Environmental Efficiency Among Corn Ethanol Plants

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Selected Paper prepared for presentation at the International Association of Agricultural Economists (IAAE) Triennial Conference, Foz do Iguaçu, Brazil 18-24 August, 2012.

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Abstract

This study evaluates the environmental efficiency of seven recently constructed ethanol plants in the North Central region of the U.S., using nonparametric data envelopment analysis (DEA). Environmental efficiency is measured and decomposed into its technical and allocative sources. Results show that, on average, plants in our sample may be able to reduce GHG emissions by a maximum of 6% or by 3,116 tons per quarter. The economic (shadow) cost of reducing greenhouse gas emissions reveals that, at current activity levels, plants may have room for simultaneous improvement of environmental efficiency and economic profitability.

Keywords: ethanol carbon footprint; environmental efficiency; shadow cost; data envelopment analysis.

1. 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. Moreover, the capacity of the industry to reduce GHG emissions per gallon of ethanol produced may also determine the opportunities opened to it in future carbon markets and in the National Renewable Fuel Standard program. This study provides information relevant to these issues by measuring the environmental performance of the industry in terms of GHG emissions per gallon produced and the economic cost (shadow price) of GHG reductions.

Input requirements and byproducts' yield per gallon of ethanol produced are critical in determining environmental performance. Previous studies have addressed the issue of input requirements and byproducts' yield of ethanol plants. Using engineering data McAloon et al. (2000) and Kwiatkowski et al. (2006) measured considerable 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. This study does not report however results on the carbon footprint of ethanol plants.

With the exception of Shapouri et al. (2005) and Perrin et al. (2009) all of these studies reported values corresponding to the average plant (not individual plants) which prevents comparison of relative performances. In addition, it is generally believed that the industry has become more efficient and technologically homogeneous since 2005. Since the data used in Shapouri et al. (2005) was collected in 2002 it may not be representative of current technologies in the industry. In contrast to Shapouri et al. (2005), Perrin et al. (2009) surveyed plants in operation during 2006 and 2007 and employed a much more restrictive sampling criterion (discussed below) which yielded a modern and technologically homogenous sample of plants. This sample is believed to be more representative of current technologies and is, hence, our data of choice to assess the environmental performance of plants. Based on these data the present study evaluates the environmental efficiency of seven recently constructed ethanol plants in the North Central region of the U.S. The returns over operating costs (ROOC)[1] that may be gained or lost by plants as a consequence of the effort to reach a given environmental target are also calculated and discussed.

2. Materials and Method

2.1. Data

The environmental performance of a plant is evaluated on the basis of emission of greenhouse gases associated with its productive activity. Greenhouse gas emissions from

[1] We evaluate economic performance based on returns over operating costs rather than profits. This is because capital costs are not included in our analysis.

plants were not directly measured but rather calculated based on observable inputs and outputs corresponding to each plant. In addition concerns regarding the environmental impact of ethanol production refer to life cycle[2] GHG emissions and not only those emissions at the processing stage. Therefore we evaluate life cycle GHG emissions associated with observable inputs and outputs. Our observations consist of 33 quarterly reports of input and output quantities and prices from a sample of seven Midwest ethanol plants. Following the non parametric efficiency literature we refer to each observation as a decision making unit (DMU). Plants produce 3 outputs (ethanol, dry distillers grains with solubles (DDGS), and modified wet distillers grains with solubles (MWDGS)) using 7 inputs[3] (corn, natural gas, electricity, labor, denaturant, chemicals, and "other processing costs").

2.2. Ethanol Plants: Characteristics

Table 1 presents some quarterly characteristics of the seven dry grind ethanol plants surveyed. According to Table 1 the plants produced an average rate equivalent to 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 included from the third quarter of 2006 until the fourth quarter of 2007 (six consecutive quarters). In addition plants could be differentiated by how much byproduct they sold as DDGS (10% moisture) compared

[2] "Life cycle" in this case includes emissions taking place at three stages of the production process: corn production (farmers), ethanol production (biorefinery), and feedlot (byproducts from ethanol plants are given a credit for replacing corn as feed in livestock production).

[3] Results of our survey contained total expenditures in labor, denaturant, chemicals, and other processing costs. As a result we calculated implicit quantities for these inputs dividing total expenditures by their corresponding price indexes. Labor and management price index associated to the Basic Chemical Manufacturing Industries was obtained from http://www.bls.gov/oes/current/naics4_325100.htm#b00-0002. Denaturant, chemicals and other processing costs were calculated based on the Producer Input Price Index for "All other basic inorganic chemicals", http://www.bls.gov/pPI/.

to MWDGS (55% moisture). Variation on this variable was significant, 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.

Table 2 displays descriptive statistics of inputs used and outputs produced by the 33 DMUs in our sample. As mentioned before the basic observations in this study corresponds to a plant in a given quarter; so two quarters of the same plant are considered as two different observations as are two plants in the same quarter.

2.3. Environmental Performance of Ethanol Plants

2.3.1. Emissions Measurement

No direct measurements of GHG emissions are available in this industry; however they can be calculated using engineering relationships. A number of computer packages have been developed to facilitate these calculations (Wang et al. 2007; Farrell et al. 2006). We used the Biofuels Energy Systems Simulator[4] (BESS). The BESS model includes all GHG emissions from the burning of fossil fuels used directly in crop

[4] BESS is a software developed by a team of specialists in the Agronomy Department at the University of Nebraska, Lincoln (Liska, et al, 2009a, 2009b, http://www.bess.unl.edu/)

production, grain transportation, biorefinery energy use, and coproduct transport. All upstream energy costs and associated GHG emissions with production of fossil fuels, fertilizer inputs, and electricity used in the production life cycle are also included. Since these calculations involve modeling of crop production and feedlot and these display regional differences, BESS includes regional scenarios and an average scenario for the whole Midwest region. Plants in our sample are scattered across the Midwest and, hence, we have used scenario 2 in BESS "US Midwest average UNL" which is deemed representative of the whole region.

The BESS calculations of GHG emissions associated with a dry mill plant are equivalent to the following linear relationship:

$$\begin{aligned} GHG_{Mg} = \ & 0.00668274\, x_c + 0.063015823\, x_{NG} + 0.0007445\, x_{elect} + 0.000316916\, u_{Eth} \\ & - 0.4197522186\, u_{DDGS} - 0.407868\, u_{MWDGS} \end{aligned} \tag{1}$$

Where GHG_{Mg} represents megagrams of life cycle CO2 equivalent greenhouse gases, x_c is bushels of corn used by the plant, u_{DDGS} and u_{MWDGS} are tons of byproduct sold as dried and modified wet respectively by the plant, x_{NG} is the total amount of natural gas used by the plant measured in MMBTUs, x_{elect} is total amount of kilowatt hours (kwh) of electricity used by the plant, and u_{Eth} is the plant's ethanol production in gallons.

Eq. (1) states that a bushel of corn used in a biorefinery is associated with about 0.0067 megagrams of GHG emitted during the production of that bushel. DDGS and MWDGS have a positive and a negative component. The former is due to additional energy used in reducing moisture.[5] The latter are "credits" attributed to byproducts (i.e.

[5] In particular MWDGS require the use of electricity to centrifuge the wet byproduct and DDGS require the use of natural gas for heating and drying the wet byproduct after the centrifuge.

reductions in GHG) due to the replacement of corn that would have been fed to livestock had the byproduct not been sold. The coefficient for ethanol production represents the combination of emissions associated with depreciable capital (0.0002050) and freight for grain transportation (0.000111916), expressed on a per gallon basis.

Eq. (1) includes outputs $u^j = \left(u_{Eth}^j, u_{MWDGS}^j, u_{DDGS}^j\right)$ and a pollution increasing subset of all inputs used by ethanol plants[6] denoted by $x_p^j = \left(x_c^j, x_{NG}^j, x_{elect}^j\right)$, where subindex p indicates pollutant. We can now re express Eq. (1) in vector notation. To do so we partition inputs and outputs into a column vector of pollution increasing inputs and output $a^j = \left(x_c^j, x_{NG}^j, x_{elect}^j, u_{Eth}^j\right)'$ and a column vector of pollution reducing byproducts $u_b^j = \left(u_{MWDGS}^j, u_{DDGS}^j\right)'$. The level of greenhouse gas emissions associated with a particular plant j as a function of observable inputs and outputs can be expressed as:

$$GHG^j = \alpha\, a^j + \beta u_b^j \tag{2}$$

Where $\alpha = \left(0.0066, 0.0630, 0.00074, 0.000316\right)$ is the 1x4 row vector of coefficients associated with pollution increasing categories a^j, and $\beta = \left(-0.419752, -0.407868\right)$ is the 1x2 row vector of coefficients associated with pollution reducing byproducts u_b^j.

2.3.2. Characterization of Potential Ethanol Technology From Individual Plant Data

Plants are constrained by a technology transforming a vector of N inputs $x = \left(x_1, x_2, ..., x_N\right) \in \Re_+^N$ into a vector of M outputs $u = \left(u_1, u_2, ..., u_M\right) \in \Re_+^M$. Observed combinations of inputs used and outputs produced $\left(x^j, u^j\right)$ are taken to be representative

[6] As described before ethanol plants use 7 inputs in production. However only three of them increase life-cycle emissions of GHGs: corn, natural gas, and electricity.

points from the feasible ethanol technology. In this study we use data envelopment analysis (DEA) to infer the boundaries of the feasible technology set from the observed points, following the notation in Färe, et al.

Observations from the technology consist of a sample of 33 DMUs producing 3 outputs and using 7 inputs. The production technology can be represented by a graph denoting the collection of all feasible input and output vectors:

$$GR = \left\{ (x,u) \in \Re_{+}^{7+3} : x \in L(u) \right\}$$

Where $L(u)$, is the input correspondence which is defined as the collection of all input vectors $x \in \Re_{+}^{N}$ that yield at least output vector $u \in \Re_{+}^{M}$.

The frontier of the graph GR and observed levels of inputs and outputs will serve as references for environmental efficiency assessment.

2.3.3. Environmental Efficiency Measurement

A given DMU (call it *j*) is deemed more environmentally efficient whenever it chooses a feasible (subject to the graph) combination of inputs and byproducts (DDGS and MWDGS) that results in lower GHG emissions while maintaining its ethanol production level at the observed value denoted by $\overline{u_{Eth}^{j}}$. Fixing ethanol production to its observed level, and assuming variable returns to scale and strong disposability of inputs and outputs the graph can be denoted by:

$$GR^{j}\left(V,S,\overline{u_{Eth}^{j}}\right) = \left\{ (x,u) : u_{b}^{j} \leq zM_{b}, x^{j} \geq zN, zu_{Eth} = \overline{u_{Eth}^{j}}, \sum_{j=1}^{33} z^{j} = 1,\ j = 1,...,33 \right\} \qquad (3)$$

Where z depicts a row vector of 33 intensity variables, M_b is the 33x2 matrix of observed byproducts, u_b^j is the 1x2 vector of observed byproducts corresponding to the jth DMU, N is the 33x7 matrix of observed inputs, , x^j is the 1x7 vector of observed inputs corresponding to the jth DMU, u_{Eth} is the 33x1 vector of observed outputs, and $\overline{u_{Eth}^j}$ is the observed ethanol production by observation j.

We define the set of all combinations of corn, gas, electricity and byproducts that result in lower emissions than those actually produced by the jth DMU as:

$$GHG_g^j\left(x_p^j, u_b^j, \overline{u_{Eth}^j}\right) = \left\{ \left(x_p^{j\prime}, u_b^j\right) : \alpha_x\, x_p^{j\prime} + \beta\, u_b^{j\prime} \le \alpha_x\, x_p^j + \beta\, u_b^j \right\} \tag{4}$$

Where α_x is a subset of the vector α previously defined which does not include the coefficient for ethanol, i.e. $\alpha_x = (0.006682, 0.063015, 0.000744)$ and the rest is as before.[7]

From Eq. (4) we can derive an isopollution line in DDGS and corn space, i.e. combinations of DDGS and corn that result in the same level of emissions keeping everything else constant. Fig. 1 depicts this set graphically in the corn and DDGS space (i.e. keeping everything else in the GHG equation fixed). The set GHG_g^j consists of all those points above the isopollution line as indicated by the arrows with direction northwest.

[7] We denote the coefficient associated with ethanol by γ =0.000316. Ethanol production and its associated coefficient are included in both sets. However, since ethanol is fixed at the observed level $\overline{u_{Eth}^j}$, the complete version of the inequality is $\alpha_x\, x_p^{j\prime} + \beta\, u_b^{j\prime} + \gamma \overline{u_{Eth}^j} \le \alpha_x\, x_p^j + \beta\, u_b^j + \gamma \overline{u_{Eth}^j}$ which after elimination is equivalent to the expression in (4).

In Fig. 1 the feasible technology set is represented by a graph displaying variable returns to scale and strong disposability of inputs and outputs as indicated by the arrows moving from the frontier ($u_{DDGS} = f\left(x_c\right)$) with direction southeast. As clearly seen in Fig. 1, the set GHG_g^j includes combinations outside the graph and hence not attainable by DMUs in the sample. The subset of observations in GHG_g^j that belong to the graph and are hence attainable by DMUs is depicted by the intersection of both sets delimited by the bold lines in Fig. 1:

$$GHG_g^j\left(x_p^j, u_b^j, \overline{u_{Eth}^j}\right) \cap GR\left(V, S, \overline{u_{Eth}^j}\right) \qquad (5)$$

The jth DMU could choose any alternative production plan within the area denoted by the bold lines to produce its ethanol production level, achieving a reduction in emissions while increasing DDGS or reducing corn or both simultaneously. In this study, the environmental **technically** efficient projection of a given observation to the boundary of the technology set follows a hyperbolic path defined by equiproportional reductions in inputs and increases in byproducts. The value of the proportionate change necessary to encounter the boundary, ETE_g^j, is defined as the environmental technical efficiency of plant j:

$$ETE_g^j\left(x_p^j, u_b^j, \overline{u_{Eth}^j}\right) = \min\left\{\lambda : GHG_g\left(\lambda x_p^j, \lambda^{-1} u_b^j\right) \cap GR\left(V, S, \overline{u_{Eth}^j}\right) \neq \varnothing\right\} \qquad (6)$$

Where λ is a scalar defining the proportionate changes and the rest is as before. We calculated the value of $ETE_g^j\left(x_p^j, u_b^j, \overline{u_{Eth}^j}\right)$ using MATLAB as indicated in Appendix A.

Environmental technical efficiency defined in Eq. (6) is illustrated in Fig. 2 by the distance from $\left(x_c^j, u_{DDGS}^j\right)$ to point A which corresponds to the environmental technically efficient allocation in corn and DDGS space.

Note however that point A does not correspond to the minimum feasible GHG level since it does not coincide with the point of tangency between the isopollution and the graph (point B). The allocation that achieves the minimum level of GHG emissions subject to the graph is called the **overall** environmental efficient allocation.

Technically, we define this minimum feasible level of GHG emissions as:

$$\underline{GHG}^j\left(\overline{u_{Eth}^j}\right) = \min_{x_p, u_b}\left\{ GHG = \alpha_x x_p + \beta u_b + \gamma \overline{u_{Eth}^j} \quad s.t.\ (x_p, u_b) \in GR\left(V, S, \overline{u_{Eth}^j}\right) \right\} \qquad (7)$$

Where $\underline{GHG}^j\left(\overline{u_{Eth}^j}\right)$ denotes minimum emissions attainable by *j* subject to observed ethanol production $\overline{u_{Eth}^j}$, x_p is the vector of pollution increasing inputs, u_b is the vector of byproducts and the rest is as defined before. The empirical calculation of Eq. (7) is described in Appendix B.

Overall environmental efficiency, E_g^j, is measured by the hyperbolic distance between a given observation j and the isopollution line corresponding to $\underline{GHG}^j\left(\overline{u_{Eth}^j}\right)$. The hyperbolic distance is computed through calculation of the reduction of observed inputs and equiproportional expansion of observed byproducts such that the isopollution corresponding to $\underline{GHG}^j\left(\overline{u_{Eth}^j}\right)$ is reached. This is illustrated by Fig. 3 where overall environmental efficiency is the distance between $\left(x_c^j, u_{DDGS}^j\right)$ and point C.

The hyperbolic movement from $\left(x_c^j, u_{DDGS}^j\right)$ to C results from the following technical relationship.

PROPOSITION. The measure of overall environmental efficiency, E_g^j, is related to minimum GHG in the following manner:

$$\underline{GHG}^j = E_g^j \alpha x_p^j + \left(E_g^j\right)^{-1} \beta b^j \qquad j = 1, 2, ..., J \tag{8}$$

See Proof in Appendix C.

We can decompose E_g^j into purely technical environmental efficiency ETE_g^j (represented graphically by the distance between $\left(x_c^j, u_{DDGS}^j\right)$ and A) and environmental allocative inefficiency EAE^j (represented graphically by the distance between A and C). Overall environmental efficiency can be expressed as:

$$E_g^j = EAE_g^j \, ETE_g^j \tag{9}$$

Therefore, we can define allocative environmental inefficiency residually as:[8]

$$EAE^j = E_g^j / ETE_g^j \tag{10}$$

Based on the solution to the problem described in Eq. (7) we calculate overall environmental efficiency by solving the implicit Eq. (8) for each observation. These measures of environmental efficiency and their decomposition, Eq. (10), are calculated for our sample of surveyed dry grind ethanol plants and reported in Table 3. The minimum feasible GHG for each DMU as defined by Eq. (7) is calculated fixing ethanol production at observed levels.

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

2.4. ROOC and Environmental Targets: Trade off or Complementarity?

From Eq. (2) there is a clear relationship between GHG and the combination of inputs and byproducts. But there is also a relationship between combinations of inputs and byproducts and the level of ROOC. Therefore, in general, a change in GHG levels through reallocation of inputs and byproducts would bring about a change in ROOC. For a given level of ethanol production, the shadow price of GHG mitigation is the change in ROOC per unit change in GHG levels. The change in ROOC denotes the plant's maximum willingness to pay (WTP) for a permit to emit GHG. We define the shadow price of a ton of GHG as:

$$SV_{GHG}^{j} = \frac{WTP}{GHG_1^j - GHG_0^j} = \frac{\pi_1^j - \pi_0^j}{GHG_1^j - GHG_0^j} \tag{11}$$

Where WTP is willingness to pay for changing emissions from GHG_0^j to GHG_1^j. GHG_0^j denotes the original level of GHG and π_0^j the corresponding level of ROOC. GHG_1^j is the "targeted" level of GHG and π_1^j denotes ROOC at this targeted level. GHG level will be targeted at the minimum GHG (i.e. $GHG_1^j = \underline{GHG}^j$), or alternatively at the level corresponding to maximum achievable ROOC by firm j, π_*^j, which we designate as GHG_*^j.

2.4.1. Shadow Cost from Observed to ROOC Maximizing Allocation

We define the ROOC maximizing combination of inputs and byproducts (subject to a given level of ethanol production to make it comparable with the GHG minimizing combination) as the allocation that solves the following problem:

$$\pi_*^j\left(r^j, p^j, r_{Eth}^j, GR\left(V,S,\overline{u_{Eth}^j}\right)\right) = \underset{x,u_b}{Max}\left\{ r_{Eth}^j\overline{u_{Eth}^j} + r^j u_b - p^j x\right\} \quad s.t.\left(u_b, x\right) \in GR\left(V,S,\overline{u_{Eth}^j}\right) \qquad (12)$$

Where r_{Eth}^j is the observed price of ethanol obtained by observation *j*, $\overline{u_{Eth}^j}$ is the observed level of ethanol production by *j*, u_b is the 2x1 column vector of variable outputs (DDGS and MWDGS), r^j represents the 1x2 vector of observed prices of variable outputs (byproducts)[9] obtained by observation *j*, x is the 1x7 vector of variable inputs (corn, natural gas, electricity, labor, denaturant, chemicals, and "other processing costs"), and p^j represents the 1x7 vector of observed prices of variable inputs paid by *j*. Quantities of labor, denaturant, chemicals and others needed to calculate GR are obtained implicitly dividing total expenditures in these categories by their price indexes described in footnote 2. Prices for these categories in equation (12) are also those in footnote 2. We will denote the allocation that solves Eq. (12) with ethanol fixed at the observed level by $\left\{(x_*^j, u_*^j)\right\}$. The level GHG_*^j is calculated by inserting these values into (2).

We define the shadow value of GHG emissions associated with moving from the observed allocation to the ROOC maximizing allocation as:

$$SV_{GHG}^j = \frac{\pi_*^j - \pi^j}{GHG_*^j - GHG^j} \qquad (13)$$

An alternative shadow cost to Eq. (13) is that which is incurred by moving from the observed to the GHG minimizing combination of inputs and byproducts.

[9] Three DMUs in our sample did not sell dried byproducts (they sold 100% MWDGS). Since we did not have reported DDGS prices for those three observations to calculate maximum ROOC we used average prices of DDGS obtained by other DMUs in the same quarter.

2.4.2. Shadow Cost from Observed to GHG Minimizing Allocation

The GHG minimizing combination is computed by solving Eq. (7) with ethanol production fixed at observed levels and minimum GHG denoted by $\underline{GHG}^j$. ROOC associated with this allocation (calculated by multiplying the GHG minimizing inputs and outputs times their respective prices) is designated as $\underline{\pi}^j$.

We define the shadow value of GHG related to a change from the observed to the GHG minimizing point as:

$$SV_{GHG}^j = \frac{\underline{\pi}^j - \pi^j}{\underline{GHG}^j - GHG^j} \tag{14}$$

Finally we consider the shadow value of GHG related to a change from the GHG minimizing to the ROOC maximizing point.

2.4.3. Shadow Cost from GHG Minimizing to ROOC Maximizing Allocation

Such a change is illustrated in Fig. 4 in the corn and DDGS space. In Fig. 4 the GHG minimizing combination is represented by point B (the isopollution line is denoted by $\underline{GHG}^j$). If relative prices are those corresponding to the slope of π_*^j then ROOC maximization is achieved at point A and this requires a decrease in corn and DDGS with respect to the GHG minimizing point. ROOC at A are denoted by π_*^j and ROOC at B are $\underline{\pi}^j < \pi_*^j$. Emissions at B are denoted by $\underline{GHG}^j$ and emissions at A are $GHG_*^j > \underline{GHG}^j$.

The shadow value associated with a change from the GHG minimizing combination to the ROOC maximizing one is defined by:

$$SV_{GHG}^j = \frac{\pi_*^j - \underline{\pi}^j}{GHG_*^j - \underline{GHG}^j} \tag{15}$$

3. Results and Discussion

3.1. Environmental Performance of Ethanol Plants

Fixing ethanol production at observed levels, measures of environmental efficiency and their decomposition are calculated for our sample of surveyed dry grind ethanol plants and reported in Table 3. Results reveal that DMUs are very efficient from a technical point of view and that most environmental inefficiency comes from allocative sources. Therefore DMUs seem to have room for GHG reductions mainly by changing input and output combinations subject to the graph. In particular, the average DMU may be able to reduce emissions by 6% which amounts to 3,116 tons of CO2 equivalent GHGs per quarter (or 0.46 pounds per gallon of ethanol produced).

The average DMU in our sample, at observed allocations, displays a GHG intensity of about 46 gCO2e/MJ. At the GHG minimizing allocation, the average DMU in our sample displays a GHG intensity of 43 gCO2e/MJ which is 6.5% lower than observed levels. This intensity is, for example, 55% lower than the target standard established by California by 2019 (86.27 gCO2e/MJ). It is of interest to know what reallocations of inputs and byproducts may actually achieve this improvement and we will go back to this point in detail later.

3.2. ROOC and Environmental Targets

Shadow costs associated with moving from observed to ROOC maximizing allocations are reported in Table 4. Given the rather large variability across observations both the median and the average are reported as measures of central tendency. Table 4 displays some observations that are unusually high and others unusually low. These disproportionate deviations from the average are due to changes in inputs that affect ROOC but do not affect emissions, i.e. labor, denaturant, chemicals, and other processing costs. These inputs are labor, denaturant, chemicals, and other processing costs. We classify as "outlier" any observation whose value exceeds the average by more than 3 times the standard deviation.

Since there seems to be a great deal of variability in shadow prices of GHG across DMUs we have plotted a histogram that shows the approximate distribution of these values in Fig. 5. The histogram does not take into account those observations deemed as outliers. We have superimposed to the histogram a normal density function that smoothes out the distribution. An important conclusion we can extract from Table 4 and Fig. 5 is the fact that almost all DMUs reduce GHG emissions by moving from observed to maximum ROOC (negative shadow values). This suggests that, under our convexity assumptions, most DMUs (including the arithmetic average and the mean of the normal density function) may be able to increase ROOC and reduce GHG *simultaneously* which would in turn imply that these DMUs face no trade off between economic and environmental goals at current combinations of inputs and byproducts.

The fact that DMUs can rearrange inputs and byproducts in such a way that they can both increase ROOC and reduce emissions prompts the following questions:

- What inputs are reduced or increased and which byproduct is reduced or increased in such a rearrangement?
- Why are plants not exploiting these reallocations that achieve greater ROOC?

The answer to the first question for the average plant is provided in Table 5. The average DMU would achieve greater ROOC and lower GHG simultaneously mainly by reducing the use of corn, natural gas, and electricity per gallon of ethanol produced, reducing the production of MWDGS, and increasing production of DDGS. A part of these reductions is achieved through elimination of inefficiencies that would take the DMUs to the technological frontier but for the most part they are achieved through rearrangements along the surface described by the boundary of the graph, Eq. (3). Rearrangements displayed in Table 5 imply giving up MWDGS to increase DDGS and reduce inputs. They are feasible in the sense that they achieve an allocation already achieved by some other DMU in the sample or a convex combination of allocations observed in the sample.

The answer to the second question is not as straightforward. As noted in the discussion of the first question our DMUs may be able to increase ROOC and reduce GHG mainly by reducing corn, natural gas, and electricity per gallon of ethanol produced and per ton of DDGS produced.[10] The apparent engineering (in)ability to maximize ethanol and DDGS yields when compared to other DMUs in the sample seems to drive the difference between observed production plans and ROOC maximizing plans for many DMUs. A note of caution is in place here.

There are many potential reasons for the failure of DMUs to attain the ROOC-maximizing allocation. First plants may not face market conditions that allow them to reallocate byproducts from dry to wet or viceversa. A rather significant livestock production relatively near the plant has to be in place for DMUs to be able to sell a

[10] Reductions in MWDGS may come as a surprise. However given relative prices it appears this was a convenient reallocation for many DMUs.

significant portion of their byproduct as wet. These market constraints are not captured by our analysis. Second the graph is assumed to be convex in our calculations. Under the assumption of convexity any difference in performance is attributed to efficiency differences rather than to technological constraints. However there may be indivisibilities in the construction and later modifications (expansions or contractions) of plants that result in non-convexities of the graph, i.e. scaling up or down of production in any proportion may not be feasible or may be very expensive once capital costs are accounted for. These non-convexities would prevent plants from choosing the ROOC-maximizing allocation depicted by the convex graph, rendering economic inefficiencies.

Shadow costs associated with moving from observed to GHG minimizing allocations, Eq. (14), for each DMU, average, and median are reported in Table 6. Nine DMUs lose ROOC while reducing GHGs, thus facing positive shadow values of GHGs, meaning a cost. Seventeen DMUs increase ROOC while reallocating to the minimum GHG level. The fact that the average willingness to pay for a change in allocation ($\pi_E^j - \pi^j$) is positive while average change in GHG is negative, results in negative average shadow values. Table 6 indicates that the average DMU may be able to increase ROOC while reducing GHG which again seems to suggest unexploited opportunities to improve both fronts. In particular the average DMU may be able to increase ROOC by about $39 per ton of GHG reduced. The seventeen firms with negative shadow prices would presumably be willing to sell permits at any small price, since there is no ROOC lost from reducing their own GHGs.

Since there seems to be a great deal of variability in shadow prices of GHG across DMUs we have plotted a histogram that shows the approximate distribution of these values in Fig. 5. The histogram does not take into account those observations deemed as outliers. The presence of outliers is mainly due, as discussed above, to changes in inputs affecting ROOC but not GHG, i.e. labor, denaturant, chemicals, and other processing costs. We have superimposed to the histogram a normal density function that smoothes out the distribution. Despite the variability across DMUs, the highest frequency of shadow values (i.e. most of the "mass" of the distribution) appears to be located around zero. This means that plants are approximately efficient in the sense that they are operating at levels for which the marginal value of GHG is around zero which is, in turn, the current GHG price that DMUs face.

According to Table 7 the average DMU achieves minimization of GHG through substantial reductions in DDGS and MWDGS which in turn allows it to significantly reduce natural gas and electricity. Finally reductions in corn per gallon of ethanol are also involved in this GHG minimization. Such reallocations not only achieve reductions in GHG but also increase ROOC (negative shadow value)

Shadow costs associated with moving from GHG minimizing to ROOC maximizing allocations, Eq. (15), for each DMU, average and median are reported in Table 8. All DMUs increase both ROOC and GHGs in moving from low GHG solution to high ROOC solution. The average DMU would forfeit $1,726 in ROOC for each ton of GHG reduced, a very high cost of regulation if that firm were required to reduce GHGs. If DMUs are forced to reduce GHG emissions below ROOC maximizing levels, these shadow values indicate that they would be willing to purchase permits if the market value is in the vicinity of $20 to $30 per ton, rather than reduce one ton of GHG emissions. The histogram (with superimposed normal density) corresponding to Table 8 is plotted in Fig.

6. This histogram as the one in Fig. 5 does not take into account those observations classified as outliers. Again, despite the variability across DMUs, the highest frequency of shadow values (i.e. most of the "mass" of the distribution) appears to be located around a very high value.

The reallocation of inputs and byproducts that would take the average DMU from the GHG minimizing to the ROOC maximizing combination is displayed in Table 9. The average DMU achieves increases in ROOC mainly through substantial increases in DDGS which in turn entails increases in natural gas and electricity, and reductions in MWDGS. Another very important component of ROOC increases is reductions of corn per gallon of ethanol produced.

Results for the average DMU in Tables 4, 6, and 8 can be combined to recover the shape of the relationship between GHG and ROOC. Plotting the three averages in the GHG and ROOC space yields the graph in Fig. 7. We denote the observed combination of the average by $\left(GHG^{j}, \pi^{j}\right)$, the ROOC maximizing combination by $\left(GHG_{*}^{j}, \pi_{*}^{j}\right)$, and the GHG minimizing combination by $\left(\underline{GHG}^{j}, \underline{\pi}^{j}\right)$. There seems to be room for simultaneous improvement of environmental and economic performance, as previously indicated in discussions of Tables 4 and 6. However, if the average firm were able to adjust inputs and byproducts to the ROOC maximizing combination, it would face an intense trade off described just above.

4. Conclusions

The purpose of this study was to contribute to the ongoing debate regarding the merits and potential of the ethanol industry in the US by investigating the current environmental performance at the individual plant level, the potential for improvement in this performance and its effects on the industry's overall emissions of greenhouse gases.

Several important conclusions can be drawn from this study. First, our results suggest that decision making units (DMUs) may have some room for improving environmental performance. However since plants are technically very efficient, most of this improvement has to come from changes in combinations of inputs and byproducts along the frontier (reduction in environmental allocative inefficiencies). By eliminating allocative inefficiencies the average DMU could apparently decrease emissions by 6%, which amounts to about 3,116 tons of CO2 equivalent GHG.

Negative shadow values of GHG from observed to ROOC maximizing combinations reveal that at current operating levels DMUs may be able to increase ROOC and reduce GHG *simultaneously* by reaching the "best practice" in the sample. Plants may not be switching to the ROOC maximizing combination because of capital costs involved in that reallocation. If such costs exist they are not being accounted for here. However these costs may be outweighed by revenue opportunities created through carbon reducing policies, e.g. renewable fuel standards, carbon markets, tax credits for carbon reducing capital investments, etc.

Additionally once DMUs achieve the ROOC maximizing allocation, our results suggest that they may face significant ROOC losses if they are forced to reduce GHG any further. In this case the average DMU in this sample would be willing to pay up to $1,726 for a permit to emit ton of GHG, rather than suffer the ROOC reduction revealed by the shadow price of reducing carbon from ROOC maximizing to GHG minimizing levels.

The measurement of corn ethanol plants environmental performance, their potential for improvement, and ROOC/emissions trade offs conducted in this study should inform the debate on whether there is a place for corn ethanol as a “clean” substitute for gasoline. In particular our results suggest that ethanol plants in our sample can produce energy with considerable lower (52% lower) GHG intensity than gasoline. Moreover these plants have some room for reducing this footprint even more by reallocating inputs and byproducts. Such reallocations would achieve a 6.5% reduction in GHG rendering energy with a GHG intensity 55% lower than gasoline. In turn these reductions may be achieved at a moderate or none economic cost as strongly suggested by a negative shadow price of $39 per gallon. Further reductions, however, can only be achieved at high economic costs.

Appendix A

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

$$\text{(A.1)} \quad \begin{aligned} &\underset{\lambda,z}{Min}\ \lambda \\ &s.t. \quad \lambda^{-1}u_b^j \le M_b z,\ \overline{u_{Eth}^j} = zM_{Eth},\ \lambda x^j \ge Nz,\ \sum_j z^j = 1 \end{aligned}$$

Where u_b^j is the vector of dried and wet byproducts, M_b is the 2xJ matrix of observed levels of byproducts, z is the Jx1 vector of intensity variables used to weight observations and construct the piecewise linear boundary of the graph, x^j is the column vector composed by observed values of all inputs used by observation j, N is the 7xJ matrix of observed values of inputs for all observations, and $\overline{u_{Eth}^{j}}$ is the observed level of ethanol production of the jth DMU.

After multiplying the constraints times λ it is easily seen that this is equivalent to the following problem:

$$\text{(A.2)} \quad \begin{aligned} &\underset{\Gamma, z'}{Min}\, \Gamma \\ &s.t. \quad u_b^j \le M_b z',\ \Gamma x^j \ge N z',\ \sum_j z^{j\prime} = \lambda,\ \lambda\, \overline{u_{Eth}^{j}} = M_{Eth} z',\ \Gamma = \lambda^2,\ z' = \lambda z \end{aligned}$$

Following Färe et al. problem (A.1) is reformulated into problem (A.2) because the only nonlinear constraint is an equality constraint (i.e. $\Gamma = \lambda^2$) and is, hence, easier to program. In particular, these sub vector hyperbolic measures of technical efficiency are calculated through a nonlinear program implemented with the FMINCON procedure in MATLAB.

Appendix B

The following program describes the problem:

$$\text{(B.1)} \quad \begin{aligned} &\underset{x, u_{DDGS}, u_{MWDGS}}{Min} \quad GHG = 0.00668274\, x_c + 0.063015823\, x_{NG} + 0.0007445\, x_{elect} \\ &\qquad\qquad - 0.4197522186\, u_{DDGS} - 0.407868\, u_{MWDGS} \\ &s.t. \quad u_{DDGS} \le M_{DDGS} z,\ \ u_{MWDGS} \le M_{MWDGS} z,\ \ \overline{u_{Eth}^{j}} = M_{Eth} z, \quad x \ge Nz, \quad \sum_j z^j = 1 \end{aligned}$$

Where u_{DDGS} is the vector of dried byproducts, M_{DDGS} is the 2xJ matrix of observed levels of DDGS, z is JX1 vector of intensity variables, u_{MWDGS} is the vector of modified wet byproducts, M_{MWDGS} is the 2xJ matrix of observed levels of MWDGS , x is the vector of all inputs, and N is the 7xJ matrix of observed levels of inputs. This program was calculated using the LINPROG routine in MATLAB.

Based on this quantity, we calculate overall environmental efficiency by solving for E_g^j implicitly through Eq. (8) for each observation.

Appendix C

Proof:

Let us denote the vector of coefficients of Eq. (1) by (α_x, β), where α_x is the vector of coefficients for corn, natural gas, and electricity, and β is the vector of coefficients for both byproducts. In addition, let us define an arbitrary output and input vector by (x_p, u_b) where $x_p = (x_c, x_{NG}, x_{elect})$ and $u_b = (u_{MWDGS}, u_{DDGS})$ and denote the jth DMU's observed output and input vector by $(x_p{}^j, u_b^j)$.

Let $(x_p, u_b) \in GHG_g^j\left(E_g^j x_p^j, u_b^j \left(E_g^j\right)^{-1}\right) \cap GR$, then $(x_p, u_b) \in GR$ and since E_g^j is a minimum:

$$\begin{aligned}(\alpha_x\, x_p + \beta u_b) &= E_g^j (0.00668274)\, x_c^j + E_g^j (0.063015823)\, x_{NG}^j + E_g^j (0.0007445) x_{elect}^j \\ &-(0.407868)\, u_{MWDGS}^j / E_g^j - (0.4197522186)\, u_{DDGS}^j / E_g^j\end{aligned}$$

Let us denote observations *j*'s minimum feasible GHG level by $\underline{GHG}^j$. There are three cases to consider:

1. Assume $(\alpha_x\, x_p + \beta u_b) < \underline{GHG}^j$, then $(x_p, u_b) \notin GR$

2. Asume $\left\{(\alpha_x\, x_p + \beta u_b) > \underline{GHG}^j\right\}$, then

$\left\{(v,w) : (\alpha_x\, v + \beta\, w) \le \underline{GHG}^j\right\} \subseteq \left\{(v,w) : (\alpha_x\, v + \beta\, w) \le (\alpha_x\, x_p + \beta u_b)\right\}$ and since the hyperplanes defining the two sets are parallel, E_g^j can not be a minimum.

Cases 1 and 2 leave the following case:

3. $\left(\alpha_x\, x_p + \beta u_b\right) = \underline{GHG}^j$. Therefore $\left(E_g^j\, \alpha_x\, x_p^j + E_g^{j-1} \beta u_b^j\right) = \underline{GHG}^j$.

Acknowledgements

Study supported by the Agricultural Research Service, University of Nebraska, and USDA regional project NC506.

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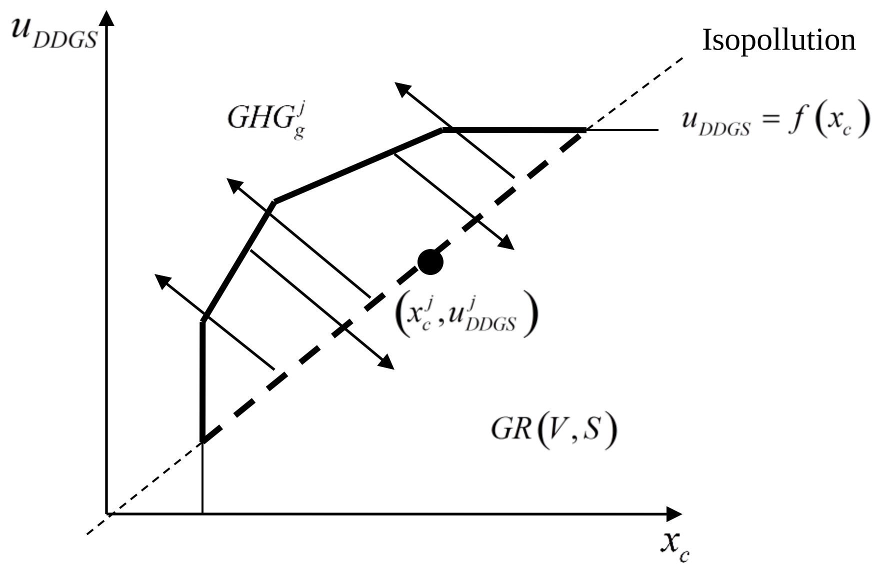

Fig. 1 - Isopollution and Sets

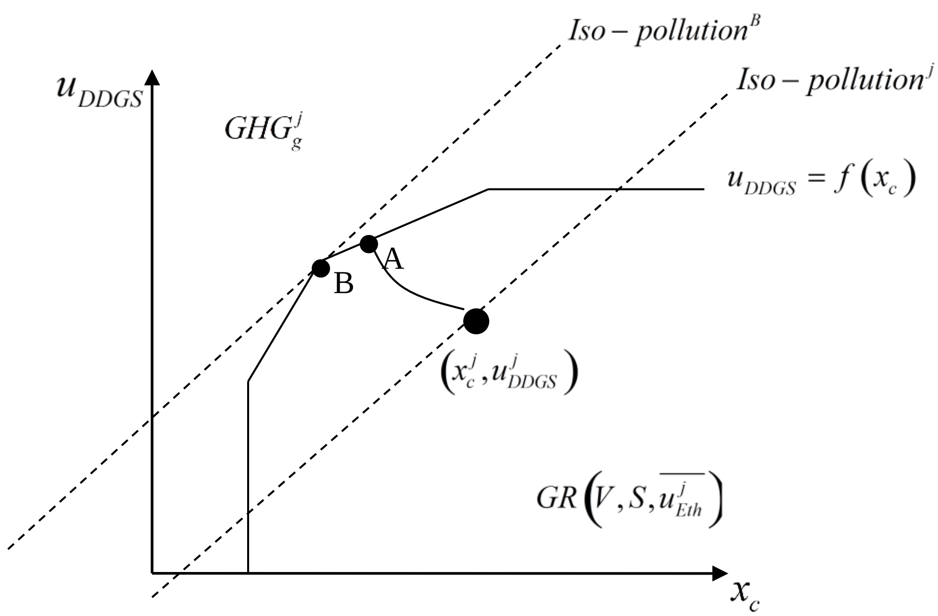

Fig. 2 - Environmental Technical Efficiency

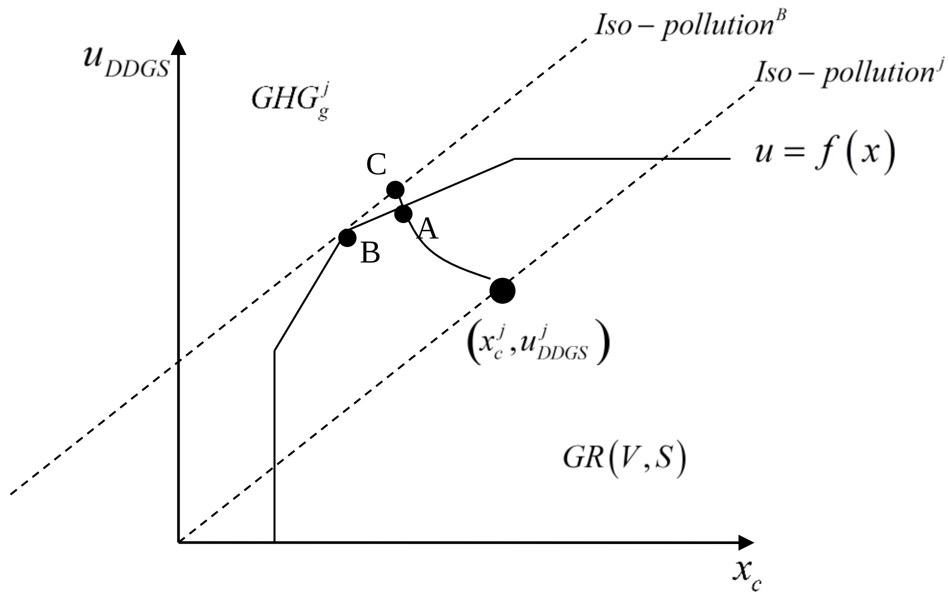

Fig. 3 - Decomposition of Overall Environmental Efficiency

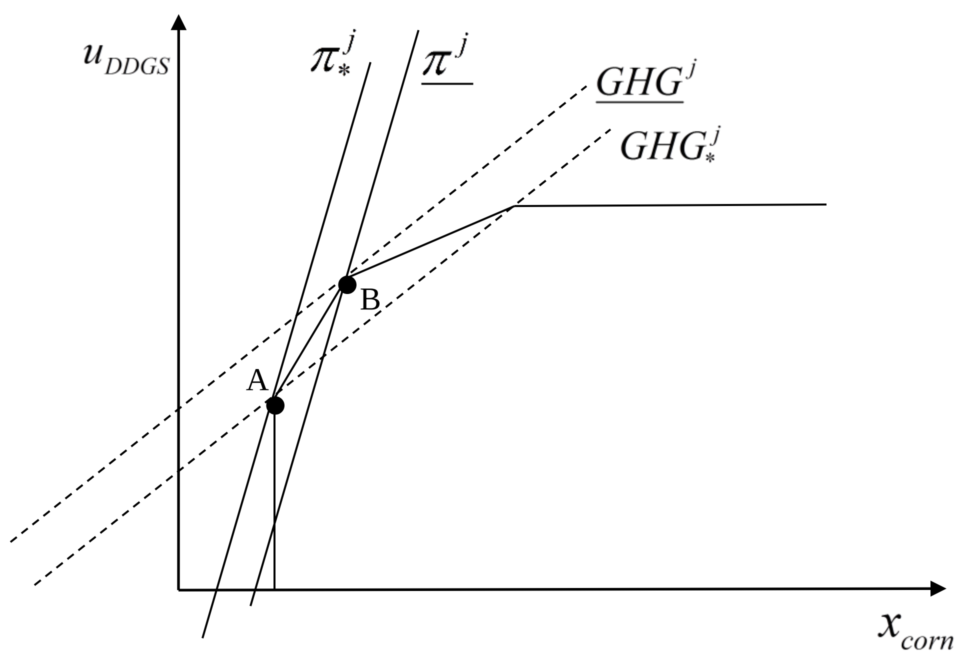

Fig. 4 - Shadow Cost from GHG Minimizing to Profit Maximizing Allocation

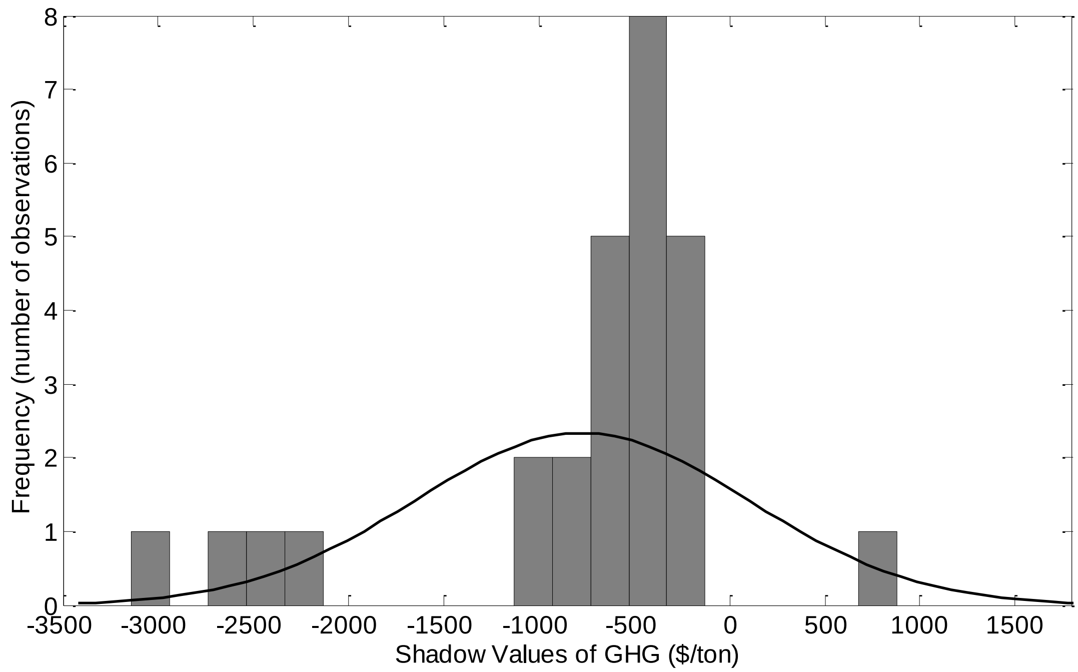

Fig. 5 - Histogram of Shadow Values (observed to ROOC-maximizing)

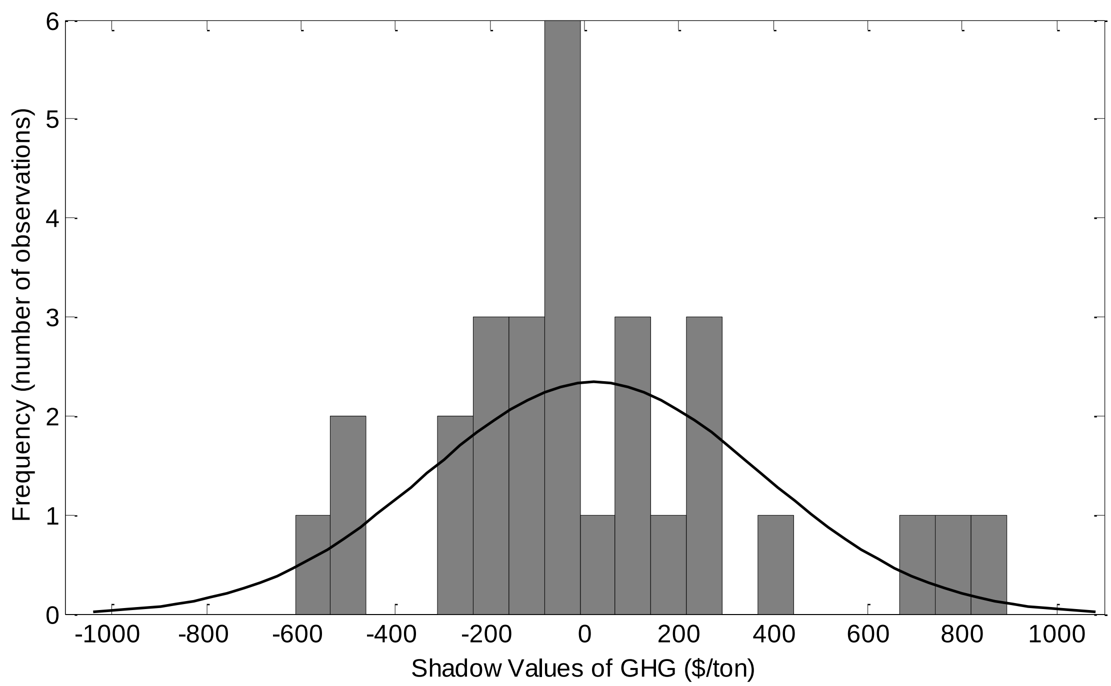

Fig. 6 - Histogram of Shadow Values (observed to GHG-minimizing)

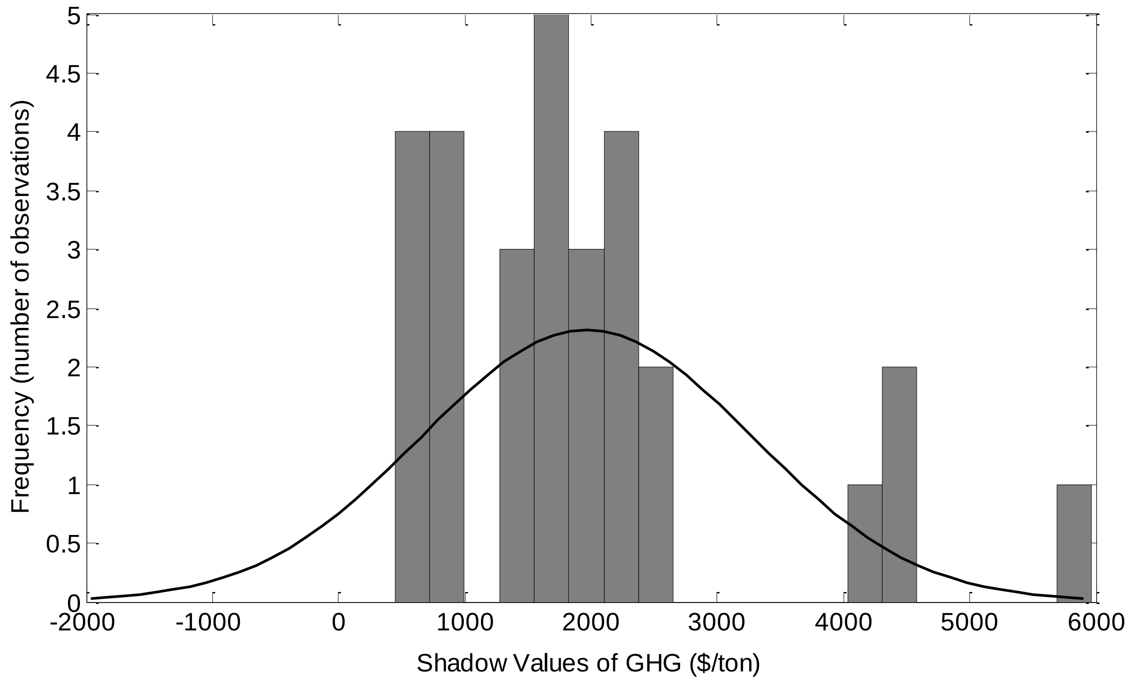

Fig. 7 – Histogram of Shadow Values (GHG Minimizing to Profit Maximizing)

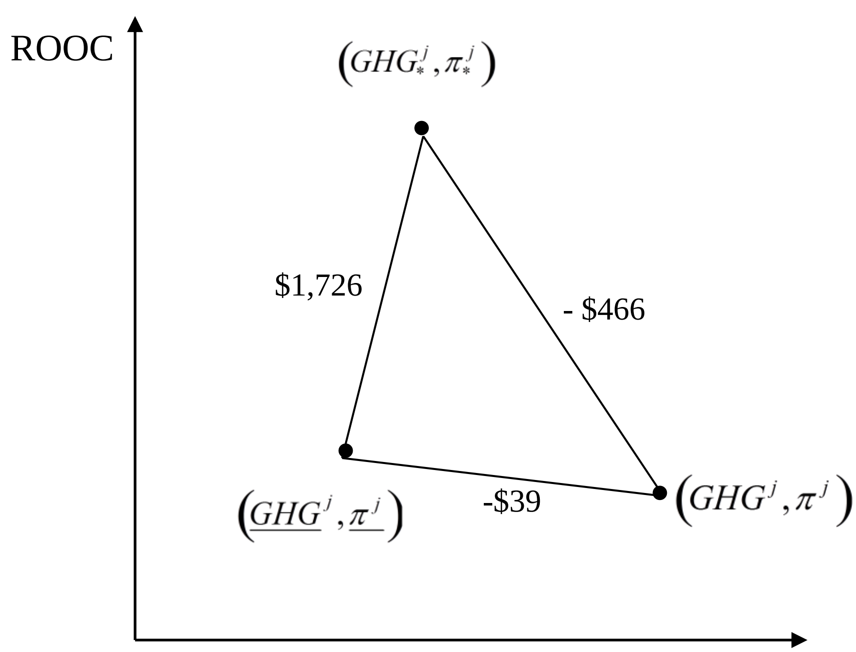

Fig. 8 - ROOC and GHG

Table 1. Characteristics of the seven surveyed plants

States Represented	Iowa, Michigan, Minnesota, Missouri, Nebraska, S. Dakota, Wisconsin				
Annual Production Rate (million gal/year)	Smallest	42.5			
	Average	53.1			
	Largest	88.1			
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. Descriptive Statistics: Inputs and Outputs

	Corn (million bushels)	Natural Gas (thousand MMBTUs)	Electricity (million kwh)	Ethanol (million gallons)	DDGS (thousand tons)	MWDGS (thousand tons)
Average	4.8	361	7,8	13.7	21.3	14.5
Std Dev	0.9	61	1.5	2.8	10	15.4
Min	3.6	297	6.7	10.6	0	0.2
Max	8	569	13.3	22,9	34.2	56.2

Table 3. Environmental Efficiency Decomposition

DMU	Technical Environmental Efficiency	Allocative Environmental Efficiency	Overall Environmental Efficiency	Reduction of GHG (tons)[a]	Reduction of GHG (%)[b]
1	0.977	0.983	0.961	3,268	6
2	1	0.931	0.931	6,227	11
3	0.985	0.970	0.956	3,617	7
4	1	0.951	0.951	3,801	7
5	1	0.993	0.993	567	1
6	0.979	0.993	0.973	2,331	4
7	1	0.948	0.948	4,697	9
8	1	0.947	0.947	4,704	8
9	1	1	1	0	0
10	0.997	0.959	0.956	3,539	7
11	1	0.989	0.989	950	2
12	1	1	1	0	0
13	1	0.940	0.940	8,007	9
14	1	0.949	0.949	4,625	9
15	1	0.944	0.944	4,804	9
16	1	0.974	0.974	2,015	4
17	1	0.985	0.985	1,098	2
18	1	0.938	0.938	5,178	10
19	1	0.987	0.987	1,133	2
20	1	1	1	0	0
21	1	0.947	0.947	4,611	9
22	1	0.967	0.967	2,736	5
23	1	0.974	0.974	2,023	4
25	1	0.985	0.985	1,199	2
26	1	0.970	0.970	2,614	5
27	1	1	1	0	0
28	1	0.917	0.917	7,941	14
29	1	0.956	0.956	3,708	7
30	1	0.961	0.961	3,068	6
31	1	0.964	0.964	2,831	6
32	0.993	0.980	0.973	2,239	4
33	1	0.992	0.992	684	1
34	1	0.914	0.914	8,662	14
Average	0.998	0.967	0.965	3,116	6

Table 4. Shadow Values of GHG: observed to profit maximizing combination

DMU	WTP for change in allocation, $\pi_*^j - \pi^j$ (\$)	Change in GHG emissions, $GHG_*^j - GHG^j$ (tons)	Shadow Value of GHG (\$/ton)
1	948,565	-2,618	-362
2	1,483,022	-5,648	-263
3	2,094,972	-2,728	-768
4	1,223,985	-3,105	-394
5	619,562	120	5,147 - outlier
6	1,263,224	-1,920	-658
7	1,515,535	-4,100	-370
8	2,398,535	-4,405	-545
9	3,199	0	INFINITE
10	850,101	-2,636	-322
11	719,229	-264	-2,726
12	1,382	0	INFINITE
13	2,175,472	-7,709	-282
14	1,597,466	-4,026	-397
15	1,751,089	-4,339	-404
16	825,632	-1,027	-804
17	1,692	0	INFINITE
18	1,540,254	-4,555	-338
19	1,230,951	-488	-2,521
20	258,318	295	877
21	1,797,859	-3,726	-483
22	1,975,711	-2,035	-971
23	781,594	-344	-2,269
24	1,041,712	-332	-3,141
25	2,192,398	-1,990	-1,101
26	9,613	0	INFINITE
27	2,301,210	-7,495	-307
28	1,252,438	-3,075	-407
29	1,439,841	-2,291	-629
30	1,106,262	-1,801	-614
31	727,808	-1,367	-532
32	1,396,934	271	5,154 - outlier
33	1,865,307	-8,663	-215
Average	1,420,685	-3,052	**-466**
Median	1,439,841	-2,636	**-546**

Table 5. Reallocation from observed to profit maximizing combination

Measure \ Category	Corn	Natural Gas	Electricity	Dry	Wet
Average Change (%)	-5.88	-3.83	-0.41	26.03	-10.23

Table 6. Shadow Values of GHG: observed to GHG minimizing combination

DMU	WTP for change in allocation, $\pi_E^j - \pi^j$ ($)	Change in GHG emissions, $GHG_E^j - GHG^j$ (tons)	Shadow Value of GHG ($/ton)
1	659,193	-3,268	-202
2	443,897	-6,227	-71
3	134,209	-3,617	-37
4	-343,266	-3,801	90
5	286,956	-567	-506
6	-526,747	-2,331	226
7	294,875	-4,697	-63
8	610,737	-4,704	-130
9	-18,561	0	INFINITE
10	-886,553	-3,539	250
11	260,637	-950	-274
12	-817,158	0	INFINITE
13	1,728,919	-8,007	-216
14	432,472	-4,625	-94
15	-221,003	-4,804	46
16	-788,455	-2,015	391
17	-842,611	-1,098	767
18	1,041,500	-5,178	-201
19	326,317	-1,133	-288
20	-542,483	0	INFINITE
21	-417,870	-4,611	91
22	1,343,752	-2,736	-491
23	-373,408	-2,023	185
24	-839,949	-1,199	700
25	1,600,339	-2,614	-612
26	-263,194	0	INFINITE
27	307,697	-7,941	-39
28	176,556	-3,708	-48
29	164,586	-3,068	-54
30	-327,399	-2,831	116
31	-649,530	-2,239	290
32	-611,531	-684	894
33	1,046,320	-8,662	-121
Average	138,988	-3,548	**-39**
Median	176,556	-3,268	**-54**

Table 7. Reallocation from observed to GHG minimizing combination

Measure \ Category	Corn	Natural Gas	Electricity	Dry	Wet
Average Change (%)	-3.05	-6.83	-1.35	-33.63	-4.11

Table 8. Shadow Values: GHG minimizing to profit maximizing combination

DMU	WTP for change in allocation, $\pi_*^j - \pi_E^j$ ($)	Change in GHG emissions, $GHG_*^j - GHG_E^j$ (tons)	Shadow Value of GHG ($/ton)
1	289,372	650	445
2	1,039,125	579	1,794
3	1,960,763	889	2,206
4	1,567,251	695	2,254
5	332,607	688	484
6	1,789,971	411	4,355
7	1,220,660	597	2,044
8	1,787,797	300	5,964
9	21,760	0	INFINITE
10	1,736,654	903	1,923
11	458,592	687	668
12	818,540	0	INFINITE
13	446,554	298	1,500
14	1,164,994	599	1,945
15	1,972,092	465	4,240
16	1,614,087	988	1,633
17	844,302	1,098	769
18	498,754	622	801
19	904,634	645	1,403
20	800,801	321	2,493
21	2,215,729	886	2,501
22	631,958	701	901
23	1,155,002	1,679	688
24	1,881,661	868	2,168
25	592,059	623	950
26	272,807	0	INFINITE
27	1,993,513	446	4,474
28	1,075,882	632	1,701
29	1,275,255	777	1,641
30	1,433,661	1,030	1,392
31	1,377,339	872	1,580
32	2,008,466	955	2,104
33	818,987	0	INFINITE
Average	1,243,777	721	**1,726**
Median	1,220,660	687	**1,778**

Table 9. Reallocation from GHG minimizing to profit-maximizing point

Category / Measure	Corn	Natural Gas	Electricity	Dry	Wet
Average Change (%)	-2.75	2.82	0.94	12.45	-97.65