EFFECT OF PRODUCTION PARAMETERS ON THE ECONOMIC FEASIBILITY OF A BIOFUEL ENTERPRISE

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Abstract

The optimal allocation of resources and efforts is needed to fulfill the latest Renewable Fuel Standard mandate. In order to warranty the success of the nascent cellulose-based biofuel industry, it is crucial to better understand the effects that production parameters have on the economic feasibility of a biofuel enterprise. The main goal of this study is to estimate the impact that the different feedstock production and biofuel conversion parameters have on the probability of economic success. To this aim, an original stochastic financial model is developed to analyze and identify the most economically relevant components of the biofuel production path. Estimation of the model was carried out using Monte Carlo simulation techniques along with parametric maximum likelihood estimation procedures. Results indicate that operational efficiency strategies should concentrate on improving feedstock yields and extending the feedstock growing season.

Keywords: *Binary response model***,** *Energy cane***,** *Marginal effects, Monte Carlo simulation, Net present value*.

Introduction

The latest Renewable Fuel Standard (RFS2) mandate is both a challenge and an opportunity for the biofuel industry. Namely, the RFS2 specifies a 36 billion gallons target for total renewable fuels in transportation fuel by 2022, of which 16 billion gallons have to be cellulosic biofuels. Additionally, cellulosic biofuels are required to reduce greenhouse gas (GHG) emissions by at least 50% compared to the petroleum fuels they would replace.

The optimal allocation of resources and efforts is needed to fulfill these new environmental and production regulations. Particularly, substantial research is needed to assess and improve the probability of economic success of current and future investments while reaching the program goals. It is crucial to better understand the effects that production factors have on the economic feasibility of a biofuel enterprise to effectively target future improvement efforts. Special attention has to be given to develop more efficient production systems to generate cellulose-based biofuels given that cellulosic biofuels represent about 45% of the RFS2 mandate.

Currently, the most promising biofuel feedstock are dedicated energy grasses due to their high biomass yield, high fiber content, broad genetic diversity, and non-competitive nature with food, feed or fiber crops (McCutchen, Avant, and Baltensperger, 2008; van der Weijde et al., 2013). In terms of feedstock conversion technologies, different options are available including hydrolysis, gasification, pyrolysis and acetone-butanol-ethanol (ABE). Among current conversion technologies, it seems that hydrolysis is the most economically feasible conversion process in the current state of the economy (Monge et al., 2014).

Even though some efforts have been made to evaluate the effect of both feedstock and biofuel production parameters on the feasibility of a biofuel enterprise, little work has been conducted to identify and assess the impact of production parameters on the probability of economic success. Previous studies have focused on the traditional sensitivity analysis, which consists in evaluating the economic feasibility of a project under a reduced and discrete set of possible production scenarios (e.g., Ribera et al., 2007; Swanson et al., 2010; Marvin et al., 2011; wright et al., 2011). Few of the preceding sensitivity analyses have included a broader range of production parameters and possible values, and little attention has been given to assess the effect that individual changes on the production parameters have on the probability of economic success.

The main objective of this study is to extend the current literature regarding economic feasibility of cellulosic biofuel production. Namely, we develop an original stochastic financial model able to analyze and identify the most economically relevant components of the biofuel production path. Current and projected energy prices along with industry and research production parameters are used to generate potential production scenarios. Simulation data are used to estimate the impact that the different feedstock production and biofuel conversion parameters have on the probability of economic success, where economic success is defined in terms of the net worth the project. This study provides insights to improve production systems by better targeting future research efforts.

Background and Literature Review

Different metrics have been developed and used to assess the economic feasibility of planned investments. In term of renewable energy projects, suggested analytical valuation tools include: Net Present Value (NPV), Benefit-Cost Ratio, Internal Rate of Return, Least Cost Planning, Payback Period and Sensitivity Analysis (Owens, 2002). All the aforementioned valuation tools are interrelated and each of them explores specific features of the project cash flow. For example, the NPV uses the time value of money to convert a stream of annual cash flow generated through the lifespan of a project to a single value for a given discount rate (Owens, 2002). Projects with positive NPV's are considered profitable or economic success[1] (Remer and Nieto, 1995).

Normally, the technical and financial components of the project are expressed in a NPV pro-forma. This pro-forma is defined at an initial valuation stage, and them it is used in the estimation of further economic feasibility metrics (e.g., Monge et al., 2014). Consequently, understanding the specific sources of variation of the NPV is of vital importance because those project parameters causing positive impacts on the NPV might also lead to improvements on other feasibility metric of interest.

The economic feasibility of using new dedicated energy crops or crop residues as feedstock sources has been extensively studied (e.g., Ribera et al., 2007; Swanson et al., 2010; Marvin et al., 2011; wright et al., 2011). However, little work has been conducted to identify and assess the impact of both feedstock and biofuel production parameters on the probability of economic success. The traditional approach to evaluate the effect of production parameter on the economic feasibility is to evaluate the NPV of a new project under a reduced and discrete set of possible production scenarios. Namely, each scenario considered includes only a limited number of production parameters at the same time and the parameters of interest are set to be equal to a discrete and predetermined set of values (e.g., Ribera et al., 2007). Recent studies have introduced more flexibility to the sensitivity analysis by defining some parameters in each considered scenario as *stochastic variables* such as feedstock yields and biofuel prices, and then calculate the probability of success (i.e., positive NPV) under the fixed parameters settings (e.g.,

[1] Besides profitability, there are other intrinsic economic components of a project that are not considered in the NPV such as the opportunity cost of time and money. In practice, other valuation metrics and analyzes are used as complements to NPV.

Richardson et al., 2007; Richardson, Lemmer, and Outlaw, 2007; Palma et al., 2011; Monge et al., 2014).

This study extends the current economic feasibility literature by developing a flexible stochastic financial model able to analyze and identify the most economically relevant components of the biofuel production path. To the best of our knowledge, this is the first study that quantifies the effect of each production parameters on the probability of observing a positive NPV. Additionally, the applications of the proposed approach can be extended to the valuation of other projects beyond renewable energy investments.

Methods

The Net Present Value (NPV) is one of the standard metrics to assess the economic feasibility of a new project. The NPV is defined as the sum of all net cash flows of a project over a period of time discounted to one equivalent present date (Remer and Nieto, 1995). In our particular case, the NPV is a function of several feedstock and biofuel production parameters such as expected feedstock yield, energy prices, biofuel conversion rate, and feedstock and biofuel production costs. Given a specific set of m inputs ($\boldsymbol{X}$), the NPV is given by the deterministic function

(1) $$NPV = f(\boldsymbol{X}).$$

In general, a project is accepted if its NPV is positive and rejected if the NPV is negative. If the net present value is equal to zero, then the investor is indifferent in the decision whether to accept or reject the project (Remer and Nieto, 1995). Through the paper, a positive NPV is considered an economic success and a non-positive NPV is seems as an economic failure.

Financial Model

The biofuel production and financial model developed and described in Monge et al. (2014) is considered for further analyses. Particularly, the hydrolysis conversion technology and its corresponding production path are used to assess the effect of feedstock and biofuel production parameters on the probability of obtaining a positive NPV. Although the proposed analysis can be extended to any biofuel production process, we focused on ethanol produced from energy cane through a hydrolysis conversion process.

Particularly, the ethanol production path is divided in two production stages: feedstock production and biofuel production. At the first stage, energy cane is planted and harvested for a period of five years. On an annual basis, the number of harvesting months (*HarvMonth*) depends upon seasonal and agronomic limitations. The overall cost to deliver energy cane as feedstock to a conversion plant is comprised of the energy cane production cost (*FeedPrdCost*), return to producers (*Return*) expressed as percentage over the production cost, variable harvesting and hauling cost (*VarHrvCost*) depending on the energy cane yield (*Yield_EC*), and fixed harvesting and hauling cost (*FxHrvCost*).

On the subsequent production stage, the energy cane feedstock supplied to the conversion plant is transformed into ethanol through a hydrolysis conversion process. It is assumed that the total feedstock demand is fully met without shortage. Moreover, the total annual feedstock demand is a function of the conversion plant's nameplate capacity (*FuelPrd*) and biofuel conversion yield (*FuelYld*). It is further assumed that total investment in the conversion plant, plant operating expenses and fixed expenses are functions of the plant's nameplate capacity. Additionally, excess electricity is generated as a by-product of transforming energy cane into ethanol. Plant revenues come from selling the produced ethanol and excess electricity at expected ethanol (*Price_Eth*) and electricity (*Price_Elec*) prices, respectively. The NPV is estimated over a 10-year planning horizon using an 8 percent discount rate. For specific details about the ethanol production path considered in this study and its corresponding financial statements see Monge et al. (2014)

Compared to the original model in Monge et al. (2014), where most of the feedstock and biofuel production parameters were fixed at current industry estimates, in this analysis we define the different production parameters of interest as random variables and allow them to take values within a continuous, reasonable range of possible alternatives.

Data Generation

Monte Carlo simulation techniques were used to generate n $\{NPV_i, \boldsymbol{X}_i\}$ samples, where the subscript i denotes the ith iteration. On each iteration the value of $\boldsymbol{X}$ was set to be a random deviation relative to the baseline scenario $\boldsymbol{\mathcal{X}}$, Namely, $\boldsymbol{X}_i$ is defined as

(2) $$\boldsymbol{X}_i = (\mathbf{1}_m + \boldsymbol{\delta}_i) \circ \boldsymbol{\mathcal{X}},$$

where the operator $\circ$ denotes the Hadamard or entrywise product, $\mathbf{1}_m$ is a m vector of ones, and $\boldsymbol{\delta}_i$ is a m vector with its elements (δ_{ij}) independent and uniformly distributed from $\omega_j -$ to $\omega_j +$.Therefore, the δ_{ij}'s can be seen as percentage deviations from the baseline scenario. A total of 10,000 iterations were simulated to analyze the effect of production parameters on the NPV. Each iteration may be a unique combination of production parameter values, consequently, every generated iteration can be considered as a realization of a possible production scenario.

The baseline scenario and the considered range of each parameter are described in Table 1. The baseline scenario represents the latest industry and research production parameters in South Texas. The parameter values are based on a discussion panel of local sugar cane producers, and energy cane yields and production cost obtained from large experimental field plot in Weslaco, Texas managed by Texas A&M AgriLife Research and Extension Center. On the baseline scenario, energy cane is harvested for 9.5 months and the production cost is equal to

\$450 per acre. Also, the producers' return for growing energy cane is set to 20 percent of the pre-harvest or standing production cost. The 2014 average energy cane yield of 20 dry short tons (dst) per acre is used as the baseline feedstock yield. The variable and fixed costs to harvest and deliver the produced feedstock to the conversion plant are equal to \$10/dst and \$92/acre, respectively. The conversion plant's nameplate capacity is 30 million gallons of ethanol a year, and one dst of energy cane yields 85 gallons of ethanol. Due to the lower current energy prices, the 2013 Energy Information Administration (EIA) Reference Scenario for ethanol and electricity were used for the 10-year planning horizon of the project (U.S. EIA, 2013). The purpose of using the 2013 energy prices was to represent a more likely future situation.

The true underlying probability distribution function of most of the production parameters is unknown, thus a uniform distribution function (Uni*f*) was assigned when appropriate. Under the uniform distribution function each possible outcome within a bounded interval has the same probability of occurrence. Interval boundary values were set to be equal to the interval limits considered in the original study or current industry observable values. In the case of ethanol and electricity prices, the projected 10-year price trends shift proportionally to the random deviation (δ_{ij}). For example, if the δ_{ij} associated with ethanol price is equal to 5 percent then the yearly ethanol prices used to estimate the NVP are 5 percent higher than the EIA Reference Scenario. The 2013 EIA Reference Scenario for both ethanol and electricity prices are shown in Figure 1.

<u>Conceptual Framework</u>

The complex deterministic function $f(\cdot)$ in equation (1) can be approximated by a functional form $h(\cdot)$. Thus, the NPV is expressed as a conditional function of $\boldsymbol{\delta}_i$ given $\boldsymbol{\mathcal{X}}$ plus an error term. Specifically,

(3) $$NPV_i = h[(\mathbf{1}_m + \boldsymbol{\delta}_i) \circ \boldsymbol{\mathcal{X}}] + \varepsilon_i$$
$$= h(\boldsymbol{\delta}_i | \boldsymbol{\mathcal{X}}) + \varepsilon_i, \quad i = 1,2,\dots,n,$$

where the ε_i's are independent and identically distributed errors, with zero mean, finite variance, and cumulative density function (CDF) F_ε.

The effect of feedstock and biofuel production parameters on the probability of economic success can be estimated by specifying the NPV in (1) as an ordinal variable. Namely, the generated NPV's are transformed to a binary variable (Y) such that

(4) $$Y = \begin{cases} 1 & if\ NPV > 0 \\ 0 & if\ NPV \leq 0 \end{cases}.$$

Then, by equation (3) the probability of observing a positive NPV (i.e., $Y_i = 1$) given a set of production parameters can be written as

(5) $$\Pr(Y_i = 1 | \boldsymbol{\delta}_i, \boldsymbol{\mathcal{X}}) = \pi_i = \Pr(NPV_i > 0)$$
$$= \Pr[h(\boldsymbol{\delta}_i | \boldsymbol{\mathcal{X}}) + \varepsilon_i > 0]$$
$$= \Pr[\varepsilon_i > -h(\boldsymbol{\delta}_i | \boldsymbol{\mathcal{X}})]$$
$$= 1 - F_\varepsilon[-h(\boldsymbol{\delta}_i | \boldsymbol{\mathcal{X}})].$$

The probability function described in equation (5) can be further used to analyze the impact that changes on the production parameters have on the probability of economic success. In a practical sense, the marginal effects are defined as the changes on the probability of economic success by increasing the production parameters in one percent relative to the baseline scenario. Particularly, the marginal effect of the jth parameter is given by the partial derivative

(6) $$\frac{\partial \pi_i}{\partial \delta_{ij}} = \frac{\partial F_\varepsilon}{\partial h} \frac{\partial h}{\partial \delta_{ij}}$$
$$= \frac{\partial h}{\partial \delta_{ij}} f_\varepsilon,$$

where f_ε is the marginal density of ε.

Model Estimation

Maximum likelihood techniques can be used to estimate the aforementioned model. Specifically, given n observations, the generic likelihood function associated with the probabilities in equation (5) can be defined as

(7) $$L = \prod_{i=1}^{n} \pi_i{}^{y_i}(1-\pi_i)^{1-y_i}.$$

With the aim to keep the results easier to interpret, it was further assumed that $h(\cdot)$ in equation (3) is given by a linear function of the form

(8) $$h(\boldsymbol{\delta}_i|\boldsymbol{\mathcal{X}}) = \beta_0 + \sum_{j=1}^{m} \beta_j\left[\left(1+\delta_{ij}\right)\mathcal{X}_j\right]$$
$$= \alpha_0 + \sum_{j=1}^{m} \alpha_j \delta_{ij},$$

where the β's are function parameters, and $\alpha_0 = \beta_0 + \sum_{j=1}^{m} \beta_j \mathcal{X}_j$ and $\alpha_j = \beta_j \mathcal{X}_j$**.** Note that the functional form in (8) is expressed as a function of the percentage deviations from the baseline scenario.

Two distribution functions were considered to model the distribution of ε. Namely, the standard normal and logistic distributions were used to analyze the effect of production parameters on the probability of economic success. These two distributions are commonly used in the literature to model binary data (e.g., Long, 1997, Hoetker, 2007).

Under the normal distribution, the probability of observing a positive NPV is given by

(9) $$\pi_i = \Phi\left(\alpha_0 + \sum_{j=1}^{m} \alpha_j \delta_{ij}\right),$$

where $\Phi(\cdot)$ is the CDF of the standard normal distribution function. Furthermore, it can be shown that the marginal effect of the jth production parameter is given by

(10) $$\frac{\partial \pi_i}{\partial \delta_{ij}} = \alpha_j \phi\left(\alpha_0 + \sum_{j=1}^{m} \alpha_j \delta_{ij}\right),$$

where $\phi(\cdot)$ is the marginal density function of the standard normal distribution.

The probability of observing a positive NPV when the errors are assumed to follow a logistic distribution is written as

(11) $$\pi_i = \frac{e^{\left(\alpha_0+\sum_{j=1}^{m}\alpha_j\delta_{ij}\right)}}{1+e^{\left(\alpha_0+\sum_{j=1}^{m}\alpha_j\delta_{ij}\right)}}.$$

Similarly, it can be shown that the marginal effect of the j^{th} production parameter is given by

(12) $$\frac{\partial\pi_i}{\partial\delta_{ij}} = \alpha_j\pi_i(1-\pi_i).$$

The marginal effects presented in this study were calculated as the average marginal effects across the n iterations. Marginal effects' standard errors were estimated using the delta method.

Results

The overall mean for the simulated NPV's was $ -29.01Mill. with a standard error of $0.71Mill. The maximum and minimum observed NPV were $174.26Mill. and $-216.95Mill., respectively. Also, based on the Monte Carlo simulations, 3,587 iterations were considered as economic successes (i.e., NPV >0) and 6,413 iterations were defined as economic failures (i.e., NPV ≤ 0). The 10,000 generated NPV are shown in Figure 2.

Normal and logistic distributions were used to model the probability of obtained a positive NPV given a set of production parameters. Model estimation results for both the normal and logistic distributions are presented in Table 2 and 3, respectively. Given the non-nested nature of the models considered in this study, the model that "best fitted" the data was selected using the Akaike information criterion (AIC) (Akaike, 1974). The AIC is a log-likelihood-based model-selection criterion adjusted by the number of independent parameters. Given a data set and several candidate models, the model with the smallest AIC is preferred. The AIC in Table 2 and 3 suggests that the preferred distribution is the logistic distribution. Therefore, the logistic distribution results are further used to discuss the impact of feedstock production and biofuel conversion parameters on the probability of economic success. It is important to note that the marginal effect estimates were robust across the two candidate models considered in this study.

The logistic distribution marginal effects of the different production parameters are presented in Table 3. These marginal effect estimates are interpreted as the percentage increase in the probability of observing a positive NPV by increasing the production parameters in one percent relative to the baseline scenario. Simulation results suggest that the probability of economic success increases by 1.45 percent if energy cane harvesting months is extended in 1 percent (or 2.85 days).

The marginal effects also indicate that increasing the feedstock production, producers' returns, harvesting and hauling cost have a negative impact on the probability of obtaining a positive NPV. Namely, increasing the production cost in 1 percent (or by $4.5/ac) reduces the probability of observing a positive NPV in 0.21 percent. Similarly, the probability of economic success is reduced in 0.03 percent when the return to producers increases in 1 percent. In addition, unit percent increases on the variable and fixed harvesting and hauling cost reduced the probability of economic success in 0.06 and 0.03 percent, respectively.

Based on the estimated marginal effects, it seems that improvements on the energy cane yield will have a significant impact on obtaining a positive NPV. Specifically, simulation results suggest that one percent increase on the feedstock yield (i.e., 0.2 dst/ac) rise the probability of economic success in 1.68 percent.

In terms of ethanol conversion parameters, results indicate that both conversion plant's nameplate capacity and biofuel conversion yield are positively related to NPV. Namely, the probability of economic success increases in 0.41 percent and 0.33 percent with respect to unit percent increases in the total annual ethanol produced and ethanol conversion yield, respectively.

Lastly, energy prices play an important role on the probability of economic success. Particularly, ethanol price, where a 1 percent positive shift on the ethanol price trend increases the probability of economic success in about 1.97 percent. Similarly, the probability of observing a positive NPV increases in 0.08 percent given a 1 percent positive shift on the electricity price trend.

Summary and Conclusions

The optimal allocation of resources and efforts is needed to fulfill the latest Renewable Fuel Standard (RFS2) mandate. Particularly, 16 billion gallons of cellulosic biofuels have to be produced by 2022. In order to warranty the success of the nascent cellulose-based biofuel industry, it is crucial to better understand the effects that production parameters have on the economic feasibility of a biofuel enterprise to effectively target future improvement efforts. The main goal of this study is to estimate the impact that the different feedstock production and biofuel conversion parameters have on the probability of economic success.

A flexible stochastic financial model is developed in this paper to analyze and identify the most economically relevant components of the biofuel production path. Although the proposed analysis can be extended to any biofuel production process, we focused on ethanol produced from energy cane through a hydrolysis conversion process. Estimation of the model was carried out using Monte Carlo simulation techniques along with parametric maximum likelihood estimation procedures.

This study provides insights to improve production systems by better targeting future research efforts. The marginal effects, defined as the change in the probability of economic success by increasing production parameter in one percent relative to the baseline scenario, were estimated for each production parameter considered on the model. Even though, all of the marginal effects are statically different that zero, in practical terms some production parameters have a modest effect on the probability of obtaining a positive NPV (e.g., return to producers, and fixed harvesting and hauling cost).

When considering only marginal effects greater than 1 percent in absolute value, simulation results suggest that the probability of economic success is positively related to feedstock yield and harvesting months. Namely, the probability of obtaining a positive NPV increases by 1.68 percent and 1.45 if the energy cane yield and harvesting months are extended in 1 percent, respectively. These findings indicate that operational efficiency strategies should concentrate on improving feedstock yields and extending the growing season.

Energy prices, particularly the price of ethanol, were also found to have a significant impact on the probability of economic success. Simulation results reveal that a 1 percent positive shift on the ethanol price trend increases the probability of observing a positive NPV in 1.97 percent. Therefore, the economic success of a cellulose-based biofuel enterprise is very sensitive to the fluctuation of energy prices.

Table 1. Baseline Scenario and Distribution Range.

Parameter	Acronym	Units	Baseline	Distribution Function
Harvest Months	*HarvMonth*	month	9.5	Unif (8.00, 11.00)
Production Cost	*FeedPrdCost*	$/acre	450	Unif (350.00, 550.50)
Return to Producers	*Return*	%	20	Unif (10.00, 30.00)
Energy Cane Yield	*Yield_EC*	dst/acre	20	Unif (17.50, 22.50)
Variable Harvesting and Hauling Cost	*VarHrvCost*	$/dst	10	Unif (7.50, 12.50)
Fixed Harvesting and Hauling Cost	*FxHrvCost*	$/acre	92	Unif (69.00, 115.00)
Ethanol Annual Production	*FuelPrd*	mill. gallon	30	Unif (25.00, 35.00)
Biofuel Yield	*FuelYld*	gallon/dst	85	Unif (75.00, 95.00)
Ethanol Prices	*Price_Eth*	$/gallon	2013 EIA Reference Case	EIA*Unif (0.75, 1.25)
Electricity Price	*Price_Elec*	$/kWh	2013 EIA Reference Case	EIA*Unif (0.75, 1.25)

Table 2. Normal Distribution Coefficient and Marginal Effect Estimates.

Parameter	Coefficient		Std. Error	Marginal Effect		Std. Error
Constant	-10.069[a]	***	0.584			
HarvMonth	1.010	***	0.059	1.442	***	0.164
FeedPrdCost	-0.144	***	0.010	-0.206	***	0.024
Return	-0.021	***	0.004	-0.030	***	0.006
Yield_EC	1.171	***	0.067	1.673	***	0.190
VarHrvCost	-0.044	***	0.005	-0.063	***	0.010
FxHrvCost	-0.021	***	0.005	-0.030	***	0.007
FuelPrd	0.286	***	0.018	0.409	***	0.047
FuelYld	0.232	***	0.016	0.331	***	0.040
Price_Eth	1.377	***	0.079	1.967	***	0.224
Price_Elec	0.055	***	0.005	0.079	***	0.011
AIC	534.732					

[a] Significance levels of 0.01, 0.05 and 0.10 are indicated by ***, ** and *, respectively.

Table 3. Logistic Distribution Coefficient and Marginal Effect Estimates.

Parameter	Coefficient		Std. Error	Marginal Effect		Std. Error
Constant	-18.438[a]	***	1.170			
HarvMonth	1.858	***	0.118	1.450	***	0.014
FeedPrdCost	-0.266	***	0.019	-0.208	***	0.007
Return	-0.039	***	0.006	-0.030	***	0.005
Yield_EC	2.155	***	0.137	1.682	***	0.008
VarHrvCost	-0.081	***	0.010	-0.063	***	0.006
FxHrvCost	-0.042	***	0.008	-0.032	***	0.006
FuelPrd	0.527	***	0.036	0.412	***	0.010
FuelYld	0.425	***	0.032	0.332	***	0.014
Price_Eth	2.529	***	0.160	1.973	***	0.011
Price_Elec	0.104	***	0.010	0.081	***	0.006
AIC	533.695					

[a] Significance levels of 0.01, 0.05 and 0.10 are indicated by ***, ** and *, respectively.

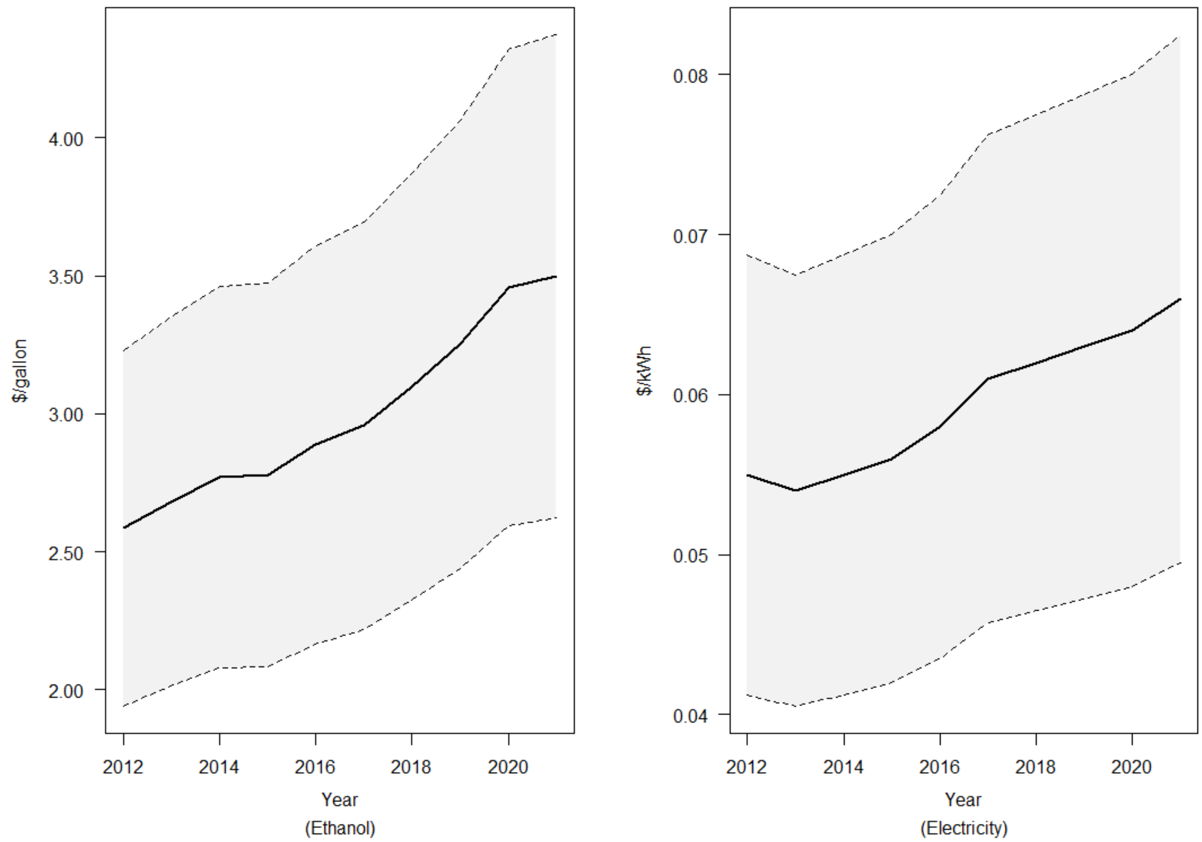

Figure 1. 2013 Ethanol and electricity EIA reference price scenario. Dotted lines represent ± 25 percent from the baseline price trend.

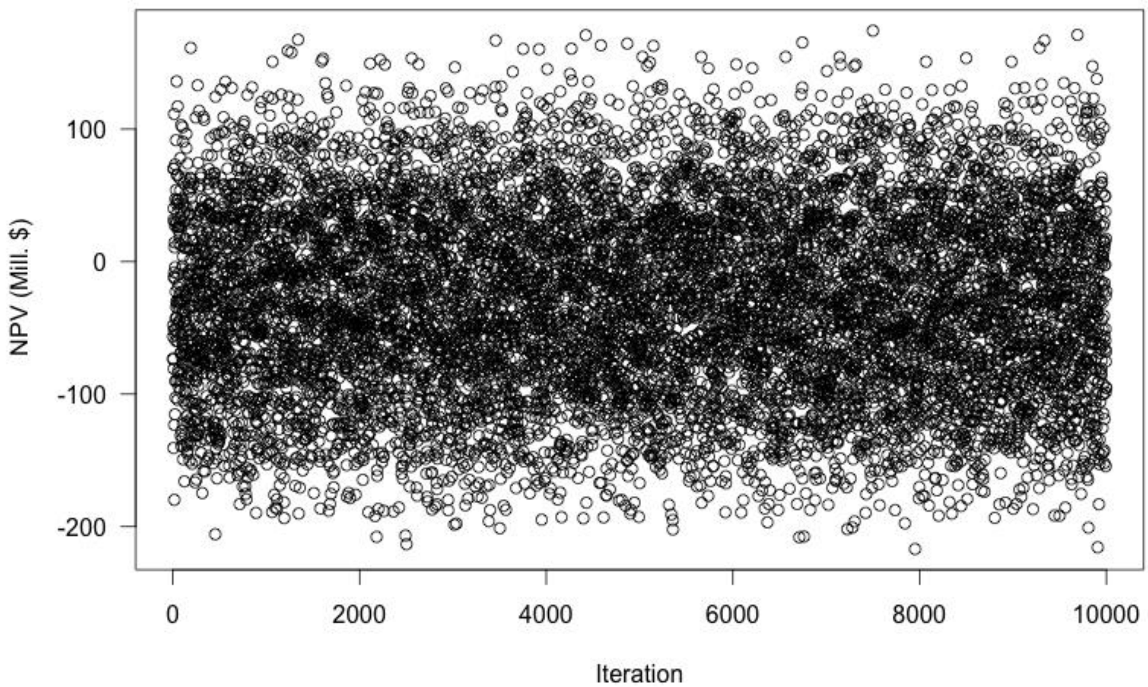

Figure 2. Monte Carlo simulated net present values.

References

Akaike, H. 1974. "A new look at the statistical model identification." *IEEE Transactions on Automatic Control* 19(6): 716–723.

Hoetker, G. 2007. "The Use of Logit and Probit Models in Strategic Management Research: Critical Issues." *Strategic Management Journal* 28: 331–343.

Long, L.J. 1997. Regression Models for Categorical and Limited Dependent Variables. Advanced quantitative techniques in the social sciences; v. 7. Thousand Oaks, California.

Marvin WA, Schmidt LD, Benjaafar S, Tiffany DG, Daoutidis P. 2012. "Economic optimization of a lignocellulosic biomass-to-ethanol supply chain." *Chemical Engineering Science* 67:68–79.

McCutchen, B. F., R. V. Avant, and D. Baltensperger. 2008. High-Tonnage Dedicated Energy Crops: The Potential of Sorghum and Energy Cane. In Proceedings of the Twentieth Annual Conference of the National Agricultural Biotechnology Council, 119–122, Columbus, OH, USA.

Monge, J.J., L. A. Ribera, J. L. Jifon, J. A. da Silva and J. W. Richardson. 2014. "Economics and Uncertainty of Lignocellulosic Biofuel Production from Energy Cane and Sweet Sorghum in South Texas." *Journal of Agricultural and Applied Economics*, 2014, vol. 46, issue 04.

Owens, G. 2002. Best Practices Guide: Economical and financial evaluation of renewable energy projects. United States Agency for International Development.

Palma, M. A., J. W. Richardson, B. E. Roberson, L. A. Ribera, J. L. Outlaw, and C. Munster. 2011. Economic Feasibility of a Mobile Fast Pyrolysis System for Sustainable Bio-crude Oil Production. *International Food and Agribusiness Management Review* 14(3): 1–16.

Ribera, Luis A., Joe L. Outlaw, James Richardson, Jorge A. Da Silva, and Henry L. Bryant. "Mitigating the Fuel and Feed Effects of Increased Ethanol Production Utilizing Sugarcane." In: J.L. Outlaw, J.A. Duffield, D.P. Ernstes (eds.) Biofuels, Food & Feed Tradeoff. St. Louis, MO: Farm Foundation, 2007, pgs. 71-78.

Richardson, J. W., B. K. Herbst, J. L. Outlaw, and R. C. Gill. 2007. "Including Risk in Economic Feasibility Analyses: The Case of Ethanol Production in Texas." *Journal of Agribusiness* 25:115–132.

Richardson, J. W., W. J. Lemmer, and J. L. Outlaw. 2007. "Bio-ethanol Production from Wheat in the Winter Rainfall Region of South Africa: A Quantitative Risk Analysis." *International Food and Agribusiness Management Review* 10(2): 181–204.

Swanson, R. M., J. A. Satrio, R. C. Brown, A. Platon, and D. D. Hsu. 2010. Techno-Economic Analysis of Biofuels Production Based on Gasification. National Renewable Energy Laboratory, Golden, CO.

U.S. Energy Information Agency. 2015. Annual Energy Outlook 2015.

van der Weijde, T., C. L. A. Kamei, A. F. Torres, W. Vermerris, O. Dolstra, R. G. F. Visser, and L. M. Trindale. 2013. The Potential of C4 Grasses for Cellulosic Biofuel Production. *Frontiers in Plant Science* 4: 1–18.

Wright, M., J. Satrio, R. Brown, D. Daugaard, and D. Hsu. 2010. Techno-Economic Analysis of Biomass Fast Pyrolysis to Transportation Fuels. National Renewable Energy Laboratory, Golden, CO.