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Technological Change and Depletion in Offshore Oil and Gas

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Abstract

A critical concern for continued growth of the world economy is whether technological progress can mitigate resource depletion. This paper measures depletion effects and technological change for offshore oil production in the Gulf of Mexico using a unique field-level data set from 1947-1998. The study supports the hypothesis that technological progress has mitigated depletion effects over the study period, but the pattern differs from the conventional wisdom for non-renewable resource industries. Contrary to the usual assumptions of monotonic changes in productivity or an inverted "U" shaped pattern, we found that productivity declined for the first 30 years of our study period. But more recently, the rapid pace of technological change has outpaced depletion and productivity has increased rapidly, particularly in most recent 5 years of our study period. We also provide a more thorough understanding of different components of technological change and depletion.

JEL codes: D24, Q32, L71

Key words: technological change, depletion and offshore oil and gas industry

Technological Change and Depletion in Offshore Oil and Gas

Resource depletion is of critical importance for maintenance of the world economy. Early studies from Malthus (1826) to the so-called Club of Rome report (Meadows et al, 1972), have argued that limited resources will of necessity constrain economic growth. Typically, the conclusions of these studies have been pessimistic with respect to the potential for continued growth, even in the near term, and have called for a reorientation of policy towards development of a “spaceship” economy (Boulding, 1966; Daly, 1991). Other more recent studies have concluded that world production of critical resources such as petroleum will peak in the near future, followed by an inevitable decline (e.g., Deffeyes, 2001).

However, these studies have been sharply criticized for understating the potential for technological change to offset resource depletion (e.g., Cole, et al, 1975). These critiques have argued that, at least in principal, an exponential growth in knowledge could provide a basis for continued technological innovation that offsets resource depletion, and thereby fuel continued growth for an indefinite period (e.g., Stiglitz, 1974; Barbier, 1999). Proponents of this latter perspective have argued that the potential for technological progress to ameliorate resource scarcity is an empirical issue. Related empirical studies using prices as indicators of resource scarcity have found mixed results, with some studies supporting diminishing resource scarcity (e.g., Barnet and Morse, 1963), while others have found the evidence to be mixed or inconclusive (Slade, 1982; Berck and Roberts, 1996).

Empirical evidence regarding resource scarcity needs to consider more than physical resource availability, but must also consider the net effects of resource depletion and technological change. Hence, thorough conceptual and empirical analyses of technological change are essential for identifying appropriate policy actions to be undertaken to mitigate potential negative effects of resource depletion.

This paper uses field level data to measure technological change in offshore oil and gas production in the Gulf of Mexico, and to test the hypothesis that technological change has succeeded in offsetting depletion effects in offshore Gulf of Mexico petroleum production over the past 50 years. This is an important area of application because energy supplies are critically important resources supporting our economy, and because petroleum and natural gas are among the most vital energy resources in today's economy. We apply Data Envelopment Analysis (DEA) to field level data in order measure changes in productivity in offshore oil operations in the Gulf of Mexico for the time period from 1947 through 1998. We also separate measures of productivity change into various component parts to better understand the nature of technological advance and resource depletion.

II. Background

The Gulf of Mexico was 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 percent of total U.S. production, respectively (U.S. Department of Interior, 2001), and the offshore fraction of domestic production has been increasing over time. Oil and gas production in Gulf of Mexico accounted for 88 and 99 percent, respectively, of total U.S. offshore oil and gas production through 1997 (U.S. Department of Interior, 2000). From 1954 through 2000, the offshore industry provided for more than $125 billion in revenue from cash bonuses, rental payments, and royalties (US Minerals Management Service, 2000). In 2000 alone, more than $5 billion of total federal revenue came from this source.

There has been a long-standing debate concerning the direction of future oil and gas production. In a sense, we are always "running out" of oil and gas. Because oil and gas are nonrenewable resources within the relevant time horizon, each barrel produced brings us one step closer to ultimate resource depletion. As low cost resources are depleted, new production must move to more remote, less productive and hence more expensive sources. Simultaneously, new technologies allow us to capitalize on reserves that were previously uneconomic to discover and extract. Thus, productivity with respect to non-renewable resources is the net result of two opposing forces: cumulative depletion of existing resource stocks[1] and technological change, which provides access to new oil and gas resources, thereby augmenting the stock of economic resources.

Decades of extraction activity in the Gulf of Mexico have resulted in the depletion of the easily accessible reserves. Indeed, during the 1980's the Gulf of Mexico was derided by some as "The Dead Sea" as extraction moved to fields that were remote, deeper, and smaller, and hence more costly to recover. Thus, in the absence of technological change, the cost of extraction, development and production will increase over time, with a corresponding decline in economic reserves. However, contrary to earlier predictions of declining production (Walls, 1994[2]) recent technological advances have revitalized oil exploration in the Gulf. Principal new technologies include deepwater technologies, dimensional (3-D) seismology, advances in computer processing power, horizontal drilling methods and steerable drill head techniques. Principally as a consequence of these new technologies, output from the Gulf of Mexico has increased in recent years (U.S. Department of Interior, 2001).

To date, no consensus exists on whether technological change has prevailed over depletion effects in U.S. fossil fuel supplies. Cleveland and Kaufmann (1997) concluded that depletion effects have outweighed technological improvements over the 1943–91 period in the lower 48 states' gas supply exploration stage using aggregated data. Fagan (1997) concluded that ongoing technological change has offset ongoing depletion analyzing the cost of oil discovery using data for 27 large U.S. oil producers over the period from 1977–94 both for onshore and offshore exploration stage. Cuddington and Moss (2001) have reached the same conclusion analyzing the cost of finding additional reserves in aggregated data over the period from 1967 to 1990 covering the exploration and development stages. Jin, Kite-Powell and Schumacher (1998) developed a framework for the estimation of Total Factor Productivity (TFP) in the offshore oil and gas industry using regional data in Gulf of Mexico, and developed preliminary estimates for TFP change from 1976 to 1995. Their results suggest that productivity change in the offshore industry has been remarkable.

We extend the past literature by focusing on field-level data for measuring productivity change in the production stage of outer continental shelf oil and gas. Traditional aggregate approaches to modeling the supply of oil and gas have been criticized because aggregation of oil and gas data across distinctive geologic provinces may obscure the effects of economic and policy variables on the pattern of exploratory and development activities (e.g., Pindyck, 1978a). In contrast, modeling exploration and drilling at the micro level of individual fields allows one to capture not only the petroleum engineering and geological characteristics of petroleum supply process, but also the economic and policy incentives motivating producers to search for and develop petroleum resources.

One focus of this paper is to measure technological change and depletion effects in the U.S. offshore oil and gas industry in the Gulf of Mexico using data from 933 fields over the period of from 1947 to 1998. A vintage model is used to examine the historical rate of technological change to see whether the technological progress has offset the depletion effects over the study period. A mathematical programming technique called Data Envelopment Analysis (DEA) is applied for computation (see, for example, Charnes et al, 1978, Färe et al, 1985).

Our hybrid model decomposes the productivity effects into effects associated with technological change and depletion. We further decompose technological change and depletion effects to provide a better understanding of the relative importance of various productivity effects over the study period. This allows us to identify the relative importance of learning by doing[3] and identifiable new technologies in mitigating resource depletion. We also decompose productivity inhibiting depletion effects into various impacts, such as moving to deeper waters versus impacts due to extraction from smaller fields. In combination these decompositions will allow us to understand better the relative role of the different reinforcing and competing influences in productivity change, and may help contribute to policies that induce investment, information sharing, industry training, and perhaps the timing and location of lease sales.

III. Measurements of Productivity Change

In recent years, conceptual models and empirical measures of productivity change have progressed from "confessions of ignorance" (e.g., Arrow, 1962) in which time plays the role as the principal explanatory variable of technological progress, to increasingly refined structural models (e.g., Romer, 1990; Aghion, and Howitt, 1992; Barro and Sala-i-Martin, 1995) and empirical methods (e.g., Griliches, 1984; Färe et al, 1994). At the same time, the literature on resource scarcity has evolved from broad aggregate measures, towards increasingly structural models focusing on more specific issues (e.g., Fagan, 1997; Cleveland and Kaufmann, 1997; Jin, Kite-Powell and Schumacher, 1998; Cuddington and Moss, 2001). This increasingly focused research provides a more thorough understanding the constituents of productivity change.

Total factor productivity (TFP) includes all categories of productivity change, which can be decomposed into technological change, or shifts in the production frontier, and efficiency change, or movement of inefficient production units relative to the frontier (e.g., Färe et al, 1994). In the endogenous growth theory framework, technological change is decomposed into two categories: innovation and learning by doing (e.g., Young, 1993)[4]. This relates to the two models of technological change—innovation (e.g., Romer, 1990), that focuses on the creation of distinct new technologies, and learning by doing (e.g., Arrow, 1962), that looks at incremental improvements with existing technologies. To date, there is no empirical evidence in the literature that identifies the portion of technological change that is attributed to innovation versus learning by doing.

Production frontier analysis provides the Malmquist indexes (e.g., Malmquist, 1953; Caves et al, 1982a, 1982b), which can be used to quantify productivity change and can be decomposed into various constituents, as described below. Malmquist Total Factor Productivity (MTFP) is a specific output-based measure of TFP. It measures the TFP change between two data points by calculating the ratio of two associated distance functions (e.g., Caves et al, 1982a, 1982b). A key advantage of the distance function approach is that it provides a convenient way to describe a multi-input, multi-output production technology without the need to specify functional forms or behavioral objectives, such as cost-minimization or profit-maximization.

Using the distance function specification, our problem can be formulated as follows. Let $\mathbf{x}=(x_1,...,x_M) \in \boldsymbol{R}^{M_+}$, $\mathbf{a} = (a_1,...,a_G) \in \boldsymbol{R}^{G_+}$, and $\mathbf{y}=(y_1,...,y_N) \in \boldsymbol{R}^{N_+}$ be the vectors of inputs, attributes and output, respectively, and define the technology set by:

$$P^t=\{(\mathbf{x}^t, \mathbf{a}^t, \mathbf{y}^t): (\mathbf{x}^t, \mathbf{a}^t) \text{ can produce } \mathbf{y}^t\}.$$

The distance function is defined at t as

$$d_o^t(\mathbf{x}^t, \mathbf{a}^t, \mathbf{y}^t) = \inf\{\phi : (x^t, a^t, y^t/\phi) \in P^t\}.$$

We use DEA to calculate distance functions and to construct various productivity measures described below. DEA a set of nonparametric mathematical programming techniques for estimating the relative efficiency of production units and for identifying best practice frontiers. Like the distance function formulation, DEA is not conditioned on the assumption of optimizing behavior on the part of each individual observation, nor does DEA impose any particular functional form on production technology. 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.

When analyzing productive efficiency for extraction of non-renewable resources such as the petroleum industry, one faces challenges not met in typical areas of production of goods and services. Production from an oil field at some point in time depends upon past production from the field due to depletion effects, in addition to the technology employed and the characteristics of the field (e.g., field size, porosity, field depth, etc). Holding inputs constant, output from a given field follows a well known pattern of initially increasing output, obtaining a peak after some years of production, then following a long path of declining output. This implies that, for purposes of measuring changes in total factor productivity, it is inappropriate to compare contemporaneous levels of output from a newly producing field to a field discovered some time ago that has been producing for 10 years and to a field that has been producing for fifty years. Rather, comparisons across fields should be done holding constant the number of years the fields have been in operation.

Thus, we measure productivity change by looking at relative productivity across fields of different vintages. By doing so, we separate productivity effects associated with aging of the field from effects due to differences in the state of technology. So, for example, the vintage model compares productivity of a field that was first exploited in 1970 and has been operating for a given years to productivity of a field that was first exploited in 1980 and has been operating for the same number of years, thus isolating the field age-related factors from technology status.

The DEA formulation with the vintage model differs from the conventional DEA formulation, such as that described in Färe, Grosskopf, and Lovell (1985). Our DEA formulation calculates the Malmquist index by solving the following optimization problem:

$$[d_o^i(\mathbf{x}_{k'j'}^i, \mathbf{a}_{k'j'}^i, \mathbf{y}_{k'j'}^i \,|\, VRS)]^{-1} = \max \phi^{k',j'}$$

subject to

$$-\phi^{k',j'}\, y_{k'j'n}^i + \sum_{k \in K(i)} \sum_{j=0}^{J(k)} \lambda_{kj} y_{kjn}^i \geq 0, \qquad n = 1,\ldots,N,$$

$$x_{k'j'm}^i - \sum_{k \in K(i)} \sum_{j=0}^{J(k)} \lambda_{kj} x_{kjm}^i \geq 0, \qquad m = 1,\ldots,M,$$

$$a_{k'j'g}^i - \sum_{k \in K(i)} \sum_{j=0}^{J(k)} \lambda_{kj} a_{kjg}^i \geq 0, \qquad g = 1,\ldots,G,$$

$$\sum_{k \in K(i)} \sum_{j=0}^{J(k)} \lambda_{kj} = 1,$$

$$\lambda_{kj} \geq 0, \qquad k \in K(i), \quad j = 1,\ldots,J(k).$$

where *K(i)* includes all fields of vintage i (i.e., discovered in year *i*) and *J(k)* is the last year of production for field *k*. Our vintage model differs from the conventional DEA formulation, in that the mixed period distance functions compare fields of different vintages for a given field year, so that our model compares outputs and inputs holding fixed the number of years that the fields have been operating. In our study, $t = i$ = 1947-1995; the output (y), input (x) and attribute (a) variables are listed in Table 1. The weighted innovation index at time t is assigned to vintage group $i = t$, and hold constant for all field years (j) in that group (i). Besides the two depletion variables, other attribute variables (e.g., water depth) are constant for each field (k) in all years. We use cumulative values for inputs ($\mathbf{x}$) and outputs ($\mathbf{y}$), because for the above technology definition (i.e., $\mathbf{x}$ can produce $\mathbf{y}$), it is more appropriate to express the production relationship on cumulative terms for a nonrenewable industry. For example, for a field, the production at t is determined by cumulative inputs (e.g., drilling) and outputs (i.e., stock depletion) up to $t\text{-}1$.

Under Variable Returns to Scale (VRS) following Ray and Desli (1997)[5] the Malmquist index defined above can be decomposed into measures associated with technological change, efficiency change and scale change:

$$MTFP_{VRS} = TC_{VRS} \cdot EC_{VRS} \cdot SC_{VRS.}$$

where TC_{VRS} is technological change under VRS, EC_{VRS} is efficiency change under VRS and SC_{VRS} is scale change. Technological change measures shifts in the production frontier. Efficiency change measures changes the position of a production unit relative to the frontier--so-called “catching up” (Färe et al, 1994). Scale change measures shifts in productivity due to changes in the scale of operations relative to the optimal scale.

Each of these measures is indicated in Figure 1. The move from point a to b represents a change in efficiency, as a production unit moves from an inefficient point, to a point along the production frontier at time t, $F^t(X_t)$. The associated measure of efficiency change is the ratio of the distance functions, fb/fa. The movement from point b to point c represents scale change. A given level of aggregate production can be produced most efficiently if all firms produce at the optimal scale, where all scale economies are realized but decreasing returns have not yet set in. This is the point where line for constant returns to scale (CRS), 0g, is tangent to the VRS production function. The associated measure of scale efficiency is the ratio of distance functions fg/fb, which is the measure of the scale change for the move from point b to point c, where in this example scale efficiency is 1 (ec/ec). Finally, technological change is measures shifts in the production frontier. The measure of technological change associated with a move from point c to point d is the ratio of the distances ed/ec.

The CRS measure of technological change can be further decomposed into measures of input biased technological change, output biased technological change and magnitude change:

$$TC_{CRS} = IBTC_{CRS} \cdot OBTC_{CRS} \cdot MC_{CRS}$$

where TC_{CRS} is technological change under CRS, $IBTC_{CRS}$ is input-biased technological change under CRS, $OBTC_{CRS}$ is output-biased technological change under CRS, MC_{CRS} is magnitude component under CRS, which is the measure of Hicks neutral technological change. Thus, if the output and input biased measures of technological change are both equal to one, then technological change is Hicks neutral.

While DEA allows one to quantitatively measure technological change, it does nothing to alleviate the "confession of ignorance" regarding what constitutes and shapes technological change. Initially in the innovation literature, data on R&D were used as a proxy for innovation.

R&D expenditures indicate the effort expended in the search for new technology, and so provides a measure of inputs to innovation, but R&D expenditures are not a good proxy for innovation (e.g., Griliches, 1984). Many firms conduct R&D fruitlessly for years, and some innovative firms create major breakthroughs with little officially recorded R&D. The measurement issues are especially troublesome for analyses that capitalize on long time series of data, as the relationship between R&D expenditures and innovation may vary systematically over time. New innovations may take advantage of past knowledge created (Romer, 1990) implying an accelerating productivity of R&D expenditures over time. On the other hand, there may be an ultimate depletion of technological advances over time (Griliches, 1994) implying an S-shaped relationship between R&D expenditures and innovation. Either of these effects will impart a bias in R&D expenditure as a measure of technological change with a long time series of data.

As patent statistics became more rapidly available, patent counts were used as a closer approximation to innovation (e.g., Schmookler, 1954; Griliches, 1984). However, patent statistics can be misleading, since many patents never see commercial application, many innovations are not patented, and some are subdivided into multiple patents, each covering one or more aspects of the innovation. In response to these issues, refinements of patent counts use citations as a weight to the patent (see Hall, Jaffe and Trajtenberg, 2001). But changes in patent policies over time may again make patent counts a misleading measure of innovation, particularly over long time periods.

Moss (1993) and Cuddington and Moss (2001) provide further refinement of measures of technological change by counting of the number of innovations each year, as reported in trade journals. This represents a significant advance, but a simple innovation count treats all innovations as having an equivalent impact on productivity. In fact, various new technologies have different levels of significance, and it is important that these differences are reflected in the computation of the technology index. A small number of major breakthroughs may have larger productivity effects than a larger number of incremental innovations. For example, during the last decade, technologies such as the 3–D seismic modeling have had some of the largest impacts on productivity and profitability.

Other measures have been taken to identify the importance of innovations, as recognized by the industry. A study by the National Petroleum Council (NPC) analyzed the needs of the industry to identify specific advances needed in each technology area and the expected level of impact of specific technological innovations, both in the short term and the long term (National Petroleum Council, 1995). The 89 companies who responded to the survey account for about 50 percent of total U.S. reserves. However, the economics literature on technological change has yet to capitalize on these industry surveys.

We refine available literature on innovations in several ways. First, we modified the Moss (1993) innovation count index to include production and management technologies, and updated the index over the full period from 1947–1998. Next, we incorporate the results of the NPC oil and gas technology surveys with the extended Moss index to construct an importance weighted innovation index. Details of the methods employed for constructing our refined technology index are discussed below. We apply these measures within a DEA framework to measure the impact of identifiable new technologies on productivity change, thereby contributing to a better understanding of nature of technological change for our application.

Application of the Model

We measure and decompose productivity change over time in the offshore Gulf of Mexico oil and gas industry. Production in this nonrenewable resource industry is positively affected by exploration–development–production efforts, resource stock size and field quality. As the most easily accessible stocks are depleted, industry must move to fields that are more remote, smaller and otherwise more expensive to operate. Thus, productivity will decline over time in the absence of new technologies that ameliorate depletion effects.

Data used in this analysis are obtained from the U.S. Department of the Interior, Minerals Management Service (MMS), Gulf of Mexico OCS Regional Office. Specifically, we develop our project database using five MMS data files:

(1) Production data, including monthly oil, gas, and produced water outputs from every well in the Gulf of Mexico over the period from 1947 to 1998. The data include a total of 5,064,843 observations for 28,946 production wells.

(2) Borehole data describing drilling activity of each of 37,075 wells drilled from 1947 to 1998.

(3) Platform data with information on each of 5,997 platforms, including substructures, from 1947 to 1998.

(4) Field reserve data including oil and gas reserve sizes and discovery year of each of 957 fields from 1947 to 1997.

(5) Reservoir-level porosity information from 1974-2000. This data includes a total of 15,939 porosity measurements from 390 fields.

Thus, the project database is comprised of well-level data for oil output, gas output, produced water output, and the quantity of fluid injected, and field-level data for the number of exploration wells drilled, total drilling depth of exploration wells, total vertical depth of exploration wells, number of development wells drilled, total drilling distance of development wells, total vertical distance of development wells, number of platforms, total number of slots, total number of slots drilled, water depth, oil reserves, gas reserves, original proved oil and gas combined reserves in BOE, discovery year, and porosity.

Although we have well-level production data, the well level is not a good unit for measuring technological efficiency due to spillover effects across wells within a given field. Rather, the field level is a more appropriate unit for measuring technological efficiency. For this reason, the relevant variables were extracted from these MMS data files and merged by year and field, so that the final data set was comprised of annual data from 933 fields over a 50-year time horizon. On average there are 370 fields operating in any particular year, and a total of 18,117 observations.

Output variables in our model are oil production and gas production, while input variables include number of platforms, platform size, number of development wells, number of exploration wells, average distance drilled for exploratory wells, average distance drilled for development wells and untreated produced water[6]. Field attributes are water depth, initial oil reserves, initial gas reserves, field porosity, and an aggregate measure of resource depletion, based on total extraction of oil and gas reserves in the Gulf of Mexico to date for each time period. Further description of the data is provided in Appendix.

One goal of the study is to measure productivity effects associated with specifically identifiable new technologies, as compared to productivity effects of less structural means, such as learning obtained through experience. Moss (1993) constructs a technology diffusion index that counts technology diffusion as it is reported in industry trade journals. First, we adapt Moss' methodology to focus on innovation, rather than diffusion, of technologies and we extend the index for our full study period, from 1947 to 1998. We modify the Moss index to reflect innovation by counting only the first time a particular technology is reported, so our index measures technological innovation rather than diffusion.

Next, we use the impact of needs for each technology in NPC survey as measure of the significance of different technologies. To do so NPC technologies are allocated to 17 categories in the simple innovation counts. Technology weights of short and long term significance from the NPC survey are then used to construct a weighted technology index. The cumulative weighted technology innovation index at time t is calculated as:

$$Innov^{W}{}_{t} = \sum_{t=t_0}^{t} \sum_{i=1}^{I} w_{i,t} \times Innov^{NW}{}_{i,t}.$$

where $Innov^{W}{}_{t}$ is the cumulative weighted technology innovation index at time t; $w_{i,t}$ is the weight for technology in category i at time t; $Innov^{NW}{}_{i,t}$ is the non-weighted technology innovation count adapted from Moss in category i at time t.

In addition to this weighted innovation index, one important innovation of the recent decades is the extent of horizontal and directional drilling. Horizontal drilling refers to the ability to guide a drillstring to deviate at all angles from vertical, which allows the wellbore to intersect the reservoir from the side rather from above. This allows a much more efficient extraction of resources from thin or partly depleted formations. Horizontal drilling is also advantagous for formations with certain types of natural fractures, low permiability, a gap cap, bottom water, and for some layered formations. A measure of horizontal & directional drilling[7] and our weighted innovation variable are used in the DEA framework to partition impacts of technological change into components associated with specific technological innovations and more routine learning by doing in the following.

We use several different versions of the model to measure and decompose productivity changes. First, a base model is used to calculate net productivity change, which measures the net effect of increases in productivity due to improvements in production technology and declines in productivity due to depletion. A net technological change index greater than one implies technological change offsets the depletion effects, while a net technological change index less than one implies depletion dominates technological change.

Next we decompose net TFP change into decreases in productivity associated with resource depletion and increases in productivity after accounting for depletion effects:

$TFP_{Net} = TFP_{Gross} \cdot TFP_{Depletion}$,

where TFP_{Net} is the net measure of TFP, which is a measure of the net change in productivity, including both increases in productivity after accounting for depletion effects (TFP_{Gross}) and decreases in productivity due to depletion ($TFP_{Depletion}$).

To carry out this decomposition, the second model includes variables that measure resource depletion: measures of historic resource extraction from the Gulf of Mexico, water depth, porosity and field size. When these variables are treated as field attributes, DEA calculates technological change after accounting for changes in these attributes, effectively holding these depletion variables fixed. The DEA results with this model provide our gross measure of TFP change, which measures increases in productivity after accounting for depletion effects. The depletion effect is then calculated as:

$TFP_{Depletion} = TFP_{Net}/TFP_{Gross}$.

Thus, dividing the net measure of technological change from Model 1 by the gross measure of technological change from Model 2 provides the measure of the decline in productivity due to depletion.

Next we decompose the gross measure of technological change into indexes that represents specific technological innovations and a residual, which we generally term learning by doing. Thus, the gross index of technological change is decomposed as:

$$TC_{Gross} = TC_{innov} \cdot TC_{LBD}$$

where TC_{Gross} is the gross index of technological change, TC_{innov} is the technological change associated with identifiable new technologies (the weighted innovation index and the measures of horizontal drilling) and TC_{LBD} is the net index of technological change that cannot be explained by specifically identifiable new technologies, and includes such factors as learning-by-doing (Arrow, 1962) and other non-structural factors.

This is accomplished by using the standard DEA decomposition of TFP change into technological change (TC), or shifts in the production frontier, and efficiency change (EC), or movements towards (or away from) the frontier. First TFP change from Model 1 is decomposed into TC and EC using standard DEA methods. This TC component incorporates all forms of technological change. This is divided by TC, as calculated in Model 3, which includes the weighted technological innovation index discussed above and the measure of horizontal drilling treated as "inputs". Thus, applying DEA to Model 3 calculates an index of technological change net of specific measurable technological innovations. So Model 3 measures shifts in the production frontier that cannot be accounted for by specific new innovations, and we generally term this residual measure of technological change as the result of from learning by doing (TC_{LBD}). This method allows us to explain a portion of technological change associated with specific innovations, and narrow our "confession of ignorance" to the residual effect. Thus, the fraction of TC associated with specific innovations is:

$TC_{Innov} = TC_{Gross}/TC_{LBD}$

In the same way, we decompose the Efficiency Change (EC) into two indexes. It is defined EC_{innov} as Efficiency Change index by DEA with additional input variables $Innov^W_t$. EC as Efficiency Change index without $Innov^W_t$. EC is always greater than EC_{innov} since $Innov^W_t$ is the increasing function of time *t*. The difference between EC and EC_{innov} is due to the impact of $Innov^W_t$. Define this effect (EC / EC_{innov}) as Diffusion index of new technology, DIFF. More $Innov^W_t$ explain the efficiency improvement, Diffusion index increases. Diffusion index measures the catching up effects of inefficient firm or field to the frontier. This implies that more firms adopt new technologies.

Next, we construct separate measures of the impacts on TFP over time due to reductions in field size and increases in water depth. Again following methodology described above, including variable(s) associated with each effect calculates the residual productivity effects after accounting for changes in the variable(s). The effect of the relevant variable(s) is calculated by dividing the TFP results of the model excluding the relevant variable(s) by the TFP result of the model including the variable(s). Model 4 excludes variables that measure field size (initial oil and gas reserves in the field). So the effect of changes in field size over time is calculated by dividing the results of the Model 4 by the results of Model 2. Similarly, Model 5 excludes a variable measuring water depth of the field. So the effect on productivity of changes in water depth over time is calculated by dividing the results of the Model 5 by the results of Model 2.

Results

The results for net TFP, gross TFP and depletion effects are presented in Figure 2. Net TFP declines by about 17 percent from 1947 through 1970, or a rate of about 0.8 percent per year. Net TFP then remains approximately constant from 1970 through about 1982, increasing by a total of about 2.5 percent over the period, or about 0.2 percent per year. TFP then increases by a total of over 33 percent during the remainder of the time horizon, or a geometric average of about 2.1 percent increase in net TFP per year for the last 15 years of the study period.

Overall, TFP increases by about 10.6 percent over time 50 year study period, for a geometric mean of about 0.2 percent per year. However, the pattern of TFP change is not monotonic. Rather, depletion effects initially outweigh productivity enhancing effects of new technology, but later in the study period technological advance overcomes depletion effects. This appears contrary to the commonly held notions of uni-directional (increasing or decreasing) changes in net productivity, or inverted "U" shaped productivity curves (e.g., Slade, 1982), whereby technology temporarily prevails, eventually to be overwhelmed by physical depletion.

However, the results *are* consistent with common reports of Gulf of Mexico production, as discussed above, with the Gulf of Mexico referred to as the "Dead Sea" in the early 1980's, and recent reports of technologies that have led to a rapid pace of productivity enhancement (e.g., 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. Recent years have seen dramatic improvements in technology that have, to date, offset increasing physical resource scarcity. It remains to be seen, however, whether we can maintain this pace of increasing productivity in the near future, or whether recent productivity gains will soon be lost to depletion, as reserves in deep waters are depleted. Forecasting future trends is always dangerous, but it may not be realistic to expect to maintain indefinitely the current accelerating rate of technological change in offshore production technology.

Fagan (1997) estimated that, holding technology constant, depletion has led to an average annual increase of 12 percent in the cost of finding new reserves over the period from 1977–94. Since Fagan estimates that the cost decreasing effects of technological change between 1978 to 1989, depletion effects outweigh the technological change effects over this portion of the study period. However, Fagan estimates that technological change has outpaced depletion effects in the period since 1989, so that net TFP increased in the final five years of her study period. Overall, Fagan finds that TFP is higher in 1994 than it was in 1978.

Together, these results suggest that, after removing effects due to improvements in technology, both the costs of finding new fields and the cost of producing from fields has been increasing over time due to depletion effects. But both Fagan's results on finding costs and our results on production efficiency show an increasing rate of technological change which offsets depletion effects over period from 1978 to 1994, and the growth rate in net TFP has been increasing over time.

Next we decompose depletion effects into those associated with changes in field size, water depth, porosity and residual depletion effects, shown in Figure 3. Field size and water depth appear to have roughly comparable effects on productivity over the study period, but initially moving to smaller field size appears to have the larger effect, while water depth has a larger effect on productivity by the end of the study period. This likely has resulted because production has moved to very great water depths in recent years, with production occurring at over a mile deep by 1997 and exploratory wells being drilled in nearly 10 thousand feet of water by 2001. However, deep water production has allowed discovery of larger fields, with recent deepwater fields producing at higher rates than has ever been previously achieved in the Gulf of Mexico. Indeed, by late 1999, more oil was produced by Gulf of Mexico deepwater fields, those in greater than 1,000 feet of water, than by fields in less than 1,000 feet (U.S. Minerals Management Service, 2000).

The results of technological change decomposition into output biased technological change (OBTC), input biased technological change (IBTC) and magnitude change (MC) are presented in Fig. 4. The magnitude component equals the technological change under joint Hicks neutrality, when the input biased and output biased components are simultaneously equal to 1 (Färe and Grosskopf, 1996). Our results show that input biased technological change equals 3.60 and output biased technological change equal 2.44, and therefore the biased technological change index, which is the product of IBTC and OBTC, is 8.78. This bias index is far from one, which is not consistent with Hicks neutral technological change. Therefore, we reject the assumption of Hicks neutrality, and technological change is biased both on the input and output sides. The IBTC is substantially larger than OBTC, reflecting more input efficient use[8]. In contrast to the parametric measurement of bias (e.g., Antle and Capalbo 1988), DEA does not provide relative measures of bias, such as input using or saving with respect to each individual input. Instead DEA measures the absolute change to assess the extent of input and output biases.

Finally, TFP change in Gulf of Mexico OCS production is decomposed into innovation, learning by doing and diffusion using the weighted innovation index discussed above. Recall that we constructed a weighted technology index by extending the Moss innovation-count index using the NPC survey of importance of technological innovations. In addition, we incorporate a measure of the use of horizontal drilling technology, as discussed above and in Appendix. Using these innovation indexes as attributes accounts for the effects of specifically identifiable new technologies. The residual component of technological change is then interpreted as a measure of the non-structural component of technological change, which we generally term "learning-by-doing" effects.

Figure 5 shows the trends for innovation, learning by doing and diffusion over period from 1947 through 1995. It shows that the learning-by-doing effect is approximately two times as large as the affect associated with specific new technological innovations. Over the 49 year study period, TFP change can be partitioned into 23.9 percent due to innovations, 45.8 percent due to learning by doing and 46.8 percent due to diffusion. This implies that the contributions to TFP of learning by doing and diffusion are each approximately double the contribution of innovation. This implies that although technological innovation is crucial for improving TFP, there are much more productivity gains from learning by doing and diffusion. Thus shows the importance of policies that focus on allowing flexibility in operations and that are not overly restrictive on diffusion of new technologies to other companies.

V. Conclusions

Over time, economists have greatly improved our understanding of the role of technological change in economic growth and of the constituents of technological change. We have progressed from "confessions of ignorance" based on mere observations that productivity increases over time, to an increasingly sophisticated understanding of the mechanisms that drive technological change and empirical measures of various components of technological change.

This paper contributes to this literature in several ways. First, we use a unique and extensive micro-level data set to provide a detailed analysis of productivity change at the production stage of offshore oil and gas. This contributes to our understanding of the extent to which technological progress has ameliorated resource depletion in this industry, and thereby the potential for technological change to fuel continued economic growth in the face of fixed stocks of non-renewable resources. Our unique data set also allows us to decompose productivity change into various constituents, which provides a more detailed understanding of the nature of productivity change for this important industry.

We apply Data Envelopment analysis (DEA) techniques (e.g., Charnes et al, 1978; Färe et al., 1985) to a unique field-level data set to measure the extent to which technological change offsets resource depletion effects. Our results show that increases in productivity have offset depletion effects in the Gulf of Mexico offshore oil and gas industry over 49 year period from 1947-1996. However, the nature of the effect differs significantly from what is typically assumed for non-renewable resource industries. During the first 30 years of the time horizon, we found productivity declines in offshore oil and gas production. But in more recent years, net productivity increased, offsetting depletion effects. Productivity change has been highest in the past 5 years, indicating that we may still be along the increasing portion of the "S" shaped technological time path. However, extrapolating trends into the future is risky, especially over longer time periods. It could well be that the pace of technological advance could slow in the near future, and depletion effects could lead to rapid declines in productivity in this important non-renewable resource industry.

We decomposed depletion effects into effects associated with changes in field size, water depth, porosity and a residual that measures aggregate resource extraction in the Gulf of Mexico. We found that each of these effects are roughly similar in magnitude, that that interesting shifts occur over time. For example, initially field size appeared to be more important than water depth. However, as new technologies allowed us to find larger fields by moving to ever deeper waters, water depth tended to have a stronger effect on reducing TFP than did field size. Once again, it remains to be seen whether this trend will continue, or whether we will quickly deplete the stock of large, deep water fields.

We also analyzed the contribution of technological change and efficiency change in sector total factor productivity (TFP). The former comprises technological innovation and learning by doing, and the latter technology diffusion and other factors. We developed an index for decomposing technological change into technological innovation and learning by doing, and we estimated the relative importance of technological innovation, learning by doing and technology diffusion on TFP. Similarly, we isolated technology diffusion from that the rest of the factors that impact on efficiency change and subsequently TFP. We compared the relative impact of these technology indicators on TFP in the industry. The results indicate that both learning by doing and diffusion of technological had a significantly larger impact on TFP than technological innovation. This implies that although technological innovation is crucial for improving TFP, there are even much more productivity gains from learning by doing (experience of engineers and mangers) and adoption of new technology in the offshore oil and gas industry. This suggests the importance of developing policies that provide flexibility in implementing available technologies.

Appendix: Data

A.1. Data Construction

Data used in this analysis are obtained from the U.S. Department of the Interior, Minerals Management Service (MMS), Gulf of Mexico OCS Regional Office. We develop our project database using five MMS data files:

(1) Production data including well-level monthly oil, gas, and produced water outputs from 1947 to 1998. The data include a total of 5,064,843 observations for 28,946 production wells.

(2) Borehole data describing drilling activity of each of 37,075 wells drilled from 1947 to 1998.

(3) Platform data with information on each of 5,997 platforms, including substructures, from 1947 to 1998.

(4) Field reserve data including oil and gas reserve sizes and discovery year of each of 957 fields from 1947 to 1997.

(5) Maximum efficiency rate data including reservoir-level porosity information from 1974-2000. The data include porosity information for 390 fields and has a total of 15,939 observations.

Relevant variables are extracted from these MMS data files and merged by year and field. Using these variables, the Gulf of Mexico regional new resource discovery and depletion over time are constructed. The variable for horizontal & directional drilling is defined as the ratio of total drilling distance to vertical drilling depth. Larger values imply a higher ratio of horizontal &

directional drilling relative to vertical drilling. We take cumulative input value data, as literature in the oil and gas supply suggest (e.g., Pindyck, 1978b), for well, drilling, horizontal & directional drilling. Drilling is assumed to affect output starting the following year, since current drilling does not affect current production. So well inputs in period t are determined by cumulative drilling through period t-1. At any point in time ultimately recoverable resources are not known. Rather, the remaining resource is estimated using current economically (not physically) known reserve stock minus resources produced to date. We also take cumulative value for output variables including oil, gas production to take account of the technological characteristics.

An aggregate depletion effect is measured using a measure of remaining resource of oil and gas separately in whole Gulf of Mexico on period t–1. We aggregate the production data both for oil and gas separately over fields, and we next calculate the cumulative value over time. The depletion measure is [1– (cumulative until (t–1) period) / (cumulative until 1995)]. This captures the effect how much resource is extracted already in each period.

DEA requires the data on input usage and on characteristics that determine output. We created the water depth (in feet) attribute as maximum water depth in the Gulf of Mexico minus water depth in each field, since production is more difficult in deeper water depth in given technology. Units of oil and gas production are barrels and thousand cubic feet, respectively. Platform size is defined as average number of slots per platform for the field. Units of oil and gas reserves are million barrel and billion cubic feet, respectively. Units of remaining oil and gas reserves in the Gulf of Mexico, and porosity are measured in percent terms. More precise description of data is in Managi (2001).

A.2. Missing Data Estimation

Complete data for porosity is available for 390 fields out of 933 fields. We use two-step estimation procedure to correct for this omitted variable problem (Heckman 1979; Greene 1981). Table A. 1 and A.2 contains estimation results from these regression models. Results for second step as OLS in Table A.2 imply that higher porosity values tend to be found in larger reservoirs, in reservoirs in which more drilling occurs and in deeper-water fields.

Table A1. Stage I Probit Estimates

Independent Variable	Estimated Coefficient	Standard Error
Intercept	811.234 ***	65.866
Discovery Year	–106.926 ***	8.679
Log Likelihood	–543.8820313	

Note: Dependent variable = 1 if porosity observed; 0 otherwise. *** Significant at the 1 percent level.

Table A2. Stage II Estimates

Independent Variable	Estimated Coefficient	Standard Error
Intercept	–134.649 *	68.843
ln(oil reserve)	0.554 *	0.335
ln(gas reserve)	2.409 ***	0.41542
ln(water depth)	15.145 *	7.91355
ln(5Yr exp drill)	1.05296 ***	0.22748
IMR	5.11798 **	1.753
R^2	0. 206	
Adj. R^2	0.196	

Note: The variable 5Yr exp drill is cumulative drilling feet of exploration wells in the field for first 5 years following discovery. 50 percent of total drilling is completed on average 5.2 year, therefore we choose 5 year, based on the assumption that MMS has data for large fields. IMR stands for Inverse Mills Ratio.

*** Significant at the 1 percent level; ** Significant at the 5 percent level; * Significant at the 10 percent level.

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Table 1. Model Specifications

	Model 1	Model 2	Model 3	Model 4	Model 5
Index calculated:	Base Model: Net TFP	Gross TFP	Innovation LBD & Diffusion	Depletion: Field Size	Depletion: Water Depth
Output Variables					
Oil production (bbl)	X	X	X	X	X
Gas production (Mcf)	X	X	X	X	X
Input Variables					
Number of platforms	X	X	X	X	X
Ave. Platform size (#slot / #platform)	X	X	X	X	X
Number of exploration wells	X	X	X	X	X
Number of development wells	X	X	X	X	X
Average Drilling Distance for Exploratory Wells	X	X	X	X	X
Average Drilling Distance for Development wells	X	X	X	X	X
Produced Water	X	X	X	X	X
Weighted Innovation Index			X		
Horizontal & Directional Drilling (Exploratory)			X		
Horizontal & Directional Drilling (Development)			X		
Attribute Variables					
Water Depth		X	X	X	
Depletion Effects (Oil)		X	X	X	X
Depletion Effects (Gas)		X	X	X	X
Oil Reserves in the Field		X	X		X
Gas Reserves in the Field		X	X		X
Porosity (Field Type)		X	X	X	X

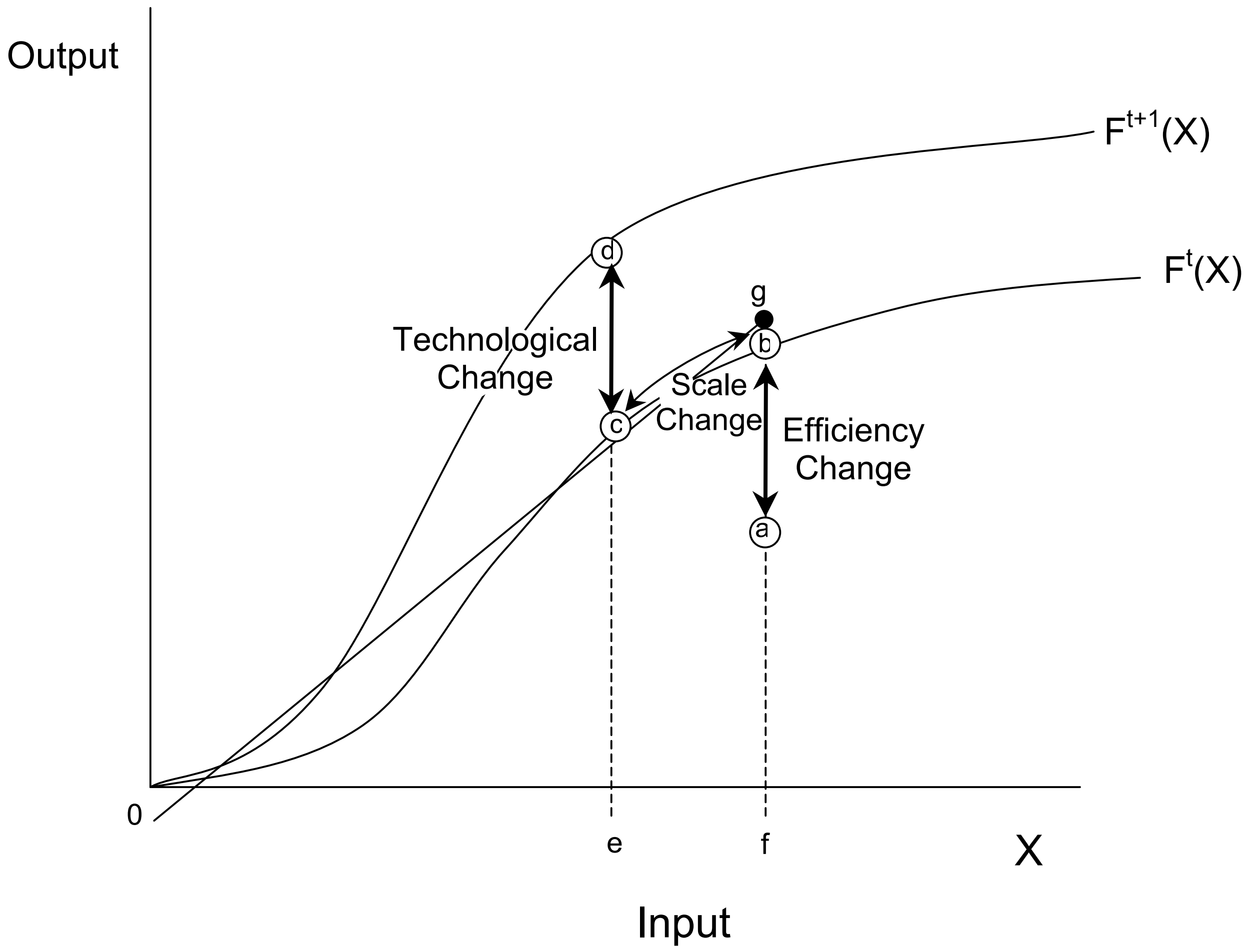

Figure 1. Components of Productivity Change with Variable Returns to Scale

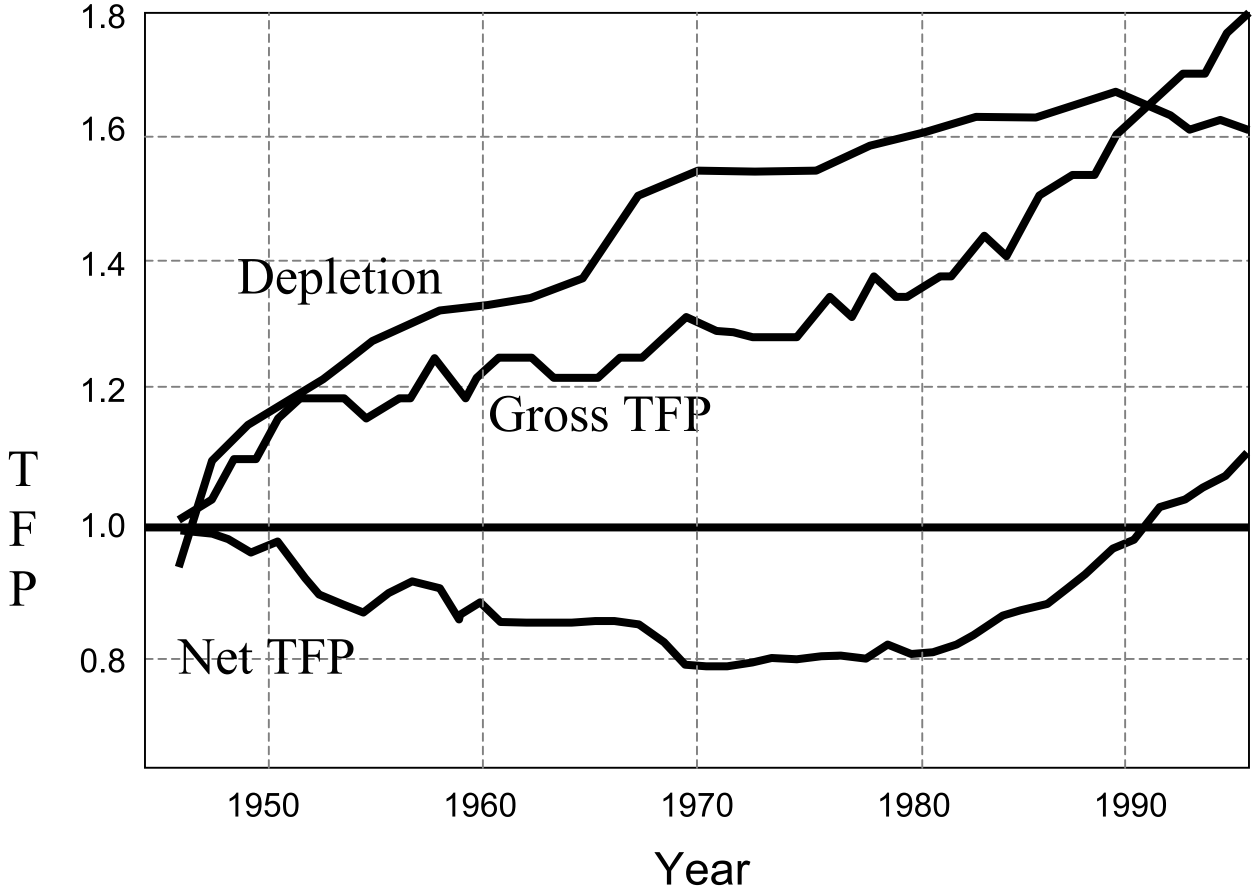

Figure 2. Net TFP, Gross TFP and Depletion[9]

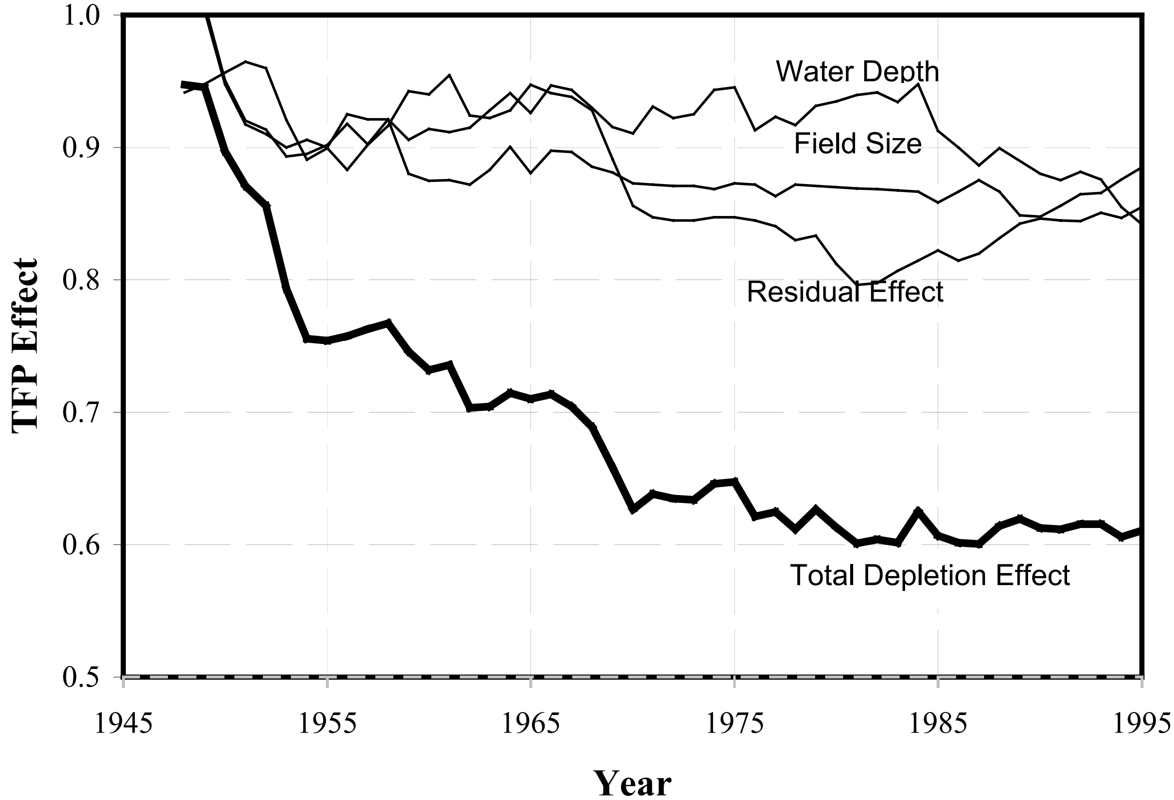

Figure 3. Decomposition of Depletion Effects

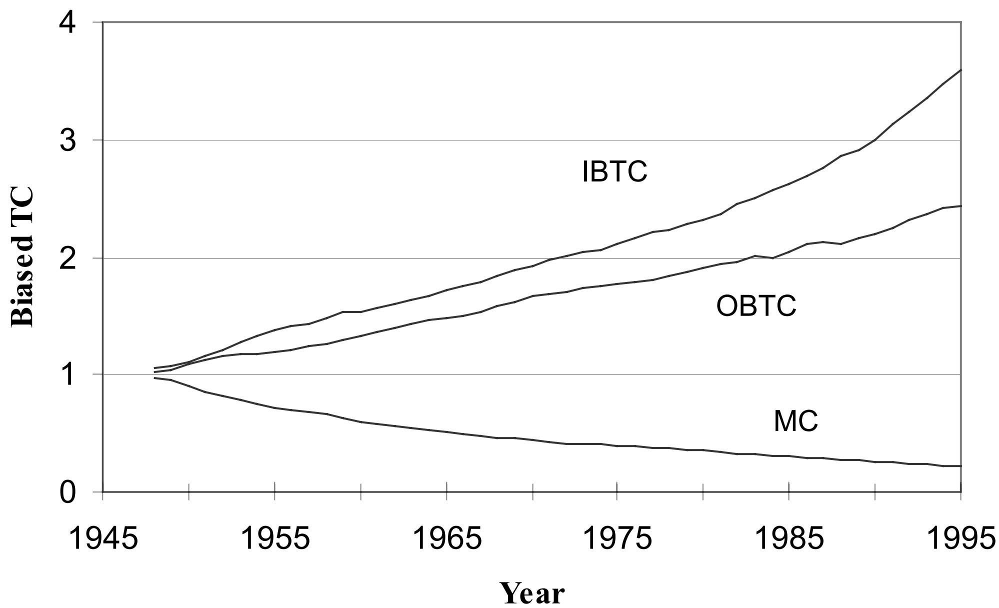

Figure 4. Decomposition of Depletion Effects

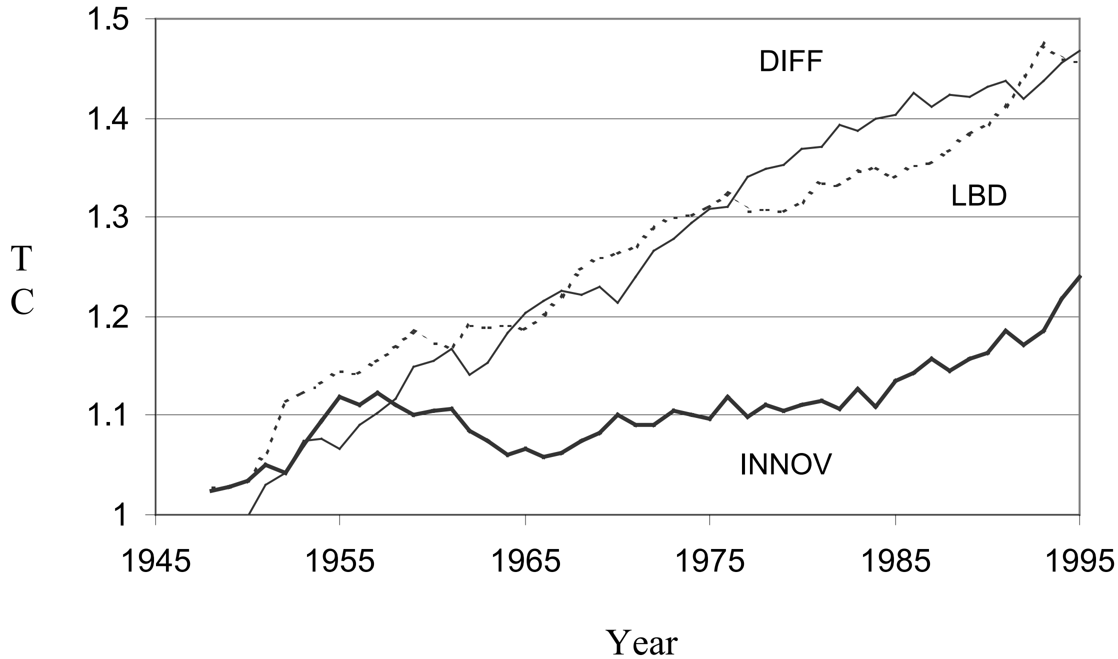

Figure 5. Innovation, Learning by Doing and Diffusion

Footnotes

[1] We define resource depletion broadly to include changes in resource quality (e.g., field size and porosity) and location (e.g., water depth).

[2] Note that Walls' analysis uses data from 1970 to 1988, with production predicted to decline monotonically over the forecast period from 1989 though 2000. In actuality, oil production from federal OCS waters increased over that entire period, and oil production in federal OCS waters in the year 2000 was approximately 2/3rds higher than in the 1988.

[3] Examples of cases where learning by doing has lead to significant cost reductions can be found in Alchain (1963) and Zimmerman (1982).

[4] Although Young (1993) use the word invention instead of innovation, his definition is same as our definition of innovation.

[5] Ray and Desli (1997) argue that MTFP index is equivalent to the ratio of the CRS distance function even if the technology is not characterized by CRS. Productivity is a long run problem thus it is measured relative to the CRS technology. In other words, MTFP index under CRS equals the MTFP index under VRS.

[6] We follow the usual convention in environmental economics of treating pollution emissions as an input to production (e.g., Baumol and Oates, 1988; Cropper and Oates, 1992). Thus, a reduction (increase) in untreated produced water, with all other inputs and outputs held fixed, represents an increase (decrease) in productivity.

[7] Appendix A describes the method used for calculating the measure of horizontal and directional drilling.

[8] This is consistent with the observation that less wells are drilled from fewer large platforms, resulting from technological innovations such as 3-D seismology, horizontal drilling, and large deep water platform.

[9] Note: The depletion effect is shown in inverted (1/Depletion) in this Figure to more clearly demonstrate the relative sizes of depletion and gross technological change.