The Shadow Price of GHG Reduction in Corn Ethanol Plants

Kassu Wamisho

Department of Agricultural Economics, University of Nebraska-Lincoln
103C Filley Hall, Lincoln, NE 68583-0922, USA
E-mail: kassuwam@gmail.com
Tell: (402) 472-3401

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Abstract

This article examines the cost of reducing CO2 emissions in a sample of recently built dry-grind corn ethanol plants. The analysis estimates a translog minimum value function that represents both the minimum cost and the minimum CO2 emissions for given levels of ethanol production. The results indicate that the average plant is able to reduce GHG emissions by 36 percent relative to the level under cost minimization, but production costs are 22 percent higher. The reallocations by which these emissions reductions are achieved are primarily the substitution of wet for dry distillers grains, with the corresponding reduction in the use of natural gas and electricity. To move from least cost to least emissions allocations, ethanol plants would on average produce 25 % more of wet byproduct and 47% less of dry byproduct. Comparing results across observations, the estimated shadow cost of emission abatement ranges from \$86 to \$190 per ton of CO2, with average value of \$124 per ton. This implied shadow cost of abatement can be used as a bench mark for pollution trading and serves to assess the potential response to biofeul regulations.

Key words: GHG abatement, shadow price of abatement, corn ethanol

1. Introduction

A common approach to measuring environmental efficiency when desirable and undesirable outputs are produced jointly is to treat the undesirable output as another variable into the production model, either as another input or as a weakly disposable bad output[1]. Such analysis is frequently based on a primal representation of the technology using Input- and output-oriented distance functions.

In this article we followed different route to measure the environmental efficiency of an industry based on a minimum value function estimated from data obtained from a sample of corn ethanol plants in the Midwest US. CO2 emissions in ethanol plants are not directly measured, but are estimated from inputs used and outputs produced. Because CO2 emissions are a linear function of outputs and inputs, the minimum value function for emissions has the same algebraic structure and parameters as the minimum value function for net cost, defined here as the cost of inputs minus the revenue from byproducts. In the case of emissions, emissions coefficients for the inputs and outputs are substituted for the prices of outputs and inputs. Given observations on firm behavior, it is possible to estimate the minimum cost function, which then also provides an estimate of the minimum GHG function. Our article exploits the relationship between the linearity of the materials balance equation and that of the minimum cost function to allow us to calculate the cost forgone to achieve the maximum decrease in GHG emissions. Empirically, we estimate the minimum value function with a translog specification, using plant-level data from a sample of recently constructed ethanol plants in the Midwest.

The earliest study to incorporate undesirable outputs in efficiency measurement was Pittman (1983) who developed an adjusted Tornqvist productivity index in which environmental effects are treated as additional undesirable outputs whose disposability is costly. Färe et al. (1989) used Pittman's data to evaluate environmental performance of US fossil fuel-fired electric utilities using a nonparametric hyperbolic distance function. Extending this, Färe et al. (1993) used a parametric mathematical programming technique based on translog output distance function to calculate an enhanced hyperbolic efficiency measure. Several empirical applications and extensions followed these seminal works. Later a directional distance function was developed that treats desirable and undesirable outputs asymmetrically (Chambers, Chung, and Färe 1996; Chung, Färe, and Grosskopf 1997; Färe et al. 2005; Ball et al. 2004; Cuesta, Lovell, and Zofio 2009). These directional output or input distance functions were estimated either using deterministic (parametric or nonparametric) or stochastic (exclusively parametric) techniques, but they do not consider

[1] Strong disposability implies that it is free of charge to dispose of unwanted inputs or outputs, weak disposability implies expensive disposal.

pollution abatement based on emission content of the inputs and outputs considered in the production process.

One of the advantages of our modeling approach is allowing an industry to choose optimal combination inputs and byproducts that minimize bad output based on the materials flow coefficients of a particular input, instead of using market price information. In addition, this technique does not need an extra pollution variable in the production process. Our approach shares some methodological similarity with recent measures of environmental efficiency based on the material balance concept (Coelli, Lauwers, and Van Huylenbroeck 2007; Welch and Barnum 2010; Lauwers 2009; Sesmero, Perrin, and Fulginiti 2010). However these studies were implemented with data envelopment analysis (DEA), a technique which is not able to accommodate measurement errors in input and output without bootstrapping.

The objective of this article specifically is to examine the potential for corn ethanol plants to reduce GHG emissions by reallocation among inputs and byproducts, and the cost of such reductions. The tradeoff between these two goals describes the opportunity cost of reducing CO2 emissions - two points on the supply curve for emissions reductions. The results of our model provide valuable information to the ethanol industry in its efforts to reduce emissions to comply with current and potential regulations. The 2007 US Energy Indecency and Security Act (EISA) required 20 to 60 percent life cycle GHG emissions reductions relative to gasoline for biofuels to qualify in meeting mandated levels of renewable fuels. The legislation requires a reduction of 20 percent for corn-ethanol, 50 percent for other advanced biofuels and 60 percent for cellulosic ethanol. The low carbon fuel standard (LCFS) of California also requires a 10 percent reduction in the carbon content of California's transportation fuels by 2020. The above regulations require that the GHG from corn ethanol have to be assessed on a full life cycle basis including emissions from energy consumed at the ethanol plants, which we examine here.

In the next section, we develop the theoretical and analytical techniques to examine the efficiency measure of the ethanol plant. The fundamental theory is based on the minimum value function for cost and GHG. In section 3, we present data and econometric estimation procedure. The empirical results of our application and implication of this article is elucidated in section 4. Summary and concluding remarks are then provided in section 5.

2. Theoretical Model

Net ethanol cost is defined here as the cost of three inputs minus the revenues from the two by products. The minimum cost function allows us, using Shephard's lemma, to obtain the optimal level of inputs given quantities of ethanol produced (e), input prices facing the firm (W), byproduct prices facing the firm (P), and the level of fixed inputs (Z). The mimimum plant-level net ethanol cost function we therefore define as:

$$C^N(e,W,P,Z) = \min_{x,y}\{WX - PY \mid (e,X,Y,Z) \in T\} \tag{1}$$

where : e is ethanol output measured in gallons; X is a vector of inputs of corn in bushels, natural gas in MBTU, electricity in KWH; and Y is a vector of ethanol byproducts, dry distillers grain (DDG) in tons of dry matter and modified wet distillers grain (WDG) in tons of dry matter. W and P are vectors of strictly positive prices for factor inputs and byproduct respectively, Z is the quantity of other fixed inputs (in $). W and P are exogenous to ethanol producers. T is the firm's production possibilities set and is assumed to be a nonempty, compact, and convex set. Under the assumptions made on T, $C^N(e,W,P,Z)$ is assumed to be twice-continuously differentiable, homogenous of degree one in variable input and byproduct prices and in fixed input quantities, concave in prices, and convex in quantities (Diewert 1971; Diewert & Wales 1987).

By applying Shepherds lemma, the *n* vector of constant output factor and byproduct demand functions are derived from the specified cost function by simply differentiating with respect to input prices and by product prices, respectively.

$$\frac{\partial C^N}{\partial W_i} = X_i^c(e,W,P,Z) \quad \text{and} \quad \frac{\partial C^N}{\partial P_i} = -Y_i^c(e,W,P,Z) \tag{2}$$

The above conditional factor and by product functions are homogenous of degree zero in factor and by product prices respectively.

Given the way CO2 emissions are calculated by regulators, there is a linear relationship between emissions and observable input use and output. Specifically, CO2 emissions are linearly related to the quantity of ethanol and two byproducts produced. We can therefore define the minimum achievable GHG emissions, for a given level of ethanol output, as

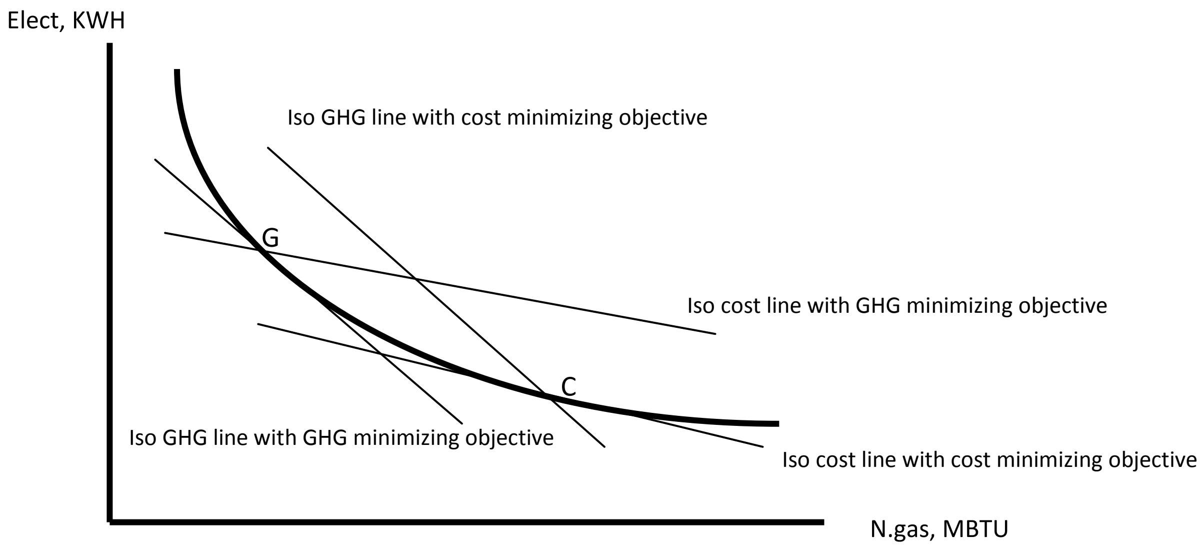
$$GHG^M(e,a,b,Z) = \min\{aX - bY \mid (e,X,Y,Z) \in T\} \tag{3}$$

Where a and b are the vectors of GHG emission coefficients per unit of factor input X and by products Y, respectively. It is obvious that this minimum function is the same as the cost minimum function in (1) above, but with GHG coefficients substituted for prices as arguments of the function. Estimation of the minimum cost function then provides an estimate of the minimum GHG function. Again invoking Shephard's lemma, evaluating the derivatives of the GHG^M function at emissions coefficients yields GHG minimizing allocation of inputs and byproduct respectively:

$$\frac{\partial GHG^M}{\partial a_i} = X_i{}^g\,(e,(a,b),Z) \text{ and } \frac{\partial GHG^M}{\partial b_i} = -Y_i^g\,(e,(a,b),Z) \qquad (4)$$

GHG^M is achieved by allowing firm to choose optimum combination of inputs and byproduct sets that minimize GHG. The emission coefficients a and b reinforce the explicit link between production technology and environmental outcomes. This technical approach is perceived as a material-balance principle which is the tenet of the law on the conservation of matter/energy. This law is an essential biophysical condition stating that the flow of materials taken from the environment for economic activities generates a flow of materials from the economy back into the environment that is of equal weight. Theoretical and methodological approach of environmental efficiency measure based on the material-balance principle is extensively discussed by (Coelli, Lauwers and Van Huylenbroeck 2007; Lauwers 2009; Welch and Barnum 2009).

We illustrated graphically on Figure 1, the correspondence between the GHG and cost minimization outcome for unit isoquant for the case of two inputs. The isoquant represents a gallon of ethanol produced, the X and Y-axis represent the BTU and KWH input of natural gas and electricity respectively. Point C on the unit isoquant represents a cost minimizing point, the tangent line at that point represents the iso-cost line, and the line crossing point C represents the all combinations of inputs with GHG emissions equal to those at point C. Likewise we can identify the allocation that results in the plant’s minimum GHG emissions, point G, and the isocost line associated with that allocation.



Equations 5 and 6 represent the isocost and iso GHG lines that pass through point C. Both are calculated using cost minimizing allocation of the three inputs and two byproducts.

$$C^C(e,w,p,Z) = WX^C - PY^C \tag{5}$$

$$GHG^C = aX^C + bY^C \tag{6}$$

Equation 7 and 8 are computed using the GHG minimizing optimal allocation of inputs and byproducts. These equations represent the iso cost and iso GHG line that pass through point G.

$$C^g = WX^g - PY^g \tag{7}$$

$$GHG^g(e,a,b,Z) = aX^g - bY^g \tag{8}$$

The iso-GHG line that passes through point C identifies a greater quantity than the corresponding line that pass through point G which indicates that producing at cost minimizing goal would lead plant to produce more GHG than a plant that produces at point G.

The minimum function above can help us to identify Discrete Shadow Price (DSP) per gallon of ethanol and Discrete Abatement (DA) of GHG emissions reduction per gallon of ethanol respectively.

$$ACE = \frac{C^g - C^C}{e};(\$/gal) \tag{9}$$

$$AER = \frac{GHG^C - GHG^M}{e};(ton/gal) \tag{10}$$

The ratio of equation 9 over 10 provides an estimate of the discrete cost per ton of GHG abatement or shadow price of emissions.

Efficiency is measured at some particular allocation point. Each plant has efficiency measurements, measured either at their actual allocation, at their minimum cost allocation, or at their minimum GHG allocation. In this article we measured Cost Efficiency (CE) as the ratio of minimum cost over the cost when plants were producing at GHG minimizing point. Likewise Environmental Efficiency (EE) is measured as the ratio of minimum achievable CO2 at GHG minimizing point over GHG at the cost minimizing point. If EE is >1 a particular firm is not environmentally efficient since the cost minimizing firm is not minimizing the level of emission in the production process. If EE is <1 a particular plant is environmentally efficient.

The above arguments allow us to evaluate whether the particular plant is economically and environmentally efficient using our estimated cost and GHG function. A plant is environmentally efficient when it chooses the minimum CO2 per gallon of ethanol. But the plant will not likely be cost efficient when it is environmentally efficient. Obviously based on figure 1, moving along the isoquant from point C to G results in an increase in environmental efficiency, but decrease in cost efficiency.

Empirically, we estimate the minimum value function with a translog specification for 3 inputs and 2 byproducts represented in equation 11 using the translog cost (Christensen, Jorgenson and Lau 1971; 1973).

$$\ln V = \alpha_o + \alpha' R + 0.5 R' \mathrm{B} R \tag{11}$$

The derivative of the translog cost with respect to input and byproduct prices yields the cost share of input and byproducts:

$$\frac{\partial \ln V}{\partial \ln r}|_{r=(w,p)} = s(e,(w,P),z) = \alpha + \sum \beta \ R + \beta_e \ln e + \beta_z \ln z \tag{12}$$

Where i=1…n and n=5, and $R = \{\ln w, \ln p, \ln e, \ln z\}$ and $r = \{w, p\}$.

Where α_o is an intercept, α' 1X7 first order coefficient parameters and B is 7X7 second order coefficient parameters.

3. The data and estimation procedure

The article uses data obtained from a survey of seven dry-grind ethanol plants from North-central Midwest states (Perrin, Fretes, and Sesmero 2009). The observations are quarterly based operating data during 2006 to 2007. The period surveyed began in the third quarter of 2006 and lasted until the fourth quarter of 2007 (not all plants were observed in all quarters) yielding 34 quarterly observations with a minimum of 3 and maximum of 7 quarters of observation per plant. The seven plants produced an average of 53.1 million gallons of denatured ethanol per year, with a range from 42.5 to 88.1 million gallons per year. For this article we calculated actual GHG emissions for each observation using emission coefficients obtained from the Biofuel Energy Systems Simulator (BESS; www.bess.unl.edu) model that was developed to compare life cycle GHG emissions from ethanol production relative to gasoline as a motor fuel, while accounting for the dynamic interactions of corn production, ethanol-plant operation, and byproduct feeding to livestock (Liska et al. 2009). Byproducts from ethanol plants are given a credit for replacing corn as feed in livestock production[2].

The econometric procedure of we followed is joint estimation of the cost function and the cost share equations using the Zellner's Iterative Seemingly Unrelated Regression (ITSUR) approach. Homogeneity and symmetry restriction were maintained[3]. We stacked the GHG and cost function together while estimating econometrically. After symmetry and homegenity restrictions, with three inputs, two byproducts, one output and a fixed variable we have 36 parameters to be estimated. In the short run, given the installed technologies, we assumed that there is no substitution possibility of corn for natural gas and electricity. We further assumed own price, output constant demand elasticity for corn is zero. These assumptions leave us to estimate a total of 33 parameters.

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[2] All GHG emissions from the burning of fossil fuels used directly in crop production, grain transportation, biorefinery energy use, and byproduct transport are included in the BESS model. All upstream GHG emissions with production of fossil fuels, fertilizer inputs, and electricity used in the production life cycle are also included (Liska et.al 2009).

[3] Symmetry and equality restrictions imposed across equations to ensure uniqueness of estimated parameters which occur in more than one equation. Equality restriction implies any one parameter appearing in several equations has the same estimated value, even though the associated asymptotic t statistics may differ.

4. Empirical results and discussion

Table 1 in the appendix displays the mean value of observed data per quarter used for our translog estimation. Table 2 presents the parameter estimates of equation 11. These parameter estimates were used to compute the minimum achievable cost and GHG, optimal level of input and byproducts as well as the shadow price for each plant. The regularity property of the cost function[4];monotonicity and curvature were maintained. Table 3 contains the level and percent change input and byproducts per gallon of ethanol under cost and GHG minimizing objective respectively. Whereas table 4 provides the change in the level of GHG as a result of input and byproduct adjustment made when a plant producing at GHG compared to cost minimizing point. The estimated minimum level of GHG and cost per gallon of ethanol at GHG and cost minimizing point is also reported in table 5. The shadow value of GHG and the cost and environmental efficiency measures are presented on table 6 through 8 respectively. Table 9 shows the Allen partial price elasticity of inputs and byproducts evaluated at mean.

At cost minimization point, the average optimal input quantities of natural gas, electricity and corn feed stock per gallon of ethanol were 0.05 BTU, 1.71 KWH and 0.29 bushel respectively. The average optimal DDG and WDG output levels were 4.9 and 1.8 lb per gallon of ethanol. Whilst at GHG minimization point, the average optimum allocation was to produce 47% less of dry and 25% more of wet byproduct, with a reduction of natural gas and electricity use by 77% and 65 % respectively, albeit corn feedstock use rose 47%. Moving from cost to GHG minimizing point, the average fraction of dried byproduct (the ratio of DDG to the total byproduct produced) falls from 0.78 to 0.58 whilst the extra natural gas used to dry byproduct fall from 0.0513 to 0.018 MBTU/gal. Looking at the other way around, Perrin, Fretes and Sesmero (2009) estimated an additional 0.00933MMBTU/gal natural gas to dry one ton of byproduct, dry matter basis, from 55% moisture (MWDGS) to 10% moisture (DDGS.) It is eminent that ethanol-plant energy use and associated GHG emissions are affected by fraction of total byproduct dried.

As shown on table 4, moving from cost minimization to GHG minimization, GHG from natural gas and electricity would fall nearly by 30 and 13 thousand tons of CO2 equivalent GHG emission respectively. The aggregate GHG offset allowance from byproducts falls by nearly 6 thousand tons of CO2 equivalent. However on aggregate the average plant cut overall emissions by nearly 25 thousand ton of CO2 equivalent when they were producing at GHG rather than cost minimizing objective.

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[4] All estimated shares were monotonic everywhere except eleven data points whereas the curvature properties satisfied at each data observation. Concavity of the cost function is satisfied if the hessian matrix is negative semidefinite and for strict quasi-concavity the nxn matrix of substitution elasticities must be negative semidefinite at each observation.

The average GHG per gallon of ethanol measured across all observations at cost minimizing allocations was 10.2lb whereas at GHG minimizing point was 6.7 lb. This suggests that moving from cost to GHG minimizing goal, on average the plant potentially reduced 3.52 lb GHG per gallon of ethanol as portrayed in table 5. The average costs at these two allocations from the sample were approximately $1.01/gal and $1.24/gal respectively. The results showed also considerable heterogeneity in the level of GHG as well as abatement cost across the plants.

The average shadow prices per plant per quarter ranges from $86 to $190 per ton with average value of $124, table 6. We also found the shadow price as small as $27 and $34 per ton for two plans in certain quarter which is an indication of the potential room to abate GHG emissions with least cost for given level of ethanol. The standard deviation within a plant showed the variation of the shadow price across quarters which off course as a result of different level of input demand and byproducts supply which intern a result of variation with respect to price of inputs and byproducts. Using the same data but with a non-parametric approach, Sesmero, Perrin , and Fulginiti (2010)found shadow prices of reducing CO2 from profit maximizing to GHG minimizing levels was $1,726 per ton.

Recently the price of the variable inputs and byproducts considered in this study has changed substantially compared to the surveyed year as shown on table 1, so does any given estimate of average shadow price can quickly changes. To capture this price changes, we run sensitivity analysis to see how the average shadow price changes with updated prices by evaluating at different inputs and byproducts price using the parameters shown on table 2. When evaluating at the mean price of the 2006/07 survey data, the mean shadow price was $119 per ton however when we updated only the price of corn to the year 2012 value, the shadow price increased to $161 per ton, this price fall to $103 when updated only the price of natural gas as depicted on table 8. We should note here that the price of corn is doubled whereas the price of natural gas fall by nearly 20 percent compared to the price during the 2006/07 survey. When we further updated both the price of corn and natural gas at the same time, we found $161 per ton. The mean shadow prices reached to $173 per ton when we evaluated it after updated all input and byproduct prices. A note here that the emission coefficients of all inputs and byproducts has not changed from what it was at the surveyed year. The shadow price of GHG basically depends on the ratio of price and emission coefficient of inputs and byproducts considered, so any changes on the price of inputs, byproducts and emission coefficients would lead to a change in the input demand and byproduct mix used which eventually determine the average shadow price.

Measured across plants the average environmental efficiency (EE) score is 0.64, showing that on average ethanol plant would be able to produce their current ethanol output with an input bundle and byproduct combination that contains 36 % less of GHG. To do so, on average the total cost of ethanol production would rise by 22 percent. As shown on Table

7, to cut emissions, for example by nearly 30 percent, some plants would raise their cost by 25% albeit for the same level of emission reduction some would raise the cost as low as 13%. Our results also indicated some plants could potentially cut their emission level by as much as 50%. When we updated all prices of input and byproduct to the year 2012 value, on average plan could reduce emission by 57 percent while to do so cost of ethanol production would rise by 46 percent as depicted on table 8.

Whether distillers grains are dried or sold wet is the key factor that determines the ability of a corn ethanol plant to reduce GHG emission since eliminating the need for drying of DDGS for corn-ethanol plants can have a significant positive effect on the level of natural gas use. Using BESS model Bremer et.al (2011) showed that Midwest corn-ethanol-livestock life cycle GHG reduction relative to gasoline was 46 to 41% when DDGS was fed to feedlot cattle for 20 to 40% diet inclusion while feeding MDGS to feedlot cattle reduced GHG emissions from the corn-ethanol-cattle system by 53 to 50%.

We presented the Allen partial price elasticities calculated from the translog cost function in table 9. The elasticity estimates are calculated at the mean of the prices, and input and byproduct cost share. The diagonal or own price elasticities for all inputs and by products are negative which indicates curvature properties actually hold for the price estimation. Own price elasticities for natural gas and electricity were inelastic but the cross price elasticities of natural gas and electricity revealed complementarity as opposed to substitution between them. However, the two byproducts showed substitution in the production process which we anticipated given the nature of byproducts production process.

5. Conclusion and policy implication

This study develops an analytical framework to explore the tradeoff between environmental efficiency and cost efficiency among corn ethanol plants. The model and estimation techniques presented are applicable to a broad range of industries. The study also shows a departure from the conventional techniques that treat undesirable output as an extra pollution variable within a production model.

Our result indicates that the average plant is able to reduce GHG emissions by 36 percent relative to the level under cost minimization, but that production costs are 22 percent higher than the minimum possible. The reallocations responsible for these emissions reductions are primarily the substitution of wet for dry distillers grains, with the corresponding reduction in the use of natural gas and electricity. Our findings revealed that on average ethanol plants would produce 25 % more of wet byproduct and 47% less of dry byproduct.

Comparing results across observations, the estimated shadow price for emissions reduction ranges from \$86 to \$190 per ton of CO2 with average value of \$124 per ton. The study also found that there was considerable heterogeneity among the corn ethanol plants in both the levels of emissions reduced and abatement cost per gallon of ethanol. The variation of GHG reductions and abatement costs per gallon of ethanol across plant results from different relative prices and variations in plant configurations even though all plants were constructed at approximately the same time and share the same basic technology, whilst the heterogeneity reflects the presence of potential room for the plant improvement in reducing GHG.

When abatement programs based on market incentives exist, as is proposed by California's LCFS, the implied shadow price of GHG can be used as a bench mark for pollution trading and serve to assess the effectiveness of existing regulation. Imposing a new regulatory requirement over biofuel would likely cause a shift in ethanol markets that favors plants that mitigate GHG.

With regard to corn ethanol plants our findings would provide valuable information to the industry in its efforts to comply with upcoming regulations, and to policy makers who must consider the CO2 abatement costs of the corn ethanol system. The analysis presented here shows the level GHG reduction and hence the shadow prices among ethanol plant are considerably dependent on the value emission coefficient of inputs and by products obtained from BESS.

References

Ball, V. E, C.A.K, Lovell, H., Luu and R., Nehring.2004. "Incorporating environmental impacts in the measurement of agricultural productivity growth." Journal of Agricultural and Resource Economics 29, 436–460.

Bremer, V. R., A.K., Watson, A.J., Liska, G. E., Erickson, K. G., Cassman, K.J., Hanford, and T. J, Klopfenstein. 2011. Effect of Distillers Grains Moisture and Inclusion Level in Livestock Diets on Green House Gas Emissions in the Corn-Ethanol-Livestock life cycle . The Professional Animal Scientist 27:449-455

Cuesta, R.A., C.A.K., Lovell, J.L., Zofío. 2019. "Environmental Efficiency Measurement with Translog Distance Functions: A parametric Approach." Ecological Economic 68:2232–2242

Chambers, R.G., Y.H., Chung, R., Färe, 1996. "Benefit and distance functions." Journal of Economic Theory 70, 407-419.

Christensen, L. R., D. W., Jorgenson and L. J., Lau.1971."Conjugate Duality and The Transcendental Logarithmic Production Function." Econometrica 39 : 255-56.

________1973. "Transcendental Logarithmic Production Frontiers." Review of Economics and Statistics 55 : 28-45.

Coelli, T.J., L., Lauwers and G., Van Huylenbroeck. 2007. "Environmental efficiency Measurement and the Materials Balance Condition." Journal of Productivity Analysis 28, 3–12.

Chung, Y.H., R., Färe, and S., Grosskopf. 1997. "Productivity and Undesirable Outputs: A Directional Distance Function Approach." Journal of Environmental Management 51, 229–240.

Diewert, W. E. 1971: "An Application of the Shephard Duality Theorem: A Generalized Leontief Production Function." Journal of Political Economy, 79, 481-507.

Diewert, W.E. and T.J., Wales.1987. "Flexible Forms and Global Curvature Conditions." Econometrica 55, 43–68.

Färe, R., G., C. A., Shawna, L., Knox and P., Carl. 1989. "Multilateral Productivity Comparisons When Some Outputs are Undesirable: A Nonparametric Approach." The Review of Economics and Statistics, Vol 71 :90-98.

Färe, R., S., Grosskopf, D.W., Noh, W.L., Weber. 2005. "Characteristics of a Polluting Technology: Theory and Practice. Journal of Econometrics 126, 469–492

Färe, R., S., Grosskopf, C.A.K, Lovell and S., Yaisawarng.1993." Derivation of Shadow Prices for Undesirable Outputs: A Distance Function Approach." Review of Economics and Statistics 75:374–380

Lauwers, L. 2009. "Justifying the Incorporation of the Materials Balance Principle into Frontier Based Eco-Efficiency Models." Ecological Economics 68 (6), 1605–1614.

Pittman, R.W. 1983. "Multilateral Productivity Comparisons with Undesirable Outputs." Econ. J. 93:883-91.

Liska, A.J, H.S. Yang, V. Bremer, D.T. Walters, G. Erickson, T. Klopfenstein, D. Kenney, P. Tracy, R. Koelsch, K.G. Cassman. 2009." BESS: Biofuel Energy Systems Simulator; Life Cycle Energy and Emissions Analysis Model for Corn-Ethanol Biofuel, 2009b; vers.2008.3.1. www.bess.unl.edu." University of Nebraska-Lincoln.

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

Sesmero J. P., R.K., Perrin and E L., Fulginiti. 2010." Environmental Efficiency Among Corn Ethanol plants." PhD dissertation, University of Nebraska- Lincoln.

U.S. Department of Agriculture, Agricultural Marketing services. Accessed in May, 2012. http://marketnews.usda.gov/portal/lg

U.S. Department of Agriculture/ National Agricultural Statistics Service. 2012. http://quickstats.nass.usda.gov/

US Energy Information Administrative Agency:. Accessed in May, 2012. http://205.254.135.7/

Welch ,E. and Barnum, D. 2010. Joint Environmental and Cost Efficiency Analysis of Electricity Generation. Ecological Economics 68 (2009) 2336–2343

I. **Table of Results**

Table 1. Descriptive Statistics of Variables used in Estimation: all are per quarter basis[5]

Variables	Unit	Mean price 2006-2007	[a]Mean price 2012	Units of input & byproduct	Mean quantity of input & byproduct	Emission coefficient
Corn	$/Bu	3.014	6.13	Bu/gal	0.349	0.00668
N.gas	$/MBTU	7.292	5.96	MBTU/gal	0.026	0.06302
Electricity	$/KWH	0.044	0.061	KWH/gal	0.570	0.00074
DDG	$/ton	93.69	202.29	lb/gal	3.438	-0.4198
WDG	$/ton	60.24	83.12	lb/gal	2.071	-0.4079
Other cost	million $	3.576		$/gal	0.262	-
Ethanol	$/gal	2.051		Mill gallon	13.64	0.032
Total cost	million $	14.15				
Total GHG	tons	44,628				

Note:[a] All prices are weighted average price of the seven studied states for month of January and February. Natural gas and electricity prices represent average industrial price from US Energy Information Administrative Agency. Corn price is obtained from USDA/NASS quick stat. The price of DDG is a 10% moisture basis whereas WDGS is a weighted average of 55-60% and 60-70 % moisture basis, and both data is from USDA Agricultural Marketing services.

[5] Among factor inputs Corn, natural gas, and electricity accounts about 83 % of total operating variable cost , whereas labor, denaturant, chemicals, and other processing costs takes the reminders. Further detail about the data and survey methodology can be obtained from Perrin et.al (2007) and Sesemero (2010) respectively.

Table 2.Parameter Estimates of the Translog Function

Parameter	Value	Parameter	Value
β_C	0.160 (0.092)	β_{DW}	0.063*** (0.017)
β_N	0.144 (0.093)	β_{WW}	-0.080*** (0.020)
β_E	0.171*** (0.026)	β_{CY}	0.276*** (0.030)
β_D	-0.337** (0.112)	β_{NY}	0.012 (0.025)
β_W	0.862*** (0.116)	β_{EY}	0.020** (0.006)
β_Y	2.005* (0.834)	β_{DY}	0.093* (0.037)
β_Z	0.126 (0.707)	β_{WY}	-0.402*** (0.042)
β_{CD}	-0.031** (0.010)	β_{CZ}	-0.015 (0.034)
β_{CW}	0.031** (0.010)	β_{NZ}	0.048 (0.040)
β_{NN}	0.047*** (0.013)	β_{EZ}	-0.005 (0.011)
β_{NE}	- 0.031*** (0.005)	β_{DZ}	0.144*** (0.032)
β_{ND}	-0.006 (0.012)	β_{WZ}	0.115** (0.035)
β_{NW}	-0.010 (0.013)	β_{YY}	-0.131 (0.234)
β_{EE}	0.030 (0.002)	β_{YZ}	0.346 (0.289)
β_{ED}	0.004 (0.004)	β_{ZZ}	-0.725** (0.279)
β_{EW}	-0.003 (0.004)	α_O	10.851*** (1.409)
β_{DD}	-0.030 (0.022)		

Note: Legend: *, ** & *** significant at 1, 5 and 10% respectively. The standard error is in the bracket. Whereas C=Corn, N=Natural gas, E=Electricity, D=DDG, W=WDG, Z=other cost, Y=ethanol output

Table 3.Average Level of Input and Byproducts per gallon of Ethanol Under two Objectives

Objective	Corn, Bu/gal	N. gas, MBTU/gal	Electricity KWH/gal	DDG, lb/gal	WDG, lb/gal	Ethanol, mill gal
Cost minimizing	0.291	0.0518	1.708	4.89	1.76	13.64
GHG minimizing	0.429	0.0183	0.391	2.59	2.20	13.64
% change from cost to GHG minimization	47%	-65%	-77%	-47%	25%	-36%

Table 4. Average GHG, ton of C02 equivalent, by inputs and byproduct under two objectives

Objective	Corn	N.gas	Electricity	DDG	WDG	Total
Cost minimizing	26,535	45,222	17,337	14,001	4,881	70,212
GHG minimizing	39,102	15,667	3,973	7,416	6,112	45,215

Table 5.GHG and Cost Reduction per gallon of Ethanol by Plant per quarter

Ethanol plant, Mil gal/quarter	Cost minimizing lb/gal	GHG minimizing, lb/gal	Difference from Cost to GHG, lb/gal	Cost minimizing $/gal	GHG minimizing $/gal	Difference from Cost to GHG, $/gal
11.93	9.97	6.93	3.04	1.17	1.46	0.29
11.97	9.92	6.69	3.23	1.08	1.25	0.17
13.09	9.63	6.75	2.88	1.05	1.19	0.14
13.14	11.49	6.80	4.69	1.10	1.44	0.34
13.15	9.27	6.77	2.51	0.87	1.06	0.18
13.34	10.04	6.65	3.39	0.82	1.01	0.19
22.03	11.82	5.91	5.91	1.04	1.42	0.37
Average	10.20	6.68	3.52	1.01	1.24	0.23

The last column “Difference (Cost to GHG), $/gal” is in absolute value

Table 6.Shadow Price ($/ton) CO2 equivalent by Plant per quarter

Plant	Ethanol, Mill gallon	Mean, $/ton	Std Dev, $/ton	Min, $/ton	Max, $/ton
1	11.93	190	20	172	217
2	11.97	86	49	27	128
3	13.09	90	34	34	120
4	13.14	146	21	125	175
5	13.15	145	48	84	189
6	13.34	106	32	66	152
7	22.03	126	6	119	131
Average	13.64	124	46	27	217

Table 7.Cost and Environmental Efficiency Measure per quarter

Plant	Ethanol, mil gal	Cost efficiency	Environmental efficiency
1	11.93	1.25	0.69
2	11.97	1.14	0.68
3	13.09	1.13	0.70
4	13.14	1.31	0.59
5	13.15	1.22	0.73
6	13.34	1.22	0.66
7	22.03	1.36	0.50
Average	13.64	1.22	0.64

Table 8.Sensitivity of average GHG shadow price to updated (2012) prices

	2006-07 survey prices	only corn price updated	only N.gas price updated	Corn &N.gas price updated	all prices updated
Shadow price, $/ton	119	161	103	167	173
Environmental efficiency	0.66	0.45	0.60	0.41	0.43
Cost efficiency	1.20	1.35	1.23	1.45	1.46

Table 9.Allen Partial Price Elasticity Evaluated at Mean Prices and Shares for the Translog Net Cost Function

	Price of				
Quantity of	Corn	N.gas	Electricity	DDG	WDG
Corn				-0.258	-0.016
N.gas		-0.507	-0.017	-0.237	-0.081
Electricity		-0.089	-0.503	-0.157	-0.093
DDG	0.703	0.337	0.090	-1.358	0.229
WDG	1.425	0.170	0.017	0.955	-2.567

Appendix

I.The price elasticity of demand for factors of production:

1.Own price elasticities of input are calculated as $\varepsilon_{ii} = \dfrac{\beta_{ii} + S_i^2 - S_i}{S_i}$

2.Cross price elasticities among inputs $\varepsilon_{ij} = \dfrac{\beta_{ij} + S_i S_j}{S_i}$

3.Cross price elasticities between inputs and by products $\mu_{ij} = -S_j^y + \dfrac{\beta_{ij}}{S_i^x}$

II. The price elasticity of demand for by products:

2.1 Own price elasticities between by product $\varepsilon_{ii} = -S_i - \dfrac{\beta_{ii}}{S_i^*} - 1$

2.2 Cross price elasticities between by products $\varepsilon_{ij} = -S_j - \dfrac{\beta_{ij}}{S_i}$

2.3 Cross price elasticities between by products and input $\eta_{ij} = S_j^x - \dfrac{\beta_{ij}}{S_i^y}$

β represents the second order parameters from the translog estimation. S_i represent the mean predicted share of inputs and byproducts. S_j^x and S_j^y used to differentiate the share of input from byproduct respectively while calculating cross price elasticity .