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# **Economic and Marketing Efficiency Among Corn Ethanol Plants**

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# **Economic and Marketing Efficiency Among Corn Ethanol Plants**

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## **Economic and Marketing Efficiency Among Corn Ethanol Plants**

### **Abstract**

In the corn ethanol industry, the ability of plants to obtain favorable prices through marketing decisions is considered important for their overall economic performance. Based on a panel of surveyed ethanol plants we extend data envelopment analysis (DEA) to decompose the economic efficiency of plants into conventional sources (technical and allocative efficiency) and a new component we call marketing efficiency. The latter measure allows us to evaluate plants' ability to contract favorable prices of corn and ethanol relative to spot market prices and its implications for their overall economic performance. Results show that plants are very efficient from a technical point of view. Dispersion in overall economic performance observed across units is mainly explained by differences in allocative and marketing sources. Our results are consistent with the view that plants with higher production volumes may perform better, in part, because they can secure more favorable prices through improved marketing performance. Plants also seem to achieve significant improvements in marketing performance through experience and learning-by-doing. These results are consistent with two facts; 1) economies of scale may not be the only reason behind the increase in the average size of plants in the ethanol industry and; 2) there might be incentives for horizontal consolidation across plants.

*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 (Tyner, 2008). It may also increase corn grower revenues (McNew) and reduce feeding costs of 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 is becoming increasingly important. Identifying and quantifying potential drivers of plants economic performance may be of interest to plant managers, government officials, farmers, and other stakeholders (e.g. banks, investors, environmental agencies). This study puts special emphasis on the ability of plants to contract favorable prices of corn and ethanol (relative to spot market prices) on the basis of their production volumes and experience in the industry. We quantify this by extending conventional non parametric measures of efficiency to include a new component called marketing efficiency and linking this measure to a vector of proposed correlates.

## **Price Bargaining in Contracts and Economic Performance**

Performance, as discussed by the theory of the firm (Gibbons), is determined by the choice of boundaries (what activities are conducted internally or outsourced) and by choices internal to the organization once the boundaries have been set. In the context of the ethanol industry the choice of boundaries is understood as the decision of plants on whether (and how)

they purchase corn directly from farmers or through elevators and whether (and how) they market their ethanol directly to blenders or through third parties. Therefore the choice of boundary is understood as marketing decisions made by plant managers. These decisions affect prices (net of transportation and marketing costs) faced by plants and, hence, their overall economic performance. Conventional methods of measurement of economic efficiency allow quantification of efficiency once the prices have been set and, thus, cannot factor in the role of marketing performance on overall economic efficiency. We propose to extend these methods in a way that permits quantification of overall economic efficiency including efficiency associated with marketing activities. 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 marketing efficiency and certain drivers believed to be important in the ethanol industry.

Differential performance across ethanol plants may be explained by managerial ability but also by constraints faced by plants in the market. 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.<sup>1</sup> Technical efficiency represents the ability of managers to achieve an engineering optimum. Allocative efficiency assumes prices are exogenous (an exception is

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<sup>1</sup> 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.

Cherchye et al. which considers non-competitive settings) and measures performance based on the alignment of the chosen input-output combination to exogenous prices. For this reason, it is not designed to measure the ability of the plant to increase operating margins by partially controlling prices through marketing decisions. In the context of the ethanol industry this could be a serious drawback.

Marketing alternatives available to plants involve conducting marketing and procurement activities directly with blenders and farmers or through intermediaries. They also involve different combinations of contracts and spot markets. The relative success of alternatives may also be affected by plants' bargaining power. By choosing a certain mix of alternatives, ethanol plants, 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 decisions, management of contracts and spots, and/or hedging. Naturally we call this new measure, marketing efficiency.

#### *Characterization of Technology from Individual Plant Data*

The 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:

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

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

### *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<sup>3</sup> and strong disposability of inputs and outputs the graph can be denoted by:

$$GR^j = \{x, u : u^j \leq z^j M, x^j \geq z^j N, \sum_{j=1}^{33} z^j = 1, j = 1, \dots, 33\} \quad (1)$$

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  $j$ th DMU,  $N$  is the 33x7 matrix of observed inputs, and  $x^j$  is the 1x7 vector of observed inputs corresponding to the  $j$ th DMU.

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

$$\pi_g^j x^j, u^j = x^{j'}, u^{j'} : p^j x^{j'} + r^j u^{j'} \geq p^j x^j + r^j u^j \quad (2)$$

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  $\pi_g^j$  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  $\pi_g^j$  includes combinations outside the graph and hence not attainable by DMUs in the sample. The subset of observations in  $\pi_g^j$  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:

$$\pi_g^j x_c^j, u_{Eth}^j \cap GR V, S \quad (3)$$

The  $j$ th 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  $j$ :

$$TE_v^j(x^j, u^j / V, S) = \min \lambda : \pi_g^j \lambda x_c^j, \lambda^{-1} u_{Eth}^j \cap GR(V, S) \neq \emptyset \quad (4)$$

Where  $\lambda$  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:

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

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:

$$\overline{\pi}^j = E_v^j p^j x^j + E_v^{j-1} r^j u^j \quad j = 1, 2, \dots, J \quad (6)$$

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:

$$E_v^j = AE_v^j TE_v^j \quad (7)$$

Therefore, we can define allocative inefficiency residually as:<sup>2</sup>

$$AE_v^j = \frac{E_v^j}{TE_v^j} \quad (8)$$

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' marketing abilities may affect, at least to some extent, the prices obtained for ethanol and paid for corn. This fact would be ignored by the conventional decomposition of efficiency. In order to capture the effect of plants' pricing strategies (integration/third parties, ability to bargain price in contracts) on performance we introduce the concept of marketing efficiency. Provided we have price 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,<sup>3</sup> and inflation. The part due to inflation is controlled for by adjusting all prices to a base quarter (3<sup>rd</sup> quarter of 2006) using the Producer Price Index (PPI) as calculated

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<sup>2</sup> In this way we minimize stronger assumptions about convexity that may result in artificially low efficiency indexes.

<sup>3</sup> Note that expectation formation on market prices will affect plants marketing decisions. Differences in price expectations are, thus, embodied in managerial efficiency.

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 channels (i.e. vertical integration and third parties as indicated in Table 1) and have different degrees of success in bargaining prices in marketing contracts. 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, in a given State and a given quarter, prices as favorable as possible relative to prevailing market prices in that State and that quarter

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 (Iso-NOR<sup>B</sup> in figure 4) and a parallel version of the iso-NOR with market prices (Iso-NOR<sup>M</sup> in figure 4). This is illustrated by the distance between D and C in figure 4<sup>4</sup> where D is the point on Iso-NOR<sup>M</sup> corresponding to an equi-proportional change in inputs and outputs from point C. 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 maximum NOR with spot market prices:

$$\pi_M^j = \frac{r^j u^{j*}}{p^j x^{j*}} ME^j \quad j = 1, 2, \dots, J \quad (9)$$

Where  $\pi_M^j$  is the NOR DMU j would have obtained had it faced market prices and used the corresponding NOR maximizing combination  $(u_M^j, x_M^j)$  (i.e.  $\pi_M^j = \frac{r_M^j u_M^j}{p_M^j x_M^j}$ ),  $ME^j$  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 with observed prices, and  $p^j x^{j*}$  are costs incurred by the  $j^{th}$  DMU at the NOR maximizing point with observed prices.

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  $\pi^j$  are higher (lower) than  $\pi_M^j$  then  $ME^j > (<) 1$ . Purely technical efficiency  $TE_v^j$  (represented graphically by the

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<sup>4</sup> The illustrated situation assumes actual prices are more favorable than spot market prices and hence Iso-NOR<sup>B</sup> is positioned above and to the left of Iso-NOR<sup>M</sup>. If actual prices were less favorable than market prices then Iso-NOR<sup>M</sup> would be located above and to the left of Iso-NOR<sup>B</sup> 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:

$$E_v^{jME} = E_v^j ME^j = AE_v^j TE_v^j ME^j \quad (10)$$

Based on values of  $\pi_M^j$  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. Not all plants reported data in all quarters so we are left with an unbalanced panel data set. We will discuss implications of this in subsequent sections. 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 signed either with elevators or farmers. Similarly, in selling ethanol, five of the seven 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.a.<sup>5</sup> Table 3.a. shows that the economic efficiency of the average DMU is 0.89 which suggests that there may 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  $\pi_M^j$  (see explanation 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 contracted 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 establishing prices to be obtained some time in advance to the quarter in which production takes place 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.

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<sup>5</sup> 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.

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 which implies that contracting prices in advance may have reduced NOR, in average, by as much as 4%. 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 a significant source of overall economic inefficiency.

Only the observation corresponding to plant 7<sup>6</sup> in the fifth quarter (DMU 26) seems to achieve allocative efficiency. The same plant achieves high scores of allocative efficiency in other quarters (DMUs 13 and 20). Plant 7 is the biggest (measured by production volumes) plant in our sample and DMU 26 corresponds in turn to the biggest volume corresponding to that plant. Crush margins (price of ethanol relative to corn) were very favorable across the nation in the period under analysis here. This amounts to a flat iso-NOR line such as Iso-NOR<sub>2</sub><sup>B</sup> in figure 3. This would in turn push plants' NOR maximizing combinations towards a high volume allocation such as point D in figure 3. Point D in figure 3 is the graphical equivalent to DMU 26 in our sample; i.e. an observation that is technically efficient and it is also big enough to, given favorable crush margins, achieve allocative efficiency.

Plant 7 is also the plant that performs the best in terms of marketing efficiency (see Table 3.b). As displayed in Table 3.b. The average marketing efficiency of this plant is 0.994 followed by plants 5 (0.988) and 1 (0.986). The characteristics of these plants vary in many respects. Plant 1 is one of the biggest plants in our sample but plant 5 is not. Plant 5, on the other hand, is vertically integrated (procures the majority of its corn directly from farmers and sells all of its ethanol directly to blenders) while plants 1 and 7 are not. Plants 5 and 7 are owned by firms that

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<sup>6</sup> Due to confidentiality issues we cannot identify the State in which this particular plant is located.

own other plants as well while plant 1 is not. Plants 1 and 7 are privately owned while plant 5 is a farmers' cooperative. Finally a general improvement in marketing efficiency in time is apparent across plants from Table 3.b. The systematic link between marketing performance and plant characteristics (size, vertical integration, experience, ownership structure, multi-plant status) will be explored in subsequent sections.

These results illustrate the importance of accounting for price bargaining in the measurement of economic efficiency. 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 now proceed to link this measure of marketing efficiency to factors that we posit may be potential correlates of marketing success.

### **Identifying Correlates of Marketing Performance**

Our unit of analysis is the plant. Due to the panel nature of our data, our unit of observation corresponds to a plant in a given quarter and we call this unit: DMU or decision making unit. Results in Table 3 reveal a significant dispersion of marketing efficiency across DMUs. Figure 5 displays a histogram showing the approximate distribution of marketing efficiency scores across DMUs. The histogram does not take into account one observation deemed as outlier.<sup>7</sup> A normal density function that smoothes out the distribution has been superimposed to the histogram in Figure 5.

The highest frequency of marketing efficiency scores (i.e. most of the “mass” of the distribution) appears to be located between 0.95 and 1. This means that plants seem to operate under prices that are close but less favorable than spot market prices. However a significant

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<sup>7</sup> This DMU reported an observed ethanol price of \$2.5 per gallon in a time where the market price was \$1.60. This put its marketing efficiency at 1.27 or more than three standard deviations (0.09) away from the average (0.97). Explanations of possible causes of this anomaly were not provided by the plant.

degree of variability across DMUs can be observed as well. High dispersion in marketing efficiency scores (jointly with differences in allocative efficiency) seem to cause high dispersion in overall economic efficiency scores across DMUs. The ability of plants to maximize their effective crush margin<sup>8</sup> relative to the market's crush margin (which is approximated here by our measure of marketing efficiency) becomes especially important for survival in a time where market prices are not very favorable. Therefore identifying potential drivers of marketing efficiency may shed some light on future entry/survival trends in the ethanol industry.

There are several characteristics that may affect a plant's marketing performance in a given quarter and, hence, shape the distribution in Figure 5. First, the size of an observation (a plant in a given quarter is classified as big if its production is higher than the median in our sample, which is 12,930,306 gallons, and it is classified as small otherwise) is thought to affect its ability to market ethanol at a higher price (net of transportation costs) and, perhaps, procure corn at lower prices. The link between size and marketing performance is explained by reductions in transportation cost (per unit) and potential increase in bargaining power.

On the corn procurement side, available empirical evidence (Schmigdal et al. 2010), seems to suggest that facilities producing larger volumes are less likely to utilize minimum price contracts and less likely to transport feedstock by truck-only (a transportation mode considered more expensive than rail). Most plants in our sample market their ethanol through third parties (i.e. marketers). Higher production volumes may enhance a plant's ability to bargain more favorable conditions with marketers because marketers may better exploit logistical and transportation infrastructure at higher volumes. In addition larger facilities may have a higher reservation price to enter into an agreement with an ethanol marketer; i.e. they may be able to do better than smaller facilities when marketing their own ethanol production. This is because plants

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<sup>8</sup> The crush margin is the difference between ethanol price and corn price.

can negotiate over larger volumes, use low cost transportation (i.e. rail), and economically afford hiring marketing staff members. Consistently with the latter, Schmigdal et al., 2010 found that plants producing larger volumes were more likely to utilize in-house ethanol marketing activities. Finally, plants capable of producing larger volumes are also associated with increased storage capacity which provides more flexibility in managing crush margins. The possible link between the production volume of a plant and its marketing performance may be tested by looking at the statistical relationship between our dichotomous measure of size and our measure of marketing efficiency.

It is generally believed that ethanol plants improve performance as they gain experience in the market. Perfecting coordination and logistics, and building marketing and information networks, are among the reasons why a plant may enhance performance as experience is accumulated. Previous empirical (Schmigdal et al.) and anecdotal evidence from specialized press suggest that either through better in-house marketing management or by bargaining better agreements with marketers, more experienced plants are likely to obtain more favorable net (of transportation costs) prices. Therefore experience is expected to increase marketing efficiency. We will test this by calculating the marginal effect of experience (measured by the number of quarters that the plant was in operation up to the time period corresponding to each observation) on marketing efficiency.

Finally there are other plant characteristics that may affect marketing efficiency such as the multi-plant nature of a DMU (i.e. whether a plant is owned by a firm that owns other plants), the degree of vertical integration, and the ownership structure. Plants have reported the same ownership structure, degree of integration, and multi-plant status for the entire period. Therefore these characteristics are non time-varying in nature. Under a panel data set, the marginal effects

of factors that are constant through time are identified only if there are no unobservable fixed effects affecting marketing efficiency. Since these plants seem to be very homogeneous from a technological standpoint and, in addition, they follow standard marketing and transportation practices we posit that the aforementioned characteristics summarize the main differences between plants. Therefore we calculate marginal effects of integration, multi-plant status, and ownership under the assumption of no unobservable fixed effects.

Verifying the role of potential correlates of efficiency involves regressing calculated efficiency scores against a set of proposed exogenous variables. Second stage regressions using OLS are usually deemed inappropriate because efficiency scores constitute a limited dependent variable (restricted between 0 and 1). Hence linearity carries a misspecification problem. One of the advantages of our definition of marketing efficiency is that OLS is not subject to misspecification as these scores are not bounded between zero and one.

In addition Simar and Wilson (1998) have warned against the use of second stage regressions as these may be subject to upward bias for small samples (Simar and Wilson, 1998). They propose a bootstrapping procedure to correct for this bias. However the upward bias is quantitatively relevant when the sample is thought to miss many observations from the actual population that could push the technological frontier upwards. This is not likely to be the case in our application mainly for two reasons. First the technology in this industry is very homogeneous as revealed by the small standard deviation across technical efficiency scores. Second, plants included in our sample are thought to be representative of the latest generation technology and, hence, are expected to drive the technological frontier in the industry minimizing potential upward biases caused by a small sample size.

## Results and Discussion

We use conventional linear pooled OLS (POLS) techniques without bootstrapping to approximate the marginal effect of drivers on marketing efficiency. The equation to be estimated is:

$$ME_{it} = A_i + \beta_1 Size_{it} + \beta_2 Exper_{it} + \beta_3 Integ_i + \beta_4 Multiplant_i + \beta_5 Coop_i + \beta_6 Integ_i * Size_{it} + u_{it} \quad (11)$$

Equation (11) posits that the marketing efficiency score of plant  $i$  in quarter  $t$  depends linearly on the size of plant  $i$  at time  $t$  (1 if big, 0 otherwise), experience of plant  $i$  at time  $t$  (quarters in operation up to quarter of observation), integration (a continuous variable bounded between 0 and 1 indicating the average of the fraction of corn purchased directly from farmers instead of elevators and ethanol sold directly to blenders instead of marketers), the multi-plant status of a DMU (1 if multi-plant, 0 otherwise), the ownership structure (1 if cooperative, 0 if privately owned firm), the interaction between integration and size, and random noise represented by  $u_{it}$ .

As previously discussed size and experience are expected to increase marketing efficiency (i.e.  $\beta_1 > 0$  and  $\beta_2 > 0$ ). Integration (conducting marketing activities in-house) may allow plants to increase their marketing efficiency by avoiding double marginalization (i.e. avoiding mark-ups charged by elevators and ethanol marketers for marketing services). On the other hand intermediaries, by pooling volumes and exploiting marketing, logistics and distribution infrastructure, may allow their clients to obtain more favorable prices. Integration, hence, is expected to be effective in enhancing marketing efficiency only for big DMUs that can, by themselves, exploit (marketing) economies of size; i.e.  $\beta_3 = 0$  and  $\beta_6 > 0$ .

The effect of the multi-plant status of a DMU is unknown. First DMUs owned by firms that own other plants may achieve better prices if the owner firm is able to exploit marketing economies of size (pooling volumes from several plants) and bargain a better deal in terms of prices net of transportation cost. On the other hand they may be part of an overall firm-level profit maximizing behavior that need not be consistent with plant-level profit maximizing behavior. Hence we do not have a prior expectation on the sign of  $\beta_4$ . Finally we have two types of ownership structures in our sample; cooperatives and privately owned firms.<sup>9</sup> 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 higher marketing efficiency scores. As a result we expect that  $\beta_5 < 0$ .

Equation (11) proposes 6 independent variables and an intercept which marginal effects are to be estimated with 32 observations (the 33 original observations minus the aforementioned outlier). It is not surprising then that, as shown by Table 5, a regression including all factors yield, mostly, statistically insignificant individual coefficients (as indicated by high individual p-values) and a globally significant model (see high F-statistic and corresponding p-value of 0.07). Our strategy to overcome this problem consist of estimating models corresponding to every possible combination of the six (the intercept is included in every model) independent factors proposed here and conducting statistical tests for model comparison. We compare models by calculating both the Akaike information criteria and the Bayesian information criteria for each one of them. These criteria have identified the following as the “best” model:<sup>10</sup>

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<sup>9</sup> 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.

<sup>10</sup> The best model, in the Akaike sense, is the one that provides the best combination of goodness of fit and parsimony. It is calculated as the model that maximizes information entropy (i.e. a combination of high accuracy and low complexity).

$$ME_{it} = \begin{matrix} 0.896 \\ (6.15E-26) \end{matrix} + \begin{matrix} 0.066 * Size_{it} \\ (0.009) \end{matrix} + \begin{matrix} 0.003 * Exper_{it} \\ (0.063) \end{matrix} + u_{it} \quad (12)$$

where p-values (probability of null hypothesis that the coefficient is not different from zero) are in parenthesis.

Before we discuss these results and their implications a note on validity of inference is in place. We have seven plants in our sample and six quarters of observations. However not all plants have reported data in all quarters so we are left with an unbalanced panel based on which we run our pooled ordinary least squares (POLS) regression. POLS estimates of marginal effects are consistent and inference valid as long as five conditions hold: population orthogonality condition, non-multicollinearity, homoskedasticity, no serial correlation (Wooldridge, 2001), and random selection of missing data. We denote our matrix of explanatory variables in  $t$  by  $\mathbf{x}_t$ .

Therefore  $\mathbf{x}_t$  includes observations of all explanatory variables for all plants that reported data in  $t$ . The population orthogonality condition is expressed as  $E(\mathbf{x}'_t u_t) = 0, \forall t$ ; and is equivalent to saying that  $u_{it}$  has mean zero and is uncorrelated with each regressor. Non-multicollinearity is defined as  $rank[\sum_{t=1}^T \mathbf{x}'_t \mathbf{x}_t] = K$ , where  $K$  is the number of model parameters ( $K=3$ ) and  $T$  is the number of periods for which data is available ( $T=6$ ). This condition rules out any linear dependencies among the explanatory variables. Homoskedasticity is defined as

$E(u^2_t \mathbf{x}'_t \mathbf{x}_t) = \sigma^2 E(\mathbf{x}'_t \mathbf{x}_t), \forall t$ , where  $\sigma^2 = E(u^2_t) \forall t$ . This means that the conditional variance of the error does not depend on  $\mathbf{x}_t$  and that the unconditional variance is the same in every period.

Finally the no serial correlation assumption can be defined as  $E(u_t u_s \mathbf{x}'_t \mathbf{x}_t), t \neq s, t, s = 1, \dots, T$ .

This condition restricts the conditional covariances of the errors across different time periods to be zero (Wooldridge, p. 171). Finally random selection of missing data requires that there be no correlation between the probability of an observation to be missing and the value of the dependent variable in that observation.

Our first concern is the possibility of endogeneity between marketing efficiency and size. Size may affect marketing efficiency through the channels previously discussed but it could be argued that marketing efficiency (which reflects how favorable prices actually obtained by the plant are relative to market prices) may also affect size. This is because, all else equal, the higher the crush margin obtained by the plant the stronger the incentives to increase production volume and, possibly, size. However a careful look at our measure of marketing efficiency reveals that it should not be expected to be systematically correlated with observed crush margins. Rather it is expected to be systematically correlated with the difference between market crush margins (that resulting from spot market price) and actually obtained crush margins. This difference is in turn determined by plant characteristics as proposed here. Nevertheless we conduct a Hausman test of the endogeneity of size running a first stage regression of size against experience and observed crush margins. The second stage regression includes size, experience, crush margins, and residuals estimated from the first stage regression. The hypothesis of endogeneity of size in this context was rejected at all levels of critical values (0.01 to 0.10).

Moreover multicollinearity problems are to be expected if there is a systematic linear relationship between experience and size. Different criteria used to test for multicollinearity failed to reject the null hypothesis of no multicollinearity.<sup>11</sup> In addition an Engel test of residual heteroskedasticity results in failure to reject the null hypothesis of homoskedasticity.<sup>12</sup> Finally the Durbin-Watson statistic (the DW-stat was 1.88 with a p-value of 0.5) suggests that there is no autocorrelation in the error structure. Finally, in the context of our survey, we have no reason to believe there is a self-selection problem in missing data. Plants reported the information

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<sup>11</sup> The average variance inflation factor (VIF) was 1.18 and the largest VIF was 1.26. In addition, regression of size against experience results in a coefficient of 0.003 with a p-value of 0.77, suggesting that there is no statistical linear relationship between size and experience.

<sup>12</sup> The value of the corresponding statistic was 0.22, significantly lower than the critical value at a 0.05 level of significance (3.84).

requested provided it was readily available. To sum up assumptions required for consistency and inference validity based on POLS results seem to hold in this context. We can now proceed to discuss the results and its ramifications with some degree of confidence.

As suggested by equation (12) the increase in size of a DMU from small to big tends to increase its marketing efficiency by 0.066.<sup>13</sup> This result is consistent with (but not a poof of) the hypothesis that plants may be able to increase net operating revenues by exploiting bargaining and transportation advantages associated with increased size (i.e. operating at a production level above the median in the sample). In reality increasing production may (despite enhancing marketing efficiency) entail costs or face capacity constraints not captured in our analysis. These issues are not factored in here so we need to be cautious before we jump to the conclusion that plants should increase size. According to equation (12) accumulation of experience (the passage of quarters in operation) tends to increase marketing efficiency by 0.003.<sup>14</sup> This, of course, does not involve a decision that the plant can make to increase marketing efficiency. It rather suggests the existence of a vegetative gain in efficiency across time. This result is consistent with visual inspection of time evolution of efficiency displayed in Table 3.b. The gain in efficiency may actually be quantitatively significant. According to our results plants may increase marketing efficiency by as much as 1.2% a year.

Finally equation (12) suggests that integration, ownership, and multi-plant status do not affect marketing efficiency in a statistically significant way. In fact coefficients of these independent variables were statistically insignificant across all possible combinations of factors.

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<sup>13</sup> This effect is statistically significant at the 1% level.

<sup>14</sup> This effect is statistically significant at the 10% level.

Particularly surprising is the result that even when included as the only regressor each one of these factors was statistically insignificant.<sup>15</sup>

## Conclusions

This study exploits data from a survey of ethanol plants and tries to pinpoint the conventional and marketing sources of plants' differential performance and their correlates. 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. Marketing efficiency defined as the ability of plants to bargain favorable contract prices (relative to market spot prices) seems to be an important source of differential performance.

Two characteristics may be associated with enhanced plants' marketing efficiency: size and experience. Results are consistent with the fact that as DMUs accumulate experience (accumulate quarters in operation in the industry), they might improve in their ability to contract favorable prices. Results are also consistent with the hypothesis that bigger plants may be able to bargain better relative prices. If this is true, then bigger plants may outperform smaller competitors, partly by securing more favorable prices (i.e. achieving higher marketing efficiency). This may offer an additional explanation to the increase in the size of the average plant observed in the industry in recent years besides technological reasons (i.e. economies of scale). Conventional DEA would not capture this potential source of differential performance.

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<sup>15</sup> Results are available from the authors. Although statistically insignificant, values of coefficient estimates seem to be consistent with the idea of gains in marketing efficiency from increased size. Integration (which usually results in a volume smaller than the volume achieved by marketers pooling production from many plants) was mostly associated with decreased marketing efficiency. Multi-plant status (associated with higher volumes since a firm can bargain over production from several plants) is associated with higher marketing efficiency.

Any change in price would be deemed exogenous and not the result of plants' characteristics that may affect their bargaining power.

As indicated by the Federal Trade Commission, incentives for 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 (integration did not have a statistically significant effect on bargaining power; i.e. marketing efficiency). On the other hand, increases in plants' production size may result in better pricing through either increased bargaining power or economies of size in transportation and logistic infrastructure. This may suggest potential incentives for increased size or horizontal consolidation (plants may pool production with other plants and bargain over pooled volumes which is already becoming a common practice in the industry). 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.

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## Appendix A

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

$$\begin{aligned} \underset{\lambda, z}{\text{Min}} \lambda \quad & \text{s.t.} \quad \lambda^{-1} u^j \leq zM \\ & \lambda x^j \leq zN \\ & z^j \in \mathbb{R}^+, \quad j = 1, 2, \dots, J \end{aligned}$$

## Appendix B

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

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

## Appendix C

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

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

## Tables

**Table 1. Characteristics of the seven surveyed plants**

States Represented	Iowa, Michigan, Minnesota, Missouri, Nebraska, S. Dakota, Wisconsin				
Annual Production Rate (m. gal/y)	Smallest	42.5			
	Average	53.1			
	Largest	88.1			
Number of 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	4	2	0	1
	Third Party/Agent	3	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
Median	4.5	336	7.3	12.9	25	5.5
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.a. Economic Efficiency Decomposition**

DMU	Conventional Overall Economic Efficiency	Technical Efficiency	Allocative Efficiency	Marketing Efficiency	Overall Economic Efficiency with Marketing Efficiency <sup>(a)</sup>
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
<b>Average</b>	<b>0.891</b>	0.998	<b>0.893</b>	<b>0.97</b>	<b>0.868</b>
Std Dev	0.07	0.01	0.07	0.09	0.10
Min	0.72	0.977	0.72	0.79	0.64
Max	1	1	1	1.27	1.02

<sup>(a)</sup> Calculated as Overall Economic Efficiency times Marketing Efficiency

**Table 3.b. Efficiency Scores Grouped by Plants and Quarters**

	Plant 1		Plant 2		Plant 3	
QUARTER	AE	ME	AE	ME	AE	ME
1	0.820	0.805	0.842	0.842	0.790	0.888
2	0.847	1.051	0.946	0.946	0.824	1.065
3	0.939	1.030	0.948	0.948	0.913	0.977
4	0.879	1.019	0.932	0.932	0.916	0.949
5	0.913	1.024	0.960	0.960	0.947	1.011
6	NA	NA	NA	NA	NA	NA
Average	0.879	0.986	0.926	0.926	0.878	0.978
Ranking	Fifth	Third	Second	Sixth	Sixth	Fourth

	Plant 4		Plant 5		Plant 6		Plant 7	
QUARTER	AE	ME	AE	ME	AE	ME	AE	ME
1	0.716	0.897	0.800	0.903	NA	NA	NA	NA
2	0.796	1.060	0.859	0.990	0.829	0.918	NA	NA
3	0.902	0.935	0.881	0.988	0.925	0.818	0.961	1.023
4	NA	NA	0.888	0.980	0.934	0.744	0.996	0.975
5	0.941	0.990	0.912	1.033	0.924	0.981	1.000	0.985
6	NA	NA	0.941	1.031	NA	NA	NA	NA
Average	0.839	0.970	0.880	0.988	0.903	0.865	0.986	0.994
	Seventh	Fifth	Fourth	Second	Third	Seventh	First	First

**Table 4. Correlates of Marketing Efficiency**

Factor	Coefficient Estimate	P-value <sup>1</sup>	Regression Statistics
Intercept	1.025	0.00	R-square =0.35
Size (Big/Small)	0.013	0.82	
Experience	0.004	0.08	F=2.27
Integration	-0.481	0.23	
Multi-plant	0.009	0.81	
Cooperative	0.224	0.32	p-val <sup>2</sup> =0.07
Size*Integration	0.106	0.33	

<sup>1</sup> Denotes the probability that the corresponding coefficient is not significantly different from zero.

<sup>2</sup> Denotes the probability that the model is jointly insignificant to explain marketing efficiency.

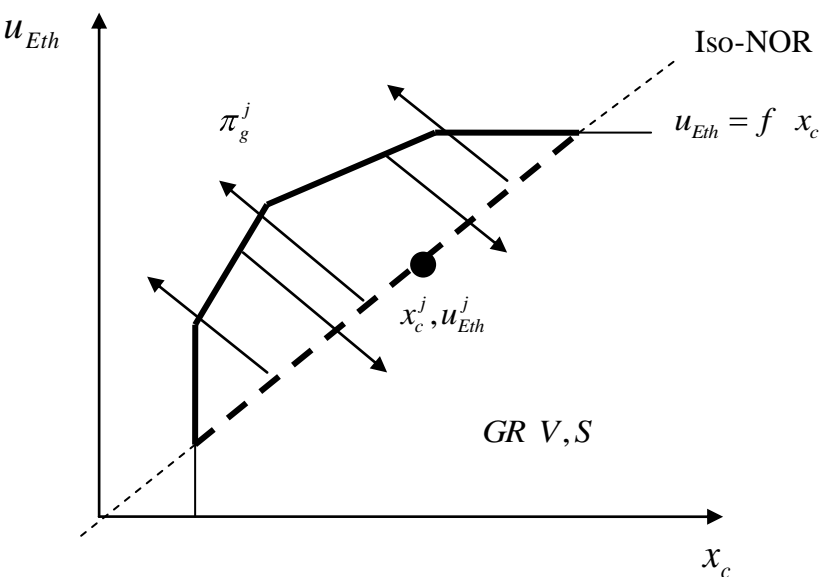
**Table 5. Potential Drivers of Marketing Efficiency**

Factor	Coefficient Estimate	P-value <sup>1</sup>	Regression Statistics
Intercept	0.908	2.34E-28	R-square =0.35
Size (Big/Small)	0.059	0.009	F=6.12
Experience	0.003	0.076	p-val <sup>2</sup> =0.006

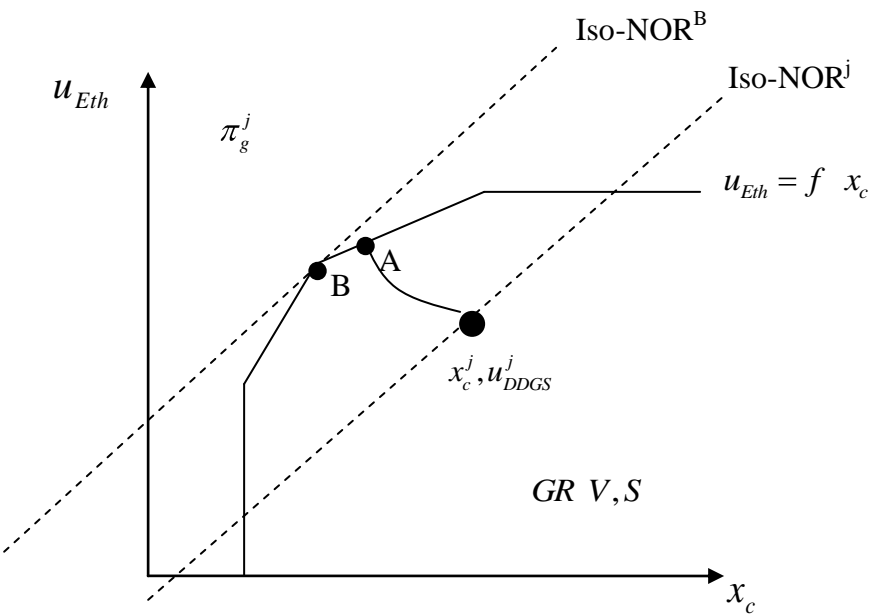
<sup>1</sup> Denotes the probability that the corresponding coefficient is not significantly different from zero.

<sup>2</sup> Denotes the probability that the model is jointly insignificant to explain marketing efficiency.

**Figures**



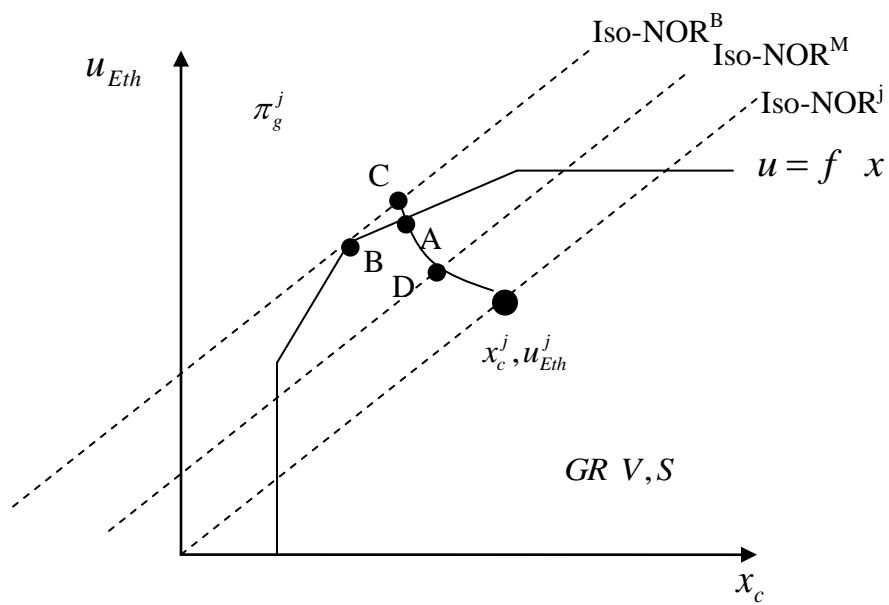
**Fig. 1 – Iso-NOR and Sets**



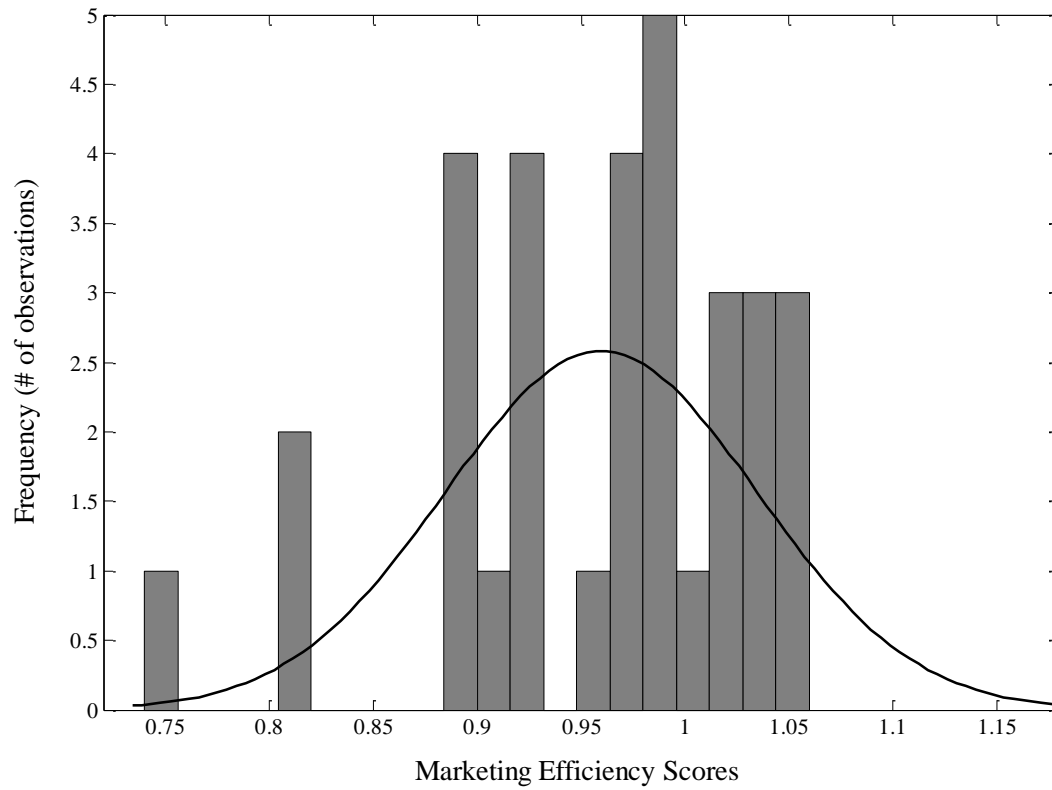
**Fig. 2 - Technical Efficiency**

**Fig. 3 - Decomposition of Overall Economic Efficiency**

Iso-NOR<sup>B</sup>



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



**Fig. 5 – Distribution of Marketing Efficiency Scores**