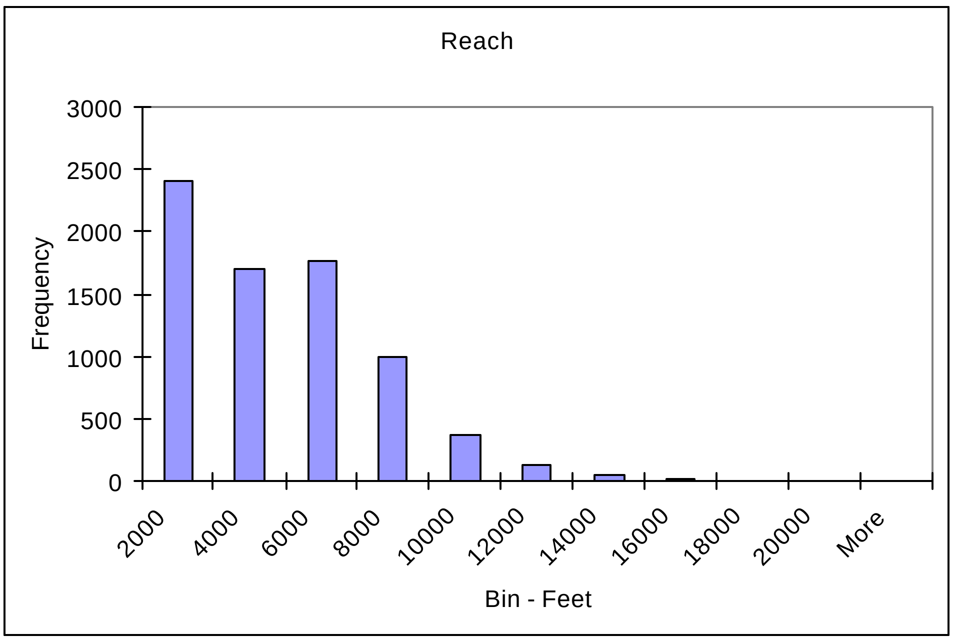
Figure A.4: Water Depth Histogram



Horizontal Reach

Increasing horizontal reach indicates higher well angles which increase complexity and mechanical contingencies. Figure A.5 depicts the distribution of wells by reach. Calculations were done in units of longitude and latitude and then converted to feet.

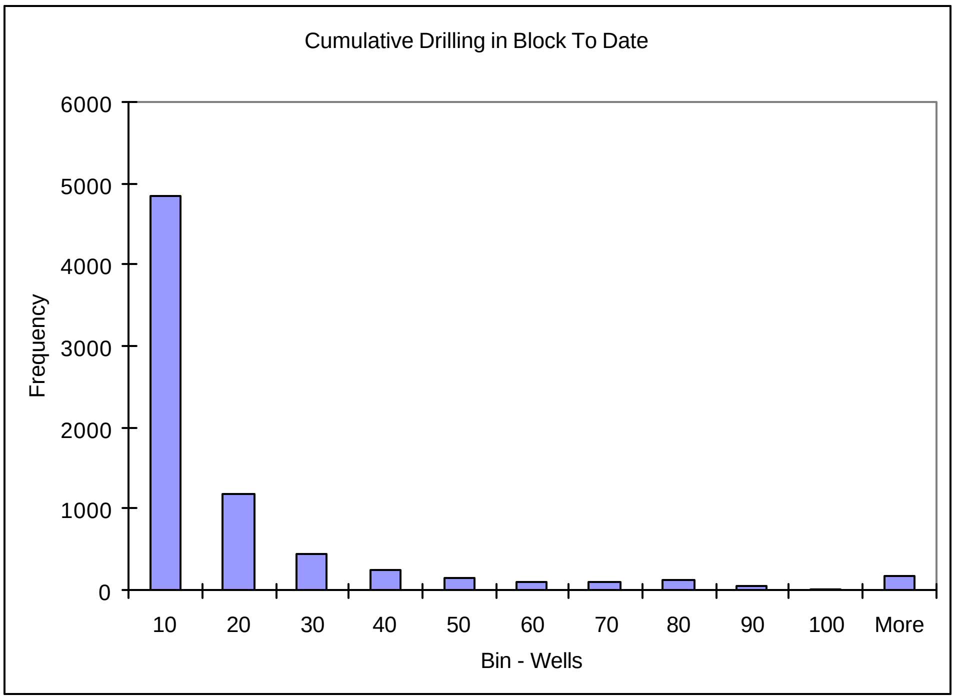
Figure A.5: Reach Histogram



Cumulative Drilling in Block To Date (BLKCUM)

This variable represents the cumulative number of wells drilled in a block to date. As can be seen in the histogram in Figure A.6, most blocks are exploited by less than 10 wells in the block.

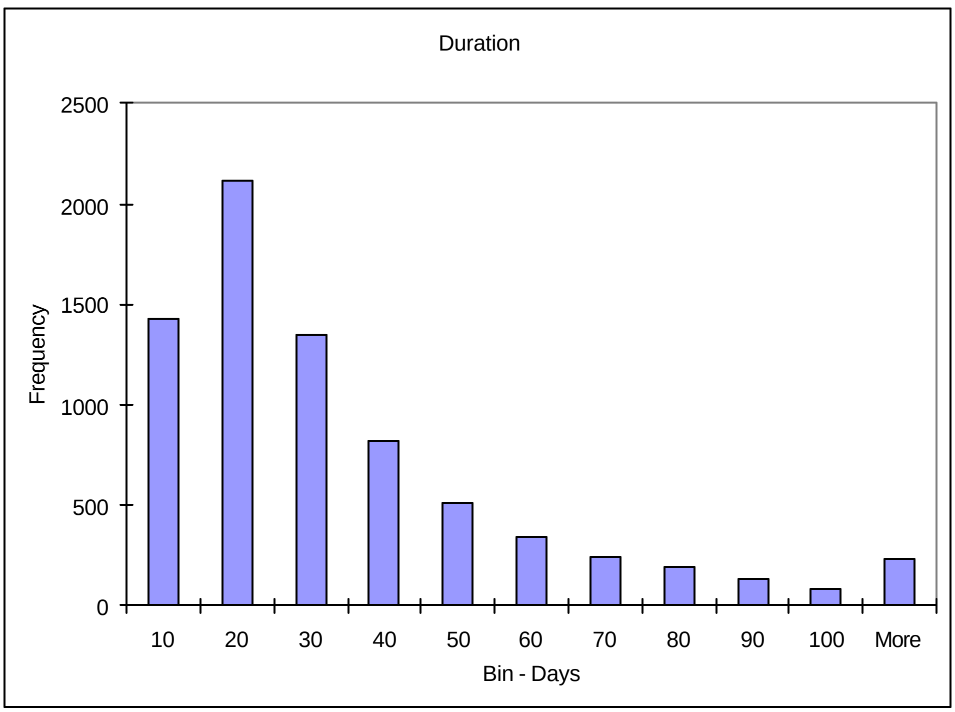
Figure A.6: BLKCUM Histogram



Duration

Duration serves as a proxy for transaction costs. There are many subtleties embedded in this vector. One, wells that are temporarily abandoned and later re-entered and completed do not record the spud date as the re-entry date in the MMS database, resulting in an exceptionally (impossibly) long duration; these outliers have been eliminated. Two, as is discussed in the body of the paper, only original holes are included in the final data set. The distribution of all wells by duration in days is given in Figure A.7.

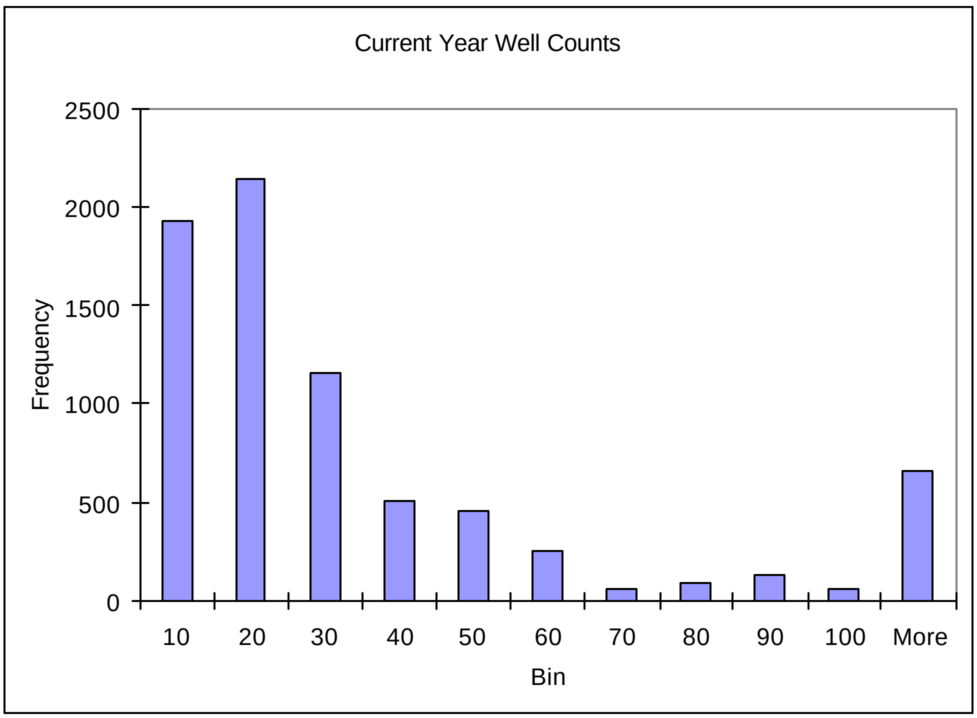
Figure A.7: Duration Histogram



Current Year Well Counts

This variable represents the current year well counts of oil companies. This variable has several interpretations as discussed in the body of the paper. Figure A.8 displays a histogram for this data.

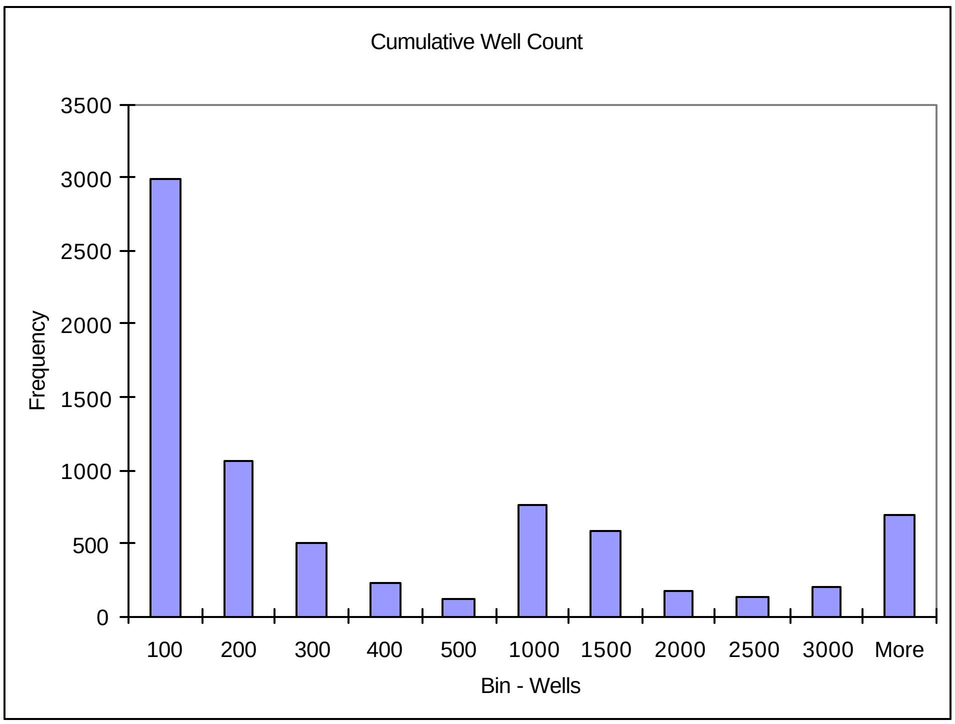
Figure A.8: Current Year Well Count (OPCY) Histogram



Cumulative Well Count of Oil Company

This variable represents the cumulative well count of each oil company over time. This variable was created based on data from 1947, but is only computed for the years 1980-2000, the years 1990-2000 being shown in Figure A.9. The distribution is significant, for it hints at the existence of at least two classes of firms.

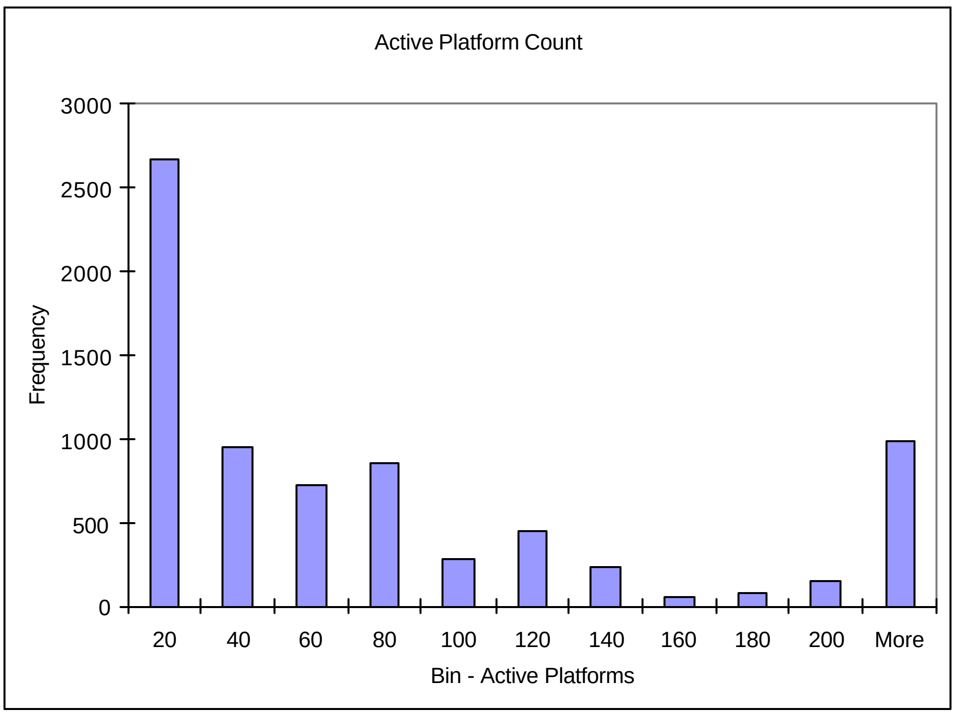
Figure A.9: Cumulative Well Count of Oil Company (OPCUM)



Active Platform Count

This variable represents the active platform count for an oil company in any given year. Note that this represents total structures, not necessarily manned (*i.e.* a structure could be a one well caisson). This distribution is interesting in that it indicates at least two classes of firms. An argument could be made that there are three classes: small (less than 20 structures), medium (up to 200), and large (over 200). Binary variables could be employed instead of a continuous variable, but that approach is not employed in this version of the research. Figure A.10 depicts the active platform count.

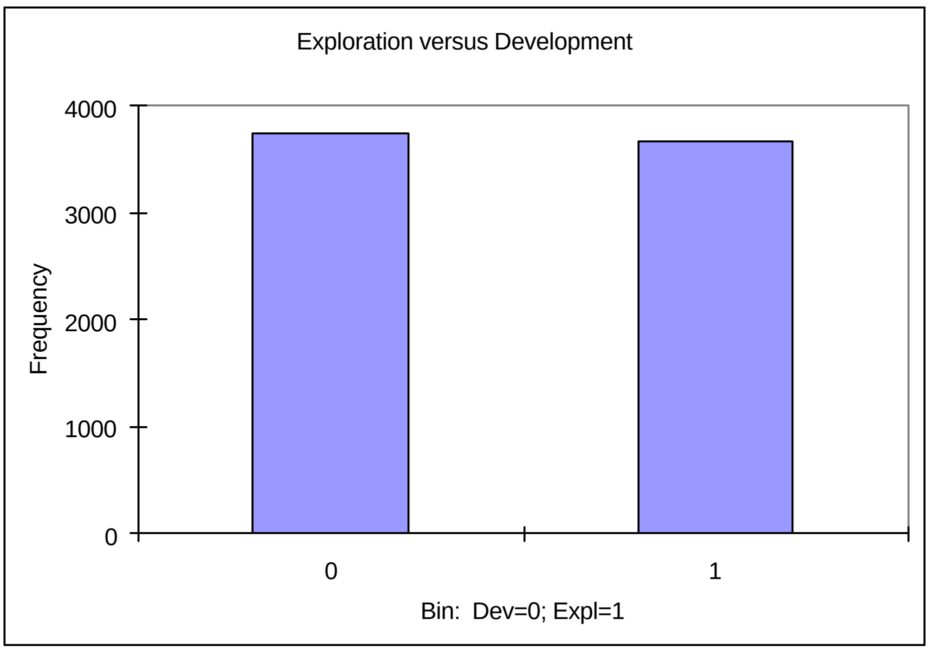
Figure A.10: Active Platform Count by Oil Company



Exploration versus Development Wells

Exploration wells, as their name indicates, are apt to suffer from greater uncertainty than development wells. This uncertainty includes the level and location of over pressures, the responsiveness of the formations to drilling muds, and the location of salt interfaces to name a few. This study only examines exploration and development wells. The distribution of these two well types in the data set is given in Figure A.11. A binary variable will be used to model this variable.

Figure A.11: Exploration and Development Well Count

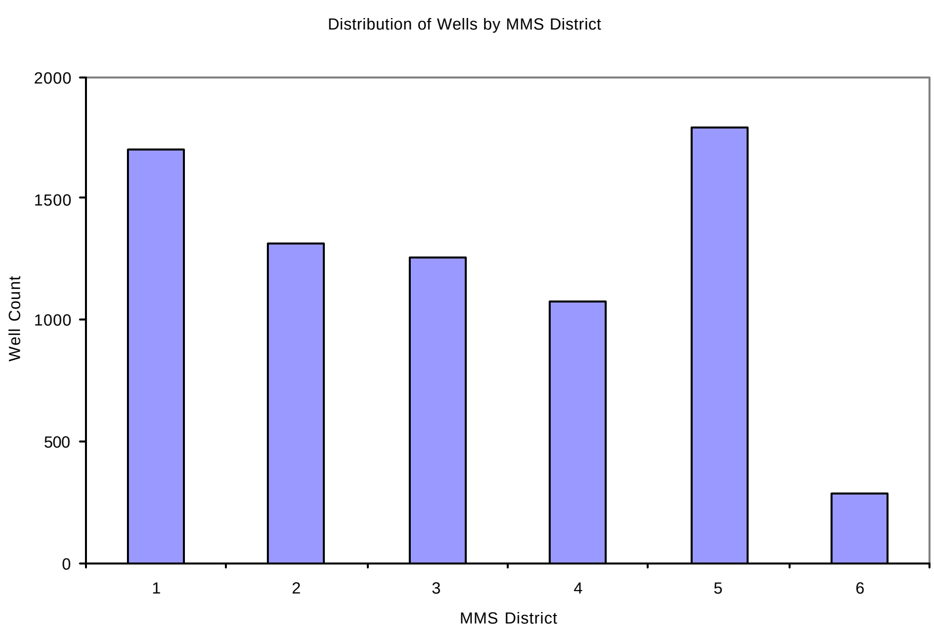


Regulatory Variables

There are six regulatory districts in the Gulf of Mexico administered by the U.S. Department of the Interior's Minerals Management Service (MMS). While consistency in enforcement across districts is a goal, it is possible that enforcement is different across districts, and this difference may influence whether or not a decision-maker chooses to turnkey drill or drill internally. The distribution of wells across districts is given in Figure A.12. A suite of dummy variables will be constructed to model MMS District. Recall the assignment of districts:

01 - New Orleans
02 - Houma
03 - Lafayette
04 - Lake Jackson
05 - Lake Charles
06 - Corpus Christi

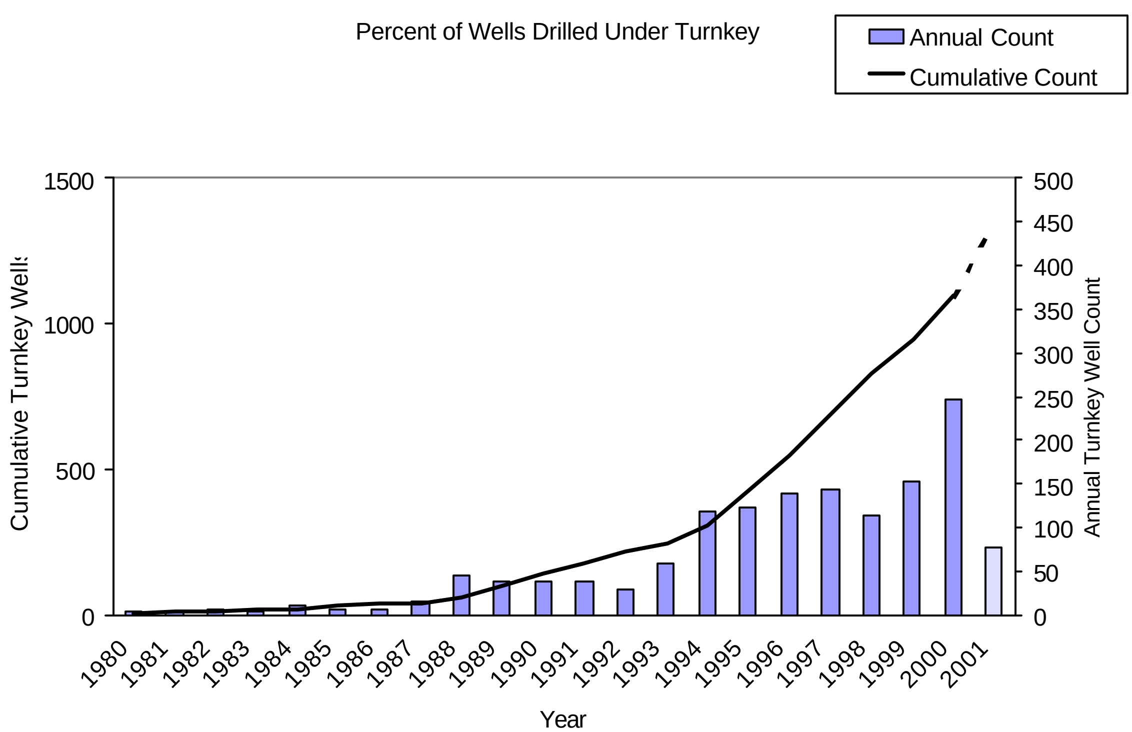
Figure A.12: Distribution of Wells Across MMS Districts



Turnkey Reputation Variables

In the early stages of turnkey industry formation, operators may have concluded that the newness of the turnkey drillers could lead to increased transaction costs. Without a track record, oil companies may have wondered whether turnkey operators could be relied upon to honor contracts, to perform in a timely fashion, to use proper drilling methods, and to operate in a safe and environmentally sensitive manner. As more turnkey wells were completed, the individual firms and the industry in general established a reputation. If this reputation is good, the potential for increased transaction costs due to the sample of factors listed above would be reduced, leading to an increase in the use of turnkey drilling, *ceteris paribus*. Figure A.13 depicts the annual turnkey well count and the cumulative turnkey well count. These variables are used to construct the TKCUM and TKPCT variables. Note that 2001 is highlighted due to a lag in reporting and the resulting incomplete database.

Figure A.13: Turnkey Well Count



Analysis of Company Variables

Based on the definitions given above, binary variables were assigned to each observation based on the company making the organizational choice. Table A.1 gives basic proportions data.

Table A.1: Company Attribute Data Summary

Binary Variable	Retail	Reserves	Capitalization
1	42%	44%	62%
0	58%	56%	38%

A.3 Correlation Coefficient Matrix

A correlation matrix was computed for all explanatory variables to investigate the magnitude of any collinearity problems. This matrix is presented in Table A.2.

Table A.2: Correlation Coefficient Matrix

	Y	DEPTH	WD	WD400	WD1000
Y	1.000000				
DEPTH	0.0870584	1.000000			
WD	-0.113091	0.153002	1.00000		
WD400	-0.123177	0.129526	0.708964	1.000000	
WD1000	-0.0972379	0.156387	0.848234	0.717632	1.000000
RCH	-0.0689692	0.193302	-0.0238100	0.0613126	-0.0105104
EVD	0.0968607	0.108401	0.145710	0.0841888	0.124178
BLKCUM	-0.0862287	-0.209884	-0.132644	-0.157149	-0.129703
TKCUM	0.164850	0.0916514	0.0738625	0.0300218	0.0621133
DUR	-0.0367676	0.633470	0.209392	0.198922	0.210763
OPCY	-0.124013	0.0690150	0.201339	0.155797	0.179697
OPCUM	-0.156201	0.127231	0.279847	0.218310	0.238192
RET	-0.173001	0.134922	0.263923	0.276984	0.257329
RES	-0.182974	0.123407	0.251308	0.260099	0.244624
CAP	-0.230830	0.119752	0.198015	0.197389	0.196578
PLAT	-0.0800348	0.0750554	-0.0135099	-0.0252208	-0.0267882
NO	-0.0637517	-0.0715379	0.246571	0.222324	0.252387
HO	0.0390792	0.124241	0.0353557	0.102074	0.0332941
LA	-0.0127832	0.107799	-0.0559189	-0.0404505	-0.0380553
JX	-0.0100739	-0.113396	-0.0557108	-0.0968730	-0.0769441
LC	0.0566720	-0.0394759	-0.154061	-0.157999	-0.156416
TKPCT	0.156540	0.111372	0.0791605	0.0241949	0.0725558

	RCH	EVD	BLKCUM	TKCUM	DUR
RCH	1.000000				
EVD	-0.300900	1.000000			
BLKCUM	0.0147357	-0.279379	1.000000		
TKCUM	0.0787368	-0.0217847	-0.0223820	1.000000	
DUR	0.148764	0.0603505	-0.112873	-0.00907493	1.000000
OPCY	0.0683087	-0.106687	0.147823	0.133463	0.0563439
OPCUM	0.0677050	-0.112271	0.104697	0.0227554	0.125166
RET	0.0770634	-0.166883	0.117871	-0.0527584	0.150359
RES	0.107476	-0.184473	0.0828570	0.0111956	0.145643
CAP	0.0758294	-0.144629	0.0100937	-0.0165818	0.166882
PLAT	0.0543240	-0.164022	0.127345	0.157297	0.0350541
NO	0.0381978	-0.0230896	0.225402	-0.00889833	-0.0103078
HO	-0.0156714	-0.0304934	-0.00333132	0.000248152	0.0362969
LA	-0.0234050	-0.00609919	0.0358422	0.00752575	0.0521903
JX	-0.00503342	0.00398524	-0.136921	-0.0184459	-0.0322412
LC	0.00585123	0.0530965	-0.103380	0.0506946	-0.0570590
TKPCT	0.0872985	-0.00429131	-0.0506181	0.830950	0.0288854

	OPCY	OPCUM	RET	RES	CAP
OPCY	1.000000				
OPCUM	0.840330	1.00000			
RET	0.539256	0.636941	1.000000		
RES	0.536501	0.593867	0.863216	1.00000	
CAP	0.364198	0.430450	0.640175	0.683193	1.000000
PLAT	0.462016	0.407201	0.413801	0.412340	0.339948
NO	0.133778	0.130743	0.130031	0.138063	0.0479207
HO	0.00423769	0.0323136	0.0350401	0.0118725	0.0363479
LA	0.0408561	0.0542177	0.0641507	0.0123111	0.00305695
JX	-0.0927102	-0.101277	-0.125423	-0.0901980	0.00793452
LC	-0.0628505	-0.0971595	-0.0943037	-0.0861506	-0.114492
TKPCT	0.158122	0.0618851	-0.0413633	0.0160449	0.0183720

	PLAT	NO	HO	LA	JX
PLAT	1.000000				
NO	0.00523549	1.000000			
HO	0.0886054	-0.253036	1.000000		
LA	0.0568118	-0.246232	-0.209490	1.000000	
JX	-0.106651	-0.224561	-0.191053	-0.185915	1.000000
LC	-0.0238683	-0.307148	-0.261316	-0.254289	-0.231909
TKPCT	0.130716	-0.0240356	-0.00904055	0.0256204	-0.0127313

	LC	TKPCT
LC	1.000000	
TKPCT	0.0546300	1.000000

Analysis and implications are discussed in the body of the paper.

APPENDIX B

Correlation Coefficients for Safety and Environment Data Set

Table B.1: Correlation Coefficients for Safety and Environment Data Set

	Y	OPCUM	PLAT	RET	DEPTH
Y	1.000000				
OPCUM	0.0371587	1.00000			
PLAT	0.0533294	0.412135	1.000000		
RET	0.0487100	0.638443	0.381014	1.00000	
DEPTH	0.0233732	0.129307	0.0710612	0.131812	1.00000
RCH	0.0527109	0.130675	0.0279267	0.131565	0.149141
WD400	0.00824358	0.199914	-0.0251959	0.224700	0.212040
EVD	-0.0845227	-0.174212	-0.156244	-0.223739	0.138842
NOWELLS	0.0851921	0.208551	0.132521	0.236174	-0.126504
NO	0.00485847	0.158620	0.0456320	0.172640	0.0000268290
HO	0.00437827	0.0436244	0.115221	0.0292784	0.102746
LAF	0.00565950	0.0514136	0.00747531	0.0504068	0.105492
JAX	-0.0252923	-0.115541	-0.112726	-0.122421	-0.139981
CC	0.0145655	-0.0676042	-0.0479126	-0.0526478	-0.0324278
DV98	0.0588875	0.0298092	0.0366064	0.000396081	0.0651807
DV97	0.100493	0.0456196	0.0306779	0.00885664	0.0266027
DV96	0.0158850	0.0336638	0.0301400	-0.00138873	0.0248468
DV95	-0.0268980	0.0533287	-0.00522132	0.0250793	-0.00868426
DV94	-0.0379486	-0.0283889	-0.00741301	0.000906795	0.00440117
DV93	-0.0514483	-0.0274889	0.00907936	0.00480182	-0.0193213
DV92	-0.0418281	-0.0339307	-0.0157772	-0.0268336	-0.0216391
DV91	-0.0109690	-0.0446533	-0.0399998	-0.00517525	-0.0166978
DV90	-0.0347644	-0.0511548	-0.0524649	-0.0142304	-0.0683090
COUNT	0.101054	0.0924282	0.0359771	0.0791374	-0.145177

	RCH	WD400	EVD	NOWELLS	NO
RCH	1.000000				
WD400	0.0978709	1.000000			
EVD	-0.329943	0.128196	1.00000		
NOWELLS	0.0851976	-0.0999113	-0.353163	1.00000	
NO	0.0816632	0.183919	-0.0523722	0.176863	1.000000
HO	-0.00970366	0.0880044	-0.0187115	-0.00869808	-0.255674
LAF	-0.0148006	-0.00866245	-0.0210417	0.0823360	-0.249814
JAX	-0.0334048	-0.0699703	0.0270783	-0.107273	-0.227317
CC	-0.0304682	-0.0842040	0.0160729	-0.0583772	-0.118953
DV98	0.0546667	0.0825932	0.0155394	-0.0173509	0.0228272
DV97	0.0544953	0.0320795	-0.0364459	0.0198373	0.00814989
DV96	0.0542116	-0.000535511	-0.0292406	0.0268744	0.0326579
DV95	0.0310795	-0.0260188	-0.0210941	0.0170542	-0.00634573
DV94	-0.00834550	-0.0401423	0.00675230	0.0172146	-0.0196184
DV93	-0.0353648	-0.0465919	-0.0227780	0.00369247	-0.00160629
DV92	-0.0344415	-0.0226678	-0.0157436	0.00921136	0.00195153
DV91	-0.0631704	0.0200710	0.0351002	-0.0306341	-0.00454978
DV90	-0.0821513	-0.00949997	0.0718596	-0.0505227	-0.0367501
COUNT	0.0609257	0.0429245	-0.146831	0.189207	0.119928

	HO	LAF	JAX	CC	DV98
HO	1.000000				
LAF	-0.212287	1.00000			
JAX	-0.193169	-0.188742	1.000000		
CC	-0.101084	-0.0987673	-0.0898728	1.000000	
DV98	0.00767476	-0.0114432	-0.0203103	-0.0358467	1.00000
DV97	-0.0124728	0.0269934	-0.00842207	-0.0430181	-0.154507
DV96	0.00307241	-0.0125001	-0.0138939	-0.0370810	-0.147263
DV95	0.0226244	-0.00208644	-0.0138092	-0.0171235	-0.131214
DV94	-0.0117299	0.00756876	0.00612183	0.0341248	-0.133530
DV93	-0.0194307	0.00536073	-0.0151824	0.0548376	-0.122518
DV92	0.0112327	0.00714460	0.0116892	-0.00714078	-0.0934196
DV91	0.00447756	-0.00723452	0.0258006	0.00769723	-0.110299
DV90	-0.00177358	-0.0143750	0.0350557	0.0532269	-0.136964
COUNT	-0.0143015	0.0206053	-0.0618279	-0.0584052	0.0397283

	DV97	DV96	DV95	DV94	DV93
DV97	1.00000				
DV96	-0.167833	1.00000			
DV95	-0.149543	-0.142531	1.000000		
DV94	-0.152182	-0.145046	-0.129239	1.00000	
DV93	-0.139631	-0.133085	-0.118581	-0.120674	1.000000
DV92	-0.106469	-0.101477	-0.0904179	-0.0920136	-0.0844253
DV91	-0.125706	-0.119812	-0.106755	-0.108639	-0.0996794
DV90	-0.156095	-0.148776	-0.132563	-0.134903	-0.123777
COUNT	0.0114867	-0.0368790	0.00363772	-0.0225508	0.00996415

	DV92	DV91	DV90	COUNT
DV92	1.000000			
DV91	-0.0760053	1.000000		
DV90	-0.0943799	-0.111433	1.00000	
COUNT	-0.00416142	0.00961313	-0.00863767	1.000000

APPENDIX C

Organization of Probability Information and Managing the Nelson-Winter Computations

C.1 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 C.1: Summary of Forecast/Outcome Data Availability, 1980-2000

Years	Forecast Types	Wind Speeds (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.

C.2 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 C.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 $\pi_{11}=\pi_{22}=1$, $\pi_{12}=\pi_{21}=0$, $\pi_1=\pi^1$, and $\pi_2=\pi^2$. Query “Step5NW” simply sums across each forecast type for each year of the study for presentation purposes.

VITA

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