Fall 12-15-2012

Essays on the U.S Biofuel Policies: Welfare Impacts and the Potential for Reduction of GHG Emission

Kassu Wamisho Hossiso
University of Nebraska-Lincoln, kassuwam@gmail.com

ESSAYS ON THE U.S. BIOFUEL POLICIES: WELFARE IMPACTS AND THE POTENTIAL FOR REDUCTION OF GHG EMISSION

By

Kassu Wamisho Hossiso

A DISSERTATION

Presented to the Faculty of

The Graduate College at the University of Nebraska

In Partial Fulfillment of Requirements

For the Degree of Doctor of Philosophy

Major: Natural Resource Sciences

Under the Supervision of Professor Richard K.Perrin

Lincoln, Nebraska

December, 2012

ESSAYS ON THE U.S. BIOFUEL POLICIES: WELFARE IMPACTS AND THE POTENTIAL FOR REDUCTION OF GHG EMISSION

Kassu Wamisho Hossiso, Ph.D.

University of Nebraska, 2012

Adviser: Richard K.Perrin and Karina Schoengold

This dissertation study investigates the impact of the US biofuel policies related to greenhouse gas (GHG) emission regulation, tax credit and renewable fuel standard (RFS2) mandate over production and consumption of ethanol as well as technical and environmental performance of corn ethanol plants. The study develops analytical models and provides quantitative estimation of the impact of various biofuel policies in each of the three chapters.

Chapter 1 of this dissertation examines the tradeoff between achieving the environmental goal of minimizing life cycle GHG emissions and minimizing production costs in recently built dry-grind corn ethanol plants. The results indicate that the average ethanol plant is able to reduce GHG emissions by 36 % relative to the level under cost minimization, but production costs are 22 % higher. 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.

Using a multi-output, multi-input partial equilibrium model, Chapter 2 explores the impact of the tax credit and RFS2 mandate policy on market price of ethanol, byproducts, corn, and other factor inputs employed in the production of corn ethanol. In the short-run, without tax credit ethanol plants will not have the incentive to produce the

minimum level of ethanol required by RFS2. In the long-run, if ethanol plants to have the incentive to produce the minimum RFS2 mandate without tax credit policy, gasoline price will need to increase by order of 50% or more relative to the 2011 price.

Chapter 3 develop meta-regression model to investigate the extent to which statistical heterogeneity among results of multiple studies on soil organic carbon (SOC) sequestration rates can be related to one or more characteristics of the studies in response to conventional tillage (CT) and no-till (NT). Regarding the difference in the rate of SOC sequestration between NT and CT, our results shows that the percentage of heterogeneity in the true treatment effect that is attributable to between-study variability is 49%, whereas 51 % is attributable to within-study sampling variability.

This page is intentionally blank

Dedication

To my late Mam.

and, to

Addis

Acknowledgments

This dissertation is a milestone in my academic career but would not have been possible at all without countless personal helps and financial supports from my adviser Dr.Perrin. I would also like to offer exceptional thanks to Dr. Liliyan Fulginiti for providing relentless intellectual guidance and unlimited zeal which has been major driving forces for completion of this dissertation. Dr. Perrin, you made me believe in myself and lifted me up from the point I made my mind to quit. I would also like to extend my gratitude to Dr.Karina Schoengold for her personal support, insights and inspiration throughout the whole process of dissertation completion. My gratitude also goes to Dr.Liska who taught me the topic that I had less familiar while writing my dissertation.

Diego Alvarez, my day to day interaction with you was beyond a classmate, you have taught me economic theory more than I have learnt at class. All Agecon members of Perrin-Fulginiti research group also deserve my sincerest thanks, their academic and research interaction has meant more to me than I could ever express.

Finally, my parents who recognized early on the value of education are my hero in my entire life. My Sisters and brother, and other family member has supported and helped me along the course of the PhD studies by giving encouragement and providing the moral and emotional support I needed to complete my dissertation.

Addis, I have not yet got words that weigh the acknowledgment you deserve for the love and caring you have given for me, you stood up all the time during my adversity.

My mam, if I have ever a power in this world I would have been wake you up to see me achieving your final wishes. May God rest your soul in heaven with peace.

Tables of Contents

Lists of Tables

List of Figures

Chapter 1: The Shadow Price of GHG Reduction in Corn Ethanol Plants

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

1.1 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.

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

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 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 Independent 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 new corn-ethanol plants, 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 the econometric estimation procedure. The empirical results of our application and implication of this article are elucidated in section 4. Summary and concluding remarks are then provided in section 5.

1.2 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:

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

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

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

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

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

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:

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

GHG^M is achieved by allowing the 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 measures based on the material-balance principle is extensively discussed by (Coelli, Lauwers and Van Huylenbroeck 2007; Lauwers 2009; Welch and Barnum 2009).

We illustrate 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.

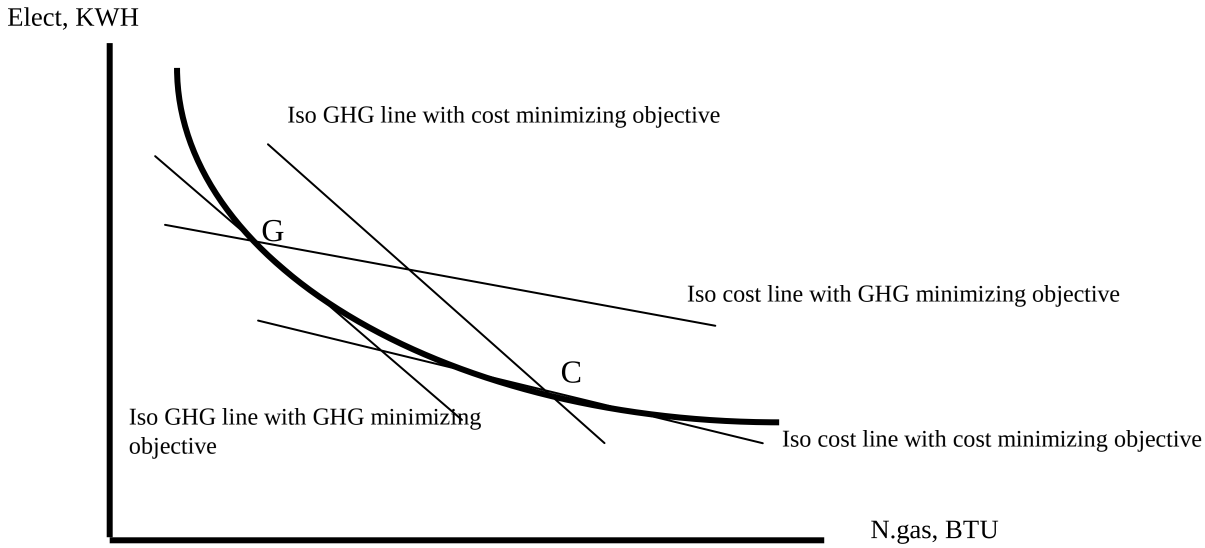

Figure 1.1 The correspondence between cost and GHG minimization outcome for unit isoquant

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.

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

$$GHG^{C} = aX^{C} - bY^{C} \quad (6)$$

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.

$$C^{g} = WX^{g} - PY^{g} \quad (7)$$

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

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

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

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

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 measure 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).

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

Where α_o is an intercept, α' 1X7 first order coefficient parameters and B is 7X7 second order coefficient parameters. Where R is natural log of $\{w, p, e, z\}$.

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

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

Where $r = \{w, p\}$

We also calculate the Allen partial price elasticities of inputs and byproducts based on the translog cost function. The elasticity estimates are calculated at the mean of the prices, and input and byproduct cost share. The appendix section presents the mathematical derivation for the above elasticities.

1.3 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

---

[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).

(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.

[3] Symmetry and equality restrictions imposed across equations to ensure uniqueness of estimated parameters which occur in more than one equation.

1.4 Empirical Results and Discussion

Table 1.1 displays the mean value of observed data per quarter used for our translog estimation. Table 1.2 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 properties of the cost function[4](monotonicity and curvature) were maintained. Table 1.3 contains the level and percent change input and byproducts per gallon of ethanol under cost and GHG minimizing objective respectively. Whereas table 1.4 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 1.4. The shadow value of GHG and the cost and environmental efficiency measures are presented on table 1.5 through 1.7 respectively. Table 1.8 shows the Allen partial price elasticity of inputs and byproducts evaluated at mean of each predicted share.

At the cost minimization point, (table 1.3), 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. The corresponding results of the GHG minimizing objective for each input and byproducts were depicted on table 1.3.

[4] All estimated shares were monotonic everywhere except eleven data points whereas the curvature properties satisfied at each data observation.

The average optimum allocation at GHG minimization point 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. Perrin, Fretes, and Sesmero (2009) estimated an additional 0.00933MMBTU/gal natural gas needed to dry an additional one ton of byproduct, dry matter basis, from 55% moisture (MWDGS) to 10% moisture (DDGS.) It is evident that ethanol-plant energy use and associated GHG emissions are affected by fraction of total byproduct dried.

The average GHG per gallon of ethanol measured across all observations at cost minimizing allocations was 10.2 lb whereas at GHG minimizing point was 6.7 lb, (table 1.4). 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 1.4. The average costs at these two allocations from the sample were approximately \$1.01/gal and \$1.24/gal respectively (table 1.4).

The average shadow prices per quarter ranges from \$86 to \$190 per ton with average value of \$124, (table 1.5). We also found the shadow price as small as \$27 and \$34 per ton for two plans in one quarter which is an indication of the potential room to abate GHG emissions with least cost for given level of ethanol. Using the same data but with a non-parametric approach, Sesmero, Perrin , and Fulginiti (2010) on average found

$1,726 per ton as the shadow costs associated with moving from GHG minimizing to the returns over operating costs maximizing allocations.

The price of the variable inputs and byproducts considered in this study has changed substantially compared to the surveyed year as shown on table 1.1, so also does any given estimate of average shadow price. To capture this change, we ran 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 1.2. When evaluating at the mean price of the 2006/07 survey data, the mean shadow price was $119 per ton, (table 1.7). However when we updated only the price of corn to the year 2012 value, the shadow price increased to $161 per ton. This price fell to $103 when we updated only the price of natural gas. 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 $167 per ton. The mean shadow prices reached $173 per ton when we evaluated after updating all input and byproduct prices. Note that the emission coefficients of all inputs and byproducts have not changed from what it was at the surveyed year.

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 1.6, 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 inputs and byproducts to the year 2012 values, on average plans could reduce emissions by 57 percent while to do so the cost of ethanol production would rise by 46 percent as depicted on Table 1.7.

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.

We present the Allen partial price elasticities calculated from the translog cost function in table 1.8. 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.

1.5 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 the undesirable output as another variable into the 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 will be then 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 the level of emissions reduction and abatement cost per gallon of ethanol. The variation of GHG reductions and abatement costs per gallon of ethanol across plant results from different in 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 serves 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 of GHG reduction and the shadow prices among ethanol plants are considerably dependent on the value of emission coefficients of inputs and by products obtained from BESS.

1.6 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.

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.

Christensen, L. R., D. W., Jorgenson and L. J., Lau.1973. "Transcendental Logarithmic Production Frontiers." Review of Economics and Statistics 55 : 28-45.

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.

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.

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

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 Econo 68 (6), 1605–1614.

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

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

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. 2012. Accesses in 2012 http://marketnews.usda.gov/portal/lg

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

US Energy Information Administrative Agency: http://www.eia.gov/

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

I. Table of Results

Table 1.1 Descriptive Statistics of Variables used in Estimation: all are per quarter basis

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 from 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 WDG is a weighted average of 55-60% and 60-70 % moisture basis, and both data are from USDA Agricultural Marketing services.

Table 1.2 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 1.3 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 1.4 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

1 t(US) = 2000 lb. The last column "Difference from Cost to GHG, $/gal" is in absolute value

Table 1.5 Shadow Price ($/ton) CO2 equivalent by Plant per quarter

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

Table 1.6 Cost and Environmental Efficiency Measure per quarter

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

Table 1.7 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 1.8 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 1

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 vector of second order parameters from the translog estimation. β_{ij} show a cross price coefficient among inputs, DDG and WDG. S_i represent the mean predicted share of each input and byproduct. S_j^x and S_j^y used to differentiate the share of input from byproduct respectively while calculating cross price elasticity .

Chapter 2: The Impact of Federal Tax Credit and Mandate on Ethanol Market

Abstract

Using a multi-output, multi-input partial equilibrium model this article examines the likely impact of changes in the ethanol tax credit and mandate policies on ethanol, byproduct and corn markets. This partial equilibrium analysis is built upon an empirical industry level cost function for corn ethanol plants with two byproducts: dried distillers grain with soluble and wet distillers grain with soluble.

In the short-run, without the tax credit, ethanol plants will not have the incentive to produce the minimum level of ethanol required by renewable fuel standard (RFS2) mandate. In the long-run, for ethanol plants to have the incentive to produce the minimum RFS2 requirement without tax credit policy, gasoline price will need to increase by order of 50% or more. Without renewing the tax credit, however RFS2 mandate estimated to raise ethanol price to $2.81 per gallon in the short run, and in the long-run to $2.63.

Producing the RFS2 mandate level of ethanol without tax credit will also push the short and long run price of corn to $6.90 and $6.60 per bushel respectively compared to $6.07 per bushel without any ethanol policies.

Our estimates of the effects of ethanol tax credit and mandate on quantity and price of ethanol, byproducts, corn and other inputs are sensitive to assumptions about the ethanol demand elasticity and price of gasoline.

Key words: ethanol, corn, tax credit and mandate

2.1 Introduction

The US congress ended the federal tax credit and tariff for ethanol at the end of 2011, winding up more than three decades of federal government subsidies given for production and consumption of ethanol. However some congressional members are still contemplating to renew the tax credit and revise the existing mandate amid growing pressure for the development of green energy based economy. The government has been subsidizing biofuels industry primarily through: the Volumetric Ethanol Excise Tax Credit (VEETC - tax credit to refiners blending ethanol with gasoline), the Renewable Fuel Standard (RFS1 & RFS2)[5], and an import tariff.

The provision of the biofuel subsidies has been justified because they reduce dependence on imported foreign oil, reduce greenhouse gas emissions and support rural farm income. The objective of VEETC and RFS mandate specifically is to encourage biofuels in greater quantity than either would without the policies. Whereas the import tariff was set to foster the competitiveness of domestic corn ethanol producers by giving a cost advantage over imported Brazilian sugarcane ethanol.

The above policies have actually spurred ethanol production, primarily ethanol from corn starch to grow from about 2 billion gallons in 2002 to nearly 14 billion gallons in 2011 and for the first time US become a net exporter of ethanol in the year 2010 (RFA,

---

[5] The Congressionally mandated RFS2 goal is to use at least 36 billion gallons of bio-based transportation fuels by 2022; 15 billion gallons can come from conventional biofuel sources such as corn starch based ethanol. Environmental Protection Agency's (EPA) analysis indicates that ethanol from corn has been capped at 15 billion gallons in year 2015 and beyond.

2011). However in 2011 alone the cost of VEETC for conventional corn starch ethanol to the Treasury in forgone revenues was more than $6 billion. Had it not expired this cost could grow close to $7 billion in 2015 and each year thereafter under the assumption that the RFS2 is fully met. Under the current market condition, the tax credit and RFS are duplicative policy tools and the tax credit has no impact on ethanol production or consumption (Babcock 2010; GAO 2009, Tyner, Taheripour, and Perkis 2010) unless a new discretionary ethanol requirement is set.

One of the criticisms that under current market condition is the justification of extending the tax credit and mandate so long as the demand for ethanol and gasoline remains strong and production of ethanol from corn is becoming a mature technology. The facets of this topic have been the subject of a great deal of research and policy debate continues on over the efficacy of biofuel policy. The ethanol tax credit and tariff are now gone. It is nonetheless useful to analyze the possible market impacts of ethanol policies in order to give valuable information to the ethanol industry, fuel consumers and policy makers to know the future market directions of ethanol.

The purpose of this article is thus to explore the primary impact of the tax credit and RFS mandate on the 2015 expected market price of ethanol, byproducts, corn, energy and other factor inputs employed in the production of corn ethanol. The text also explores the distributional implication of these ethanol policies to ethanol producer and consumer as well as tax payers. The paper also seeks to offer additional contribution in providing perspective on ethanol byproduct markets under new alternative ethanol policies.

The approach taken is a multi-output, multi-input partial equilibrium market model. This equilibrium analysis is built upon an empirical industry level cost function for the corn based ethanol industry with two byproducts- dried distillers grain and solubles (DDG) and wet distillers grain with solubles (WDG). The model comprises three outputs: ethanol, DDG and WDG, four variable inputs (corn, natural gas, electricity, labor and other), and one fixed input, aggregate plant and equipment.

The rest of this article is organized as follow: section 2 presents brief overview of the economics of ethanol from which we developed our theoretical model. Subsection two is devoted to explain the analytical model. The data and model calibration procedure displayed in section three. Results with detailed discussion are presented in section 4 and the final portion wrap up with the conclusion and implication of the article.

2.2 Theoretical Model

2.2.1 The Economics of Ethanol

Under competitive market condition the price of ethanol is determined by market supply and demand interaction. However the presence of multiple government subsidy policies such as VEETC, RFS and excise tax has affected the price, supply and the demand for ethanol. The demand for ethanol is largely derived from the gasoline demand and has gotten some of its value for its energy content as a fuel substitute, additive value as oxygenate fuel use and octane enhancer (Babcock, Barr and Carriquiry 2010;De Gorter and Just 2008; Miranowski 2007; Tyner, Taheripour, and Perkis 2010).

Considering only the domestic ethanol industry, the demand curve for ethanol D in Figure 2.1 reflects the value that blenders/ fuel refiners place on different volumes of ethanol-the demand for ethanol represents the blender's derived demand. The supply curve S_s represents the shortrun domestic supply of ethanol in US. S_l represents the longrun ethanol supply curve.

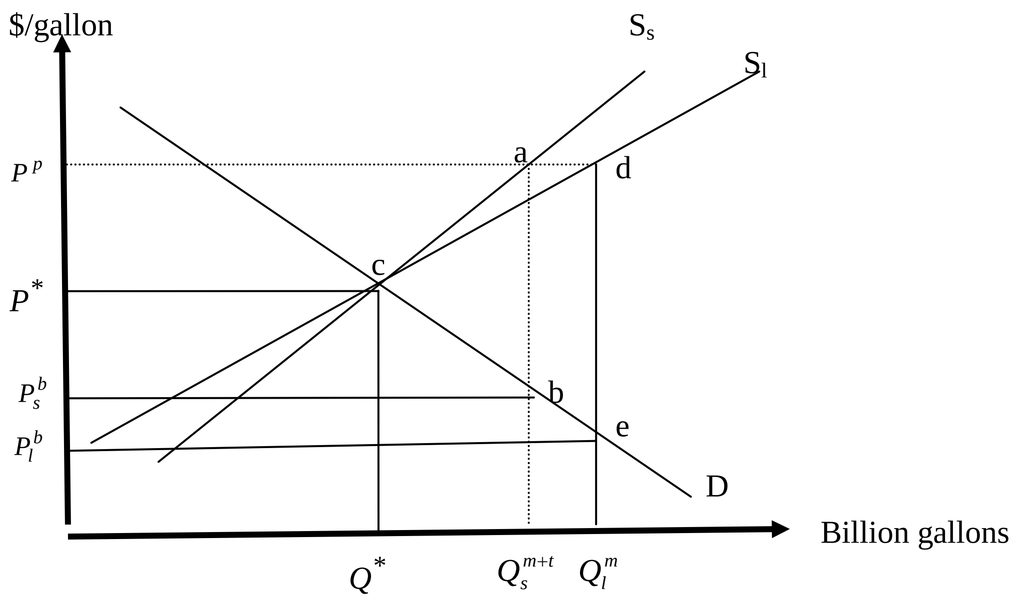

Figure 2.1 Illustration of the supply and demand curves of ethanol

The RFS2 mandate is an established floor level of consumption requiring blending of specified amount of ethanol annually into U.S. transportation fuels. The 2012 requirement under RFS2 is 13.2 billion gallons. The RFS objective is to force blenders to use more biofuels than they would without the mandate, whereas the VEETC support discretionary blending above and beyond the market levels (Babcock, Barr and Carriquiry 2010; GOA 2009; Tyner, Taheripour, and Perkis 2010).

With already installed capacity, without any government subsidy provision the initial short and longrun market equilibrium price and quantity of ethanol are Q^* and P^* respectively, point c on figure 2.1. However, for example, with the tax credit and RFS mandate put in place, in the short run ethanol production would go to and beyond the mandated quantity level, Q_s^{m+t}. At Q_s^{m+t}, ethanol producers are willing to supply at price P^p, whereas blenders' willingness to pay price P_s^b otherwise they are not willing to blend the required amount of ethanol. The same argument holds in the long-run period. The market equilibrium point, point C, represents an underlying short and long-run equilibrium.

RFS2 mandate is binding if and only if the required amount of ethanol exceeded what is offered by the market, otherwise the mandate is non-binding. Therefore Q_s^{m+t} become a non-binding mandate if the required mandated RFS2 is surpassed by the market level that is being produced. Q_l^m represents the year 2015 and beyond level of ethanol production that could be produced with effective capacity of the ethanol plants (the sum of the capacity currently operating and plant under construction). At Q_l^m, plants are assumed to supply a gallon of ethanol at a price, P^p but fuel refiners are willing to pay only P_l^b. This creates a wedge of 'de' size as shown on figure 2.1. We find point 'e' based on the differences between quantity of ethanol obtained at capacity and the actual production at point Q_s^{m+t}, price P^* and elasticity of ethanol demand. The size of 'ab' is the $0.45 per gallon ethanol tax credit. Removing the two wedges 'ab' and 'de' using

comparative statistics gives us the underlying short and long run market equilibrium point 'C'. The above figure illustrates how we reached to the market equilibrium point based on the demand and supply curves. The model calibration section exposits numerically how we reached this market equilibrium point.

Byproducts[6] from corn ethanol plants represent a key component of total industry's revenue, and in 2011 alone about 16% of a corn based dry milling ethanol plant's revenue comes from DGS sales (RFA, 2011). Recently with ever increasing corn and soybean prices and strong growth in DGS availability, the DGS market orientation has changed the landscape of domestic livestock feed ration and hence DGS became a partial substitute in many livestock and poultry rations for feed grains and soybean meal (Jones et.al 2007; Westcott 2007; Klopfenstein, Erickson, and Bremer 2008).

Any ethanol policy intervention would certainly affect the price and quantity level of the two byproducts. The analytical model section captures the two byproducts in our displacement model. In most previous biofuel economic studies DGS has often been incorporated in an adhoc fashion. Hence it is imperative to see the impact of various ethanol policies on byproducts market since DGS production changes along with ethanol production while their price track the price of both corn and soybean meal. Few studies

---

[6] For ease of exposition DGS represents both DDG and WDG from corn ethanol plant. The major by-product feeds from current corn-based ethanol are corn gluten feed and corn germ meal from wet-mill ethanol plants, and distiller's grains from dry- grind ethanol plant. Distiller's grains from dry-mill ethanol plants: Dried Distillers Grain (10% mmoisture), Modified Wet Distillers Grain (50-55% moisture) , Wet Distillers Grain (65-70% Moisture), distillers' dried grains with soluble (DDGS), and condensed distillers' soluble (CDS). A bushel of corn processed into ethanol by dry mills produces approximately 17.5 pounds of distillers' spent grains (RFA 2012;Hoffman and Baker, 2010).

(Babcock 2007;Beckman, Keeny and Tyner 2011; Taheripour et.al 2010; Tokgoz et al.2007, Tyner and Taheripour 2007) have included DGS into their partial equilibrium models to evaluate the economic impacts of biofuel production and only few of these studies explicitly distinguish wet and dry in the manner of this article. It is crucial to model the byproducts separately to get an improved understanding of the byproducts market with the changing biofuel policies.

Overall our modeling approach has two principal advantages over the past studies: first our model comprises four factor inputs and fixed capital needed to produce ethanol. This allows measuring the impact of ethanol policies not only in corn market but also in natural gas and electricity market as opposed to many of the past studies that focused only in corn market. Secondly we explicitly modeled the byproducts as disaggregated into dry and wet to measure the consumer surplus in both byproduct markets.

2.2.2 The Equilibrium Displacement Model

We assume there is N number of ethanol plants producing a homogeneous ethanol and byproducts. The production technology of this ethanol industry is represented with dual cost function $C(Y,W)$, where Y is an 3*x1* vector of outputs (ethanol, DDG and WDG) and W is 5x1 vector of four variable inputs (corn, natural gas, electricity, labor and other) and one fixed input (aggregate plant and equipment). Outputs are sold at a corresponding vector of prices, P .

The demand for ethanol and byproducts output is represented as;

$$Y^d = f(P^d) \tag{1}$$

Where P^d represents a vector of 3*x1* demand prices of ethanol, DDG and WDG. The demand for ethanol reflects the value that blenders place on different volumes of ethanol whereas DGS demand reflects livestock producers' value for dry and wet byproducts. We further assume that the ethanol industry operates under perfect competition and production technology of the representative firm in the industry represented by constant returns to scale. An initial zero-profit equilibrium in product and factor markets also considered. Hence $C(Y,W)$ represents the industry-level joint cost function and this cost function is assumed to be twice continuously differentiable, concave and nondecreasing in input price. It is also homogenous of degree one with input prices and outputs.

Market clearing condition on equation 2 represents the long run equilibrium condition that marginal cost of each output is equal to domestic prices for respective outputs.

$$\frac{\partial C(Y,W)}{\partial Y} = P^S \tag{2}$$

Where P^S is the vector of supply price of ethanol and DGS.

Using Shephard's lemma, optimal factor demand can be obtained using equation 3.

$$\frac{\partial C(Y,W)}{\partial W} = X(Y,W) \tag{3}$$

Equation 3 represents the derived demand for input X in the production of a given levels of ethanol and DGS.

Factor supply or the joint output is given by Equation 4 and it is a function of input prices.

$$X = g(W) \qquad (4)$$

Ethanol price wedges due to ethanol tax credit to blenders represented as

$$\frac{P_1^S}{P_1^d} = \mathbf{1+}\ \tau \qquad (5a)$$

Where P_1^S represents per gallon ethanol producers price and P_1^d is the per gallon price of ethanol that blenders pay.

τ is the wedge on the price of ethanol between what blenders pay and ethanol producers receive This wedge is measured as a percentage of the initial equilibrium price of ethanol, and is considered an exogenous policy variable, in our case it is the per gallon amount of tax credit.

The ethanol consumption mandate will also create an output wedge between what the ethanol pans willing to produce and fuel refiners willing to blend with prevailing market prices. Mathematically this is shown in equation 5b below:

$$\frac{Y_1^m}{Y_1^*} = 1 + \omega \qquad (5b)$$

Where, Y_1^m is the 2015 and beyond minimum level of ethanol quantity consumption, i.e., 15 billion gallons of corn ethanol. Whereas Y_1^* is the short and long run market

equilibrium quantity level which actually corresponds to Q^* on figure 2.1 above. ω is the wedge that captures the percentage change in the quantity of ethanol to reach to the mandated level.

The current technological structure of the US ethanol industry is adapted and some of the elasticities are econometrically estimated from a recent survey of Midwest ethanol plants (Perrin, Fretes and Sesmero 2009). Our model treats the U.S. ethanol economy as being closed to international ethanol trade.

Derivatives of the cost function could be expressed in terms of various elasticities and share parameters. Totally differentiating equations 1 through 5 and converting them into elasticity form, yields system of logarithmic differential equation, from 6 through 11, expressed in terms of relative changes and elasticities.

$$d \ln Y = \mathrm{H} d \ln P^d \qquad (6)$$

Where H is a 3x3 price elasticity of demand for ethanol and DGS

$$\mathrm{E}_{P^s Y} d \ln Y + \mathrm{E}_{P^s W^d} d \ln W^d = d \ln P^s \qquad (7)$$

Where $\mathrm{E}_{P^s Y}$ and $\mathrm{E}_{P^s W^d}$ represent 3X3 and 3 X 5 matrices of output supply elasticities and marginal cost elasticities with respect to input price . The mathematical detail for how we calculated the elasticities is presented in the mathematical footnotes in appendix 2.

$$\mathrm{E}_{XY} d \ln Y + \mathrm{E}_{XW} d \ln W^d = d \ln X \qquad (8)$$

Where E_{XW} is a 5X5 output-constant derived demand elasticity matrix and E_{XY} *is* a 5 by 3 elasticity of demand for input X with respect to output Y. Elasticity of input with respect to output is equal to unit Y under constant return to scale.

A factor supply function in elasticity forms gives us:

$$d\ln X = \Sigma d\ln W^{s} \quad (9)$$

where Σ is a 5 by 5 excess factor supply elasticity matrix. Since there is no wedge between price of input demand and supply, the following relationship holds W^{s} = W^{d} = W

the tax credit and mandate wedges in the percentage form from equation 5a and 5b are converted into the following forms :

$$d\ln P^{s} - d\ln P^{d} = d\tau \quad (10)$$

$$d\ln Y_1 - d\ln Y_1^{*} = d\omega \quad (11)$$

The above equations are solved to evaluate the changes in market outputs and inputs price and quantity that would occur under different ethanol policies. The equilibrium displacement model framework of this portion is taken from Perrin (2009). The welfare gains and loss in each market are also calculated in the usual manner via as a change in producer surpluses, consumer surpluses, and government tax revenue.

2.3 Model Calibration

We first seek market equilibrium outcomes by parameterizing the corn ethanol demand and supply curves for the year 2015. This market equilibrium point, we call it a baseline (or status quo), is the situation in which no tax credit and mandate policies against which we simulate the impact of renewing the tax credit, and RFS2 mandate policy both in the short and long-run, point C on figure 2.1. We summarize how we reached the long run market equilibrium outcome as follow: we first assume constant elasticity supply and demand curves for corn ethanol, and calibrated to fit 2011 data. These supply and demand curves are assumed to be linear. We again assumed that the effective capacity of corn ethanol production in 2015 will be about 14.25 billion gallons (existing capacity plus capacity of plants under construction). We further assume that in 2015 plant is willing to supply a gallon of ethanol at wholesale price that prevailed in year 2011. We take the year 2011 producer price of ethanol as the average wholesale FOB price for Midwest, $2.55 per gallon. We computed the price that blenders willing to pay for a gallon of ethanol based on the 2011 price of ethanol, 2015 quantity supply of ethanol at the capacity, and the demand elasticity of ethanol[7]. Finally using the comparative statistic we estimated our base model (or status quo), i.e., the market equilibrium outcomes, by removing the wedge between per gallon price that ethanol producers willing to sell and fuel refiners willing to buy. This market equilibrium point,

[7] The formal equation used is : $d \ln Y = \eta d \ln p^d$, where η is price elasticity of ethanol demand.

Point C on figure 2.1, represents the short and long run market equilibrium point. The fact that our base configuration is based on the year 2011 data, using comparative statistics removing the $045 per gallon of ethanol tax credit that was active in year 2011, will give us the short-run market equilibrium outcomes.

With respect to byproduct market, throughout the analysis we assumed both DDG and WDG have constant demand and supply curves. The supply elasticity of DDG and WDG are econometrically estimated based on a translog cost function we built on chapter 1. Moreover, the derived demand elasticities of corn, natural gas and electricity are also econometrically estimated using a translog cost function. We also calculated excess factor supply elasticity for all input considered[8]. Where there is no complete information for the remaining elasticity of inputs, the article uses information from related studies and configured these elasticities in a manner consistent with our model. Details of the elasticity figures and the value of other relevant parameters are presented from table 2.1 through 2.6.

Key assumptions made were that ethanol and the two byproducts quantity is the domestically produced in the US with no imports. We also assume that the demand curve for ethanol shifts out by due to a change in the wholesale premium gasoline price at the rack. To determine the size of the shift in ethanol demand, we assumed that ethanol serves as an imperfect substitute to gasoline in US market. To invoke this shift in ethanol demand, we used cross demand elasticity of ethanol with respect to gasoline price 1.056 as estimated by Miranowski (2007).

---

[8] The mathematical appendix section shows how we computed the excess supply elasticity.

The short and long run corn ethanol supply elasticities used are 0.65 and 0.25 based on Elobeid & Tokgoz (2008), and Miranowski (2007) respectively. Whereas the short and long run corn demand elasticities for corn ethanol are -0.89 and -2.9 obtained from Miranowski (2007) and Luchansky & Monks (2009) respectively. The remaining elasticities for factor input and byproducts are listed on the parameters and values description section at the end of the text. The short-run and long-run periods for all inputs and outputs are differentiated based on types of demand and supply elasticity curves used in the model.

2.4 Sensitivity Analysis

We simulate the impact of extending tax credit and mandate from the short and long-run market equilibrium point we described above. The two scenarios we built from our baseline outcome are:

(1) Extending tax credit, i.e., $0.45 per gallon to ethanol blenders/refiners

(2) Mandate , enforcing producers to produce the minimum level of ethanol required by RFS2

In order to investigate the sensitivity of price and quantity of ethanol as well as byproducts and all inputs to ranges of gasoline price at the rack, we run sensitivity analysis based on a possible percent increase in wholesale premium gasoline price from the base year to the anticipated short and long run period. In the base model, we take $3.18 per gallon average wholesale rack price of premium gasoline.

We ran the above scenarios each time for both short and long run period. The wide range of parameter values of demand and supply elasticity for ethanol and factor inputs shown from table 1A through 1f suggests that the outcomes of the different policy scenarios of depend on these parameters.

2.5 Empirical Result

The results of the ethanol policy simulations are summarized in tables 2.7 through 2.13. The results in table 2.7 through 2.9 contain the short and long-run market prices and quantities changes in output markets in combination with changes in some key assumptions. Table 2.10 and 2.11 shows the results of the welfare changes, i.e. change in consumer and producer surplus as a percent of initial value from the baseline outcome when the new alternative policies prevail in the ethanol, byproduct and factor markets. Table 2.12 and 2.13 contain the change on natural gas and electricity factor market price and quantities.

2.5.1 The Market Effects of Ethanol without Tax credit and Mandate

We first summarized the baseline short and long-run market equilibrium outcomes for all outputs and inputs considered in this model. Thus the long-run market equilibrium quantity of ethanol for 2015 estimated to be is 12.16 billion gallon, a 9% fall from the base quantity level. The per gallon market equilibrium price of ethanol is $2.39, a 6 % fall to the ethanol producer and 17 % rise to the ethanol refiners compared to what they were getting in the base configuration. Since the production of both byproducts trail along with the level of ethanol production, any change in quantity of ethanol production certainly affect the prices and quantity supply of both byproducts. At the estimated market equilibrium, corn price is $6.07 per bushel. The above results are presented on the second column of table 2.7. We now start to seek the market outcomes

of the impact of extending the $0.45 per gallon tax credit to ethanol blenders, enforcing RFS2 mandate of 15 billion gallon of ethanol from year 2015 and beyond. We also ran a sensitivity analysis to see the impact of gasoline price on the market outcomes of price and quantity of ethanol and other key variables.

2.5.2 The Short-run Market Effects of Ethanol Tax credit and Mandate

In the short run with the extension of the tax credit, ethanol production will reach an estimated 13.24 billion gallon per year (bgy), 9% increase from market equilibrium outcome. Ethanol producers are willing to supply this for $2.60 whereas refiners willing to buy for $2.15 per gallon which shows the $0.45 per gallon tax credit to be distributed almost equally. Under the mandate of 15 bgy, the price that ethanol producer willing to supply will be $2.94 per gallon while ethanol refiners buy at $1.76. The outcome from this mandate is a $1.20 per gallon price wedge between what producers would be willing to supply and what fuel blenders willing to pay voluntarily. The detail of the results are shown on table 2.7.

We injected a 10% change on gasoline price in our equlibruim market outcome and computed the impact of this price change on the markets for ethanol and associated products, with and without tax credit and mandate policy scenario. While without tax credit and mandate, the 10% change in gasoline price alone will induce an additional 0.68 billion gallons of ethanol and $0.13 per gallon raise on the price that ethanol producer use to supply and fuel refiners used to buy as shown on table 2.7. While producing at the RFS2 minimum mandate level, the 10% change on gasoline price will drive down the

producer price of ethanol to $2.81 per gallon, shrinking the wedge between producer and refiners to $0.77 per gallon compared to without gasoline price shock.

We can argue that had the tax credit been extended and again at the same time there would be a 10 % change in gasoline price, the overall ethanol production would increase close to 14 bgy, i.e., by adding up the additional gain of 0.68 bgy from a 10% gasoline price effect on the final quantity of ethanol we obtained with the tax credit. Technically we can obtain 14 billion gallon of ethanol, close to the RFS2 mandated level, with $0.45 per gallon subsidy.

In this segment, for ease of exposition among four of the policy simulations result on the byproducts market (table 2.7), we only discuss the market outcomes that we obtained without tax credit and mandate policy with the combination of the impact of a change on premium gasoline price. With the tax credit, the equilibrium quantities of DDG rise almost by 1.24 mmt (7.4%) while its price falls by $13 per ton (6%) compared with the longrun equilibrium market outcomes. Likewise production of WDG will rise by 1.1 mmt (8.5%) and its price fall by $11 per ton (9%). Without the tax credit and mandate policy, a 10% increase in gasoline price alone induced almost a 6% increase in ethanol supply which eventually would increase the supply of both byproducts. This change in ethanol supply actually resulted in an additional 0.8 and 0.7 mmt of DDG and WDG respectively while their per ton price fell by about $7 as shown on table 2. Changing the price of gasoline while producing at mandated level of ethanol will not bear any change on the quantity and price of both byproducts from what we obtained without change in premium gasoline price.

In factor market, all factor input will change linearly and proportionally with the percentage change in quantity of ethanol in both policy interventions we analyzed. A particular market that deserves attention is a corn market since as high as 40 percent of domestically produced corn goes to ethanol production and the cost of corn in the total operating cost of ethanol is nearly 72%. Extending tax credit will in short-run stimulate the demand for corn by 9%, that will lead the overall corn demand for the year to reach to 4.8 billion bushel while price of corn will increase to $6.4 per bushel (5.4%). Whereas without any policy interventions, a 10% change in gasoline price alone resulted in an additional quarter billion bushel of corn demand and $0.20 per bushel price differential from the equilibrium outcomes. Therefore the demand for corn would go up about 5 billion bushel and per bushel price will rise to $6.6, if we were certain of the tax credit and a 10% increase in premium gasoline. Ethanol plant would demand about 5.4 billion of bushels to produce at the mandate level and this pushes the price of corn upward to $6.90 per bushel as shown on table 2.7. Overall the price of corn will increase by 5 to 14 % in all of the policy simulations we ran.

Returns to the owners of the capital will increase by 12% if the tax credit is implemented while with binding mandate this increase would be around 31 % compared with the market equilibrium outcome without any interventions. With respect to the energy market, the change in the price of both electricity and natural gas was insignificant, i.e., less than one percent as presented on table 2.11.

2.5.3 The Long-run Market Effects of Ethanol Tax credit and Mandate

In this section we reran the same policy analysis but using long-run elasticities of demand and supply curves. Extending the tax credit will actually spur greater production of ethanol, 15.11 billion of gallons, surpassing slightly the 15 bgy mandate, (table 2.8). Ethanol producers will sell for $2.64 while blenders could be willing to pay $2.19 per gallon, an 11% raise and 9% fall respectively compared with the base market equilibrium price of $2.39. While with mandate policy scenario, it is quite interesting to see that both prices would change the same as with the tax credit. It turn out that the outcomes leave the wedge between these two prices almost equal to the $0.45 per gallon tax credit and much less than a $1.20 price wedge we obtained with the same (mandate) scenario in the short-run. Without any tax credit and mandate, a 10% increase in gasoline price will result only an additional 0.57 billion gallon ethanol and a nickel per gallon price change. With a combination of mandate and a 10% increase on gasoline price change, however, the price producer receive will not change but refiners would be willing to pay almost $0.10 higher.

We further ran a sensitivity analysis with 50 and 60 % change in the price of premium gasoline compared to the base line price, results on table 2.8 and 2.9. The impact of 50% change would result exactly the same quantity and price change for outputs and inputs except ethanol producer price as obtained with the mandate outcome as shown on table 2.8, column 2. The implication of this outcome is that the amount of ethanol produced would just be equivalent to the required mandate but the price wedge created between ethanol producers and refiner because of mandate policy will vanish.

We further increased the change in gasoline price to 60% to see price and quantity impact across producer and consumer. Without tax credit and mandate policy, ethanol production would reach 15.6 bgy, i.e., an additional 3.4 billion gallon and $0.30 per gallon change from market equilibrium table 2.8. However had it been with tax credit extended, ethanol production would have been 18.5 billion gallon and per gallon price would $2.93 and $2.48 to ethanol producer and refiners respectively. Ethanol producer willing to supply the required minimum mandate level of ethanol with $2.63 per gallon irrespective of the change in price of premium gasoline but ethanol refiners would pay more as the price of gasoline goes up and eventually would willing to pay higher than that the ethanol producers willingness to supply, as shown on the last column of table 2.8. The mandate by itself will increase the price of ethanol by $0.56 and $0.24 per gallon to the ethanol producers and decrease to ethanol fuel refiners by $0.24 and 0.19 per gallon in the short and long run respectively, results on table 2.7 and 2.8.

With respect to byproduct markets, DDG production would increase to 21 mmt while per ton price falls around $180. Production and price of WDG also follows change in ethanol production as does DDG, hence the quantity of WDGS will be as high as 16 mmt while its price will fall as low as $70 per ton with a higher gasoline price as depicted on table 2.8.

In the factor markets, the renewal of the tax credit induces more production of ethanol and eventually the demand for corn would reach to close to 5.4 billion of bushels and the price of corn hit almost $6.6 per bushel, (table 2.8). Under assumption of constant gasoline price, with each tax credit and mandate policy intervention, there will be an

approximately 8% increase on the price of corn. The corn price will go close to $7.20 per bushel and the total corn demand will jump to 6.6 billion bushel if the tax credit extended and at the same time the current gasoline price increased by 60%.

Overall extending the tax credit could potentially stimulate ethanol production and eventually create an upward pressure on the demand for corn. Depending on the simulated outcomes, some of our results conform with the findings of (Babcock & Fabiosa 2011; Taheripour and Tyner 2010) [9] that expansion of ethanol has contributed to higher corn prices.

Livestock producers face substantially higher feed costs. To livestock producers the key determinant of ethanol policy change is how much cost advantage does livestock producers could get from the net effect in the domestic feed market as a result of high DGS supply against high corn price.

With regard to energy consumption, the demand for both natural gas and electricity will increase linearly with the percentage change in ethanol quantity under each policy simulation we ran. However the equilibrium market price of electricity and natural gas are barely affected by additional demand for energy from ethanol industry. Some of the factor market outcomes for selected inputs are presented on table 2.12 and 2.13.

---

[9] If the blender tax credit had been abolished and if no mandates had been adopted, subsidies contributed an average of $0.14 per bushel (8%) to the increase in corn prices averaging across 2006–2009 (Babcock & Faiosa 2011). Between 2004 and early in 2008, out of $4/bushel increase, US ethanol subsidy contributed only $1 (25%), and the remaining $3 was attributed due to the demand pull of higher crude oil price (Taheripour and Tyner 2010).

2.5.4 The Short and Long-run Welfare Implication of Tax Credit and Mandate

In this segment, we examine the change in consumer and producer surplus in the ethanol, byproduct and factor markets under tax credit and mandate policies and their sensitivity to the change in gasoline price both in short and long run period.

In the short-run, renewing the tax credit alone would result in a 10% (3 billion dollars) gain to ethanol buyers as a consumer surplus while with the mandate this gain will reach to 29 % (8.5 billion dollars). The percent change is computed from the initial value of ethanol obtained at the market equilibrium outcome. We further explored the sensitivity of consumer and producer surplus for a 10% change in the premium gasoline price from the current $3.05; see the results presented on table 4. Under mandate scenario, the gain in the consumer surplus dropped to 16% (4.7 billion dollar) by the time we administered a 10% change gasoline price. Without tax credit and mandate, an increase in gasoline price will result ethanol fuel consumer to gain 6% (1.7 billion dollar**)** as consumer surplus compared to what they used to get at the equilibrium market outcome.

In the long-run, the gain in consumer surplus generally will be smaller compared than the short-run. Moreover the size of gain in consumer surplus in each case of tax credit and mandate policy will be more or less similar. Without tax credit and mandate and again if gasoline price increases by 10%, there will be a 2% loss in consumer surplus. By the time gasoline price increased by 60%, there will be 15% loss in a consumer

surplus at the mandate level.   Without tax credit and mandate policy, the gain in consumer surplus will be around 14% (4 billion dollars).

Under a tax credit, expanded ethanol production came at substantial cost as forgone revenue to the government. For example, extending the tax credit in the short-run the cost of the subsidy as forgone revenue will be 21% (6 billion dollars) while in the long-run it would go up to 23% (7 billion dollars) of the initial value of ethanol.

Based on results on table 2.7 and table 2.8**,** the cost of the mandate would be 61% of the initial value of ethanol in short run and ultimately fall to 22% in the long-run if we assume with constant gasoline price. When we relaxed the constant gasoline price assumption and increased gasoline by 10 %, this cost dropped and eventually get zero by the time gasoline price increased by 50% (based on table 2.9). The above cost is the cost pass along to the fuel consumer at the pump because of binding ethanol consumption mandate.

As it can be retrieved from table 2.8, under mandate, ethanol plants would willing to sell for $2.94 per gallon which is $1.20 per gallon higher than what fuel refiners are voluntarily willing to pay. However to meet the yearly blend amount issued by EPA, ethanol blenders will obtain a gallon of ethanol at whatever price ethanol producers are to supply. Eventually blenders pass through the price difference to motor fuel buyers at the pump. Moreover, it is apparent that the provision of a tax credit and mandate policy also led to an additional deadweight losses (DWL) that range from 1 to 6% of the initial value of ethanol. The DWL will be higher under mandate than tax credit policy in the

short-run but the converse is true in the longer run. It is also true that as the price of gasoline increases, the DWL shrinks.

Table 2.10 and 2.11 also present selective results of the consumer surplus for both dry and wet byproducts with each tax credit and mandate policy. The gain in consumer surplus from WDG as a percentage of its initial value is higher for WDG than DDG in all policy simulations. The gain in consumer surplus for both WDG and DDG will fall substantially with an increase in gasoline price.

In the factor market for brevity we only present the producer surplus of corn producers and ethanol plant owners. By extending the tax credit alone, in the long-run the gain in producer surplus to corn producers will be 10% of the initial value of corn that at market equilibrium, which is twice the level of change in the short run. We calculated the initial value of corn based on the market equilibrium price of corn and the quantity of corn, 10.7 billion bushels, the 2011 cropping year domestic corn production. The percent gain in the producer surplus will be constant at 12 % irrespective of the change in gasoline price at the mandate level since the additional demand for corn and its price is constant. Without tax credit and mandate intervention, a 60% increase in gasoline price will offer the highest gain to corn producer. In fact every increase in the price of corn allows the corn producers to gain proportional surplus whereas corn consumers lose some surplus since they have to pay more for a bushel of corn.

To ethanol plant owners each ethanol policy intervention and in also corn price movements have a direct implication to sustain the ethanol production business. We computed the producer surplus of ethanol plant owner as a percentage of the rent value at

the initial equilibrium point. In the short-run the gain in producer surplus is higher in the mandate than tax credit scenario. The tax credit alone will give almost a 10% gain to ethanol owners as producer surplus of the initial value of rent. Without tax credit and mandate, a 10% increase in gasoline price alone will render a 6% gain in producer surplus to the ethanol plant owners. In the long run, returns to plants owners will start to decline with both policy interventions. In the long-run the gain as producer surplus as a result of mandate wills substantially small (3%), contrary to the huge gain (26%) obtained in the short-run. The increase in gasoline price alone will give higher gain of producer surplus in short-run than in the long-run.

In this model with initial zero-profit equilibrium in the ethanol markets, all revenue losses or gains are passed through to the ethanol input markets, which of course include owners of ethanol plants (capital). It is evident that the net social benefit would be less with tax credit and mandate compared to no policies.

2.6 Conclusion and Policy Implications

This article constructed a multi-output, multi-input partial market equilibrium model to explore the short and long run impacts of changing the two key ethanol policy drivers: the tax credit and the RFS2 mandate. The model was calibrated according to the year 2011 observations. The study provides some quantitative estimates of the impacts of possible extension of tax credit and binding RFS2 mandate impacts on the prices and quantities of ethanol, byproducts, corn and other inputs with the combination of change in existing price of gasoline over a range of different assumptions.

In the short run, irrespective of the tax credit policy, the production of ethanol will be consistently below the mandated 15 bgy by 12 to 14 % . Yet contrary to this in the long-run, extending the tax credit will stimulate ethanol plants to produce above the minimum mandate amount.

In the long-run, if ethanol plants are to produce the mandated level without tax credit policy, gasoline price would need to increase by order of 50% relative to the 2011 level. In addition, as long as the RFS2 mandate is in place, there will be a wedge between the prices that ethanol producers are willing to sell and fuel blenders are willing to pay. This wedge will shrink as the price of gasoline increases and eventually vanishes as gasoline price increased by 50%. In the short-run, the RFS2 mandate will create wedge as large as $1.20 per gallon.

With respect to the corn market, our empirical results asserted that the mandate alone will increase the corn price by $0.83 and $0.50 per bushel in short and long run

respectively. If there were a 10% increase in gasoline price with no policies, the price of corn will rise to \$6.27 (short-run) and \$6.17 (long-run) per bushel.

In the long-run, the gain of ethanol plant owners as producer surplus from either policy will be just 3% as a percent of the initial value of rent, substantially lower than the 10-26% gain in the short-run. Likewise, the gain of ethanol consumers from the policies shrinks as the price of gasoline increases

It is just a year now that the tax credit and tariffs supports for ethanol expired, and it is unlikely that these financial incentives will be renewed. Entry of new ethanol plants seems not realistic given that the corn ethanol industry has already reached the production capacity required to meet the RFS2 requirement. Our quantitative analysis indicates that without extending the tax credit and mandate, achieving the effective mandated requirement is unlikely. Ethanol plants operate at less than full capacity or some ethanol plants may close at least temporarily unless the price of gasoline increases substantially.

To sum up the key question is whether the ethanol industry can fully utilize their current and future capacity to supply the minimum RFS2 required quantity without a tax credit or mandate to do so. Among host of factors our analysis underscores that without tax credit extension, if gasoline price increase by order of 50% and above 2011 level, ethanol production and consumption will achieve the minimum level of ethanol required by the RFS2.

I. Parameters and Values Used to Calibrate the Model

Table 2.1 Parameters used to calibrate the model

Parameters	Value	Source/explanation
Demand elasticity of Ethanol, short-run	-0.89	Miranowski, (2007
Demand elasticity of Ethanol, longrun	-2.9	Luchansky & Monks (2009)
Supply elasticity of Ethanol, short-run	0.29	Miranowski, (2007),
Supply elasticity of ethanol, long-run	0.65	Elobeid & Tokgoz (2008)
Demand elasticity of ethanol with gasoline	1.06	Miranowski, (2007)
Demand elasticity of DDG	-1.28	Bechman et.al (2010)
Demand elasticity of WDG	-0.40	Babcock (2009)
Demand elasticity of investment capital	-0.74	Goolsbee (1999)
Demand elasticity of labor	-0.61	Rich (2010)
Ethanol produced in one bushel	2.86	Renewable Fuel Association (2012)
MMBTU per gallon ethanol needed	0.0263	Perrin et.al (2008)
KWH per gallon ethanol needed	0.5700	Perrin et.al (2008)

Table 2.2 Value of Variables used to calibrate the model (raw data)

Parameters	Value	Source/explanation
Ethanol price ($/gal)	2.55	Ethanol FOB price, Average for Midwest
Ethanol supply (billion gallons)	13.95	2011 actual production, RFA (2012)
Ethanol supply (billion gallons)	14.25	Domestic production with 2015 capacity, RFA (2012)
Gasoline price ($/gal)	3.05	Premium gasoline rack price, EIA (2012)
DDG price ($/ton)	202.29	Weighted average for corn belt states (10% moisture basis), USDA Agricultural Marketing services: http://marketnews.usda.gov/portal/lg
[a]DDG supply (mmt)	18.9	U.S. Census Bureau Division of Manufacturing
WDG Price ($/ton)	83.18	Weighted average for corn belt states (55-60% and 60-70 % moisture), USDA Agricultural Marketing services: http://marketnews.usda.gov/portal/lg
[a]WDGS supply (mmt)	14.53	U.S. Census Bureau Division of Manufacturing
Corn supply, billion bushels	10.7	U.S. corn long-term projections for 2011/2012
[b]Corn price ($/bushel)	6.40	Weighted average farm price of corn (USDA/NASS)
Electricity price ($/KWH)	6.89	Industrial price, EIA (2012)
Natural gas ($/MMBTU)	4.91	Industrial price, EIA (2012)

Note: [a]Quantity of DDG and WDG is from U.S. Census Bureau Division of Manufacturing, Mining and Construction Statistics - Report M311J - Fats and Oils, Oilseed Crushing (Table 4b).
[b]Corn price is national average obtained from USDA/NASS quick stat.

Table 2.3 Econometrically estimated elasticity parameters based on translog cost function[10]

Parameters	Value
Derived demand elasticity of corn	-0.02
Derived demand elasticity of electricity	-0.14
Derived demand elasticity of natural gas	-1.06
Supply elasticity of DDG	1.34
Supply elasticity of WDG	1.26
Cross supply price elasticity between DDG with WDG	0.04
Cross supply price elasticity between WDG with DDG	0.099

[10] The remaining inverse output supply elasticity in the 3 by 3 matrix is recovered using homogeneity and reciprocity restriction. The homogeneity restriction implies $\sum_{j=1}^{n}\eta_{ij} = 0$. The reciprocity restriction implies $S_j\eta_{ij} = S_i\eta_{ji}$, where S_j, S_i are share of input in total cost for output i. where η_{ij} is price elasticity of output. Where, $n = 3$ and $i \neq j$. The same approach is used to recover the 5 by 5 derived demand elasticity for inputs.

Table 2.4 Calculated excess input supply elasticity used to calibrate the model

	Short-run			Long-run		
	total market supply elasticity	Market share to ethanol	Excess supply to ethanol	total market supply elasticity	Market share to ethanol	Excess supply to ethanol
Corn	0.23	0.335	1.68	0.62	0.350	2.75
Electricity	0.10	0.004	50.0	2.10	0.004	696
Natural gas	1.89	0.031	65	0.59	0.030	36
labor & other	0.77	5E-05	27951	1.38	5E-05	40280
Capital			0.001			5

Note: Market share to ethanol is an author calculation based on the 2011 and projected data. For corn is from USDA, Natural gas and electricity based on data from US Energy Information Administration. Labor is from US Census Bureau. Other (enzyme, chemical, water, other) is based on US Census Bureau, Division of Manufacturing.
Sources of Short and long run total supply elasticity respectively; Corn: Gardner (2007), Moss, Livanis & Scmitz (2010). Electricity and Natural gas: AEO (2010), National Energy Models (EMF 2003). Labor: Rich (2010). Capital: Edgerton (2010)

Table 2.5 The cost share of input/Marginal Cost elasticity used in both short and long run model

	Cost share
Corn	0.72
Electricity	0.01
Natural gas	0.05
Labor & other	0.10
Capital	0.11

Note: the details how these shares were calculated presented in table 1f. The share of capital is calculated as the share of rent from the total revenue.

Table 2.6 Parameters used to compute the cost share of variable inputs

Cost component	Quantity of input Per gallon of ethanol	Average price
Corn	2.86	6.01
Electricity	0.5700	0.0688
Natural gas	0.0202	5.00
Additional N.gas for drying 60% of DGS	0.0093	5.00
Labor & management	0.0005	113.1
Other (enzyme, chemical, water , other)	0.0013	194.1

Note: Price and quantity definition for corn, electricity and natural gas are: $/bushel, $/kWh and $/MMBTU respectively.

Note: Implicit quantity indexes is calculated by dividing survey sample expenditures on personnel and on all other processing inputs by the sample-period average values of the respective price indexes. Share of each input is the cost share in total revenue. The cost of each input is computed taking the price of input multiplied by the quantity index. The quantity index of the four inputs, except capital, is computed by taking the average input requirement per gallon of ethanol obtained from Perrin et.al (2009) and multiplying it by the 2011 annual ethanol production. The price of labor is the Employment Cost Index (series CIS101) from the Bureau of Labor Statistics; the price of other is the Producer Price Index for the ethyl alcohol manufacturing industry (series PCU325193325193) from the Bureau of Labor Statistics (http://www.bls.gov/data/#prices). For further understanding how the author computed the cost components refer table 2 and equation 4 in Perrin et.al (2009).

II. Tables of Results

Table 2.7 The Shor-trun policy impacts: estimated market-clearing prices and quantities of outputs

	Initial base value	Market equilibrium	Constant gasoline price		10 % gasoline price increase	
			With Tax credit	With Mandate	Without mandate & tax credit	With Mandate
Ethanol, billion gal	14.3	12.16	13.24	15.00	12.84	15.00
Ethanol producer ,$/gal	2.55	2.39	2.60	2.94	2.52	2.81
Ethanol consumer ,$/gal	2.05	2.39	2.15	1.76	2.52	2.04
DDG, mmt	19.3	16.9	18.1	20.1	17.7	20.1
Price of DDG, $/ton	202	222	209	189	214	189
WDG, mmt	14.8	12.7	13.8	15.5	13.4	15.5
Price of WDG, $/ton	83	98	88	70	92	70
Corn, billion bushel	5.1	4.39	4.78	5.40	4.63	5.40
Price of corn, $/bushel	6.4	6.07	6.38	6.89	6.27	6.89

Table 2.8 The Long-run policy impacts: market-clearing prices and quantities of outputs

	Constant gasoline price		10 % increase in gasoline price		60% increase in gasoline price
Variables	With Tax credit	With Mandate	Without mandate & tax credit	With Mandate	Without mandate & tax credit
Ethanol, billion gallon	15.11	15.0	12.73	15.0	15.57
Ethanol producer price, $/gal	2.64	2.63	2.43	2.63	2.68
Ethanol consumer price, $/gal	2.19	2.19	2.43	2.28	2.68
DDG, mmt	20.4	20.3	17.6	20.3	20.9
Price of DDG, $/ton	186	187	215	187.4	180
WDG, mmt	15.7	15.6	13.3	15.6	16.1
Price of WDG, $/ton	69	70	93	70	64
Corn, billion bushel	5.4	5.4	4.6	5.4	5.59
Price of corn, $/bushel	6.59	6.57	6.17	6.57	6.67

Table 2.9 The Long-run mandate policy impacts: market-clearing prices and quantities of ethanol with 50% increase in premium gasoline price

Variables	Constant gasoline price	10 % increase	50 % increase	60 % increase
Ethanol, billion gallon	15.0	15.0	15.0	15.0
Ethanol producer price, $/gal	2.63	2.63	2.63	2.63
Ethanol consumer price, $/gal	2.19	2.28	2.68	2.71

Note: Under the mandate policy, the change on gasoline price has only effect on the ethanol consumer price. Hence mandate has no effects on the rest of the quantity and price variable.

Table 2.10 Short-run effect of shock on consumers (CS) and producer surplus (PS), as a percent of the initial value at the market equilibrium point

		Constant gasoline price		10 % gasoline price increase	
Variables	Initial market value at equilibrium (Billions dollar)	With Tax credit	With Mandate	Without mandate & tax credit	With Mandate
Ethanol, CS	29.0	10.4	29.3	5.7	16.0
DDG, CS	3.8	6.4	19.5	3.9	19.5
WDG, CS	1.2	12.2	37.8	7.3	37.8
Corn producer, PS	65	5.0	12.1	3.2	12.1
Ethanol Plant owners, PS	4.5	9.9	26.0	6.2	26.0
Cost to tax payers (% of initial value of ethanol)	-	20.5		0.0	
Dead Weight Loss (% of initial value of ethanol)	-	0.84	5.8	0.0	3.7

Note: the change in a PS for ethanol plant owner is computed from the initial value of the rent. The cost to tax payers and DWL are computed as percent loss from the Initial value of ethanol.

Note: The initial value of each output is computed as a product of price and quantity from initial market equilibrium outcome, i.e., without any policy intervention, whereas for Ethanol Plant owner's is the rent at year 2011. Initial corn value is calculated for the entire corn market based on the total production in year 2011/12.

Table 2.11 Long-run Effect of shock on consumers (CS) and producer surplus (PS)as a percent of the initial value at the market equilibrium point

Variables	Constant gasoline price: With Tax credit	Constant gasoline price: With Mandate	10 % increase in gasoline price: Without mandate & tax credit	10 % increase in gasoline price: With Mandate	60% increase in gasoline price: Without mandate & tax credit	60% increase in gasoline price: With mandate
Ethanol, CS	9.4	9.0	2.1	4.9	13.9	15.4
DDG, CS	21.2	20.3	3.3	20.3	25.5	20.3
WDG, CS	40.2	38.4	6.1	38.4	48.4	38.4
Corn producer, PS	10.6	11.6	2.1	11.6	12.4	11.6
Ethanol Plant owners, PS	3.1	3.0	0.7	3.0	3.5	3.0
Cost to tax payers (% of initial value of ethanol)	24.8		0.0		0.0	
Dead Weight Loss (% of initial value of ethanol)	2.3	2.1	0.0	1.7	0.0	0.43

Table 2.12 The Short-run estimated market-clearing prices and quantities of energy inputs

	Market equilibrium	Constant gasoline price: With Tax credit	Constant gasoline price: With Mandate	10 % gasoline price increase: Without mandate & tax credit	10 % gasoline price increase: With Mandate
Natural gas, billion BTU	8.39	10.03	11.34	9.74	11.34
Natural gas, $/MBTU	4.89	4.91	4.92	4.90	4.92
Electricity, billion KWH	8.34	9.96	11.25	9.66	11.25
Electricity, cent/KWH	6.88	6.90	6.92	6.90	6.92

Table 2.13 The Long-run estimated market-clearing prices and quantities of energy inputs

	Constant gasoline price: With Tax credit	Constant gasoline price: With Mandate	10 % gasoline price increase: Without mandate & tax credit	10 % gasoline price increase: With Mandate	60 % gasoline price increase: Without mandate & tax credit	60 % gasoline price increase: With Mandate
Natural gas, billion BTU	11.40	11.32	9.65	11.32	11.74	11.32
Natural gas, $/MBTU	4.91	4.91	4.90	4.91	4.92	4.91
Electricity, billion KWH	11.34	11.27	9.58	11.27	11.69	11.27
Electricity, cent/KWH	6.89	6.89	6.89	6.89	6.89	6.89

2.7. Reference

Babcock, B. A. 2008 "Distributional Implications of U.S. Ethanol Policy." Review of Agricultural Economics, 30:533-542.

________.2010. "Mandates, Tax Credits, and Tariffs: Does the U.S. Biofuels Industry Need Them All." Ames, IA, Iowa State University CARD Policy Brief 10-PB1

Babcock ,B. A, and J.F, Fabiosa. 2011."The Impact of Ethanol and Ethanol Subsidies on Corn Prices: Revisiting History." Center for Agriculture and Rural Development Policy Brief 11-PB 5 April 2011. Iowa State University.

Babcock, B.A., K. Barr, and M. Carriquiry.2010. "Costs and Benefits to Taxpayers, Consumers, and Producers from U.S.Ethanol Policies."Staff Report 10-SR-106.Center for Agricultural and Rural Development, Iowa State University.

Beckman, J., R.Keeny and W.,Tyner.2011."Feed Demands and Coproduct Substitution in the Biofuel Era." Agribusiness, Vol. 27 (1) 1–18

De Gorter, H., and D.R. Just.2010."The Social Costs and Benefits of Biofuels: The Intersection of Environmental, Energy and Agricultural Policy." Applied Economics Perspectives and Policy 32(1):4-32.

_______. 2008. "Water" in the U.S. Ethanol Tax Credit and Mandate: Implications for Rectangular Deadweight Costs and the Corn-Oil Price Relationship." Review of Agricultural Economics—Volume 30, Number 3

Elobeid, A., and S., Tokgoz.2008."Removing Distortion in the U.S. Ethanol Market: What Does it Imply for the United States and Brazil? "Amer. J. Agr. Econ. 90(4): 918–932 Environmental Protection Agency (EPA).Renewable Fuel Standard Program (RFS2) Regulatory Impact Analysis. Feb, 2010. EPA-420-R-10-006

Government Accounting Office. 2009. "Biofuels Potential effects and challenges of required increases in production and use Report to Congressional Requesters." GAO-09-446 United States Government Accountability Office, August 2009

Goolsbee, A. 1998. "Investment tax incentives, prices, and the supply of capital goods." The Quarterly Journal of Economics, 113(1):121–148,

Hoffman, L. and Baker, A.2011." Estimating the Substitution of Distillers' Grains for Corn and Soybean Meal in the U.S. Feed Complex. "FDS-11-I-01, U.S. Department of Agriculture, ERS, October 2010,

______.2010. "Market Issues and Prospects for U.S. Distillers' Grains Supply, Use, and Price Relationships." FDS-10K-01, U.S. Dept of Agriculture, ERS,Dece 2010.

Jones, C., G., Tonsor, R., Black, and S. Rust. 2007. "Economically Optimal Distiller GrainInclusion in Beef Feedlot Rations: Recognition of Omitted Factors." Paper presented at NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, Chicago, IL, April 16-17

Klopfenstein, T.J., G.E. Erickson, and V.R. Bremer. 2008. "Use of distillers co-products in diets fed to beef cattle." In B.A.,Babcock et al. (ed.) Using distillers grains in the U.S. and international livestock and poultry industries. The Midwest Agribusiness Trade Research and Info Center, Ames IA: ISU. pp. 5–55.

Luchansky, M. and J. Monks. "Supply and Demand Elasticities in the U.S. Ethanol Fuel Market." Energy Economics. 31 (2009): 403 – 410.

Miranowski, J. A. “Biofuel Incentives and the Energy Title of the 2007 Farm Bill.” American Enterprise Institute. Available at: http://www.aei.org/docLib/20070515_miranowskifinal.pdf

Mueller, S. 2010.”2010 National dry mill corn ethanol survey.” Springer Science and Business Media B.V. 2010. Available at http://www.erc.uic.edu/PDF/mueller/2008_corn_ethanol_survey.pdf

Office of Nebraska Government website www.neo.ne.gov; retrieved on 2012

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

Perrin, R.K.2009. “Notes on Log Linear Comparative Statics.” Notes for AECN 840, Department of Agricultural Economics, University of Nebraska-Lincoln

Renewable Fuels Association. The 2011 and 2012 Ethanol Industry Outlook http://www.ethanolrfa.org/pages/statistics

Rich, P.D. 2010.“Changing Elasticities of Labor Demand in U.S. Manufacturing.” Atl Econ J 38:157–168

Shapouri, H., and P.Gallagher.2005. “USDA’s 2002 Ethanol Cost-of-Production Survey. Agricultural Economic Report no. 841.” US Dept. of Agriculture.

Taheripour, F., W.T, Hertel, E.W.,Tyner, F.J., Beckman and K.D., Birur. 2010. “Biofuels and their by-products: Global economic and environmental implications.” Biomass and Bioenergy 34:278–289.

Tyner, W.E., F., Taheripour and D., Perkis. 2010. “Comparison of a Fixed Versus Variable Biofuel Incentives.” Energy Policy 38:5530-5540

Tyner, W.E., & F., Taheripour. 2009.” Renewable energy policy alternatives for the future.”American Journal of Agricultural Economics, 89(5), 1303–1310.

Tokgoz, S., A., Elobeid, J., Fabiosa, D., Hayes, B.A., Babcock and T., Yu. 2007. “Emerging Biofuels: Outlook of Effects on U.S. grain, oilseed, and livestock markets (Staff Report 07-SR 101).” Ames, IA: Iowa State University, Department of Economics.

US Census Bureau, Division of Manufacturing. Retrieved on, April 2012. http://www.census.gov/manufacturing/cir/historical_data/m311j/index.html

USDA’s Agricultural Marketing Service: USDA Corn Belt Weekly Feedstuffs, 2011.

USDA/NASS quick stat http://quickstats.nass.usda.gov/

Westcott, P.C. (2007). “Ethanol expansion in the United States: How will the agricultural sector adjust?”(FDS-07D-01). Washington, DC: United States Dept of griculture.

Appendix 2

Mathematical Footnotes

I. Market clearing condition

Equation 2 presented in the analytical model represents the market clearing condition where the derivative of cost function $C(Y,W)$, with respect to output, Y gives us the marginal cost.

$$\frac{\partial C(Y,W)}{\partial Y} = C_y = P^s \qquad 1a$$

Total differentiation of C_y gives us:

$$C_{yy}dy + C_{yw}dw = dP^s$$

1b

$$P^s \frac{dP^s}{dY}\frac{Y}{P^s}\frac{dY}{Y} + P^s \frac{dP^s}{dW}\frac{W}{P^s}\frac{dW}{W} = P^s \frac{dP^s}{P^s} \qquad 1c$$

$$\mathrm{E}_{P^sY} d\ln Y + \mathrm{E}_{P^sW^d} d\ln W^d = d\ln P^s \qquad 1d$$

Where E_{P^sY} is the vector of price elasticity of outputs

$\mathrm{E}_{P^sW^d}$ is the vector marginal cost elasticitiy with respect to input

II. Optimal factor demand can be obtained using equation 3.

$$\frac{\partial C(Y,W)}{\partial W} = C_w = X(Y,W) \qquad 2a$$

Totally differentiating of C_w

$$C_{wy}dy + C_{ww}dw = dX \qquad 2b$$

$$\frac{dX}{dY}\frac{Y}{X}\frac{dY}{Y}X + \frac{dX}{dW}\frac{W}{X}\frac{dW}{W}X = \frac{dX}{X} \qquad 2c$$

$$\mathrm{E}_{XY} d\ln Y + \mathrm{E}_{XW} d\ln W = d\ln X \qquad 2d$$

Elasticity of input with respect to output, E_{XY}, can be computed based on the following property $C_{wy} = C'_{yw}$ and it implies:

$$\mathrm{E}_{XY} = \left(\frac{\hat{S}_y^s}{\hat{S}_x^d}\right)\mathrm{E}'_{P^sW^d} \qquad 2e$$

$\mathrm{E}'_{P^sW^d}$ is the inverse of the vector marginal cost elasticitiy with respect to input

$\hat{S}_y^s$ the vector of the share of output Y in the total revenue

$\hat{S}_x^d$ are the vector share of input X in the total cost

III. Excess supply elasticity of input mathematically depicted as

$$\Sigma_i = \frac{(\eta_i^t) - (\sigma_i^r / S_i^r)}{S_i^e} \qquad 3a$$

Σ_i = the excess supply elasticity of input i

η_i^t =total market supply elasticity of input i

σ_i^r =elasticity of demand of input i by the rest of economy

S_i^e =market share of input i to ethanol

S_i^r =market share of input i to the rest of the economy.

Chapter 3: Soil Organic Carbon Sequestration in Corn Belt States: A Meta Regression analysis

Abstract

This study investigated the extent to which statistical heterogeneity among results of multiple studies on soil organic carbon (SOC) sequestration rate in response to conventional tillage (CT) and no-till (NT) can be related to one or more characteristics of the studies. The analysis employed a random effect meta-regression technique using the data obtained from recently published experimental trials under continuous corn (CC) and corn soybean (CS) rotation system from selected Corn Belt states.

Regarding the difference in the rate of SOC sequestration between NT and CT, our results shows that the percentage of heterogeneity in the true treatment effect that is attributable to between-study variability is 49%, whereas 51 % is attributable to within-study sampling variability.

We find that 26% of the between-study variance is explained by the explanatory variables considered, and the remaining between-study variance appears almost zero. The regression results support the argument that the difference between NT and CT decreases as measurement depth increases. The results also show that the higher the initial SOC the higher the NT SOC sequestration rate relative to the CT sequestration rate. A test for publication biases in the analysis indicated no evidence for the presence of small-study effects.

Key words: SOC sequestration rate, no-till, conventional tillage, Meta regression

3.1 Introduction

Results from many individual experimental studies across Midwest states and globally showed considerable heterogeneity on the results of rate of SOC sequestration in response to NT and CT practices. Given the range and variability of estimated sequestration rate, this study combines the results of independent studies and doing regional assessments in order to uncover the source of this heterogeneity.

Large areas of cropland in U.S. Corn Belt are being gradually converted from CT to conservation tillage particularly to NT systems, and this change is partly driven by the fact that widespread adoption of conservation tillage, specifically NT, would sequester a substantial amount of SOC than CT (Christopher et.al 2009; Gal et.al 2007; Baker et.al 2007; Al-Kaisi and Yin 2005; Lal et.al 1998; West and Post 2002; Blanco-Canqui & Lal, 2007). However, it is an unsettled argument whether such practices actually sequester SOC. Higher SOC sequestration in NT systems is reported in many studies when soil was sampled up to 30cm depth. However in a few studies where sampling extended deeper than 30cm (Ga'l et.al 2007; Ogle et.al 2008) and in experimental trials based on gas exchange measure (Verma et.al 2005; Baker et al. 2007), NT showed a higher or lower SOC sequestration.

Approximately 49% of agricultural SOC sequestration can be achieved by adopting conservation tillage and residue management (Lal et al. 1998). However SOC loss consistently increases with percentage residue harvest (Blanco-Canqui & Lal 2007). The partial or complete removal of corn stover to produce biofuel reduces the amount of residue returned to the soil and may increase the risk of soil degradation and eventually leads to depletion of the SOC pool and greenhouse gases (GHG) emission of (Lal 2002 2004; Johnson et.al 2004 2007). SOC

sequestration is a key component in the life cycle of biofuel production (Ney & Schnoor 2002; Adler et al., 2007) and crucial in determining the GHG reduction potential of biofuels relative to fossil fuels (Anderson-Teixeira et.al 2009). Various studies have quantified changes in SOC under potential biofuel crops. Results are variable and have yet extensive effort is needed to develop coherent pictures (Johnson et.al 2007; Wilhelm et.al 2007).

In the time of recent trend toward development of cellulosic biofuel production from crop residues, it is crucial to put forward research findings related to SOC sequestration to understand the relative advantage of conservation tillage over the CT. There is disparity among reported experimental results on the relative advantage of NT over CT in SOC sequestration rate and yet this is the information we should discern in such kind of study. Hence a regional assessment, examining data from distinct cultivation systems could justify a broad understanding of NT and CT effects on SOC in Corn Belt states. Therefore analyzing the results of different studies with heterogeneous results across Corn Belt states using Meta regression analysis is essential to elucidate the source of heterogeneity, particularly now when large areas of cropland are being converted to long-term NT systems based on the premise that NT soils sequester SOC.

There have been several meta-analyses and scientific literature reviews on the effects of NT and CT on SOC globally (West and Post 2002; Alvarez 2005; Angers and Eriksen-Hamel 2007; Angers et al. 1997; Six et al 2002; Anderson-Teixeira et.al 2009) and also regionally in North America (Christopher et.al 2007; Blanco-Canqui et.al 2007; Ogle et.al 2003).

The purpose of this study is therefore to conduct a Meta-regression analysis to investigate the extent to which statistical heterogeneity among results of multiple studies on SOC sequestration can be related to one or more characteristics of the studies. The analysis would help us to explore study-to-study variation of SOC sequestration rate by determining the extent to which methods,

design and data affect reported results. The analysis is based on recently peer reviewed published studies on SOC sequestration from long-term paired experiments exclusively under continuous corn (CC) and corn soybean (CS) rotation system . The data collected were from multiyear paired experiments that ran at least for five years. To give fresh perspective and augment the rapid development in approach of SOC measurements, only published studies since year 2000 are included in our sample. In the study we also investigate publication and related biases since most meta-analysis are susceptible to such problems.

The remainder of the paper is organized into four sections. Section 2 exposits the theoretical model. This theoretical and analytical model is based on Meta regression and its estimation procedure is using random effect model. Section 3 describes the data and material used in this study. The empirical results of our application and implication of this study is presented in section 4, and in the last section summary and concluding remarks are then provided. The appendixes section contains results and figures from the regression analysis, and a tabular summary of the data used in our meta-analyses.

3.2 Theoretical Model

Meta-analysis is widely applied in the medicine, economics and many other social sciences fields (Thompson and Higgins 2002; Stanley and Jarrell 1998; Stanley 2001) and now this technique is increasingly applied in physical science such as ecology and biology. Particularly the application is gaining attention in the field of global change ecology (Manley et.al 2005). The analysis is a quantitative method of combining the results of independent studies

to investigate the extent to which statistical heterogeneity between results[11] of multiple studies that can be related to one or more characteristics of the studies (Fox 2009; Thompson and Higgins 2002; Stanley 2001).

3.2.1 Meta-Regression Model

The model here is based on random effects with a generic form shown in equation 1. For the subject i in the study j, we can write the basic underling model for outcome Y_{ij}

$$Y_{ij} = \beta_0 + \beta_i X_{ij} + \upsilon_j + \varepsilon_{ij} \tag{1}$$

We assume that each study j provides total of n studies to estimate the effect of interest, i, which here is a difference in rate of SOC sequestration from NT to CT. Each study also reports a standard error for this estimate, σ_i, which we assume is known. Inference is based on the assumption that the studies are a random sample of some hypothetical population of studies. β_0 is an intercept of the regression model.

β is a k × 1 vector of regression coefficients to estimate, and X_i is a 1 × k vector containing the observed trial-level explanatory variables for study j. Explanatory variables used here are initial SOC, depth of the soil sampled, yield of corn and soybean, mean annual temperature and dummy for crop rotation (continuous corn verses corn-soybean rotation).

[11] Heterogeneity is inevitable in meta-analysis since individual studies are never identical with respect to study populations and other factors that can cause differences between studies (Van Houwelingen et.al 2002).

Our model allows for residual heterogeneity, assuming that the true effects follow a normal distribution around the linear predictor:

$$Y_i \mid \theta_i \sim N(\theta_i, \sigma_i^2) \text{, where } \theta_i \sim N(X_i\beta, \tau^2) \tag{2}$$

$$\varepsilon_{ij} \sim N(0, \sigma_e{}^2) \text{ and } \upsilon_j \sim N(0, \tau^2) \tag{3}$$

θ_i is a true effect and has a normal distribution around the linear predictor, $X_i\beta$. Here ε_{ij} is within study error term whereas υ_j is between study error. τ^2 is between study variance and should be estimated from the data[12].

As shown on equation 4, β_i, is determined by the true effect θ_i plus the within-study error ε_i. In turn, θ_i, is determined by the mean of all true effects, μ and the between-study error υ_i. More generally, for any observed effect β_i,

$$\beta_i = \theta_i + \varepsilon_i = \mu + \upsilon_i + \varepsilon_{ij} = \beta X_i + \upsilon_i + \varepsilon_{ij} \tag{4}$$

There are two levels of sampling and two sources of error when we are dealing with random effect model. At first, the true effect sizes θ_i are distributed about μ with a variance τ^2 that reflects the actual distribution of the true effects about their mean. Second, the observed effect β_i for any given θ_i will be distributed about that θ_i with a variance σ^2 that depends primarily on the sample size for that study. Therefore, in assigning weights to estimate μ, we

[12] In the random effects model, there is between-study as well as within-study components of the variance term (Borenstein et.al 2007).

need to deal with both sources of sampling error – within studies (ε_{ij}), and between studies (υ_j). An excellent treatment of this approach can be found from (Borenstein et.al 2007; Harbord and Higgins 2008)

As Harbord and Higgins (2008) presented in their analysis, all algorithms for random-effects meta-regression first estimate the between-study variance, τ^2, and then estimate the coefficients, β, by weighted least squares by weighting using $1/(\sigma_i^2 + \tau^2)$ [13]. The method used to decompose the variance is to calculate the total variance and then to isolate the within-studies variance. The variance between-studies (τ^2) is obtained as the difference between these two values. The proportion of between-study variance explained by independent variables can be calculated by comparing the estimated between-study variance, $\hat{\tau}^2$, with its value when no covariates are fit, $\hat{\tau}_o^2$. Adjusted R^2 is the relative reduction in the between-study variance as shown in equation 5.

$$R_{adj}{}^2 = (\hat{\tau}_o^2 - \hat{\tau}^2) / \hat{\tau}_o^2 \qquad (5)$$

3.2.2 Mechanism to Investigate Publication Biases

In this section we provide the mechanism to investigate publication and small sample bias using funnel plots and Egger test (Egger et al. 1997; Harbord and Harris 2009). If publication bias exists, any meta-analysis based on it will be similarly biased (Sterne et.al 2000; Palmer and Peters 2008). Funnel plot is a visual method used to test for the likely presence of

[13] The default algorithm in our regression is residual (restricted) maximum likelihood (REML), and directly maximizes the residual (restricted) log likelihood using Stata command (Harbord and Higgins 2008).

publication and related biases in meta-analysis[14]. Publication bias may lead to asymmetrical funnel plots, however this bias is only one of a number of possible causes of funnel-plot asymmetry (Sterne and Harbord 2004)[15].Judgment based on such visual interpretation for asymmetry is inherently subjective (Harbord and Harris 2009). Rather we used an Egger test based on a linear regression approach to measure funnel plot asymmetry (Egger et al. 1997) shown in equation 6 below.

$$effect_i = \delta_1 + \alpha_1 S.E_i + \varepsilon_i \tag{6}$$

$effect_i$ in our case is the difference in ΔSOC sequestration rate of each study i, $S.E_i$ is the standard error of study j. We can test for H0: α_1=0, this simple meta-regression model is to investigate whether a research literature is affected by publication selection (Egger et al. 1997; Harbord and Harris 2009; Stanley and Doucouliagos 2011).

3.3 Material/Data Used in this Study

Based on the criteria we set, we found 13 peer-reviewed published studies that reported rate of SOC sequestration in nine states (Illinois, Indiana, Iowa, Minnesota, Nebraska, South Dakota, Ohio, Pennsylvania and South Dakota). The total number observations are 78, see on table 3.8.

---

[14] Funnel plot is a simple scatter plots of the treatment effects (difference in rate of SOC sequestration in our case) estimated from individual studies against a measure of study size here in our case a standard error of the effect size (Sterne et.al 2005; Palmer and Peters 2008;Sterne and Egger 2001; Harbord and Harris 2009).

[15] Egger et al. (1997) pointed out potential sources of asymmetry in funnel plots: Selection biases (e.g. Publication bias), true heterogeneity (e.g. Size of effect differs according to study size), Data irregularities (e.g. Poor methodological design of small studies, Inadequate analysis), Heterogeneity due to poor choice of effect measure.

Key data gatherer were soil depth, duration of tillage study, yield of corn and soybean[16], types of rotations, mean annual precipitation and temperature at experimental sites. In addition, the standard error of the rate of SOC sequestration for each study was gathered. If these standard errors were not reported, we estimated taking the mean of SOC sequestration rate and divide by the number of replication of experimental plots. Furthermore, if specific details such as yield, temperature and precipitation of the study were not reported, we estimated them based on the county level information where the experiment was conducted.

Studies were included in the data set if the following criteria were met: (1) paired studies that compared NT with CT exclusively under continuous corn and corn-soybean rotation system. The tillage could be a multisystem with fertilizer treatment but with no residue treatment trials. To be part of the analysis, each study must also report at least the rate of SOC sequestration and initial or final SOC value. We dropped studies, if the specific paired tillage experimental studies included crops other than corn and soybean in the CC and CS crop rotation. (2) SOC was sampled to depths ≥15cm.[17] (3) experiments that ran at least five years, since a multiyear experimental study is necessary as there is difficulty to adequately detect a small change in SOC stock over a time period of less than 5yr (Post et.al. 2001; Ellert et.al 2002; Baker et.al 2007; personal communication with Varvel 2011). Almost all of the studies reviewed were from dry land agriculture trails except four irrigated trials from Nebraska. Except 3 eddy covariance studies , the majority of samples are based on the standard method for assessment of SOC sequestration using soil sampling of long-term tillage research trial plots.

---

[16] The yield for corn and soybean are the average yield during the experimental period. For those studies that didn't report yield during the experimental period, we used the average yield of the county where the experimental trails ran.

[17] The necessity of deeper depth sampling is for improved accuracy in the assessment of C or N sequestration with no-till versus conventional tillage systems is vital (Ga'l et.al 2007).

3.4 Empirical Results and Discussion

Table 3.1 and 3.2 portray the summary statistics of the data used in this study. The results of the regression analysis are summarized from Tables 3.3 through 3.7. The summary statistics indicate that the duration of the studies varied from 4 to 51 year, with an average of 16 years. The average depth of the soil sampled under both tillage practices across all studies was 30 cm. The dependent variable which is the difference in the rate of SOC from NT to CT has a mean value of 0.09 Mg C $ha^{-1}yr^{-1}$.

The percentage of between-study heterogeneity that is attributable to variability in the true treatment effect is 49%, whereas 51 % is attributable to within-study sampling variability. Our regression results also show that 26% of the between-study variance is explained by the explanatory variables considered, and the remaining between-study variance appears almost zero, 0.003, depicted on table 3.3. We examined whether specific variables in the regression analysis explain any of the heterogeneity of treatment effects between studies. The joint test for all five independent variables gives a p-value of 0.009, indicating there is evidence for an association of at least one or more of the explanatory variables with the size of the treatment effect.

The positive coefficient on the initial SOC on table 3.3 indicates that the predicted rate of SOC sequestration under NT relative CT increases. We can infer based on this result that on average a plot under NT sequester 0.086 Mg C ha-^{1}yr^{-1} more SOC than CT. The plotted figure with fitted meta-regression line of the rate of ΔSOC against the initial SOC on Figure 3.2 shows that at the low level of initial SOC the difference between these two tillage systems was smaller

and close to zero, but as the initial SOC level is higher the NT system gains more rate sequestration of SOC than the corresponding CT system.

Negative regression coefficients on the depth of soil measurement support the contention that the relative no-till advantage over conventional tillage declined with deeper measurement depth. Figure 3.4 also shows the clear relationship between depth and SOC sequestration rate. This result conforms to the argument that SOC gain from NT that is based on shallow sample depth disappears when deeper samples are included (Angers et al.1997; Dolan et al. 2006; Baker et.al 2007; Six et al. 2002; Gal et.al 2005; Vandenbygaart et al. 2002, 2003).

Our regression result on Table 3.3 and 3.5 also showed that for every bushel of corn yield increase, keeping other factor constant , the rate of ΔSOC sequestration under NT system increases 0.001 Mg C $ha\text{-}^{1}yr^{-1}$ higher SOC than CT. However for every bushel increase in a soybean yield provides a 0.004 to 0.013 Mg C $ha\text{-}^{1}yr^{-1}$ fewer SOC sequestration rate to NT than CT. Agronomically it is believed that the actual effect of the different tillage practices on soil C storage is highly dependent on the types of crops produced in the field (Ga´l et.al 2007; Huggins et.al 2007; Varvel 2006). In this regard corn has a greater biomass production than soybean and combination of this quantity of biomass with NT practices may give an additional advantage for corn to sequester more SOC than the CT.

The dummy variable rotation for coefficient measures the average difference in SOC sequestration rate between CC and CS rotation given the same level of initial SOC, depth, corn and soybean yield and temperature variables. After controlling the above explanatory variables, NT system sequesters 0.05 Mg C $ha\text{-}^{1}yr^{-1}$ less SOC than CT when the rotation system is under continuous corn than corn-soybean, shown on table 3.3. The above result seems odd from the agronomic stand point under ideal condition. Various studies in Midwest showed that SOC

sequestration under continuous corn has been normally higher than under corn–soybean rotation (Lal et al. 1997; Paustian et al. 1997; Gal et.al 2007; Jagadamma et.al 2007; Jarecki and Lal 2003). It is also believed that differences in SOC sequestration between crop rotations is largely influenced by the quantity of crop residues returned to the soil. However the differential in SOC sequestration in our analysis may be due to rotation or other factors other than rotation that we have not controlled for in the regression. Studies indicated that tillage effects on SOC storage have been characterized either as a single factor or in combination with crop residue management, N fertilization, or both (Huggins et.al. 2007 Havlin et al. 1990; Franzluebbers et al. 1994; Paustian et al. 1997).

It is informative to compare the intercept (our base variable in the dummy, CC) on the equation to be estimated when all other explanatory variables are dropped from the equation. The intercept on the result of this simple regression is the average difference that we can get for a rate of ΔSOC when the rotation is under continuous corn system. From table 3.4 result therefore, plots under CC would provide 0.0161 Mg C ha-^{1}yr^{-1} fewer rate of ΔSOC to NT than CT. The coefficient on this dummy is the difference in the average a rate of ΔSOC of CC relative to CS. The above results offer comparison of-means-test between CC and CS rotation system. The estimated difference between CC to CS is 0.037 Mg C ha-^{1}yr^{-1}. However this difference is not statistically significant as shown on table 3.4.

Among other factors, the differential effects of rotation on SOC sequestration rate in both tillage systems may vary by the depth of the soil. Clap et.al (2000) argued that very little crop residue was mechanically buried below 15 cm in the NT treatment unless moved by earthworm activity. Fourteen years of experiment on tillage and rotation interaction, (Huggins et.al 2005), indicated that significant contributions to greater SOC under CC for Chisel Plough and NT, as

compared with Mold board Plough, occurred from C storage below tillage operating depths (30- to 45-cm). To put the above arguments in perspective, we added an interaction variable of the dummy rotation with depth-this actually would allow us to have different slope and give more exposition on the relationship among tillage practices, crop rotation and depth. Using our new interaction variable, we then tested whether the effect of continuous corn and corn-soybean rotation over rate of ΔSOC is the same at all depth of the soil.

We are now testing the hypothesis that the average difference in rate of SOC sequestration between NT and CT are identical for CC and CS rotation that have similar depth of soil measurement. Under the null hypothesis the coefficient over the dummy and interaction term must both be zero. Our F test value gave us $F(2, 70) = 3.14$ and $Prob > F=0.0495$. Therefore we rejected the above hypothesis, implying that there would be variation in SOC sequestration between CC and CS at the same depth of soil. Another important hypothesis we test is that the difference in rate of SOC sequestration (from NT to CT) is the same for CC and CS rotation system across all depth of soil. Our test $F(1, 70) = 3.19$, $Prob > F = 0.0470$. We then accepted the hypothesis that the difference in ΔSOC sequestration rate is similar across all depth.

Another important factor that can influence the relative impacts of tillage practices on SOC sequestration rate is the temperature. The regression results both on Table 3.3 and 3.5 and Figure 3.5 shows the effects of average regional temperature variation on SOC sequestration over the difference between NT to CT had a significant correlation between temperature variable and differential SOC sequestration rates. The regression results reveal that a one degree Celsius increase in temperature would reduce the sequestration of NT to CT by -0.0612 (table 3.3).

Publication Bias and Model Validation

The diagonal lines on figure 3.5 are representing the 95% confidence limits around the summary treatment effect. As shown on the figure 3.5, the 95% of the studies lied within the funnel defined by these straight lines and the plot resembled a symmetrical, inverted funnel. This may suggest the absence of publication bias. To avoid subjective judgment we performed a test of small-study effects based on equation 6. The estimated bias coefficient shown on Table 3.7 is -0.202 with a standard error of 0.295, giving a p-value of 0.496. The test thus provides no evidence for the presence of small-study effects. Figure 3.6 also asserted the absence of this bias. Finally we launched a model validation and check for outliers and influential studies based on the statistics available from prediction[18]. Figure 3.7 suggests that the assumption of normal random effects is sufficient, and there are no notable outliers because the largest standardized shrunken residual is only slightly over 2.

[18] This probability plot can be used to check the assumption of normality of the random effects, although because this assumption has been used in generating the predictions, only gross deviations are likely to be detected.

3.5 Conclusion

In this study we used meta-regression model to explore the sources of study-to-study variation on the reported results of SOC sequestration rate due to NT and CT in selected Corn Belt states.

Our analysis underscores that nearly half of the variation on the results of reported rate of SOC sequestration between published studies is due to variability in the true treatment effect while the remaining half is as a result of within study sampling variation. Our regression result also showed a quarter of between-study variance is explained by the explanatory variables considered, and the remaining within-study variance appears very small.

Although most of the coefficient of explanatory variables in the regression results exhibited expected sign from agronomic stand point, some of the coefficients were not significant. An important point we can infer based on our analysis is that the rate of SOC sequestration differences between NT and CT disappears as measurement depth increases. On average No-Till system sequesters more SOC than conventional tillage for every bushel of corn yield increases however the opposite was true for the case of soybean yield. The observed gain in SOC sequestration rate of CT over NT when the crop rotation system was under continuous corn contrast with previous results and agronomic practices in Corn Belt states, this may be attributed to several factors other than variables which we cannot fully observed and controlled in our study.

In the analysis we only showed the absence of publication bias or small study effect via funnel plot and a test for funnel plot asymmetry. One should note that these tests do not offer a solution to the bias problems if any exist rather alert us the potential presence of the problem.

Therefore correcting for publication bias will make an important practical ways to provide better understanding on Meta-analysis results.

Overall the combined results clearly showed that there is considerable variation in the rate of SOC sequestration in response to NT and CT across the study states. In addition to the tillage management, the presence of having heterogeneous biophysical characteristics such as yield, initial SOC, temperature and other explanatory variables we listed, difference trial design and quality as well as publication selection bias are responsible for heterogeneity in reported differences in SOC sequestration rate.

Our analysis is subject to several limitations such as the assumption we made on standard error, and other explanatory variables, as a result estimated coefficients and results should be interpreted with caution.

I. Tables of Result

Table 3.1 Summary statistics for the variables under this study

Variable	Mean	Std. Dev.	Min	Max
[19]Rate of ΔSOC, Mg C ha^{-1} yr^{-1}	0.088	0.47	-1.13	2.4
Initial SOC, Mg C ha^{-1}	54	29	21	159
Duration, year	16	15	4	51
Depth, cm	30	18	15	75
Corn yield, bu ha^{-1} yr^{-1}	132	47	66	245
Soybean yield, bu ha^{-1} yr^{-1}	40	15	24	92
Temperature, ^{O}C	9.4	1.7	6.2	11.1
Rain fall, mm/annum	837	126	580	1112

Note: total observations=78

Table 3.2 Rate of ΔSOC sequestration by depth of soil measured

Depth, cm	Rate of Δsoc, Mg C ha^{-1} yr^{-1}	Depth frequency (%)
15	-0.03	47.4
20	-0.08	2.6
30	0.16	23.1
45	0.51	5.1
46	0.05	5.1
60	0.28	14.1
75	-0.04	2.6

Note: 63% of the observations are under Corn-soybean rotation while the remaining 37% is Continuous corn

[19] The dependent variable is the difference in SOC sequestration rate from NT to CT.

Table 3.3 Joint Meta-regression results: the dependent variable is rate of ΔSOC, Mg C/ha/yr

REML estimate of between-study variance	tau2=0.003
% residual variation due to heterogeneity	I^2-res 49.43%
Proportion of between-study variance explained	Adj R^2= 25.83%
Joint test for all covariates	Model F(6,71)= 3.14
With Knapp-Hartung modification	Prob > F= 0.0087

Explanatory variables	Coeff.	At mean
Initial SOC	0.0016*	0.086
	(2.12)	
Depth	-0.0014	-0.042
	(-0.98)	
Corn yield	0.0008	0.106
	(1.64)	
Soybean yield	-0.013*	-0.520
	(-2.13)	
temperature	-0.057*	0.536
	(-2.34)	
Continuous corn rotation	-0.0495	
	(-1.05)	
_cons	0.860**	
	(2.81)	

t statistics in parentheses;* p<0.05, ** p<0.01, *** p<0.001; The F-table distribution at 95% is F(6,71)=2.23

Note the mean is calculated based on the mean observed values for each variable shown on table 3.1.

Table 3.4 Independent regression results for continuous corn and corn-soybean rotation

	Coef.	Std. Err.	t	P>t
continuous corn rotation	0.0367	0.0311	1.18	0.241
_cons	-0.0161	0.0251	-0.64	0.523

Adj R-squared =2.07%; I^2 residual = 80.27%

Table 3.5 Joint regression results: the dependent variable is rate of Δsoc, Mg C/ha/yr

REML estimate of between-study variance	tau2= 002
% residual variation due to heterogeneity	I^2-res= 52.74%
Proportion of between-study variance explained	Adj-R^2= 45.9%
Joint test for all covariates	Model F(7,70)= 3.80
With Knapp-Hartung modification	Prob > F= 0.0015

Explanatory variables	Coeff.	At mean
Initial SOC	0.0042**	0.227
	(3.23)	
Depth	-0.0013	-0.039
	(-0.98)	
Corn yield	0.0008	0.106
	(1.71)	
Soybean yield	-0.0042	-0.168
	(-1.73)	
temperature	-0.0612*	-0.575
	(-2.53)	
continuous corn	0.115	
rotation	(1.32)	
depth*cont	-0.0064*	
	(-2.22)	
_cons	0.675*	
	(2.15)	

t-statistics in parentheses;* p<0.05, ** p<0.01, *** p<0.001. The F-table distribution F(7,70)=2.14

Note the mean is calculated based on the mean observed values for each variable shown on table 3.1.

Table 3.6 Joint Meta-regression results: the dependent variable percentage change in SOC

REML estimate of between-study variance	tau2=35.8
% residual variation due to heterogeneity	I^2-res 99.98%
Proportion of between-study variance explained	Adj R^2= 31.02%
Joint test for all covariates	Model F(6,71)= 6.66
With Knapp-Hartung modification	Prob > F= 0.0000

Explanatory variables	Coeff.
Initial SOC	0.0614*
	(2.00)
Depth	-0.164**
	(-3.10)
Corn yield	0.0219
	(1.37)
Soybean yield	0.0429
	(0.87)
temperature	1.548**
	(3.08)
Continuous corn rotation	-3.578*
	(-2.22)
_cons	-24.86***
	(-4.32)

t statistics in parentheses;* $p<0.05$, ** $p<0.01$, *** $p<0.001$. The F-table distribution at 95% is F(6,71)=2.23

Table 3.7 Egger's test for small-study effects: Regress standard normal deviate of intervention effect estimate against its standard error

Std_Eff	Coef.	Std. Err	t	P>t
Slope	-0.054	0.012	4.43	0.000
Bias	-0.202	0.295	-0.68	0.496

Test of H0: no small-study effects, P = 0.496

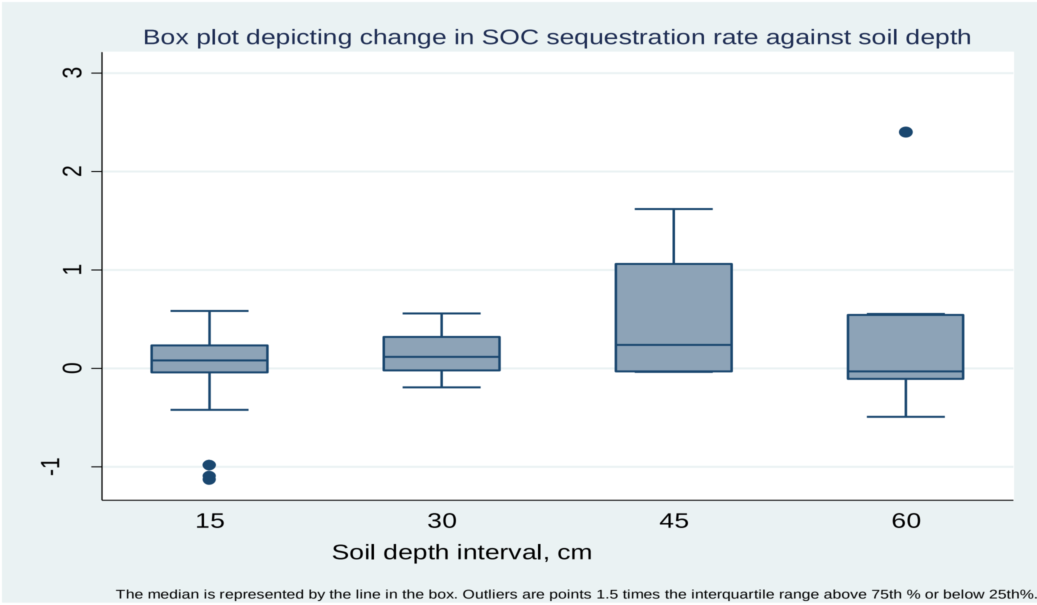

Figure 3.1Boxplot depicting change in SOC against the depth of soil (cm) with 15cm interval

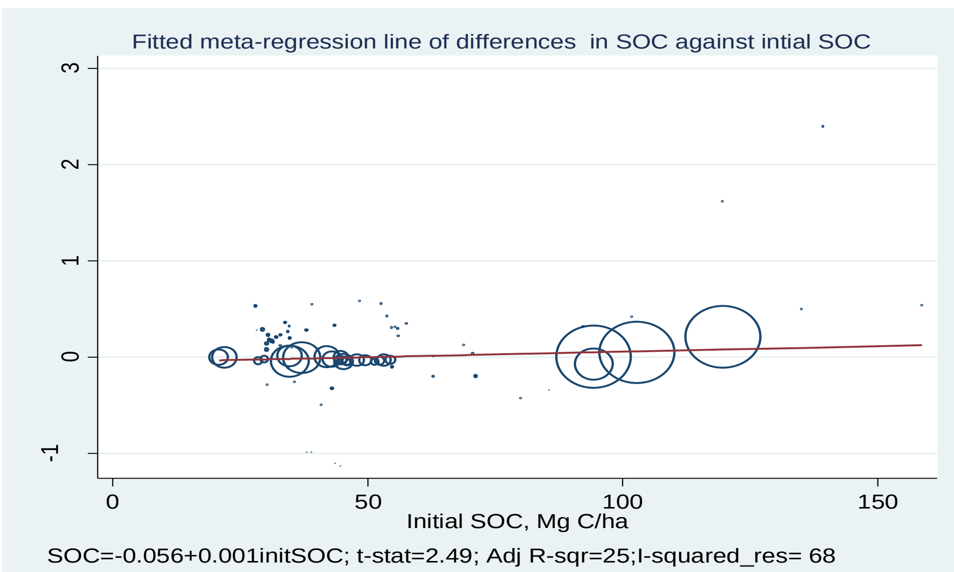

Figure 3.2 “Bubble” plots[20] of Meta regression line of the ΔSOC (NT-CT) against the initial SOC level

---

[20] A “bubble plot” is to a graph that a fitted regression line together with circles representing the estimates from each study, sized according to the precision of each estimate (the inverse of its within-study variance, σ_i^2). The area of each circle is inversely proportional to the variance of the difference in ΔSOC sequestration rate estimate.

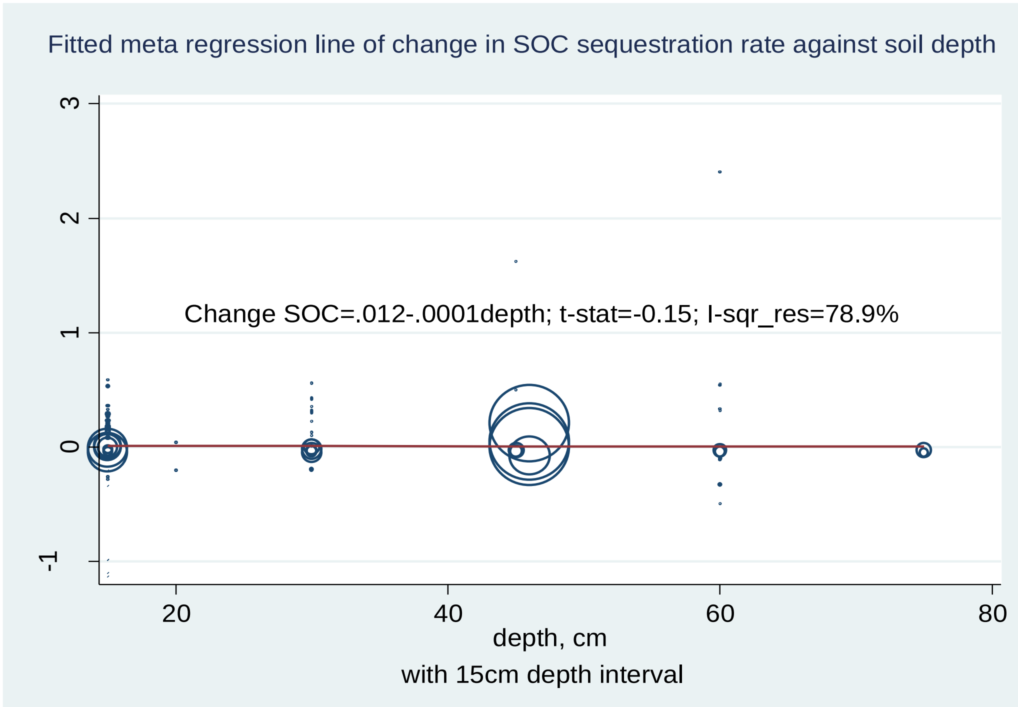

Figure 3.3 "Bubble" plots of Meta regression line of the ΔSOC (NT-CT) against the depth of SOC measured

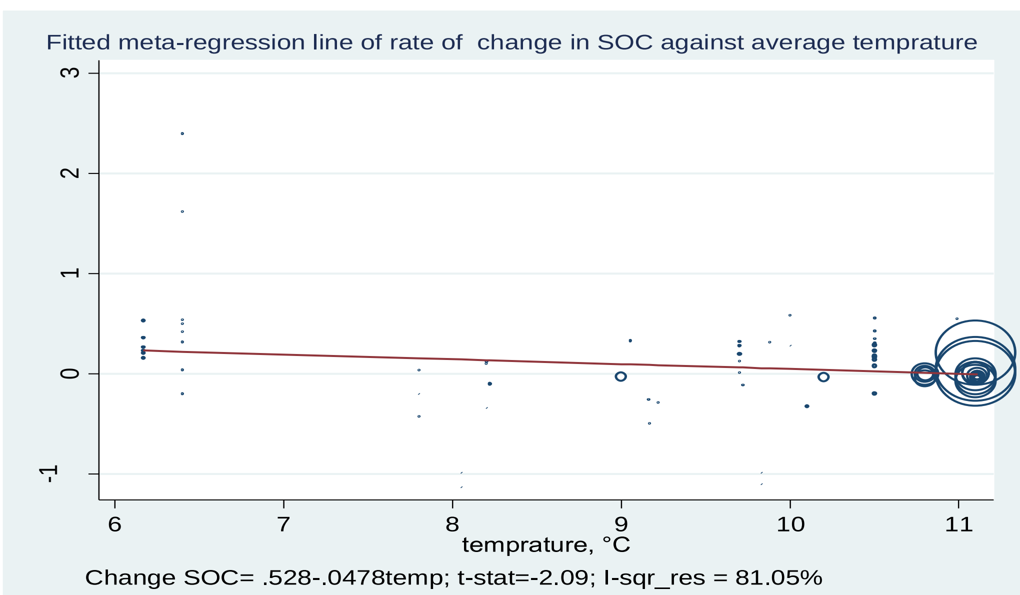

Figure 3.4 "Bubble plot" with fitted meta-regression line ΔSOC against average temperature of the experimental sites.

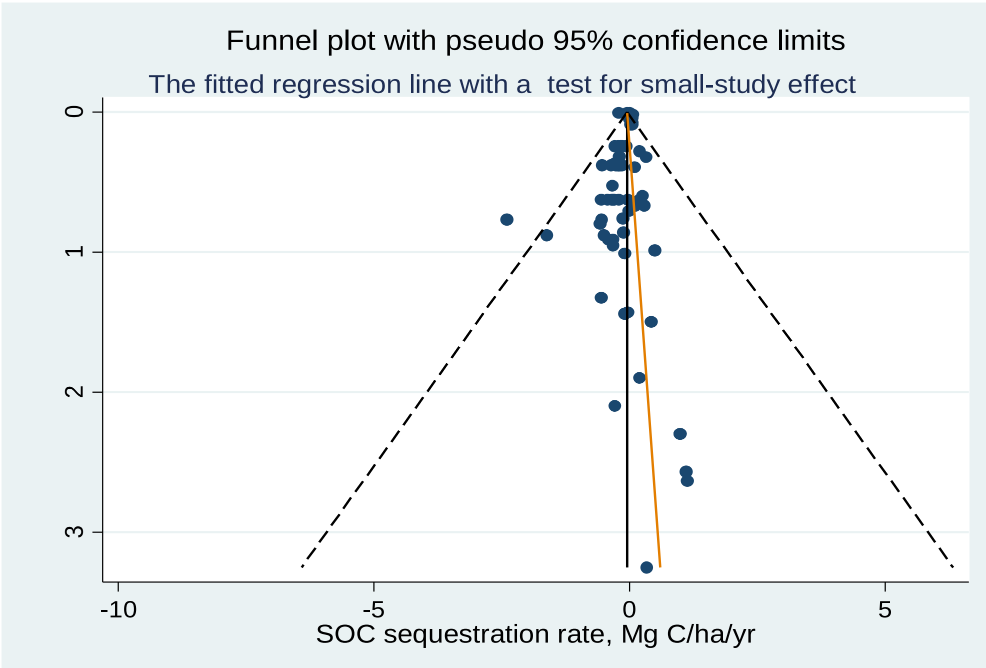

Figure 3.5 Funnel plot, using SOC sequestration rate against their standard error[21]

[21] The diagonal lines representing the 95% confidence limits around the summary treatment effect, i.e., [summary effect estimate ± (1.96 × standard error)] for each standard error on the vertical axis. This shows the expected distribution of studies in the absence of selection biasesy, 95% of the studies should lie within the funnel defined by these straight lines. Because these lines are not strict 95% limits, they are referred to as "pseudo 95% confidence limits" (Sterne and Harbord, 2004).Results from small studies will therefore scatter widely at the bottom of the graph, with the spread narrowing among larger studies. In the absence of bias, the plot will resemble a symmetrical, inverted funnel.

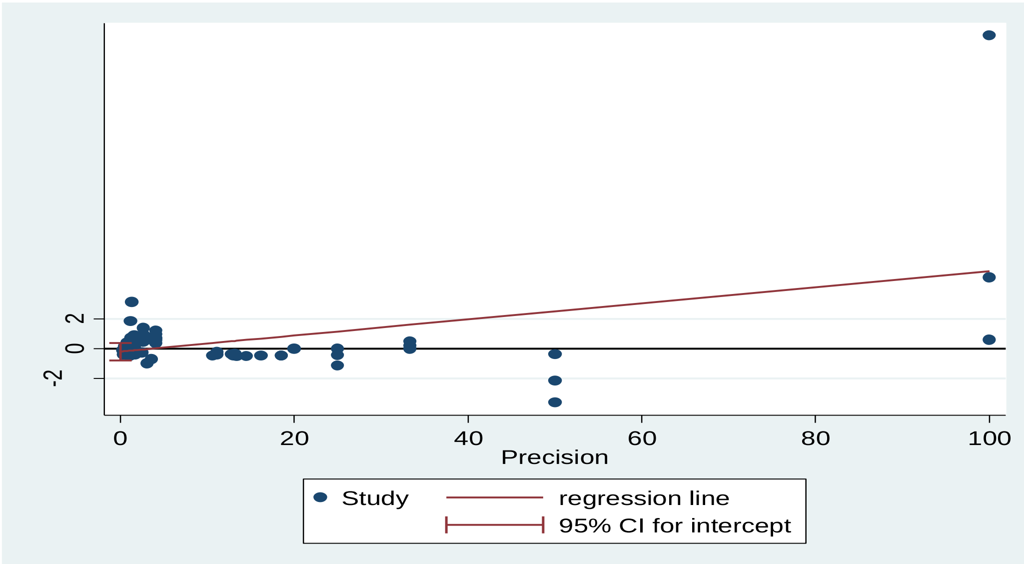

Figure 3.6 Publication biases estimated using Egger test

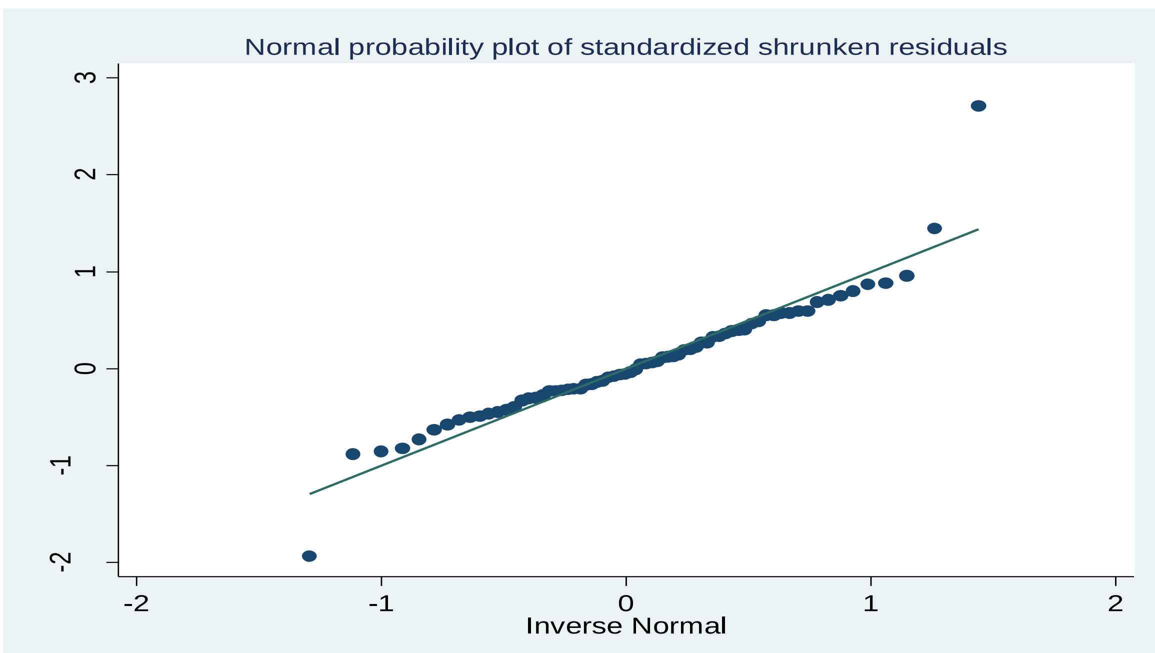

Figure 3.7 Normal probability plot of standardized shrunken residuals

References

Adler, P.R, D., S.J., Grosso, W.J.,Parton .2007. Life-cycle assessment of net greenhouse-gas flux for bioenergy cropping systems. Ecological Applications, 17, 675–691.

Adviento-Borbe M.A.A., M.L. Haddix, D.L. Binder , D.T. Walters, A. Dobermann.2007.Soil greenhouse gas fluxes and global warming potential in four high-yielding maize systems, Global Change Biology 13, 1972–1988

Al-Kaisi, M.M., X.,Yin, M.A., Licht, 2005. Soil carbon and nitrogen changes as influenced by tillage and cropping systems in some Iowa soils. Agric. Ecosyst. Environ. 105, 635–647.

Al-Kaisi, M.M., X.,Yin. 2005. Tillage and crop residue effects on soil carbon and carbon dioxide emission in corn-soybean rotations. J. Environ. Qual. 34, 437–445.

Alvarez, R. 2005. A review of nitrogen fertilizer and conservation tillage effects on soil organic carbon storage. Soil Use Manage. 21:38–52.

Anderson-Teixeira K.J., S.C. Davis, M.D. Masters, E.H. Delucia.2009. Changes in soil organic carbon under biofuel crops. Global Change Biology Bioenergy 1:75-96.

Angers, D.A., M.A., Bolinder, M.R., Carter, E.G., Gregorich, C.F., Drury, B.C., Liang, P.R., Voroney, R.R., Simard, R.G., Donald, R.P., Beyaert, J.,Martel.1997. Impact of tillage practices on organic carbon and nitrogen storage in cool, humid soils of eastern Canada. Soil Till. Res. 41, 191–201.

Angers,D.A., N.S.,Eriksen-Hamel. 2007.Full-Inversion Tillage and Organic Carbon Distribution in Soil Profi les: A Meta-Analysis. Soil Sci. Soc. Am. J. 72:1370-1374

Baker J.M., T. E. Ochsner, R. T. Venterea, T. J. Griffis. 2007.Tillage and soil carbon sequestration—What do we really know? Ag. Ecosys. Environ. 118,.

Blanco-Canqui H. and R. Lal.2008.No-tillage and soil-profile carbon sequestration: An on-farm assessment, Soil Science Society of America Journal 72, 693-701.

Borenstein, M., Hedges, L., Rothstein, H. 2007. Meta-Analysis Fixed effect vs. random effects www.Meta-Analysis.com

Christopher, S.F., R. Lal, and U. Mishra. 2009. Regional study of no-till effects on carbon sequestration in the Midwest United States. Soil Sci. Soc. Am. J. 73:207–216.

Clapp, C.E., R.R.,Allmaras, M.F.,Layese, D.R., Linden, R.H., Dowdy.2000. Soil organic carbon and 13C abundance as related to tillage, crop residue and nitrogen fertilization under continuous corn management in Minnesota. Soil Till. Res. 55, 127–142.

Dolan, M.S., C.E. Clapp, R.R. Allmaras, J.M. Baker, and J.A.E. Molina. 2006. Soil organic carbon and nitrogen in a Minnesota soil as related to tillage, residue and nitrogen management. Soil Tillage Res. 89:221–231.

Egger, M., G.D., Smith, M., Scheider and C., Minder. 1997. Bias in meta-analysis detected by a simple graphical test. British Medical Journal 316: 629-34.

Ellert, B. H., H. H. Janzen, and T. Entz. 2002. Assessment of a method to measure temporal change in soil carbon storage. Soil Science Society of America Journal 66:1687–1695.

Franzluebbers, A.J., M.A.,Arshad, 1996. Water-stable aggregation and organic matter in four soils under conventional and zero tillage. Can. J. Soil Sci. 76 (3), 387–393.

Gal A., T.J. Vyn, E. Micheli, E.J. Kladivko, W.W. McFee. 2007. “Soil carbon and nitrogen accumulation with long-term no-till versus moldboard plowing overestimated with tilled-zone sampling depths.” Soil & Tillage Research 96, 42–51

Harbord, R.M., J.P., Higgins..2008. Meta-regression in Stata. The Stata Journal, No. 4, pp. 493–519
Harbord, R.M., R.J., Harris. 2009. Updated tests for small-study effects in meta-analyses. The Stata Journal, No. 2, pp. 197–210
Havlin, J.L., D.E. Kissel, L.D. Maddux, M.M. Claassen, and J.H. Long. 1990. Crop rotation and tillage effects on soil organic carbon and nitrogen. Soil Sci. Soc. Am. J. 54:448–452.
Huggins, D.R., R.R. Allmaras, C.E. Clapp, J.A. Lamb, and G.W. Randall. 2007. Corn–soybean sequence and tillage effects on soil carbon dynamics and storage. Soil Sci. Soc. Am. J. 71:145–154.
Jarecki, M.K., R., Lal, R.,James.2005. Crop management effects on soil carbon sequestration on selected farmers' fields in northeastern Ohio. Soil Till. Res. 81, 265–276.
Johnson, J.M.F., D. Reicosky, B. Sharratt, M. Lindstrom, W. Voorhees, and L. Carpenter-Boggs. 2004. Characterization of soil amended with the byproduct of corn stover fermentation. Soil Sci. Soc. Am. J. 68:139–147.
Khan, S.A., R.L. Mulvaney, T.R. Ellsworth, and C.W. Boast. 2007. The myth of nitrogen fertilization for soil carbon sequestration. J. Environ. Qual. 36:1821–1832.
Lal, R. 2004. Is crop residue a waste? J. Soil Water Conservation. 59:136–139.
Lal, R., B. 2002. Soil carbon dynamics in cropland and rangeland. Environmental Pollution 116 (2002) 353–362
Lal, R., J.M. Kimble, R.F. Follett, and C.V. Cole. 1999. The potential of U.S. cropland to sequester carbon and mitigate the greenhouse effect. Lewis, Boca Raton, FL.
Lal, R., Kimble, J., Follett, R.F., Cole, C.V., 1998. The Potential for US Cropland to Sequester Carbon and Mitigate the Greenhouse Effect. Sleeping Bear Press, Ann Arbor, MI, p. 128.
Moorman, T.B., C.A., Cambardella, D.E.,James, D.L.,Karlen, L., A. Kramer.2004. Qquantification of tillage and landscape effects on soil carbon in small Iowa watersheds. Soil & Tillage Research 78 : 225–236
Ney R.A, J.L.,Schnoor.2002. Incremental life cycle analysis: using uncertainty analysis to frame greenhouse gas balances from bioenergy systems for emission trading. Biomass and Bioenergy,22, 257–269.
Ogle, S.M., F.J. Breidt, M.D. Eve, and K. Paustian. 2003. Uncertainty in estimating land use and management impacts on soil organic carbon storage for US agricultural lands between 1982 and 1997. Global Change Biol. 9:1521–1542.
Olson, K.R., J.M. Lang, and S.A. Ebelhar. 2005. Soil organic carbon changes after 12 years of no-tillage and tillage of Grantsburg soils in southern Illinois. Soil Tillage Res. 81:217–225.
Palmer, T. M., J. L. Peters, A. J. Sutton, and S. G. Moreno. 2008. Contour-enhanced funnel plots for meta-analysis. Stata Journal 8: 242–254.
Paustian, K., Andren, O., Janzen, H.H., Lal, R., Smith, P., Tian, G., Tiessen, H., Van Noordwijk, M., Woomer, P.L., 1997. Agricultural soils as a sink to mitigate CO2 emissions. Soil Use Manag. 13, 230–244.
Pikul, J.L., Jr., J.M.F. Johnson, T.E. Schumacher, M. Vigil, and W.E. Riedell.2008. Change in surface soil carbon under rotated corn in eastern South Dakota. Soil Sci. Soc. Am. J. 72:1738–1744.

Post, W.M., and K.C. Kwon. 2000. Soil carbon sequestration and land-use change: Processes and potential. Glob. Change Biol. 6:317–327.
Russell, A.E., D.A. Laird, T.B. Parkin, and A.P. Mallarino. 2005. Impact of nitrogen fertilization and cropping system on carbon sequestration in Midwestern Mollisols. Soil Sci. Soc. Am. J. 69:413–422.
Six, J., C. Feller, K. Denef, S.M. Ogle, and J.C.M. Sa. 2002. Soil organic matter, biota and aggregation in temperate and tropical soils effects of no-tillage. Agronomie 22:755–775.
Stanley, T.D., and H.C.,Doucouliagos. 2010. Picture this: A simple graph that reveals much ado about research. Journal of Economic Surveys 24: 170-191.
Stanley, T.D. 2008. Meta-regression methods for detecting and estimating empirical effect in the presence of publication selection. Oxford Bulletin of Econ. and Statistics 70:103-27.
Stanley, T.D., 2005."Beyond Publication Bias", Journal of Economic Surveys 19 , 309-45.
Stanley, T.D. 2001."Wheat From Chaff: Meta-analysis as quantitative literature review," The Journal of Economic Perspectives 15 :131-150.
Stanley, T.D. and Jarrell, S.B. 1998.Gender wage discrimination bias? A meta regression analysis. Journal of Human Resources 33: 947–973.
Sterne, J. A. C., and R. M. Harbord. 2004. Funnel plots in meta-analysis. Stata Journal 4: 127–141.
Sterne, J. A. C., and M. Egger. 2001. Funnel plots for detecting bias in meta-analysis: Guidelines on choice of axis. Journal of Clinical Epidemiology 54: 1046–1055.
Sterne, J. A. C., D. Gavaghan, and M. Egger. 2000. Publication and related bias in meta-analysis: Power of statistical tests and prevalence in the literature. Journal of Clinical epidemiology 53: 1119–1129.
Thompson, S. G., and J. P., Higgins. 2002. How should meta-regression analyses be undertaken and interpreted? Statistics in Medicine 21: 1559–1573.
Ussiri, D. A.N. and R., Lal. 2009. Long-term tillage effects on soil carbon storage and CO2 emissions in continuous corn cropping system from an alfisol in Ohio. Soil & Tillage Research, 104, 39–47.
Vandenbygaart, A.J., X.M.,Yang, B.D.,Kay, J.D.,Aspinall. 2002.Variability in carbon sequestration potential in no-till soil landscapes of southern Ontario. Soil Till. Res. 65, 231–241.
Vandenbygaart, A.J., E.G.,Gregorich, , D.A., Angers.2003. Influence of agricultural management on soil organic carbon: a compendium and assessment of Canadian studies. Can. J. Soil Sci. 83, 363–380.
Van Houwelingen, H. C., L. R. Arends, et al.2002. "Advanced methods in meta-analysis: multivariate approach and meta-regression." Statistics in Medicine. 21(4):589-624.
Varvel, G.E. 2006. Soil organic carbon changes in diversified rotations of the western Corn Belt. Soil Sci. Soc. Am. J. 70:426–433.
Verma,S.B..2005 Annual carbon dioxide exchange in irrigated and rainfed maize-based agroecosystems. Agricultural and Forest Meteorology 131, 77-96.
West, T.O., and W.M. Post. 2002. Soil organic carbon sequestration rates by tillage and crop rotation: A global data analysis. Soil Sci. Soc. Am. J. 66:1930–1946.
Wilhelm W.W., J.M.F. Johnson, D.L. Karlenc, and D.T. Lightle. 2007.Corn stover to sustain soil organic carbon further constrains biomass supply. Agronomy Journal 99, 1665-1667

Appendix 3

Table 8 Summary of the data from published studies used in a meta-regression analysis of SOC sequestration under no-till (NT) and conventional tillage (CT)

Author	Rate of Δsoc, Mg C ha^{-1} yr^{-1}	Initial SOC, Mg C ha^{-1}	Duration, Year	Soil depth, cm	State
Venterea et.al (2006)	-0.20	70.6	5	20	MN
Venterea et.al (2006)	1.00	62.8	5	20	MN
Venterea et.al (2006)	-2.10	101.8	5	30	MN
Venterea et.al (2006)	-1.60	92.2	5	30	MN
Venterea et.al (2006)	-2.50	135.0	5	45	MN
Venterea et.al (2006)	-8.10	119.5	5	45	MN
Venterea et.al (2006)	-2.70	158.6	5	60	MN
Venterea et.al (2006)	-12.0	139.2	5	60	MN
Olson et.al (2005)	0.24	29.8	12	15	IL
Olson et.al (2005)	0.45	28.6	12	15	IL
Olson et.al (2005)	0.22	43.0	12	30	IL
Olson et.al (2005)	0.45	46.0	12	30	IL
Olson et.al (2005)	0.32	47.8	12	45	IL
Olson et.al (2005)	0.42	46.0	12	45	IL
Olson et.al (2005)	0.37	49.5	12	60	IL
Olson et.al (2005)	0.46	52.3	12	60	IL
Olson et.al (2005)	0.32	53.3	12	75	IL
Olson et.al (2005)	0.56	51.4	12	75	IL
Jareckia et.al (2004)	0.39	44.9	13	30	OH
Jareckia et.al (2004)	0.38	54.4	14	30	OH
Ussiri & Lal (2008)	0.00	44.8	43	30	OH
Ussiri & Lal (2008)	2.00	45.3	43	30	OH
Ussiri & Lal (2008)	0.0001	20.8	43	15	OH
Ussiri & Lal (2008)	-0.002	21.9	43	15	OH
Khan et.al (2007)	-0.70	34.7	51	15	IL
Khan et.al (2007)	2.20	34.7	51	15	IL
Khan et.al (2007)	-0.30	42.0	51	15	IL
Khan et.al (2007)	0.40	37.1	51	15	IL
Khan et.al (2007)	3.70	94.3	51	46	IL
Khan et.al (2007)	-0.30	94.3	51	46	IL
Khan et.al (2007)	-10.70	119.6	51	46	IL
Khan et.al (2007)	-2.43	102.7	51	46	IL
Verma et.al (2005)	-1.13	37.9	4	15	NE
Verma et.al (2005)	-0.51	68.8	4	30	NE
Verma et.al (2005)	-0.80	34.8	4	15	NE
Verma et.al (2005)	-0.04	62.9	4	30	NE
Verma et.al (2005)	-1.30	34.6	4	15	NE

Verma et.al (2005)	-0.40	64.0	4	30	NE
Moorman et.al (2004)	-3.40	28.1	12	15	IA
Moorman et.al (2004)	-7.00	48.4	12	15	IA
Al-Kaisi et.al (2005)	7.90	44.6	7	15	IA
Al-Kaisi et.al (2005)	1.80	35.7	7	15	IA
Al-Kaisi et.al (2005)	6.90	38.0	7	15	IA
Al-Kaisi et.al (2005)	2.00	30.3	7	15	IA
Al-Kaisi et.al (2005)	6.90	38.9	7	15	IA
Al-Kaisi et.al (2005)	7.70	43.5	7	15	IA
Blanco-Canqui & Lal (2007)	-4.76	55.3	15	60	OH
Blanco-Canqui & Lal (2007)	-6.63	39.1	12	60	OH
Blanco-Canqui & Lal (2007)	3.34	34.4	30	60	OH
Blanco-Canqui & Lal (2007)	4.94	40.9	10	60	PA
Blanco-Canqui & Lal (2007)	-2.65	43.5	8	60	PA
Blanco-Canqui & Lal (2007)	1.98	54.7	20	60	PA
Blanco-Canqui & Lal (2007)	1.62	43.0	5	60	PA
Varvel (2006)	-5.60	52.7	10	30	NE
Varvel (2006)	-4.30	53.8	10	30	NE
Varvel (2006)	-3.10	54.7	10	30	NE
Varvel (2006)	-3.50	57.5	10	30	NE
Varvel (2006)	-3.00	55.8	10	30	NE
Varvel (2006)	-2.20	56.0	10	30	NE
Varvel (2006)	-2.90	29.4	10	15	NE
Varvel (2006)	-2.30	30.5	10	15	NE
Varvel (2006)	-1.70	31.2	10	15	NE
Varvel (2006)	-1.80	30.7	10	15	NE
Varvel (2006)	-1.40	30.2	10	15	NE
Varvel (2006)	-0.80	30.2	10	15	NE
Russell et.al (2005)	-1.47	32.8	12	15	IA
Russell et.al (2005)	-1.23	35.1	12	15	IA
Russell et.al (2005)	-0.47	38.4	12	15	IA
Russell et.al (2005)	2.40	96.7	12	15	IA
Russell et.al (2005)	4.05	85.5	12	15	IA
Russell et.al (2005)	5.10	79.9	12	15	IA
Pikul et.al (2008)	-2.30	32.0	11	15	ND
Pikul et.al (2008)	-1.77	31.4	11	15	ND
Pikul et.al (2008)	-5.86	28.0	11	15	ND
Pikul et.al (2008)	-2.54	32.9	11	15	ND
Pikul et.al (2008)	-2.92	34.3	11	15	ND
Pikul et.al (2008)	-3.94	33.8	11	15	ND
Jagadamma et.al (2007)	4.48	71.2	23	30	IL