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Total factor productivity growth and convergence in the petroleum industry: Empirical analysis testing for convexity

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ABSTRACT

While economic theory acknowledges that some features of technology (e.g., indivisibilities, economies of scale and specialization) can fundamentally violate the traditional convexity assumption, almost all empirical studies accept the convexity property on faith. In this contribution, we apply two alternative flexible production technologies to measure total factor productivity growth and test the significance of the convexity axiom using a nonparametric test of closeness between unknown distributions. Based on unique field level data on the petroleum industry, the empirical results reveal significant differences, indicating that this production technology is most likely non-convex. Furthermore, we also show the impact of convexity on answers to traditional convergence questions in the productivity growth literature.

1. Introduction

Indivisibility implies that inputs and outputs are not necessary perfectly divisible and also that scaling up or down the entire production process in infinitesimal fractions may not be feasible. Start-up and shut-down cost in electricity generation are just one good example (O'Neill et al., 2005). Scarf (1986, 1994) stresses the importance of indivisibility in selecting among technological options. Economies of scale and specialization (implied by the presence of indivisibilities and other forms of non-convexities in production) entail that higher per-capita production increases the extent of the market, facilitates the division of labor, and increases the efficiency of production.[1] These economically important features of technology, together with the well-known case of externalities, fundamentally violate the convexity of the production possibility set (see Farrell, 1959, for an overview). However, in traditional empirical analysis (e.g., traditional parametric production analysis, or even nonparametric production analysis), these features are dismissed through the imposition of the convexity axiom. In reality, it is clear that non-convexities in production are sufficiently important to explain behavior in some industries and are critical in the development of the new growth theory (see, e.g., Romer, 1990, on nonrival inputs). In a similar vein, McFadden (1978) already recognized that the importance of convexity in production analysis lies in its analytic convenience rather than its economic realism.

Therefore, given its relevance to both economic theory and associated empirical analysis, one cannot ignore the potential impact of non-convexity.[2] However, almost no previous studies have directly tested for the existence of non-convexity in production using rigorous statistical techniques. Nevertheless, non-convexities in production play an important role in the theoretical micro-economic literature and have been studied for decades (see, e.g., Frank, 1969 or Villar, 1999). For instance, the general equilibrium theory of non-convex technologies has been thoroughly analyzed (e.g., Bobzin 1998; Joshi, 1997, or more recently, Chavas and Briec, 2012). Recently, operational methods to derive linear prices supporting a competitive equilibrium in markets with non-convexities based on mixed integer programming have been devised (e.g., O'Neill et al., 2005).

In this contribution, we apply two alternative flexible production models using nonparametric specifications of technology and test the validity of the non-convexity assumption in production. One non-convex specification of production technology (NCP) is the Free Disposable Hull model (initiated by Deprins et al. (1984)). It only imposes the assumption of strong or free disposability of both inputs and outputs. Another more common technology specification adds convexity to these strong disposability axioms to form a convex nonparametric production model

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[1] Wibe (1984) shows that scale elasticity is generally larger than one for all output levels when reviewing studies of engineering production functions.

[2] Even if this implies the risk of producing less "elegant" results than with standard approaches: in particular, empirical results are harder to report because they become local rather than global in nature (see infra).

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(CP) (see, e.g., the seminal article of Farrell (1957), or Afriat (1972), Färe et al. (1994), among others). Based on distance functions as representations of technology (and their interpretation as efficiency indicators) computed relative to both these non-convex and convex nonparametric specifications of technology, following Briec et al. (2004), we test the significance of the differences using Li's (1996) nonparametric test of closeness between two unknown distributions resulting from independent or dependent observations. Obviously, if convexity of technology is questionable, then also the more specific assumption of convexity of either input or output sets separately is doubtful.

Simar and Wilson (2008) develop a complementary view on the statistical properties of these convex and non-convex nonparametric frontier estimators that highlights a kind of asymmetry in imposing both assumptions. If the true production possibility set is convex, then CP and NCP estimators are consistent and should yield approximately the same estimates for large datasets, though the NCP model normally has a slower rate of convergence. However, if technology is non-convex, then the NCP model remains consistent while the CP model offers an inconsistent approximation.

These nonparametric specifications require large data sets for production technologies to avoid the small sample error problem. Furthermore, to avoid any aggregation bias, the analysis should ideally focus on firm-level data with sufficient detail regarding the production process. Here, we apply this test of convexity to unique field-level data from the petroleum industry in the US Gulf of Mexico over the period from 1947 to 1998. Although the production possibility set of oil and gas development and exploitation is acknowledged to be non-convex in part of the literature (see, e.g., Devine and Lesso, 1972 and further arguments below), we are unaware of there being previous economic studies that put this assumption to an empirical test. Hence, whether the above NCP methodology yields a relevant reference technology in this industry becomes a most interesting empirical question for testing.

Furthermore, a topic that has received widespread attention with the appearance of endogenous growth theories is the question of convergence in productivity levels (see Islam, 2003 for a survey). In view of the importance of non-convexities for growth theory (Romer, 1990), we consider the suggestion by Bernard and Jones (1996, p. 1043) that "future work on convergence should focus much more carefully on technology". In particular, we investigate the issue of convergence/divergence in total factor productivity change using a recent discrete time Luenberger productivity indicator (Chambers, 2002) computed relative to nonparametric technology specifications, while testing for the significance of the eventual differences between the CP and NCP models. The very length of the observation period provides ample scope to test the impact of the convexity assumption on the eventual convergence of total factor productivity growth rates.

The choice between non-convexity and convexity in measuring total factor productivity change relates to the nature of technical change. The NCP model has the advantage of eventually allowing for local instead of global technical change (see, e.g., the discussion in Tulkens, 1993, and infra). Note that we believe this is the first paper defining local and global technological change precisely. While this distinction between local and global technological change plays a role in some theoretical work (see, e.g., Atkinson and Stiglitz, 1969, among others), we are aware of only few empirical works raising this issue. If NCP is the true representation of technology, then previous empirical work on the convergence issue might not be reliable. Anticipating one of the key results, this study only finds convergence for the NCP model.

This contribution is structured as follows. Section 2 reviews the background literature. Section 3 presents the Luenberger productivity indicator as well as its underlying distance functions, the distinction between local and global technical change in our analysis, and the econometric models employed to test for convergence. Section 4 introduces the sample of petroleum field data from the Mexican Gulf. The next section presents the empirical results and provides the outcomes of the statistical tests. The final section offers some concluding remarks.

2. Non-convexity in production and in petroleum industry: Literature review

The literature on non-parametric production analysis (see e.g., Afriat, 1972 or Varian, 1984) typically uses convexity only as an instrumental regularity property of technology justified by the assumed economic optimization hypotheses. Thus, convexity is motivated by economic objectives (such as cost minimization or profit maximization) rather than being an inherent feature of technology. Similarly, the parametric approach (see, e.g., Bauer, 1990) sometimes imposes regularity restrictions on the parameters of cost, revenue and profit functions, but it does not systematically test for the convexity assumption of technology.

As a result, the impact of convexity in technology (or lack thereof) on the cost function is often ignored. While the general property of the cost function as non-decreasing in outputs is well known, it seems often forgotten that cost functions estimated on convex (non-convex) technologies are also convex (non-convex) in the outputs. Jacobsen (1970) was one of the first to point out that convexity of the cost function in the outputs is due to convexity of the technology (see proposition 5.2). In other words, a cost function estimated on a convex technology is smaller or equal to the same function estimated on a non-convex technology (see Briec et al., 2004).

Several empirical studies suggest violations of convexity in a wide variety of industries (e.g., Tone and Sahoo, 2003). Indivisibilities are an obvious feature of real-world production settings (see Scarf 1986, 1994). The phenomena of economies of scale and specialization have also been empirically tested in the literature. The empirical evidence of process analysis, which derives production relations directly from theoretical and practical engineering knowledge, has found evidence of violations of convexity (see Wibe, 1984). Economies of scale are especially well documented. For instance, Chenery (1949) studied engineering production functions of the pipeline transportation of natural gas and derived a (non-linear) cost function that exhibits economies of scale. Some evidence of increasing returns has been reported in, for example, chemical industries and the manufacturing of process equipment, air pollution control equipment, and biopharmaceutical equipment (e.g., see the survey in Wibe (1984)). Some other economic analyses documenting these types of violations of convexity include Yang and Rice (1994) and Borland and Yang (1995).

We provide an analysis of the offshore oil and gas industry, which faces substantial sunk cost investments in terms of development, exploration and knowledge, which are the main source of non-convexity in production (see Devine and Lesso, 1972, or Frair and Devine, 1975). This description is mainly based on the economic literature on petroleum production. This ignores the complex details of reservoir (e.g., "undersaturated" (oil) vs. "saturated" (oil and gas) reservoirs depending on temperature and pressure conditions; natural or artificial (mechanical or gas) lift; among others) and production (e.g., issues related to gas, oil and water separation, the design of the whole surface flow system, among others) engineering in petroleum production systems (see, for instance, Gua et al. (2007) for details).

Some details are essential to consider for our purpose. For instance, once an oil field is found after extensive seismic study via the drilling of an exploratory well, other "step-out wells" are drilled to obtain more precise information on the characteristics of the field (with size being one critical factor). Osmundsen et al. (2010) is a recent study exploring the reasons for the observed decreasing productivity of exploratory well drilling. Assuming that entering the production phase is an option (e.g., because of favorable well flow tests), the above information is exploited to decide on possible locations for the production wells (specified by map coordinates and depth).

An offshore oil field is developed by drilling directionally from a series of fixed platforms, whereby drilling and completion costs for a production well are a function of the length and angle of the hole drilled from the platform to the target. Each platform involves a huge investment, the precise costs depending on water depth and the number of wells to be drilled from the platform. Thus, the "platform location problem" is a complex integer optimization problem aiming to minimize the sum of platform and drilling costs by determining the number, size, and location of the platforms and the allocation of wells to platforms. Needless to say, small deviations from optimality can generate substantial inefficiencies. For example, injection wells and other capital equipment for extraction are sunk and cannot readily be changed because of their geometric features.

Further, difficult optimization issues at the level of the oil field might include, for instance, the determination of the production rate for each time period that is optimal in the sense of maximizing the total discounted after-tax cash flow over a specific planning horizon in multilayer oil and gas fields, which is achieved by exercising control over the number of active wells during the field's exploitation period (e.g., Babayev, 1975). In addition, Neiro and Pinto (2004) argue that the planning and scheduling of subsystems of the petroleum supply chain (oil field infrastructure, crude oil supply, refinery operations and product transportation) require non-convex and nonlinear mixed-integer optimization models (see also the survey by Durrer and Slater (1977)). In brief, optimization problems in this sector are challenging because of the integer nature of certain decisions, the nonlinearities and dynamics involved, and the intrinsic uncertainties surrounding critical parameters (see, e.g., Dempster et al., 2000).

However, in most of the rather limited economic literature on the oil sector, the issue of convexity seems to be totally ignored (e.g., Osmundsen et al., 2010 for a recent example). Just to offer one more example representative of similar studies, we can look to Cuddington and Moss (2001), who estimate average cost functions for additional petroleum applying error correction models over the period 1967–1990. Using aggregate data from the US, they find that the impact of technological change on finding costs for crude oil is large.

3. A discrete-time Luenberger productivity indicator: Definitions, technology specifications, global vs. local technical change, and the analyis of convergence

Total factor productivity growth, traditionally estimated by the Solow residual, yields an index number reflecting shifts in technology resulting from output growth that remain unexplained by input growth (Hulten, 2001). Recently, awareness has grown that ignoring inefficiency may bias productivity measures. Chambers and Pope (1996) define a discrete-time Luenberger productivity indicator in terms of the differences between directional distance functions (see also Chambers, 2002). Indicators (indexes) denote productivity measures based on differences (ratios) (see Diewert, 2005).

This is the most general primal productivity indicator currently available, as it is based upon the directional distance function as a general representation of technology (Luenberger, 1992; Chambers et al., 1998). Due to its dual relation to the profit function, the latter distance function generalizes the traditional input- or output-oriented (Shephard, 1970) distance functions, which are dual to the cost and revenue functions, respectively.[3] Chavas and Briec (2012) employ such directional distance functions to explore general equilibrium in a non-convex setting.

This section discusses a three-step approach to analyzing total factor productivity in the petroleum industry. In the first step, a discrete time Luenberger productivity indicator is defined. Next, the directional distance functions constituting this indicator are measured relative to two different technology specifications: one non-convex and the other convex. Finally, the distinction between local and global technical change is explicitly defined. In the second step, these two models are compared using a nonparametric test statistic for comparing densities, which was developed by Li (1996). In the third step, we investigate whether there is β- and/or σ-convergence in the productivity change for both models using proper econometric models.

3.1. Definitions of technology, distance function and Luenberger productivity indicator

Using the index set $I=\{1,\ldots,I\}$ for production units, let $x=(x^1,\ldots,x^N)\in\Re_+^N$ and $y=(y^1,\ldots,y^M)\in\Re_+^M$ be the vectors of inputs and outputs, respectively, and define the technology or production possibility set as follows:

$$T_t=\{(x_t,y_t)\,|\,x_t \text{can produce } y_t\} \tag{1}$$

This technology set T consists of all feasible input vectors x_t and output vectors y_t at time period t and satisfies certain minimal axioms sufficient to define meaningful distance functions (see Afriat, 1972). Multi-input and multi-output production technologies and their boundaries (frontiers) can be characterized by distance or gauge functions, without any assumption of optimizing behavior on the part of individual observations.

In economics, distance functions are related to the notion of the coefficient of resource utilization (Debreu, 1951) and to efficiency measures (Farrell, 1957). Avoiding the hypothesis of optimizing behavior may be an advantage, particularly for micro-level analyses that extend over a long time series with significant uncertainty, irreversibility and fixed and/or sunk costs. These conditions also apply to the petroleum industry. In such cases, assumptions of static efficiency for every production unit in all time periods are likely suspect. Therefore, we believe the productivity measurement of petroleum exploitation at sea is best evaluated using a methodology allowing for inefficiencies.

Luenberger (1992) generalizes the traditional Shephardian distance functions by introducing the shortage function, which provides a flexible tool capable of accounting for both input contractions and output improvements when measuring efficiency. Following Chambers et al. (1998), the proportional distance function is defined as follows:

$$D^t(x_t,y_t;\ -x_t,y_t)=\max\{\delta:\ ((1-\delta)x_t,(1+\delta)y_t)\in T_t\} \tag{2}$$

This distance function completely characterizes the technology at period t. Note that this proportional distance function is a special version of the shortage or directional distance function. The latter is defined using a general directional vector $(-g_i,\ g_o)$, whereas the proportional distance function employs the special case $(-g_i,\ g_o)=(-x,\ y)$. To save space, in the remainder the notation for the proportional distance function is simplified by suppressing the directional vector.

[3] Hence, the more popular input- and output-oriented Malmquist productivity indexes (Caves et al., 1982, or Färe et al., 1994) based upon these Shephardian distance functions are less general than the Luenberger productivity indicator.

Following Chambers (2002), the Luenberger productivity indicator in discrete time is defined as follows:

$$L((x_t,y_t)(x_{t+1},y_{t+1})) = \frac{1}{2}\left[(D^t(x_t,y_t) - D^t(x_{t+1},y_{t+1})) + (D^{t+1}(x_t,y_t) - D^{t+1}(x_{t+1},y_{t+1}))\right]. \quad (3)$$

This formulation represents an arithmetic mean between the period t (first difference) and the period $t+1$ (second difference) Luenberger indicators, each of which consists of a difference between proportional distance functions evaluating observations in periods t and $t+1$ with respect to a technology in period t and period $t+1$. Using an arithmetic mean avoids an arbitrary selection from among the base years. This Luenberger productivity indicator can be decomposed into two components:

$$L((x_t,y_t)(x_{t+1},y_{t+1})) = \left[D^t(x_t, y_t) - D^{t+1}(x_{t+1}, y_{t+1})\right] + \frac{1}{2}\left[(D^{t+1}(x_{t+1}, y_{t+1}) - D^t(x_{t+1}, y_{t+1})) + (D^{t+1}(x_t, y_t) - D^t(x_t, y_t))\right], \quad (4)$$

where the first difference represents the efficiency change (EC) and the second term, which is an arithmetic mean of two differences, represents the technological change (TC). While the EC measures changes in the relative position of a production unit relative to the changing frontier, the TC component provides a measure of the change in the production frontier or productivity changes that are due to innovation. To be more precise, TC measures the arithmetic mean of the productivity change measured from the observation in period t and period $t+1$ relative to the production frontiers in both periods.

To estimate productivity change over time, four distance functions are needed: within-period and mixed-period distance functions for each field and each time period. For the mixed-period distance function, we have two years, t and $t+1$. For example, $D^t(x_{t+1}, y_{t+1})$ is the value of the proportional distance function for the input–output vector for period $t+1$ and technology in period t.

Now, we turn to the specification of technology relative to which these distance functions are estimated. Given the focus on testing the convexity assumption, we look for a framework that allows the definition of both a convex and a non-convex representation of technology.

3.2. Non-convex and convex technologies

In principle, distance functions can be estimated using parametric, semi-parametric or nonparametric specifications of the directional distance function representing technology. The vast majority of empirical productivity studies seems to employ deterministic, nonparametric technologies. However, an example of an empirical productivity study using both nonparametric and parametric technologies is Atkinson et al. (2003). While it is common to employ traditional convex nonparametric frontier technology specifications, in this study we also compute a directional distance function relative to a non-convex technology. Therefore, we are able to compare these two measurements in their effect on the Luenberger productivity indicator and test for the validity of the convexity axiom. Note that the estimated production frontiers (both CP and NCP) are based on relative benchmarking among observed units in the marketplace rather than on absolute production possibilities (e.g., engineering estimates). Thus, allowing for any eventual inefficiency among observations, these frontier estimates provide inner approximations — i.e., the (non-)convex hull of an underlying unknown true technology.

The construction of nonparametric, deterministic technologies is based on the minimum extrapolation principle: to envelop all observations and extend these using production axioms about what is considered feasible. Imposing convexity, strong disposability of inputs and outputs (i.e., monotonicity), and variable returns to scale to obtain a flexible representation of technology, the proportional distance function for CP characterizing the technology at t (T_t) is defined as:

$$D^t_c(x_t,y_t) = \max_{\delta}(\delta_t \,|\, (1-\delta_t)x_t \geq \lambda_t X_t; (1+\delta_t)y_t \leq \lambda_t Y_t;\ \lambda_t e = 1;\ \lambda_t \geq 0)\}, \quad (5)$$

where δ is the maximal proportional amount by which outputs (y_t) can be expanded and inputs (x_t) can be reduced simultaneously given the technology. Y_t and X_t are the matrices of outputs and inputs; e is a unit vector, and λ is a vector of activity variables. This CP model involves using mathematical programming techniques to estimate the relative efficiency of all production units relative to best-practice frontiers.

Notice that free disposability is an almost generally accepted assumption in production economics. This implies that marginal products of inputs, marginal rates of substitution between inputs, and marginal rates of transformation between outputs are assumed to be non-negative. Obviously, congestion of production factors violates this assumption and can, e.g., be modeled using the weaker axiom of ray or weak disposability. However, we can interpret monotonicity as a congestion adjustment to the production possibility set, i.e., the distance functions for monotonized technologies include a mixture of technical efficiency and congestion. Alternatively, monotonicity can be motivated by the fact that it does not interfere with the Pareto–Koopmans classification of technical efficiency. Anyway, in the context of testing convergence issues we think it is fair to consider free disposability as a minimal assumption.

Next, the NCP can be formulated as follows. The non-convex technology is obtained from two minimal assumptions: all inputs and outputs are strongly disposable, and there are variable returns to scale. Thus, the proportional distance function for the NCP technology at t is defined as (see Deprins et al., 1984):

$$D^t_{nc}(x_t,y_t) = \max_{\delta}\{\delta_t \,|\, (1-\delta_t)x_t \geq \lambda_t X_t;\ (1+\delta_t)y_t \leq \lambda_t Y_t;\ \lambda_t e = 1;\ \lambda^i_t \in \{0,1\}, \forall i \in I\} \quad (6)$$

Notice that the convex monotone hull (5) is obtained by replacing the binary integer constraint on the activity variables $\lambda^i \in \{0,1\}, \forall i \in I$ in (6) by $\lambda \geq 0$. Details on the actual calculations of the distance functions under the CP and NCP models are provided in Appendix A. Earlier applications of the NCP model to evaluate technical change include Tulkens (1993) and Tulkens and Malnero (1996), among others.

Obviously, the following relation between proportional distance functions for the CP and NCP technologies holds:

$$D^t_c(x_t,y_t) \geq D^t_{nc}(x_t,y_t). \quad (7)$$

In other words, the distance (or inefficiency) relative to a convex technology is always larger or equal to the distance relative to a non-convex technology (see Briec et al., 2004). Consequently, the number of efficient units compared to a convex technology is always smaller or equal to the one relative to a non-convex technology. Furthermore, all efficient units under a convex model are also efficient under a non-convex model, but the reverse need not be true.

Though the inefficiency relative to CP is always larger or equal to the distance relative to NCP and the number of efficient units to a CP is always smaller or equal relative to a NCP, it is impossible to sign the effect on the EC component. The same remark applies to the TC component. Hence, the effect of convexity on the Luenberger productivity indicator and its decomposition is a priori unclear.

3.3. Global vs. local technical change in the context of convex vs. non-convex technologies

The notion of global and local technical change has been discussed since at least the work by Atkinson and Stiglitz (1969). The basic intuition is simple enough: technical change need not lead to a global shift of the production technology, but may lead to a local change for some specific segment of technology. Fig. 1 shows a convex technology at period t and two possible shifts of this technology in the next period $t+1$: the first one leads to the outward shift of observation 3 only yielding a local technical progress (dashed line), the second one leads to an outward shift of all observations resulting in technical progress everywhere (long dashed line). Similar figures could be devised illustrating the same phenomena in input space (along an isoquant) or in output space (along a transformation curve).

Notice that some assumptions on technology automatically impose the type of global technical change illustrated in Fig. 1. For instance, constant returns to scale leads to a cone technology whose shifts over time always affect all scale levels. For this reason, our CP and NCP models instead impose the more flexible variable returns to scale assumption. Furthermore, local technical change plays a role in part of the new growth theory. For instance, Basu and Weil (1998) propose a theoretical model in which local technological change explains growth, convergence clubs, and divergence in the real economy. Local technical change is known to lead to path dependency, local learning, and (in)efficiency dynamics (see Stiglitz, 1987; Foray, 1997; Antonelli, 2006, among others).

Few authors have elaborated upon the difference between global and local technical change in relation to the difference between convex and non-convex technologies. For instance, Tulkens and Vanden Eeckaut (1995) mention local and global technical change, but fail to offer precise definitions. Equally so, Tulkens (1993) offers one definition of local technical change (page 202), but fails to explicitly contrast it to what is being measured with respect to traditional convex technologies. Using the NCP model, Los and Verspagen (2009) find that technological change and diffusion (distance to frontier) regarding CO_2 emissions of passenger cars differ substantially between different segments: TC for gasoline cars is larger than for diesel cars, and TC varies across different ranges of engine capacity. While they illustrate this local technical change (their Fig. 3), they do not formally define it.

Therefore, we are the first to offer a series of precise definitions of global and local technical change related to the use of convex vs. non-convex technologies. First, we define global technical

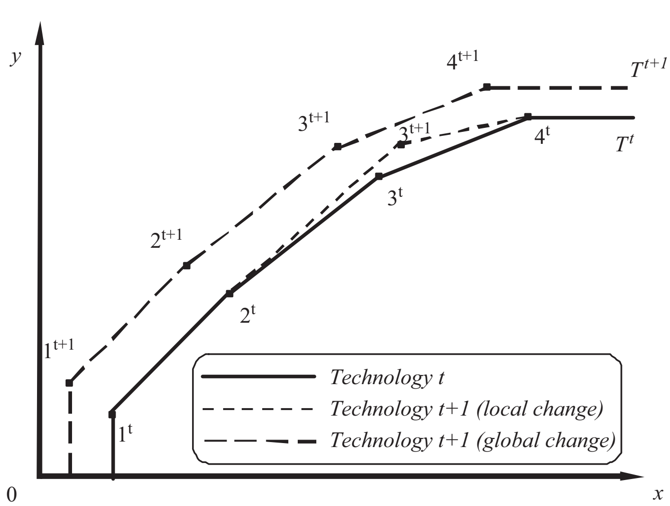

Fig. 1. Global and local technical change.

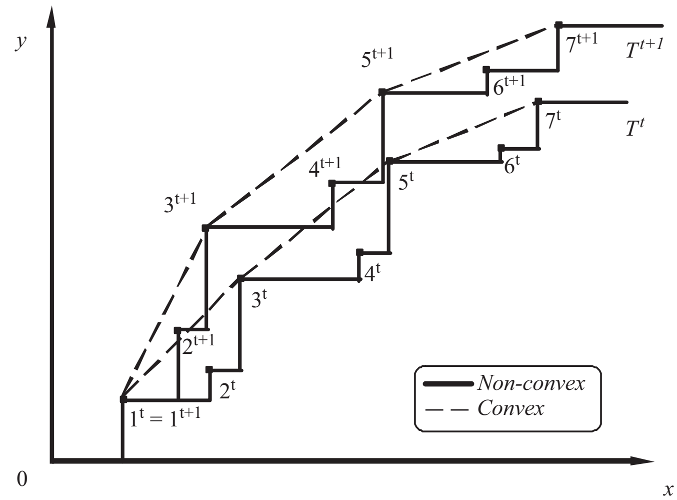

Fig. 2. Local and global productivity change under non-convex and convex technologies (conditions (8) and (9)).

progress as the one resulting from efficient observations at two time periods that do experience positive TC between these periods t and $t+1$ relative to CP:

$$PTC1_c^{t,t+1} = \{(x,y) \ : D_c^t(x_t,y_t) = 0 \wedge D_c^{t+1}(x_{t+1},y_{t+1}) = 0 \wedge \mathrm{TC}_c^{t,t+1} > 0\} \tag{8}$$

By contrast, we define local technical progress as the one resulting from efficient observations at two time periods in terms of NCP while being inefficient w.r.t. CP that do experience positive TC in terms of NCP between these two time periods:

$$PTC1_{nc}^{t,t+1} = \{(x,y) \ : D_{nc}^t(x_t,y_t) = 0 \wedge D_c^t(x_t,y_t) > 0 \wedge D_{nc}^{t+1}(x_{t+1}, y_{t+1}) = 0 \wedge D_c^{t+1}(x_{t+1}, y_{t+1}) > 0 \wedge \mathrm{TC}_{nc}^{t,t+1} > 0\} \tag{9}$$

Recall that given (7), it is easier to obey conditions (9) than to satisfy conditions (8). Both these definitions are illustrated in Fig. 2. While observations 3, 5 and 7 satisfy conditions (8), observations 2, 4 and 6 meet conditions (9). In a similar vein, global technical standstill or regress could be defined by a zero or a negative TC component, respectively. Since this is less interesting for our purpose, these definitions are suppressed.

One can now conceive two alternative definitions in which the requirement of efficiency in both periods is gradually relaxed. First, one can require the observations to be efficient in the second period $t+1$ but not necessarily in the first period t, while obtaining a positive TC in terms of NCP between both time periods. This leads to a slightly relaxed global technical progress definition as follows:

$$PTC2_c^{t,t+1} = \{(x,y) \ : D_c^t(x_t,y_t) > 0 \wedge D_c^{t+1}(x_{t+1}, y_{t+1}) = 0 \wedge \mathrm{TC}_c^{t,t+1} > 0\} \tag{10}$$

and a local technical progress definition as follows:

$$PTC2_{nc}^{t,t+1} = \{(x,y) \ : D_{nc}^t(x_t,y_t) > 0 \wedge D_c^t(x_t,y_t) > 0 \wedge D_{nc}^{t+1}(x_{t+1}, y_{t+1}) = 0 \wedge D_c^{t+1}(x_{t+1}, y_{t+1}) > 0 \wedge \mathrm{TC}_{nc}^{t,t+1} > 0\} \tag{11}$$

Second, one can alternatively require the observations to be efficient in the first period t but not necessarily in the second period $t+1$, again obtaining a positive TC in terms of NCP between both time periods. This leads to another slightly relaxed global technical progress definition:

$$PTC3_c^{t,t+1} = \{(x,y) \ : D_c^t(x_t,y_t) = 0 \wedge D_c^{t+1}(x_{t+1}, y_{t+1}) > 0 \wedge \mathrm{TC}_c^{t,t+1} > 0\} \tag{12}$$

and a corresponding local technical progress definition as follows:

$$PTC3_{nc}^{t,t+1} = \{(x,y) \ : D_{nc}^{t}(x_t,y_t) = 0 \wedge D_{c}^{t}(x_t,y_t) > 0 \wedge D_{nc}^{t+1}(x_{t+1}, y_{t+1}) > 0 \wedge D_{c}^{t+1}(x_{t+1}, y_{t+1}) > 0 \wedge \mathrm{TC}_{nc}^{t,t+1} > 0\} \quad (13)$$

It is simply clear that these technical change definitions on a CP model affect more observations than on a NCP model.

However, it is not possible to abandon the efficiency requirement altogether, otherwise no global vs. local distinction can be maintained. It should be noted that both global and local are defined without recourse to a mathematical distance metric.

3.4. Statistical analysis of productivity growth and convergence

As already stated in the Introduction, the estimates of NCP are statistically consistent for a wide range of distributions (e.g., Park et al., 2000). Consistency also applies for the CP approximation, but only if the true production set is convex. Hence, if the true production set is convex, then CP and NCP models are both consistent and generally yield approximately the same results in large datasets. However, if the production set is non-convex, then CP set yields an inconsistent approximation while NCP remains consistent. Therefore, in large-scale applications, convexity constitutes a potential source of specification error but cannot improve the statistical fit (see Simar and Wilson, 2008). Notice that these results are obtained under a deterministic postulate according to which no noise is allowed in the technology: if the data would contain noise, then both CP and NCP frontier estimators become inconsistent. Also note that these results are asymptotic and little is known about the small sample properties of these estimators. Further observations on inferential issues in particular related to the NCP model are found in Cesaroni (2011) (otherwise see Simar and Wilson, 2008).

The convexity axioms in production have almost never been exposed to rigorous empirical testing. Using the same NCP model above, Grifell-Tatjé and Kerstens (2008) document the impact of convexity in evaluating cost efficiency differences in an assessment of Spanish electricity distribution, while Tone and Sahoo (2003) illustrate the relevance of process indivisibilities in a multi-stage model of production. As already argued in Ramey (1991), Inman (1995) and Hall (2000) using a different modeling approach, non-convex costs also matter in, e.g., car manufacturing due to changes in the number of shifts and in the shutting down of plants for some time. Recently, Copeland and Hall (2011) explicitly test for convex and non-convex cost functions in USA car assembly firms and find the latter model to fit the data best.

However, test procedures for testing the convexity hypothesis in the CP model are available. In particular, we apply the nonparametric (Li's, 1996) test to examine the differences in the distribution of the efficiency scores. Li's (1996) method tests the closeness of two distributions using sample distributions based on the kernel density method. The convexity hypothesis is accepted if there is no statistically significant difference in the efficiency estimates of the two CP and NCP models. This test ideally requires large samples. In small samples, it can confuse non-convexities with the small sample error associated with the relaxed NCP model. Specification tests can only test production assumptions under conditions in which those assumptions cannot improve the fit of the estimators.

Following the convergence literature, we also report estimates on the β-convergence and σ-convergence (e.g., Barro and Sala-i-Martin, 1992). The β-convergence notion refers to a tendency of firms or sectors with relatively low initial productivity levels to grow relatively quickly, while σ-convergence suggests a decreasing variance of differences in productivity levels, building upon the proposition that growth rates tend to decline as firms or sectors approach their steady state. In our contribution, convergence is tested at the field level.

In particular, we estimate the following model consisting of a simple unconditional speed-of-convergence equation (see Steger, 2000):

$$\Delta \ln y_{it(i)} = \alpha + \beta \ln y_{i0} + e_i, \quad (14)$$

where $\Delta \ln y_{it(i)}$ shows the indicators of average productivity changes, technological changes (TC), and efficiency changes (EC) from year 0 to year t for each field i, $\Delta \ln y_{i0}$ indicators represent the initial level (field discovered) of these same indicators, and e_i represents an error term. The indicators might result from either CP or NCP. We intend to analyze whether initial high productivity is associated with lower productivity changes (or TC or EC) later on. A negative value for β is interpreted as support for the β-convergence hypothesis, since it means that those with lower initial productivity levels have grown faster over time. Whether or not we observe convergence might crucially depend on the choice of (non-)convexity assumption.

The σ-convergence notion normally refers to a decrease over time in the cross-sectional variation (usually measured by the standard deviation) of the natural logarithm of the variable under study (see de la Fuente, 2002, for a review). Notice that β- and σ-convergence are related concepts: β-convergence is a necessary, but not sufficient condition for σ-convergence.

Despite the popularity of productivity estimates using frontier technologies, notice that few frontier technology studies have analyzed questions surrounding convergence. Available frontier-based convergence studies focus most of the time on countries (e.g., Arcelus and Arocena, 2000; Henderson and Russell, 2005; Kumar and Russell, 2002), regions (e.g., Salinas-Jiménez, 2003), or sectoral analysis (e.g., Gouyette and Perelman, 1997). Among the studies focusing on firm-level data within a given industry is the article by Alam and Sickles (2000) on the U.S. airlines industry. Our study focuses on a single industry observed over a long time period.

4. Sample description

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 have developed a unique micro-(i.e., field-) level database using three MMS data files: (i) production data including monthly well-level oil and gas outputs from 1947 to 1998 (a total of 5,064,843 observations for 28,946 production wells); (ii) borehole data describing drilling activity for each well from 1947 to 1998 (a total of 37,075 observations); and (iii) field reserve data including oil and gas reserve sizes and the discovery year of each field from 1947 to 1998 (a total of 957 observations). Relevant variables were extracted from these data files and merged by year and field across wells.

Due to spillover effects across wells within a given field, the field level is a more appropriate unit for measuring performance than the well. Indeed, crude oil production displays common-property conditions for which field wide unitization offers a solution. If each firm drills in a competitive way, this results in too many wells and too high extraction rates leading to premature depletion of natural subsurface pressure. Loss of pressure makes the natural gas dissolved in the oil come out of solution. This reduces oil mobility and can lead to significant amounts being permanently trapped. The oil retaining some mobility must be artificially lifted at higher marginal costs. This explains, for instance, why companies often engage in joint ventures to exploit a field to internalize the externalities between wells within each field.

The final data set comprises 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. Thus, the database includes field-level annual data over the period 1947 to 1998 for the following variables. Output variables are oil output and gas output. Input variables are 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 reserves, and untreated produced water. See Appendix B for a table with descriptive statistics.

Furthermore, we measure productivity change by looking at relative productivity across fields of different vintages. In so doing, we are able to separate productivity effects associated with the stock depletion of the field from effects due to differences in the state of the technology. This vintage model differs from the conventional nonparametric model specification in that the mixed period distance functions compare fields of different vintages for a given field year, so that the model compares outputs and inputs while holding fixed the number of years that the fields have been operating. Thus, we use cumulative values for inputs and outputs because for this nonrenewable industry, it is more appropriate to express the production technology in cumulative terms. For example, for a field, the production at t is determined by cumulative inputs (e.g., the total number of exploration and development wells drilled up to $t-1$) and outputs up to $t-1$. See Appendix A for a more detailed description of this vintage model.

5. Empirical estimation results

5.1. Luenberger productivity indicator results

We first examine the convexity hypothesis by comparing the convex and convexity-free production models in terms of both the resulting growth rates and the number of firms involved in bringing about technical change. The Luenberger indicator in Fig. 3 shows how the gross productivity in offshore oil and gas grows by 24.9% and 29.7% over the study period (a yearly growth rate of about 0.50% and 0.60%) under the assumptions of NCP and CP, respectively. Although the general trend of these productivities is very similar, their magnitude is clearly different, with smaller TFP growth occurring under NCP.

Turning to specific periods, we can see that growth is moderate during the 1980s. The latter result is consistent with common reports regarding Gulf of Mexico production: it was referred to as the "Dead Sea" in the 1980s. More recent productivity growth has probably occurred because production has moved to very great

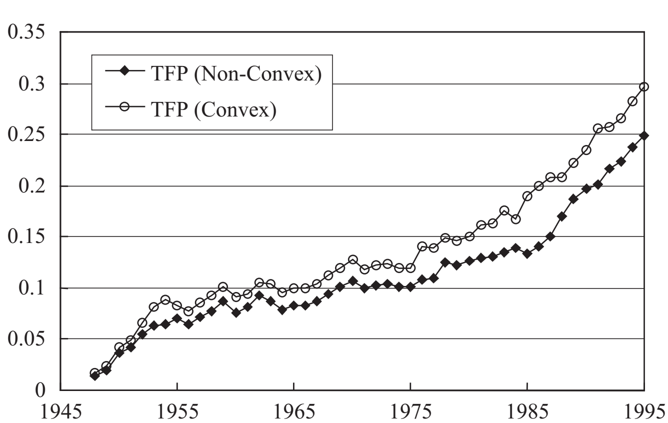

Fig. 3. Productivity change in petroleum industry under non-convex and convex assumptions.

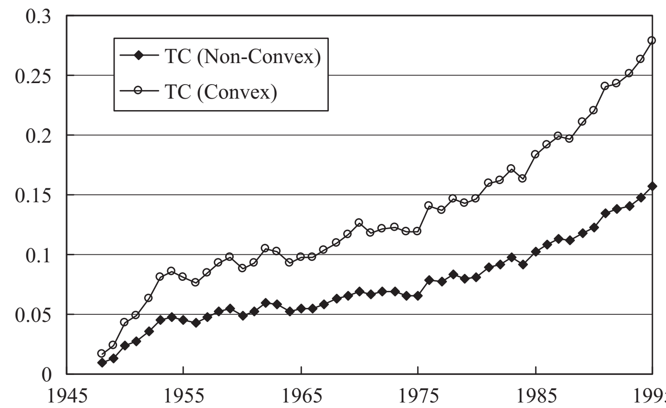

Fig. 4. Technological change in petroleum industry under non-convex and convex assumptions.

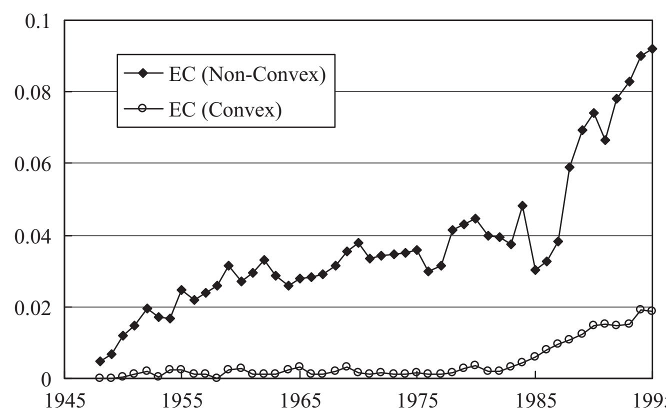

Fig. 5. Efficiency change in petroleum industry under non-convex and convex assumptions.

water depths in about the last decade or so. While production occurred at a depth of over a mile by 1997, exploratory wells were being drilled in nearly 10,000 feet of water by 2001. This deepwater production has allowed the discovery of larger fields.

We also decompose productivity effects into those associated with new innovation (TC) and with catch-up effects (EC) in Figs. 4 and 5. We find significant differences in their sources of TC and EC. The results for TC are provided in Fig. 4. TC increases by 15.7% and 27.8% over the study period under the assumptions of NCP and CP, respectively. Thus, there are significant increases in TC when imposing the convexity assumption, while TC is relatively smaller under non-convexity. In contrast, in Fig. 5 we find a significant increase of EC in the non-convex model, while EC is much smaller in the convex model. EC increases 9.2% and 1.9% over the study period under the assumptions of NCP and CP, respectively.

Table 1 reports descriptive statistics of the growth rates over the years for the Luenberger indicator decomposition in the first horizontal part, and indicates the average number of observations experiencing progress, regression, and no change per year in the second part. The third part of the table specifically indicates the average number of observations involved in global or local technological progress per year according to definitions $PTC1_i^{t,t+1}$ to $PTC3_i^{t,t+1}$ where $i \in \{c, nc\}$ (see (8)–(13)).

The analysis of the yearly growth rates in the first part confirms the preceding Figs. 3–5 in that EC constitutes about one third of productivity growth under NCP, while it explains only a fraction (about 6%) in CP. Even though productivity growth is smaller, we find on average more units experiencing both a positive and a

Table 1
Productivity indicator: descriptive statistics.

Descriptive statistics	Non-convex production			Convex Production		
	TFP	TC	EC	TFP	TC	EC
Mean	0.50	0.31	0.18	0.60	0.56	0.04
Standard deviation	0.23	0.27	0.25	0.25	0.31	0.23
Minimum	−0.74	−0.69	−0.12	−0.81	−0.77	−0.09
Maximum	1.23	1.22	0.67	1.26	1.31	0.43
Mean # obs. with component > 0	204	211	192	185	195	178
Mean # obs. with component < 0	139	134	156	116	124	140
Mean # obs. with component = 0	27	25	22	69	51	52
Mean # obs. in $PTC1_i^{t,t+1}$ $i \in \{c,nc\}$	–	57	–	–	35	–
Mean # obs. in $PTC2_i^{t,t+1}$ $i \in \{c,nc\}$	–	61	–	–	45	–
Mean # obs. in $PTC3_i^{t,t+1}$ $i \in \{c,nc\}$	–	63	–	–	38	–

negative productivity, TC, and EC component under the NCP than under the CP model in the second part. This is probably a consequence of the fact that on average fewer units experience a zero productivity, TC, or EC component under the NCP compared to the CP model.

In addition, focusing on the TC component in the third horizontal part of the table, one observes first that the yearly average number of observations that are compatible with global or local positive TC varies rather substantially depending on the exact definition retained. Since more observations experience local compared to global TC, technological progress seems to involve many players in industry under NCP rather than just a few star performers under CP. Second, the ratio of observations experiencing local compared to global technical change varies between a low 35% (61/45) and a high 66% (63/38) on average per year depending on the exact definition retained. Clearly, more to substantially more observations tend to push the frontier up- and outward under NCP than CP.

Interpreting these empirical phenomena, the lower productivity for NCP might be an indication of local rather than global changes in the production frontier. Also the larger average number of production units involved in bringing about the technical change points to a local and dispersed growth phenomenon. Atkinson and Stiglitz (1969) analyze the generation of new technologies and introduce the hypothesis that technological change can take place only in a limited technical space, defined in terms of both factor intensity and scale. Technological change is localized because it has limited externalities and affects only a limited span of the techniques contained by a given isoquant (see also Stiglitz, 1987; Foray, 1997; Antonelli, 2006).

Since technological improvements are in fact associated with a specific input space, the convexity assumption is likely to overestimate the true changes in technology. This could explain the higher growth rate under CP and the almost exclusive reliance on TC as a motor of growth. In fact, in this study convexity seems to somewhat obscure the role of EC in productivity growth: while it plays almost no role under CP, the catching up component (EC) is crucial in explaining productivity growth under NCP. It reveals an intense diffusion process whereby new techniques and knowledge seem to be continuously absorbed by the majority of players in the industry. If existing resources are not fully utilized in production initially (due to technical inefficiencies and variations in capacity utilization, among others), then one can expect significant scope for such variations in EC as revealed by NCP.

Table 2 shows the results of Li (1996) test to determine whether or not each of the production models NCP and CP has a different distribution of values for the proportional distance functions (i.e., "efficiency scores"), as well as the resulting productivity indicator and its TC and EC components. In all of these cases, the empirical results indicate that the two different distributions of CP and NCP follow statistically significant different patterns. Therefore, we reject the null hypothesis of distribution closeness between NCP and CP.

Table 2
Results on the closeness of efficiency/productivity distributions.

Indicators	z-test statistics	Conclusion
Efficiency score	3.582***	Reject null hypothesis
Productivity change	4.723***	Reject null hypothesis
Technological change	5.942***	Reject null hypothesis
Efficiency change	3.499***	Reject null hypothesis

*** Significant at 1% level.

Table 3
Testing β-convergence of productivity changes.

Parameter	TFP	TC	EC
Non-convex production			
β	−0.009**(−2.69)	−0.012**(−2.39)	−0.007***(−4.71)
R^2	0.036	0.027	0.052
Convex production			
β	−0.004 (−1.63)	−0.003 (−1.52)	−0.006** (−2.86)
R^2	0.012	0.010	0.039

Note — Values in parentheses are *t*-values. * Significant at 10% level. ** Significant at 5% level. *** Significant at 1% level.

To the best of our knowledge, there appear to be no valid theoretical arguments for assuming a priori that the set of production possibilities is truly convex (see also McFadden, 1978). In this empirical study, the economically important industry of petroleum exploitation reveals violations of the convexity hypothesis. Therefore, NCP seems to have a comparative advantage for analyzing TFP.

5.2. Convergence results

In this subsection, we investigate the β-convergence phenomenon in the petroleum industry. Table 3 presents the estimation results for convergence in average productivity changes, technological changes, and efficiency changes for a change in a crucial technology assumption. The results show that productivity change, as well as both of its components, converge in the NCP model over the observation horizon. In contrast, productivity and efficiency changes do not seem to be converging in CP, though the EC is converging. Notice that the speed of convergence of EC is about identical in both models. Therefore, we have confirmed strong evidence for productivity convergence among petroleum fields,

Table 4
Testing σ-convergence of productivity changes.

Standard deviations	TFP	TC	EC
Non-convex production			
1947	0.283	0.293	0.262
1998	0.256	0.243	0.250
Convex production			
1947	0.243	0.302	0.224
1998	0.256	0.312	0.239

assuming that NCP provides a true measurement. These results might imply that technology diffusion behind productivity convergence expands opportunities for secondary firms to catch up to leading firms. Applying the standard assumption of CP yields altogether different conclusions.

Now we turn to testing for the eventual existence of σ-convergence for productivity, TC, and EC in the NCP and CP models. Table 4 reports cross-sectional standard deviations of productivity changes for the two years 1947 and 1998 at the beginning and end of the sample period. The 1998 standard deviations are greater than those of 1947 for the CP model, while the reverse is true for NCP. Therefore, assuming NCP, we are able to find the tendency of poor fields to grow faster in a cross-section bivariate regression of growth rates on initial productivity level and also the tendency of the sample dispersion of productivities to diminish. In contrast, no sign of σ-convergence emerges under the traditional CP.

6. Conclusions

After reviewing traditional theoretical arguments for non-convexities in production, this study raises doubts regarding the ability of traditional convex production technologies to explain the real-world phenomenon of industrial production. We examine data on the petroleum industry using unique field-level data. We find that the traditional convex production model fits our data rather poorly and that the shape of the technology is likely non-convex. The existing evidence suggests that non-convexities may exist in petroleum fields as well as in some other industries (such as electricity generation, car assembly among others). In the light of this preliminary empirical evidence presented in this study, there is no good reason to take the convexity of production possibility sets for granted in general. Therefore, more studies are called for that explicitly test for the validity of the convexity of technology.

The whole issue of testing for convexity raises a host of challenges. Just to mention one, it is important to recall that the shape of the production technology is a crucial determinant of the properties of value functions summarizing optimal economic behavior. For instance, it affects the property of the cost function with respect to changes in outputs: while in general the cost function is non-decreasing in outputs, cost functions estimated on convex (non-convex) technologies are convex (non-convex) in the outputs (Jacobsen, 1970). This could have consequences regarding tests of regularity conditions for traditional parametric estimation approaches. While substantial progress has been made in the development of flexible functional forms (see, e.g., Gallant and Golub, 1984 or Tishler and Lipovetsky, 1997) and the testing of monotonicity and curvature properties (also in a frontier estimation context: see Michaelides et al., 2010 and O'Donnell and Coelli, 2005), it could be a challenge to combine flexible functional forms allowing for eventual convexity or not in outputs and the testing of traditional regularity conditions.

If in some distant future these results invalidating convex technologies would be replicated in other industries, then serious implications for standard micro-economic theory could follow. This is because the equilibrium of the firm and the existence of competitive markets normally depend on the convexity of technology. It is therefore necessary for researchers to explicitly test for the assumption of convexity when the true empirically estimated technology may well be non-convex (e.g., according to engineers).

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Appendix A. Efficiency estimation based on non-convex production assumption

When analyzing productive efficiency with regard to the extraction of non-renewable resources, such as in the petroleum industry, one faces challenges not met in typical applications to the single-period production of goods and services. For example, production from an oil field at some point in time depends upon cumulative past production from the field (due to depletion effects), in addition to the technology employed and the attributes of the field (e.g., field size, porosity, water depth). Holding inputs constant, output from a given field follows a well-known pattern of an initially increasing output rate, obtaining a peak after some years of production, and then follows a long path of declining output (e.g., Pindyck, 1978). This implies that, for the purpose of measuring changes in productivity, it is inappropriate to compare contemporaneous levels of output from a newly producing field with those of a field that has been producing for ten years or 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 the aging of the field from effects due to differences in the state of the technology. The CP formulation with the vintage model differs from the conventional CP formulation (as described in, e.g., Färe et al., 1994). Similar to the approach of Managi et al. (2004), our CP formulation calculates the distance function by solving the following optimization problem:[4]

$$D_c^i(\mathbf{x}_{k'j'}^i,\mathbf{y}_{k'j'}^i) = \max_{\delta^{k'j'},\lambda_{kj}} \delta^{k'j'}$$

subject to

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

[4] Note (Managi et al., 2004) apply a more traditional Malmquist productivity index method.

Table B1
Descriptive statistics of inputs and outputs over the years 1947–1998 (N=18,117).

	Unit	Mean	Std. Dev.	Min	Max
Oil output	Barrels	1.05E+07	3.74E+07	0.1	5.23E+08
Gas output	Million cubic feet	1.10E+08	2.46E+08	0	3.09E+09
No. of exploration wells drilled	–	9.11	10.89	1	142
No. of development wells drilled	–	28.69	67.74	1	871
Total drilling distance of exploration wells	Meter	8832.31	3627.67	0	22086.5
Total drilling distance of development wells	Meter	7381.28	4435.97	0	22457
No. of platforms	–	5	10.80	1	121
Water depth	Meter	169.33	286.69	9	5330
Oil reserve	Million barrels	2.36E+04	6.18E+04	100	5.42E+05
Gas reserves	Billion cubic feet	2.58E+05	3.95E+05	100	3.20E+06
Untreated produced water	Ton	7.92E+06	3.16E+07	0	5.16E+08

$$\sum_{k\in K(i)}\sum_{j=0}^{J(k)}\lambda_{kj}\,x^i_{kjm} \le (1-\delta^{k',j'})x^i_{k'j'm},\quad m=1,\ldots,M,$$
$$\sum_{k\in K(i)}\sum_{j=0}^{J(k)}\lambda_{kj}=1,$$
$$\lambda_{kj}\ge 0,\quad k\in K(i),\quad j=1,\ldots,J\,(k). \tag{A1}$$

where j is the field year, k is the field number, $K(i)$ includes all fields of vintage i (i.e., discovered in year i), $J(k)$ is the final year of production for field k, and λ_{kj} is the weight for field k at field year j.

In a similar manner, our NCP formulation calculates the distance function by solving the following optimization problem:

$$D^i_{nc}(\mathbf{x}^i_{k'j'},\mathbf{y}^i_{k'j'}) = \max_{\varpi^{k'j'},\lambda_{kj}} \varpi^{k'j'}$$

subject to

$$\sum_{k\in K(i)}\sum_{j=0}^{J(k)}\lambda_{kj}\,y^i_{kjn} \ge (1+\varpi^{k',j'})y^i_{k'j'n},\quad n=1,\ldots,N,$$
$$\sum_{k\in K(i)}\sum_{j=0}^{J(k)}\lambda_{kj}\,x^i_{kjm} \le (1-\varpi^{k',j'})x^i_{k'j'm},\quad m=1,\ldots,M,$$
$$\sum_{k\in K(i)}\sum_{j=0}^{J(k)}\lambda_{kj}=1,\ \lambda_{kj}\in\{0,1\}\forall j\in S$$
$$\lambda_{kj}\ge 0,\quad k\in K(i), j=1,\ldots,J\,(k). \tag{A2}$$

We refer to this simple algorithm because it points to an important difference in the logic that lies behind convex vs. non-convex methodologies. The role of the integrality constraint is indeed essential to identify a relationship of dominance between observed production plans. On the one hand, an observation is declared efficient and considered to be part of the boundary of the reference technology if it is un-dominated. On the other hand, an observation is declared inefficient (i.e., it lies in the interior of the technology) if it is dominated by at least one other observation. In the latter case, the mixed integer program identifies a most dominating observation that serves as a reference since it corresponds to the maximum of the computed efficiency measure.

In contrast, the linear programs used in the convex case seek to compute a distance with respect to the frontier of a convex envelope of the data. While dominance also plays some role in identifying this envelope, the additional requirement of convexity introduces the possibility that un-dominated observations can be declared inefficient because they do not lie in the convex envelope of the data. Note that the NCP model treats only a specific and real peer unit, or a collection of such units in the case of a non-unique solution, as a benchmark at the optimum for the efficiency measure. Thus, the NCP model provides a more conservative inner approximation and estimation of the production possibility set than does CP.

Appendix B. Descriptive statistics of the sample

(See Table B1 below).

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