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A Nonparametric Frontier Measure of Marketing Efficiency: An Illustration with Corn Ethanol Plants.

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RESEARCH ARTICLE

A nonparametric frontier measure of marketing efficiency: An illustration with corn ethanol plants

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Abstract
This article extends nonparametric measures of efficiency to accommodate the concept of marketing efficiency, which measures changes in net revenues brought about by firms' use of marketing channels other than spot markets. The measure is appropriate for firms operating under atomistic competition with imperfect information. The proposed measure displays two important features: (a) it uses the alternative of a spot price-based counterfactual to distinguish marketing from allocative efficiency, and (b) it allows for the fact that firms operate in different spot markets and have access to diverse sets of prices. We illustrate this approach with a unique dataset from ethanol plants in the U.S. Corn Belt. [EconLit citations: C61, D2, L2].

1 | INTRODUCTION

Many firms in different markets typically use a combination of marketing strategies (i.e., contracts and spot markets) to sell their outputs and procure their inputs. Decisions regarding the combination of these marketing strategies have the potential to significantly affect firms' economic performance and yet measurement of marketing efficiency (ME) has not been considered in conventional efficiency measurement techniques. Previous studies have addressed the issue of producers' marketing performance in different industries (e.g., Anderson & Brorsen, 2005; Cabrini, Irwin, & Good, 2007; Hagedon, Irwin, Good, & Colino, 2005; Cunningham, Brorsen, & Anderson, 2007; Dietz, Aulerich, Irwin, & Good, 2009). Although these studies provide relevant insights, they do not recognize that changes in prices associated with alternative marketing strategies may lead to reallocations of inputs and outputs along a technological frontier. Therefore, formally linking frontier measures of performance with pricing effects of alternative marketing techniques seems a promising avenue to measure marketing performance.

We extend conventional nonparametric measures of firm economic efficiency to capture a new component we refer to as ME. Our analysis focuses on the ability of firms to contract favorable prices of inputs and outputs, relative to (exogenous) spot market prices. As such, the method is particularly suitable for industries in which: (a) firms operate in atomistic markets but high-price volatility causes deviations between spot and contract prices, and (b) firms have imperfect information on input and output prices that exist in alternative locations, channels, and future time periods, so they can benefit from marketing efforts. Our proposed measure creates a counterfactual benchmark using spot prices around a firm's location. The net revenue under this counterfactual is used as a baseline against which the net revenue obtained with the firm's chosen marketing channels is compared.

This concept is illustrated with an efficiency decomposition of a sample of corn ethanol plants. The corn ethanol industry provides a particularly fertile ground for application of this technique as the plants in this sample used a combination of bilateral contractual arrangements and spot market operations to sell ethanol and procure corn. Our sample covers a time period (2006–2008) in which prices were particularly volatile and firm struggled to find an appropriate balance between contracting and operating in open spot markets, and between in-house and subcontracted marketing. Ethanol sales amounted to about 80% of total revenue among surveyed plants and corn amounted to 70% of plants' operating costs. Therefore, changes in prices of ethanol and corn associated with alternative marketing strategies are bound to have a high impact on overall's plant economic performance. Plants in this survey provided information on input and output prices obtained with marketing techniques they employed, while spot market prices in regions where plants operate were obtained from other sources.

Application of the technique developed here can shed light into a number of questions regarding firms' marketing performance. First, the proposed measure reveals whether the use of alternative marketing strategies improves firms' marketing performance relative to simply trading in spot markets. Second, deviations in marketing performance associated with the use of multiple marketing channels (relative to performance under exclusive use of spot markets) can reflect mismanagement, but could also be explained by risk aversion, or issues related to the process by which price expectations are formed. Therefore, we econometrically examine whether, and to what extent, efficiency scores attained by surveyed ethanol plants during the sample period were correlated with experience and scale of production.

2 | MEASUREMENT AND DECOMPOSITION OF ECONOMIC EFFICIENCY

Differential performance across firms may be explained by managerial ability but also by constraints faced by those firms. Evaluating firms' performance subject to constraints requires modeling and quantification of these constraints. Frontier methods developed in production economics (Coelli, Prasada Rao, O'Donnell, & Battese, 2005) provide the tools to quantify technological constraints. Technological frontiers may be calculated from a sample of firms either parametrically or nonparametrically. The latter is especially suitable for small samples without outliers. Based on this frontier conventional measures of economic efficiency typically decompose overall efficiency into technical and allocative sources. Technical efficiency represents the ability of managers to achieve an engineering optimum. Allocative efficiency measures performance based on the alignment of the input–output allocation relative to exogenous prices.

2.1 | Characterization of technology from firm data

Firms sampled are assumed to share a technology that transforms a vector of N inputs into a vector of M outputs. Observed combinations of inputs used and outputs produced are taken to be representative points from the feasible production technology. In this article, we use data envelopment analysis (DEA) to identify the boundaries of the feasible technology set from the observed points. Following the notation in Färe, Grosskopf, and Lovell (1994), we represent the production technology by a graph denoting the collection of all feasible input and output vectors; $GR = \{(\boldsymbol{x}, \boldsymbol{u}) \in \mathbb{R}_+^{N+M} : \boldsymbol{x} \in L(\boldsymbol{u})\}$, where $L(\boldsymbol{u})$ is the input correspondence, which is defined as the collection of all input vectors $\boldsymbol{x} \in \mathbb{R}_+^N$ that yield at least output vector $\boldsymbol{u} \in \mathbb{R}_+^M$.

2.2 | Conventional decomposition of economic efficiency

A given decision-making unit (DMU) is deemed economically efficient whenever it chooses a feasible input–output combination that maximizes net operating revenues (NORs) given prices. In this section, we proceed to calculate and decompose economic efficiency assuming that prices are exogenous so there is no marketing strategy that affects prices at which outputs are sold and inputs are purchased.

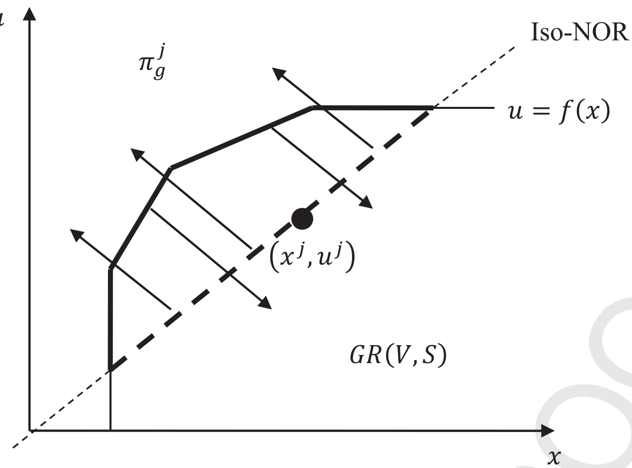


FIGURE 1 Iso-NOR and sets

Assuming variable returns to scale and strong disposability of inputs and outputs,[1] we denote the graph representing the feasible technology by:

$$GR(V,S) = \left\{ (\boldsymbol{x}, \boldsymbol{u}) \colon \boldsymbol{u} \leq \boldsymbol{z'M}, \boldsymbol{x} \geq \boldsymbol{z'N}, \sum_{j=1}^{J} z^j = 1 \right\}, \tag{1}$$

where $GR(V,S)$ denotes the graph of a technology displaying variable returns to scale and strong disposability of inputs and outputs, $\boldsymbol{z'}$ depicts a row vector of J intensity variables, $\boldsymbol{M}$ is the JxM matrix of observed outputs, $\boldsymbol{N}$ is the JxN matrix of observed inputs, and $(\boldsymbol{x}, \boldsymbol{u})$ are vectors of inputs and outputs.

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:

$$\left(\boldsymbol{x}_g^j, \boldsymbol{u}_g^j\right) = \left\{ \left(\boldsymbol{x}^{j'}, \boldsymbol{u}^{j'}\right) \colon \boldsymbol{r}^j \boldsymbol{u}^{j'} - \boldsymbol{p}^j \boldsymbol{x}^{j'} > \boldsymbol{r}^j \boldsymbol{u}^j - \boldsymbol{p}^j \boldsymbol{x}^j \right\}, \tag{2}$$

where $\boldsymbol{p}^j$ is the 1xN vector of input prices paid and $\boldsymbol{r}^j$ the 1xM vector of output prices received by the j*th* DMU and the subscript g denotes greater than observed NOR.

To illustrate the set defined by (2) let us define an Iso-NOR line in a bidimensional input–output space corresponding to the j*th* DMU as those combinations of input and output that result in the same level of NOR given $\boldsymbol{r}^j$ and $\boldsymbol{p}^j$. Figure 1 depicts this set graphically. The set $(\boldsymbol{x}_g^j, \boldsymbol{u}_g^j)$ consists of all the points above the Iso-NOR line as indicated by the arrows with direction northwest.

In Figure 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 ($\boldsymbol{u} = f(\boldsymbol{x})$) with direction southeast. As clearly seen in Figure 1, the set $(\boldsymbol{x}_g^j, \boldsymbol{u}_g^j)$ includes combinations outside the graph and hence not attainable by DMUs in the sample. The subset of observations in $(\boldsymbol{x}_g^j, \boldsymbol{u}_g^j)$ 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 Figure 1. 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 article a hyperbolic graph efficiency measure, defined as the equiproportional reduction in inputs and expansion of outputs that the DMU could have achieved. Input-based or output-based measures of efficiency focus on either input contraction or output augmentation. The former is more aligned with a focus on cost minimization, whereas the latter is more appropriate with revenue maximization. More consistent with maximization of net revenue

[1] When variable returns to scale are allowed for, the calculated frontier is the boundary of the convex hull of the set of observations in input/output space.

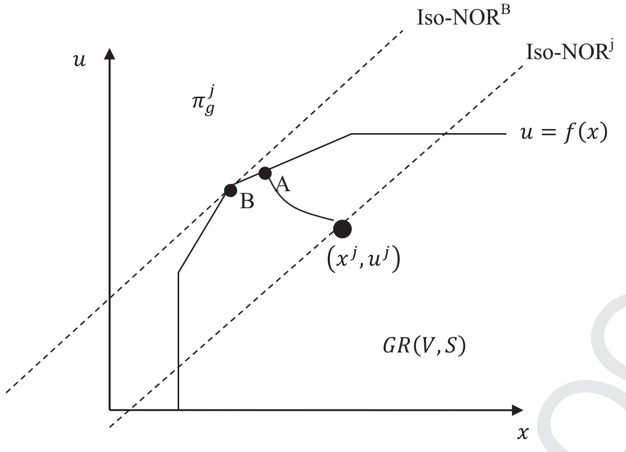


FIGURE 2 Technical efficiency

(which is the behavioral premise in our study) are techniques that seek a projection to an efficient input–output bundle. The hyperbolic distance is a well-established measure that seeks both contraction of inputs and expansion of outputs simultaneously (Ray, 2004).[2]

Therefore, the technically efficient projection of a given observation to the boundary of the technology set follows a hyperbolic path defined by these equiproportional changes. The value of the proportionate change necessary to reach the boundary, TE^j, is defined as the technical efficiency of plant j:

$$TE_V^j(\mathbf{x^j}, \mathbf{u^j} | V, S) = \min \left\{ \lambda : (\lambda \mathbf{x^j}, \lambda^{-1}\mathbf{u^j}) \in GR(V, S) \right\}, \tag{3}$$

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

Technical efficiency defined in Equation (3) is illustrated in Figure 2 by the distance from $(\mathbf{x^j}, \mathbf{u^j})$ to point A, which corresponds to the technically efficient allocation in input–output space. This distance is denoted by a curved line because we are using a hyperbolic measure of efficiency. Note, however, that point A does not correspond to the maximum feasible NOR level because it does not coincide with the point of tangency between the Iso-NOR and the graph (point B.) For a given set of prices achieved by firm j, the allocation that achieves the maximum level of NOR subject to the graph is called the overall economic efficient allocation for firm j.

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

$$\pi_*^j = \max_{\mathbf{x},\mathbf{u}} \left\{ \pi^j = \mathbf{r^j u} - \mathbf{p^j x}, \quad s.t.(\mathbf{x}, \mathbf{u}) \in GR(V, S) \right\}, \tag{4}$$

where π_*^j denotes maximum NOR attainable by j subject to the graph and achieved prices 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 π_*^j. The hyperbolic distance is computed through calculation of the equiproportional reduction of observed inputs and expansion of observed outputs such that the NOR corresponding to π_*^j is reached. This is illustrated by Figure 3 where overall economic efficiency is the distance between $(\mathbf{x^j}, \mathbf{u^j})$ and point C.

[2] The hyperbolic distance is nonlinear in its arguments. A linear alternative to our approach is a directional distance function. This approach would not affect the estimated frontier, but the overall efficiency measure and its decomposition would differ because the projection to the frontier might occur at a different point.

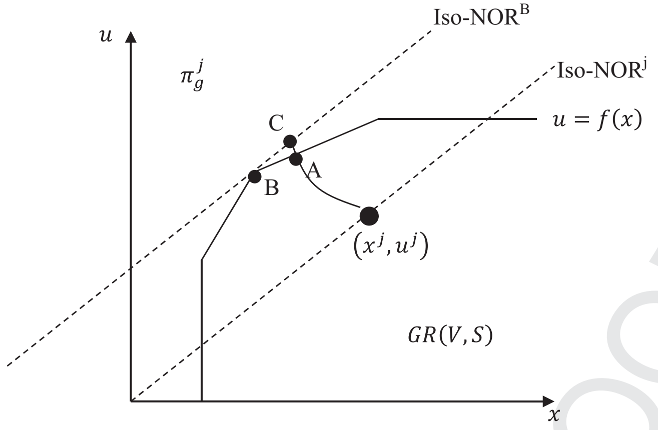


FIGURE 3 Conventional decomposition of overall economic efficiency

As the movement from $(\boldsymbol{x^j}, \boldsymbol{u^j})$ to C is a hyperbolic one, the measure of overall economic efficiency, E_v^j, is related to maximum NOR in the following manner:

$$\pi_*^j = E_v^{j-1}\boldsymbol{r^j u^j} - E_v^j \boldsymbol{p^j x^j} \qquad j = 1, 2, \ldots, J. \tag{5}$$

We can decompose E_v^j into technical efficiency TE_v^j (graphically, the distance between $(\boldsymbol{x^j}, \boldsymbol{u^j})$ and A); and allocative efficiency AE_v^j (the distance between A and C):

$$E_v^j = AE_v^j TE_v^j. \tag{6}$$

Therefore, we can define allocative inefficiency residually as:

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

Based on the solution to the problem described in Equation (4), we calculate overall economic efficiency by solving the implicit Equation (5) for each observation.

2.3 | A new efficiency component: ME

This study defines ME of a plant as the percentage change in revenue and cost associated with the use of marketing channels other than spot markets. Conventional decomposition of economic efficiency assumes prices are exogenous (an exception is Cherchye, Kuosmanen, & Post (2002), which considers noncompetitive market settings) and measures performance based on the alignment of the chosen input–output combination to exogenous prices. It ignores the possibility that with imperfect information, some plants might improve operating margins through marketing efforts.

Marketing alternatives available to plants involve marketing and procurement negotiations directly with suppliers and customers or through intermediaries. They also involve different combinations of contracts, futures markets, and spot markets. To identify changes in NORs due to use of marketing channels other than spot markets, we exploit differences between prices actually achieved (those that result from the chosen combination of marketing channels) with spot prices available to the plant. Our proposed technique uses spot prices around a plant's location to construct an allocative efficient counterfactual allocation. The net revenue under this counterfactual is used as a baseline against which the actually obtained net revenue (emerging from contracted prices and chosen input/output allocation) is compared.

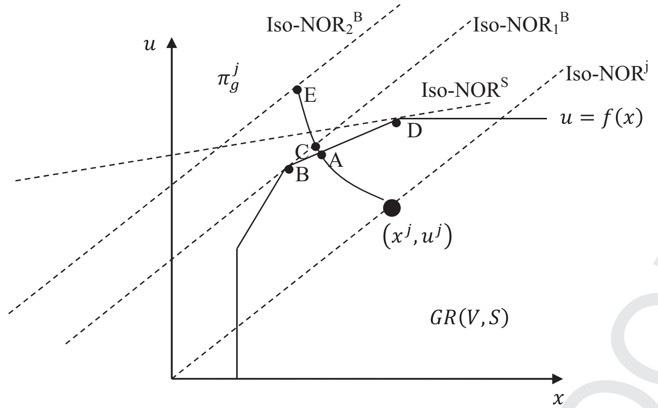


FIGURE 4 Decomposition of overall economic efficiency with marketing efficiency

Differences between achieved and spot prices may be influenced by managers' ability to negotiate better prices in marketing contracts. It may also be influenced by the managers' bargaining power that may, in turn, be affected by time-varying plant characteristics (e.g., scale of production, experience). Finally, marketing success may also be explained by the degree of risk aversion of plants' managers and/or by differences in accuracy of managers' price expectations. We take the difference between spot prices and prices achieved by plants through their marketing choices to represent the result of managers′ marketing decisions, whatever their motivation. A second-stage regression can reveal systematic correlations between ME and hypothesized influencing factors.

Using achieved and spot prices, we implement the concept of ME in the context of nonparametric hyperbolic efficiency analysis. We measure ME as the equiproportional increase in revenue and reduction in operating cost resulting from the difference between prices achieved by managers and spot market prices. ME scores exceeding 1.0 indicate that plant's marketing decisions increased NOR relative to NOR with spot prices, whereas scores less than 1.0 indicate that plant's marketing decisions reduced NOR relative to NOR with spot prices.

One alternative counterfactual against which ME can be measured is the most favorable set of prices observed in the sample. However, many agricultural markets including the corn-ethanol vertical supply chain examined here are characterized by persistent geographical price dispersion, suggesting limited spatial arbitrage (Graubner, Balmann, & Sexton, 2011). In such trading environments, measuring ME against the most favorable set of prices in the sample would incorrectly assume that the most favorable set of prices are feasible to all firms in the sample regardless of their location. Therefore, we use local spot market prices to ensure that efficiency is measured relative to a feasible counterfactual. Nevertheless, the most favorable prices would constitute an adequate counterfactual if firms operate in markets with strong spatial arbitrage.

The concept of ME is illustrated in Figure 4. Under achieved prices, the *jth* DMU would find combination B to be the NOR maximizing allocation. The *conventional* overall economic efficiency (i.e., without ME) is measured as the hyperbolic distance between the observed point ($\boldsymbol{x}^j$, $\boldsymbol{u}^j$) and point C, where maximum NOR (NOR$_1$^{B}) is attained.

Let us assume that spot prices in this quarter were actually more favorable than achieved prices, yielding an Iso-NOR line such as Iso-NOR^S. Under this set of prices, the *jth* DMU would have found allocation D to be the NOR-maximizing allocation. Allocation D is a counterfactual allocation that yields NOR^S, a higher level of NOR than allocation B under achieved prices (recall that the height of the intercept of an Iso-NOR line reflects NOR expressed in units of output). To translate forgone NOR (due to marketing decisions that resulted in prices less favorable than spot market prices) into a measure of hyperbolic efficiency, we need to find the equiproportional expansion of outputs and contraction of inputs starting from allocation C that would yield the counterfactual outcome NOR^S under achieved prices. The Iso-NOR line corresponding to the level of NORs denoted by NOR^S at achieved rather than spot prices is depicted by Iso-NOR$_2$^{B} in

Figure 4.[3] Therefore, measuring marketing (in)efficiency amounts to calculating the hyperbolic distance from point C on Iso-$NOR_1{}^B$ to point E on the counterfactual Iso-$NOR_2{}^B$. We note that point E is the hyperbolic equivalent of point D, the maximum NOR with spot market prices. This distance represents forgone NOR associated with prices attained through the use of marketing channels other than spot markets[4] and can be analytically expressed as:

$$\pi_S^j = \left(\boldsymbol{r}^j \boldsymbol{u}^{j*}\right)(ME^j)^{-1} - \left(\boldsymbol{p}^j \boldsymbol{x}^{j*}\right)ME^j \quad j = 1, 2, \ldots, J, \tag{8}$$

where π_S^j is the NOR, DMU j would have obtained had it operated in the spot market only and chosen the corresponding NOR maximizing input/output combination $(\boldsymbol{u}_S^j, \boldsymbol{x}_S^j)$ (i.e., $\pi_S^j = \boldsymbol{r}_S^j \boldsymbol{u}_S^j - \boldsymbol{p}_S^j \boldsymbol{x}_S^j$),[5] ME^j is ME of DMU j, $(\boldsymbol{u}^{j*}, \boldsymbol{x}^{j*})$ is the NOR maximizing input–output combination under prices attained with the chosen marketing channels, $(\boldsymbol{r}^j \boldsymbol{u}^{j*})$ is the maximum revenue obtained by DMU j at attained prices, and $(\boldsymbol{p}^j \boldsymbol{x}^{j*})$ is the minimum cost incurred by DMU j at achieved prices.

Equation (8) can be solved numerically or analytically. To solve it analytically note that, after multiplying both sides of (8) by ME^j, one can rewrite (8) as an implicit quadratic equation. An application of the quadratic formula reveals that $ME^j = \frac{-\pi_S^j +/- \sqrt{{\pi_S^j}^2 + 4(\boldsymbol{p}^j \boldsymbol{x}^{j*})(\boldsymbol{r}^j \boldsymbol{u}^{j*})}}{2(\boldsymbol{p}^j \boldsymbol{x}^{j*})}$. As the first term in the numerator is negative, the negative root results in negative ME scores. Therefore, the positive root will always be chosen.

Based on values of π_S^j, we calculate ME by solving the implicit Equation (8) for each observation. As NOR with spot prices can be lower or higher than NOR with achieved prices, ME^j will not be bounded between zero and one. In fact if observed NOR π^j is higher than π_S^j, then $ME^j > 1$. Measures of technical efficiency and allocative efficiency do not differ from those conventionally used in the literature. Technical efficiency TE_v^j is represented graphically by the distance between (x_c^j, u_{DDGS}^j) and A in Figure 4. Allocative efficiency AE_v^j is represented graphically by the distance between A and C in Figure 4 (inefficiency caused by the use of an input/output combination that does not maximize NOR under attained prices). Overall efficiency with ME, E_v^{jME}, is then defined by:

$$E_v^{jME} = TE_v^j AE_v^j ME^j. \tag{9}$$

We illustrate the above framework with a sample of surveyed dry-grind ethanol plants. We do so by calculating conventional and expanded measures of economic efficiency and their decomposition for these plants. We first characterize the data collected and the plants surveyed, and then calculate their economic efficiency.

3 | ILLUSTRATION WITH A SAMPLE OF ETHANOL PLANTS

Little to no publicly available data on the economic and technical performance of the current generation of ethanol plants are available. Previous studies have calculated input requirements and by-products' yield per gallon of ethanol produced by plants. Using engineering data, McAloon, Taylor, and Yee (2000) and Kwiatkowski, McAloon, Taylor, and Johnson (2006) measured considerable improvement in plant technical efficiency between 2000 and 2006. Shapouri and Gallagher (2005) reported input requirements and cost data based on a USDA sponsored survey of plants for the year 2002. Wang, Wu, and Huo (2007) and Plevin and Mueller (2008) reported results based on spreadsheet models of the industry (GREET and BEACCON, respectively.) Pimentel and Patzek (2005) and Eidman (2007) reported average performances of plants although they do not clearly indicate the sources of their estimates. Finally, Perrin, Fretes, and

[3] As combination C is located on Iso-$NOR_1{}^B$, a hyperbolic projection amounts to a movement to a parallel Iso-NOR line (such as Iso-$NOR_2{}^B$) corresponding to net operating revenues of NOR^S.

[4] The illustrated situation assumes spot prices are more favorable than achieved prices and hence Iso-$NOR_2{}^B$ is positioned above and to the left of Iso-$NOR_1{}^B$. If spot prices were less favorable than achieved prices, then Iso-$NOR_2{}^B$ would be located below and to the right of Iso-$NOR_1{}^B$ and the marketing efficiency score would be higher than one.

[5] This is also the level of NOR that the plant would achieve under attained prices and a "marketing efficient" combination of inputs and outputs such as the one represented by point E in Figure 4.

Sesmero (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 and Gallagher (2005) and Perrin et al. (2009), all of these studies reported values corresponding to the average plant (not individual plants), which prevents comparison of relative performances. In addition, it is generally believed that the industry has become more efficient and technologically homogeneous since 2005. The data used in Shapouri and Gallagher (2005) were collected in 2002. Perrin et al. (2009) surveyed plants in operation during 2006 and 2007 and employed more restrictive sampling criteria (discussed below), which yielded a technologically homogenous sample of recent vintage plants. This sample is scattered across the full ranges of the Corn Belt, providing contrasting environments particularly suited to the measurement of variations in marketing performance. Moreover, the period of time covered in the survey is particularly useful for implementation of our proposed ME measure, as it corresponds to a period of high-price volatility and use of diverse marketing channels by plants. These are the data of choice in this study.

We apply our proposed technique to a small sample of firms with a highly homogenous technology (i.e., without obvious outliers). As originally demonstrated by Gong and Sickles (1992) and extensively discussed afterwards (Badunenko, Henderson, & Kumbhakar, 2012), there is an increased risk of distorting efficiency measures with stochastic frontiers due to misspecification (i.e., imposing an incorrect parametric form) as: (a) the sample reduces in size, and/or (b) the number of periods in a panel shortens (larger N than T), and/or (c) the technology increases in complexity (as number of parameters increase and cross-parameter constraints decrease). Monte Carlo analyses have revealed that deterministic nonparametric frontier methods can perform substantially better (reduce distortion in efficiency measurement) than stochastic frontiers if any of the aforementioned problems is present. This is the case with our application, where problems (a) and (b) are present, and very likely problem (c) is present as well. Therefore, the nonparametric frontier approach is particularly suitable for this sample.

The data consist of 33 quarterly reports of input and output quantities and prices from a sample of seven ethanol plants in seven different states in the Midwest that started production in or after 2005.[6] We refer to each quarterly observation as a DMU. DMUs are assumed to share a technology that transforms a vector of seven inputs (corn, natural gas, electricity, labor, denaturant, chemicals, and “other processing costs”) into three outputs (ethanol, dried distiller's grains with 10% moisture content [DDGS], and modified wet distiller's grains with 55% moisture content [MWDGS]). Results of our survey contained expenditures in labor, denaturant, chemicals, and other processing costs and, as a result, we calculated implicit quantities of these inputs dividing expenditures by their corresponding price indexes. Not all plants reported data in all quarters resulting in an unbalanced panel dataset. Although the size of the dataset imposes limitations, it does contain unique information on plant management decisions.

We implement the previously developed measure of ME to identify changes in NORs due to use of marketing channels other than spot markets. Identification is achieved by contrasting NOR under prices reported by plants (i.e., achieved by plants) with NOR under spot prices available to the plant, measured here as the state-wide average quarterly spot price. Although we would have preferred to employ spot prices at a local level, we use state-level spot prices for ethanol and corn instead because the former are not available to us. Although marketing decisions are also likely to affect by-product prices, there are no readily available data on spot market prices of DDGS and MWDGS at the state level. Therefore, for revenue and cost categories different from corn and ethanol, spot prices coincide with achieved prices.

State-level data on corn spot prices were obtained from USDA NASS Agricultural Prices. Ethanol spot prices were obtained from *Ethanol and Biodiesel News*, 2006 and 2007 (now *Ethanol and Biofuels News*). Other factors than ME no doubt contribute to the discrepancy between plant-achieved prices and state-level prices, but these data provide a satisfactory empirical base for initial application of this technique. We later show that ME scores we obtain are significantly correlated with plant characteristics, providing support for the hypothesis that these measures of price discrepancies are indeed related to ME.

[6] We have adjusted all prices to a base quarter (third quarter of 2006) using the Producer Price Index (PPI) as calculated by the Bureau of Labor Statistics.

TABLE 1 Characteristics of the seven surveyed plants[a]

States Represented	Iowa, Michigan, Minnesota, Missouri, Nebraska, S. Dakota, Wisconsin				
Production (MGY)	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			
Percentage of by-product sold as dry DGS	Smallest	0			
	Average	54			
	Largest	97			
		Corn	Ethanol	DDGS	MWDGS
Primary Market Technique	Spot	0	0	1	2
	Customer contract	7	2	2	2
	Third party/agent	0	5	3	2

[a]Data from Perrin et al. (2009).

3.1 | Characteristics of surveyed plants

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 by-product they sold as DDGS (10% moisture) compared to MWDGS (55% moisture). Variation on this variable was significant, averaging 54% of by-product sold as DDGS, but ranging from one plant that sold absolutely no by-product as DDGS to another plant that sold nearly all by-product (97%) as DDGS.

Plant marketing strategies are also characterized in Table 1. In purchasing input feedstock, all plants used contracts signed either with elevators or farmers as their main procurement technique. In selling ethanol, five of the seven plants used third parties or agents. Third parties are marketers that, for a fee, conduct the commercialization (including transportation and logistics) of ethanol. Although trading through intermediaries implies a surplus loss for ethanol plants due to marketing fees, these intermediaries, by pooling volumes and exploiting their size, may be able to obtain better prices than those the individual plant would have obtained. By-product marketing across plants displayed a higher degree of variance. Marketing of MWDGS was split fairly evenly between all marketing options. On the other hand, plants seem to have marketed DDGS mainly through third parties.

Table 2 displays descriptive statistics of inputs used and outputs produced by the 33 DMUs in the sample. As mentioned before, in this article, a DMU corresponds to a plant in a given quarter; so two quarterly reports of the same plant are considered as two different observations as are two plants in the same quarter.[7] Table 2 reveals a significant dispersion of DMUs in terms of size. The biggest DMU produced 23 million gallons of ethanol in a quarter, whereas the smallest produced 10.6 million gallons.

[7] We use quarterly rather than individual firm observations because the survey provides this wealth of information allowing us to learn about potential changes in plant behavior across time.

TABLE 2 Descriptive statistics of DMUs: Inputs and outputs[a]

Average	Corn (Million Bushels)	Natural Gas (Thousand MMBTUs)	Ethanol (Million Gallons Per Quarter)	Corn Price ($/bushel)	Ethanol Price ($/gallon)	Corn Price Deviation (Achieved/Spot)	Ethanol Price Deviation (Achieved/Spot)
Average	4.8	361	13.7	3.01	1.94	0.95	0.98
SD	0.9	61	2.8	0.68	0.23	0.14	0.12
Min	3.6	297	10.6	1.54	1.48	0.69	0.61
Max	8	569	22.9	4.05	2.71	1.51	1.14

[a]Data from Perrin et al. (2009).

3.2 | Price information

Table 2 reveals that corn and ethanol prices have varied widely within the sample. The last two columns of Table 2 also show large differences between prices actually attained by firms and spot prices available in their region. These figures reveal that by using different contracting arrangements plants, on average, were able to pay a price for corn 5% lower than the spot price but also obtained a price for their ethanol 2% lower than the spot price. However, values in this table also reveal substantial variability across plants. Some plants paid significant premiums over spot prices for corn. And some plants obtained, for their output, a price considerably higher than the spot price available in the area surrounding the plant.

4 | RESULTS: EFFICIENCY AND ITS DECOMPOSITION

Measures of economic efficiency and decomposition into technical, allocative, and marketing sources calculated for the sample of surveyed dry-grind ethanol plants are reported in Table 3. All codes employed to generate these measures are provided in the Supporting Information Appendix. Hyperbolic measures of efficiency introduce nonlinearities in constraints, so we calculate TE_v^j using MATLAB FMINCON routine for nonlinear programming problems. We also calculate maximum NORs using programming routines in MATLAB. This table shows that the economic efficiency of the average DMU is 0.89, so there seems to be, on average, potential for improvement in NORs. Results also show a substantial part of overall inefficiency is explained by allocative sources. This means that although DMUs tend to be efficient in an engineering sense, they are choosing bundles of inputs and outputs that are not consistent with maximization of NORs at achieved prices.

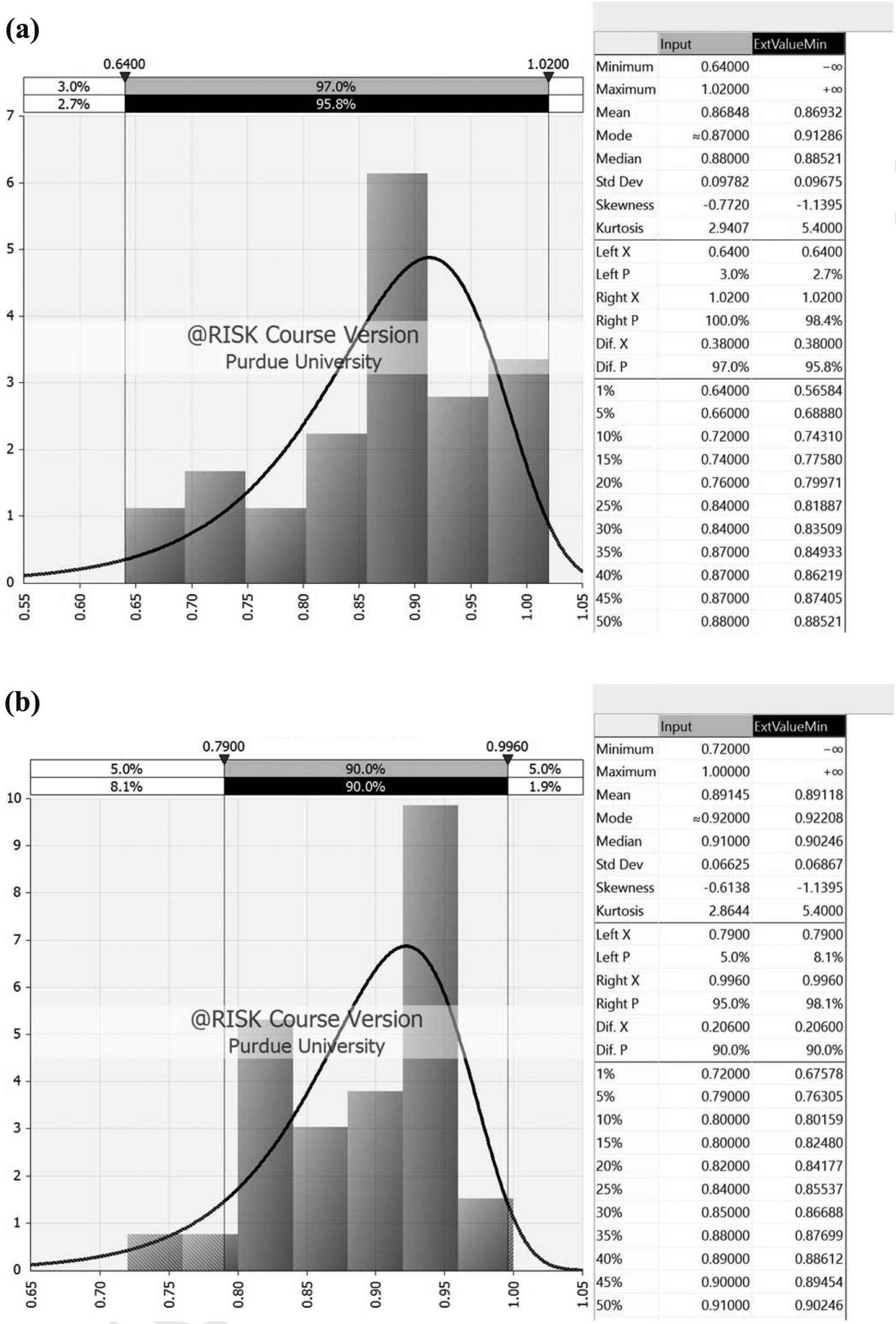
Based on computed values of π_S^j (see explanation of Equation (8)), we calculate ME by solving the implicit Equation (8) for each observation using the FZERO procedure in MATLAB. Technical and allocative efficiency are calculated according to Equations (3) and (7). We observe a significant dispersion in ME across DMUs, as indicated by a standard deviation of 0.09 and the broad range of the estimates (minimum of 0.79 and maximum of 1.27). The ME index average is 0.97. This average ME implies that in their choice of marketing strategies, plants gave up on average 3% of NOR relative to the NOR they would have obtained had they operated at spot market prices. By including ME, the overall average economic efficiency is reduced from 0.89 to about 0.87. We report the effect of ME on higher moments of the distribution of overall efficiency scores in Figure 5. Comparing Figures 5a and 5b illustrates that including ME increases the standard deviation (from 0.07 to 0.1) and negative skewness (i.e., fattens the tail of the distribution over low scores) of the overall economic efficiency distribution.

Caution is recommended when interpreting our proposed measure of marketing inefficiency. Marketing inefficiency as defined here depicts a measurable deviation from maximum feasible profits but this deviation is not necessarily reflecting flawed managerial decisions. For instance, contracting prices in advance of production decreases uncertainty. Reduced uncertainty is valuable because of risk aversion or because "price lock-ins" guarantee a given profitability that can be used as collateral when raising capital. These are benefits of contracting that we have not explicitly

TABLE 3 Economic efficiency decomposition

DMU	Technical Efficiency (1)	Allocative Efficiency (2)	Conventional Overall Economic Efficiency (3 = 1*2)	Marketing Efficiency (4)	Overall Economic Efficiency With Marketing Efficiency (5 = 3*4)
1	0.977	0.84	0.82	0.81	0.66
2	1	0.84	0.84	0.90	0.76
3	0.985	0.80	0.79	0.89	0.70
4	1	0.72	0.72	0.90	0.64
5	1	0.80	0.80	0.90	0.72
6	0.979	0.87	0.85	1.05	0.89
7	1	0.95	0.95	0.93	0.88
8	1	0.82	0.82	1.06	0.88
9	1	0.83	0.83	0.92	0.76
10	0.997	0.80	0.80	1.06	0.84
11	1	0.86	0.86	0.99	0.85
12	1	0.94	0.94	1.03	0.97
13	1	0.96	0.96	1.02	0.98
14	1	0.95	0.95	0.92	0.90
15	1	0.91	0.91	0.98	0.89
16	1	0.92	0.92	0.82	0.81
17	1	0.90	0.90	0.93	0.84
18	1	0.88	0.88	0.99	0.87
19	1	0.88	0.88	1.02	0.89
20	1	0.996	0.996	0.97	0.97
21	1	0.93	0.93	0.91	0.87
22	1	0.92	0.92	0.95	0.87
23	1	0.93	0.93	0.75	0.74
24	1	0.89	0.89	0.98	0.87
25	1	0.91	0.91	1.02	0.93
26	1	1	1	0.99	0.99
27	1	0.96	0.96	0.99	0.95
28	1	0.95	0.95	1.01	0.96
29	1	0.92	0.92	0.98	0.91
30	1	0.94	0.94	0.99	0.93
31	0.99	0.92	0.91	1.04	0.95
32	1	0.80	0.80	1.27	1.02
33	1	0.94	0.94	1.03	0.97
Average	0.998	0.89	0.89	0.97	0.86
SD	0.01	0.07	0.07	0.09	0.10
Min	0.98	0.72	0.72	0.79	0.64
Max	1	1	1	1.27	1.02

*Measures 1, 2, and 4 are calculated as described in Equations (3), (7), and (8), respectively.



(a)

	Input	ExtValueMin
Minimum	0.64000	−∞
Maximum	1.02000	+∞
Mean	0.86848	0.86932
Mode	≈0.87000	0.91286
Median	0.88000	0.88521
Std Dev	0.09782	0.09675
Skewness	-0.7720	-1.1395
Kurtosis	2.9407	5.4000
Left X	0.6400	0.6400
Left P	3.0%	2.7%
Right X	1.0200	1.0200
Right P	100.0%	98.4%
Dif. X	0.38000	0.38000
Dif. P	97.0%	95.8%
1%	0.64000	0.56584
5%	0.66000	0.68880
10%	0.72000	0.74310
15%	0.74000	0.77580
20%	0.76000	0.79971
25%	0.84000	0.81887
30%	0.84000	0.83509
35%	0.87000	0.84933
40%	0.87000	0.86219
45%	0.87000	0.87405
50%	0.88000	0.88521

(b)

	Input	ExtValueMin
Minimum	0.72000	−∞
Maximum	1.00000	+∞
Mean	0.89145	0.89118
Mode	≈0.92000	0.92208
Median	0.91000	0.90246
Std Dev	0.06625	0.06867
Skewness	-0.6138	-1.1395
Kurtosis	2.8644	5.4000
Left X	0.7900	0.7900
Left P	5.0%	8.1%
Right X	0.9960	0.9960
Right P	95.0%	98.1%
Dif. X	0.20600	0.20600
Dif. P	90.0%	90.0%
1%	0.72000	0.67578
5%	0.79000	0.76305
10%	0.80000	0.80159
15%	0.80000	0.82480
20%	0.82000	0.84177
25%	0.84000	0.85537
30%	0.85000	0.86688
35%	0.88000	0.87699
40%	0.89000	0.88612
45%	0.90000	0.89454
50%	0.91000	0.90246

FIGURE 5 (a) Distribution of overall efficiency scores with marketing efficiency. (b) Distribution of overall efficiency scores without marketing efficiency

modeled. It may also be that the same marketing and procurement strategies would result in higher average ME in some other period of time.

Given lack of information about these managers′ risk aversion, we cannot distinguish between low ME scores due to risk aversion versus those due to unsuccessful pricing strategies. In the case that forgone NOR are completely

TABLE 4 Efficiency of DMUs grouped by size

	Allocative Efficiency
Average	0.893
Average—big[a]	0.922
Average—small	0.863
Big/small	1.068

[a]A DMU is classified as big if it produces more than the sample median (13 million gallons). It is small otherwise.

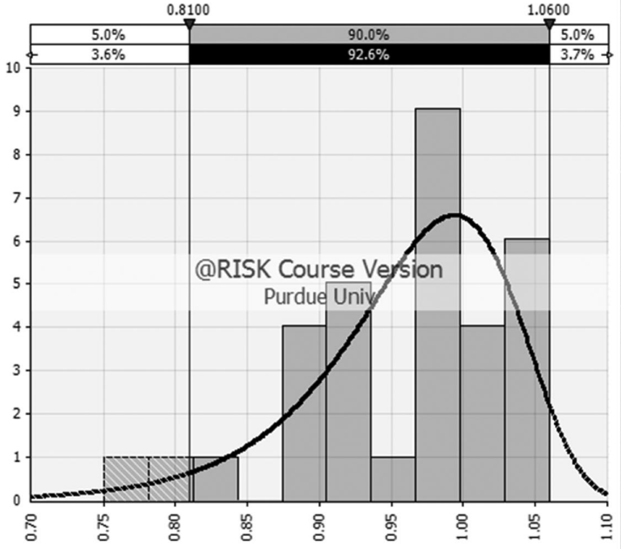
TABLE 5 Efficiency scores grouped by plants and quarters

	Plant 1		Plant 2		Plant 3	
QUARTER	AE	ME	AE	ME	AE	ME
1	0.820	0.805	0.842	0.901	0.790	0.888
2	0.847	1.051	0.946	0.925	0.824	1.065
3	0.939	1.030	0.948	0.921	0.913	0.977
4	0.879	1.019	0.932	0.911	0.916	0.949
5	0.913	1.024	0.960	0.986	0.947	1.011
6	NA	NA	NA	NA	NA	NA
Average	0.879	0.986	0.926	0.929	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	0.91	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
Ranking	Seventh	Fifth	Fourth	Second	Third	Seventh	First	First

explained by risk aversion on the part of plant managers, our measure of ME provides an approximate measure of "shadow" cost of risk aversion; that is, it tells us how much NOR plant managers sacrificed in order to reduce risk. If, on the other hand, plant managers are risk neutral, low ME scores suggest mismanagement of marketing channels during this period.

The results in this section show that both marketing and allocative efficiency are important components of overall economic efficiency among these ethanol plants. The only DMU that achieved allocative efficiency is DMU 26, which corresponds to plant 7 in the fifth quarter. This plant also achieves high scores in other quarters (DMUs 13 and 20). This plant had the largest production volume in the sample, with DMU 26 representing its largest quarterly output. One would expect large plants to be more profitable when the ratio of output price to input price is favorable. That ratio was high, by historical standards, during the period of this survey. A high-price ratio is represented by a flat Iso-NOR line such as Iso-NOR^S in Figure 4. This would, in turn, push plants' NOR maximizing combinations toward a high-volume allocation such as point D in Figure 4, where NOR is higher. Table 4 confirms this by showing that larger DMUs (those producing more than 13 million gallons, which is the median of the sample) achieved, on average, higher allocative efficiency than their smaller counterparts. Plant 7 also performs best in terms of ME (see Table 5). As reported in Table 5, the average ME of this plant is 0.994 followed by plants 5 (0.988) and 1 (0.986).



Statistics

	Input	ExtValueMin
Minimum	0.75000	−∞
Maximum	1.06000	+∞
Mean	0.96031	0.96140
Mode	≈0.99000	0.99358
Median	0.98000	0.97315
Std Dev	0.07468	0.07151
Skewness	-0.9897	-1.1395
Kurtosis	3.8781	5.4000
Left X	0.8100	0.8100
Left P	5.0%	3.6%
Right X	1.0600	1.0600
Right P	95.0%	96.3%
Dif. X	0.25000	0.25000
Dif. P	90.0%	92.6%
1%	0.75000	0.73710
5%	0.81000	0.82798
10%	0.89000	0.86811
15%	0.90000	0.89228
20%	0.90000	0.90995
25%	0.91000	0.92411
30%	0.92000	0.93610
35%	0.93000	0.94663
40%	0.95000	0.95613
45%	0.98000	0.96490
50%	0.98000	0.97315

FIGURE 6 Distribution of marketing efficiency scores

The evolution in time of marketing efficiencies for each plant in our sample (Table 5) results in an average increase of 0.025 units of efficiency per quarter (i.e., 1% per year). This reveals that plants seem to achieve higher ME through time perhaps due to factors such as accumulated experience. We now turn our attention to this and other questions regarding potential factors associated with ME among these firms.

The measure proposed succeeds in providing information about the forgone profits associated with a departure from the maximum feasible NOR. It is also successful in providing information about the importance of ME relative to other potential sources of inefficiencies like technical and allocative, in explaining differences in economic performance *among* plants. This approach though, as all other inefficiency measures of this type, does not provide information on the reasons why marketing inefficiency happens. The natural next step is to shed light on the reasons.

5 | FACTORS INFLUENCING ME

Many factors can influence ME scores of DMUs. Some may display considerable variation of over time (e.g., experience, production volumes), whereas others may not (ownership structures, degree of outsourcing of marketing activities). We now examine the link between these factors and marketing performance.

5.1 | Potential factors

Results in Table 3 reveal significant dispersion of ME across DMUs. Figure 6 displays a histogram of the unconditional distribution of ME scores.[8] We use an extreme value minimum (EVM) density function to smooth out the distribution and we superimpose it on the histogram in Figure 6. The EVM achieves the best fit to the unconditional distribution of ME scores as indicated by the Akaike and Bayesian Information Criteria. This function accurately approximates the moments of the data as indicated by the comparative columns at the right of the figure. The mean ME score is 0.96. The

[8] One observation is omitted from the histogram as an outlier. This DMU reported an observed ethanol price of $2.5 per gallon in a time where the spot 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.

distribution is negatively skewed with about 70% of probability mass accumulated below one. However, a significant fraction of plants achieved a ME score close to one. The histogram also reveals a significant degree of variability in ME scores across DMUs that, in turn, seems to increase dispersion in overall economic efficiency scores.

Although the distribution of unconditional ME scores is of interest, quantifying the influence of plant characteristics on the conditional expectation of these scores would also be informative. Such quantification would reveal the extent to which ME is correlated with systematic factors, as opposed to random (good or bad fortune). There are several characteristics that may affect a plant's marketing performance in a given quarter. First, the size of a DMU may be positively linked to marketing performance because of increased bargaining power, ability to hire marketing staff members, and reductions in transportation cost per unit due to logistical efficiencies[9] (Kotrba, 2006; Schmidgall, Tudor, Spaulding, & Winter, 2010). Second, ethanol plants may improve performance as they gain experience in the market (Schmidgall et al., 2010). Perfecting coordination and logistics, and building marketing and information networks, are among the reasons why a plant may enhance performance with experience. Other characteristics that may affect ME include time-constant factors such as ownership structure, the degree of vertical integration, and multiplant status (i.e., whether a plant is owned by a firm that owns other plants or not).

5.2 | Empirical evidence

Based on evidence provided by previous studies, as well as anecdotal knowledge of the industry, we model ME as a function of plant characteristics:

$$ME_{it} = \alpha_i + \beta_1 Size_{it} + \beta_2 {Size_{it}}^2 + \beta_3 Exper_{it} + e_{it}. \tag{10}$$

Equation (10) posits that the ME score of plant *i* in quarter *t* is associated with a plant-specific fixed effect α_i (which collects the effect of unobservables such as managerial ability and risk aversion, as well as the effect of observables such as ownership, integration, and multiplant status), the size (defined as million gallons of ethanol produced in quarter *t*) and size squared of plant *i* at time *t*, experience of plant *i* at time *t* (defined as the number of quarters in operation prior to quarter of observation), and random noise represented by e_{it}.[10]

Unobservable time-constant factors are likely to correlate with time-varying factors in our context,[11] so we use fixed effects to consistently estimate β_1, β_2, and β_3. Our estimation then captures within-plant effects, which is consistent with the plant-specific counterfactual based on which ME is defined.

We transform Equation (10) by subtracting mean values through time from all variables (e.g., $ME_{it} - \frac{1}{T-s+1}\sum_{t=s}^{T} ME_{it}$, where *s* and *T* are the first and the last time period for which plant *i* reported data). Consequently, we express our estimating equation in terms of time de-meaned variables and error term:

$$ME'_{it} = \beta_1 Size'_{it} + \beta_2 \left({Size_{it}}^2\right)' + \beta_3 Exper'_{it} + e'_{it}. \tag{11}$$

As previously discussed, experience and size are expected to increase ME. This means that we expect $\beta_3 > 0$ and $\beta_1 + \beta_2 {}^* Size'_{it} > 0$. At the mean, $Size'_{it} = 0$, so the latter condition simplifies to $\beta_1 > 0$. Simar and Wilson (1998) warned that second-stage regressions, as the one in (11), may be subject to upward bias in small samples due to the presence of serial correlation across computed values of the dependent variable. They suggest a bootstrapping method to correct for that bias. We implement a simpler version of the algorithm proposed by Simar and Wilson (2007). Our procedure is

[9] Most plants in this sample market 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.

[10] Our main results are highly robust to inclusion of other time-varying observables such as time dummies, so we present here the most parsimonious specification.

[11] Evidence suggests that size may be related to ownership (privately owned firms tend be bigger than farmers-owned coops) and integration (bigger plants may be more likely to integrate vertically), and experience may be positively correlated with vertical integration (Schmidgall et al., 2010).

made simpler by the fact that our measure of ME is not truncated. Estimation of Equation (11), implemented as shown in the Supporting Information Appendix, results in the following expression:

$$\underset{}{ME'_{it}} = \underset{(0.06)}{0.17^{*}} Size'_{it} - \underset{(1.83e-09)}{4.84e-09^{*}} \left(Size_{it}{}^{2}\right)' + \underset{(0.006)}{0.019^{*}} Exper'_{it} + e'_{it}, \tag{12}$$

where bootstrapped standard deviations (after 1,000 iterations) are reported in parentheses. The combination of coefficients and bootstrapped standard deviations indicate that the effects of size and experience on ME are statistically significant at 1%.

Multicollinearity, heteroskedasticity, and autocorrelation can all invalidate inference in the context of an unbalanced panel like ours (Wooldridge, 2002). The test for multicollinearity failed to reject the null hypothesis of no multicollinearity (the variance inflation factor was 1.04). In addition, an Engel test of residual heteroskedasticity results in failure to reject the null hypothesis of homoskedasticity (the test statistic was 1.99, which is significantly lower than the critical value of 3.84 at a 10% level of significance). Finally, the Durbin–Watson statistic suggests that there is no autocorrelation in the error structure (the Durbin–Watson statistic was 2.55 with a *p*-value of 0.19). In the context of this survey, we have no reason to believe there is a self-selection problem in missing observations, which are associated with the timing in the collection of the survey data. These features of our data lend credence to our results, which we now proceed to discuss.

As suggested by Equation (12), an increase in production by 1 million gallons per quarter is associated with an increase in ME by 0.17 (at the plant's mean). This result is consistent with the hypothesis that plants may be able to increase NORs by exploiting bargaining and logistical advantages associated with increased size. Caution in the interpretation of this result is suggested as increasing production may entail costs or face capacity constraints, none of which is captured in this analysis. According to Equation (12), accumulation of experience tends to increase ME by 0.019 units per quarter in operation. This result seems to confirm that experience is partially responsible for gains in ME through time shown in Table 5.

Good or bad fortune may still play an important role in ME, as may risk aversion and other factors such as managerial ability. We avoid omitted variable bias associated with these unobservables that vary little (or not at all) over time by including fixed effects in the second-stage model. Moreover, while our omission of key variables *explaining* ME calls for cautious interpretation of results from the second-stage regression, it does not invalidate the ME measure itself.

6 | CONCLUSIONS

This article has developed a formal measure of firms' marketing performance based on changes in NORs brought about by firms' use of marketing channels other than spot markets. This measure is based on the construction of a spot-price counterfactual against which the actual outcome is compared. This measure can be applied to a wide range of industries characterized by atomistic competition (firms are price takers in all markets) with imperfect information—firms do not know prices that exist in all locations, all channels, and all future time periods. In this case, firms may benefit from efforts that seek to discover which marketing strategies will result in the best prices. As an illustration of the potential usefulness of this measure, the concept was applied to a sample of ethanol plants that provided unique but somewhat limited data on quantities and prices of inputs and outputs.

The empirical illustration with corn ethanol plants reveals that, over the period of time covered by the survey, there was considerable dispersion in ME scores among the plants in our dataset. This lead to more heterogeneous economic efficiency than detected by traditional DEA efficiency measurement. Moreover, ME seem to constitute an important component in overall economic efficiency. These results suggest that our measure of ME holds relevant informational content. The unconditional mean of ME scores was 0.96 and most decision units (70%) would have obtained the same or higher NOR during this period if they had simply traded on the spot markets. We were, however, limited in our ability to measure spot market conditions for ethanol in close proximity to the plants.

Marketing inefficiency detected in our application may capture a marginal reduction in NOR that plants are willing to accept in exchange for reduction in price uncertainty provided by contracts relative to spot markets. But our analysis does find a systematic link between ME, experience, and size. Due to data limitations, we could not identify whether marketing efficiencies related to size were due to bargaining power, to logistical efficiencies, or to more efficient marketing departments (i.e., managers that are better able to identify successful hedging strategies). Therefore, it is not possible to determine whether the positive but weak association between size and ME creates any incentives for horizontal consolidation, which is a concern of regulators (2010 Report by the Federal Trade Commission). Further research addressing these issues may be of interest to both industry stakeholders and policy makers.

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SUPPORTING INFORMATION

Additional Supporting Information may be found online in the supporting information tab for this article.

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