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Efficiency of New Ethanol Plants in the U.S. North-Central Region[1]

Juan P Sesmero, Richard K Perrin and Lilyan E Fulginiti[2]

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[2] PhD candidate, and Professors, Department of Agricultural Economics, University of Nebraska, Lincoln. juampase@hotmail.com, rperrin@unl.edu, lfulginiti@ unl.edu

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Abstract

Continuation of policy support for the U.S. corn ethanol industry will depend upon the greenhouse gas (GHG) effects of the industry, and its economic viability. The environmental and economic performance of ethanol plants is determined by the productivity of new technologies and, in addition, by the efficiency with which technologies are used (technical efficiency) and output and inputs are combined (economic efficiency). This study estimates the technical and economic efficiency of seven recently-constructed ethanol plants in the North Central region of the US during 2006-2007. It uses nonparametric data envelopment analysis (DEA) and investigates both the drivers and implications of inefficiency differentials. In terms of drivers, results are consistent with the hypothesis that economic (profit) efficiency of productive units tends to be positively correlated with their size. Regarding implications results show that, on average, the maximum feasible reduction in Greenhouse Gases (GHG) emissions that can be achieved by these ethanol plants, when comparing across plants, is very limited (7,769 milligrams). We calculate that, by eliminating inefficiency, plants can achieve a 17% increase in returns over operating costs per gallon of ethanol produced, or about 12 cents a gallon. Therefore, plants can potentially increase their returns improving their economic viability. By enhancing economic viability, public policies can profoundly affect survival of this industry.

Keywords:

JEL Classification:

Introduction

The U.S. corn ethanol industry has benefited from government support due to its potential to achieve a rather wide set of goals: mitigating emissions of greenhouse gases (GHG), achieving energy security (diversifying energy sources), improving farm incomes and fostering rural development among others. Continuation of policy support, however, is being debated due to doubts about the direct and indirect GHG effects of the industry, as well as its economic viability. measured as the level and sensitivity of profits to changes in corn, ethanol and energy prices. Moreover, the capacity of the industry to reduce overall GHG emissions will also determine the opportunities opened to it in future carbon markets.

The economic viability of plants depends on their profitability. The profitability of plants is captured by returns over operating costs; i.e. the difference between revenue and processing and feedstock costs which is, in turn, driven by differences in prices paid for inputs and received for outputs across plants. Given prices, the input-output combination achieved by the plants will depend both on their technical and their allocative performance. Technical performance of plants is usually expressed in terms of input requirements per unit of output; i.e. how many physical units of each input are used per physical unit of output produced. Allocative performance is measured by the potential increase in profits that can be obtained by changing the input-output mix.

In addition we are interested in the environmental performance of the industry. This aspect relates to the industry's effect on GHG emissions. Environmental efficiency depends on corn net of byproduct yield and on energy use per gallon of ethanol produced.

Relative to technical efficiency, environmental efficiency focuses on a subset of all inputs used in production.

In rapidly evolving industries (like the ethanol industry) it is relatively common to observe significant dispersion across production units both in terms of technical, environmental and economic performance. This is a very important aspect of the industry's evolution since if performance differences are due to factors that are out of the managers' control, like market conditions and differences in local regulations, then there would be little room for improvement and these efficiency calculations are not informative.

Previous studies have addressed the issue of technical and economic performance of ethanol plants. Using engineering data, McAloon et al. (2000) and Kwiatkowski et al. (2006) measuredconsiderable improvement in plant efficiency between 2000 and 2006. Shapouri, et al. (2005) reported input requirements and cost data based on a USDA-sponsored survey of plants for the year 2002. Wang et al. (2007) and Plevin et al. (2008), reported results based on spreadsheet models of the industry (GREET and BEACCON, respectively.) Pimentel et al. (2005) and Eidman (2007) reported average performances of plants although they do not clearly indicate the sources of their estimates. Finally Perrin et al. (2009) reported results on input requirements, operating costs, and operating revenues based on a survey of seven dry-grind plants in the Midwest during 2006 and 2007 and this is the source of the data used in this study.

With the exception of Shapouri et al. (2005) and Perrin et al. (2009) all of these studies reported values corresponding to the industry's average plant which, as argued before, are not necessarily informative of the overall industry's situation and evolution, in particular when dispersion across plants is important. Regarding dispersion, Shapouri et al. (2005) conducted a survey of 21 dry-mill ethanol plants and found significant dispersion across them. Given that the only significant restriction in sampling was that the plants had to be dry-mill, the cause of dispersion could not be isolated asthey can be attributed to many other factors. It is then impossible to isolate the impact of the technology used, the size and age of the plant fromthose under the control of the manager. In fact this paper argues that dispersion in ethanol yield per bushel of corn was directly related to factors such asthe plant's efficiency, the plant's age, types of equipment, and the amount of fermentable starch in the corn kernels not under the control of the manager as well as those factors depend on managerial ability.

In line with Shapouri et al. (2005), Perrin et al. (2009) also found significant dispersion of returns over operating costs across plants in the sample. However, in contrast to Shapouri et al. (2005), this study employed much more restrictive sampling criteria (discussed below) which yielded a modern and technologically homogenous sample of plants. Therefore, this study will exploit the survey initially reported and discussed in Perrin et al. (2009) to isolate the effects on performance dispersion of efficiency-related sources and determine potential for improvement in the industry.

To sum up, dispersion in economic performance across plants may imply that there is potential for improvement in the industry which may enhance its economic viability. We take advantage of the new plant level data provided in Perrin et al. and add to that study by examining the potential improvements in efficiency -environmentally, technically and allocativelly- that could indicate a path to improved economic viability.. This is important given studies that have been influencing the policy debate about nthe merits of the ethanol industry used input requirements consistent with obsolete technologies and refer to the performance of an 'average plant.'. In an attempt to give updated and in depth information this study looks at seven recently-constructed ethanol plants in the Mid-West and takes advantage of information contained in their differences to infer the potential for improved performance. It does so by estimating technical, environmental, and allocative efficiencies of each production unit to compare with that of the best performers in an effort to isolate potential managerial improvments.

We first characterize the plants surveyed, and conduct an analysis of technical efficiency of ethanol plants. We then investigate the potential link between the size of productive units and their efficiency due to returns to scale. We then calculate the maximum feasible reduction of GHG emissions. Finally, to investigate the industry's potential economic viability, we report results on allocative efficiency of plants and calculate the maximum feasible increase in returns over operating costs implied by elimination of both technical, environmental and allocative inefficiencies.

The surveyed plants

The sampling criteria in Perrin et al. were as follows. The plant must have started production (or been updated) after mid-2005 with a capacity of about 50,000 million gallons per year or more, so as to represent recent technology. Plants must have a minimum of three quarters of operating data, starting at least one month after the plant opened. Finally, the plants should be located in or near small towns of approximately 10,000 or less, to facilitate companion studies of the impact of the plants on rural communities within the twelve-state North Central region of the U.S. Eighteen plants met these criteria but only seven accepted the invitation to participate.

Table 1 presents the characteristics of the plants surveyed for this study. Seven dry-grind ethanol plants were surveyed from north-central Midwest states. The plants produced an average rate of 53.1 million gallons of ethanol per year, with a range from 42.5 million gallons per year to 88.1 million gallons per year. The period surveyed began in the third quarter of 2006 and lasted until the fourth quarter of 2007 (six consecutive quarters). In addition, so as to eliminate startup inefficiencies from our results, all but one of the plants was online prior to the start of the 2006 to 2007 survey period. The Michigan plant was the exception, having come online in the first quarter of the survey period, the third quarter of 2006. For this plant, we included only data from the last five quarters, ignoring the startup quarter.

Table 1 also characterizes the plants in terms of number of employees. Our survey plants employed an average of 39.6 employees. Furthermore, plants could be differentiated by how much byproduct they sold as dry distillers grains (DDGs) as compared to modified wet distillers grains (MWDGs). We found the plants varied significantly in this variable, averaging 54% of byproduct sold as DDGs, but ranging from one plant that sold absolutely no byproduct as DDGs to another plant that sold nearly all byproduct (97%) as DDGs.

Finally, Table 1 briefly characterizes plant marketing strategies. In purchasing input feedstock, five of the six plants purchased corn via customer contracts. Similarly, in selling ethanol, five of the six plants used third parties or agents. Byproduct marketing across plants displayed a higher degree of variance. Marketing of DDGs was split fairly evenly between spot markets and third parties/agents. An even higher variability was observed for MWDGs, where no one marketing strategy (spot market, customer contract, or third party/agent) was significantly more prevalent across plants than any other.

Our basic observations in this study are not plants per se, but instead each observation corresponds to a plant in a given quarter; so two quarters of the same plant are considered as two different observations and two plants in the same quarter are also considered as different observations. Our sample is not balanced (i.e. we don't have observations for all plants in all quarters) and the number of observations per quarter can also be found in Table 1 but, in total, they amount to 34 observations. Following the literature on DEA efficiency analysis, we will refer to the observations as decision making units (DMUs).

Technical Efficiency and Environmental Performance

We define technical inefficiency by how much the decision making units (DMUs) can increase outputs and reduce inputs simultaneously. We measure that inefficiency as the difference between a given DMU's input-output quantities and the quantities achieved by the DMU's with the "best practice" in the sample. It is important to note, however, that what is attributed to "inefficiency" could be the result of differences in the circumstances/environment of these plants which have impacts on the input-output quantities. These could include different regulation in the different states/counties.

Environmental performance could be defined in many ways depending on the which factors are consider critical for the environment at that particular time and location. It could be captured by the pressure that plants put on water availability, on marginal land, on the use of chemical inputs and water pollution, on local air pollution, on industrial waste, on GHG emissions, and the like. Since continuation of policy support will be defined specifically on the basis of life-cycle emissions of GHG, we will use this variable as the metric to evaluate environmental performance. Moreover, GHG emissions are determined by the amounts of corn (net of byproducts produced), natural gas, and electricity used by plants. The amount of corn used by plants is important because of the emissions released during the production process of the crop. Byproducts produced (distillers' dried grains, DGS) replace corn used in animal diets and so it must be recognized as a "credit" in life-cycle analysis as it prevents emissions that would otherwise have occurred from the production of corn used as feed. The use of electricity is also a source of GHG emissions from a life cycle perspective since it is mainly produced from burning fossil fuels. Finally the use by the plant of natural gas for heat is an additional direct source of GHG emissions. Therefore if there is potential to reduce natural gas and corn use and increase byproducts per gallon of ethanol produced, then there is potential for reducing the life-cycle GHG emissions from the ethanol industry. With a given technology, a reduction in inputs and an increase in byproducts per gallon of ethanol produced is only possible through elimination of technical inefficiencies.

Method and Data

This study estimates the technical efficiency of seven recently-constructed ethanol plants in the North Central region of the US during 2006-2007 using data from Perrin et al. Nonparametric, data envelopment analysis (DEA) is the method used.

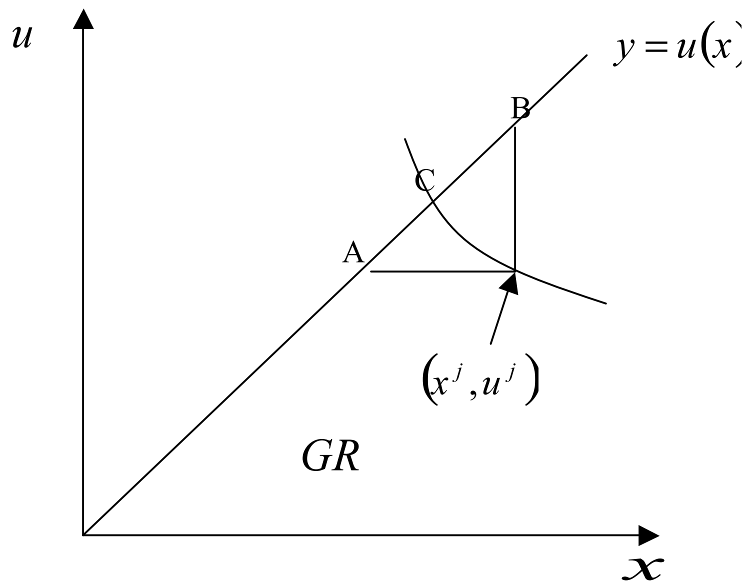
To illustrate the methodology used in this paper, let us assume we have a sample of J DMUs. Each DMU produces M outputs using N inputs. Therefore the data set consists of a matrix M [3] of output observations and a matrix N [4] of input observations.

A production technology transforming a vector of N inputs $x = (x_1, x_2, ..., x_N) \in \Re_+^N$ into a vector of M outputs $u = (u_1, u_2, ..., u_M) \in \Re_+^M$ can be represented by the input correspondence and the graph of the technology. The input correspondence of the technology, denoted by $L(u)$, is the collection of all input vectors $x \in \Re_+^N$ that yield at least output vector $u \in \Re_+^M$. Therefore the input correspondence maps outputs $u \in \Re_+^M$ into subsets $L(u) \subseteq \Re_+^N$ of inputs, i.e. $L : \Re_+^M \to 2^{\Re_+^N}$. Moreover, the graph of a given technology is defined as the collection of all feasible input-output vectors, i.e. $GR = \{(x,u) \in \Re_+^{N+M} : x \in L(u)\}$. Figure 1 illustrates a graph representation of technology for the case of one output and one input. The graph (GR) in this case is the area below the line $y = u(x)$.

[3] M is an MxJ output matrix in which each column shows levels of the M outputs produced by the j^{th} DMU.

[4] N is an NxJ input matrix where each column shows levels of the N inputs used by the j^{th} DMU.

Figure 1. Graph of a one-input one-output technology



We compute efficiency by calculating, simultaneously, the maximum feasible expansion in outputs and shrinkage in inputs relative to the graph representation of plants' technological possibilities. The inefficiency of a DMU is calculated as the distance from that DMU's observation to the frontier of the graph. This distance will depend both upon the direction in which we approach the frontier from the observation and the characteristics of the surface of the graph. We will discuss the determinants of the surface of the graph now and will address the direction of the change later.

The surface of the graph depends upon the behavior of the technology under proportional changes in the size of the technology and also under changes in the mix of inputs and outputs. The former is captured by the notion of returns to scale and the later by disposability of inputs and outputs. Returns to scale determine whether a proportional increase in outputs is feasible after an increase in all inputs in the same proportion. Disposability, on the other hand, determines whether the sum of inputs from two DMUs can produce the sum of their outputs. We will assume, throughout the paper that the technology displays strong disposability which means that the sum of inputs of two observations in the data can produce the sum of their outputs.

Since they will be used later for efficiency computation, we will discuss definitions of the graph under three types of returns to scale: constant, non-increasing and variable returns to scale. [5]

The combination of returns to scale and disposability determines the characteristics of the surface of the graph but, as argued before, efficiency also depends upon the direction in which we approach the frontier from the observed input-output combination. As Figure 1 shows for a constant returns to scale technology, the j^{th} production unit could expand outputs and reduce inputs in many directions and reach the frontier of the graph at any point within the segment $\overline{AB}$. The maximum equiproportionate expansion in outputs and reduction in inputs feasible for the j^{th} production unit yields the hyperbolic movement from point (x^j, u^j) to point C illustrated in figure 1. This distance is called the graph measure of technical efficiency and can be stated, for a general technology (i.e. without imposing returns to scale and disposability), as:

$$F_g(x^j, u^j / ., .) = \min\{\lambda : (\lambda x^j, \lambda^{-1} u^j) \in (GR)\} \quad j = 1, 2, ..., J \tag{4}$$

[5] For a more detailed discussion on different types of disposability and returns to scale see Färe et al. (1994).

When there is more than one output and more than one input, efficiency can also be measured as maximum feasible shrinkage and expansion of *some* but not all inputs and outputs used and produced by the DMU (e.g. reductions in corn and natural gas, and increases in ethanol assuming all other inputs and byproducts constant.) This measure is called a sub-vector graph-efficiency measure.

For a technical definition suppose we can decompose the output matrix M into two subsets: a subset of outputs that we want to expand M_α and a subset that we want to keep fixed $M_{\hat{\alpha}}$ so that $M = (M_\alpha, M_{\hat{\alpha}})$. Moreover, suppose we can also partition the input matrix N into variable N_β and fixed $N_{\hat{\beta}}$ inputs so that $N = (N_\beta, N_{\hat{\beta}})$.

In line with these decompositions we will denote the sub-vectors of inputs as $x = (x_\beta, x_{\hat{\beta}})$ and of outputs as $u = (u_\alpha, u_{\hat{\alpha}})$ where x_β is the subset of inputs that we want to contract and u_α is the subset of outputs that we want to expand. Then we apply the hyperbolic measure defined in (4) to the subsets of inputs and outputs that we want to contract and expand respectively. A technical definition of sub-vector graph efficiency is:

$$F_g\left(x^j, u^j / .,.\right) = \min\left\{\lambda : \left(\lambda x_\beta^j, x_{\hat{\beta}}^j, \lambda^{-1} u_\alpha^j, u_{\hat{\alpha}}^j\right) \in (GR)\right\} \quad j = 1, 2, ..., J \tag{5}$$

Using the hyperbolic graph-efficiency method, we measure the productive activity of ethanol plants producing three outputs (ethanol, dry DGS, and wet DGS) and using eight inputs (corn, natural gas, electricity, labor, denaturant, other chemicals, water and waste, and other processing costs.) The vector of netputs[6] with respect to which we measure efficiency depends upon the goal of the study. First, we are interested in environmental and profit efficiency of plants which requires that we simultaneously adjust input and

[6] In the context of production, a netput is a quantity that is positive if the quantity is output by the production process and negative if it is an input to the production process

output quantities.[7] When "too many" inputs and outputs are allowed to vary, often, the algorithm yields a high number of efficient observations due to a dimensionality constraint. So, ideally, we would want to include those netputs that are most important both for GHG emissions and profits. As corn, energy, and electricity amount to about 85% of total operating costs of plants and as they are also, the most important drivers of direct GHG emissions from the ethanol industry, they need to be included in the efficiency measure if this is to be meaningful. Byproducts are produced jointly with ethanol and are important for GHG emissions and as a source of revenue for plants. Ethanol is the main source of revenue for these plants. Therefore, all three outputs are included in the efficiency measure.

Technical Efficiency

We follow Färe et al. and calculate here sub-vector hyperbolic graph-efficiency for all 34 observations in our sample. We start by calculating efficiency assuming a constant returns to scale technology and we will later calculate this measure for a variable returns to scale technology. The sub-vector graph-efficiency of a constant return to scale, strong disposability technology can be defined as:

$$F_g\left(x^j, u^j / C, S\right) = \min\left\{\lambda : \left(\lambda x_{\beta}^j, x_{\hat{\beta}}^j, \lambda^{-1} u_{\alpha}^j, u_{\hat{\alpha}}^j\right) \in \left(GR / C, S\right)\right\} \quad j = 1, 2, ..., J \qquad (6)$$

The measure in (6) can be mathematically implemented through the following non-linear programming problem:

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[7] This is obvious for profit efficiency but requires some explanation for environmental efficiency. The level of (life-cycle) GHG emissions from ethanol plants depends not only on inputs but also on the amount of byproducts produced since these receive "credits" as they replace feed corn.

$$
\begin{aligned}
\underset{\Gamma,z'}{Min}\,\Gamma \qquad s.t.\quad & u_{\alpha}^{j} \le z'M_{\alpha} \\
& \lambda u_{\hat{\alpha}}^{j} \le z'M_{\hat{\alpha}} \\
& \Gamma x_{\beta}^{j} \le z'N_{\beta} \\
& \lambda x_{\hat{\beta}}^{j} \le z'N_{\hat{\beta}} \\
& \Gamma = \lambda^{2} \\
& z' \in \Re_{+}^{J}
\end{aligned} \tag{7}
$$

We run program (7) for four different combinations of input-output sub-vectors. We will now give justification for each combination and denote their notation:

1. All outputs (ethanol, dry byproduct, and wet byproduct) with corn, gas and electricity. As argued before including all inputs may create dimensionality problems [8] and hence only corn, gas and electricity were included. These three categories are the main drivers of both plants' costs and GHG emissions.
2. All outputs with corn and natural gas. Since electricity contributes less than corn and gas to both cost and GHG emissions we exclude it to check sensitivity of the results with the previous sub-vector to dimensionality constraints.
3. Byproducts with corn, gas and electricity. This sub-vector is especially considered for evaluation of environmental performance of plants. As we will discuss in more detail below, potential improvements of DMUs in terms of GHG emissions will depend upon maximum feasible shrinkage of corn, gas and electricity simultaneously with maximum feasible expansion of byproducts.

[8] In fact efficiency indexes were calculated for all inputs and outputs and we found a very high proportion of efficient units as a result.

4. Byproducts with corn and natural gas. We exclude electricity to check sensitivity of the results in sub-vector 3 to dimensionality constraints.

The reader may note that we have not included a sub-vector consisting of ethanol and inputs excluding byproducts. This is due to the technological features of ethanol plants. Since an important portion of natural gas and electricity is used for drying byproducts, excluding byproducts and including gas and electricity would confound a greater use of these inputs (for a given ethanol production) as inefficiency when it is most likely due to an increase in production of dried byproduct.

Although hyperbolic measures of efficiency are usually calculated through linear programs, when only sub-vectors of both inputs and outputs are involved there is no way to linearize problem (7). Consequently these four sub-vector hyperbolic measures of technical efficiency were calculated through a non-linear program implemented with the FMINCON procedure in MATLAB. Results are reported in Table 2 for all 34 observations in our sample. Table 3 summarizes those results by reporting descriptive statistics.

A hyperbolic efficiency index of 0.9 means, that there is room for a reduction of 10% in the amount of inputs used as reference and an increase in 10% in outputs used as reference, while keeping all other inputs and outputs constant.

In particular, the "Corn-Gas-Electricity-Outputs" case is measured as the maximum equiproportional shrinkage of all three inputs and expansion of all three outputs that can be achieved by a given DMU, assuming all other inputs and outputs constant. In the same way "Corn-Gas-Output" assumes shrinkage of those two particular inputs and expansion of all three outputs with everything else fixed. "Corn-Gas-Electricity-Byproduct" calculates simultaneous reduction in the three inputs and expansion of byproducts keeping ethanol, and all other inputs and outputs constant. "Corn-Gas-Byproduct" allows for reduction of corn and gas and expansion of byproducts keeping ethanol, electricity and all other inputs and outputs constant.

An interesting point to note from Table 3 is that DMUs could have, on average, simultaneously reduced corn, gas and electricity and increased ethanol and byproducts (dry and wet) by 0.8%. On the other hand, the sample does not show much variability across DMUs (standard deviation of 0.018) and a rather large part of the sample can be classified as technically efficient (74%) which implies that only 26% of DMUs show potential for technical improvement. Finally, excluding ethanol and electricity from the reference does not change the results significantly.

Environmental Performance

It has been argued above that continuation of political support will depend upon the environmental performance of the ethanol industry measured by life-cycle GHG emissions. We do not have direct observations on emissions but rather we calculate GHG levels using the Biofuels Energy Systems Simulator[9] (BESS).

Among a number of existing models that perform life cycle energy and GHG emissions assessments of biofuel systems (Wang et al. 2007; Farrell et al. 2006), we use BESS because it allows modification of all input parameters This is a very convenient feature of the software since our goal is to calculate the GHG emissions level of DMUs in

[9] BESS is a software developed by a team of specialists in the Agronomy Department at the University of Nebraska, Lincoln. http://www.bess.unl.edu/

the sample in Perrin et al. that provided input requirements and other characteristics of technologically newer plants.

The BESS software uses a linear relationship between inputs (corn, gas, and electricity), byproducts, and GHG[10] emissions. The linear relationship in BESS, developed and simulated by Liska et al. is:

$$GHG = 0.00025\, kg\ corn + 0.00006 \left(MJ\, Gas + \frac{MJ\, Gas}{Ton\ Dried} Tons\ Dried \right) + 0.0007 Kwh\, Electricity - 0.00024211\, kg\ byp \tag{8}$$

where $kg\ corn$ and $kg\ byp$ are kilograms of corn used and byproducts produced respectively, $MJ\, Gas$ represents megajoules of gas used for production of ethanol, $Kwh\, Electricity$ is total kilowatt hours of electricity used for production and, $\frac{MJ\ Gas}{Ton\ Dried} Tons\ Dried$ is the total amount of megajoules used for drying byproducts.[11]

Re-writing this expression in terms of the units of measurement in this study yields:

$$GHG = 0.0000098\ (bu\ corn) + 0.063\ (MMBTUsGas_{all\ wet}) + 0.094\ (Tons\ Dried) + 0.0007 (Kwh\ Electricity) - 0.219\ (Tons\ Wet) \tag{9}$$

where $bu\ corn$ are bushels of corn, $Tons\ Dried$ and $Tons\ Wet$ are tons of byproduct sold as dried and wet respectively, and $MMBTUsGas_{all\ wet}$ is the total amount of gas used for purposes other than drying byproducts.

Equation (9) has a very important implication for environmental efficiency measurement. It defines the environmental efficiency frontier against which each plant's

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[10] Since life-cycle GHGs include different types of gases (CO2, CH4, and N2O), the total is measured in terms of carbon dioxide equivalents (CO2e).
[11] The amount of gas used per ton of byproduct dried varies across DMUs and in fact some of them could not report an exact quantity so we use an average of those plants which did report these values and applied it to all plants.

performance will be measured. In other words the linear relationship depicted by (9) is a mix of inputs and byproducts that, for a given level of output, minimizes GHG. [12]

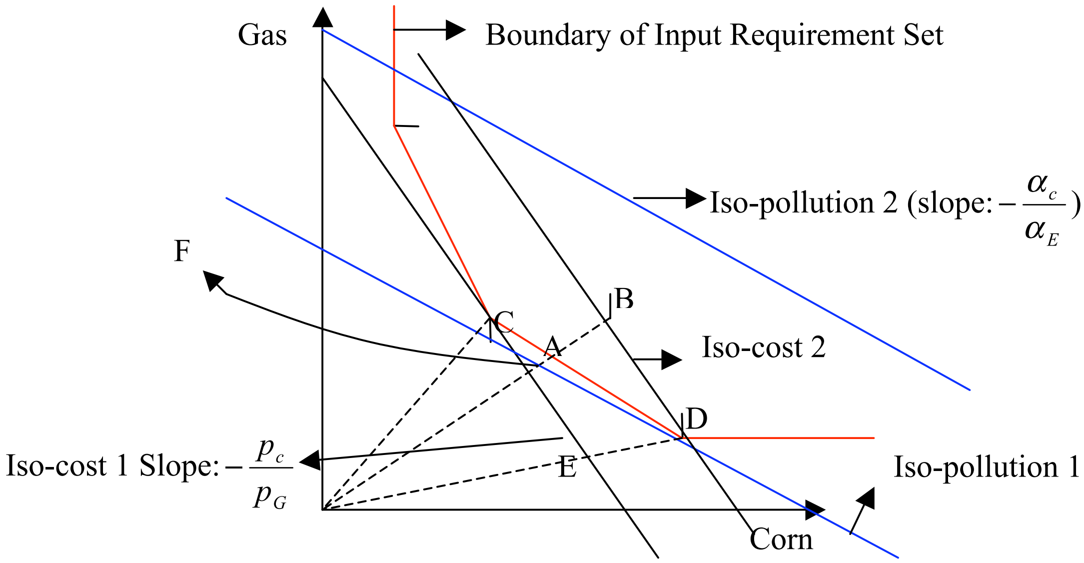
The concept of environmental efficiency is illustrated in Figure 2 where observations are displayed in corn-gas space (i.e. keeping the levels of all other inputs and outputs constant.)[13] We also plot an iso-pollution line (i.e. combinations of corn and gas that keep the level of GHG constant) and, for reasons that will become clear later, an iso-cost line (i.e. combinations of corn and gas that keep total expenditure in these two categories constant) with an arbitrary slope.

The iso-pollution line is directly derived from (9) with byproducts and electricity fixed. Since GHG emissions depend positively on both corn and gas then higher (lower) levels of these inputs yield (lower) higher levels of GHG which can be captured graphically as a shift in the iso-pollution line away from (towards) the origin.

Figure 2. Illustration of Maximum GHG reduction

[12] Notice that efficiency frontiers in this study, other than the environmental efficient frontier, are defined by the best performer of the seven plants. The environmental efficient frontier is defined by the relationships built in BESS.

[13] We keep everything else constant only with the purpose of illustrating the idea behind environmental efficiency although our calculations in this section will allow other variables to vary.



Point B is corn-energy inefficient and by reducing both inputs radially to point A on the red line (the boundary of the input requirement set), technical inefficiency is eliminated. Moreover since this new combination corresponds to an iso-pollution line closer to the origin, the amount of GHG emissions is also reduced. Point A is technically efficient but it does not correspond to the minimum level of GHG achievable. In fact the minimum feasible level of GHG is achieved by input combination D which yields a pollution level corresponding to iso-pollution 1. The input combination in D implies an increase in corn and a decrease in energy with respect to the technically efficient point A.

Let us now go back to the cases in which four different subsets of inputs and outputs are variable. Technically, one can define the minimum feasible GHG emissions as:

$$\underline{GHG} = \min_x \left\{ \begin{aligned} &GHG = (0.0000098)x_c + (0.063)x_G \\ &\qquad + (0.094)x_{DB} + (0.0007)x_{EL} - (0.219)x_{WB} \\ &s.t. \quad (x,u) \in GR \end{aligned} \right\} \tag{10}$$

Where x_C are bushels of corn, x_G are MMBTUs of natural gas, x_{DB} are tons of dried byproduct, x_{EL} are kilowatt hour of electricity, and x_{WB} are tons of wet byproduct. The input-output combination that minimizes GHG is denoted by (x^E, u^E).

Moreover, the input-output combination that is technically efficient (located at the boundary of the graph) is that defined by (7). In particular, it is the measure corresponding to sub-vector 3 (byproducts with corn, gas, and electricity) and we will denote the technically efficient input-output combination by (x_T^j, u_T^j). Plugging (x_T^j, u_T^j) into (9) yields the technically efficient level of emissions denoted by GHG_T^j. Finally we denote the j^{th} observed input-output combination by (x^j, u^j).

We now define environmental efficiency by the distance between minimum feasible GHG emissions and observed GHG emissions:

$$EE^j = \frac{\underline{GHG}}{GHG^j} \tag{11}$$

Where $\underline{GHG}$ is the hypothetical quantity defined in (10) and it is obtained from the combination (x^E, u^E), and GHG^j are observed emissions which is obtained by plugging the combination (x^j, u^j) in equation (9).

We can decompose EE^j into purely technical efficiency (which coincides with the hyperbolic technical efficiency of sub-vector 3 computed in the previous section) and allocative inefficiency. Allocative inefficiency is related to the input-output mix rather than levels[14] and can be defined as:

[14] Environmental allocative inefficiency was and it was illustrated in Figure 2 by the distance between the iso-pollution corresponding to combination A and iso-pollution corresponding to point D.

$$EE^j = \frac{\underline{GHG}}{GHG_T^j} \tag{12}$$

Where $\underline{GHG}$ and GHG_T^j are as defined above.

Lastly note that in reality plants chose input-output combinations given a zero price of GHG. Therefore, in general, there is no reason to expect that plants will choose the GHG minimizing combination of inputs and outputs. However, if the price of GHG was positive then, a natural question would arise: what would be the price of GHG that would induce plants to choose the GHG-minimizing input-output combination? To address this issue we need to calculate the profit-maximizing input-output combination first so we will delay this discussion to the section in allocative efficiency.

To calculate measures of technical, allocative and overall environmental efficiency as defined above, three estimates are needed: the minimum feasible GHG level (i.e. $\underline{GHG}$), the observed GHG level of each DMU (i.e. GHG^j) and the GHG level corresponding to the "technically efficient" input-output combination of each DMU (i.e. GHG_T^j).

The minimum feasible GHG level is calculated applying the following linear program to our sample:

$$\begin{aligned} \underset{u_{\hat{\alpha}}^j, x_{\hat{\beta}}^j}{Min} GHG = & (0.0000098) x_c^j + (0.063) x_G^j + (0.094) x_{DB}^j \\ & + (0.0007) x_{EL}^j - (0.219) x_{WB}^j \\ s.t. \quad & u_\alpha^j \le z' M_\alpha,\ u_{\hat{\alpha}}^j \le z' M_{\hat{\alpha}},\ x_\beta^j \le z' N_\beta,\ x_{\hat{\beta}}^j \le z' N_{\hat{\beta}},\ z' \in \Re_+^J \end{aligned} \tag{13}$$

This program was calculated using the LINPROG routine in MATLAB.

The technically efficient level of GHG for the j^{th} DMU denoted by GHG_T^j is calculated by plugging the technically efficient levels of inputs and outputs (x_T^j, u_T^j) into equation (9). The technically efficient combinations (x_T^j, u_T^j) are calculated based on the sub-vector 3 technical efficiency levels reported in column 4 of table 2. We use sub-vector 3 for our analysis because it includes all variables relevant to GHG emissions.

We report in Table 4 measures of environmental efficiency for all 34 DMUs. We report overall environmental efficiency and both the technical and allocative components of this measure. Some interesting conclusions can be drawn. Ethanol plants can, on average, reduce GHG emissions by 28% by eliminating technical and allocative environmental inefficiencies (this is inferred from the average environmental efficiency of 0.72). Although this is an important figure from the point of view of each firm it translates to an average reduction of 7,770 milligrams of GHG, a trivial amount for the environment.[15]

Scale and Technical Efficiency

It has been argued that the technology in the ethanol industry displays increasing returns to scale. If this is the case and if, in addition, we calculate efficiency assuming constant returns to scale then we should expect a positive correlation between size and efficiency, i.e. bigger plants should be, in average, more efficient that smaller ones. When the number of observations is not big enough (as it is our case) second stage regressions to identify sources of inefficiencies are not possible. Therefore, to verify the consistency of this hypothesis with our data we partition efficiency results according to size categories of DMUs and comparing the average performances across categories.

[15] Some calculations reveal that elimination of environmental inefficiencies would imply a total reduction of the order of 0.00026 tons of GHG emissions in our whole sample.

We conducted the partitioning by classifying DMUs into big (production of more than 13.5 million gallons[16] –MG-), medium (more than 12.5MG and up to 13.5MGY) and small (up to 12.5MG). This categorization yielded groups of 8 big, 14 medium and 12 small DMUs. The average efficiency for each group and for the different input-output sub-vectors are reported in Table 5.

Although small and medium units show a similar average efficiency, big units seem to be more efficient than smaller units in all four sub-vectors which *may* be an indicator of increasing returns to scale. We highlight the probable nature of this relationship since note that increasing returns to scale are not necessary for bigger units to be more efficient. Therefore the fact that bigger units are more efficient does not necessarily imply that returns to scale are increasing as the difference may well be due to managerial efficiency in bigger units rather than technological advantages.

Therefore we proceed to obtain measures of returns to scale in our sample. In order to accomplish this we will first decompose the technical efficiency measures obtained before into purely technical efficiency and scale effects. We will illustrate this decomposition using the most complete input-output sub-vector in this study: sub-vector 1, including all outputs along with corn, gas, and electricity.

Calculation of technical efficiency can be done on the basis of a technology displaying constant returns to scale (CRS), decreasing returns to scale (DRS), increasing returns to scale (IRS), or variable returns to scale (VRS). Technical efficiency with variable returns to scale is defined as (Färe et al.):

$$F_g\left(x^j, u^j / V, S\right) = \min\left\{\lambda : \left(\lambda x_\beta^j, x_{\hat{\beta}}^j, \lambda^{-1} u_\alpha^j, u_{\hat{\alpha}}^j\right) \in \left(GR / V, S\right)\right\} \; j = 1, 2, ..., J \qquad (14)$$

[16] We remind the reader that a DMU corresponds to production of one plant in one quarter and hence an amount of 13.5MG would correspond to 54MG a year, and 12.5MG would correspond to 50MG a year.

The measure in (14) can be computed through the following non-linear programming problem:

$$\underset{\Gamma,z'}{Min}\,\Gamma \qquad s.t. \quad \begin{aligned} u_{\alpha}^{j} &\le z'M_{\alpha} \\ \lambda u_{\hat{\alpha}}^{j} &\le z'M_{\hat{\alpha}} \\ \Gamma x_{\beta}^{j} &\le z'N_{\beta} \\ \lambda x_{\hat{\beta}}^{j} &\le z'N_{\hat{\beta}} \\ \Gamma &= \lambda^{2} \\ \sum_{j=1}^{J} z'^{j} &= 1 \end{aligned} \tag{15}$$

For our analysis we will also need to define technical efficiency for a non-increasing returns to scale technology:

$$F_{g}\left(x^{j},u^{j}/N,S\right)=\min\left\{\lambda:\left(\lambda x_{\beta}^{j},x_{\hat{\beta}}^{j},\lambda^{-1}u_{\alpha}^{j},u_{\hat{\alpha}}^{j}\right)\in\left(GR/N,S\right)\right\}\ j=1,2,...,J \tag{16}$$

The measure in (16) can be computed as the value of Γ in the following non-linear programming problem:

$$\underset{\Gamma,z'}{Min}\,\Gamma \qquad s.t. \quad \begin{aligned} u_{\alpha}^{j} &\le z'M_{\alpha} \\ \lambda u_{\hat{\alpha}}^{j} &\le z'M_{\hat{\alpha}} \\ \Gamma x_{\beta}^{j} &\le z'N_{\beta} \\ \lambda x_{\hat{\beta}}^{j} &\le z'N_{\hat{\beta}} \\ \Gamma &= \lambda^{2} \\ \sum_{j=1}^{J} z'^{j} &\le 1 \end{aligned} \tag{17}$$

According to Färe et al. scale inefficiency is the ratio between technical efficiency with constant returns to scale as defined in (6) and computed through (7), to technical efficiency with variable returns to scale as defined in (14) and computed by (15):

$$S_{g}\left(x^{j},u^{j}\right)=F_{g}\left(x^{j},u^{j}/C,S\right)/F_{g}\left(x^{j},u^{j}/V,S\right) \tag{18}$$

If ratio (18) is higher than one and if, in addition, the ratio of technical efficiency with constant returns to technical efficiency with non-increasing returns is higher (equal) than one, the observation shows decreasing (increasing) returns to scale.

Provided our exercise includes all outputs produced by DMUs, the non-linear programs (7), (15) and (17) can be linearized and calculated with the LINPROG routine in MATLAB. The results for all 34 observations are reported in Table 6. This table shows that CRS are overwhelmingly observed across DMUs. A total of 25 DMUs display CRS, 6 exhibit IRS, and only 3 display DRS.

The analysis in Table 7 aims at identifying patterns of returns to scale based on the DMU's size. The results reported in this Table were obtained by partitioning the 34 results on returns to scale reported in Table 6 based on size of the DMUs. All three groups show predominantly CRS. However, 29% of medium-sized DMUs display increasing returns to scale.

In conclusion bigger units seem to be, on average, more technically efficient than smaller units. The analysis here seems to support the hypothesis that this efficiency differential is due to increasing returns to scale in the industry's technology. However, results reported in Table 7 are far from providing irrefutable proof of the existence of increasing returns to scale. An alternative potential explanation for the efficiency differential across sizes might be better managerial skills in bigger plants.

Economic Viability and Allocative Efficiency

As argued before an increase in profitability by plants through a better choice of their input-output mix may turn out to be a very important factor in enhancing the industry's overall economic viability. Our purpose in this section is to determine the potential for an increase in profit efficiency by DMUs both through an increase in technical and allocative efficiency.

When productive units choose their input-output combinations may do so in a perfect or an imperfect market. The characteristics of the market structure may affect the efficiency estimates and thus we will discuss both cases separately. We will proceed to discuss the case of competitive markets first and we will introduce market imperfections later.

When Market Prices are Exogenous

DEA measures of allocative efficiency determine how DMUs could readjust inputs and outputs to increase profit or revenue or decrease cost given market prices. In this sample the plants received different prices for their outputs and paid different prices for the procurement of their inputs. Provided we have observations of different plants located in different states and across time, differences among prices paid and received by DMUs can be due to spatial patterns, managerial efficiency, and other local conditions. All prices have been deflated using the Producer Price Index (PPI) with the third quarter of 2006 as base.

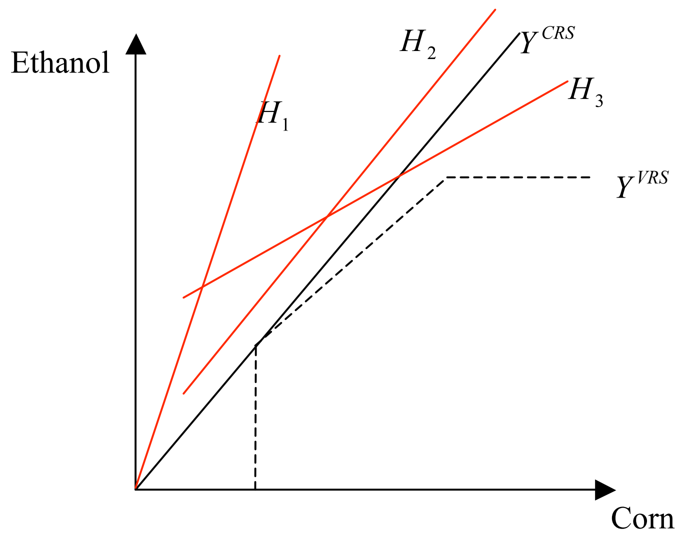
The potential differences due to managerial and other local considerations are difficult to deal with. Since we have one plant per state we have a perfect correlation between space and manager and hence only if we had enough spatial-price data to adjust data points to a base state, we would be able to distinguish differences in plants' prices due to managerial efficiency from those due to the spatial distribution of prices or other local conditions. Due to data limitations, we are not able to decompose these two effects. Our definition of "managerial efficiency" then includes any other spatial and local differences not controlled for.

We assume that DMUs follow a profit-maximizing strategy and based on this notion, our main purpose in this section is to come up with a measure of profit efficiency of DMUs. Measures of profit efficiency are based on the maximum profit that can be obtained by the DMU relative to a graph representation of the technology. If, in addition, to the input and output matrices N and M, output prices r^j and input prices p^j are given for each observation, maximum profit can be calculated subject to the technology's graph.

We follow Färe et al and defined the graph under constant returns to scale and variable returns to scale .The two graphs are illustrated in Figure 3. The profit-maximizing input-output mix in a constant returns to scale technology (Y^{CRS}) is usually not well defined. Price hyperplane 1 (H_1) implies zero production, hyperplane 2 (H_2) yields an infinite number of profit maximizing input-output mixes (since it has the same slope as Y^{CRS}) and hyperplane 3 (H_3) implies unbounded production. Furthermore there is only one price hyperplane (H_2) that would rationalize positive levels of production and hence all DMUs producing a positive but finite amount either face the same price hyperplane or are failing in maximizing profits.

We assume a variable returns to scale graph illustrated in the figure by the area below Y^{VRS}.

Figure 3. Profit Maximization under different returns to scale



In this section we will continue to use the input-output sub-vector consisting of all outputs, corn, natural gas, and electricity. The maximum profit of a DMU relative to a variable returns to scale graph can be calculated with the following linear programming problem (Färe et al.)

$$\begin{aligned} \pi\left(r^j, p^j / V, S\right) = \underset{\lambda, z'}{Max}\ & r^j u^{\hat{\alpha}} - p^j x^{\hat{\beta}} \\ s.t. \quad & u_{\hat{\alpha}}^j \leq z' M_{\hat{\alpha}} \\ & x_{\beta}^j \leq z' N_{\beta} \\ & \lambda x_{\hat{\beta}}^j \leq z' N_{\hat{\beta}} \\ & \sum_{j=1}^{J} z'^j = 1 \end{aligned} \tag{19}$$

Where $\pi\left(r^j, p^j / V, S\right)$ denotes maximum profits, the optimal value of λ is the measure of relative profit efficiency, r^j represents price of outputs, $u^{\hat{\alpha}}$ is the sub-vector of outputs that are allowed to vary (all of them in this case), p^j is the price of inputs, $x_{\hat{\beta}}^j$ and x_{β}^j are variable and fixed inputs respectively and the $z's$ are intensity factors used to construct the piecewise frontier.

We will now use maximum profit (19) to calculate a graph measure of overall efficiency from which in turn we can infer allocative efficiency of DMUs. Due to the hyperbolic nature of the graph measure, the measure of overall economic efficiency is not the ratio of observed to maximum profit (see discussion in Färe et al. 1994, section 8.2). However, the appropriate indicator of profit efficiency in this case is still closely related to maximum profits through the following expression derived by Färe et al. (p. 214):

$$\pi\left(r^j, p^j\right) = r^j u^j / O_g\left(x^j, u^j, p^j, r^j / C, S\right) - p^j x^j * O_g\left(x^j, u^j, p^j, r^j / C, S\right) \quad (20)$$

Where $\pi\left(r^j, p^j\right)$ denotes maximum profits from (19) and the rest is as before.

Therefore, to obtain overall profit efficiency, we calculate maximum profits solving program (19) using the LINPROG procedure in MATLAB. We then obtain the graph measure of overall efficiency by solving the implicit function (20) numerically in MATLAB with the FZERO sub-routine.

Finally a graph measure of allocative efficiency can be calculated residually as:

$$A_g\left(x^j, u^j, r^j, p^j / V, S\right) = O_g\left(x^j, u^j, p^j, r^j / V, S\right) / F_g\left(x^j, u^j, p^j, r^j / V, S\right) \quad (21)$$

Where $F_g\left(x^j, u^j, p^j, r^j / V, S\right)$ is the measure of technical efficiency relative to the variable returns to scale graph previously calculated and reported in column 3 of table 6.

We report results in Table 8. First, on average, plants can increase profits by 15% which for the average DMU in thesample, would imply an increase in profits of approximately 55 cents per gallon. Second, the standard deviation of profit efficiencies across plants is 0.08 which is significantly higher than that of the technical efficiency measures reported in Table 3. Third, the percentage of efficient points is just 6% as opposed to the 74% of technically efficient observations reported in Table 3. These results suggest that managers are relatively successful at optimizing the available technology but they are not as successfull when choosing the profit maximizing netput combinations given market prices and local conditions. This could be the source of significant profit losses.[17]

The profit efficiency measures reported in Table 8 are based on the assumption that prices faced by DMUs are exogenously given. However, many authors found evidence that suggests otherwise. The impact of ethanol plants on local corn prices have been estimated to range from an increase of 2¢ to 25¢ per bushel (Coltrain; Farm Journal; National Corn Growers Association; Top Producer; and Urbanchuk and Kapell). McNew and Griffith (2005) also studied the impact of ethanol plants on local grain prices and found that there were significantly positive responses for corn prices around ethanol plants. Gallagher, Wisner, and Brubacker (2005) examined the pricing systems for corn in the vicinity of processing plants and also found evidence of a positive impact.

The positive impact of the plant on local prices of corn is due to spatial competition between the plant and the terminal market for the procurement of corn. Therefore it may be the case that the bigger the plant, the more intense the competition with the terminal market, the higher the impact on the price of corn and hence the lower the profitability of the plant, all else equal. Thus the size of the plant may be negatively related to profits through an increase in the price the plant pays for corn.

Alternatively, regulators have shown concern that the size of the plant may positively impact the price it receives for its ethanol due to exertion of market power.[18] This fact

[17] We would like to remind the reader that our definition of 'managerial efficiency' might include spatial or local conditions that are not choices for managers/decision makers.

[18] In fact, Section 1501(a)(2) of the Energy Policy Act of 2005 imposes an annual requirement on the Federal Trade Commission to "perform a market concentration analysis of the ethanol production industry" and report it to Congress and to the Administrator of the Environmental Protection Agency. So far no evidence of strong market concentration has been found.

would create a positive relation between plant size and profitability which would tend to outweigh the negative link caused by size-corn price relationship discussed above.

The overall effect of size on profitability will ultimately depend upon the intensity of the two links between size and profitability: the corn-price link which causes a negative relation between size and profits and the ethanol-price link which causes a positive relation between them.

Profit Efficiency Drivers

As before, we cannot run second stage regressions to identify the quantitative relationship between size and profit efficiency. We described above two alternative hypothesis. In order to find evidence that would allow rejection of one of them we check the relationship between profit efficiency and size by partitioning the efficiency results reported in Table 8 into three groups based on their size and comparing the average performance of different categories. We conducted the partitioning based on the same classification as before and the results are reported in Table 9.

Table 9 reveals a positive relation between size and profit efficiency across all sizes; i.e. big DMUs show higher profit efficiency than medium DMUs which in turn are more efficient than small DMUs. Moreover, the differences in average profit efficiency between big DMUs and the rest is significant and considerably higher than the difference in technical efficiency as reported in Table 5. This result may be due to market power or the existence of certain local markets conditions that favor profits in places where bigger DMUs are located. To obtain evidence on this issue we group the observations by plants. Results of this exercise are reported in Table 10.

Since each plant is located relatively far away from the others they face their own local market conditions. If efficiency differences across sizes have to do with local market conditions rather than size-related factors then significant differences in average efficiency should also be observed across plants. Table 10 reports average profit efficiency per plant (from 1 to 7). First, compared to Table 9, standard deviations have significantly decreased, except for plant 4. This implies that most of profit efficiency dispersion is due to variability across plants rather than across time and within plants.

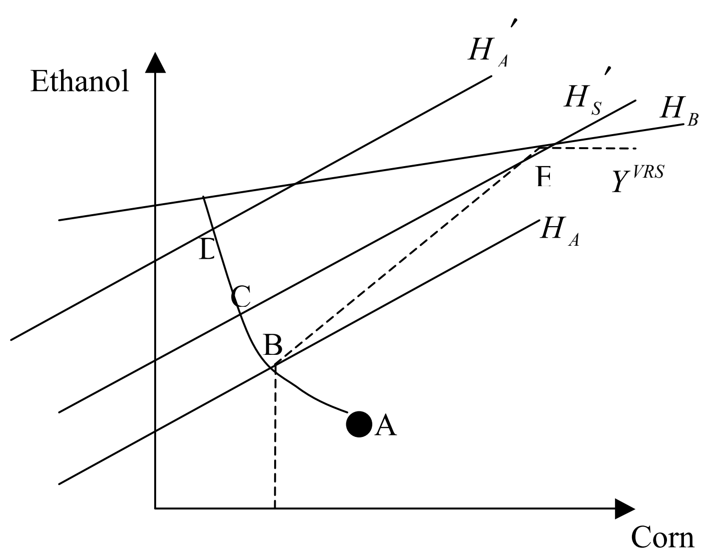
Second, average efficiency across plants is rather homogeneous. Only plant 7 seems to be, on average, significantly more efficient than the other plants. DMUs corresponding to plant 7 are classified as big so this could be biasing average profit efficiency estimates of big plants upwards. However only 3 observations out of 8 classified as big correspond to plant 7 and hence there is still a significant portion of efficiency differences across size that is not explained by local market conditions. This may be pointing towards the fact that bigger plants do exert some kind of market power either by controlling quantities sold or by managing contracts in a more efficient way than their smaller counterparts. If there is a relationship between quantities and prices which is reflected in profit efficiency then we should consider this fact when evaluating DMUs to adjust price endogeneity.being endogenous to quantities.

When Market Prices are Endogenous.

It is possible that larger plants exert some market power in input and/or output markets. Including this type of endogeneity in our framework is not a straightforward task. In fact the lack of extensions of DEA methods to incorporate market imperfections has been noted before (Cherchye et al.). Given that we are now in uncharted territory we will first illustrate our problem in Figure 4 and based on this intuitive interpretation we will propose a simple way of adjusting profit efficiency for price endogeneity.

Suppose DMUs face a variable returns to scale technology. The price hyperplane faced by the j^{th} DMU can be represented algebraically by $E^j = \frac{\pi^j}{p_E^j} + \frac{p_C^j}{p_E^j} C^j$. Suppose, as may be suggested by the positive relation between size and profit efficiency that, the bigger the DMU the higher the price received for ethanol, all else equal. Then we would expect, at least *in average*, the price hyperplane faced by big DMUs to be flatter than the one faced by small DMUs.

Figure 4. Profit Efficiency with Endogenous Prices



Suppose observation A in Figure 4 is classified as small. In the figure the average price for big DMUs is illustrated by price hyperplane H_B and the price hyperplane faced by observation A is denoted by H_A. The distance between A and B represents the graph-technical inefficiency in which this DMU has incurred and the distance between B and C represents allocative inefficiency. However if prices are endogenous and the price hyperplane for a point like E is depicted by H_B, then the DMU could enhance its performance if H_B corresponds to a higher profit. Therefore the DMU could increase profits by not only adjusting the input-output mix but also by facing more convenient relative prices. (Alternatively, if H_B corresponds to a lower profit then that means that the DMU has chosen the correct size in the sense that it would have achieved a lower profit if it had chosen a larger scale.)

However, the hyperplanes H_B and H_A correspond to different relative prices. We therefore calculate the hyperplane H_A' that depicts the same profit level as H_B but with prices corresponding to H_A. Based on this hyperplane we calculate the distance between C and D and interpret it as "size" efficiency, i.e. the expansion (or contraction if H_A' happens to be to the southeast of H_A) of profits that the DMU would face if it increases its scale of production. The same procedure can be developed to evaluate a big DMU that could shrink its scale and face a hyperplane corresponding to average prices of small DMUs.

Therefore we calculate a hyperbolic measure of "size" efficiency for each DMU and include it as a component of their overall graph profit efficiency. We do this for small and big DMUs separately. We define small (big) DMUs as those whose total production of ethanol is below (above) the median of the sample.

Our size-efficiency index for the j^{th} small DMU can be implicitly defined by:

$$SE\left(r^B, p^B / V, S\right) = r^j u^j / O_g^S\left(x^j, u^j, p^j, r^j / V, S\right) - p^j x^j * O_g^S\left(x^j, u^j, p^j, r^j / V, S\right) \qquad (21)$$

Where $SE\left(r^{B},p^{B}\right)$ denotes maximum relative profit that the DMU would achieve if it changed its operation scale to a big one and faced prices r^{B} and p^{B} and O_g^s represents overall graph efficiency measure of profit efficiency. Moreover prices r^{B} and p^{B} are weighted[19] averages of prices faced by big DMUs. Overall maximum profit $\pi\left(r^{B},p^{B}\right)$ is calculated through the following linear program:

$$\begin{aligned}
&\pi\left(r^{B},p^{B}/V,S\right)=\underset{u,x}{Max}\left\{r^{B}u^{\alpha}-p^{B}x^{\beta}\right\} \\
&s.t. \qquad u_{\alpha}\le z'M_{\alpha}^{B} \\
&\qquad\qquad x_{\beta}\le z'N_{\beta}^{B} \\
&\qquad\qquad x_{\hat{\beta}}\le z'N_{\hat{\beta}}^{B} \\
&\qquad\qquad \sum_{j=1}^{J}z'^{j}=1
\end{aligned} \tag{22}$$

Where M_{α}^{B} and N_{β}^{B} are the matrices of observed outputs and inputs corresponding to the sub-sample of big DMUs.

Similarly, the size-efficiency of the j^{th} big DMU can be defined by:

$$SE\left(r^{S},p^{S}\right)=r^{j}u^{j}/O_{g}^{B}\left(x^{j},u^{j},p^{j},r^{j}/V,S\right)-p^{j}x^{j}*O_{g}^{B}\left(x^{j},u^{j},p^{j},r^{j}/V,S\right) \tag{23}$$

Where $SE\left(r^{S},p^{S}\right)$ denotes maximum relative profit that the DMU would achieve if it changed its operation scale to a small one and faced prices r^{S} and p^{S}. Moreover prices r^{S} and p^{S} are average of prices faced by small DMUs. Overall maximum profit $\pi\left(r^{S},p^{S}\right)$ is calculated through the following linear program:

[19] Where the weights are the share of the value of each DMU's production in total value of production.

$$
\begin{aligned}
&\pi\left(r^{S}, p^{S} / V, S\right)=\underset{u, x}{Max}\left\{r^{S} u^{\alpha}-p^{S} x^{\beta}\right\} \\
&s.t. \qquad u_{\alpha} \leq z' M_{\alpha}^{S} \\
&\qquad\quad x_{\beta} \leq z' N_{\beta}^{S} \\
&\qquad\quad x_{\hat{\beta}} \leq z' N_{\hat{\beta}}^{S} \\
&\qquad\quad \sum_{j=1}^{J} z'^{j}=1
\end{aligned} \tag{24}
$$

Where M_{α}^{S} and N_{β}^{S} are the matrices of observed outputs and inputs corresponding to the sub-sample of small DMUs.

Measures (22) and (24) were calculated using the LINPROG procedure in MATLAB.

Finally a graph measure of allocative efficiency for big and small DMUs can be calculated residually as:

$$A_{g}^{B}\left(x^{j}, u^{j}, r^{j}, p^{j} / V, S\right)=\frac{O_{g}\left(x^{j}, u^{j}, p^{j}, r^{j} / V, S\right)}{F_{g}\left(x^{j}, u^{j}, p^{j}, r^{j} / V, S\right) * O_{g}^{B}\left(x^{j}, u^{j}, p^{j}, r^{j} / V, S\right)} \tag{25}$$

$$A_{g}^{S}\left(x^{j}, u^{j}, r^{j}, p^{j} / V, S\right)=\frac{O_{g}\left(x^{j}, u^{j}, p^{j}, r^{j} / V, S\right)}{F_{g}\left(x^{j}, u^{j}, p^{j}, r^{j} / V, S\right) * O_{g}^{S}\left(x^{j}, u^{j}, p^{j}, r^{j} / V, S\right)} \tag{26}$$

Where $F_{g}\left(x^{j}, u^{j}, p^{j}, r^{j} / V, S\right)$ is the measure of technical efficiency relative to the variable returns to scale graph previously calculated and reported in column 3 of table 6 and $O_{g}\left(x^{j}, u^{j}, p^{j}, r^{j} / V, S\right)$ is the overall graph-efficiency measure with exogenous prices calculated implicitly in (20).

To sum up, there are two sources of profit inefficiency in the case of endogenous prices. The first is the usual allocative inefficiency caused by the use of an inappropriate input-output mix and it is represented in the figure by the distance between B and C. The second source of profit inefficiency has to do with the fact that by choosing the “wrong” scale the DMU is forgoing the possibility of exploiting price endogeneity and increasing profits through a positive price effect.

Results of size-efficiency are reported in Tables 10 and 11 for small and big DMUs respectively. After our correction for endogeneity, small DMUs have a high average allocative efficiency (0.98) and a low average size-efficiency (0.86). This suggests that average prices faced by big DMUs are such that small DMUs would have been better off by increasing the size of operations and taking advantage of more convenient relative prices.

Big DMUs on the other hand display a significantly higher average size-efficiency (0.985) as compared to their smaller counterparts, but a lower average allocative efficiency (0.958). These values seem to indicate that profit inefficiency of big plants was mostly driven by allocative factors rather than by forgoing price endogeneity opportunities. This fact is consistent with the hypothesis that big plants face more convenient relative prices than small plants. The reader should note, however, that this is not a test of market power but rather a verification of the consistency of the data with the hypothesis of price endogeneity.

Carbon Price and GHG Minimization by DMUs

The purpose of this final section is to answer the following question: what would be the price of GHG that would induce plants to choose the GHG-minimizing input-output combination?

Now that we have calculated maximum feasible profits for each DMU we can compute the profits that would be forgone if DMUs were to choose the GHG-minimizing input-output mix and based on this we can calculated the price of carbon that would induce DMUs to choose such a mix.

The profits forgone for minimizing GHG is the difference between the maximum feasible profits defined in (19) and calculated in the profit efficiency section and the profits at the GHG-minimizing mix. The GHG minimizing mix was denoted by (x^E, u^E) and calculated in the environmental efficiency section. Profits at this mix are computed by plugging (x^E, u^E) into the profit function of each DMU. Finally the price of carbon that would induce DMUs to minimize GHG is that which reduce profits by the difference described above. These prices are calculated for each DMU and are reported in Column 5 of table 4.

The prices are surprisingly high. In average, DMUs should have to pay a price of $70 per milligram of CO2 to have enough incentives to choose the GHG-minimizing input-output mix. Therefore, not only the potential for the industry as a whole to reduce GHG emissions is very limited as discussed in the environmental efficiency section but also it would take an extremely high price of carbon to induce them to achieve this reduction.

Conclusions

In this study, we find that:

1) Seventy one percent of the observations were located on the best practice frontier which means that the percentage of observations that have potential for technical improvement is below twenty nine percent. There is little dispersion in technical

efficiency across plants. This indicates that from a technical/engineering point of view, plants are performing well.

2) The average reduction of GHG emissions achievable through a simultaneous shrinkage of corn, natural gas and electricity and an expansion of byproducts (given ethanol production levels) is about fifteen percent. Calculated carbon prices necessary to induce plants to minimize GHG are implausibly high, averaging about $70 per ton of CO_2.

3) Results here tend to support the hypothesis that technology in this industry displays constant returns to scale although increasing returns are not inconsistent with our results.

4) On average, it appears that decision-making units (DMUs) might have been able to increase their profits significantly, even though they were technically quite efficient. However, much of these gains were attainable by changing plant size, and this analysis does not consider returns to such capital investments. There analysis suggests that larger firms realized more favorable input and output prices, though it is not clear whether this is due to market power, better marketing prowess, or favorable geographic location of the larger plants.

To sum up, the potential for technical and environmental improvement in the industry is limited given the high average performance measures estimated in this study. On the other hand, there seems to be some room for improvements in profits and economic performance due to managerial choices. If this is the case, the economic viability of this industry could be enhanced. More research is needed to identify potential causes of spatial and local environmental differences across plants so that it would be possible to isolate managerial ability from issues that are not controllable by the plant manager but that could be a result of local policies and regulations.

References

Cherchye, L., Kuosmanen, T., and Post, T. 2002. Non-parametric production analysis in non-competitive environments. *International Journal of Production Economics* 80, 3, 11, Pages 279-294

Coelli, T., Lauwers, L., and Van Huylenbroeck, G. *Environmental efficiency measurement and the materials balance condition.* Journal of Productivity Analysis; Volume 28, Numbers 1-2 / October, 2007.

Coltrain, D. Economic Issues with Ethanol, Revisited. *Kansas State University*, September 2004. Available at http://www.agmanager.info/agribus/energy/ (accessed March 1, 2005).

Eidman, Vernon R. 2007. Ethanol Economics of Dry Mill Plants, Ch3 in *Corn-Based Ethanol in Illinois and the U.S.*, Department of Agricultural and Consumer Economics, University of Illinois, November.

Färe, R., S. Grosskopf and C.A.K. Lovell, *Production Frontiers*, Cambridge: Cambridge University Press, 1994.

Farm Journal Media *Beef Today.* "Comfy on the High Plains." November 2004.

Farrell, A. E., R. J. Plevin, B. T. Turner, A. D. Jones, M., O'Hare, and D. M. Kammen. 2006. Ethanol can contribute to energy and environmental goals. *Science* 311(5760): 506–508.

Kwiatkowski, Jason R., Andrew J. McAloon, Frank Taylor and David B. Johnson. 2006. Modeling the process and costs of fuel ethanol production by the corn dry-grind process. *Industrial Crops and Products* 23:288-296.

Liska, A.J H.S. Yang, V. Bremer, D.T. Walters, G. Erickson, T. Klopfenstein, D. Kenney, P. Tracy, R. Koelsch, K.G. Cassman. 2009. *BESS: Biofuel Energy Systems Simulator; Life Cycle Energy and Emissions Analysis Model for Corn-Ethanol Biofuel*. vers.2008.3.1. www.bess.unl.edu. University of Nebraska-Lincoln.

McAloon, Andrew, Frank Taylor and Winne Yee. 2000. *Determining the Cost of Producing Ethanol from Corn Starch ad Lignocellulosic Feedstocks*. National Renewable Energy Laboratory, NREL/TP-580-28893.

McNew, K. and D. Griffith. 2005. "Measuring the Impact of Ethanol Plants on Local Grain Prices" *Review of Agricultural Economics* 27, (2).

National Corn Growers Association. "Ethanol Economics – Ethanol's Effect on Corn Prices. Available at http://www.ncga.com/ethanol/main/economics.htm#corn (accessed March 1, 2005).

Perrin, R.K, Fretes, N, and Sesmero J.P., 2009. Efficiency in Midwest US Corn Ethanol Plants: a Plant Survey. *Energy Policy*. 37, 4, April 2009, Pages 1309-1316

Pimentel, David and Tad W. Patzek. 2005. Ethanol Production Using Corn, Switchgrass, and Wood; Biodiesel Production Using Soybean and Sunflower. *Natural Resources Research*, Vol. 14, No. 1 (March.)

Plevin, R J, and S Mueller. 2008. The effect of CO2 regulations on the cost of corn ethanol production. *Environ. Res. Lett*. 3 024003 .

Shapouri, Hosein and Paul Gallagher. 2005. USDA's 2002 Ethanol Cost-of-Production Survey. *Agricultural Economic Report No. 841*, U.S. Dept of Agriculture (July.)

Top Producer. "Jump-Start the Grain Belt." January 2005.

Urbanchuk, J.M. and J. Kapell. Ethanol and the Local Community. AUS Consultants/SJH & Company, June 21, 2002. Available at: http://www.ncga.com/ethanol/pdfs/EthanolLocalCommunity.pdf.

Wang, Michael, May Wu and Hong Huo. 2007. Life-cycle energy and greenhouse gas emission impacts of different corn ethanol plant types. *Environ. Res. Lett*. 2.

Table 1. Characteristics of the seven surveyed plants

States Represented	Iowa, Michigan, Minnesota, Missouri, Nebraska, S. Dakota, Wisconsin				
Annual Production Rate (m. gal/y)	Smallest	42.5			
	Average	53.1			
	Largest	88.1			
Number of Plants by Start-Up Year	<2004	1			
	2005	4			
	2006	2			
Number of Employees	Smallest	36			
	Average	39.6			
	Largest	46.4			
Number of Survey Responses by Quarters	03_2006	5			
	04_2006	6			
	01_2007	7			
	02_2007	7			
	03_2007	7			
	04_2007	2			
Percent of Byproduct Sold as Dry DGS	Smallest	0			
	Average	54			
	Largest	97			
Primary Market Technique		Corn	Ethanol	DDGS	MWDGS
	Spot	0	0	3	1
	Customer Contract	5	1	0	1
	Third Party/Agent	0	5	2	2

Table 2. Technical Efficiency

Category / Observ.	Corn-Gas-Electricity-Outputs	Corn-Gas-Outputs	Corn-Gas-Electricity-Byproduct	Corn-Gas-Byproduct
1	0.9158	0.9158	0.9053	0.9053
2	1	1	1	1
3	0.9703	0.9677	0.9644	0.9604
4	0.9999	0.9998	0.9999	0.9998
5	1	1	1	1
6	0.9553	0.9553	0.9537	0.9537
7	1	1	1	1
8	1	1	1	1
9	1	1	1	1
10	0.9904	0.9838	0.9861	0.9673
11	1	1	1	1
12	1	1	1	1
13	1	1	1	1
14	1	1	1	1
15	0.9766	0.9751	0.9643	0.9606
16	1	1	1	1
17	1	1	1	1
18	1	1	1	1
19	1	1	1	1
20	1	1	1	1
21	1	1	1	1
22	0.9922	0.9914	0.989	0.9872
23	1	1	1	1
24	1	1	1	1
25	1	1	1	1
26	1	1	1	1
27	1	1	1	1
28	1	1	1	1
29	1	1	1	1
30	0.9998	0.9998	0.9996	0.9996
31	1	1	1	1
32	0.9665	0.9599	0.9632	0.9599
33	1	1	1	1
34	0.9738	0.9738	0.9619	0.9619

Table 3. Technical Efficiency-Descriptive Statistics

	Corn-Gas-Electricity-Outputs	Corn-Gas-Outputs	Corn-Gas-Electricity-Byproduct	Corn-Gas-Byproduct
Average	0.992	0.992	0.991	0.990
Std Dev	0.018	0.018	0.021	0.021
Max	1	1	1	1
Min	0.92	0.92	0.91	0.91
% of Efficient Points	74	74	74	74

Table 4. Environmental Efficiency and Feasible Reduction of GHG Emissions

DMU	Technical Environmental Efficiency	Allocative Environmental Efficiency	Overall Environmental Efficiency	Carbon Price that would induce Min GHG	Maximum Reduction of GHG (mg)
1	0.96	0.91	0.87	141	4197
2	1	0.65	0.65	92	11876
3	0.97	0.70	0.68	292	10069
4	1	0.79	0.79	67	6043
5	1	0.94	0.94	62	1766
6	0.98	0.96	0.94	151	2010
7	1	0.90	0.90	118	3233
8	1	0.69	0.69	171	10350
9	1	0.79	0.79	295	5830
10	0.99	0.72	0.72	199	8610
11	1	0.95	0.95	63	1653
12	1	0.96	0.96	84	1281
13	1	1	1	0	0
14	1	0.91	0.91	111	3141
15	0.99	0.68	0.68	154	10576
16	1	0.76	0.76	141	7107
17	1	0.77	0.77	139	6806
18	1	0.97	0.97	41	972
19	1	0.97	0.97	198	1019
20	1	1	1	0	0
21	1	0.91	0.91	84	3002
22	0.99	0.71	0.70	192	9332
23	1	0.75	0.75	126	7291
24	1	0.91	0.91	77	2357
25	1	0.92	0.92	121	2418
26	1	0.97	0.97	63	1008
27	1	1	1	0	0
28	1	0.91	0.91	76	3159
29	1	0.77	0.77	80	7215
30	1	0.75	0.75	125	7234
31	1	0.70	0.70	165	8627
32	0.99	0.84	0.83	132	5398
33	1	0.97	0.97	75	1059
34	1	0.79	0.79	63	8166
Average	0.996	0.85	0.85	115	4788
Std Dev	0.01	0.11	0.11	70	3577

Table 5. Average Efficiency by Size

Input-Output sub-vectors / Category	Corn-Gas-Electricity-Outputs	Corn-Gas-Outputs	Corn-Gas-Electricity-Byproduct	Corn-Gas-Byproduct
BIG	0.991	0.991	0.9891	0.989
MEDIUM	0.989	0.989	0.987	0.986
SMALL	0.996	0.996	0.993	0.991

Table 6. Technical and Scale Efficiency Indices

DMU	Corn-gas-electricity-outputs NIRS	Corn-gas-electricity-outputs VRS	Scale Efficiency	Returns to Scale
1	0.9158	0.9558	0.9582	IRS
2	1	1	1	CRS
3	0.9703	0.9711	0.9992	CRS
4	1	1	0.9999	DRS
5	1	1	1	CRS
6	0.9553	0.9821	0.9727	IRS
7	1	1	1	CRS
8	1	1	1	CRS
9	1	1	1	CRS
10	0.9904	0.9928	0.9976	IRS
11	1	1	1	CRS
12	1	1	1	CRS
13	1	1	1	CRS
14	1	1	1	CRS
15	0.9981	0.9981	0.9785	DRS
16	1	1	1	CRS
17	1	1	1	CRS
18	1	1	1	CRS
19	1	1	1	CRS
20	1	1	1	CRS
21	1	1	1	CRS
22	0.9922	0.9944	0.9978	IRS
23	1	1	1	CRS
24	1	1	1	CRS
25	1	1	1	CRS
26	1	1	1	CRS
27	1	1	1	CRS
28	1	1	1	CRS
29	1	1	1	CRS
30	0.9998	1	0.9998	IRS
31	1	1	1	CRS
32	0.9665	0.9897	0.9766	IRS
33	1	1	1	CRS
34	1	1	0.9738	DRS
Average	0.9938	0.9966	0.9957	
Std Dev	0.017	0.009	0.010	

Table 7. Returns to Scale and Optimal Size

Category of DMUs	DMUs	CRS		IRS		DRS	
	#	#	%	#	%	#	%
Big	8	6	75	1	12.5	1	12.5
Medium	14	9	64	4	29	1	7
Small	12	10	83	1	8.5	1	8.5

Table 8. Profit Efficiency

DMU	Overall Graph Efficiency	Allocative Graph Efficiency	Technical Efficiency	Maximum Increase in Profits (cents per gallon)
1	0.93	0.98	0.96	18
2	0.99	0.99	1	5
3	0.86	0.89	0.97	51
4	0.97	0.97	1	9
5	1	1	1	0
6	0.95	0.97	0.98	16
7	1	1	1	0
8	0.91	0.91	1	27
9	0.89	0.89	1	39
10	0.90	0.91	0.99	32
11	1	1	1	0
12	1	1	1	0
13	1	1	1	0
14	1	1	1	0
15	0.94	0.94	1	19
16	0.96	0.96	1	14
17	0.98	0.98	1	8
18	1	1	1	0
19	0.94	0.94	1	22
20	1	1	1	0
21	1	1	1	0
22	0.94	0.94	0.99	22
23	0.96	0.96	1	14
24	1	1	1	0
25	0.98	0.98	1	7
26	1	1	1	0
27	1	1	1	0
28	1	1	1	0
29	1	1	1	0
30	0.95	0.95	1	14
31	0.97	0.97	1	9
32	0.95	0.96	0.99	15
33	1	1	1	0
34	0.98	0.98	1	6
Average	0.97	0.97	0.997	10
Std Dev	0.04	0.03	0.01	12.81
Efficient Points (%)	44	44	82	

Table 9. Profit Efficiency of DMUs Grouped by Size

Statistic \ DMU Size	BIG	MEDIUM	SMALL
Average	0.92	0.84	0.83
Std Dev	0.07	0.05	0.10
Efficient Points (%)	29	0	7

Table 10. Profit Efficiency with Endogenous Prices – Small DMUs

DMU	Overall Economic Efficiency	"Size" Efficiency	Technical Efficiency	Allocative Efficiency
1	0.93	0.9096	0.9558	1
3	0.86	0.9951	0.9711	0.8932
4	0.97	1.0715	1	0.9059
5	1	1.0307	1	0.9701
9	0.89	0.7818	1	1
10	0.90	0.9558	0.9928	0.9519
11	1	0.9175	1	1
16	0.96	0.7627	1	1
17	0.98	0.8328	1	1
21	1	0.8115	1	1
23	0.96	0.6703	1	1
24	1	0.736	1	1
25	0.98	0.8574	1	1
30	0.95	0.7676	1	1
31	0.97	0.7781	1	1
32	0.95	0.8005	0.9897	1
33	1	1.0258	1	0.9748
Average	0.96	0.86	0.99	0.98
Std Dev	0.0413	0.1180	0.0124	0.0342

Table 11. Profit Efficiency with Endogenous Prices – Big DMUs

DMU	Overall Economic Efficiency	"Size" Efficiency	Technical Efficiency	Allocative Efficiency
2	0.99	1.1297	1	0.8736
6	0.95	1.0775	0.9821	0.9003
7	1	0.9385	1	1
8	0.91	1.0902	1	0.8335
12	1	1.0748	1	0.9303
13	1	1.1322	1	0.8842
14	1	0.9195	1	1
15	0.94	0.9432	0.9981	1
18	1	0.9299	1	1
19	0.94	0.9932	1	0.9471
20	1	1.0889	1	0.9184
22	0.94	0.9127	0.9944	1
26	1	0.8958	1	1
27	1	1.0023	1	0.9977
28	1	0.8525	1	1
29	1	0.8696	1	1
34	0.98	0.8953	1	1
Average	0.9793	0.9850	0.9985	0.9579
Std Dev	0.0304	0.0951	0.0045	0.0566