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This study estimates a variable cost function for corn ethanol plants, using data from a unique survey of Midwest plants. The objective is to better understand the effect of prices and scale of production on Marshallian shutdown price, input choice, and by-product choice. We estimate a novel specification of a cost function capable of accommodating two distinctive features of ethanol plants' technology: (1) the production process results in by-products that can be sold in different forms in response to price signals, and (2) decisions on the mix of by-products may be subject to constraints, such as thin livestock markets or imperfect price foresight. This cost function is estimated by nonlinear seemingly unrelated regression with correlated random effects. Constant returns to variable inputs, homotheticity, and proportionality of by-products to ethanol production, assumptions held in previous studies, are strongly rejected by our analysis. Increases in ethanol production require less than proportional increases in corn and other variable inputs when the increases are achieved through increased capacity utilization as opposed to capacity expansion. Moreover, the reduction in input requirements per gallon, reduces both cost and greenhouse gas emissions per gallon. Constraints in by-product marketing decisions seem to slightly increase Marshallian shutdown price.

Dans la présente étude, nous estimons une fonction de coût variable à l'aide des données tirées d'une enquête réalisée auprès des usines de production d'éthanol de maïs dans le Midwest. L'objectif de notre étude vise à mieux comprendre l'effet des prix et de l'échelle de production sur le seuil de rentabilité selon Marshall, le choix des intrants et le choix des sous-produits. Nous estimons une fonction de coût spécifiée pour tenir compte de deux éléments distinctifs de la technologie des usines de production d'éthanol : 1) le processus de production génère des sous-produits qui peuvent être vendus sous diverses formes en réaction aux signaux de prix; 2) les décisions concernant l'éventail de sous-produits peuvent être confrontées à des contraintes telles que des marchés du bétail restreints ou des prévisions imparfaites concernant les prix. Cette fonction de coût est estimée à l'aide d'une régression non linéaire sans corrélation apparente avec effets aléatoires corrélés. Certaines hypothèses émises dans des études antérieures, telles que les rendements constants des intrants variables, l'homothéticité et la proportionnalité des sous-produits de la production d'éthanol, sont nettement rejetées par notre étude. L'augmentation de la production d'éthanol nécessite des augmentations inférieures aux augmentations proportionnelles de maïs et autres intrants variables lorsque l'augmentation découle d'un accroissement de la capacité de production comparativement à une expansion de capacité. De plus, la diminution des intrants nécessaires à la production d'un gallon d'éthanol réduit à la fois le coût et les émissions de gaz à effet de serre par gallon. Les contraintes auxquelles sont confrontées les décisions de commercialisation des sous-produits semblent augmenter légèrement le seuil de rentabilité selon Marshall.

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INTRODUCTION

Ethanol prices have been influenced by policies (Volumetric Ethanol Excise Tax Credit, consumption mandates in the Renewable Fuels Standard, and the ethanol import tariff) and by market forces including the prices of oil and corn. Many studies have enhanced our understanding of the biofuels market both in the United States (de Gorter and Just 2008; Serra et al 2011a, 2011b; Beckman et al 2012; Du and McPhail 2012; Lapan and Moschini 2012; Mallory et al 2012; Meyer et al 2012) and in the European Union (EU; Banse et al 2007; Burgeon and Tréguer 2010; Buse et al 2012). The influence of price swings on ethanol and food trade flows among the United States, Brazil, and the EU has also been studied (e.g., Hertel et al 2010). However, our knowledge of the workings of the ethanol industry at the plant level, and in particular of their cost structure and associated vulnerability to price swings, is less profound.

The average variable cost (AVC) function for plants in an industry is critical in entry and exit decisions,[1] and in choice of input and by-product combinations. Previous studies have examined average capital cost of ethanol plants and the link between size and feedstock cost due to spatial characteristics of corn markets (Gallagher et al 2005, 2007; Kotrba 2006). However, the relationship between prices of inputs, relative profitability of by-products, scale economies of production, and AVC has not been studied in detail based on plant-level data.

Previous studies of ethanol plants' cost structure (e.g., McAloon et al 2000; Pimentel and Patzek 2005; Shapouri and Gallagher 2005; Plevin and Mueller 2008; Perrin et al 2009; Schmit et al 2009, 2011) either assumed a constant level of output or assumed a constant AVC if output were to change.[2] Lessons from the former set of studies are limited as they may not be applicable to different plant sizes or output levels. On the other hand, studies that assume a constant AVC are, explicitly or implicitly, assuming that plants operate with a technology that is homothetic in variable inputs and displays constant returns to variable inputs (CRVIs). Homotheticity and CRVI, in turn, imply that: (1) AVC is independent of plant size, (2) AVC is independent of the level of plant output, (3) the marginal impact of by-product price changes on AVC is independent of the scale of production, and (4) quantities of inputs used per gallon of ethanol produced are independent of scale of production.

These limitations have given us little insight into how AVC might respond to changes in prices given the technological relationships governing ethanol's production process. Moreover, these limitations have also precluded previous studies from providing any insights into plants' likely response to changes in relative prices of wet and dry distillers' grains, and how this response mediates the impact of these price changes on AVC. These are important relationships that deserve exploration. This study sheds light into these issues via the estimation of a plant-level AVC function.

[1] While AVC is informative of entry/shutdown price, it is not synonymous. The theory of entry and exit under uncertainty and partial irreversibility (Dixit 1989) reveals that there may be a wedge (especially in the short run) between AVC and entry/shutdown prices. Financial factors (e.g., leverage, hedging, and risk management) may also influence shutdown decisions.

[2] The same assumptions have been made in estimating corn ethanol life-cycle emissions (e.g., Wang et al 2007; Liska et al 2009).

The contributions of this study are threefold: (1) this is, to our knowledge, the first econometric estimation of plant-level corn ethanol technological parameters, (2) we test, rather than assume, homotheticity and CRVIs, and (3) we model Marshallian shutdown price by incorporating a by-product supply function into AVC, a function that is estimated jointly with input demand and that allows choices of by-product mix (dry vs. wet) to be responsive to their relative prices. These contributions provide important insights into the effect of scale of production on AVC and greenhouse gas emissions per unit of output, and the degree to which price swings affect by-product choice and production decisions for plants of varying size.

Our identification strategy consists of exploiting a panel of technology and price information to specify input demand and by-product supply and to recover the variable cost function through integration. This variable cost function is innovative in that it incorporates by-product supply and it is capable of accommodating unobservable constraints in by-product markets resulting from issues, such as imperfect price foresight, risk aversion, long-term contracts, and limited access to wet by-product markets. The variable cost function developed here has desirable asymptotic properties regarding by-product prices. In particular, the relevance of by-product mix to AVC vanishes when both by-product types are equally profitable, and increases when the relative profitability of one by-product rises without bound. This variable cost function may be applicable to a range of industries where firms produce by-products that can be sold "as is" or further processed; for example, petrochemical, steel, pulp and paper, and food processing.

MODEL AND ESTIMATION

The Ethanol Production Process

The present analysis assumes that ethanol plants are cost minimizers for given levels of output, given that large capital adjustment costs limit plants' ability to scale production up or down and that input and output contracts may further limit scale adjustments. The ethanol variable cost function specifies the minimum cost of producing a given quantity of ethanol, given input and by-product prices and levels of fixed inputs (capital). This function is relevant to the plant's shutdown decision, since a plant may consider shutting down operations when output price is insufficient to cover AVC. The objective of this section is to model the total (and average) variable cost function in the ethanol industry at the plant level.

As discussed by Chambers and Pope (1993) there are two approaches to modeling firms' cost functions. One is to specify a dual indirect cost function and recover input demands and output supplies through differentiation using Shephard's lemma. A cost function, however, would relate cost to by-product quantity, while we are interested in relating the net cost of ethanol to by-product price. This could be achieved by estimating a restricted profit function, but we found it difficult to specify a functional form that would incorporate all of the specific characteristics of ethanol plant operation that we identify below. An alternative approach, which we follow in this study, consists of specifying input demand and output supply relationships with desirable properties, then recovering the cost function through integration, also consistent with Shephard's lemma. Given data on ethanol plants' technology, we specify demand and supply relationships and recover the cost function through integration.

The vast majority of ethanol in the United States is produced by dry-mill plants, therefore this study only considers dry-milling technology. In the basic dry-mill process the grain is ground into a meal, which is mixed with enzymes and water to form a mash that is cooked and fermented. The resulting beer is separated from the stillage and distilled. The remaining mash, or stillage, provides valuable by-products, which are a central issue to us in estimating the cost structure of the ethanol industry. A centrifuge is used to separate solubles from the solid materials, which are known as distillers grains. At this point, the distillers grains contain water and solubles (about 55% moisture) and can be fed directly to livestock, a feed known as modified wet distillers grains and solubles (MWDGS). Alternatively, heat may be applied to bring the moisture content down to about 10% to facilitate storage and transportation, producing dried distillers grains and solubles (DDGS) that are traded around the world. MWDGS is perishable within a few days, and its bulk makes transportation expensive, hence it is a feasible product only where there is extensive livestock production within a 40-mile radius or so (Konecny and Jenkins 2008). Hence, a dry-mill plant can produce one or both of these by-products in addition to ethanol.[3] The fraction of distillers grains and solubles that is sold as DDGS versus MWDGS is a choice firms make, presumably based on profitability signals.

For any given output level, ethanol plants combine inputs in fixed proportions (Gardner 2007; Lambert et al 2008; Stewart and Lambert 2011). But the individual and combined efficiency with which inputs are used may vary as scale of production per quarter changes. Therefore, our specification allows for nonconstant returns to inputs (inputs may not vary proportionally with output) and nonhomotheticity (i.e., inputs may vary at different rates with respect to output). Given the lack of previous studies, we have no *a priori* knowledge of whether the technology exhibits either constant returns to scale or homotheticity in variable inputs. Hence, estimation of the variable cost function should allow for variable returns and nonhomotheticity in variable inputs.

Modeling Ethanol AVC Function

The most important inputs in the ethanol production process are corn, natural gas (used throughout the process up to and including the drying of by-products for DDGS), and electricity. Other inputs include labor, denaturant, chemicals, and other administrative costs, which are aggregated in this study into a single category "other processing costs." Based on the nature of ethanol production technology just discussed, we define the demand relationships for corn and electricity by plant i at time t (we refrain from using subscripts to indicate plant and period for notational ease) as

$$q^c = \alpha_1^c y^{\alpha_2^c} \tag{1}$$

$$q^{el} = \alpha_1^{el} y^{\alpha_2^{el}} \tag{2}$$

where y is the ethanol production level (in million gallons per quarter), q^c is quantity of corn (in million bushels per quarter), q^{el} is quantity of electricity (in kilowatt hours per quarter), and the rest are parameters.

[3] Technological advances have allowed another by-product, corn oil, to be extracted. While corn oil is becoming increasingly relevant to the dry-mill industry, it is not considered here as plants surveyed in our sample had not adopted this technology by the time they were surveyed.

Natural gas is used in fixed proportions with corn and electricity to ferment and distill ethanol and it is also used in the heating of wet by-products to produce dry by-product. Therefore, the quantity used of natural gas will depend upon ethanol production and dry by-product production. This relationship can be specified as

$$q^{ng} = \alpha_1^{ng} y^{\alpha_2^{ng}} + \alpha_3^{ng} q^d \tag{3}$$

where q^{ng} is the quantity of natural gas used (MMBTUs per quarter), α_1^{ng} and α_2^{ng} are parameters determining the quantity of natural gas used for ethanol production, q^d is the quantity of dry by-product (tons of dry matter per quarter), and α_3^{ng} denotes the quantity of natural gas used per unit of dry by-product produced. The second term in Equation (3′) is linear because the amount of natural gas required to dry by-products was described by plant managers as being proportional to the amount of by-product dried.[4]

The coefficient α_3^{ng} was directly reported by managers so that the term $\alpha_3^{ng} q^d$ can be calculated for each plant at each quarter. Hence, the estimating equation can be reexpressed as

$$q^{ng,eth} = q^{ng} - \alpha_3^{ng} q^d = \alpha_1^{ng} y^{\alpha_2^{ng}} \tag{3'}$$

where $q^{ng,eth}$ is the amount of natural gas used specifically for ethanol production by plant i at time t.

Revenue from by-products is subtracted from input costs to calculate net variable costs for ethanol production. This is common for this and other industries characterized as having a primary product plus by-products (Perrin et al 2009; Hofstrand 2014). Subtraction of by-product revenue from variable cost permits calculation of the Marshallian shutdown price for an ethanol plant; that is, the level below which primary output price is insufficient to keep the plant in operation. Thus, modeling of the variable cost function necessitates modeling of the choice of by-products given their prices.

The quantity of total by-product produced has a technical upper bound. This upper bound is usually expressed as a function of the quantity of ethanol produced (McAloon et al 2000; Kwiatkowski et al 2006; Wang et al 2007; Liska et al 2009) by the plant in a given period of time. We denote this upper bound by $\overline{q^b(y)}$. The proportion of all by-product produced that is sold as DDGS will depend upon its profitability relative to MWDGS. This is, in turn, determined by the price of DDGS, the price of MWDGS, and the price of natural gas as this input is involved in additional drying operations necessary to obtain DDGS.

We denote the free-on-board price of DDGS faced by plant i at time t by p^d, p^{ng} is the price of natural gas, p^w is the free-on-board price of MWDGS, and p^b is the profitability of converting a ton of MWDGS to DDGS. Because MWDGS can be transformed into DDGS at a one-to-one rate (both are measured on a dry matter basis) corner solutions should be expected in the by-product mix, absent market frictions. Specifically, in absence of market rigidities, if $p^b = p^d - \alpha_3^{ng} p^{ng} - p^w > 0$, then all by-product will be dried

[4] This is due to technological features of drying, which is independent of the ethanol production process.

and sold as DDGS. If the reverse is true then all by-product will be sold as MWDGS. Therefore, under no rigidities in by-product market adjustments, the DDGS supply curve would converge to a staircase function where

$$q^d = \begin{cases} q^d = 0 & \text{if } p^b < 0 \\ 0 < q^d < \overline{q^b(y)} & \text{if } p^b = 0 \\ q^d = \overline{q^b(y)} & \text{if } p^b > 0 \end{cases} \tag{4}$$

where q^d is the quantity of by-product sold as DDGS, and $\overline{q^b(y)}$ represents the technical upper bound in by-product production.

Despite the linear technological transformation between DDGS and MWDGS, corner solutions are not always observed empirically (Perrin et al 2009). Interior solutions in by-product mix may be caused by plants' diversification due to price uncertainty (i.e., imperfect foresight), transaction costs, or the size of nearby livestock operations (which limit the fraction of by-product that can be sold as MWDGS). Depending on how strong rigidities are, shifts between DDGS and MWDGS caused by changes in p^b may be drastic or moderate and they may or may not take place when p^b takes values around zero. Based on this knowledge we choose to specify DDGS supply as a particular case of the generalized logistic (GL) function. As we will discuss in more detail this function asymptotically approaches the one-step staircase function (4) so its estimation permits gauging the extent to which unobservable constraints affect mix of by-products chosen. This algebraic representation of the supply of DDGS is

$$q^d = \frac{\overline{q^b(y)}}{\left[1 + \alpha_3^b \exp\left(-\alpha_4^b\left(p^b\right)\right)\right]} \tag{5}$$

where q^d is the quantity of by-product sold as DDGS, and α_3^b and α_4^b are parameters affecting the position and slope of the logistic curve. This function is q^{d^1} in Figure 1. According to Equation (5′), DDGS supply is a fraction $\frac{1}{[1+\alpha_3^b \exp(-\alpha_4^b(p^b))]}$ of total by-product production $\overline{q^b(y)}$. This fraction converges to one as p^b becomes positive and large and it converges to zero as p^b becomes negative and large in absolute value. Estimating a GL function is different from estimating the well-known Probit or Logit functions as the former is a continuous response function while the latter represent probabilities of the occurrence of a binary response random variable.

The inflection point of DDGS supply occurs at a relative profitability $p_*^b = \frac{\ln(\alpha_3^b)}{\alpha_4^b}$. The expression in Equation (5′) allows for DDGS supply to have an inflection point at a p^b different from zero, which may be the case due to unobserved constraints. In fact, the inflection point (assuming α_4^b is finite) will occur at zero if and only if $\alpha_3^b = 1$. Another important and desirable characteristic of Equation (5′) is that an increase in α_3^b increases the supply of DDGS for all $p^b > 0$ and reduces it for all $p^b < 0$. This amounts to a relaxation of constraints in by-product mix decisions and is illustrated in Figure 1 by a rotation of the supply curve from q^{d^1} to q^{d^2}.

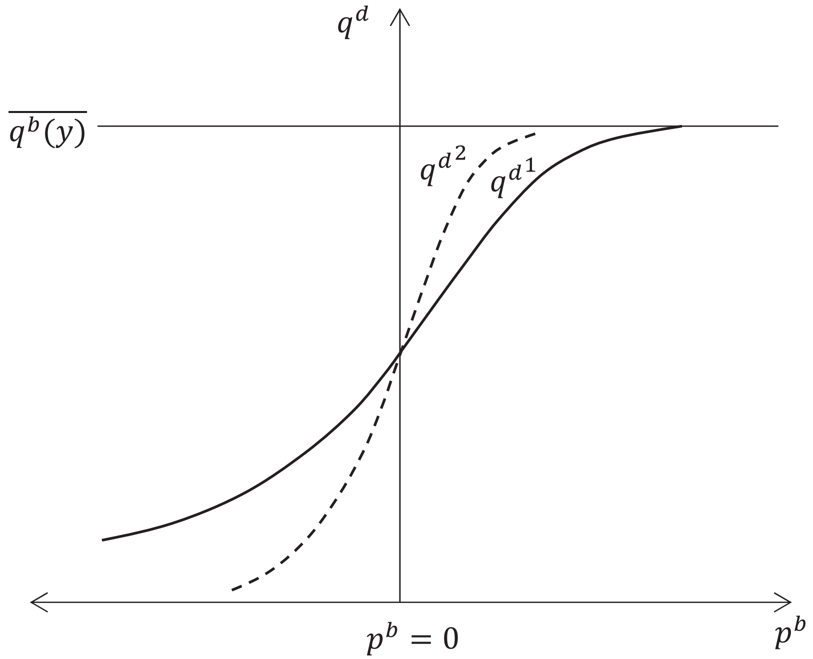

Figure 1. DDGS supply—GL function

The GL specification (5′) converges asymptotically to the staircase function (4) as $\alpha_4^b \to \infty$. This is because as $\alpha_4^b \to \infty$ the price at which the inflection point occurs converges to zero and the slope of (5′) at the inflection point converges to infinity. These are properties of the staircase function (4). Therefore, the specification in Equation (5′) is general enough to nest (asymptotically) the case of no rigidities. In addition, the GL is an integrable function and this property will be exploited to recover the variable cost function. Alternative (integrable) specifications of the DDGS supply have drawbacks. Specifying DDGS supply with a high (e.g., third)-order polynomial does not add flexibility compared to the GL and would increase the number of parameters to be estimated.

Engineering softwares describing ethanol technology (Wang et al 2007; Liska et al 2009) have assumed a linear relationship between total by-product production and ethanol production (i.e., $\overline{q^b(y)} = \theta y$, where θ is positive). We test this assumption by specifying the total by-product production as $\overline{q^b(y)} = \alpha_1^b y^{\alpha_2^b}$. This specification allows for a nonlinear relationship between ethanol production and by-product that nests the linear case when $\alpha_2^b = 1$. Therefore, Equation (5′) becomes

$$q^d = \frac{\alpha_1^b y^{\alpha_2^b}}{\left[1 + \alpha_3^b \exp\left(-\alpha_4^b p^b\right)\right]} \qquad (5')$$

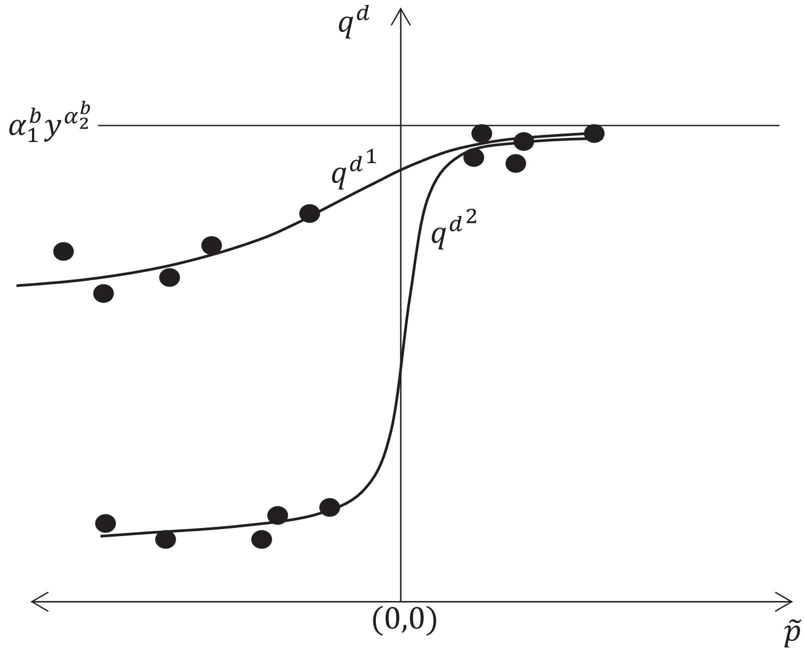

Figure 2. DDGS supply—GL function

Since $q^d + q^w = \alpha_1^b y^{\alpha_2^b}$, MWDGS supply can be expressed as

$$q^w = \alpha_1^b y^{\alpha_2^b}\left[1 - \frac{1}{\left[1 + \alpha_3^b \exp\left(-\alpha_4^b p^b\right)\right]}\right] \tag{6}$$

By Shephard's lemma the total variable cost function can be recovered by integrating demand and supply equations with respect to their corresponding prices. As mentioned before there are other inputs that constitute part of the plants' variable cost. We treat these inputs as a composite labeled "other processing cost." We use the price index of this composite to impose homogeneity by normalizing all other prices in the system.

The spatial proximity of plants to large livestock populations may have been a critical determinant of a plant's ability to sell both types of by-products. Lack of access to a large nearby livestock populations may limit the plant's ability to sell a significant portion of by-products as MWDGS. This situation is depicted by the function q^{d^1} in Figure 2, whereas the function q^{d^2} represents a situation with access to a large livestock population. Therefore, we include a measure of the thickness of livestock markets accessible to the plant, namely, the inventory of beef cows within the county in which the plant operates.[5]

[5] We have also estimated the model with county-level dummies indicating plants operating in areas with livestock inventory above the sample's median. This makes results less susceptible to outliers with very high or very low livestock inventories. The model was also estimated with

The geographic extension of a plant's market is limited by the relatively short shelf-life of MWDGS and also by competition from other ethanol plants. Beef cattle constitute the main destination of by-products as inclusion rates (the percentage of by-products that can be safely included in total diet) among milk cows, poultry, and swine are much smaller (Hoffman and Baker 2010). Once the measure of livestock market is included, Equations (5′) and (6) become

$$q^d = \frac{\alpha_1^b y^{\alpha_2^b}}{\left[1 + \left(\alpha_3^b + \alpha_I^b I\right) \exp\left(-\left(\alpha_5^b \tilde{p} + \alpha_{Ip}^b I\tilde{p} + \alpha_6^b\right)\right)\right]} \tag{7}$$

$$q^w = \alpha_1^b y^{\alpha_2^b} - \frac{\alpha_1^b y^{\alpha_2^b}}{\left[1 + \left(\alpha_3^b + \alpha_I^b I\right) \exp\left(-\left(\alpha_5^b \tilde{p} + \alpha_{Ip}^b I\tilde{p} + \alpha_6^b\right)\right)\right]} \tag{8}$$

where $\tilde{p}$ is the normalized net return from DDGS relative to MWDGS for plant i in period t, and $I\tilde{p}$ is the product of county-level livestock inventory and the normalized net return from DDGS for plant i in period t.

We combine Equations (7) and (8) to obtain the following two equations which facilitate estimation

$$q^b = q^d + q^w = \alpha_1^b y^{\alpha_2^b} \tag{9}$$

$$\frac{q^d}{q^b} = \frac{1}{\left[1 + \left(\alpha_3^b + \alpha_I^b I\right) \exp\left(-\left(\alpha_5^b \tilde{p} + \alpha_{Ip}^b I\tilde{p} + \alpha_6^b\right)\right)\right]} \tag{10}$$

where $\tilde{p} = \frac{p^b}{p^o} = \frac{p^d - \alpha_3^{ng} p^{ng} - p^w}{p^o}$ and p^o is the price index of the composite of "other inputs." In Equation (9) the livestock inventory is allowed to affect both the horizontal position (through α_I^b) and the slope (through α_{Ip}^b) of the equation specifying the fraction of by-product sold as DDGS.

Integrating demand functions (1)–(3′), and supply relationships (7) and (8) with respect to normalized prices yields, the following normalized variable cost function with homogeneity in prices imposed

$$\begin{aligned}\widetilde{VC} = {} & C + \widetilde{p^c}\alpha_1^c y^{\alpha_2^c} + \widetilde{p^{el}}\alpha_1^{el} y^{\alpha_2^{el}} + \widetilde{p_{it}^{ng}}\alpha_1^{ng} y^{\alpha_2^{ng}} \\ & -\alpha_1^b y^{\alpha_2^b}\left\{\widetilde{p^w} + \frac{ln\left[1 + \left(\alpha_3^b + \alpha_I^b I\right)^{-1} \exp\left(\alpha_5^b \tilde{p} + \alpha_{Ip}^b I\tilde{p} + \alpha_6^b\right)\right]}{\left(\alpha_5^b \tilde{p} + \alpha_{Ip}^b I\tilde{p} + \alpha_6^b\right)} - \frac{ln\left[1 + \left(\alpha_3^b + \alpha_I^b I\right)^{-1}\right]}{\left(\alpha_5^b \tilde{p} + \alpha_{Ip}^b I\tilde{p} + \alpha_6^b\right)}\right\}\end{aligned}$$

state-level livestock information to capture the possibility that livestock markets extend beyond the boundaries of the plant's county. All results and insights are robust to the choice of proxy. Results from these estimations are available from the authors upon request.

where the constant of integration with respect to DDGS and MWDGS prices has been defined as $\alpha_1^b y^{\alpha_2^b} \frac{ln[1+(\alpha_3^b+\alpha_I^b I)^{-1}]}{(\alpha_5^b \widetilde{p^c}+\alpha_{Ip}^b I\tilde{p}+\alpha_6^b)}$ and the sum of all other constants of integration is denoted as C. The demand for "other inputs" (labor and other processing costs) is calculated residually as

$$q^o = C + \alpha_1^b y^{\alpha_2^b} \left\{ \left(\widetilde{p^d} - \widetilde{p^{ng}} \alpha_3^{ng} - \widetilde{p^w} \right) - \frac{ln\left[1 + \left(\alpha_3^b + \alpha_I^b I\right)^{-1} \exp\left(\alpha_5^b \tilde{p} + \alpha_{Ip}^b I \tilde{p} + \alpha_6^b\right)\right]}{\left(\alpha_5^b \tilde{p} + \alpha_{Ip}^b I \tilde{p} + \alpha_6^b\right)} \right\} \quad (11)$$

The fact that the demand for "other inputs" has a different functional form than the rest of the inputs is not problematic in this context as this composite is not expected to be used in fixed proportions. This is in contrast to other situations in which homogeneity in functional form does matter for economic analysis (Mahmud et al 1987).

The unnormalized variable cost function can be obtained by multiplying both sides of the normalized variable cost by p_{it}^o

$$\begin{aligned} VC = {} & Cp^o + p^c \alpha_1^c y^{\alpha_2^c} + p^{el} \alpha_1^{el} y^{\alpha_2^{el}} + p^{ng} \alpha_1^{ng} y^{\alpha_2^{ng}} \\ & -\alpha_1^b y^{\alpha_2^b} \left\{ p^w + p^o \frac{ln\left[1 + \left(\alpha_3^b + \alpha_I^b I\right)^{-1} \exp\left(\alpha_5^b \tilde{p} + \alpha_{Ip}^b I \tilde{p} + \alpha_6^b\right)\right]}{\left(\alpha_5^b \tilde{p} + \alpha_{Ip}^b I \tilde{p} + \alpha_6^b\right)} - p^o \frac{ln\left[1 + \left(\alpha_3^b + \alpha_I^b I\right)^{-1}\right]}{\left(\alpha_5^b \tilde{p} + \alpha_{Ip}^b I \tilde{p} + \alpha_6^b\right)} \right\} \end{aligned} \quad (12)$$

The AVC of an ethanol plant can be calculated by dividing both sides of (12) by ethanol production

$$\begin{aligned} AVC = {} & Cp^o y^{-1} + p^c \alpha_1^c y^{\alpha_2^c - 1} + p^{el} \alpha_1^{el} y^{\alpha_2^{el} - 1} + p^{ng} \alpha_1^{ng} y^{\alpha_2^{ng} - 1} \\ & -\alpha_1^b y^{\alpha_2^b - 1} \left\{ p^w + p^o \frac{ln\left[1 + \left(\alpha_3^b + \alpha_I^b I\right)^{-1} \exp\left(\alpha_5^b \tilde{p} + \alpha_{Ip}^b I \tilde{p} + \alpha_6^b\right)\right]}{\left(\alpha_5^b \tilde{p} + \alpha_{Ip}^b I \tilde{p} + \alpha_6^b\right)} - p^o \frac{ln\left[1 + \left(\alpha_3^b + \alpha_I^b I\right)^{-1}\right]}{\left(\alpha_5^b \tilde{p} + \alpha_{Ip}^b I \tilde{p} + \alpha_6^b\right)} \right\} \end{aligned} \quad (13)$$

Defining the constant of integration with respect to by-product prices as $\alpha_1^b y^{\alpha_2^b} \frac{ln[1+(\alpha_3^b+\alpha_I^b I)^{-1}]}{(\alpha_5^b \tilde{p}+\alpha_{Ip}^b I\tilde{p}+\alpha_6^b)}$ yields an AVC function displaying desirable asymptotic properties. As one by-product becomes significantly more profitable than the other, the fraction of by-product sold in that form (denoted by the term in brackets) converges to one and the role of the less profitable by-product in the AVC function vanishes.[6] When both types of by-product are equally profitable (i.e., $\tilde{p} = 0$) the by-product part of the AVC function converges to $\alpha_1^b y^{\alpha_2^b - 1} p^w$ which is equal to $\alpha_1^b y^{\alpha_2^b - 1}(p^d - \alpha_3^{ng} p^{ng})$.

[6] Note that when p_{it}^d becomes very large relative to p_{it}^w (i.e., $\tilde{p}_{it}$ converges to ∞) the fraction of by-product sold as DDGS converges to one and the by-product part of the AVC function tends to $\alpha_1^b y^{\alpha_2^b - 1}(p^d - \alpha_3^{ng} p^{ng})$ because $p^o \frac{ln[1+(\alpha_3^b+\alpha_I^b I)^{-1} \exp(\alpha_5^b \tilde{p}+\alpha_{Ip}^b I\tilde{p}+\alpha_6^b)]}{(\alpha_5^b \tilde{p}+\alpha_{Ip}^b I\tilde{p}+\alpha_6^b)}$ converges to $p^o \tilde{p} = p^d - \alpha_3^{ng} p^{ng} - p^w$.

Econometric Estimation

After taking logarithm on both sides of Equations (1), (2), (3′), and (9), and including Equation (10), the system of equations to be estimated can be reexpressed as

$$lnq^{c} = \gamma_1^{c} + \alpha_2^{c} lny \tag{14}$$

$$lnq^{el} = \gamma_1^{el} + \alpha_2^{el} lny \tag{15}$$

$$lnq^{ng,eth} = \gamma_1^{ng} + \alpha_2^{ng} lny \tag{16}$$

$$lnq^{b} = \gamma_1^{b} + \alpha_2^{b} lny \tag{17}$$

$$\frac{q^d}{q^b} = \frac{1}{\left[1 + \left(\alpha_3^b + \alpha_I^b I\right)\exp\left(-\left(\alpha_5^b \tilde{p} + \alpha_{Ip}^b I\tilde{p} + \alpha_6^b\right)\right)\right]} \tag{18}$$

The seemingly unrelated regression (SUR) system (14)–(18) can be estimated by pooling the data. However, technological and behavioral heterogeneity across plants may cause inconsistency of parameter estimates obtained with pooled data. Sources of heterogeneity in our sample (e.g., regional specificities or plant's location, managerial ability) are likely to be correlated with time-varying factors (prices and output). Estimation techniques that can successfully accommodate this issue include fixed effects and correlated random effects.[7]

Fixed effects techniques either preclude estimation of intercepts (if implemented by time demeaning the data) or result in inconsistent estimates due to the incidental parameters problem (if firm-specific dummies are used) as shown by Lancaster (2000). In the context of this study the former limitation is particularly harmful as it prevents quantification of the level of the AVC function and thus of the Marshallian shutdown price.

In this situation, the Mundlak–Chamberlain (MC) device (Mundlak 1978; Chamberlain 1982) provides a useful alternative. Consistent estimation can be attained in the presence of unobservable heterogeneity sources that are correlated with observable time-varying regressors, while preserving nonlinearity of the by-product mix equation. Furthermore, the MC device, in contrast to other correlated random effects techniques, saves on degrees of freedom while still producing estimates of intercepts, thus allowing recovery of the variable cost function. The approach suggested by MC attempts to identify technological and behavioral responses across plants as distinct from technological and behavioral responses within plants. Here we identify responses across plants with changes in average plant output, and changes within plants with changes in output given capacity.

Within-plant responses are estimated through the MC device by redefining some parameters in the system (14)–(18). Specifically, the MC device is implemented by imposing $\gamma_1^c = \alpha_{MC}^c + \alpha_{avg}^c \overline{lny}_i$, $\gamma_1^{el} = \alpha_{MC}^{el} + \alpha_{avg}^{el}\overline{lny}_i$, $\gamma_1^{ng} = \alpha_{MC}^{ng} + \alpha_{avg}^{ng}\overline{lny}_i$, $\gamma_1^{b} = \alpha_{MC}^{b} +$

[7] Regular random effects assume independence between unobserved heterogeneity and observable time-varying factors and are, thus, inadequate in this context.

$\alpha^b_{avg}\overline{lny}_i$, and $\alpha^b_6 = \alpha^b_{\bar{\tilde{p}},MC}\bar{\tilde{p}}_i + \alpha^b_{\overline{I\tilde{p}}}\overline{I\tilde{p}}_i$; where $\overline{lny}_i$ denotes the average of lny_{it} over t, $\bar{\tilde{p}}_i$ denotes the average of $\tilde{p}_{it}$ over t, and $\overline{I\tilde{p}}_i$ is the average of $I_{it}\tilde{p}_{it}$ over t. On the other hand, estimation of the system by pooled seemingly unrelated regression (PSUR) simply proceeds by treating γ^c_1, γ^{el}_1, γ^{ng}_1, γ^b_1, α^b_6 as scalar parameters to be estimated. Econometric estimation of the system (14)–(18) allows us to recover all parameters involved in Equation (13) except for C which is calculated residually.

DATA

The data for estimation of system (14)–(18) consist of quarterly reports of seven ethanol plants each located in a different state of the North Central Region of the United States (Perrin et al 2009). To be included in the survey a plant must have started production (or restarted) after mid 2005 with a capacity close to 50 million gallons per year or more, so as to represent modern technology. This resulted in a sample of dry-mill, natural gas-fired plants, using the most current ethanol processing technology. The period surveyed included from the third quarter of 2006 until the fourth quarter of 2007 (six consecutive quarters) but not all plants reported data in all quarters resulting in an unbalanced panel.[8] Descriptive statistics of the sample of participating ethanol plants are reported in Table 1.

The surveyed plants produced an average rate of 13.7 million gallons per quarter (55 million gallons per year), with a coefficient of variation of 0.21 across the whole sample. Production figures in Table 1 also reveal considerable within-plant variability of production over time (i.e., coefficient of variation of within-plant ethanol production is 0.05). On average, both types of by-products have a similar return (average return of DDGS relative to MWDGS is close to zero). However, there is wide variation in relative by-product returns as indicated by large coefficient of variations both across plants in the sample, and within-plant over time.

On average 64% of by-product was sold as DDGS, but this ranged from one plant that sold absolutely no by-product as DDGS to another plant that sold nearly all by-product (97%) as DDGS. Table 1 shows substantial variability of the fraction sold as DDGS both within and between plants. Values in Table 1 also reveal considerable between and within-plant variability on natural gas and electricity usage in the sample. This within- and between-plant variability across cost and revenue categories allows identification of cost parameters under PSUR and MC seemingly unrelated regression (MCSUR).[9]

[8] Despite the unbalanced nature of the panel we have little reason to be concerned about inconsistency due to self-selection in missing data. Surveys occurred over a period of three quarters, so that some plants could report later periods than others, and one plant had not started up during the first quarter of the survey. Quarters for which certain plants did not report information are not the result of shutdowns. Plants were in fact operating, but could not share that information for a variety of reasons.

[9] Further information about the sampling criteria, the characteristics of these plants, and how they compare to other estimates in the literature can be found in Perrin et al (2009).

Table 1. Summary statistics of seven surveyed plants

States represented	Iowa, Michigan, Minnesota, Missouri, Nebraska, S. Dakota, Wisconsin	
Number of survey responses by quarters	03_2006	5
	04_2006	6
	01_2007	7
	02_2007	6
	03_2007	7
	04_2007	2
Ethanol production	Average	13.7 million gallons per quarter
	Coefficient of variation (whole sample)	0.21
	Coefficient of variation (within plant)	0.05
Corn consumed	Average	0.35 bushels per gallon
	Coefficient of variation (whole sample)	0.20
	Coefficient of variation (within plant)	0.05
Natural gas consumed	Average (whole sample)	0.026 MMBTUs/gallon
	Coefficient of variation (whole sample)	0.17
	Coefficient of variation (within plant)	0.043
Electricity consumed	Average (whole sample)	0.57 kWh/gallon
	Coefficient of variation (whole sample)	0.20
	Coefficient of variation (within plant)	0.06
By-Product net returns	Average (whole sample)	−1.80 ($ per metric ton)
	Coefficient of variation (whole sample)	−14.9
	Coefficient of variation (within plant)	−0.46
Fraction of by-product sold as DDGS	Average (whole sample)	0.64
	Coefficient of variation (whole sample)	0.49
	Coefficient of variation (within plant)	0.075

Table 2. Results from estimation

Coefficient	Equation	Notation	Mundlak–Chamberlain SUR	Notation	Nonlinear PSUR
Corn intercept	(14)	α^{c}_{MC}	−0.45	γ^{c}_{1}	0.18
Corn intercept mean		α^{c}_{avg}	0.18*	NA	NA
Corn elasticity		$\boldsymbol{\alpha^{c}_{2}}$	**0.78*****	$\boldsymbol{\alpha^{c}_{2}}$	**0.93*****
Electricity intercept	(15)	α^{el}_{MC}	0.54	γ^{el}_{1}	−0.95
Electricity intercept mean		α^{el}_{avg}	0.29	NA	NA
Electricity elasticity		$\boldsymbol{\alpha^{el}_{2}}$	**0.71*****	$\boldsymbol{\alpha^{el}_{2}}$	**1.02*****
Natural gas intercept	(16)	α^{ng}_{MC}	−9.61***	γ^{ng}_{1}	−5.37***
Natural gas intercept mean		α^{ng}_{avg}	0.83***	NA	NA
Natural gas elasticity		$\boldsymbol{\alpha^{ng}_{2}}$	**0.51*****	$\boldsymbol{\alpha^{ng}_{2}}$	**1.08*****
By-Product intercept	(17)	α^{b}_{MC}	−3.44***	γ^{b}_{1}	−2.96***
By-Product intercept mean		α^{b}_{avg}	0.55	NA	NA
By-Product elasticity		$\boldsymbol{\alpha^{b}_{2}}$	**0.50****	$\boldsymbol{\alpha^{b}_{2}}$	**0.82*****
Fraction of by-product sold as DDGS	(18)	α^{b}_{3}	0.24***	α^{b}_{3}	0.27**
		α^{b}_{I}	0.00003***	α^{b}_{I}	0.00003***
		α^{b}_{5}	0 (imposed)	α^{b}_{5}	0 (imposed)
		$\alpha^{b}_{\bar{p},MC}$	0 (imposed)	NA	NA
		$\alpha^{b}_{I\bar{p}}$	0.000002***	NA	NA
		α^{b}_{Ip}	−0.000000006	α^{b}_{6}	0.0000004

Notes: ***Significant at 1% level.
**Significant at 5% level.
*Significant at 10% level.

RESULTS

Results revealed that firms surrounded by thin livestock markets do not adjust their by-product mix to observed price signals (estimates of α^{b}_{5} and $\alpha^{b}_{\bar{p},MC}$ are virtually zero and statistically insignificant across specifications). This is unsurprising as limited access to nearby livestock markets constraints the amount of by-product that can be sold at observed MWDGS prices. We reestimated all models imposing a zero value for these parameters, as supported by a likelihood ratio test (which implements the statistical principle of downward selection of Gallant and Jorgenson 1979).

Results from estimation of our models are reported in Table 2. In the presence of heteroskedasticity or serial correlation the nonlinear least squares estimator is consistent and unbiased but inefficient and inference is compromised. We use the iterative feasible (sample error covariance is used as an estimator of the true covariance matrix) generalized nonlinear least squares method, which results in efficient estimation. This approach consists of transforming the data by the Cholesky decomposition of the error covariance matrix estimator. A new set of parameters are estimated with the transformed data and the corresponding residuals are used to repeat the process. This process continues until coefficient estimates and the estimates of the error covariance matrix converge within some predetermined tolerance range.[10]

Under both specifications the estimated cost function satisfies the regularity conditions derived from economic theory, at all observation points.[11] Around 70% of estimated parameters are statistically significant at the 10% level and, in particular, all but one input scale elasticity parameters (in bold in Table 2), are significantly different from zero at the 1% level (that elasticity is significant at 5%). This suggests that, despite the small sample size, reasonable precision is achieved. Results from the pooled model are statistically and quantitatively different from the MC model. This underscores the importance of distinguishing between within- and between-plant variability in production relationships. We now focus our attention on within-plant responses and, consequently, discuss parameter estimates from the MC model.[12]

One-sided Neyman–Pearson tests result in failure to reject the hypotheses (at the 1% level) that $\alpha_2^c \geq 1, \alpha_2^{el} \geq 1$, and $\alpha_2^{ng} \geq 1$. We can then assert with reasonable confidence that plants in this sample did not operate under CRVIs as is assumed by engineering softwares[13] (Wang et al 2007; Liska et al 2009) and some economic analyses (e.g., Perrin et al 2009) of ethanol plants. Similarly, hypotheses $\alpha_2^c - \alpha_2^{el} = 0, \alpha_2^c - \alpha_2^{ng} = 0$, and $\alpha_2^{el} - \alpha_2^{ng} = 0$ are also rejected at the 1% level, which means that homotheticity of technology is also rejected. Therefore, two of the most common assumptions regarding ethanol plants' technology (homotheticity and CRVIs) are rejected by this analysis.

We find increasing returns to corn, electricity, and natural gas ($\alpha_2^c, \alpha_2^{el}, \alpha_2^{ng} < 1$); that is, increases in production require less than proportional increases in these inputs. It is apparent from results in Table 2 that MC estimates detect larger returns to variable input levels relative to the pooled approach. MC estimation captures the intraplant link between inputs and outputs while pooled regressions also consider changes in inputs and outputs across plants. The MC approach reveals locally decreasing short-run AVCs for all plants. Moreover, higher returns to variable input levels in the MC model relative to pooled estimation are consistent with returns to input levels being larger when a plant of a given capacity increases production relative to returns to input levels resulting from increased capacity. This suggests that, perhaps due to the nature of the ethanol production technology, production below nameplate capacity may be associated with technical inefficiencies in the production process.

[10]This procedure was implemented with the ifgnls option of the nlsur command in STATA (StataCorp LP, College Station, TX).

[11]Homogeneity of degree one in prices, continuity, symmetry, concavity in prices, and monotonicity in prices are satisfied globally.

[12]A model in which we specify a linear by-product mix choice function was also estimated. Results from the linear model are similar to the nonlinear one but Akaike information criterion and Bayesian information criterion tests suggest statistical superiority of the nonlinear specification. Results from the linear model are available from the authors upon request.

[13]These softwares are designed to describe input–output relationships of a representative plant to conduct life-cycle analysis of greenhouse gases.

The hypothesis that total by-product produced increases linearly with ethanol production ($\alpha_2^b = 1$) is rejected at the 1% level. Under MC estimates, by-product increases less than proportionally with ethanol output ($\alpha_2^b < 1$), consistent with increasing returns to corn if the materials balance condition holds. Regarding the choice of by-product mix, the positive sign and statistical significance of α_I^b reveals that plants with access to thick livestock markets tend to sell a higher fraction of by-product as MWDGS. Furthermore, the quantitative and statistical insignificance of α_{Ip}^b suggests that not even plants with access to thick livestock markets are responsive to short-term changes in price signals when choosing by-product mix. In contrast, $\alpha_{I\bar{p}}^b$ is positive and statistically significant, indicating that plants that face better relative prices over time for DDGS than for MWDGS do tend to sell a higher fraction of by-products as DDGS. Combining these results with those of pooled models suggests that plants choose the fraction of by-product sold as DDGS based on long-term trends of relative profitabilities, and that this fraction varies little over time in response to short-run changes in price signals.[14]

IMPLICATIONS OF ESTIMATED PARAMETERS

Corn Price, Scale of Production, and Variable Cost

Corn constitutes about 70% of an ethanol plant's operating cost, and corn prices have varied dramatically from \$2 per bushel in 2005 to \$6 in 2008, back to \$3 in 2009, to \$7 in 2011, and down to \$4.4 by the end of 2013 (Hofstrand 2014). Given the high share of corn in total cost, such drastic swings translate into high volatility of ethanol production cost. Results in Table 2, however, also suggest that when a plant increases production within its capacity, it uses less corn per gallon of ethanol. Therefore, plants operating at low capacity may be more vulnerable to an increase in corn price. We now examine this issue quantitatively.

The price of corn affects AVC through two distinct channels. First, it affects AVC directly through feedstock cost. Second, given that corn and by-products are substitutes in the livestock feed market, their prices are correlated. This creates an additional channel through which corn prices affect AVC, namely, changes in by-product revenue. The latter effect makes AVC less sensitive to the price of corn. Hurt et al (2008) estimate the relationship between by-product and corn prices as $p^d = 1.52 + 0.205\, p^{sm} + 22\, p^c$, where p^d is price of DDGS (\$ per dry ton), p^{sm} is price of soybean meal (\$ per dry ton), and p^c is price of corn (\$ per bushel). We further assume that changes in corn price affect both by-product prices equally, so that changes in corn price do not affect the by-product allocation choice.

We are interested in quantifying the effect of changes in corn price on AVC, given the plant's output. Figure 3 depicts the relationship between the price of corn, scale of production, and AVC under parameter estimates with the MC approach. AVC values depicted in Figure 3 were calculated using prices of electricity and natural gas expected in 2015, which are \$0.07/kWh (obtained from US DOE, 2014) and \$4 per million BTUs (obtained from AgWeb's Farm Commodity Futures Prices and Agriculture), respectively. A range of corn prices was simulated and by-product prices are calculated as a function of corn price following the function estimated in Hurt et al (2008).

[14]At the sample mean, coefficient estimates imply that a 1% increase in county-level livestock inventory reduces the fraction of by-product sold as DDGS by 0.13%.

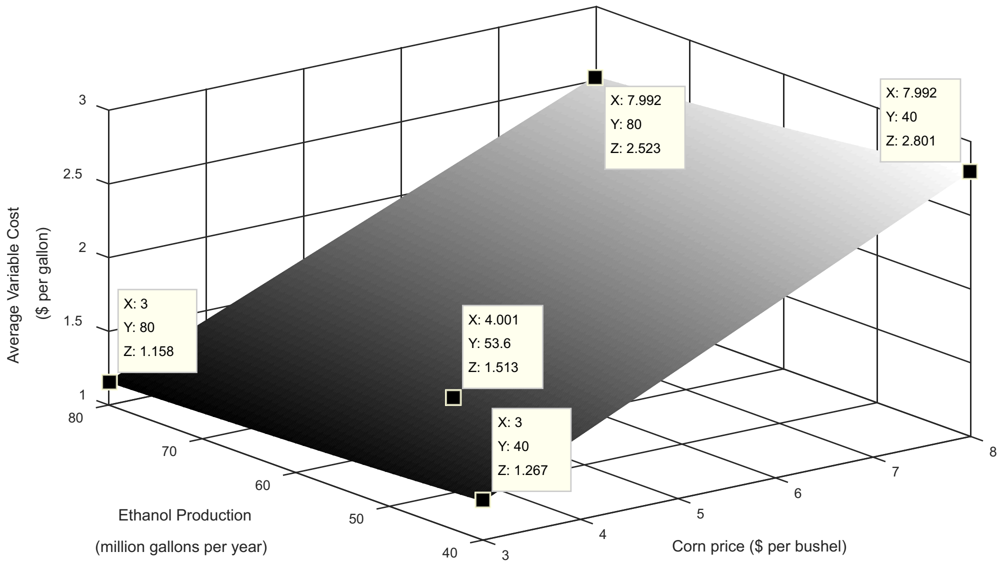

Figure 3. Scale of production, price of corn, and average variable cost

Data points inserted on the corners of the surface reveal important information. Following the trajectory of the surface along the corn price axis for the smallest and largest scales of production in the figure, reveals that an increase in corn price increases cost less as output increases. For a plant with a capacity of 80 million gallons per year or more, an increase in corn price from \$3/bushel to \$8/bushel (the range within which corn price has fluctuated since 2008) increases AVC by \$1.53/gallon if the plant produces 40 million gallons per year and by \$1.35/gallon if the plant produces 80 million gallons per year.

While previous literature has addressed the issue of potential economies of size in capital cost of ethanol plants (Gallagher et al 2005; Kotrba 2006) and the link between size and feedstock cost due to spatial characteristics of corn markets (Gallagher et al 2007), there is still a dearth of information on the relative importance of scale of production on plants' AVC. The results in Table 2 show that an increase in the scale of production has ambiguous effects on AVC. On one hand, an increase in the scale of production results in increased input productivity as revealed by elasticities of input with respect to output that are lower than one. On the other hand, an increase in the scale of production reduces by-product yield per gallon of ethanol produced as revealed by an elasticity of by-product with respect to ethanol production lower than one. Figure 3 reveals that the former effect dominates the latter resulting in economies of scale.

Figure 3 also reveals that economies of scale are not independent of corn price. If inputs and by-products varied linearly with ethanol production ($\alpha_2^c = \alpha_2^b = 1$) the marginal effect of corn price on AVC would be independent of scale of production. However, the hypotheses $\alpha_2^c = \alpha_2^b = 1$ were rejected under all specifications. Following the surface along the scale of production axis for the highest and lowest corn prices in the figure, reveals that an increase in the scale of production from 40 million gallons per year to 80 million gallons per year reduces AVC by about \$0.10 per gallon under a low corn price (\$3 per bushel) and by about \$0.30 per gallon under a high corn price (\$8 per bushel).

Finally, we have inserted a data point on the surface of Figure 3 that identifies the Marshallian shutdown price relevant to expected prices over 2015 (\$4 per bushel of corn, \$0.07 per kilowatt hour of electricity, \$4 per MMBTU of natural gas, \$134.6 per metric ton of DDGS matter). As revealed by this data point, the predicted Marshallian shutdown price is approximately \$1.51/gallon. We can use estimated parameters and Equation (13) to decompose this shutdown price into its different terms. A total of \$1.40/gallon corresponds to feedstock cost, \$0.04/gallon to electricity, \$0.07/gallon to natural gas, \$0.30/gallon to the composite of other processing costs, and by-product sales reduce the AVC by \$0.30/gallon.

Scale Elasticities and Carbon Intensity of Corn Ethanol

Scale elasticity estimates are important in determining greenhouse gas emissions associated with ethanol production. Corn production and natural gas use are responsible for the majority of greenhouse gases emitted in the production of corn ethanol by dry-mill plants. Elasticities of corn and natural gas with respect to ethanol production estimated with the MC approach suggest that plants that produce more tend to use less corn and natural gas per gallon of ethanol.

The reduction in emissions per gallon of ethanol produced (i.e., carbon intensity) occur when increases in production are attained through enhanced utilization of nameplate capacity rather than increased nameplate capacity. This indicates that it may be important to account for the plant's actual output level (as opposed to nameplate capacity) when calculating the carbon intensity of corn ethanol, an issue ignored in life-cycle accounting models (e.g., Argonne's Greenhouse gases, Regulated Emissions, and Energy use in Transportation—GREET—model by Wang et al 2007, and Biofuel Energy Systems Simulator—BESS—by Liska et al 2009) that assume constant input–output ratios.

By-Product Mix and AVC

Parameter estimates reported in Table 2 indicate that plants adjust their by-product mix very little in response to short-run price signals. Results further show that plants located near large livestock populations sell, on average, a lower fraction of by-products as DDGS. Insights emerging from predicted fractions of by-product sold as DDGS are consistent across specifications. The models predict that firms without access to thick livestock markets will sell about 80% of their by-products as DDGS. On the other hand, firms with access to thick livestock markets will sell about 56% of by-product produced as DDGS.

While analysis in the previous section was conducted under the assumption of efficient by-product markets ($p^b = p^d - \alpha_3^{ng} p^{ng} - p^w = 0$), evidence suggests that deviations of p^b from zero have occurred frequently (Schroeder 2009). Market and contracting factors presumably limit plants' ability to exploit arbitrage. Examples of these factors are access to extensive nearby livestock populations, and the portion of by-products sold in advance by contract which may be decided under imperfect price foresight.

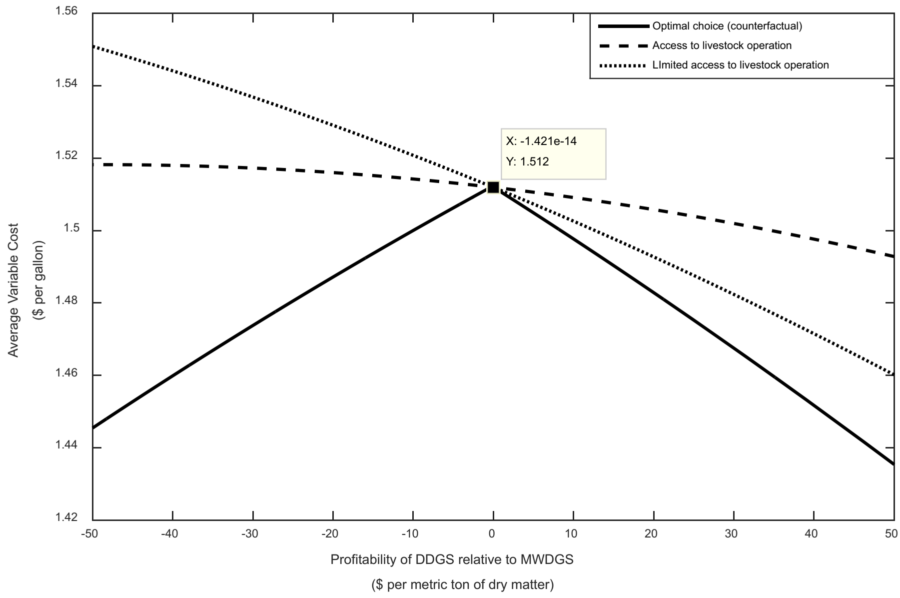

Figure 4. Access to livestock markets and ethanol average variable cost

Figure 4 plots AVC at different relative profitabilities (p^b in our model) between DDGS and MWDGS[15] for plants under three distinct situations: (1) optimal choice (resulting from staircase function which corresponds to unlimited access to both markets and perfect arbitrage), (2) access to large livestock operations (MCSUR with $I = 19{,}000$ which is the maximum county-level livestock inventory in our sample), and (3) limited access to livestock operations (MCSUR with $I = 0$ which is the minimum county-level livestock inventory in our sample). Note that the first of these three situations is a counterfactual state constructed for use as a benchmark against which estimated responses (2 and 3) can be compared. With the exception of by-products, prices are evaluated at their expected 2015 levels, which were obtained from AgWeb's Farm Commodity Futures Prices and Agriculture (corn and natural gas) and US DOE (2014; electricity).

Simulations plotted in Figure 4 indicate that plants without access to thick MWDGS markets will see their AVC considerably increased relative to the benchmark when returns from MWDGS rise relative to DDGS. Plants with limited access to MWDGS markets do not suffer significant deviations from the optimal by-product mix when DDGS is more profitable than MWDGS ($p^b > 0$). These plants, on average, tend to sell most of their by-product production as DDGS. On the other hand, when $p^b > 0$, plants with access to MWDGS experience a greater deviation from the optimal mix. This is because these plants tend to diversify their by-product sales between DDGS and MWDGS (56% as

[15]Simulation started with a maximum profitability of DDGS and minimum profitability of MWDGS. Then proportional reductions in returns from DDGS and equi-proportional increases in returns from MWDGS were generated, which resulted in different levels of p^b. Natural gas required for drying was set at the sample average.

DDGS and 44% as MWDGS), but are unresponsive to changes in relative profitability once the portfolio of by-product types has been established.

The above analysis considers a rather wide range of relative profitabilities of by-products but remains silent regarding the plausibility of such range. To explore this issue, we use data on prices of DDGS, MWDGS, and natural gas. Data on natural gas price are readily available but data on by-product prices are scattered. Schroeder (2009) and Hoffman and Baker (2010) provide information on spot price differentials between DDGS and MWDGS from 2007 to 2010. Both studies show price differentials that are, at times significantly lower than drying costs ($p^b < 0$) and at times significantly higher ($p^b > 0$). Deviations from the no-arbitrage point ($p^b = 0$) may have ranged from −\$40 to \$30 during the period considered by Schroeder (2009). Therefore, increases in AVC of ethanol due to constrained by-product mix choice may have been substantial during the sample period. It should be noted that our ability to extrapolate our insights on by-product mix choice (and, especially, the quantitative magnitudes) to the current situation of plants is limited given the emergence of corn oil extraction as a third by-product.

CONCLUSIONS

This study estimates ethanol plants' AVCs, using a plant-level data set. This cost function allows us to examine the responsiveness of by-product mix choice to their relative prices, and to test assumptions of homotheticity and CRVIs that are commonly encountered in engineering studies as well as in past economic studies. This deepens our understanding of how price swings affect the cost structure of plants of varying size. It also provides information on the effect of changes in scale of production on average cost and carbon intensity of the ethanol product.

To analyze the impact of prices and scale of production on AVC, we propose a novel variable cost function. This variable cost function accommodates varying degrees of constraints in by-product markets and displays desirable asymptotic properties regarding the marginal effect of by-product mix on AVC. We used the MC device to distinguish effects of production changes at the intensive margin (changes in capacity utilization) versus the extensive margin (changes in capacity). The assumptions of homotheticity and constant returns were econometrically rejected for changes at the intensive margin.

Results from this model also indicate that as plants increase production at the intensive margin they use less electricity, natural gas, and less corn per gallon of ethanol (which means that they also produce less by-product). Thus, production increases at the intensive margin appear to reduce both cost per gallon and greenhouse gas per gallon of ethanol. Overall, these results suggest that a reduction in ethanol demand not only puts strains on plants' profitability through a reduction in output price, but may also reduce ethanol's cost-effectiveness and increase its carbon intensity if it forces plants to operate below capacity. An increase in carbon intensity associated with unutilized production capacity lessens the case for policy support right when it is needed the most due to a decrease in cost-effectiveness.

Econometric results also indicate that plants have indeed faced constraints in adjusting the mix of by-products in response to price signals. These constraints (either observables like lack of access to nearby livestock operations or unobservables, such as risk aversion and imperfect foresight on by-product prices) may result in moderate increases in AVC if prices substantially deviate from a no-arbitrage situation (i.e., DDGS and MWDGS are equally profitable).

Regarding the validity of results based on a 2006–07 survey, for plants in 2015 and beyond, note that all estimated equations—except the one describing choice of by-product mix—represent technological relationships. Results should therefore be relevant to plants of similar size and vintage, despite changes in price regime. According to the State of Nebraska Energy Statistics Service (2015), about 70% of plants operating in the United States as of 2015 produce within the range output represented in this sample.

Finally, while significant technological changes in basic ethanol processing have not been apparent in the last few years, important modifications in by-product production technology have occurred to produce corn oil as an additional by-product. Therefore, while insights on increasing returns to variable inputs could reliably describe the technological situation of many plants today, our ability to describe the overall impact of by-products on AVC on these modified plants is limited. However, the framework developed here is applicable to these new technological conditions, which constitutes an interesting research opportunity.

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