Australian Agricultural and Resource Economics Society

55th Annual AARES National Conference, 8 – 11 February, Melbourne, VIC 2011

Economic and Marketing Efficiency Among Corn Ethanol Plants

Juan P Sesmero[*,1], Richard K Perrin[2] and Lilyan E Fulginiti[3]

[1] Department of Agricultural Economics, Purdue University, IN 47907-2056, USA

[2, 3] Department of Agricultural Economics, University of Nebraska, Lincoln, NE 68583, USA

[*] Corresponding author. KRAN 591A, West Lafayette, IN 47907-2056, USA. E-mail address: jsesmero@purdue.edu . Tel.: 1(765) 494-7545.

FIRST DRAFT: PLEASE DO NOT CITE

Acknowledgements

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

Economic and Marketing Efficiency Among Corn Ethanol Plants

Abstract

We extend data envelopment analysis (DEA) to decompose the economic efficiency of a sample of ethanol plants into internal (technical and allocative) and boundary (marketing) sources. This decomposition allows us to evaluate the channels through which different plant characteristics affect plant performance. Results show that plants are very efficient from a technical point of view. Plants with higher production volumes seem to perform better not because of economies of scale but because they can secure more favorable prices (higher marketing efficiency) and execute production plans accordingly (higher allocative efficiency). This may rationalize the increase in the size of the average plant observed in the industry in recent years despite evidence of close to constant returns to scale. This suggests that plants may have incentives to horizontally integrate. Our results do not seem to point towards the existence of strong incentives to vertically integrate. Plants seem to have achieved significant improvements in performance through experience and learning-by-doing. Plants that are privately owned do not seem to perform better that those owned by farmers' cooperatives.

Key words: corn ethanol, data envelopment analysis, economic efficiency decomposition, marketing efficiency, mergers

Introduction

Based on current scientific knowledge ethanol seems to be a viable “clean” substitute of fossil liquid fuels (although it can only substitute for fossil fuels at a relatively small scale) even considering indirect land use changes associated with increased production (see re-calculations by the California Air Resources Board). It may also favor corn (McNew) and livestock producers (Van Wart and Perrin). However, in the last few years (especially since 2007) increases in corn prices and reductions in oil prices (and hence in ethanol prices) have hit the industry. In addition, a considerable amount of volatility in commodity markets has increased uncertainty and shorten plants’ planning horizon (Tyner, 2009). As a result the ability of plants to make production and marketing decisions that maximize their operating margins becomes critical. Identifying and quantifying potential drivers of plants economic performance may be of interest to plant managers, government officials, famers, and other stakeholders (e.g. banks, investors, environmental agencies). We draw from the theory of the firm (Gibbons, 2005) and the theory of the industry’s life cycle (Williamson, 1975 and Stigler, 1951) to shed some light on these potential drivers.[1] In particular we integrate economic efficiency measures and firm/industry theories by defining and calculating a new source of economic efficiency (marketing efficiency) and linking it to characteristics of the plants hypothesized as drivers of performance by the aforementioned theories.

DEA Analysis: Intensive and Extensive Margins

Performance, as discussed by the theory of the firm (Gibbons), is determined by the choice of boundaries (which activities are conducted internally and which are outsourced) and by

[1] Given available data we can only identify and quantify correlates of economic performance rather than actual drivers. However the aforementioned theories propose certain causalities that will guide the correlation analysis in this study. We can then discuss the consistency of correlations with causalities proposed by the theories.

choices internal to the organization once the boundaries have been set. We call the former, efficiency at the extensive margin, and the latter efficiency at the intensive margin. Conventional methods of measurement of economic efficiency allow quantification of internal efficiency. We propose to extend these methods in a way that permits quantification of efficiency at the extensive margin and its role on the overall economic performance of the firm. Once we have calculated overall performance and decomposed it into its internal (technical and allocative) and boundary (marketing/procurement) sources, we find the statistical link between these sources and drivers proposed by the theories of the firm and industry's life cycle.

Empirical assessments of the theory of the firm usually link potential drivers to actual measures of performance. The most commonly used measures of performance are returns over assets (ROA), returns on equity (ROE), and Tobin's Q (Dybvig et al.) Differential performance may be explained by managerial ability but also by constraints faced by plants in the market. Studies using ROA, ROE, and Tobin's Q do not model constraints but rather assume all plants face the same constraints which can be distortive if constraints vary across plants.

Evaluating plants' performance subject to constraints requires modeling and quantification of those constraints. Frontier methods developed in production economics (Coelli et al.) provide the tools to quantify technological constraints. Technological frontiers may be calculated parametrically or non-parametrically. The latter is especially suitable for small samples. Since we have 33 observations in our sample we will pursue a non-parametric calculation of the technological frontier. Based on this frontier conventional measures of economic efficiency decompose overall efficiency into technical and allocative sources.[2] Technical efficiency represents the ability of managers to achieve an engineering optimum.

[2] A third component sometimes included is a measure of input congestion. This component measures the extent to which too much of one input (given quantity of other inputs) reduces the productivity of the plant.

Allocative efficiency assumes prices are exogenous (an exception is Cherchye et al. which considers non-competitive settings) and measures performance based on the alignment of the chosen input-output combination to exogenous prices. Therefore conventional non-parametric measurement of performance assumes all sources of inefficiency are internal to the plant. For this reason, it can not evaluate performance at the extensive margin; i.e. the ability of the plant to increase operating margins by partially controlling prices through the integration/outsourcing decision. In the context of the ethanol industry this could be a serious drawback. Decisions by plants on whether to conduct marketing and procurement activities internally (vertical integration) or externally through contracts and spot markets may partially affect prices that they pay and receive. We propose to extend conventional DEA methods to account for increases in operating margins (measured by net operating revenues or NOR) due to favorable pricing attained through vertical integration, management of contracts and spots, and/or hedging. Naturally we call this new measure, marketing efficiency. Obtaining measures of efficiency at both the intensive and extensive margins will allow us to identify the channels through which drivers of performance proposed by the theory of the firm affect plant success in the corn ethanol industry.

Characterization of Technology from Individual Plant Data

Our data consist of 33 quarterly reports of input and output quantities and prices from a sample of seven ethanol plants in the Midwest. We refer to each quarterly observation as a decision making unit (DMU.) DMUs are assumed to share a technology that transforms a vector of 7 inputs (corn, natural gas, electricity, labor, denaturant, chemicals, and “other processing costs”) into 3 outputs (ethanol, dried distiller’s grains with 10% moisture content (DDGS), and modified wet distiller's grains with 55% moisture content (MWDGS).) Observed combinations of inputs used and outputs produced are taken to be representative 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. The production technology can be represented by a graph denoting the collection of all feasible input and output vectors:

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

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 $u \in \Re_{+}^{M}$.

Conventional Decomposition of Economic Efficiency

A given DMU is deemed economically efficient whenever it chooses a feasible (subject to the graph) input-output combination that maximizes NOR given prices. In this section we proceed to calculate and decompose economic efficiency assuming that prices are exogenous and hence there is no marketing strategy that can affect prices at which ethanol is sold and corn procured.

Assuming variable returns to scale[3] and strong disposability of inputs and outputs the graph can be denoted by:

$$GR^{j}(V,S) = \left\{ (x,u) : u^{j} \le zM, x^{j} \ge zN, \sum_{j=1}^{33} z^{j} = 1,\ j = 1,...,33 \right\} \tag{1}$$

Where z depicts a row vector of 33 intensity variables, M is the 33x3 matrix of observed outputs, u^{j} is the 1x3 vector of observed outputs corresponding to the jth DMU, N is the 33x7 matrix of observed inputs, and x^j is the 1x7 vector of observed inputs corresponding to the jth DMU.

We define the set of all combinations of inputs and outputs resulting in higher NOR than that actually achieved by the jth DMU as:

$$\pi_g^j \; x^j, u^j \; = \quad x^{j\prime}, u^{j\prime} \; : p^j x^{j\prime} + r^j u^{j\prime} \geq p^j x^j + r^j u^j \tag{2}$$

Where p^j is the vector of input prices paid and r^j the vector of output prices received by the j*th* DMU and the subscript *g* denotes greater than observed NOR.

We define an iso-NOR line in ethanol and corn space corresponding to the j*th* DMU as those combinations of ethanol and corn that result in the same level of NOR given p^j and r^j. Fig. 1 depicts this set graphically in the corn and ethanol space (i.e. keeping all other inputs and outputs fixed.) The set π_g^j consists of all those points above the iso-NOR line as indicated by the arrows with direction northwest.

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 ($u_{Eth} = f \; x_c$) with direction southeast. As clearly seen in Fig. 1, the set π_g^j includes combinations outside the graph and hence not attainable by DMUs in the sample. The subset of observations in π_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:

$$\pi_g^j \; x_c^j, u_{Eth}^j \; \cap GR \; V, S \tag{3}$$

The jth DMU could choose any alternative production plan within the area denoted by the bold lines achieving a feasible increase in NOR.

We apply in this study a hyperbolic graph efficiency measure which means that the **technically** efficient projection of a given observation to the boundary of the technology set follows a hyperbolic path defined by equi-proportional reductions in inputs and increases in outputs. The value of the proportionate change necessary to reach the boundary, TE^{j}, is defined as the technical efficiency of plant j:

$$TE_{v}^{j}\ \ x^{j},u^{j}/V,S\ \ =\min\ \ \lambda:\pi_{g}^{j}\ \ \lambda x_{c}^{j},\lambda^{-1}u_{Eth}^{j}\ \ \cap GR\ \ V,S\ \ \neq\varnothing \qquad (4)$$

Where λ is a scalar defining the proportionate changes and the rest is as before.

Technical efficiency defined in Eq. (4) is illustrated in Fig. 2 by the distance from x_{c}^{j},u_{Eth}^{j} to point A which corresponds to the technically efficient allocation in corn and ethanol space. Note however that point A does not correspond to the maximum feasible NOR level since it does not coincide with the point of tangency between the iso-NOR and the graph (point B.) The allocation that achieves the maximum level of NOR subject to the graph is called the **overall** economic efficient allocation.

Technically, we define this maximum feasible level of NOR as:

$$\overline{\pi^{j}}=\max_{x,u}\quad \pi^{j}=p^{j}\,x+r^{j}\,u \quad s.t.\ \ (x,u)\in GR\ \ V,S \qquad (5)$$

Where $\overline{\pi^{j}}$ denotes maximum NOR attainable by *j* subject to the graph and observed prices, x is the vector of inputs, and u is the vector of outputs and the rest is as defined before.

Overall economic efficiency under variable returns to scale, E_{v}^{j}, is measured by the hyperbolic distance between a given observation j and the iso-NOR line corresponding to $\overline{\pi^{j}}$. The hyperbolic distance is computed through calculation of the reduction of observed inputs and equiproportional expansion of observed byproducts such that the iso-NOR corresponding to $\overline{\pi^{j}}$

is reached. This is illustrated by Fig. 3 where overall environmental efficiency is the distance between x_c^j, u_{Eth}^j and point C.

Since the movement from x_c^j, u_{Eth}^j to C is a hyperbolic one, the measure of overall economic efficiency, E_v^j, is related to maximum NOR in the following manner:

$$\overline{\pi^j} = E_v^j \; p^j \, x^j + \; E_v^j{}^{-1} r^j \, u^j \qquad j = 1, 2, ..., J \tag{6}$$

We can decompose E_v^j into purely technical efficiency TE_v^j (represented graphically by the distance between x_c^j, u_{DDGS}^j and A) and allocative inefficiency AE_v^j (represented graphically by the distance between A and C.) Overall efficiency can be expressed as:

$$E_v^j = AE_v^j \, TE_v^j \tag{7}$$

Therefore, we can define allocative inefficiency residually as:[3]

$$AE_v^j = \frac{E_v^j}{TE_v^j} \tag{8}$$

Based on the solution to the problem described in Eq. (5) we calculate overall economic efficiency by solving the implicit Eq. (6) for each observation.

Limitations of Conventional Decomposition and Marketing Efficiency

Plants' bargaining or marketing strategies may affect, at least to some extent, the prices obtained for ethanol and paid for corn. This fact is ignored by the conventional decomposition of efficiency. In order to capture the effect of plants' pricing strategies (integration, contracts, and spots) on performance we introduce the concept of marketing efficiency. Provided we have price

[3] In this way we minimize stronger assumptions about convexity that may result in artificially low efficiency indexes.

observations for 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 inflation. The part due to inflation is controlled for by adjusting all prices to a base quarter (3rd quarter of 2006) using the Producer Price Index (PPI) as calculated by the Bureau of Labor Statistics. The managerial and spatial parts however, are more difficult to deal with.

Managerial differences are due to the fact that plants use different marketing arrangements (including spot markets, contracts, and marketers as described in Table 1) to procure their inputs and sell their outputs. Since we have one plant per state we have a perfect correlation between space and manager and hence distinguishing between managerial and spatial sources of price differentials requires quarterly data on prices at the State level. Using these data as a basis we introduce in this section a new concept capturing the ability of plant managers to obtain prices as favorable as possible in their State.

We denote market prices (as opposed to prices reported by plants) faced by the j*th* DMU as r_M^j, x_M^j . Output market prices faced by the j*th* DMU, r_M^j , consist of ethanol market price r_{eth}^j and prices directly reported by plants in all other revenue categories (byproducts). Input market prices x_M^j consist of corn market prices and prices directly reported by plants in all other cost categories. State level data on corn prices is publicly available from USDA NASS Agricultural Prices. Ethanol prices, on the other hand, were obtained from 2006 and 2007 publications of Ethanol and Biodiesel News magazine (now Ethanol and Biofuels News).

Using these prices we are now ready to define our novel concept of marketing efficiency. Technical and allocative efficiency do not change. We introduce, however, marketing efficiency as an additional component of overall economic efficiency. Marketing efficiency denotes the increase (reduction) in revenue and equi-proportional reduction (increase) in operating cost resulting from the ability of the managers to secure prices more (less) favorable than spot market prices. Therefore we are, in fact, comparing two levels of NOR under the same input-output allocation but different sets of prices (spot market prices and prices actually obtained). Graphically this amounts to measuring the distance between two iso-NOR lines. However since the two iso-NOR lines are calculated based on different prices they display different slopes rendering them not comparable. To make the comparison possible we measure the distance between iso-NOR under observed prices and a parallel version of the iso-NOR with market prices. This is illustrated by the distance between D and C in figure 4.[4]

We measure the distance between both iso-NOR lines by implementing the following procedure. The marketing efficiency of the j^{th} DMU is defined as the hyperbolic distance between maximum NOR with observed prices and NOR obtained under NOR maximizing combination and spot market prices:

$$\pi_M^j = r^j u^{j*} \quad ME^j \;{}^{-1} - p^j x^{j*} \quad ME^j \qquad\qquad j = 1, 2, ..., J \qquad\qquad (9)$$

Where π_M^j is the NOR DMU j would have obtained had it faced market prices and used NOR maximizing combination (i.e. $\pi_M^j = r_M^j u^{j*} - p_M^j x^{j*}$), ME^j is marketing efficiency of the j*th* DMU, $r^j u^{j*}$ are revenues obtained by the j*th* DMU at the NOR maximizing point, and $p^j x^{j*}$ are costs incurred by the j*th* DMU at the NOR maximizing point.

Since NOR with market prices can be lower or higher than NOR with observed prices, ME^j will not be bounded between zero and one. In fact if observed NOR π^j are higher (lower) than π_M^j then ME^j >(<) 1. Purely technical efficiency TE_v^j (represented graphically by the

[4] We have illustrated a situation in which actual prices are more favorable than spot market prices and hence Iso-NOR^B is positioned above and to the left of Iso-NOR^M. If actual prices were less favorable than market prices then Iso-NOR^M would be located above and to the left of Iso-NOR^B and the marketing efficiency score would be lower than one.

distance between x_c^j, u_{DDGS}^j and A), and allocative efficiency AE_v^j (represented graphically by the distance between A and C) stay the same. Marketing efficiency is calculated as explained in (9) and the new overall efficiency is "adjusted" by factoring in marketing efficiency. Overall efficiency with market efficiency, E_v^{jME}, can be expressed as:

$$E_v^{jME} = E_v^j ME^j = AE_v^j TE_v^j ME^j \tag{10}$$

Based on values of π_M^j we calculate marketing efficiency by solving the implicit Eq. (9) for each observation.

Conventional and expanded measures of economic efficiency and their decomposition are calculated for a sample of surveyed dry grind ethanol plants. We first characterize the data collected and the plants surveyed, and then calculate their economic efficiency.

Data

Until recently, no publicly-available data on the economic and technical performance of the current generation of plants was available. Previous studies have calculated input requirements and byproducts' yield per gallon of ethanol produced by plants. Using engineering data McAloon et al. (2000) and Kwiatkowski et al. (2006) measured considerable improvement in plant technical 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.

With the exception of Shapouri et al. and Perrin et al. 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. was collected in 2002 it may not be representative of current technologies in the industry. In contrast to Shapouri et al., Perrin et al. surveyed plants in operation during 2006 and 2007 and employed a much more restrictive sampling criteria (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 economic performance of plants and their drivers.

Data by Perrin et al. consists of 33 quarterly reports of input and output quantities and prices from a sample of seven ethanol plants in the Midwest. Results of our survey contained total expenditures in labor, denaturant, chemicals, and other processing costs and, as a result, we calculated implicit quantities of these inputs dividing total expenditures by their corresponding price indexes. Observed combinations of inputs and outputs are taken to be representative points from the feasible ethanol technology. In this study we use non parametric programming methods (Färe, et al) to infer the boundaries of the feasible technology set. We model the technology as a multiple input-output graph and all efficiency measures are defined in reference to that graph.

Ethanol Plants: Characteristics

Table 1 presents some 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 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 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, plant marketing strategies are also characterized in Table 1. 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 others.

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.

Calculation and Decomposition of Efficiency

Conventional measures of economic efficiency and their decomposition, Eq. (7)-(8), are calculated for our sample of surveyed dry grind ethanol plants and reported in Table 3.[5] Table 3 shows that the economic efficiency of the average DMU is 0.89 which suggests that there may

[5] We calculated the value of TE_v^j using MATLAB as indicated in the Appendix A. Maximum NOR have also been calculated using programming routines in MATLAB.

have been some room for improvement in profitability. Almost all the observed inefficiency comes from allocative sources as indicated by the average value but also by the dispersion observed in this source across DMUs. This in turn means that although most DMUs are operating in the technological frontier they are doing so in points that do not coincide with the NOR-maximizing point (such as point B in Fig. 3).

Based on computed values of π_M^j (see description of Eq. 9) we calculate marketing efficiency by solving the implicit Eq. (9) for each observation. The FZERO procedure in MATLAB was used in calculations. Technical and allocative efficiency are the same as before. Measures of marketing efficiency and adjusted overall economic efficiency are also displayed in Table 3. The average of marketing efficiency indexes is 0.97. This reveals that, in average, plants obtained less favorable relative prices than those observed in spot markets by integrating or managing contracts to sell ethanol and buy corn. We should not, however, jump to the conclusion that plants were inefficient in marketing and procurement activities. First integrating or contracting provide certainty to plants which is valuable to managers either because they are risk averse and/or because “price lock-ins” guarantee a given profitability which is commonly used as collateral to raise more capital from investors or banks. These benefits of contracting are not factored in here. In addition significant dispersion is observed across DMUs as denoted by a standard deviation of 0.09 and a big difference between minimum (0.79) and maximum (1.27) values. In fact the two main sources of dispersion in plant performance are the allocative and marketing components.

Overall economic efficiency changes when marketing efficiency is included in the analysis. The average overall economic efficiency is reduced from 0.89 to about 0.87. This reduction reflects the fact that contracted prices were less favorable than spot market prices faced by DMUs in their States. Furthermore standard deviation increases from 0.07 to 0.1. In light of these results marketing efficiency seems to be an important component in overall economic efficiency. Allocative efficiency continues to be an important component while technical efficiency does not seem to be an important source of overall economic inefficiency.

These results illustrate the importance of accounting for price bargaining in the measurement of efficiency. In this particular case most plants are penalized for operating with prices less favorable than spot prices. In fact only one DMU is rewarded for contracting prices more favorable than spots. These results suggest that DMUs could have obtained higher NORs by waiting and using spot markets to procure corn and sell ethanol. The analysis does not, however, incorporate risk aversion, production planning, capital management, and stochastic components that may well rationalize contracting at prices below spot.

We will proceed now to link these measures of performance at the intensive and extensive margin to potential drivers proposed by the theory of the firm and the theory of industry's life cycle.

Identifying Drivers of Performance

The theory of the firm (TF), as unified by Gibbons (2005), and the theory of the industry's life-cycle (ILC) originated by Williamson (1975) and Stigler (1951), combine insights from the transaction costs, property rights, rent-seeking, and incentive-based approaches to identify drivers of boundary choices by a firm and the impact of those choices on performance both at the intensive and extensive margin.

According to Stigler's theory of the industry's life-cycle, plants built at non-initial stages of the industry are more likely to maximize economic performance by increasing size and exploiting economies of scale (i.e. they should be operating at ranges of technology displaying non-increasing returns to scale). We posit that the ethanol industry is not in its initial stages. It is an industry with a high frequency and scale of transactions, with well established upstream-downstream channels and with a homogeneous and well known technology. Therefore we condense Stigler's argument in the following hypothesis.

H1 (returns to scale): DMUs in our sample display non-increasing returns to scale (exploit economies of scale).

Returns to scale may be calculated by combining technical efficiency under variable, non-increasing and constant returns to scale. 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 has already been defined and measured. Technical efficiency with constant returns to scale technology is:

$$TE_c^j\left(x^j, u^j / C, S\right) = \min\left\{\lambda : \left(\lambda x^j, \lambda^{-1} u^j\right) \in GR\left(C, S\right)\right\}, \quad j = 1, 2, ..., J \qquad (11)$$

We calculated the value of $TE_c^j\left(x^j, u^j / C, S\right)$ using MATLAB as indicated in Appendix B.

Technical efficiency with non-increasing returns to scale technology is:

$$TE_n^j\left(x^j, u^j / N, S\right) = \min\left\{\lambda : \left(\lambda x^j, \lambda^{-1} u^j\right) \in GR\left(N, S\right)\right\}, \quad j = 1, 2, ..., J \qquad (12)$$

We calculated the value of $TE_n^j\left(x^j, u^j / N, S\right)$ using MATLAB as indicated in Appendix C.

Scale inefficiency can be defined in terms of two ratios. The ratio between technical efficiency with constant returns to scale as defined in (11) to technical efficiency with variable returns to scale as defined in (4):

$$S_1^j\left(x^j,u^j\right)=TE_c^j\left(x^j,u^j/C,S\right)/TE_v^j\left(x^j,u^j/V,S\right) \tag{13}$$

The second ratio is that between technical efficiency with constant returns (11) and technical efficiency with non-increasing returns to scale (12):

$$S_2^j\left(x^j,u^j\right)=TE_c^j\left(x^j,u^j/C,S\right)/TE_n^j\left(x^j,u^j/N,S\right) \tag{14}$$

As developed by Färe et al. if ratio (13) is lower than one and if, in addition, ratio (14) is lower than (equal to) one, the observation shows decreasing (increasing) returns to scale. The measures defined in (11) and (12) are calculated with the FMINCON routine in MATLAB. The results for all 33 observations are reported in Table 4. This table shows that the majority of DMUs (and hence the average DMU) are operating in portions of the technology which are very close to displaying CRS; i.e. the average scale efficiency is very close to 1. A total of 19 DMUs display CRS, 12 exhibit IRS, and 2 display DRS. Results in Table 4 are consistent with H1. Plants operating in the corn-ethanol industry do not seem to display strong increasing returns to scale. In fact, most plants seem to be operating at close to constant returns to scale. This is consistent with predictions from the Stigler's theory of the industry's life cycle for industries at non-initial stages of evolution.

According to the theory of the firm, integration, by avoiding double marginalization[6], may reduce the price at which corn is procured and increase the price obtained for ethanol. Conventional DEA would not capture this potential gain. Any change in price would be deemed exogenous and not the result of a careful boundary choice by the plant. In the extension

[6] Integration between an ethanol plant and an elevator reduces procurement costs for the ethanol plant since the elevator's mark-up is not included in the final price of the corn.

developed here, however, the effect of integration on prices is captured by our measure of marketing efficiency. Through enhanced marketing efficiency, integration may increase overall economic efficiency.

In addition integration may also increase allocative efficiency if it is associated with a reduction in input and output price volatility which, in turn, allows managers to plan production ahead. In the ethanol industry downstream integration is more likely to reduce price uncertainty. Some plants market their own ethanol while others rely on marketers. A common feature of different arrangements in the industry between ethanol plants and marketers is that the ethanol producer determines its own output level, and then the marketer has to sell the entire production.[7] Under integration (the plant sells ethanol directly to blenders or brokers) the producer may negotiate price and quantity simultaneously which may allow the production department and the marketing department to coordinate and choose the appropriate combination of inputs and outputs. To sum up integration may enhance both marketing and allocative efficiency. It may increase the former by avoiding double marginalization and the latter by reducing uncertainty. This conjecture inspires the following hypothesis.[8]

H2 (integration - performance): There is a positive correlation between the degree of vertical integration of a DMU and both marketing and allocative efficiency.

The measure of integration is the average of upstream integration and downstream integration. The former is calculated as the percentage of total corn purchased directly to farmers rather than elevators. The latter is the percentage of ethanol sold directly to blenders and brokers instead of marketers. Our data shows that upstream integration is, on average, higher than downstream integration; i.e. 53% of corn is purchased directly from farmers while 29% of

[7] Report on ethanol market concentration, Federal Trade Commission.
[8] Observation 32 was deemed an outlier and removed in testing hypotheses 2-7. The marketing efficiency of that observation was higher than the average by more than three times the standard deviation.

ethanol is sold directly to blenders. Moreover plants in our sample have declared a mix of integration and outsourcing in the corn side (Harrigan 1984, labeled this organizational hybrid *taper integration*) and full or no integration on the ethanol side.

As displayed in Table 5.a. only allocative efficiency seems to be statistically correlated with integration. Furthermore, as shown in Table 6, there is a positive (although rather low) correlation between integration and allocative efficiency. Therefore integration seems to improve economic efficiency by enhancing the ability of plants to align the input-output combination to prices. Integration, per se, does not seem to help plants achieve better relative prices through elimination of double marginalization; i.e. there is no statistically significant relationship between vertical integration and marketing efficiency. The latter result may be due to the fact that while trading through intermediaries (elevators and marketers) implies a surplus loss for ethanol plants (due to double marginalization), these intermediaries, by pooling volumes and exploiting their size, may be able to obtain better prices than those the individual plant would have obtained. If marketers transfer some of the additional surplus obtained from better pricing to ethanol plants then plants may see the loss from double marginalization outweighed by this transfer.

Table 5.b. shows the strength of the statistical link between different factors and efficiency when different subsets of more than one factor (N-way ANOVA) are tested. This table shows that the link between integration and efficiency is not robust; i.e. integration seems to be statistically relevant in explaining efficiency in two subsets (Time-Integration, and Time-Size-Integration) and statistically irrelevant in two other subsets (Integration, and Size-Integration).

A second factor to be considered here is size. There is a rather large subset of the theory of the firm that concerns itself with the link between the size of a DMU and its economic performance. This literature discusses and tests the "Law of Proportionate Effect" (Gibrat's Law). This law depicts that a firm's growth rate and economic performance (usually measured by ROA, ROE or Tobin's Q) is independent of its size; Gibrat (1931). On the other hand, Baumol (1959) hypothesized that performance increases with the size of the firm. There are several reasons why a bigger DMU may display a better economic performance than their smaller counterparts. Some of the most important reasons range from economies of scale, to superior transportation and storage capacity, to a better bargaining power in contracting and trading. Audretsch *et al*. (2002) provides a detailed survey of empirical work on the link between firm size and economic performance and highlights the following conclusion: "Both firm size and age are (positively) correlated with the survival and growth of entrants" (Geroski, 1995, p. 434).

The average capacity in the ethanol industry has steadily increased (Urbanchuk, 2008). The increase in average size coupled with the fact that plants in our sample do not seem to be obtaining increasing returns to scale (results and discussion of Hypothesis 1) suggests that there may be a benefit from increasing size beyond technological reasons. Attainment of more favorable prices due to a better bargaining position (as proposed by the literature following Baumol) would not be identified by the conventional DEA decomposition but it can be captured by the concept of marketing efficiency introduced here. In addition, enhanced storage and transportation capacity may translate into higher flexibility in production and increased allocative efficiency. Therefore we posit Baumol's hypothesis of a positive link between size and economic performance and test it in the context of the ethanol industry based on our sample.

H3 (size - performance): There is a positive correlation between, on one hand, size of a DMU and, on the other, its marketing and allocative efficiency.

According to our results in Table 5.a. the size of a DMU seems to have a statistically significant relationship with its economic performance. Moreover, as indicated by positive correlation coefficients in Table 6, bigger DMUs attain better economic performance through both better price bargaining (marketing efficiency) and better planning of production given prices (allocative efficiency). Table 5.b. reveals the robustness of the link between size and efficiency. In fact size is statistically correlated with all types of efficiency in all subsets except the subset that includes all factors. The latter may be due to the small size of the sample (33) relative to the number of explanatory variables included (3).

Failure to reject H3 denotes a statistical connection between the size of a DMU and its performance. On the other hand rejection of H2 seemed to suggest that the benefits obtained by DMUs from integration (avoiding double marginalization) where outweighed by better pricing achieved by marketers through pooling of volumes. If this were true, bigger DMUs may also be able to extract a higher surplus through integration (avoiding double marginalization) and yet, they may still be able to bargain favorable prices due to their size. This should make integration more effective in enhancing economic efficiency only for bigger plants. This can be tested by looking at the statistical relationship between efficiency, and the interaction between integration and size.

H4 (integration*size - performance): There is a positive correlation between the interaction term (integration*size) and performance.

Given p-values displayed and Table 5.a. and correlation coefficients in Table 6 we fail to reject H4. Low p-values in Table 5.a. denote a statistically significant relationship between the interacting term integration*size and economic efficiency. Table 5.b. reveals that this link is robust across subsets. In addition the positive correlation coefficients between the interacting term and economic efficiency in Table 6, suggests that integration may be more effective in enhancing efficiency the bigger the DMU. Results are consistent with the fact that integration may allow DMUs to bargain favorable prices while, at the same time, avoiding double marginalization.

Despite the individual and/or joint effect of integration and size on efficiency, there is a branch of the empirical literature on the theory of the firm that looks at the potential link between the size of a firm and its integration decision (Hortacsu et al.). If integration is in fact more effective in enhancing efficiency the bigger the DMU, we would expect that bigger DMUs would be more likely to integrate vertically than their smaller competitors. As a result of this conjecture we posit the following hypothesis.

H5 (size - integration): There is a positive correlation between the size of a DMU and its degree of vertical integration.

An analysis of variance (ANOVA) between size and integration reveals that there is a statistically significant relationship between these factors at a 1% significance level.[9] In addition the correlation coefficient between both variables is 0.31. Therefore we fail to reject H5. Results from testing H3-H5 seem to suggest that size operates on economic efficiency through at least two channels. First, it operates directly by enhancing the ability of plants to bargain better prices and by increasing allocative efficiency. Second, it seems to operate on efficiency by both increasing the likelihood of integration and the effectiveness of integration on enhancing efficiency.[10] Therefore there seems to be non-technological benefits from increasing size that

[9] The ANOVA results in a p-value of 0.002.
[10] This effect is non-linear in the sense that integration may be modeled as a function of size and this function, interacted with size itself, affects efficiency.

may rationalize the recent trend of increase in average plant size in the industry.[11] Finally, a word of caution is in place here. Results from testing of H3 and H4 suggested that integration may enhance efficiency when plants are big. But testing of H5 revealed a correlation between size and integration. As a result the correlation between the interaction term and efficiency may be confounding the effect of size with the effect of integration given size.[12]

According to the organizational approach to the theory of the firm, since different ownership structures imply different governance schemes, ownership may affect the internal efficiency and performance of plants. We have two types of ownership structures in our sample; cooperatives and privately owned firms.[13] Cooperatives are usually formed by farmers who, in turn, supply feedstock to the plant. Thus the objective function of the plant may incorporate the welfare of farmers which, in turn, may not be consistent with the plants' NOR maximization. As a result we posit the following hypothesis.

H6 (cooperative status - performance): There is a negative correlation between the cooperative status of a DMU and its economic performance.

As indicated by Table 5.a. the cooperative status of a DMU does not seem to be statistically linked to its performance. Therefore we reject H6. This suggests that managers in cooperatively owned plants may not incorporate the welfare of their members (farmers) in their objective function. It is also possible that these plants incorporate members' welfare but they

---

[11] Another potential reason for changes in the integration decision is experience. According to the theory of the firm (Qian), plants tend to increase integration as they gain more experience. We can not test this based on our sample as plants have declared the same level of integration throughout the period under analysis.

[12] If efficiency does in fact depend on size (e.g. E(size)) and, in addition, integration depended on size (e.g. I(size)) modeling efficiency as a function of the interaction would result in E (size*I(size)). This may well be capturing the overall effect of size and not of integration through size.

[13] Some plants are owned by private firms which are, in turn, owned by public corporations. We do not distinguish here between plants owned (at least partially) by public corporations and those that are not. We treat all privately owned plants homogeneously in terms of ownership.

may be increasing efficiency through another source that partially outweighs NOR losses. In fact DMUs corresponding to cooperatively owned plants in our sample tend to be of bigger size.

Another source of efficiency improvement is learning-by-doing. Usually firms enhance efficiency as they learn more about their own technology and the functioning of the markets in which they operate. Since our sample includes observations from 7 plants during 6 quarters, learning-by-doing should be captured by increases in average efficiency across time. Therefore to find out whether learning seems to be improving efficiency among plants in our sample we posit and test and following hypothesis.

H7 (time - performance): There is a positive correlation between time and economic performance.

Based on results in Table 5.a. and 6 we fail to reject H7. In fact time and all types of efficiency (overall, allocative, and marketing) seem to be statistically significantly correlated at 1% level of significance. Table 5.b. seems to confirm the robustness of this link; time is significantly correlated with all types of efficiency in all subsets. Moreover the correlation coefficients in Table 6 show that time (or learning) seems to enhance allocative efficiency more than marketing efficiency. This result may be explained by the fact that allocative efficiency is a source of internal efficiency in the plant. It represents the ability the marketing and the production departments to coordinate activities and align prices paid and received with a specific production plan. This internal source of performance should be expected to increase as plants gain more experience and shake out initial inefficiencies. On the other hand, marketing efficiency is a boundary source of performance. The ability of plants to obtain more favorable prices depends on their bargaining power which may not be significantly affected by experience but rather by other factors such as size as demonstrated above.

Average Effect of Size, Time, and Integration on Efficiency

Results from the ANOVA are consistent with the hypotheses that time and size may increase overall economic efficiency through both the intensive (allocative) and extensive (marketing) margins. In order for us to have a better grasp of the quantitative effect these factors may have on efficiency we partition the sample into big and small DMUs, DMUs belonging to first and second half of the period under analysis, and DMUs with a degree of integration above the median (0.30) and below the median. We have calculated average efficiency for each subgroup and compare them. Results are presented in Table 8.

Consistently with the positive correlation in Table 7, overall economic efficiency seems to have improved through time as indicated by row 13 of Table 8. This improvement is mostly explained by increases in both marketing and allocative sources as opposed to technical efficiency. Overall efficiency is calculated to increase about 7% from the first half of the period to the second when marketing efficiency is ignored. When marketing efficiency is included in the analysis the increase in overall efficiency is in the order of 9%.

In the DEA methodology, high allocative efficiency occurs when there is an alignment between prices and scale of production; given a technological frontier, low (high) prices tend to support low (high) production scales. Spot prices were extremely favorable at the beginning of the period and smoothly deteriorated afterwards. We hypothesis that the increase in allocative efficiency during the period under analysis may be explained by the fact that plants' capacity was, in average, too small for prices as favorable as those at the beginning of the period. Although some plants increased capacity during the period, average capacity did not completely adjusted to initial prices so that, as prices deteriorated, they became more aligned with existing average capacity. Increases in marketing efficiency across time suggest that plants improved their ability to bargain more favorable prices as they gained more experience in the market.

In addition results in Table 8 suggest that increases in size (from small to big) increase overall efficiency by 7% without considering marketing efficiency, and 11.5% when marketing efficiency is accounted for. This improvement is achieved both through bargaining of better prices and increases in allocative efficiency presumably through reductions in price uncertainty. This in turn may reconcile two empirical facts in the industry; lack of evidence of increasing returns to scale and increases in average plant size.

From testing of H3 and H4 integration appeared to increase efficiency of big DMUs. We discussed then that the correlation between the interaction term and efficiency may have been confounding the effect of size with the effect of the interaction given size. Results in the last row of Table 8 seem to confirm our suspicions. Integration does not seem to increase overall efficiency (or its components) when we focus our attention on big DMUs with high and low levels of integration.

These results are obtained based on quarterly observations from different plants. So an interesting question to ask is whether these results are robust within plants; i.e. is there any evidence of learning-by-doing when we look at the evolution of individual plants rather than averages of the whole population? Is there any evidence that plants have increased their efficiency by increasing size? The answers to these questions can be found in Table 9.

Plants in our sample (as opposed to DMUs) are, in average, 12% more efficient in price bargaining when they increase size from small to big. They are also, in average, 7% more allocative efficient when they increase size. Finally results suggest that plants became more efficient both in price bargaining (12%) and production planning given prices (10%) in time. This is consistent with our hypothesis of learning-by-doing in the corn ethanol industry.

Conclusions

This study exploits data from a survey of ethanol plants and tries to pinpoint the internal and boundary sources of plants' performance and their drivers. Results reveal that DMUs are very efficient from a technical point of view as suggested by a standard deviation of 1% in technical efficiency. However, our results also show dispersion across plants' overall economic efficiency. Bigger DMUs seem to perform better than smaller ones not because of economies of scale but because they can secure more favorable prices (higher marketing efficiency) and execute production plans accordingly (higher allocative efficiency). This may rationalize the increase in the size of the average plant observed in the industry in recent years.

As indicated by the Federal Trade Commission, integration and market power in the ethanol industry has always been a concern of regulators. Exertion of market power in this industry would be economically inefficient for the conventional reasons (loss of economic surplus) but also for environmental reasons; i.e. if ethanol production is cut back more fossil fuels will be burnt and more gases will be emitted into the atmosphere. Our results do not seem to point towards the existence of incentives to vertically integrate. On the other hand, increases in size of a DMU seem to result in better pricing through bargaining. This may suggest potential incentives for horizontal consolidation. Calculations from the Federal Trade Commission (FTC) indicate a reduction in concentration in the ethanol industry during 2008 and 2009, and an increase in concentration in 2010. So far, however, the calculated Herfindahl-Hirschman Indexes (HHI) seem to indicate that the corn ethanol industry remains un-concentrated. The apparent inconsistency between results obtained here (there seems to be economic benefits from merging and pooling production volumes) and those obtained by the FTC may be explained by several factors. First, according to the FTC, bankruptcies of a few large firms during 2009 and 2010 had a de-concentrating effect in the industry. Second, high profitability triggered a wave of entry into the industry that remained very strong until 2009. Entry has a de-concentration effect that may have offset consolidation, resulting in a low HHI. Entry has decelerated since 2009. Finally, the FTC measures concentration at the national level. Increases in size and/or consolidation may be occurring at smaller regional scales.

References

Audretsch, D., Klomp, L., Santarelli, E., and Thurik, A. 2004. Gibrat's Law: Are the Services Different? Review of Industrial Organization; May 2004; 24, 3; pg. 301.

Cherchye, L., Kuosmanen, T., and Post, T. 2002. “Non-parametric production analysis in non-competitive Environments.” Int. J. Production Economics 80 (2002) 279–294.

Coelli, T., P. Rao, and G. Battese, 1998, *An Introduction to Efficiency and Productivity Analysis*, Kluwer Academic Publishers, Boston.

Dybvig, P. and Warachka, M. 2010. “Tobin’s Q Does Not Measure Performance: Theory, Empirics, and Alternative Measures.”

Eidman, V. “Ethanol Economics of Dry Mill Plants.” In *Corn-Based Ethanol in Illinois and the U.S.*: A Report from the Department of Agricultural and Consumer Economics, University of Illinois, 2007.

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

Farrell, A., Plevin, R., Turner, B., Jones, A., O'Hare, M. and Kammen, D. "Ethanol can contribute to energy and environmental goals." *Science* 2006; 311(5760): 506–508.

Gibbons, Robert. 2005. "Four Formal(izable) Theories of the Firm?" Journal of Economic Behavior and Organization 58: 202-247

Harrigan KR. 1984. Formulating vertical integration strategies. *Academy of Management Review* **9**: 638–652.

Hortacsu, Ali and Syverson, Chad (2007) "Vertical Integration and Production: Some Plant-Level Evidence," University of Chicago mimeo.

Kwiatkowski, J., McAloon, A., Taylor, F. and Johnson, D. "Modeling the process and costs of fuel ethanol production by the corn dry-grind process." *Industrial Crops and Products* 2006; 23: 288-296.

McAloon, A., Taylor, F. and Yee, W. "Determining the Cost of Producing Ethanol from Corn Starch and Lignocellulosic Feedstocks." *National Renewable Energy Laboratory,* 2000; NREL/TP-580-28893.

McNew, K., and D. Griffith. "Measuring the Impact of Ethanol Plants on Local Grain Prices." Review of Agricultural Economics 27 (2005):164 - 180.

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

Pimentel, D. & Patzek, T. (2005). Ethanol production using corn, switchgrass, and wood: biodiesel production using soybean and sunflower. Natural Resources Research, 14(1), 65–76.

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

Qian, L., Agarwal, R. and Hoetker, G. 2009. Configuration of Value Chain Activities: The Effect of Pre-Entry Capabilities, Transactions Hazard and Industry Evolution on the Decision to Internalize.

Shapouri, H. and Gallagher, P. "USDA's 2002 Ethanol Cost-of-Production Survey." Agricultural Economic Report No. 841, U.S. Dept of Agriculture, 2005.

Stigler, G. J. 1951, "The division of labor is limited by the extent of the market." The Journal of Political Economy, **59**(3): 185-193.

Tyner, W. August 16-22, 2009. "The Integration of Energy and Agricultural Markets." Presented at the 27th International Association of Agricultural Economists Conference Beijing, China.

Urbanchuk, J. 2008. "Contribution of the Ethanol Industry to the Economy of the United States." Prepared for the Renewable Fuels Association, February 20, 2008

Van Wart, J. and Perrin, R. 2009. "Spatial Welfare Impacts of a Grain Ethanol Plant." Faculty Publications: Agricultural Economics Department, University of Nebraska, Lincoln.

Williamson, O. E. 1975, *Markets and hierarchies, analysis and antitrust implications*, New York, Macmillan.

Appendix A

The measure in (4) can be computed as the value of λ in the following programming problem:

$$
\begin{aligned}
\underset{\lambda,z}{Min}\ \lambda \qquad\qquad s.t. \quad & \lambda^{-1}u^{j} \leq zM \\
& \lambda x^{j} \leq zN \\
& z^{j} \varepsilon\ \Re^{+}, \quad j = 1, 2, ..., J
\end{aligned}
$$

Appendix B

The measure in (9) can be computed as the value of λ in the following programming problem:

$$\underset{\lambda,z}{Min}\,\lambda \qquad s.t. \quad \lambda^{-1}u^{j} \leq zM$$

$$\lambda x^{j} \leq zN$$

$$\sum_{j=1}^{J} z^{j} = 1$$

Appendix C

The measure in (10) can be computed as the value of λ in the following programming problem:

$$\underset{\lambda,z}{Min}\,\lambda \qquad s.t. \quad \lambda^{-1}u^{j} \leq zM$$

$$\lambda x^{j} \leq zN$$

$$\sum_{\mathrm{j}=1}^{J} z^{j} \leq 1$$

Tables

Table 1. Characteristics of the seven surveyed plants

<table>
<tr><td>States Represented</td><td colspan="5">Iowa, Michigan, Minnesota, Missouri, Nebraska, S. Dakota, Wisconsin</td></tr>
<tr><td rowspan="3">Annual Production Rate (m. gal/y)</td><td>Smallest</td><td colspan="4">42.5</td></tr>
<tr><td>Average</td><td colspan="4">53.1</td></tr>
<tr><td>Largest</td><td colspan="4">88.1</td></tr>
<tr><td rowspan="6">Number of Survey Responses by Quarters</td><td>03_2006</td><td colspan="4">5</td></tr>
<tr><td>04_2006</td><td colspan="4">6</td></tr>
<tr><td>01_2007</td><td colspan="4">7</td></tr>
<tr><td>02_2007</td><td colspan="4">7</td></tr>
<tr><td>03_2007</td><td colspan="4">7</td></tr>
<tr><td>04_2007</td><td colspan="4">2</td></tr>
<tr><td rowspan="3">Percent of Byproduct Sold as Dry DGS</td><td>Smallest</td><td colspan="4">0</td></tr>
<tr><td>Average</td><td colspan="4">54</td></tr>
<tr><td>Largest</td><td colspan="4">97</td></tr>
<tr><td rowspan="4">Primary Market Technique</td><td></td><td>Corn</td><td>Ethanol</td><td>DDGS</td><td>MWDGS</td></tr>
<tr><td>Spot</td><td>0</td><td>0</td><td>3</td><td>1</td></tr>
<tr><td>Customer Contract</td><td>5</td><td>2</td><td>0</td><td>1</td></tr>
<tr><td>Third Party/Agent</td><td>0</td><td>5</td><td>2</td><td>2</td></tr>
</table>

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	199
Max	8	569	13.3	22.9	34.2	56.2

Table 3. Economic Efficiency Decomposition

DMU	Conventional Overall Economic Efficiency	Technical Efficiency	Allocative Efficiency	Marketing Efficiency	Overall Economic Efficiency with Marketing Efficiency[a]
1	0.82	0.977	0.84	0.81	0.66
2	0.84	1	0.84	0.90	0.76
3	0.79	0.985	0.80	0.89	0.70
4	0.72	1	0.72	0.90	0.64
5	0.80	1	0.80	0.90	0.72
6	0.85	0.979	0.87	1.05	0.89
7	0.95	1	0.95	0.93	0.88
8	0.82	1	0.82	1.06	0.88
9	0.83	1	0.83	0.92	0.76
10	0.80	0.997	0.80	1.06	0.84
11	0.86	1	0.86	0.99	0.85
12	0.94	1	0.94	1.03	0.97
13	0.96	1	0.96	1.02	0.98
14	0.95	1	0.95	0.95	0.90
15	0.91	1	0.91	0.98	0.89
16	0.92	1	0.92	0.87	0.81
17	0.90	1	0.90	0.93	0.84
18	0.88	1	0.88	0.99	0.87
19	0.88	1	0.88	1.02	0.89
20	0.996	1	0.996	0.97	0.97
21	0.93	1	0.93	0.93	0.87
22	0.92	1	0.92	0.95	0.87
23	0.93	1	0.93	0.79	0.74
24	0.89	1	0.89	0.98	0.87
25	0.91	1	0.91	1.02	0.93
26	1	1	1	0.99	0.99
27	0.96	1	0.96	0.99	0.95
28	0.95	1	0.95	1.01	0.96
29	0.92	1	0.92	0.98	0.91
30	0.94	1	0.94	0.99	0.93
31	0.912	0.993	0.92	1.04	0.95
32	0.80	1	0.80	1.27	1.02
33	0.94	1	0.94	1.03	0.97
Average	**0.891**	**0.998**	**0.893**	**0.97**	**0.868**
Std Dev	0.07	0.01	0.07	0.09	0.10
Min	0.72	0.979	0.72	0.79	0.64
Max	1	1	1	1.27	1.02

[a] Calculated as Overall Economic Efficient times Marketing Efficiency

Table 4. Returns to Scale of DMUs

DMU	Technical Efficiency VRS	Technical Efficiency NIRS	Technical Efficiency CRS	Scale Efficiency CRS/VRS	Category
1	0.977	0.955	0.955	0.977	IRS
2	1	1	1	1	CRS
3	0.985	0.976	0.976	0.991	IRS
4	1	1	1	1	CRS
5	1	1	1	1	CRS
6	0.979	0.977	0.977	0.997	IRS
7	1	1	1	1	CRS
8	1	0.985	0.985	0.985	IRS
9	1	1	1	1	CRS
10	0.997	0.991	0.991	0.994	IRS
11	1	1	1	1	CRS
12	1	1	1	1	CRS
13	1	1	1	1	CRS
14	1	1	1	1	CRS
15	1	0.953	0.951	0.951	DRS
16	1	0.979	0.979	0.979	IRS
17	1	1	1	1	CRS
18	1	0.949	0.949	0.949	IRS
19	1	1	1	1	CRS
20	1	1	1	1	CRS
21	1	1	1	1	CRS
22	1	0.975	0.975	0.975	IRS
23	1	0.993	0.993	0.993	IRS
24	1	1	1	1	CRS
25	1	1	1	1	CRS
26	1	1	1	1	CRS
27	1	1	1	1	CRS
28	1	0.967	0.967	0.967	IRS
29	1	0.944	0.944	0.944	IRS
30	1	1	1	1	CRS
31	0.993	0.983	0.983	0.990	IRS
32	1	1	1	1	CRS
33	1	1	0.976	0.976	DRS
Average	0.998	0.997	0.996	0.999	

Table 5.a. Potential Drivers of Economic Efficiency with Marketing Efficiency

Factor	Overall Efficiency (Prob>F[1])	Allocative Efficiency (Prob>F[1])	Marketing Efficiency (Prob>F[1])
Integration	0.30	**0.08**	0.30
Size*Integration	**0.01**	**0.06**	**0.05**
Time (Quarter:1-6)	**~ 0**	**~ 0**	**0.01**
Cooperative	0.81	0.64	0.89
Size (Big/Small)	**~ 0**	**0.01**	**0.01**

[1] This column displays the p-values of the hypothesis that the corresponding variable has no effect on overall economic efficiency; i.e. the closest this value to zero the stronger the effect of the treatment variable on efficiency.

Table 5.b. Correlates of Overall Economic Efficiency, Allocative Efficiency, and Marketing Efficiency

	Time			Size			Integration			Size*Integration		
	OE[(a)]	AE[(b)]	ME[(c)]	OE[(a)]	AE[(b)]	ME[(c)]	OE[(a)]	AE[(b)]	ME[(c)]	OE[(a)]	AE[(b)]	ME[(c)]
Time	**~ 0**	**~ 0**	**0.01**	-	-	-	-	-	-	-	-	-
Size	-	-	-	**~ 0**	**0.01**	**0.01**	-	-	-	-	-	-
Integration	-	-	-	-	-	-	0.30	**0.08**	0.30	-	-	-
Size*Integration	-	-	-	-	-	-	-	-	-	**0.01**	**0.06**	**0.05**
Time-Size	**~ 0**	**~ 0**	**0.02**	**~ 0**	**0.05**	**0.04**	-	-	-	-	-	-
Time-Integration	**~ 0**	**~ 0**	**~ 0**	-	-	-	**~ 0**	**~ 0**	**0.01**	-	-	-
Size-Integration	**-**	**-**	**-**	**0.01**	**0.08**	**0.01**	0.60	0.17	0.22	**-**	**-**	-
Time-Size*Integration	**~ 0**	**~ 0**	**0.03**	-	-	-	-	-	-	**~ 0**	**~ 0**	0.11
Time-Size-Integration	**~ 0**	**~ 0**	**~ 0**	0.39	0.56	0.26	**0.01**	**0.01**	**0.04**	-	-	-

(a) Adjusted Overall Economic Efficiency, (b) Allocative Efficiency, (c) Marketing Efficiency

Table 6. Correlation between Efficiency Sources and Factors

Factor	Overall Efficiency	Allocative Efficiency	Marketing Efficiency
Time	0.74	0.75	0.39
Size	0.57	0.43	0.45
Integration	N/A	0.07	N/A
Integration*Size	0.34	0.25	0.27

Table 7. Average Effect of Time, Size, and Integration on Performance

	Marketing Efficiency	Technical Efficiency	Overall Efficiency with Marketing Efficiency	Allocative Efficiency	Overall Efficiency
Average	**0.974**	**0.998**	**0.868**	**0.893**	**0.891**
Average - Big	0.993	0.999	0.914	0.922	0.921
Average - Small	0.953	0.997	0.820	0.863	0.860
Big / Small	**1.042**	**1.002**	**1.115**	**1.068**	**1.070**
Average - 1	0.879	0.993	0.697	0.800	0.794
Average - 2	1.001	0.996	0.850	0.853	0.850
Average 3	0.968	1.000	0.895	0.924	0.924
Average first half	0.949	0.996	0.814	0.859	0.856
Average 4	0.941	1.000	0.869	0.924	0.924
Average 5	1.002	0.999	0.944	0.943	0.942
Average 6	1.152	1.000	0.994	0.871	0.871
Average second half	1.032	1.000	0.936	0.913	0.912
Second half/First half	**1.087**	**1.003**	**1.150**	**1.062**	**1.066**
Average – Big Integrated	0.985	0.997	0.896	0.909	0.918
Average – Big Non-Integrated	1	1	0.931	0.931	0.918
Integrated/Non-Integrated	**0.985**	**0.997**	**0.963**	**0.978**	**1**

Table 8. Average Effect of Time and Size per Plant

Efficiency Source / Factor	Marketing Efficiency	Allocative Efficiency
Average Size Effect (per plant)	1.12	1.07
Average Time Effect (per plant)	1.12	1.10

Figures

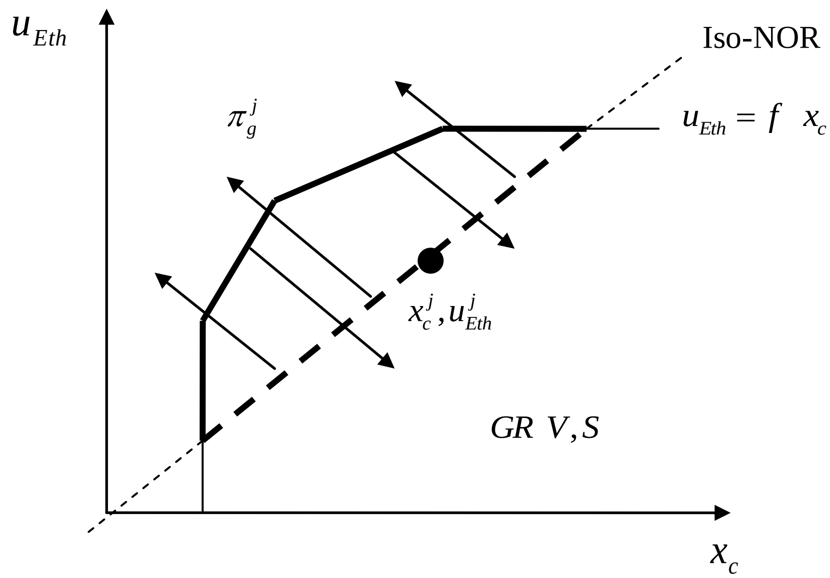

Fig. 1 – Iso-NOR and Sets

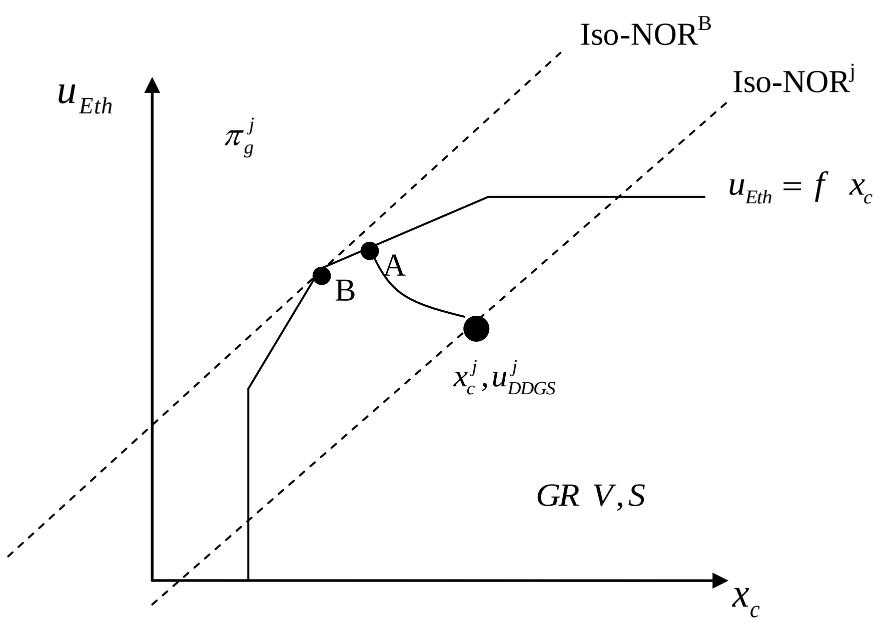

Fig. 2 - Technical Efficiency

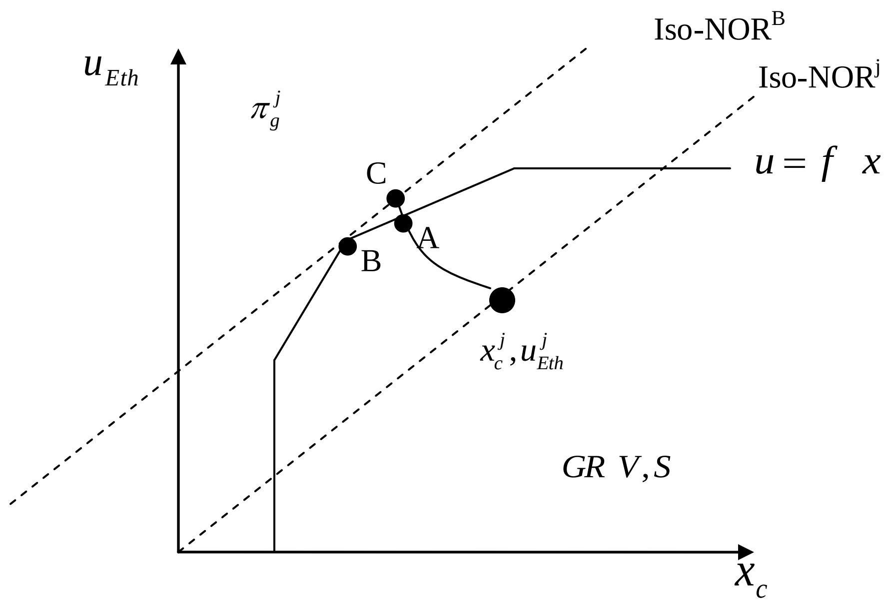

Fig. 3 - Decomposition of Overall Economic Efficiency

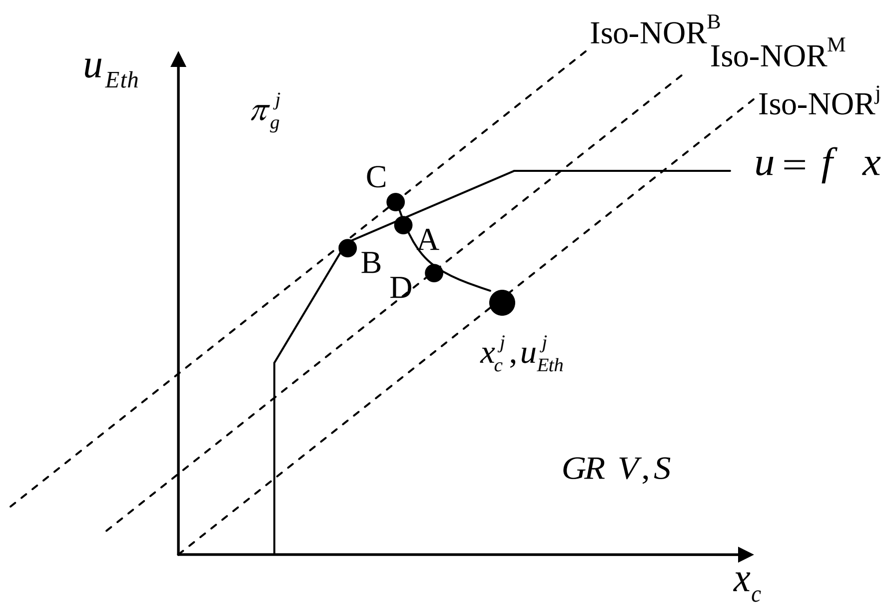

Fig. 4 - Decomposition of Overall Economic Efficiency with Marketing Efficiency