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Forecasting Energy Supply and Pollution from the Offshore Oil and Gas Industry

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Abstract *Sound energy and environmental policies require reliable forecasts of production and pollution, as well as supply response to policy actions. In this study, we describe a model for forecasting long-term production and pollution in the offshore oil and gas industry in the Gulf of Mexico under different scenarios. A model based on disaggregated field-level data is used to forecast production and pollution through to the year 2050. The time path for resource depletion is determined as the net effect of technological progress and depletion under alternative scenarios for new discoveries. We also quantify potential efficiencies that could result from changing the design of regulations from the current command-and-control regime, to an approach that allows more flexible means of achieving the same environmental goals.*

Key words Forecasting, energy supply, R&D, technological change, environmental regulations, environmental pollutions, offshore oil and gas industry.

JEL Classification Codes D24, L71, Q32, Q48.

Introduction

Predicting when oil will be depleted is relatively straightforward once one has good estimates of future rates of production and the amount of oil that remains to be produced. Proven reserves, however, do not represent total oil resources, but are an

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estimate of the minimum amount that would be produced if no further discoveries were made, no advances in technology occurred, and if there were no changes in prices or other economic conditions. In fact, these parameters are in a constant state of flux. Therefore, economic and political factors play an important role in forecasting future production, and an enormous amount of data is required to capture various complexities in the analysis (Lynch 2002).

Evidence suggests that increases in productivity have offset depletion effects in the Gulf of Mexico offshore oil and gas industry over a 49-year period from 1947–96 (Managi *et al.* 2004a).[1] Initially, depletion effects outweighed productivity-enhancing effects of new technology, but in the later periods, technological advance offset depletion. This result is consistent with common reports of Gulf of Mexico production. The Gulf of Mexico was referred to as the "Dead Sea" in the early 1980s, but with recent reports of new technologies, a rapid pace of productivity enhancement led the Gulf of Mexico to become one of the most promising petroleum production areas in the world (Bohi 1998). This should not, however, be taken as an indication that productivity will necessarily continue to follow this U-shaped curve of increasing productivity. It remains to be seen whether this pace of increasing productivity can be maintained in the future, or whether recent productivity gains will soon be lost to depletion as reserves in deep waters are depleted.

Reducing the environmental impact of offshore operations is one of the most pressing challenges facing the oil and gas industry in the U.S. today. In recent decades, environmental concerns led to the imposition of numerous new regulations on oil and gas operations. Indeed, some have argued that environmental concerns may be more important than physical scarcity of oil (Adelman 1975). Although these regulations have provided the basis for many environmental improvements by industry, compliance has become costly and increasingly complex. In 1996, the petroleum industry, including refining, spent as much on environmental protection as it spent searching for new domestic supplies: $8.2 billion (American Petroleum Institute 2001). Jin and Grigalunas (1993a,b) examined the impact of environmental regulation on firms in the oil and gas industry using the optimal control model assuming constant technology. Their results indicate that rising environmental compliance costs lead to reductions in investment and production, implying that fewer resources will be developed and associated economic benefits will decline.

The objective of this paper is to forecast oil and gas production based on different economic and policy scenarios. Historical data are used to simulate the evolution of the industry to date. Following the U.S. Energy Information Administration (EIA), we use disaggregated data to forecast regional production (U.S. Department of Energy 2001). We estimate oil and gas production and the resultant pollution formation at the field level using sub-model results and then aggregate over the fields to the regional level. Our estimated model is used to construct a simulation model of the industry over time. We then simulate the future of the offshore oil and gas industry under alternative assumptions regarding future oil and gas prices, technological change, and alternative environmental policies. We address various policy questions, such as identifying potential cost savings that could result from innovative pollution control measures and the associated benefits that can be derived from flexible regulatory approaches, such as market-based approaches for pollution control.

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[1] The Gulf of Mexico is one of the first areas in the world to begin large-scale offshore oil and gas production. Since then, offshore operations in the Gulf of Mexico have played an important role in production and stabilization of energy supply in United States. Federal offshore oil and gas production accounted for 26.3% and 24.3% of total U.S. production, respectively (U.S. Department of Interior 2001), and the offshore fraction of production has been increasing over time. Oil and gas production in Gulf of Mexico accounted for 88% and 99%, respectively, of total U.S. offshore oil and gas production through 1997 (U.S. Minerals Management Service 2000).

Literature Review

In the forecasting literature, most projections take a top-down (or aggregated) approach (Hubbert 1967; Cleveland and Kaufmann 1991; Pesaran and Samiei 1995; Moroney and Berg 1999).[2] They use overall estimates of resource potential and estimate future production. Other aggregated model includes rational expectations econometric models (Epple 1985; Walls 1994). Although they have an advantage of incorporating uncertainty and capturing the dynamics of the exploration processes, the models must be highly simplified in order to obtain analytical solutions to the optimization problems. There are clear advantages to using micro-level data, since aggregation of data across distinctive geologic provinces may obscure the effects of economic and policy variables on the pattern of exploratory activities (Pindyck 1978a). Typically, field-level forecasts of discovery and production account for depletion. (Smith and Paddock 1984; Eckbo, Jacoby, and Smith 1978; Drew, Schuenemeyer, and Bawiec 1982; Nehring 2001). However, none of these models include an explicit treatment of technological change. As a result, forecasts of future oil and gas supply from a region usually show a declining trend, which reflects only the effect of resource depletion (Porter 1990; Energy Modeling Forum 1991; Walls 1994). Impacts of technological change have been analyzed using a disaggregated model (U.S. Department of Energy 2001) and an aggregated finding-cost model (Cuddington and Moss 2001). However, neither of these models accounts for increasing stringency of environmental regulations, nor do they consider pollution levels. Thus, the tradeoff between production and pollution from environmental regulation has not been investigated in the offshore oil and gas industry.

Methodology and Estimation Results

We model the oil and gas production and pollution systems considering the technological change using field-level data in the Gulf of Mexico (see Appendix for data description). The model uses regression techniques in both the aggregated industry-level and disaggregated field-level. The general logic of the model is illustrated in figure 1. This section discusses the methodology and estimation results for each of the following steps: determine technological change (Step 1), determine the number and size distribution of fields (Step 2), determine inputs (Step 3), determine outputs of oil, gas, and pollution levels (Step 4).

The detailed flow of our methodology is illustrated in figure 2. First, we specify the policy scenario. This includes information such as R&D expenditure (to induce technological change), oil and gas prices (to encourage new field discoveries), stringency of environmental regulation, and the associated regulatory regime (command-and-control versus flexible regulations). These policy options are indicated in bold letter in figure 2.

Step 1: Technological Change

In this section, we provide the determinants of the level of production technology from information on R&D expenditures and the level of environmental technology

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[2] Walls (1992) presented a comprehensive survey of studies on modeling and forecasting of petroleum supply. Her survey covers various geologic/engineering and econometric models that describe the relationship between exploratory drilling and discovery.

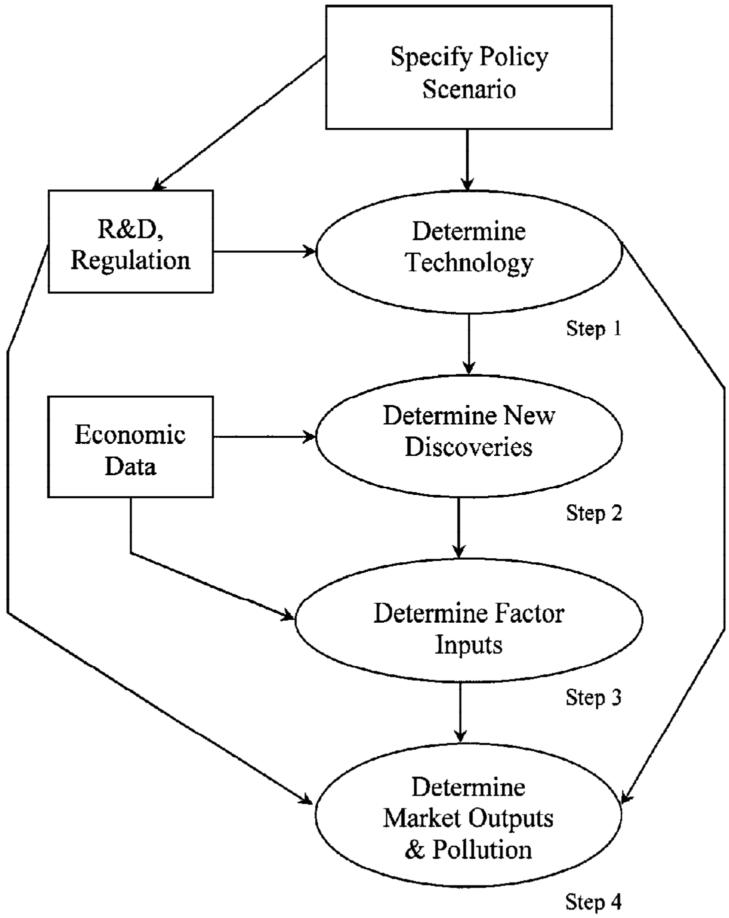

Figure 1. Overview of the Forecasting Model

from environmental regulations. Recently, energy models have been expanded to represent endogenous technological change through R&D or learning by doing. For example, Goulder and Schneider (1999) investigated the impact of including induced technological change in the form of R&D efforts (see Jaffe, Newell, and Stavins (2002) for theoretical review). R&D in a particular year will affect technological change several years down the road when the induced innovation process has been completed (Griliches 1984).[3] The process of technological change, however, is quite complex and still poorly understood. Contemporaneous impact analysis of R&D is needed to determine the immediate cost of R&D. But time lags are needed to consider the longer-term gains associated with innovation and consequent improvements in productivity. We expect the R&D to have a positive, long-term impact on technological change. The functional specification relating improvements in technologies and R&D is given by following equation:

[3] We treat investment in R&D as exogenous since our model simulates only the Gulf of Mexico, whereas the profitability of R&D reflects all sources worldwide.

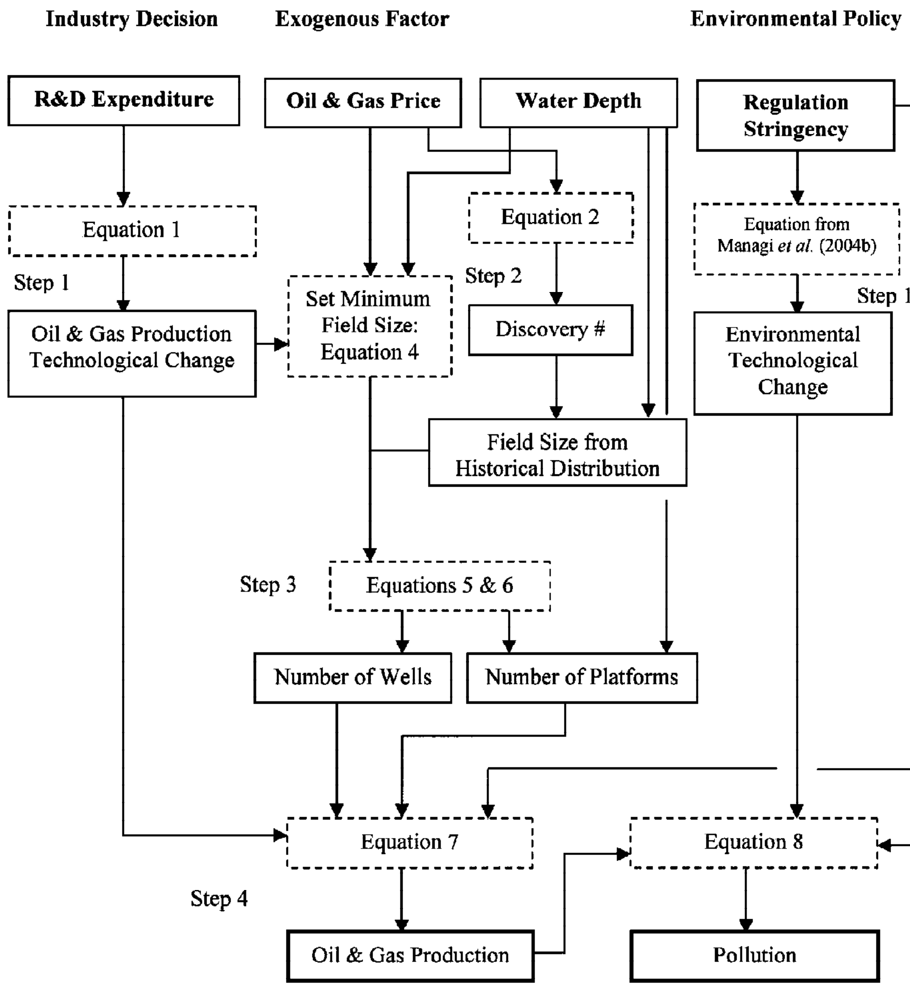

Figure 2. Flow Chart of the Methodology

$$Y_t = \alpha + \sum_{i}^{N} \beta_i X_{t-i} + \varepsilon_t, \tag{1}$$

where Y_t denotes technological change indexes (*i.e.*, change in *tech*) at time t, which is explained below,[4] and X_t denotes R&D expenditure at time t. The term β_i is the coefficient of X_{t-i}, which indicates how technological change is affected by R&D expenditures i years lagged. The term α is a constant term and ε_t is a stochastic term, which together comprise the "unexplained" components of technological change.

[4] Our technological change data is available upon request.

The expected dynamic lagged effects of independent variables can be examined by imposing theoretical restrictions on the coefficients of the lagged values of these variables.

Managi *et al.* (2004a) used Data Envelopment Analysis (DEA) to estimate the technological change indexes using a unique and extensive micro-level data set. Technological change measures shifts in the production frontier. DEA is a set of nonparametric mathematical programming techniques for estimating the relative efficiency of production units and for identifying best practice frontiers (*e.g.*, Färe, Grosskopf, and Lovell 1994). DEA does not impose any particular functional form on production technology, and it is not conditioned on the assumption of optimizing behavior on the part of each individual observation. Avoiding these maintained hypotheses may be an advantage, particularly for micro-level analyses that extend over a long time series, where assumptions of technological efficiency of every production unit in all time periods might be suspect. Further, in a non-renewable resource industry, input use might appear contemporaneously suboptimal due to sunk and irreversible costs, even when it is optimal from a dynamic point of view. The data for DEA estimation includes field-level annual data for the following variables: oil output, gas output, the number of exploration and development wells drilled, the total drilling distance of exploration and development wells, the number of platforms, water depth, oil reserve, gas reserve, untreated water produced, and discovery year.

We employ the Almon polynomial distributed lag model, which is an estimation procedure for distributed lags that allows the coefficients of the lagged independent variables to follow a variety of patterns as the length of the lags increases (Almon 1965). The use of Almon polynomials remedies the problem of collinearity. The use of Almon lags requires the determination of the maximum lag length, where we choose the lag length in order to minimize the Akaike Information Criteria (AIC) (Harvey 1990). The results of replicating the Almon lag model are reported below:[5]

$$
\begin{aligned}
\Delta tech_t = {} & 100.378 + \underset{(2.72)}{2.059} \ln(R\ \&\ D_{t-2}) + \underset{(2.72)}{1.716} \ln(R\ \&\ D_{t-3}) \\
& + \underset{(2.72)}{1.373} \ln(R\ \&\ D_{t-4}) + \underset{(2.72)}{1.029} \ln(R\ \&\ D_{t-5}) + \underset{(2.72)}{0.686} \ln(R\ \&\ D_{t-6}) \\
& + \underset{(2.72)}{0.343} \ln(R\ \&\ D_{t-7}) - \underset{(-2.11)}{0.452} \ln(\Delta tech_{t-1})
\end{aligned}
$$

$$
\text{Adj. } R^2 = 0.4520 \qquad \text{AIC} = 37.1085 \qquad \text{Durbin } h = 0.2897.
$$

The results show statistically significant results.[6] The creation of dynamic effects of R&D investments on production technological change has a two- to seven-year lag relationship.

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[5] We employed the linear form. End point restriction is used in the specification, and the coefficient of seven years' lag ($t - 7$) is set to zero. t statistics are in parentheses. The coefficients are significant at 5%. Since we use the linear form with one-side end point restriction, all of the t statistics in lagged R&D are same (Almon 1965). The variable *tech* is multiplied by 100.

[6] We note the problem of the Almon lag method. It assumes that lagged effects follow a polynomial, and therefore, the results might overestimate the significance of lagged effects. Thus, the reliability of this model heavily depends on the assumption of polynomial form. DEA is a data-driven technique, and annual index change tends to fluctuate (Färe and Grosskopf 1997). However, the fluctuation is not so large that the trend of cumulative index, which is the multiplication of past annual change, is smooth over time. We add the lagged technological change variable to control this fluctuation.

Similar to the estimation of production technological change, environmental technological change is estimated using DEA estimation (Managi *et al.* 2004b). These authors use environmental output data composed of 33 different types of water pollutants in the four EPA categories, oil spill volume data from the Coast Guard, and environmental input data from environmental regulation compliance cost. The four categories of EPA are Conventional Pollutants, Non-conventional Organic Pollutants, Non-conventional Metal Pollutants, and Radionuclides. Conventional Pollutants include oil and grease and TSS. Environmental technological change measures the shifts in the environmental abatement frontier. Since higher stringency of environmental regulations adds significantly to industry costs, industry might increase R&D to develop better environmental technologies to reduce compliance cost. Therefore, environmental regulation will stimulate the innovation and diffusion of technologies that facilitate compliance (see Jaffe, Newell, and Stavins (2002) for a literature review of theoretical and empirical analysis). Managi *et al.* (2004b) used lagged measures of the stringency of environmental regulations to identify the dynamic impacts on environmental technological change. They found the long-term positive impact of environmental regulation on environmental technological change. The stringency of environmental regulations is defined in the Appendix. This model is used to forecast environmental technological change in this paper.

Step 2: New Field Discovery

We generate new discoveries of oil and gas fields, including size and water depth of each new field discovery, where oil and gas price is the factor explaining the number of new field discoveries. A random field size based on historical field size distribution at each water depth is used, and the distribution can change over time to consider depletion.[7] Then, we determine which prospects are economic by setting the minimum profitable field based on the real price of oil and gas in 2000 dollars per barrels of oil equivalent (BOE), technology level, and water depth using stochastic frontier analysis. Thus, if field size is smaller than minimum profitable field size, we eliminate it from the simulation process.

The number of newly discovered fields is specified as a function of oil and gas prices.[8] We expect a positive sign on the price of oil and gas, since higher prices offer an incentive for firms to place greater effort on exploration (see Erickson and Spann (1971) for a detailed discussion between price and discovery). We specify our discovery number function as:

$$disc.\ number_t = f\,(price_t). \tag{2}$$

A linear model is used for parameter estimation, where n is the number of observations:[9]

$$disc.\ number_t = 7.8922 + \underset{(1.83)}{0.5918}\ price_t$$

$R^2 = 0.4268$ $n = 49$ DW $= 2.1925$ $\rho = -0.05366$,

[7] It is difficult to control resource size in a conventional econometric framework and it is not suitable for forecasting. Thus, we utilize the method developed in Eckbo, Jacoby, and Smith (1978) and assume discovery is generated as a random variable. The detailed documentation for this process is available on request.
[8] Technology, depletion, and water depth are statistically insignificant in this specification.
[9] t statistics are in parentheses. The time period analyzed is 1946–95.

where ρ is the estimate of the first-order serial correlation. The coefficient on price is of the correct sign and is statistically significant at the 10% level.

Eckbo, Jacoby, and Smith (1978) modeled the minimum economic field size based on the information of oil and factor prices. The minimum field size that is profitable for a firm in our model is determined by the state of technology, oil and gas prices, and water depth, since the level of technology and water depth determine the factor prices.[10] Other things being equal, minimum field size will decrease if technology and/or price increase and if water depth is shallower.

We used the stochastic frontier production model to determine the minimum field size (Aigner, Lovell, and Schmidt 1977; Meeusen and van den Broeck 1977). In this study, the stochastic frontier function for minimal field size is specified as:

$$y = f(x) \exp(v + u), \tag{3}$$

where v and u form the composite error term in a standard stochastic frontier model, with u being a truncated random variable capturing the divergence of field size from the minimum profitable field (*i.e.*, the observed field size is greater than the frontier minimal), and v is a normal variable that comprises measurement error. A logarithmic transformation is applied to linearize equation (3):

$$\ln y_i = \ln x_i\beta + v_i + u_i, \tag{4}$$

where i is the field index, and x_i is a vector of the explanatory variables (*price*, *technology*, *and water depth*); v_i is the random error term, independently and identically distributed as $N(0,\sigma_v^2)$; u_i is a non-negative random variable truncated at zero and independently and identically distributed as $N(\mu,\sigma_u^2)$.

The minimum economic field size is our output variable. We examined a number of explanatory variables (*i.e.*, elements of vector x). The results of the parameter estimates are summarized below.[11] All of the coefficients have the correct sign and are statistically significant at a high level ($p < 0.0001$).

$$\ln y_i = 11.993 - \underset{(-9.068)}{8.978} \ln tech_t + \underset{(8.085)}{0.395} \ln water\ depth_i - \underset{(-2.540)}{0.345} \ln price_t$$

$$\sigma^2 = \sigma_v^2 + \sigma_u^2 = \underset{(14.146)}{1.934} \qquad \gamma = \sigma_u^2/\sigma_v^2 = \underset{(0.059)}{0.703} \qquad \mu = \underset{(-0.313)}{-0.193}$$

$$\text{log likelihood} = -1{,}453.2538 \qquad n = 832,$$

where γ is an indication of the relative contribution of v to error term, and μ is the mode of the normal distribution.[12] A higher value of γ shows that a one-sided error component (*i.e.*, u) dominates the symmetric error components (*i.e.*, v) (Kumbhakar and Lovell 2000).[13]

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[10] New discoveries larger than this threshold value are assumed to be developed immediately. Thus, analysis of asset management and delayed development is not considered in this model.
[11] t statistics are in parentheses.
[12] If $\mu = 0$, the density function is half-normal.
[13] The sensitivity of water depth is larger than that of price. However, both are much smaller compared to technology indexes. The one-sided error term captures the possibilities that actual minimum economic field size might be larger than frontier estimates. We need to note, however, our estimates might be underestimates compared to the industry estimates that appeared in *Oil and Gas Journal*. Alternative methods of minimum economic size include Eckbo, Jacoby, and Smith (1978), though it requires the cost data.

Step 3: Factor Inputs

For fields that are economically producible, factor inputs, such as the number of platforms and the number of wells in the field, are generated using information on field size and water depth. When newer, larger fields are discovered and developed, there is a derived demand for new offshore structures that serve as inputs to production.[14] We use the cumulative number of platforms and wells for the same reason as in the production function described below. We specify our platform and well number functions as:

$$\sum_{t=1947}^{t} platform_{it} = f\,(field\ size_{it},\ water\ depth_{it}) \tag{5}$$

$$\sum_{t=1947}^{t} well_{it} = f\,(field\ size_{it}). \tag{6}$$

We expect the field size (note: this is the *actual size* and not the *minimum economic size*) to have a positive effect on the number of wells and platforms and water depth to have a negative effect on the number of platforms, since a smaller number of larger platforms is typically installed in deeper waters. In each field, field size increases over time because of reserve addition and revision and decreases because of resource extraction. In contrast, water depth remains constant over years for each field. Thus, both the number of platforms and wells increases when field size increases and decreases when field size decreases. Considering the predictability of past platforms and wells, we use a two-way random effects model to estimate this relationship.[15] The following shows the results of linear model parameter estimation.[16] The estimated coefficients are significant and have the expected sign.

$$\sum_{t=1947}^{t} platform_{it} = 2.7296 + \underset{(57.13)}{0.0378}\ \ field\ size_{it} - \underset{(-4.48)}{0.001055}\ \ water\ depth_{it}.$$

$R^2 = 0.9582$ $\quad n = 15{,}725$ $\quad DW = 1.7999$ $\quad \rho = 0.09695$

$$\sum_{t=1947}^{t} well_{it} = 12.2658 + \underset{(67.54)}{0.3451}\ \ field\ size_{it}.$$

$R^2 = 0.9427$ $\quad n = 15{,}725$ $\quad DW = 1.8599$ $\quad \rho = 0.09506.$

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[14] Pindyck (1978b) studies nonrenewable resource production using an optimal control model. He assumes that production cost is only the function of proved reserve base. If we also consider the platform, as well as additional production cost variables, we are able to derive a production as a function of these variables.
[15] See Baltagi (2001) for econometric methods for panel data.
[16] t statistics are in parentheses. All of the coefficients are significant at 1%. The time period analyzed is 1946–95. The unit of *field size* in this table is MMbbl.

Step 4: Production and Pollution

Finally, we generate production and pollution paths over time. Production of oil and gas is determined by technology, the stringency of environmental regulations, the number of platforms, and the number of wells. Pollution levels are determined from environmental regulations, technology, and production. We then aggregate these field-level estimates to the regional level. In our field-level analysis, we use cumulative values for factor inputs (*e.g.*, wells and platforms) and outputs (*oil, gas, and pollution*), since it is more appropriate to express the production relationship on cumulative terms for a nonrenewable industry. For example, for any field, the production at *t* is determined by cumulative inputs (*e.g.*, the total number of wells drilled) and extraction up to *t*–1. In addition, the industry must comply with relevant environmental regulations, so we use environmental stringency as an explanatory variable. We specify our field-level production function as:

$$\sum_{t=1947}^{t} production_{it} = f(tech_t, env.\,stringency_t, \sum_{t=1947}^{t-1} platform_{it}, \sum_{t=1947}^{t-1} well_{it}), \qquad (7)$$

where *production* is the quantity of oil and gas produced in million barrels of oil equivalent (10^6 BOE); *tech* is the technological change index; *env. stringency* is the stringency of environmental regulations governing offshore oil and gas operations, measured as environmental compliance cost in dollars per unit of oil and gas production in the region.[17] The variable *platform* represents the total number of platforms, *well* is the total number of exploratory and development wells, *i* is the field index, and *t* is time (*i.e.*, year). Note that our simplistic model does not take into account the many important institutional changes (*e.g.*, fiscal regime, acreage auctions, leasing conditions) that affect production in the US Gulf of Mexico (see Boué (2002) for detail).

We use a two-way random effects model to estimate this relationship. The expected sign for *tech* is positive, since improvements in technology are expected to increase production (Lynch 2002). The expected sign of *env. stringency* is negative, since more stringent regulations are expected to reduce production, with technology held fixed (Jin and Grigalunas 1993a,b). The expected signs for the cumulative number of platforms and wells are positive. As explained in Step 3, both of the platform and well values decrease once the field size starts to decrease. Therefore, these two variables eventually put an end to annual production. The estimation results of the production model are:[18]

$$\sum_{t=1947}^{t} production_{it} = -35.6939 + \underset{(22.07)}{21.9450}\, tech_t - \underset{(-15.32)}{0.3222}\, env.\,stringency_t$$

[17] Note that the technological change index and the stringency of environmental regulations are time-series data instead of cross-sectional time-series data. This is because we do not forecast these variables in a cross-sectional time-series base (*i.e.*, field level). Therefore, we assume both of the indexes remain the same over the fields in each year (*i.e.*, the industry in each field can utilize the same technology and face the same regulation stringency level in the same year).

[18] t statistics are in parentheses. All of the coefficients are significant at 1%. The time period analyzed is 1946–95. ρ is the coefficient of serial correlation.

$$+ \ 1.8567 \sum_{t=1947}^{t-1} platform_{it} \ + \ 0.6052 \sum_{t=1947}^{t-1} well_{it}$$

$$(40.75) \qquad\qquad (101.01)$$

$$R^2 = 0.9745 \qquad n = 15{,}725 \qquad DW = 1.7957 \qquad \rho = 0.09624.$$

All the coefficients have the correct sign and are significant at a high level ($p < 0.0001$). The coefficient on *tech* is highly significant with a positive sign; therefore, if technological change increases with other variables held fixed, production increases. Our results indicate that technological change plays a significant role in production in the offshore oil and gas industry in the Gulf of Mexico. This is not surprising since technological progress, such as 3D seismology and horizontal drilling, have drastically improved the efficiency of production. In forecasting production, we assume production ends if estimated cumulative production starts to decrease compared to last year's cumulative production. This assumption is required since we are not able to obtain the decision-making process of shut-in of wells and/ or removal of platforms.

Pollution is the by-product of oil and gas production and hence is also expressed in cumulative terms.[19] Our environmental output data set is composed of 33 different types of water pollutants in the four EPA categories and oil spill volume data from the Coast Guard. However, since there are no techniques that integrate 34 different pollution outputs, we use produced water as a proxy for environmental pollution. Our dependent variable, however, needs to explain the discharged pollution level after treatment; therefore, untreated produced water needs to be adjusted by the treatment level. We use environmental Total Factor Productivity (TFP), as calculated in Managi (2002) and Managi *et al.* (2004b), as a measurement of treatment level. In general, a productivity index is defined as the ratio of an index of output growth divided by an index of input growth over two periods. TFP is the comprehensive productivity index that attempts to include all outputs and all inputs used in the production process. Changes in the TFP index can tell us how the amount of total output produced from a unit of total input has changed over time. In addition to this standard measure of TFP, Managi (2002) and Managi *et al.* (2004b) estimated TFP, including environmental compliance cost (as a proxy for the regulation compliance efforts), in the input side and environmental pollutions in the output side. Thus, this TFP with environmental data implies more market output and less environmental pollution can be produced given standard market and environmental input. Taking the ratio of TFP with and without environmental factors, defined as environmental TFP [(TFP with environment) / (TFP without environment)], it is possible to measure the productivity (or efficiency) of pollution abatements. Therefore, an increase in the environmental TFP implies that less environmental pollution can be released for the given environmental input. Dividing the untreated produced water before treatment by environmental TFP, we create a proxy for discharged pollution level after the treatment. The initial value of environmental TFP is one, and the improvement in environmental abatement technology is shown as a value of envi-

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[19] The drilling fluids, drill cuttings, deck drainage, well treatment fluids, proposal sand, and sanitary and domestic wastes are also important factors in the regulations in addition to the environmental regulations applied to production. Considering the data availability, however, we assume the regulations only applied to production. See U.S. EPA (1976, 1985, 1993a,b, 1999) and Managi (2002) for a detailed history of the regulations.

ronmental TFP to be more than one. In summary, we specify our environmental pollution function using the two-way random model as:

$$\sum_{t=1947}^{t} pollution_{it} = f(env.tech_t,\ env.stringency_t,\ \sum_{t=1947}^{t} production_{it}), \tag{8}$$

where *pollution* is a proxy for environmental pollution, *env.tech* is the environmental technological change index as detailed in Managi *et al.* (2004b), environmental stringency as measured by the estimated cost of complying with environmental regulations (see Appendix for detailed description), and production is the quantity of oil and gas produced, as measured by million BOE.

Standard TFP can be decomposed into measures associated with technological change and efficiency change using DEA (*e.g.*, Färe, Grosskopf, and Lovell 1994). Managi *et al.* (2004b) applied this decomposition to the environmental TFP, and the environmental technological change index is estimated using DEA. Since technological change measures shifts in the production frontier, the interpretation of environmental technological change is that it measures shifts in the pollution abatement frontier (*i.e.*, the measurement of the best environmental technology level). The larger the number implies the better use of environmental technologies.

The expected sign for *env.tech* is negative, since improvements in technology are expected to reduce pollution (Jaffe, Newell, and Stavins 2002). The expected sign for *env.stringency* is negative, since more stringent regulations are expected to reduce the pollution. The expected sign for *production* is positive, since pollution is the by-product of production. The result of linear estimations is summarized as follows:[20]

$$\sum_{t=1947}^{t} pollution_{it} = -0.9990 \underset{(-3.14)}{-\ 1.0106}\ env.tech_t$$

$$\underset{(-3.44)}{-\ 0.0203}\ env.\ stringency_t + \underset{(130.10)}{0.2397} \sum_{t=1947}^{t} production_{it}$$

$R^2 = 0.9611$ $n = 15{,}725$ DW = 1.8299 $\rho = 0.09611$.

We use a linear relationship to look at a first-order linear approximation to some true non-linear relationship. All of the coefficients are statistically significant ($p <$ 0.0001) and have the correct sign. Our results indicate that environmental technological change plays an important role in reducing pollution in the offshore industry. Compared to the impact of *tech* on production, however, the effect of pollution reduction on technological change is smaller (around 16% of production technological change impact). We speculate that this may be because there is little flexibility in command-and-control regulations.

[20] t statistics are in parentheses. All of the coefficients are significant at 1%. The time period analyzed is 1946–95.

The estimated cumulative numbers of platforms and wells generated to date are used to update cumulative oil and gas production and pollution.[21] The percentage of variation explained by the production model is $R^2 = 0.9900$ and by the pollution model is $R^2 = 0.9944$. Therefore, our model fits the data very well.

Forecasting: Policy Scenario Analysis

Various scenarios for technological change, environmental policy, and depletion were constructed. We estimate the impact of changes in policy variables on technological change, estimated as a function of R&D, environmental stringency and discovery number, and oil and gas prices. We then trace the effects through discovery, input usage, resource production, and pollution emitted. The following sections describe the construction of scenarios, prediction capability of the model, and each forecasting result.

The Scenarios

The relevant variables for projecting future production and pollution are: (1) technological change, (2) number of new discoveries, (3) stringency of environmental regulation, and (4) the form for environmental regulations (*e.g.*, market-based versus command-and-control).

Sensitivity analyses are used to determine how the results change under higher and lower policy scenarios, with a total of 11 scenarios including baseline scenario (see table 1). The baseline scenario uses average historic rates for technological change, environmental stringency indexes, and the number of new field discoveries.[22] Environmental technological change follows the environmental stringency scenario using results of the Almon lag distributional model estimation. We use the reference case oil and gas price scenario proposed by the EIA for the period 2002 to 2020, which uses the average rate of change to project prices through 2050 (U.S. Department of Energy 2001).

Next we use various sensitivity analyses to analyze the impact of alternative assumptions regarding technological change, depletion, and environmental regulations, as summarized in table 1. We construct two alternative scenarios for R&D expenditures, one where R&D increases linearly over time, where the annual rate of increase is +1% of baseline R&D expenditure, and another where R&D decreases, where the annual rate of decrease is –1% of baseline R&D (see figure 3a for R&D and figure 3b for technological change scenarios).

The depletion effect is modeled by varying the oil and gas prices, which induce the discoveries of the fields. Once the number of discoveries is determined, their field sizes are generated as random variables based on the historical distribution of the field size at each water depth. If the generated field size is larger than estimated minimum economic field size, the data is used for further simulation process. We control the oil and gas price scenarios following EIA forecasting. We consider an optimistic case, where industry continues to find new fields at historic rates through

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[21] It is assumed that: (1) new technologies are applied to all existing fields, instead of only newly discovered fields and (2) new environmental regulation is only implemented in new fields; *i.e.*, all existing fields follow old regulations.

[22] The time periods to be considered as historical rate of technological change are 1946–95, 1969–98 for environmental stringency, and 1963–2001 for discovery number.

Table 1
Summary of Policy Scenarios

Policy Scenario	Description
Technological Change	
Baseline: Historic rates	Constant over time
High technological change	R&D increase linearly[1]
Low technological change	R&D decrease linearly
Discovery Number of New Fields	
Baseline	Follow the EIA reference case oil and gas price scenario
Most optimistic scenario:	
Historic rate of discoveries	Follow the EIA high oil and gas price scenario
Less optimistic scenarios:	
No discovery after 2015	Number of discoveries decreases until 2015
No discovery after 2030	Number of discoveries decreases until 2030
No discovery after 2045	Number of discoveries decreases until 2045
Stringency of Environmental Regulation	
Base case	Average historic rate
High stringency	Rate equals that for highest historic decade[2]
Low stringency	Low case equals the baseline case minus the absolute Value of the difference between the high and base case
Flexible Environmental Policy	
Base case	Command-and-control
Flexible regulations:	
Apply to all fields	Adopt the value from Popp (2003) for all fields
Apply to new fields only	Adopt the value from Popp (2003) for new fields

Notes:
[1] Technological change index follows the relationship estimated in the above section. We estimate that the R&D value keeps the same technological change value as the baseline case. We then construct the high and low R&D cases and estimate each technological change scenario.
[2] The decade 1981–90 shows the highest increase of stringency in the history.

2050. Note that this scenario actually leads to an increasing number of discoveries through 2050, due to improvements in technology. We also consider less optimistic cases, where the rate of discovery declines linearly over time, and new discovery completely ceases at some time prior to 2050. Our three less optimistic scenarios specify new discovery ceasing in 2015, 2030, and 2045 (figure 3c). In all cases, we assume the baseline level of technological change for all of the discovery scenarios. Two scenarios are also constructed for the stringency of environmental regulations. The lower scenario has the stringency of environmental regulations increasing more slowly than historic rates, and the higher scenario has stringency of environmental regulation increasing more rapidly than historic rates (figure 3d). The high scenario is based on the assumption that the stringency of environmental regulations grows at the rate of the decade with the fastest growing environmental stringency in our data set (1981–90). The low scenario is based on the assumption that the stringency of environmental regulations increases at a lower rate than the baseline case. In this

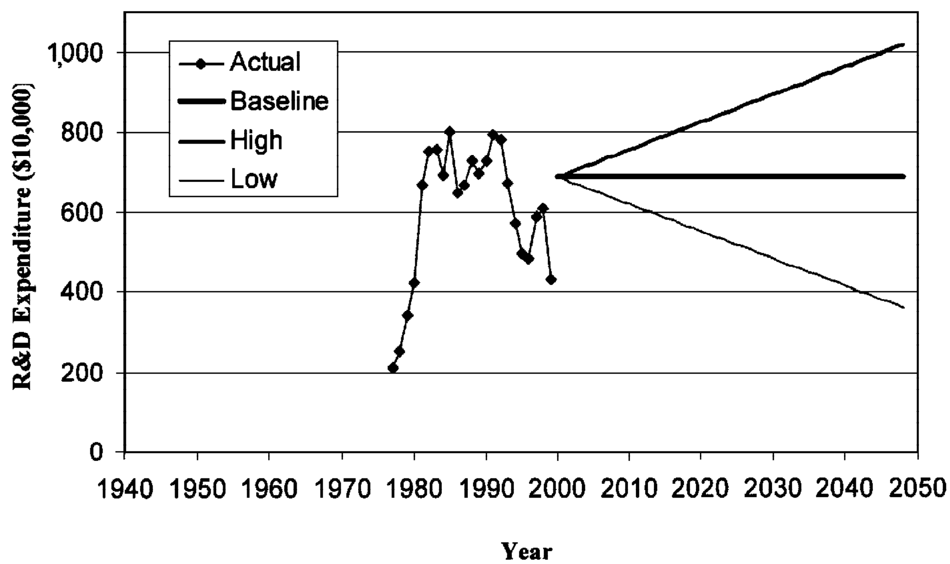

Figure 3a. R&D Expenditure Scenario

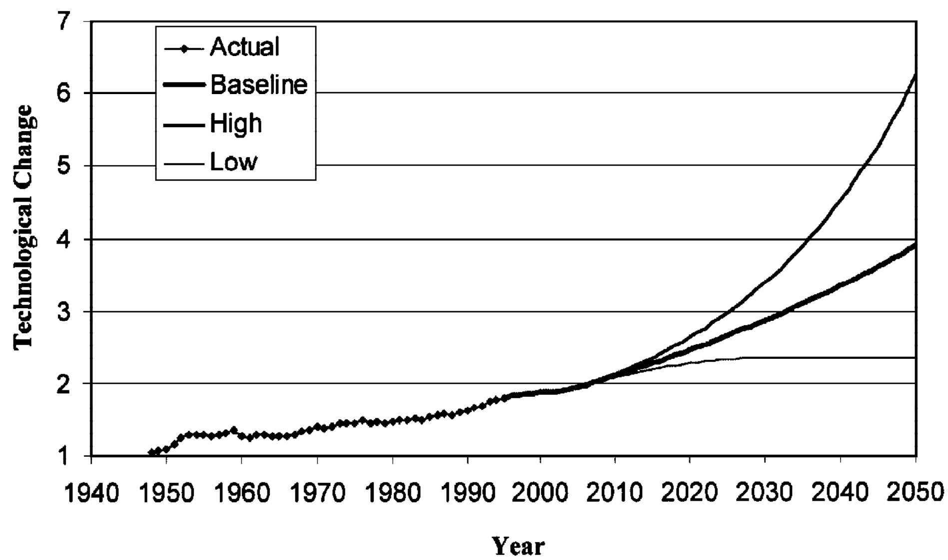

Figure 3b. Technological Change Scenario

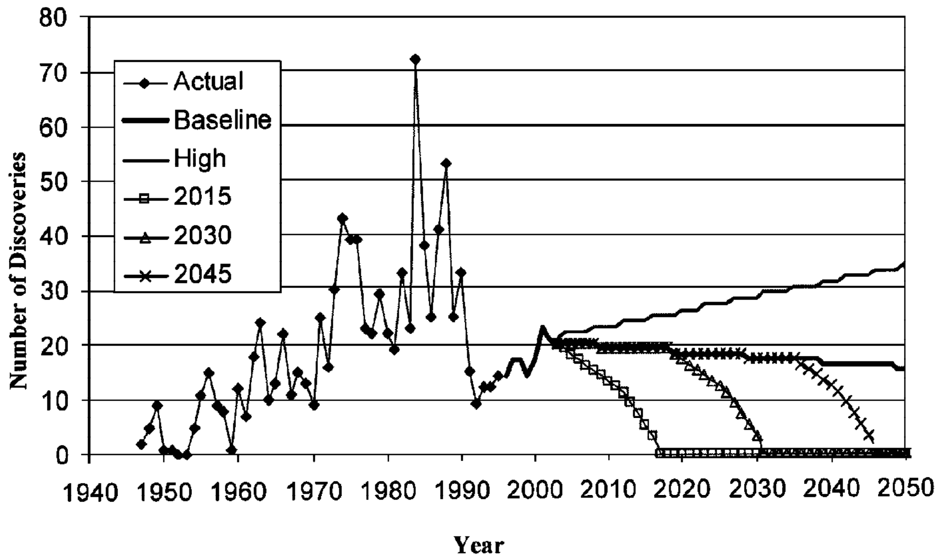

Figure 3c. Discovery Number Scenario

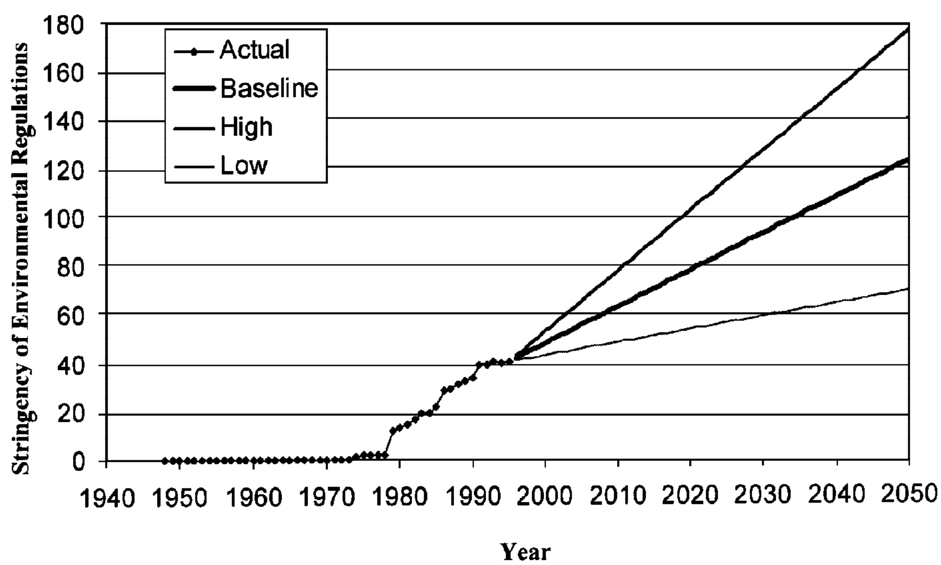

Figure 3d. Environmental Regulation Scenario

case, we take the rate of the baseline case minus the absolute value of the difference between the high and base case.

The next sets of scenarios are used to identify the impact of changing the design of environmental regulations. Historically, regulation in offshore oil and gas operations has used the command-and-control approach. But there has been growing recognition in government and industry of the need for more cost-effective approaches to environmental protection. The recommendations include the development of a more flexible policy and regulatory framework, which includes more efficient recovery technologies to reduce environmental impacts. The American Petroleum Institute (API) has emphasized these concerns with a call for "common sense" regulatory development (API 1996). Unlike approaches that mandate specific technologies, "common sense" approaches would give oil and gas producers more flexibility in determining how they can best meet standards, yielding the same environmental benefits at lower costs. The associated benefits (*i.e.*, increase in production by keeping the same pollution level) that can be derived from flexible approaches, such as market-based approaches for pollution controls are estimated.[23] We consider a case where flexible environmental regulations apply to all existing fields and a case where flexible regulations apply only to new fields. None of the estimates comparing the effectiveness of flexible regulations in the oil and/or gas industry, however, is available in the literature. Therefore, we use the results of Popp (2003), where estimates of the effect of newly granted patents (as a proxy for technological innovation) are used to determine the increase in removal efficiency of new scrubbers generated by a new SO_2 pollution control patent. Popp used data between 1979 and 1997 to compare command and control before the Clean Air Act (CAA) of 1990 and permit trading after the CAA. Popp (2003) found that permit trading is 2.217 times more efficient than the command and control method. We use this value, 2.217, to estimate the less negative impact of regulation to oil and gas production estimates.

Results

Scenario (1) in table 2 (also in figures 4a and 4b) shows the baseline forecast of annual production and pollution, respectively. The annual rate of production and pollution are calculated as the first difference of estimated successive cumulative production and pollution yields. Three-year moving averages of annual estimates are presented.[24] The highest annual production of approximately 1.8 billion barrels was attained in 2020. This is followed by a gradual decrease in production for the remainder of the forecast period. The baseline forecast of production of oil and gas shows an annual increase of 1.5% until 2020, followed by a decline of approxi-

[23] In the literature, there is an ongoing discussion as to which different environmental policy instruments provide firms with incentives to invest in environmental R&D. Many works have been carried out under the assumption of perfect competition (Magat 1978; Milliman and Prince 1989; Jung, Krutilla, and Boyd 1996; and Parry 1998). These authors support the viewpoint that market-based regulations are likely to be more effective in stimulating innovation than those that mandate fixed technological or performance standards. Less consistent with the above findings are the works of Magat (1978) and Malueg (1989), who showed that relative incentives might vary depending on the firm's specific technologies and elements of instrument design. Montero (2002) shows that the command-and-control method may offer greater R&D incentives for technological innovation than do market-based instruments when strategic interactions in the permits and output markets are not perfectly competitive markets.

[24] Hereafter, three-year moving averages of annual estimates are used to draw annual production and pollution.

Table 2
Policy Scenarios Results (Units of Billion Barrels)

Policy Scenario	Production Forecasting (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Year											
2005	1.242	1.249	1.209	1.410	1.410	1.410	1.242	1.207	1.278	1.781	1.265
2010	1.598	1.669	1.509	1.602	1.602	1.602	1.591	1.521	1.676	1.826	1.650
2015	1.344	1.558	1.186	1.451	1.451	1.451	1.331	1.216	1.472	2.318	1.429
2020	1.820	1.965	1.592	1.891	1.891	1.753	1.677	1.684	1.954	2.382	1.909
2025	1.559	1.700	1.222	1.738	1.738	1.368	1.200	1.397	1.719	2.158	1.665
2030	1.139	1.599	0.810	1.590	1.590	0.988	0.674	0.959	1.317	1.928	1.257
2035	1.006	2.247	0.672	1.637	1.637	0.898	0.279	0.804	1.207	1.765	1.373
2040	1.357	2.196	0.442	1.935	1.372	0.820	0.000	1.137	1.577	1.820	1.503
2045	0.862	2.408	0.216	1.908	0.841	0.635	0.000	0.629	1.133	1.642	1.043
2049	0.915	2.645	0.214	1.809	0.565	0.260	0.000	0.665	1.239	1.687	1.131

Policy Scenario	Pollution Forecasting (1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year									
2005	0.342	0.344	0.331	0.388	0.388	0.388	0.388	0.333	0.350
2010	0.330	0.342	0.311	0.331	0.331	0.331	0.331	0.316	0.345
2015	0.347	0.379	0.315	0.374	0.374	0.374	0.279	0.327	0.368
2020	0.357	0.407	0.313	0.371	0.371	0.371	0.284	0.331	0.384
2025	0.309	0.376	0.257	0.345	0.345	0.279	0.262	0.277	0.341
2030	0.344	0.464	0.268	0.418	0.418	0.260	0.218	0.303	0.386
2035	0.207	0.400	0.110	0.337	0.337	0.179	0.014	0.127	0.290
2040	0.264	0.496	0.153	0.376	0.376	0.224	0.000	0.214	0.317
2045	0.176	0.526	0.067	0.389	0.149	0.054	0.000	0.126	0.287
2049	0.154	0.574	0.035	0.321	0.119	0.023	0.000	0.102	0.214

Note: Policy Scenario (1) Baseline, (2) High technological change, (3) Low technological change, (4) High new discovery, (5) 2045, (6) 2030, (7) 2015, (8) High environmental stringency, (9) Low environmental stringency, (10) Flexible regulation for all fields, and (11) Flexible regulation for new fields.

mately 1.5% per year after 2020. This decline occurs because the depletion of old wells outweighs new discoveries. It is anticipated that in 2050, annual production will decrease to 0.9 billion barrels, 65% of 2000 production. This level of production is comparable to that reported during the oil shock years of 1972 to 1974.

For comparison, Nehring (2001) used detailed data on deepwater operations in the Gulf of Mexico to forecast gas production from known and future discoveries through 2010. His work shows that production of oil and gas will continue to increase, reaching its peak in 2008, and will start to fall in 2009. Further, he points out that data, which indicates production is expected to start falling earlier than in our forecast, is mainly because the former ignores the importance of technological change in oil and gas production. Our forecast is close to that of the EIA for the Gulf of Mexico (U.S. Department of Energy 2001). They forecasted that oil production will increase until 2017, and then begin to decrease; while the forecast for gas production would continue to increase throughout the forecast period, 2020. The summation of oil and gas production in BOE is expected to reach its maximum in year 2018. They do not forecast beyond 2020.

Our model forecasts that pollution will reach its peak in 2014. At this time, the level of pollution will be the same as that experienced in the late 1980s. This peak in pollution is expected to set in somewhat earlier than the peak in oil and gas produc-

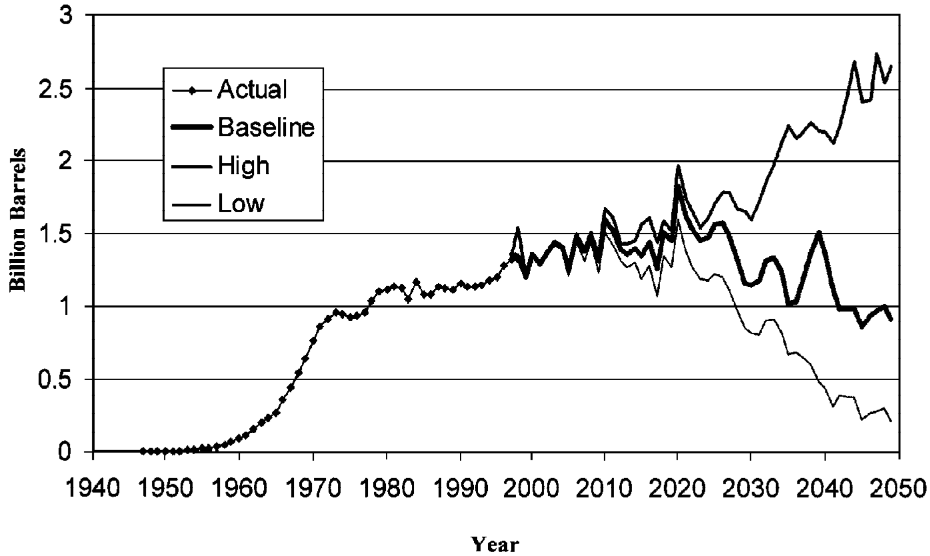

Figure 4a. Forecast of Annual Production (Technological Change Scenario)

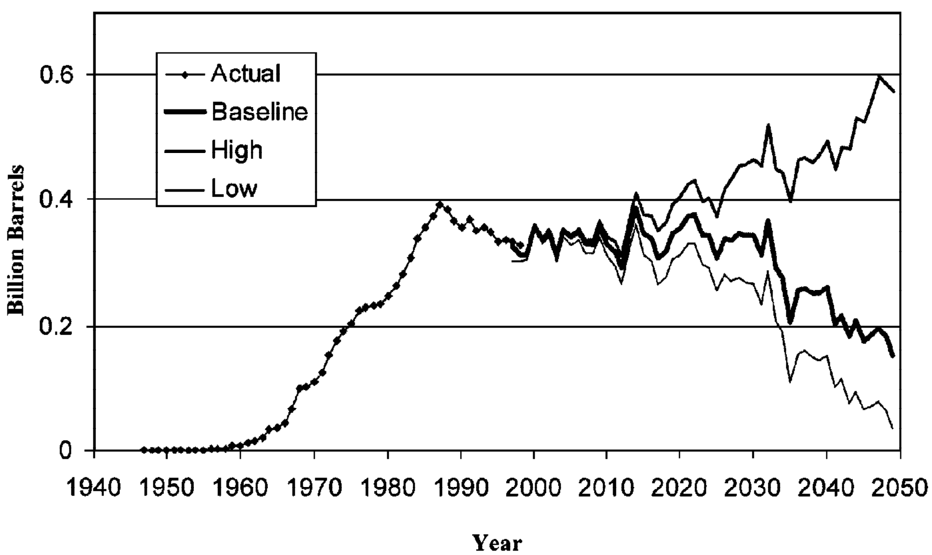

Figure 4b. Forecast of Annual Pollution (Technologial Change Scenario)

tion because of improvements in environmental technology induced by more stringent environmental regulation.

Scenarios (2) & (3) in table 2 (and figures 4a and 4b) show projections of annual production and pollution, respectively, based on technological change scenarios detailed in table 1. In the high technological change scenario, production is expected to continue to increase and reach its maximum of 2.65 billion barrels in 2050. This level of production is twice that recorded in 2000. Under this scenario, technological change fully mitigates the depletion effects. In contrast, the low technological change scenario shows declining oil and gas production, with final production of only 0.2 billion barrels in 2050. This is barely 16% of 2000 production and 77% lower than the baseline case for 2050. Pollution is forecast to increase more (274% from baseline year 2050) in the high technology scenario than in the low technology scenario (77% decrease from baseline year 2050). This is expected in that high pollution is associated with high levels of production. Thus, increasing the levels of technological change has a beneficial effect on oil and gas production, but a detrimental effect on pollution. Due to this pollution increase in the high technological change scenario, adequate environmental regulations are necessary to maintain an appropriate balance between production and pollution discharge.

Scenarios (4), (5), (6), and (7) in table 2 show projections based on different scenarios for field discoveries, as detailed in table 1. In the case of high rates of new discovery, production continues to increase 2.5% per year, on average, until 2040 and remains relatively constant thereafter. In the case of no new discovery after 2015, production and pollution decrease, eventually ceasing in 2037. In the case of no new discoveries after 2030, production and pollution continue to decrease and produce only around 28% and 15% of baseline, respectively. In the case of no new discovery after 2045, production decreases to 60% of the baseline. Pollution also decreases to 77% of the baseline scenario. The results show the long-term significance of new discoveries, which is determined by technological change and depletion effects.

Scenarios (8) & (9) in table 2 show forecasts of annual production and pollution based on the environmental regulation scenarios detailed in table 1. The differences of high and low environmental regulation scenarios are smaller than those of technological change scenarios. For the high environmental regulation case, production and pollution are less than that of the baseline environmental regulation. In 2050, both production and pollution are expected to fall by 30% below the baseline. Under a low environmental regulation case scenario, production and pollution are above the baseline. In 2050, production is expected to rise 35% above the baseline, while pollution will be 40% above the baseline. Environmental regulations have a significant impact on the pollution level and production.

Scenarios (10) & (11) in table 2 show forecasts based on flexible regulation scenarios in table 1. Given the negative impact of environmental regulation to production, use and analyses of flexible regulation is investigated. If flexible regulations are applied to all existing fields, production is forecast to increase around 45%, on average, compared to the baseline scenario of command-and-control. If flexible regulation is applied to only new fields, production increases by 10% compared to the baseline. These two scenarios give the upper and lower bounds, respectively, of the benefits of using flexible environmental regulations, based on available results for benefits from improving flexibility of regulations.

The annual level of pollution per unit production tended to fall over the entire forecast period, even though pollution does not start to decrease until 2030. In the baseline scenario, this ratio declines by 32% over the forecast period and around 6% annually. Environmental regulation can reduce pollution in two ways: first through its impact on production, and second by inducing environmental technological change. For all policy scenarios investigated, there is no significant affect on the pollution-to-production ratio, except in the flexible regulatory scenario. All other things being equal, a flexible regulatory environment is expected to reduce the existing level of pollution by 30%.

Conclusion

In this study, we describe a model for analyzing long-term production and pollution in the offshore oil and gas industry in the Gulf of Mexico. Reliable baseline forecasts of production and pollution and the response to different policy actions are critical to assessing long-term energy and environmental policies. An improved understanding of the potential role of technology and environmental policy provides policy-relevant information for designing and implementing sound environmental policies. Forecasts of production and pollution through 2050 are generated from the model using disaggregated field-level data. In our baseline scenario, oil and gas production increases by approximately 1.5% per year until 2020, when a declining trend sets in. Pollution levels remain relatively constant until 2014 and start to decrease gradually thereafter. Our sensitivity analysis of the results demonstrates the importance of measuring technological progress accurately if reliable forecasts of production and pollution level are to be made.

We have used different scenarios to explore the significance of various factors in determining forecasts. Alternative scenarios are used to explore how results vary with alternative assumptions regarding: (1) R&D expenditures, (2) depletion of reserves, (3) environmental regulations, and (4) flexible regulations in the Gulf of Mexico. As shown in table 3, technological change had the greatest effect by increasing production by 189%, while stringency of environmental regulations had the smallest impact. The number of new discoveries has significant impact on maintaining long-term production. The scenario of no new discovery after 2015 shows that production decreases and is expected to cease in 2037. If flexible regulations are applied, production is forecast to increase around 10 to 45%, on average, compared to the baseline scenario of command-and-control.

The model developed in this study provides an approach for measuring and analyzing the impact of production and pollution from technological change and measures the impact of different policy scenarios. This is important in the sense that environmental regulations promulgated by the Environmental Protection Agency entail a compromise and tradeoff for different stakeholders: the regulatory agency, the oil and gas industry, and public interest groups. Quantitative measure of the potential impacts of technological change and environmental regulations can contribute to those public debates and lead to more informed policy decisions. In using environmental standards, it is important that the regulator gives industry enough time to develop solutions that protect the environment, while still meeting important user requirements. Time may also be needed to examine whether a solution may pose other hazards. One way of dealing with the problem of compliance time is with phased implementation—to give firms innovation waivers that initially exempt them from regulations. Another strategy is the setting of long-term standards that requires development of new technology.

It would be an interesting topic of future work to determine the impact of environmental regulations applied to drilling (see U.S. EPA [1999] for recent proposed guidelines regarding drilling fluids). Since the regulations to drilling fluids incur cost to the industry and thus reduce the number of wells drilled, our forecasting of production and pollution (as a by-product of production) would be an overestimate.

Table 3
Summary of Policy Scenarios Results

Policy Scenario	Size of the Impacts (Comparison with Baseline Year 2050)
Technological Change	
High technological change	+189% (production), +274% (pollution)
Low technological change	–77% (production), –77% (pollution)
Discovery Number of New Fields[1]	
Most optimistic scenario:	
Historic rate of discoveries	+98% (production), +101% (pollution)
Less optimistic scenarios	
No discovery after 2015	Production ceases in 2037
Stringency of Environmental Regulation	
High stringency	–30% (production), –30% (pollution)
Low stringency	+40% (production), +40~50% (pollution)
Flexible Environmental Policy	
Flexible regulations:	
Apply to all fields	+45% (production)
Apply to new fields only	+10% (production)

Note:
[1] Here we show the two extreme cases. The other two results of no new discoveries after 2030 and 2045 fall in between these two extreme cases.

One of the major limitations of this study is the lack of extraction and drilling cost data; therefore, our model is not based on formal theory. If cost data were available, theoretically consistent econometric modeling by Deacon (1993) could be used.[25] For example, the *Joint Association Survey on Drilling Costs* (JAS) published by the American Petroleum Institute might be used (see Managi *et al.* [2004c] for cost estimations). The JAS data, however, are grouped into nine depth intervals in each of the offshore areas in the Gulf of Mexico (*e.g.*, offshore Louisiana and offshore Texas). Thus, some regional aggregation is required as a price for using theoretical consistent modeling. Other important aspects to consider are institutional changes (*e.g.*, fiscal regime, acreage auctions, and leasing conditions) in the U.S. Gulf of Mexico (Boué 2002). These factors affect production and pollution levels significantly over the long-term, and econometric modeling needs to be considered for future research.

[25] The model requires estimates of three functions: reserve additions, drilling cost, and production cost (Deacon 1993). Other theoretically justified model includes Pesaran (1990) that estimates an econometric model of offshore oil production in the UK.

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Appendix: Data

Research and Development (R&D) expenditures for oil and gas recovery is obtained from the Energy Information Administration's Financial Reporting System (FRS) database over 1977 to 1999.[26] This R&D includes funding from the federal government and private companies. The FRS database does not distinguish between onshore and offshore R&D. The impact of new technologies is most obvious in offshore, but they have allowed many new onshore developments as well. Therefore, we use summation of onshore and offshore R&D. There are also international spillover effects that have not been considered in this study. The R&D expenditure of the oil companies funding has shown a declining trend, on average, since 1990. Creusen and Minne (2000) show that oil companies are reluctant to commit themselves to risky projects to improve their market position and introduce radically new products. On the other hand, industry at least in the U.S. was rapidly reorganizing the way it conducted research to exploit ever greater economies from joint efforts, partnerships, consortia, and a general migration of the R&D function from the producers to the service industry and universities.

Data used in this analysis were obtained from the U.S. Department of the Interior, Minerals Management Service (MMS), and the Gulf of Mexico OCS Regional Office. We have developed a unique micro-level database (*i.e.*, field) using three MMS data files: (1) production data, including well-level monthly oil and gas outputs from 1947 to 1998 (a total of 5,064,843 observations for 28,946 production wells); (2) borehole data describing drilling activity of each well from 1947 to 1998 (a total of 37,075 observations); (3) field reserve data including oil and gas reserve sizes and discovery year of each field from 1947 to 1997 (a total of 957 observations).[27]

Relevant variables were extracted from these data files and merged by year and field. Thus, the project database includes field-level annual data for the following variables: oil output, gas output, number of exploration and development wells drilled, total drilling distance of exploration and development wells, number of platforms, water depth, oil reserve, gas reserve, untreated produced water, and discovery year.

To measure a tendency towards stringent environmental regulation, we use environmental compliance cost for preventing water pollution and oil spills. Our environmental compliance cost is based on *ex-ante* estimates since we do not have the *ex post* cost studies.[28] We compiled a data file for water pollution and oil spill prevention costs from 15 *Federal Register* (*FR*) documents (*e.g.*, *FR* 1986, 1988, and 1990), five EPA documents (*e.g.*, U.S. EPA 1976, 1985, and 1993), five engineering documents, and one Coast Guard document which contain the *ex-ante* capital cost, operation, and maintenance cost estimates for each set of regulations. These environmental regulations require phased implementation over a period of years and regulations are occasionally revised, which implies a variation in stringency over time. Each of the capital, operation, and maintenance costs are estimated based on the project type, whether the field is an oil and gas joint project, an oil-only project, or a gas-only project after 1986. There is no distinguishing project type before 1986. See Managi (2002) for detailed estimation methods and references.

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[26] The data is available from www.eia.doe.gov/emeu/finance/frsdata.html. The unit of R&D is $10,000.

[27] Detailed description of these data files can be found at www.gomr.mms.gov. See Managi (2002) and Managi *et al*. (2004a) for more detailed data construction for this study.

[28] Harrington, Morgenstern, and Nelson (2000) looked at *ex ante* cost estimates of environmental regulations to the *ex post* cost estimates and compared the accuracy of estimates of the direct costs of more than two dozen regulations. They conclude, at least for EPA and OSHA rules, unit pollution reduction costs estimates are often accurate.