ECONOMIC ANALYSIS OF VOLUNTARY CARBON OFFSET MARKET AND BIOENERGY POLICIES

A Dissertation

by

LAYLA SHIVA

Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Chair of Committee,	David A. Bessler
Co-Chair of Committee,	Bruce A. McCarl
Committee Members,	Henry L. Bryant
	Haeshin Hwang
Head of Department,	C. Parr Rosson

December 2014

Major Subject: Agricultural Economics

ABSTRACT

This work studies the economic implications of some United States greenhouse gas mitigation related policies. The main items focused on in this work are: 1) possible agricultural entry into a voluntary carbon offset market, 2) use of marginal land for switchgrass production and 3) agriculture and energy market effects of renewable fuel standards and the integration between these two markets.

The first element of the study addressed participation in a voluntary carbon offset market under alternative baseline specifications. We find that a per unit baseline augmented with a low initial level hybrid baseline for biofuel provides effectiveness in terms of additionality, leakage and program cost. We also find that voluntary offset markets promote large scale mitigation which decreases traditional agricultural production and so decreases consumers' surplus and increase producer's surplus.

The second study component examines the economic implications of growing switchgrass on marginal land. We simulate production patterns and market conditions when using or not using marginal land with and without a carbon offset program. We find using marginal land contributes heavily in satisfying RFS mandates and takes the pressure off of conventional land use. However with a simultaneous offset program we find that most of the switchgrass goes to electricity generation and that the pressure on conventional land use is unabated.

The third study component examines the energy–agriculture linkage using a structural vector autoregression model. The results of directed acyclic graph presents at contemporaneous time corn price fluctuations cause changes in soybean and ethanol prices. We perform conditional forecasting, taking into account the renewable fuel standards policies, and compare the forecasted path of prices with and without the renewable fuels mandates. Results of prices forecasts conditional on RFS requirements present an increase in all prices in the model by 2022 except for the crack ratio.

DEDICATION

To my dearest parents, Tahereh and Reza, and beloved husband, Hamid Reza.

ACKNOWLEDGMENTS

There are many wonderful people in my life that assisted me during my doctoral studies. They were beside me through this rough road and consistently supported me. I would like to take this chance to express my gratitude to all of them.

First and foremost, I would like to thank my advisors Dr. Bruce McCarl and Dr. David Bessler for their invaluable support and guidance. Every moment of working with them was a great honor and a precious learning experience for me. I am always amazed by Dr. McCarl's extraordinary multi-tasking ability, knowledge and modeling genius. I could not have finished this dissertation without his encouragement and financial support. Also, I always enjoyed discussing research problems with Dr. Bessler because of his brilliant knowledge and novelty. His insightful comments and patience in explaining ideas was of great assistance throughout the course of my research.

I would also like to express my gratitude to Dr. Henry Bryant, my committee member, for his constructive suggestions, guidance and his help in providing data for part of this research. I am also thankful to Dr. Haeshin Hwang, my other committee member, who has been supporting me since I was doing my Master of Science degree.

I also like to acknowledge Dr. David Leatham, who gave me the great opportunity to pursue my PhD in Texas A&M University. Also my special thanks to Dr. Shelly Peacock and Ms. Dee Cochran for their guidance through these years. Many thanks to my fellow student friends in the Agricultural Economics Department at Texas A&M for providing such a wonderful environment to work and grow.

I would like to sincerely appreciate my parents, Tahereh and Reza for their unconditional love, support, and sacrifice. They taught me strength and courage to pursue my dreams. Without their help and encouragement, I could not have stood the hard years of being far from home. I am also thankful to my dearest brother Amir, for always being there for me. His eternal support from the moment I started this path has always been my strength. Also I appreciate my sister and best friend, Mahsa. She has been a constant source of love and concern all these years.

Special thanks to my family, Nahid, Rahim, Masoomeh and Shima for their love, support and prayers. Thanks to my dear Uncle Ali and his lovely wife Candi also my dear Uncle Reza and her wife Razi, for their care and strong belief in me.

I would like to express my deep appreciation to love of my life, Hamid Reza. I feel very fortunate that I met him three years ago when I was just completed my qualifying exams. From then on, we have shared the same dreams every day. His love and support for me is limitless and wordless. His sharp and prompt advices assist me in many ways.

To all of you, thank you.

NOMENCLATURE

CORP	Corn Price
ETHP	Ethanol Price
CRKR	Crack Ratio
EPROD	Ethanol Production
SOYP	Soybeans Price
CATTP	Cattle Price
HOGP	Hog Price
CO_2e	Carbon Dioxide Equivalent
CO_2	Carbon Dioxide
CH_4	Methane
N_2O	Nitrous Oxide
RFS	Renewable Fuel Standard
EIA	Energy Information Administration
GHG	Green House Gas

TABLE OF CONTENTS

Page

LIST OF FIGURES

Page

Page

LIST OF TABLES

Page

Page

CHAPTER I

INTRODUCTION

Agriculture, energy and climate change have a complex relationship. Both agriculture and most forms of energy generation emit greenhouse gasses (GHGs) contributing to climate change. Agriculture also produces commodities that can be used to produce energy, perhaps reducing the amount of GHGs emitted. Additionally, there are agricultural actions by which GHG emissions can be reduced, contributing to a mitigation of climate change that involve altered operations or bioenergy feedstock production (Field et al. 2014). These actions, in turn, will influence agricultural markets. Despite agriculture being widely acknowledged as a possible GHG mitigation strategy, its implementation has been low and alternative policy designs may be needed. This thesis investigates these issues. We will specifically examine:

- Agricultural mitigation supply under a mandatory and a voluntary market design;
- Agricultural production possibilities for bioenergy feedstocks using marginal lands;
- Agricultural market interrelationships with energy markets.

Each of these is further discussed below.

1.1 Agriculture as a Mitigation Source

Climate change has become a major social concern. One principal driving force is societal GHG emissions, the bulk of which come from fossil fuel usage, but another significant component involves agriculture and forestry. Agricultural related GHG mitigation strategies have been argued to be cost effective options that can contribute in global climate change management (Field et al. 2014) but the extent of their contribution depends on prices and market rules. This thesis will investigate GHG market designs in terms of their ability to cost effectively encourage agricultural GHG mitigation.

Cap and trade schemes are one possible policy vehicle for implementing GHG emission limits. To implement this, the government sets a limit or cap on the amount of GHGs that may be emitted. The cap is sold, auctioned, or otherwise distributed to firms in the form of emission permits. Firms then are required to hold permits equivalent to their emissions. They can trade the permits.

An issue with cap and trade scheme is that in implementation the agricultural and forestry (AF) sectors are not very likely to be covered by a cap. To date the AF sectors have been outside the cap in all implemented schemes and in the US it is unlikely that the AF sectors will be capped (Murray 2010). Recently attention has been paid to voluntary participation programs with market based incentives, where AF can voluntarily choose to produce carbon offsets. If a farmer chooses to join the program (opt in), then she is going to be directly paid for the GHG abatement and also will be provided with liability for any future greenhouse gas emissions.

Because of asymmetric information between the regulator, who pays for the abatement and the farmers, who provide it, we are facing an adverse selection issue in this market. In particular while there is the desire to only pay for additional GHG offsets the market design must prevent this. A design that regulators frequently use to avoid paying for non-additional production is the baseline method. In this policy design, the regulator sets a baseline and pays for reduction in emissions below the baseline level.

Another challenge facing policy makers regarding offset markets is leakage. Leakage occurs when mitigation activities by covered entities causes direct or indirect GHG emissions by uncovered entities. For instance, promoting mitigation policies in a political jurisdiction may increase fossil fuel prices; this may, in turn, lead to reallocation of production of fossil fuels elsewhere, in another political jurisdiction that has less strict mitigation rules (Hennessy et al. 2007).

The first essay of this thesis considers modeling voluntary carbon offset programs in agriculture when farmers can choose to opt in. In this work we simulate carbon market participation under alternative baseline schemes and carbon prices to see the effect on farmer's decisions to opt in or not. To do this we use the agricultural part of the Forest and Agriculture sector optimization model Green House Gas (FASOM-GHG) version (Lee et al. 2004; Adams et al. 2005; Beach et al. 2010). We will also perform a marginal cost comparison among different scenarios, and figure out the additionality and leakage consequences across alternative carbon prices and market designs. Also we will examine the international leakage by looking at price and export change in some major countries. The international leakage argument is that regulation in one country may shift production to other countries (Murry et al. 2004; Searchinger et al. 2008). Rise in other countries exports and prices could indicate international leakage.

1.2 Agriculture as a Biofuel Feedstock Producer

Agriculture could also mitigate GHGs through production of alternative bioenergy sources (Schneider and McCarl 2003; McCarl 2008). Bioenergy is produced when biomass, commodities are converted to liquid fuels, heat or electricity. Today, we use agricultural products such as corn and sugarcane to produce ethanol and biodiesel as substitutes for gasoline and diesel with some limited use of processing by products for heat and electricity. Providing substitute products generally involves recycling of carbon dioxide (CO_2), a greenhouse gas, because plant growth absorbs CO_2 while combustion releases it (McCarl 2008). Thus producing bioenergy can replace fossil fuel intensive products or production processes and reduce GHG emissions (McCarl 2008).

The main federal biofuel policy is the renewable fuel standard (RFS). The Energy Policy Act of 2005, introduced what is now called RFS1; this required 7.5 billion gallons of renewable fuel be blended by 2012. This policy was expanded by the 2007 Energy Independence and Security Act, which requires higher volumes plus differentiates among biofuels based on their lifecycle GHG content, the features of which are now called RFS2. RFS2 promotes the use of advanced biofuel to be substituted partially for conventional ethanol by 2022.

Recently substantial attention has been paid to biofuels in response to rising petroleum prices, renewable fuel mandates, GHG emission reduction desires, food versus fuel land competition, energy security desires and clean air activities, among other forces. Profitability of biofeedstock production in recent years has led to land use conversion from conventional crops and other uses. Replacing conventional crop lands with crops produced for energy use reduces conventional production and leads to higher prices. Also since grains have been heavily used to feed animals, livestock products and prices are likely affected. This is commonly called a conflict between food and fuel production. In addition, another outcome of using food crops for energy could be land replacement by conversion of land somewhere else through deforestation, which will also affect GHG emissions (Swinton et al. 2011; Searchinger et al. 2008).

Use of marginal land, which is not currently used for growing food crops, could lessen the conflict between food and fuel production. Economists describe marginal land as a land at the extensive margin of production (Barlowe 1986). Tilman et al. (2006) found that low input production on poor quality land can yield biomass. Also some studies have focused on the possible use of marginal lands developing estimates of the input cost and yields when using them to grow biomass (Berndes 2002).

The second essay of this thesis will analyze the economics of raising energy crops on marginal land. Specifically, we will examine the potential contribution of switchgrass grown on marginal land in fulfilling the RFS2 requirements on advanced biofuels and how this is influenced by carbon market incentives. Also we will study the net greenhouse gas emission effects that arise as well. Finally, we will examine the effects on major commodity prices, consumers' surplus and producers' surplus.

1.3 Agricultural Market Interrelationships with Energy

Production of biofuels affects agricultural markets through diversion of land to produce biofeedstocks. This diversion in turn leads to a reduction in supply of other products and a likely rise in prices. Since ethanol is an oxygen enhancing additive and a replacement for gasoline, its price has a relationship with gasoline and also crude oil. Moreover a rise in oil-based fuel prices increases production costs for crops and, in turn, their prices. Here we explore price interrelationships.

In the third essay of this thesis we examine the dynamics and contemporaneous causality between agricultural and energy markets. To do this, we model the energy–agriculture linkage using a structural vector auto regression (VAR) model. This model lets us quantify the relative importance of various contributing factors as they effect prices in both markets. The Lingam algorithm from the machine learning literature is used to achieve identification of the structural parameters in contemporaneous time. We also perform conditional forecasting, taking into account the renewable fuel standard policies, and compare the forecasted path of prices with and without the renewable fuels mandates.

CHAPTER II

ECONOMIC ANALYSIS OF VOLUNTARY AGRICULTURAL GREENHOUSE GAS OFFSET MARKET DESIGNS

2.1 Introduction

Agriculture is potentially a source of emission reductions and sequestration enhancements both of which can offset greenhouse gas emissions from other sectors. A number of studies indicate that the agricultural sector could make significant contributions in a societal climate change mitigation effort, thus would involve practices such as altering soil tillage, fossil fuel use, pesticide application, fertilization rates, rice management, bioenergy production and moving land to grass or forests (McCarl and Schneider 2000).

A major component of greenhouse gas (GHG) policy has been cap and trade where emitters have a permitted maximum net emission level but can buy or sell emission permits. However, in most proposed policy the agricultural sector is not a capped sector – one that is subject to a permitted limit. Rather agriculture is typically regarded as an offset supplying sector. Namely, agriculture produces offsets where an offset is a reduction in GHG emissions or an increase in carbon sequestration created by an unregulated party that can be used to counterbalance emissions from a regulated party under the GHG emission cap (Murray et al. 2012). Such offsets could be sold into the GHG permit market if the agricultural entities are willing and allowed to participate.

In particular, the cap and trade scheme under the proposed, but never ratified, American Clean Energy and Security Act of 2009 (ACESA, or HR 2454) included agriculture and forestry efforts as offsets. Some other policy proposals that include agriculture as an offset are: a) the Regional Greenhouse Gas Initiative (RGGI) in the Northeastern United States that caps emissions from the electric power sector and allows for offsets from other sectors and regions; b) the cap and trade system arising in California where agriculture will participate as an offset via farmland conservation and agricultural management strategies, and c) the European Union's Emission Trading System (EU ETS). Strengthening the capacity of the forest and agricultural sectors to capture CO_2, protect biodiversity, pursue more climate friendly agricultural practices and carry out mandatory accounting for grassland and cropland management are some of the actions allowed through EU ETS.

Offsets are advocated by policy makers since they are outside of regulated sectors and reduce the atmospheric concentration of GHGs. Consequently their inclusion helps reduce compliance cost, and gives time for regulated sectors to develop low cost strategies. The cost reduction from allowing offsets can be substantial. For example, analyses of recent federal U.S. cap and trade proposals indicate that the inclusion of offsets could reduce compliance cost by over 50% (Murray et al. 2012). Figure 1 portrays the potential situation where the panel on the left depicts the capped sector and the one on the right is the offset market. The cap is the vertical line (Cap) for the capped sector and the marginal cost of emissions reduction is the positively sloped line labeled (MC-capped). With no offset market the price of abatement would be at Pcap. When there is an offset market, the difference between the cap and the marginal cost of capped sector emissions reductions would be the excess demand facing the uncapped sector (D-uncapped). In turn the tradable permit price will decrease to P* with offsets being purchased and the cap requirement being satisfied by reductions in the both the capped and uncapped, offset, sectors (A-CAP and A_uncap respectively).

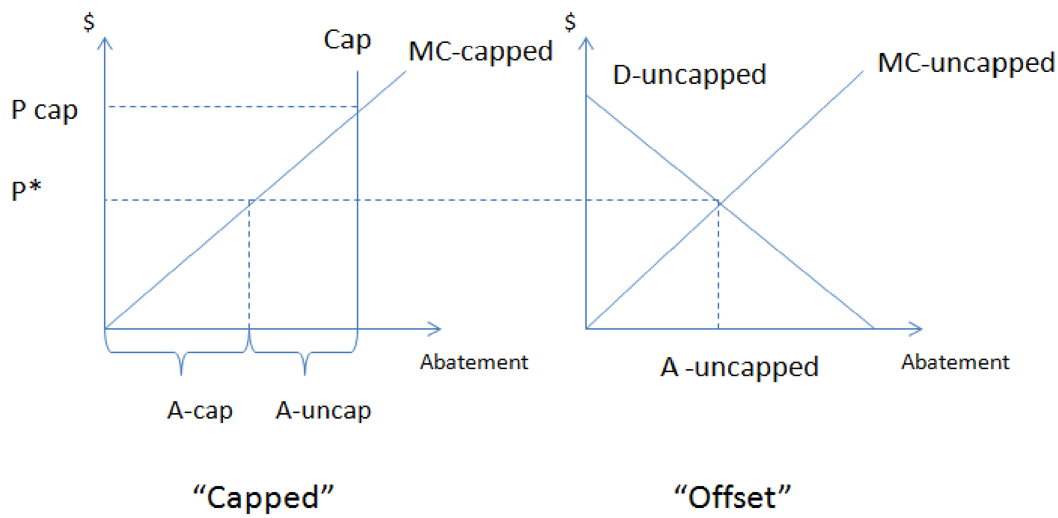

Figure 1. Offset markets decrease the overall compliance costs (Murray et al. 2012).

Such a market reduces the overall cost of complying with the cap plus creates a stream of revenue (A-uncap* P^*) to the offsetting sector (Pattanayak and Butry 2005). An offset program would bring uncapped sectors into GHG reduction programs voluntarily providing they are eligible.

Agriculture and forestry (AF) could have been capped sectors but are not generally being considered so for several reasons. Some major reasons are transactions costs of measuring, monitoring and enforcing limits on AF, that arise since the AF sectors consists of many entities most of which are small (Florida Farm Bureau Federation 2009). Also heterogeneous conditions across the landscape and time in the form of varying soil types, weather and crop mix can cause GHG emissions to differ so much that uniform rules, and protocols are not applicable (Florida Farm Bureau Federation 2009). Also AF are subject to problems in the forms of additionality, leakage, uncertainty and permanence (Chazournes and Boisson 1998). Each will be discussed below.

Additionality refers to a concern that credit buyers pay for GHGs that 100% offset global net emissions to the atmosphere. In particular, in the international GHG regulatory discussion (Chazournes and Boisson 1998; Shrestha and Timilsina 2002), policymakers have reflected a desire to only credit GHG offsets that would not have occurred under the normal course of business (commonly called business as usual). Similarly, credit buyers would naturally desire to pay only for GHG offsets that they can claim credit for under regulatory schemes. Thus, buyers would not wish to pay for potential offsets that someone would disallow. The widely held stance arising is that the rulemaking and regulatory structure should only grant credits for GHG offsets that are additional to what would have occurred under business as usual.

Since some GHG mitigating actions produce private net benefits for landowners and have historically been adopted under business as usual in the absence of a GHG offset program their use can be judged non additional. Furthermore this adoption is often farmer's private information and is not necessarily known to purchasers. This information asymmetry means the purchaser cannot observe what the enrolled farmer would have done without the payment. The information asymmetry and the business as usual adoption is the source of the problem of additionality (Murray, Sohngen and Ross 2007).

Leakage constitutes another challenge to carbon offset policy designers (Chazournes and Boisson 1998; Metz 2001). Market forces coupled with less than global coverage by a GHG regulatory program can cause net GHG emission reductions within one region to be offset by increased emissions in other regions. For example, suppose crop land use within a region is altered in the name of a GHG offset program resulting in increased sequestration, less emissions and less crop production. But suppose, in turn, that there are crop land expansion reactions in other regions replacing the lost production leading to increased emissions in those regions. This implies that the global net emission reduction is less than would be implied by just looking at the regional effects of the program (Murray, McCarl and Lee 2004).

Uncertainty is a third major challenge (Chazournes and Boisson 1998). Land-use based production of GHG offsets will be subject to production and sampling uncertainty (Kim and McCarl 2009). Production uncertainty arises from year-to-year weather variations along with the uncertain incidence of fire, diseases and pests coupled with many other factors (Heath and Smith 2000).

Uncertainty also arises due to sampling issues. Measurement of GHGs across the landscape is not possible due to the pervasiveness of carbon. Collectively the natural production and sampling uncertainty will exist and thus the purchaser of potential GHG offsets will be at risk of having the quantity of purchased offsets falling below the claimed level of offsets causing the purchaser to be out of compliance with regulatory limits.

Permanence is another major issue that may be keeping AF mitigation in the offset category (Metz 2001). The total quantity of potentially creditable GHG offsets generated by AF, particularly sequestration, projects cannot be guaranteed to be permanent because of potential reversal of practices or the potential incidence of uncontrollable events that would lead to release of the sequestered GHGs like a forest fire. In addition differential annual amounts of GHG activities generally arise over time.

This research examines AF sector participation in a voluntary carbon offset market and does an empirical study on the nature of contributions in terms of additionality and leakage. If a farmer chooses to join the program (opt in), she receives a GHG credit for her change in net emissions relative to the assigned baseline and is subject to liability for any future increases in emission. On the other hand, if the farmer chooses not to opt in, she will receive no payments and will not be subject to liability for increasing GHG emissions. In such optin procedures a key factor is likely the baseline establishment and payment eligibility procedures. We will examine several baseline establishment and payment eligibility procedures and their effectiveness across alternative carbon equivalent prices to see what happens in terms of magnitude of participation rates plus will examine additionality and leakage implications.

Herein we assume that agricultural producers can voluntarily opt in entering a carbon trading program as sellers of offsets. Participants that opt in receive a GHG credit for sales plus pay for emissions increases. We also assume producers who do not opt in to the program, receive no payments and have no liabilities if they increase emissions. We assume the system is symmetric and that payments and penalties are charged at the same rate and this equals the carbon price.

To do our empirical analysis we need to model the farmer's voluntary decision as to whether to participate or not participate in the carbon offset crediting program (hereafter called opt in). We will do this by simulating market participation using the Forest and Agriculture Sector Optimization Model-Green House Gas version (FASOM-GHG) (Lee et al. 2007; Beach and McCarl 2010).

2.2 Brief Literature Review

The Kyoto Protocol states that emission reductions from an offset market project should be "*…. additional to any that would occur in the absence of such activities*" (Chazournes and Boisson 1998). However, establishing a practical approach to insure additionality is difficult. Several studies propose using a screening contract method under the assumption of heterogeneous service providers to improve additionality (Ferraro 2008; Wu and Babcock 1995). Wu and Babcock (1996) use mechanism design (specifically a principal- agent model) to overcome information asymmetry between farmers and the government. Information asymmetry arises since the government knows only the distribution of farmers' production situations, rather than farm-specific information.

Bushnell (2011) discussed adverse selection possibilities in the carbon offset markets since the regulator does not know the exact distribution of business as usual (BAU) emissions amounts and some farmers can take advantage by mimicking high cost type farmers. Mason and Plantinga (2011) tried to solve the adverse selection problem in the presence of information asymmetries proposing use of an incentive-compatible principal-agent dynamic contract. Mezzatesta et al. (2013) used propensity score matching methods to estimate the level of additionality from enrollment in cost-share programs for six conservation practices.

2.2.1 Additionality and Baselines

The problem of additionality is closely related to the establishment of the baseline. Ideally, an opt in offset producer receives sellable credits or direct payments for the difference between a baseline and their net emissions whenever these emissions fall below the baseline (Horowitz and Just 2013). Each field or farm can be assigned an emissions baseline that it must do better than in order to merit payments.

Several studies have proposed that the payment scheme needs to be tailored to producer activities. Antle et al. (2003) argued that there would be greater efficiency using per-tonne offset contracts rather than practice based per-hectare contracts as do Murray and Baker (2011).

Fell and Morgenstern (2010) discuss uncertainty in baseline emissions and offset supply. Predicting the unobserved emissions baseline after program implementation is difficult, making the baseline estimates uncertain. Also, asymmetric information between the regulator and the offset entity complicates precise assignment of the baseline (Murray et al. 2012). Using a baseline to reduce non additionality is a popular method suggested in the literature. Horowitz and Just (2013) examine characteristics of an optimal baseline in the context of a cap-and-trade scheme where the baseline is applied to a sector not covered by the cap but sells offsets to the capped sectors. With the objective of maximizing the surplus of both sectors minus damage to the environment, they find that it is desirable to set a low baseline. This finding is similar to the study on the voluntary opt-in component of the sulfur dioxide emission trading program in (Montero 2000). This study favors a low baseline, which allows payments for non-additional production raises the costs of achieving a given level of additional offsets. Essentially, a low baseline allows all the low cost abatement opportunities to participate and at the same time the non additional credit producers receive large windfall profits from the credit buyer. This turns out to be efficient because the transfer does not affect the objective, which considers only the total welfare. Our study will focus on baseline determination.

2.2.2 Leakage

Practicing GHG mitigation policies in one country can cause additional production and consequently emission rise in another country which called international leakage. The basic argument is that regulation in one country may shift production to other countries (Pethig 1976) and that could cause GHG emissions to increase too. There are some energy related studies in the literature that consider the effects of mitigation policies such as carbon tax, tradable permits in one country on potential leakage in the rest of world (Bernstein, Montgomery and Rutherford 1999).

Babkier (2005) estimates the potential international leakage in an energy context at 130% because of reallocation of energy intensive industries away from OECD countries.

On the other hand, Barker et al. (2007) investigate the potential carbon leakage from six EU Member States which implemented environmental tax reform and find small leakage effects. Lee et al.(2007) studied the likely effects of agricultural emission abatement on non- host countries. They found that at a $100 price total U.S. production falls by 2.5% and traded production falls by 6.5% but that production in non-U.S. Annex B and non-Annex B countries grew by 2.66% and 12.22% correspondingly. Rise in production of other countries results from comparative advantage shifts and indicates that leakage would happen.

2.3 Baseline and Participation Alternatives

Today a main issue in designing carbon offset market is assignment of an applicable baseline which removes non additionality at the lowest transaction cost. Also the baseline in a voluntary program must treat individual producers and not the sector as a whole, thus the baseline must be scalable applying equally to a range of participants from few optin producers to many. For this reason we examine per unit optin baselines (per acre for crops, per animal for livestock, per gallon for biofuel, per btu for biopower) and compare their efficiency with the programs with no baseline and a perfect baseline.

To define a per unit baseline, we calculate the per unit amount of GHG emissions produced in different categories of agricultural activities, such as cropping, livestock management, grazing and bioenergy. We will also develop a hybrid baseline that is largely the same as a per unit one, but has alternative features for previously unused strategies like biopower.

From the standpoint of controlling additionality and leakage the ideal scheme is one of full coverage where all are liable for emissions plus all are rewarded for emissions reductions. However, this is not generally going to be possible for a non-capped, offsetting sector. Rather than one needs to examine voluntary participation.

In our examination of voluntary participation we specify several baseline alternatives. These are motivated by several concerns and assumptions.

- One wishes the offsets generated to be additional to what would have happened in the absence of the program.
- One is dealing with opt in participants and non participants and the baseline must be able to cover a variable number of opt in participants - being scalable.
- One can broadly observe practices before the program in regions so has an idea of typical patterns of emissions by producer groups as well as total emissions.
- Some of the potential producer groups are already using potential emission mitigating strategies while other strategies may not being used at meaningful levels (i.e. afforestation and bioenergy may be acting at much lower levels than possible)

To guide this discussion consider the following simple model including an objective function and the constraints:

$$\text{Max } pr * (f_p(X_p, O_p) + f_{np}(X_{np})) - (c_p(X_p, O_p) + c_{np}(X_{np})) + op * OIO \qquad (1)$$

$$S.T. \;\; ru_{p,i}(X_p, O_p) + ru_{np,i}(X_{np}) \leq b_i \qquad (2)$$

$$ne_{p,i}\,(X_p, O_p) - OIO = 0 \qquad (3)$$

$$ne_{np,i}(X_{np}) - NOIO = 0 \tag{4}$$

Where pr is the agricultural product prices, *p* identifies opt in participants, *np* identifies non participants, *f* the production function for both types of participants, *X* is activity level, *O* is offset strategies used, *c* is a cost function for the participants, *op* is the offset price, *OIO* is offsets from opted in participants, *i* is resources, *ru* is a resource use function, *b* is resource endowment, *NOIO* is net offsets from non-participants that are not eligible for payments. Also *ne* is a function that gives net emission consequences of producing *X* while using offset strategy *O*.

Below are some participation and baseline issues.

1) The no program, base scenario will simulate the case in which there is no carbon crediting program and hence, the carbon price is zero. This gives us the emission produced in a baseline without any program that encourages agriculture sector to offset carbon. If the model above is solved with *op=0* then one gets a base solution with the optimal levels $OIO^b$and $NOIO^b$. This will be the ***BASE*** scenario in the analysis below.
2) The "mandatory" scenario with a total sector baseline in which case the agriculture sector is entirely covered by the offset program and is paid for offsets but also incurs liabilities if emissions increase. Therefore the objective function is replaced with

$$Max\ pr * \left(f_p(X_p, O_p) + f_{np}(X_{np})\right) - \left(c_p(X_p, O_p) + c_{np}(X_{np})\right)$$
$$+op * ((OIO + NOIO) - (OIO^b + NOIO^b)) \tag{5}$$

also when the model is solved with *op*>0 then one gets a solution that indicates the amount of offsets produced when the entire sector is capped and they are paid only for offsets above the baseline plus penalized for offsets below the baseline. This will be called the ***full coverage baseline or mandatory*** scenario below.

3) The "zero baseline" scenario represents a voluntary carbon crediting program but without a baseline. In that case the opt in participants will get paid if they reduce carbon emissions and will incur liabilities for emission increases. Also producers that do not optin do not receive payments or liabilities. Such a scenario is likely to have additionality and adverse selection issues. All farmers can claim for additional GHG mitigation, but because of hidden information the truth will be unknown to the buyer. In the real world this scenario will be simple to administer but it is not efficient as non additional producers are getting paid too. If the model above (equation 1-4) is solved with *op*>0 then one gets a solution that indicates the amount of offsets produced when opting in with a zero baseline i.e. they get paid for all offsets.

4) The optin-perfect baseline scenario involves a "perfect baseline" where optin producers are only paid for better performance compared to the no program base situation. This scenario captures both additionality (actual reductions relative to what would have happened without crediting) and leakage (increases in non-participant emissions outside the program). If the model above has a new variable added for the amount of optin carbon paid for (*POIO*) and one adds a constraint limiting payments to be less than amount of opted in offsets plus another limiting

payments to be less than or equal to the additional offsets considering these from participants and no-participants minus the baseline levels as follows

$$POIO \leq OIO \tag{6}$$

$$POIO \leq OIO + NOIO - (OIO^b + NOIO^b) \tag{7}$$

In turn one modifies the objective function to pay those that are truly additional and solves for $op > 0$,

$$Max\ pr * \left(f_p(X_p, O_p) + f_{np}(X_{np})\right) - \left(c_p(X_p, O_p) + c_{np}(X_{np})\right) + op * (POIO) \tag{8}$$

This generates the participating offset quantity paid for under a perfect baseline. This would be quite difficult to implement given the information needs to specify the baseline quantities plus the limit imposed on participating volumes related to non participants. This will be called the ***perfect baseline*** scenario below.

5) In setting up the "per unit" baseline the basic concept is to take activities that create greenhouse gas emissions and offsets and subtract the per unit rates from the baseline (per acre for crops, per animal for livestock, per ton of the forest product, per unit of bioenergy produced). In the modeling case this would be the emissions found when the base model was solved. This renders the amount of emissions offset or added sequestration being paid for to be the amount that arises under the scenario per unit minus the baseline rate per unit. In turn we compute baseline offset rates for:

    - cropping on an average acre basis
    - bioenergy on a gallon of fuel or btu of electricity basis

- livestock enteric fermentation on a per animal basis
- livestock manure on a per animal in a manure treatment system basis
- afforestation on a per acre afforested basis
- forest management on a per acre managed basis
- deforestation management on a per acre deforested basis

For example to calculate the per unit baseline for crop production, we need to figure out the regional amount of emissions from different categories of GHG net emission related to this activity, such as soil sequestration, fuel, fertilizer and pesticide use, irrigation, and so on, for all of the regional acres of each crop using common practices in the region. All the GHG types are converted to the CO_2 equivalent through GWP. Then we need to divide the total amount of emissions by the amount of crop acres to get the per acre emission baseline rate.

In our simplified algebraic model this would be the average amount of offsets divided by the units of *X* produced, such as:

$$Bne = (OIO^b + NOIO^b)/(X_p^b + X_{np}^b) \tag{9}$$

Where the superscript b identifies the base levels of offsets and production. In turn one then modifies the equation (3) above to become

$$ne_p(X_p, O_p) - Bne * X_p - OIO = 0 \tag{10}$$

Subsequently one solves for *op*>0. This formulation modifies *OIO* so that it is difference between the emissions from X_p and the average per unit (say per acre) amount (*Bne*) generated under the baseline condition. This gives producers an incentive to do better than say the average current per unit offset rate in the region. This generates a scalable baseline and would not be extremely difficult to implement where one needs to compute the average offsets per unit activity. This will be called the ***per unit baseline*** scenario below.

6) It is likely that some GHG offset strategy possibilities will be used in very low quantities and may not really have ways to improve them in terms of GHG net offsets. Such a case arises in practice with afforestation and bioelectricity where the baseline quantities are small. Moreover for both it is possible that the ne_p (X_p,O_p) when implemented could be quite close to *Bne* providing it could be calculated (ie if $X_p + X_{np}$ is not zero). In turn, this would mean that under the per unit baseline there would be no incentive to bring such activities into use (i.e. if $ne_p(X_p,O_p)/X_p = Bne$). To correct for this we partition the X_p terms into terms that are operating at "reasonable" non zero levels (X_{pr}) and those that are "unreasonably small" (X_{ps}). We will also use the per unit baseline approach for X_{pr} but a perfect baseline approach for X_{ps} as follows:

$$Max\ pr * \left(f_{pr}(X_{pr},O_{pr}) + f_{ps}(X_{ps},O_{ps}) + f_{np}(X_{np})\right) - \left(\ c_{pr}(X_{pr},O_{pr})\right.$$

$$\left.+c_{ps}(X_{ps},O_{ps}) +\ c_{np}(X_{np})\right) + op * (OIO_{pr} +\ POIO_{ps}) \tag{11}$$

$$S.T.\ ru_{pr,i}(X_{pr},O_{pr}) + ru_{ps,i}(X_{ps},O_{ps}) + ru_{np,i}(X_{np}) \le b_i, \tag{12}$$

$$ne_{pr}(X_{pr},O_{pr}) - Bne * X_{pr} - OIO_{pr} = 0, \tag{13}$$

$$ne_{ps}(X_{ps},O_{ps}) - OIO_{ps} = 0, \tag{14}$$

$$ne_{np,i}(X_{np}) - NOIO = 0, \tag{15}$$

$$POIO_{ps} \le OIO_{ps} - (BL_{ps}^{b}) \tag{16}$$

Where $POIO_{ps}$ is the amount of offsets paid for that were created by opt in producers for the small category of offsets and BL_{ps}^{b} is the amount of those items in the baseline. This gives producers of the "reasonable" non zero level opportunities (X_{pr}) an incentive to do better than the average current per unit offsets in a region while giving producers of those that are "unreasonably small" (X_{ps}) an incentive to move beyond the total amount in the baseline. This will be called the ***hybrid baseline*** scenario below.

Note another approach could also be used where one computes the small amount of offsets by the total potential activity levels

$$Bne_{ps} = (OIO_{ps}^{b} + NOIO_{ps}^{b})/(Potential_{ps}) \tag{17}$$

Thus if there was a small amount of afforestation in an areas (say 1,000 acres) relative to the afforestation potential (say it is judged to be 10 million acres) then one could take the total base offset amount from the 1,000 acres and divide it by 10 million making the per acre amount 1/100,000 smaller and use this as the per acre *Bne* amount. This is not investigated herein as we don't have estimates of regional potential for bioenergy and afforestation.

2.4 Structure of FASOM-GHG Model

The modeling approach used in this study is based on the Forest and Agricultural Sector Optimization Model (FASOMGHG) that has been used in the EPA RFS analysis (EPA 2009; Beach and McCarl 2010; Beach et al. 2010) plus in prior carbon market studies (Lee, McCarl and Gillig 2005; Murray, McCarl and Lee 2004) . It is also an extension of the ASMGHG agriculture only GHG model (Schneider and McCarl 2003). FASOMGHG is a dynamic, nonlinear programming model of the US forest and agricultural sectors(Lee 2002; Adams et al. 2005; Beach et al. 2010).It is an inter temporal optimizing model that simulates behavior in the agricultural and forestry products market and land in response to market forces. The objective function of this dynamic optimization is to maximize the net present value of the sum of producers' and consumers' surplus across the agriculture and forestry sectors over the planning horizon while all the markets are at perfectly competitive market equilibrium. Commodities and factor prices are endogenous, determined by the supply and demand relationships in all markets included within the model. The constraints of the model includes crop and livestock mixes; resource limits for land, water, and labor; balances on primary, secondary, and blended feed commodities; trade balances; and GHG balances. This model structure simulates market equilibria under perfect competition in the product and factor markets and thus simulates what would happen under the alternative offset programs.

The GHG payment is dedicated to those net GHG reductions above the baselines from agriculture, including sequestration activity. To calculate for the gain in GHG under a model scenario, we need to subtract off the baseline from the GHG offset. Different GHG price signals, mitigation policy, production possibilities, and management can lead to different GHG reduction activities. Due to net change in GHG computed by the account-specific GHG balance equations, the payments can be either positive or negative. The GHG amounts reflect emission activity, sequestration activity, and biofuel related offset activities. The GHG prices will be exogenous to the agricultural sectors and it is a fixed GHG price on a carbon equivalent basis. This is a reasonable assumption given that approximately 84% of US GHG emissions arise in the energy sector, so it is clear the energy sector will play the primary role in carbon price determination (Adams et al. 2005). To do an opt in analysis, the FASOM-GHG model was modified to allow agricultural producers to voluntarily enter a carbon crediting program. The objective functions and constraints are adapted under each scenario.

FASOMGHG quantifies the GHG emission stocks produced and sequestered by agriculture and forestry. Also, the GHG emission reductions in other sectors caused by mitigation actions in agriculture sector could be followed by FASOM. The GHGs that are counted in the model are: CO_2, CH_4, and N_2O. Since some of the agriculture activities have multi-GHG impact, we need to do multidimensional trade-offs between model variables and net GHG emissions. 100-year global warming potential (GWP) values, helps us with this trade-offs in the model. All the GHGs are converted to carbon dioxide equivalent. FASOMGHG model uses the IPCC GWPs for the GHGs as follows:

- $CO_2 = 1$ $CH_4 = 21$ $N_2O = 310$

Major categories of GHG mitigation strategies included in FASOMGHG is listed in Table 1, along with the GHGs directly affected by each.

To calculate the per acre scenario, we have defined different baselines categories regarding specific activities in agricultural sector. To calculate these baselines all types of GHG emission emerging from each activity has been taken into account. Here are the GHG accounts that have been considered in this study:

Baseline_agtill	Baseline offset from tillage
Baseline_crop	Baseline offset from crop production
Baseline_croptopastchange	Baseline offset from crop to pasture land use change
Baseline_cropfrompastchange	Baseline offset from pasture to crop land use change
Baseline_foresttocropchange	Baseline offset from forest to crop land use change
Baseline_forestfromcropchange	Baseline offset from crop to forest land use change
Baseline_bioenergy	Baseline offset from bio energy
Baseline_enteric	Baseline offset from enteric fermentation
Baseline_manure	Baseline offset from manure
Baseline_bioenergypen	Baseline offset from bio energy penetration
Baseline_idlepasture	Baseline offset from idle pasture
Baseline_pasturelandusechange	Baseline offset from pasture land use
Baseline_grazinguse	Baseline offset from grazing land use

For instance to calculate baseline_crop, all net emissions related to crop will be taken into accounts. This includes carbon dioxide from soil sequestration, diesel use, grain drying, irrigation pumping, and histosols coupled with the nitrous oxide from fertilization plus a few other cases. Notice in this case each one of these GHG is multiplied by its GWP to convert it into a carbon dioxide equivalent measure. Also to calculate the unit, we need to add up all the cropped acreage in the solution of base case for a crop. The per acre baseline then is calculated by dividing total GHG from cropping by total crop units.

Table 1 GHG mitigation strategies

Source/Sink	Mitigation Strategy	GHG Affected CO_2	CH_4	N_2O
Forestry				
Afforestation	Sequestration	X		
Reforestation	Sequestration	X		
Timberland management	Sequestration	X		
Harvested wood products	Sequestration	X		
Agriculture				
Manure management	Emission		X	X
Crop mix alteration	Emission, sequestration	X		X
Crop fertilization alteration	Emission, sequestration	X		X
Crop input alteration	Emission	X		X
Crop tillage alteration	Emission, sequestration	X		X
Grassland conversion	Sequestration	X		
Irrigated/dry land conversion	Emission	X		X
Rice acreage	Emission	X	X	X
Enteric fermentation	Emission		X	
Livestock system change	Emission		X	X
Livestock herd size	Emission		X	X
Bioenergy				
Conventional ethanol	Fossil fuel substitution	X	X	X
Cellulosic ethanol	Fossil fuel substitution	X	X	X
Biodiesel	Fossil fuel substitution	X	X	X
Bioelectricity	Fossil fuel substitution	X	X	X

*Source: (Adams et al. 2005).

In the hybrid scenario the bioenergy baseline is defined only in terms of the processing regarding amount of bioenergy production in gallons of fuel or BTU of bioelectricity and we force it to use crops from opt in production. The bioenergy forms modeled are

- Biofeedstock for electricity generation from energy crops such as switchgrass, willow and hybrid poplar also it could be from milling residues, or forest logs.

- Biofeedstock for conventional and cellulosic ethanol produced from corn, switchgrass or other agricultural energy crops.
- Biofeedstock for biodiesel.

In a mitigation practice if the final emission is less than the baseline's emission and the sequestration is more than baseline' sequestration then pursuing that GHG mitigation leads to doing better than in baseline.

2.5 Results

We start running a zero baseline scenario and show non additionality and leakage effects of no baseline in the model. We then present the additionality gained by using per unit and hybrid scenario. We also compare participation rate and leakage changes for carbon equivalent price variations. Marginal cost of zero, perfect, per unit and hybrid baselines are also presented. At the end we show market and welfare effects and also international leakage under per unit and hybrid scenarios.

2.5.1 Additional GHG Abatement and Baseline Approaches

A major issue regarding voluntary offset program is to study its effectiveness in reaching the environmental aims compare to the business as usual case (Ferraro and Pattanayak 2006). In the other words, the program designers are seeking additional improvement regarding GHG offsets. One likely element of causing non additionality is that participants of the program have been mitigating in the absence of any program. The other elements of non additionality relates to non-participants in the program. The overall additionality of the program is not just the amount that the participants would add to GHG abatement, since emission could increase by those who are not enrolled in the program (Segerson 2013). This is a source of leakage.

To address concerns about additionality including this non participant leakage; we present offsets by participant, emission by non-participants (leakage) and net GHG offset (additional amount) in a voluntary program with a zero baseline in Figure 2 for a range of carbon equivalent prices. As this figure is displaying, the additional offset is lower than what participants claim since part of it is reduced by increased emissions from non-participants out of the program. As a result, the payment to participants for GHG abatements is much higher than what is truly additional and this is not cost effective. Thus a baseline is needed.

Including a non zero baseline in the voluntary carbon offset program can help the policy designer to make a more effective program. Here the baseline will be calculated under no program situation and we will pursue different means of subtracting the "what would have occurred amount" from GHG abatements produced by participants. In this study, as we explained before we simulated our model and compare the results of scenarios under perfect, per unit and hybrid baselines.

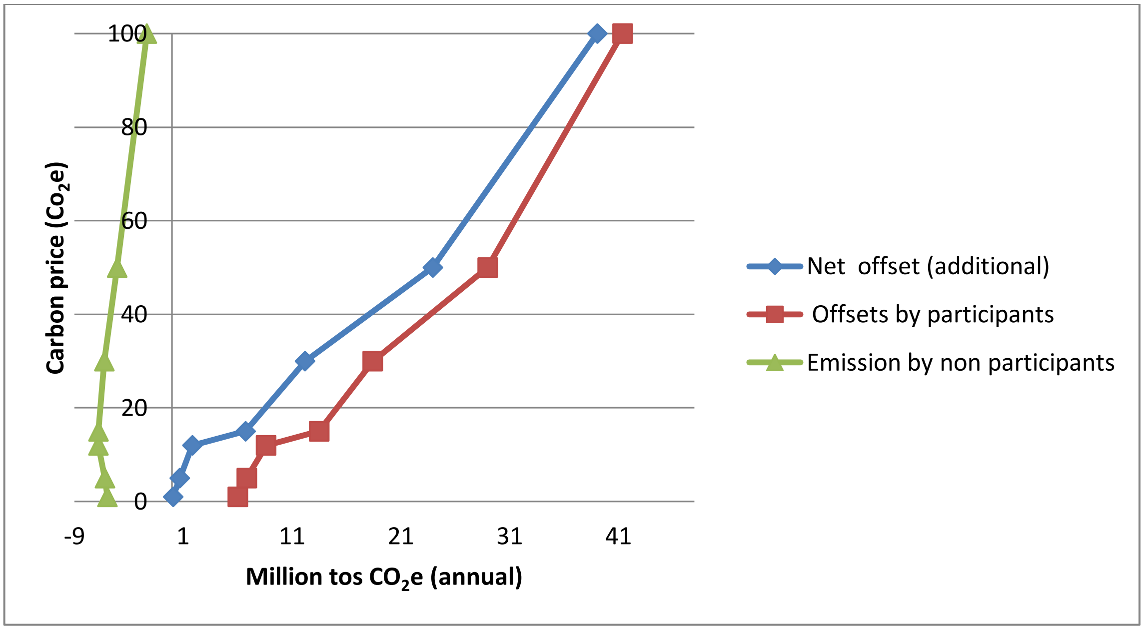

Figure 2. Presenting non additionality concern in a voluntary program.

Implementing the perfect baseline to account for full additionality, in the real world would be very demanding given the information required to compute credits. But it is an informative scenario in our study, since it provides the best case outcome.

In Figure 3, we present results on the additional offsets and the offsets by participants under each baseline at 30 \$ CO_2e. Additional offsets are calculated by computing participants' offsets minus non participants' emissions as they differ from the base case (no program). As one can see in Figure 3, by including baseline in per unit and hybrid scenarios we gain more additionality. As one can see the amount of non additional offsets paid for is highest under the zero baseline case and is lowest under the perfect baseline.

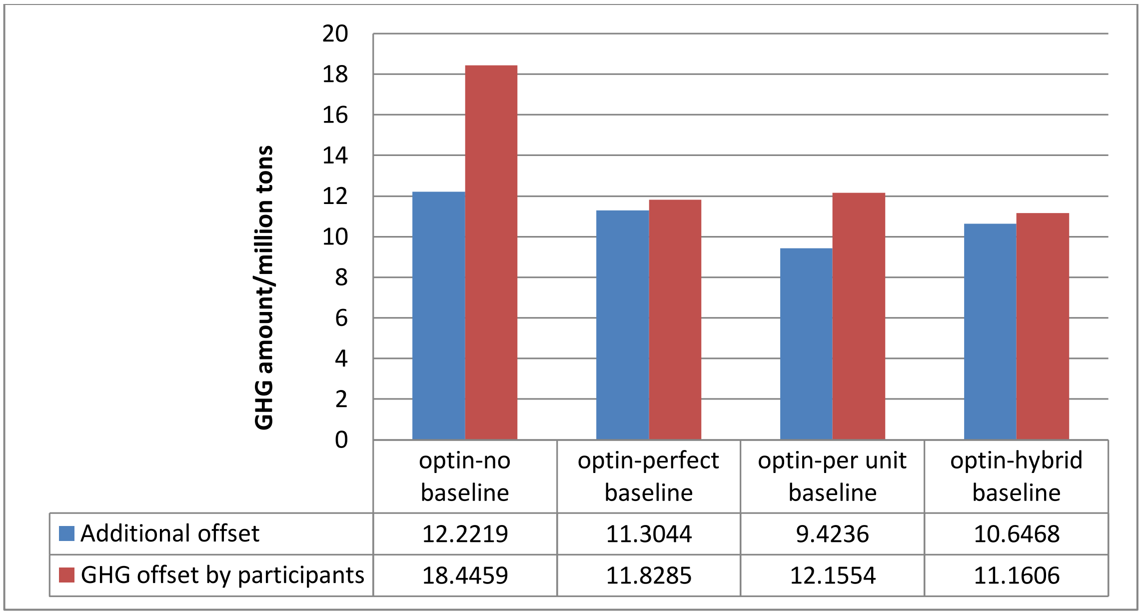

Figure 3. Additionality gained by including baseline in the program design.

2.5.2 Participation Rate and Carbon Price Effect

The offsets sold into the program for the cases of the mandatory program and the voluntary programs with zero baseline, perfect, per unit and hybrid baselines are presented for a range of carbon equivalent prices in Figure 4. The highest participation rate among the voluntary program baseline alternatives is for the program with zero baseline since non additional abatement producers are also included in the payment plan which is not cost effective. We will compare the program's marginal cost in next section.

As one can see in Figure 2, the quantity of GHG abatement that is purchased from participants rises under each program as the carbon price increases. Mitigation strategies vary as carbon price changes. More high cost mitigation practices are possible under higher CO_2e prices, and that is the reason for the increasing abatement rate at higher CO_2 prices. At lower carbon prices low cost strategies such as change in tillage practice, fertilizer application, diet and manure management, which are more consistent with existing production are used and higher carbon prices shift the mitigation activities to forestry and biofuels (McCarl and Schneider 2001).

For lower CO_2e prices the participation rate for GHG abatement in the per unit scenario is higher or very close to the abatement under the perfect baseline. For instance at 12$ CO_2e, the abatement under the per unit baseline is about 4.5 times more than that under the perfect baseline. But this ratio changes for the prices higher than 30 $ CO_2e, with the per unit amount being 16% less than that the perfect baseline at a 100 $ CO_2e price. This is largely because the bioenergy possibilities are not being pursued because of the closeness of the per unit baseline to the potential amount and the fact that this does not allow expansions in scale (as discussed under the formation of the hybrid baseline above). The hybrid baseline scenario alters this and shows offset levels close to the perfect baseline.

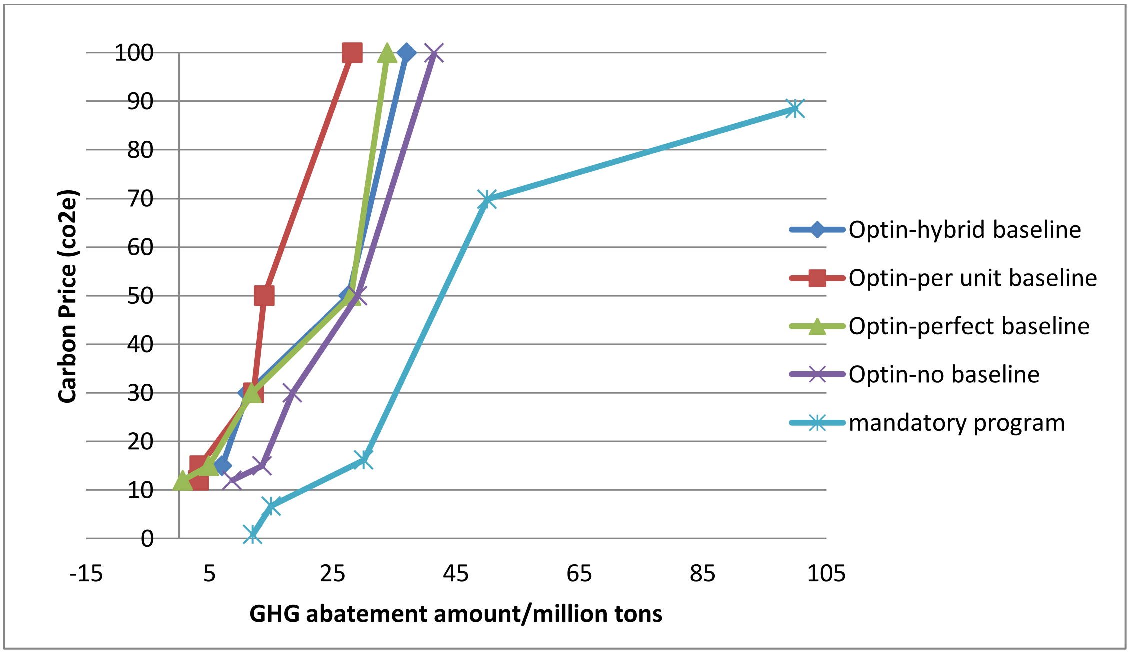

Figure 4. Annual GHG offset by participants in each program changing with CO_2e prices.

The relative reduction in total GHG offset from the no program (base) is compared among the scenarios in Table 2. For instance at 30 \$ CO_2e the level of overall GHG offset under the mandatory program is about 1.5 times higher than that under the per unit baseline program. Although the mandatory program generates the maximum GHG mitigation potentials in agriculture sector, there are arguments against mandatory carbon offset programs in agriculture due to food security and property rights issues plus virtually all discussion today involves voluntary participation.

Table 2 Relative change from base for total GHG annual reduction in million tons CO_2 equivalent.

Carbon Price (CO_2e)	mandatory	optin-zero baseline	optin-perfect baseline	optin-per unit baseline	optin-hybrid baseline
30	0.285	0.215	0.199	0.166	0.187
50	1.228	0.422	0.49	0.2	0.481
100	1.557	0.687	0.584	0.475	0.654

Higher Carbon prices reduce non additionality through reduction of non participant leakage. The relationship between carbon price and non participant leakage is presented in the Figure 5 for the per unit and hybrid baselines and also for the zero baseline scenario. Higher carbon prices create more participation incentives, and so the scale of optin offset is larger and the leakage effect is smaller (Murray, McCarl and Lee 2004) as one can see in Figure 5. The leakage decreases the stricter the baseline.

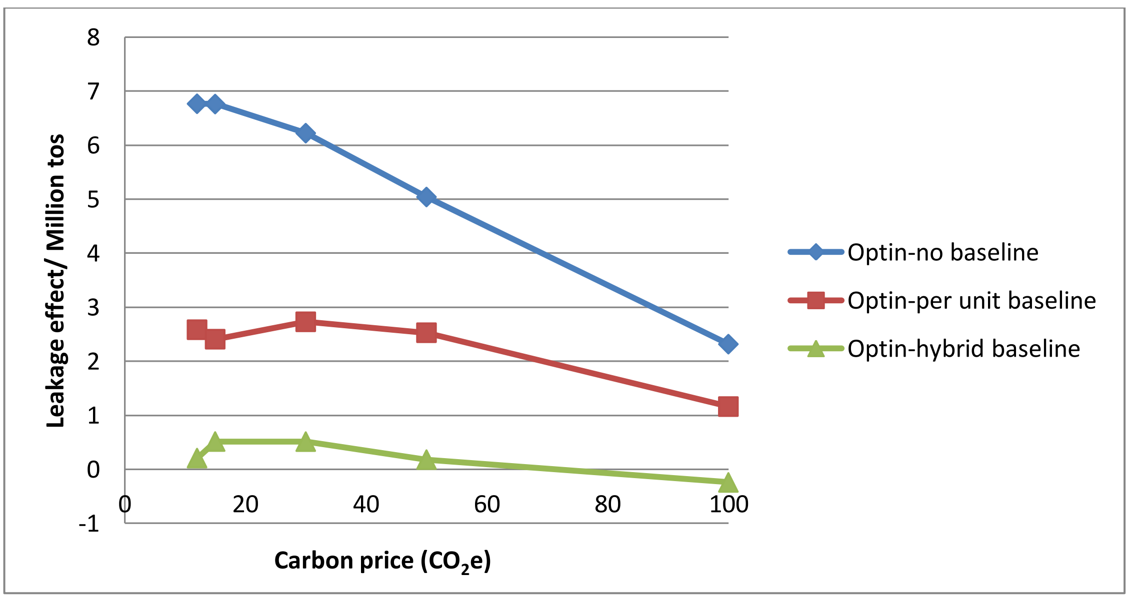

Figure 5. Leakage effects as a function of carbon price.

2.5.3 Marginal Cost of GHG Offset

We compute the "program marginal cost" in each scenario using an annualization approach described by Richards and Stokes (2004) and Im et al. (2007). Program marginal cost is calculated as the difference in annualized net carbon payment divided by additional annualized carbon offset for each carbon price increment (Im et al. (2007) ; Latta et al. 2010). The carbon payment in this study goes to the offsets produced by those who participate in the program. But the amount of offset we consider in the calculation is only the additional ones to the base case.

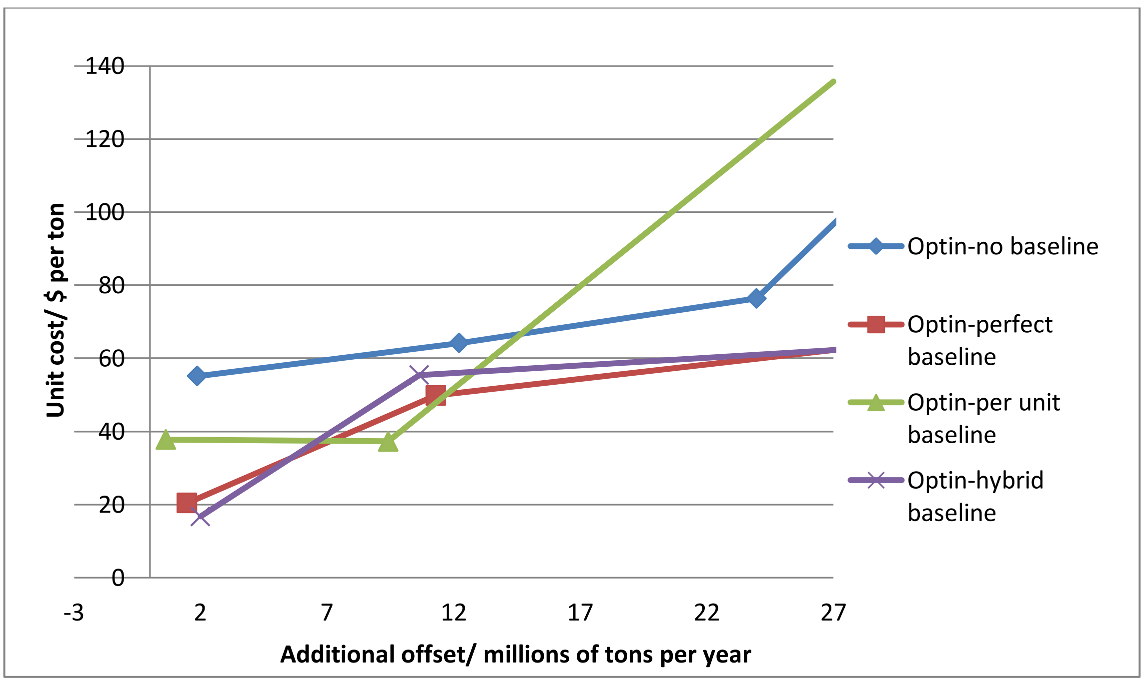

Figure 6. Program marginal cost of additional offset.

Figure 6 presents the program marginal cost under each baseline scenario in this study computed across alternative offset prices. The marginal cost of program in the zero baseline case is higher than that under the perfect baseline. That is because the payment to the non-additional producers is eliminated in the perfect baseline so the program cost decreases. The per unit baseline scenario's marginal cost is below the perfect baseline scenario's marginal cost when the carbon price is around 30$ CO_2e. Also for more than 15 billion tons offset per year, the marginal cost of per unit baseline scenario would grow higher than no baseline case. The reason is lack of incentives for biofuel related mitigation activities at per unit baseline and thus other more expensive alternatives are used at higher carbon prices. Therefore the rate of claimed offset to additional offset gets higher for per unit scenario compare to no baseline scenario. The marginal cost of hybrid baseline is less than no baseline and it is close to perfect baseline at all the prices and offset ranges since it makes more incentives for biofuel production and more additional offset is happening.

The comparison of total program cost between per unit and hybrid scenario is also presented in Figure 7. As one can see in Figure 7, the program cost in hybrid scenario is less than that under the per unit baseline, since the hybrid scenario allows growth in the bioenergy category and makes the offset program more efficient (higher relative additionality).

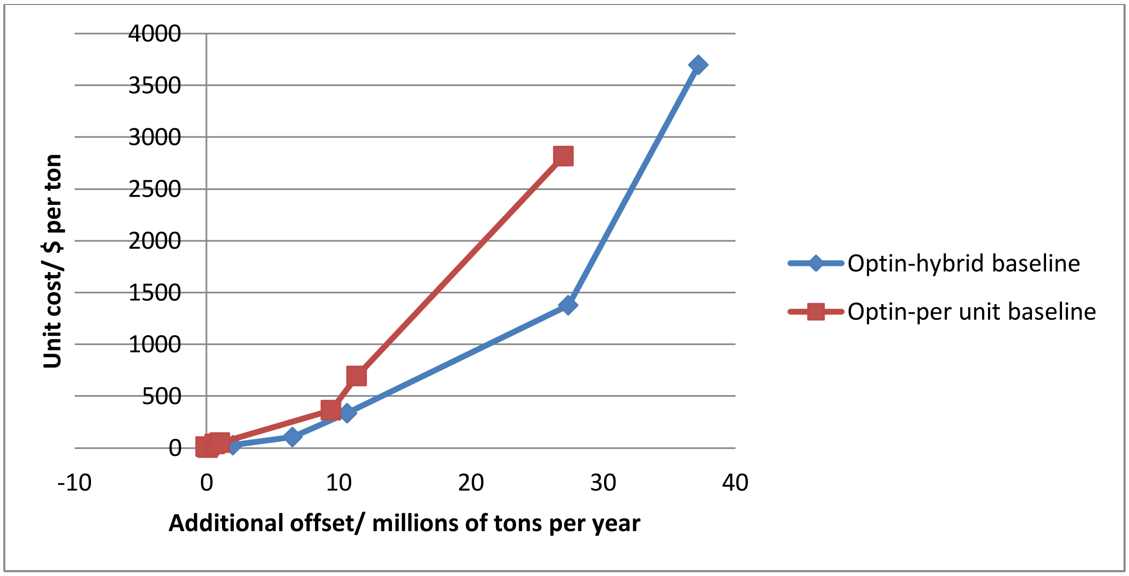

Figure 7. Total program cost of additional offset for per unit and hybrid baseline scenarios.

2.5.4 Market Effects

Large scale mitigation efforts in US agriculture are likely to decrease traditional agricultural production and therefore increase related commodity prices and land values (Schneider and McCarl 2003). The fisher index price of farm product and processed product is showing relative rise of 0.54 and 0.60 from base respectively in per unit scenario for 50 $\$CO_2e$ by the year 2025. Also the farm production and processed commodity production decrease 0.58, 0.50 from base case in this scenario. The fisher price and production indices are reported in Table 3.

As Schneider and McCarl 2003 discussed, the effect of carbon prices on emission intensive technologies provide incentives for alternatives makes farmers to shift more land to mitigation strategies and reduce production. The results of our estimation of US export of farm product shows 0.41 relative decrease with respect to the base case in per unit scenario by the year 2025.

2.5.5 Welfare Distribution

Agricultural welfare impacts of the per unit baseline with respect to carbon equivalent prices are shown in Figure 8. Consumers' welfare decreases slightly because of higher commodity prices. On the other hand, producers' welfare increases as emission reduction is now a source of income and the abatement adds to welfare (Schneider and McCarl 2003). Less agricultural production and higher prices cause the producer's surplus to increase. The rate of growth in producers' welfare increases at higher CO_2e prices. The surplus discussed here does not cover the social cost and benefits of externalities such as the value of GHG emission reduction or changes in erosion.

Also foreign welfare; which is the sum over foreign consumers and producers welfare is slightly decreasing. Foreign consumers would be worse off because of less US export and higher commodity prices, but foreign producers would gain advantage due to less US export. In total the loss in foreign consumers' welfare exceeds the gain in foreign producers' surplus. Also the total welfare in agriculture sector is increasing since the increase in producer's welfare offsets the losses in consumers and foreign welfare.

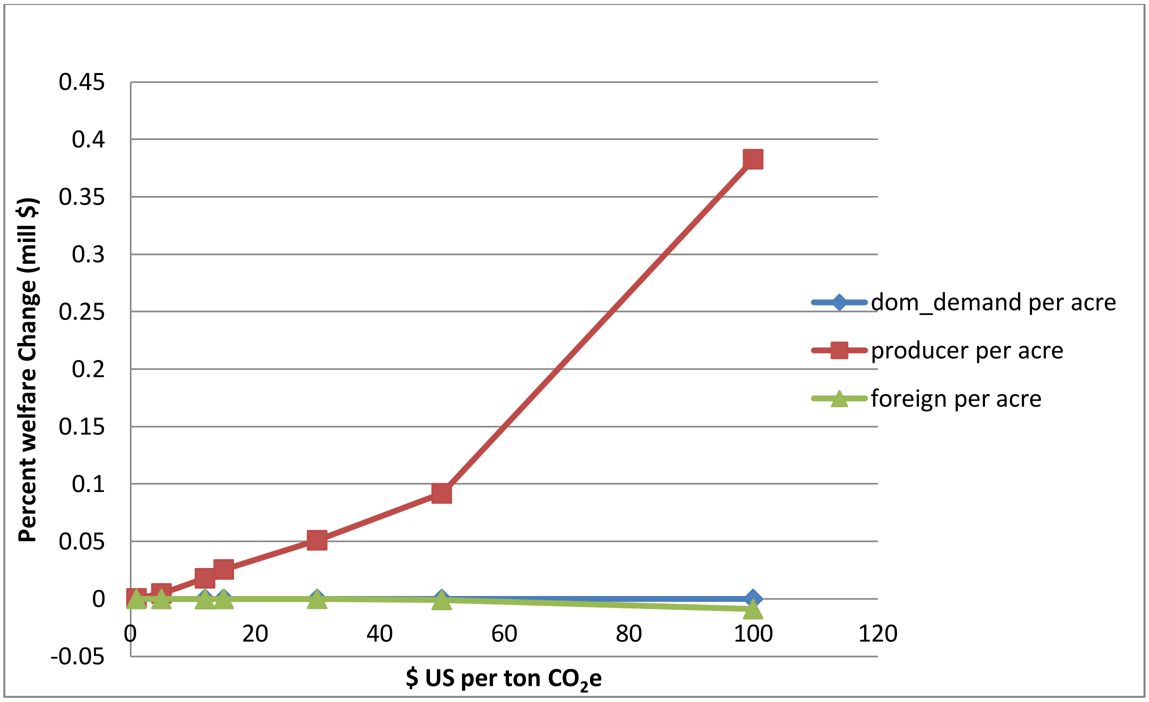

Figure 8. Annual welfare distribution in per unit scenario.

We have also presented results on the comparison of consumers', producers' and foreign welfare under the per unit and hybrid baseline scenarios in Figure 9. The consumer's welfare decreases under the hybrid scenario because of higher prices at higher carbon prices compared to the per unit baseline caused by the greater amount of bioenergy production.

Also the production will decrease in the hybrid scenario compare to per unit baseline scenario. One can compare national production, price and export price of farm products and processed commodities between two scenarios at Table 3. In addition, lower export from US causes the foreign welfare to decrease as presented in the Figure 8 and Figure 9.

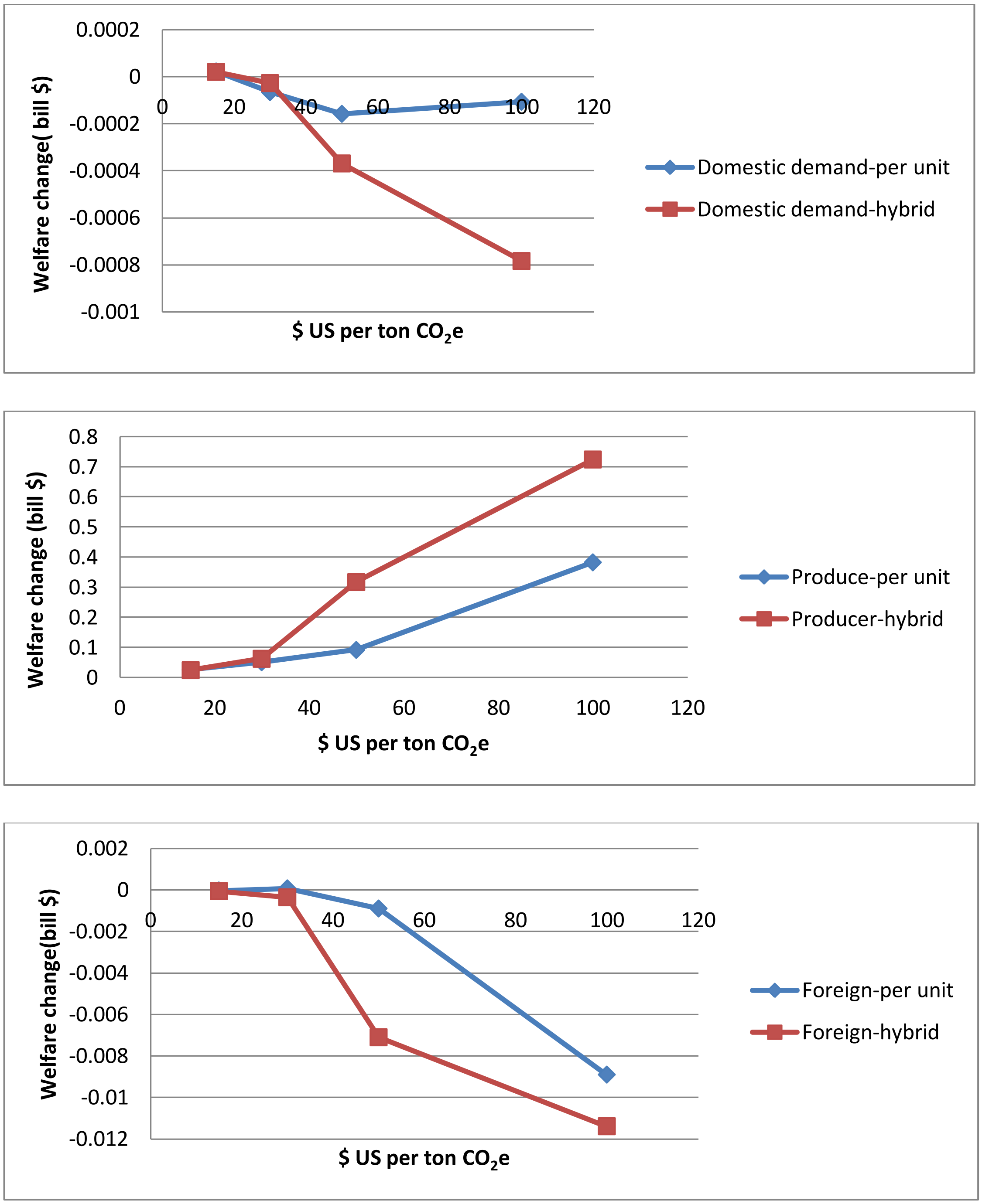

Figure 9. Comparison of welfare change in per unit and hybrid scenarios.

Table 3 Production, Price and Export Index comparison in per unit and hybrid baseline scenarios at 2025.

National Index	Per unit baseline	Hybrid baseline	Per unit baseline	Hybrid baseline
	50 $ CO_2e		100 $ CO_2e	
All Farm Production	-0.58	-2.37	-1.82	-3.57
All Farm Price	0.54	2.31	1.77	2.43
All Farm Export	-1.61	-3.35	-2.34	-5.2
All Processed Production	-0.05	-0.31	-0.28	-0.46
All Processed Price	0.6	2.48	2.44	3.71
All Processed Export	-0.8	-4.37	-4.24	-6.89
Livestock Production	0.19	-0.13	0.2	0.05
Livestock Price	0.03	0.69	0.16	1.87

2.5.6 International Leakage

GHG mitigation policies in one country can cause additional production and consequently emission increases in another country which called international leakage. Regulation in one country may shift production to other countries because of a shift in comparative advantage. In this work we also study the effects of US voluntary carbon offset market on international production and from that infer leakage. For this reason we present the export and price index of some selected countries such as NC-Euro, West Africa, China and Brazil in Table 4 and Table 5. Table 4 presents the comparison of the export and price indices for an optin program with a zero baseline and the per unit baseline at 50 $ CO_2e. The results indicate less increase in the export and price index in all countries except for the Euro region under the per unit baseline compared to the zero baseline case. This means that under the per unit baseline international leakage is likely to be less compared to the zero baseline case. Increase in export of a country shows higher production in those countries and as a result portends higher GHG emissions.

Table 4 Annual percent change from base in export quantity and price change under different baseline scenarios at 50 $ CO_2e.

	No baseline		Per unit	
	Export	price	Export	price
NC-Euro	-0.0400	0.8000	0.2400	1.9500
W-Africa	0.9100	1.9300	0.2500	0.4100
China	11.7600	4.2800	1.9200	0.5300
Brazil	0.4700	1.5600	0.1800	0.4800

Table 5 Annual percent change from base in export price and quantity in per unit and hybrid baseline scenarios.

	30$ CO_2e		100$$CO_2$e	
	Export	price	Export	price
Optin per unit baseline scenario:				
NC-Euro	0.26	2.15	-0.27	0.20
W-Africa	0.07	0.00	0.91	2.03
China	0.08	-0.11	12.49	4.88
Brazil	0.42	0.00	0.60	2.20
Optin hybrid baseline scenario:				
NC-Euro	0.56	2.05	0.20	-4.49
W-Africa	0.00	0.07	-0.66	2.39
China	0.59	0.21	17.61	8.78
Brazil	0.18	0.45	1.17	3.59

Also the international leakage is compared for two carbon prices under the per unit and hybrid baseline cases in Table 5. Price and Export index shows an increase as the carbon price rise except for the region NC-Euro. The reason could be less US production plus fewer exports from US to other countries at higher carbon prices (as one can see in Figure 3). Also the international leakage in hybrid baseline is larger at higher carbon prices again due to higher bioenergy production and more diverted conventional production, as one can compare the results of 30 and 100 \$ CO_2 in Table 5.

2.6 Conclusions

Here we examined alternative designs for agricultural participation in a voluntary GHG mitigation trading scheme. Examining the consequences of alternative baselines for participation we find the baseline specification is very important relative to program cost and additionality. In particular, when producers are able to opt in with a zero baseline, we find the highest participation rates, but the smallest amount of additional offsets because of countervailing actions by non-opted in producers plus the participation of many with non additional, business as usual, practices. This occurs since there is no baseline that eliminates market entry by business as usual, non-additional participants. Thus the volume of claimed offsets is high but the additional amount is low with much paid to non-additional producers. Therefore we conclude that a baseline is essential.

In turn we examine the consequences of alternative baseline cases measuring their effectiveness in terms of additionality, leakage and program cost. First we introduce a perfect baseline scenario paying only for GHG mitigation above the levels in the baseline which embodies a strong assumption of no hidden information that prohibits non additional offsets from entering the program. While this generates the most additionality among the optin cases we believe it is virtually impossible to implement.

Second we suggest a per unit baseline where we assign all mitigation activities on a per acre or per animal or per unit bioenergy produced GHG amount that they must do better than in order to be paid. We find this baseline works well but generates substantially less offsets at higher prices due to its discriminatory effects against bioenergy alternatives that are little used in the baseline case. In particular we find the per unit baseline works best when the units of the potential implementation are essentially equal to their without carbon price levels - when the acres are all farmed or animals produced. However this does not do well when the per unit emissions are close to the baseline per unit amount and the volume produced is small. In that case the incentive to do better than the baseline per unit amount distorts the incentive to vastly expand the units produced above the baseline levels.

Thus we introduced a hybrid baseline where for the strategies with small unit levels in the base situation need to do better than the total offset in the base model. In that case substantially more offsets are realized with a smaller program marginal cost.

The results of this study shows that when moving away from a mandatory program a scalable per unit baseline is critical with adjustments for items one wishes to allow to expand in scale.

In this study we have also considered the effect of voluntary carbon offset market with per unit and hybrid baselines on price, production and export indices for US. The results showed a rise in agricultural prices and a fall in production and export of farm and processed commodities. Encouraging mitigation efforts through carbon offset markets in US agriculture is likely to decrease traditional agricultural production and therefore increase related commodity prices and land values. Higher commodity prices and less production lead to lower consumers and higher producers' surplus. Less exports from US to other countries also causes the overall foreign surplus to decrease. Since biofuel is more encouraged under hybrid baseline, producers' surplus is higher than in per unit baseline scenario.

Studying price and export indices of some selected countries helps in appraising whether there might be an increase in international leakage if a voluntary carbon offset program is implemented. Results showed that using a per unit baseline in the voluntary programs decreases the international leakage. Also at higher carbon equivalent prices the international leakage is higher except for NC- Euro.

CHAPTER III

ECONOMIC ANALYSIS OF GROWING SWITCHGRASS ON MARGINAL LAND

3.1 Introduction

Energy independence, reducing greenhouse gas (GHG) emissions and rural economy enhancement are some of the main reasons for promoting biofuel production in the US. The biofuel requirements under the Energy Independence and Security Act of 2007, also called RFS2, mandates increasing the biofuel volume to 36 billion gallons by 2022, of which 16 billion gallons will be cellulosic biofuel (Renewable Fuels Standard Association, 2012).

Producing biofuel and devoting cropland to biofeedstock production raises the challenging discussion of food versus feed involving diverted land, reduced conventional production, and accompanying price rises. Researchers raise two main concerns to the renewable fuel mandates. First, the reduction of cropland devoted to food and feed production lowers aggregate production and leads to higher food prices (Runge and Senauer 2007). Second concern that the resultant higher food prices causes development of lands elsewhere with possible deforestation and associated GHG emissions (Searchinger et al. 2008; Fargione et al. 2008).

The primary feedstock for US ethanol production is maize or corn (*Zea mays*) grain and also sorghum (*Sorghum bicolor*), but the RFS2 imposes a maximum amount on ethanol from such sources. This coupled with competing feed and food demands for grain supplies leads attention to ligno cellulosic biofeedstocks (Schmer et al. 2008) such as switchgrass, crop residues, and woody biomass (Philp, Guy and Ritchie 2013). Cellulosic biofuels can also achieve higher GHG emission reduction compared to conventional biofuel (almost 3 times) (Renewable Fuel Association).

Recently feedstock production on marginal lands has been the subject of increased attention by bioenergy producers and policy makers. Milbrandt et al. (2014) defines marginal land as land with inherent disadvantages or lands marginalized by natural or artificial forces (or both). This type of land usually has low economic value due to its low productivity or high cost to cultivate. In the literature, this type of land has been called low-quality land as well. Using marginal land instead of cropland to produce cellulosic biofuel may overcome some of the fuel versus food-feed criticism of RFS we discussed before.

In this study we will examine the economic implications of growing switchgrass (Panicum virgatum L.) on marginal land under RFS requirements. Key agronomic advantages of switchgrass as a bioenergy crop are its stand longevity, relatively low herbicide and fertilizer input requirements, drought and flood tolerance, ease of supervision, hardiness in poor soil and climate conditions, and widespread adaptability in temperate climates (McLaughlin and Adams Kszos 2005). Switchgrass is a perennial that once planted lasts 10 years or more, but can be harvested every year by conventional hay equipment (Jensen et al. 2007). Furthermore switchgrass can relatively produce high yield on marginal land plus it needs less fertilizer and pesticides, and helps in emission reduction of both water and GHGs (Robertson et al. 2011).

Switchgrass as a biofeedstocks can be used in production of energy following several different methods. It can be used to produce cellulosic ethanol which is more efficient than grain based ethanol through a process of fermentation. Also it can be used alone or cofired with coal or other fossil fuels to produce heat or electricity; and it can be used to produce ethanol or other synthetic biofuels through gasification or pyrolysis (Jensen et al. 2007).

This research analyzes the economic implications and cost competiveness of growing switchgrass on marginal land. We will simulate the amount of switchgrass that is produced on marginal land under RFS2 and compare the production patterns and market conditions with and without using marginal land under alternative carbon prices. To do this we will use the Forest and Agricultural Sector Optimization Model GHG version (FASOM- GHG) (Beach and McCarl 2010; Adams et al. 2005).

Specifically we will examine how use versus non use of marginal land in the form of the USDA land classification cropland pasture can contribute to fulfilling the RFS2 cellulosic biofuels requirements, under carbon prices of zero, 5, and 30 $per ton CO_2e. Moreover, we will examine the change in GHG offsets crop prices and welfare.

3.2 Brief Literature Review

Some recent studies have addressed marginal land potentials and possibilities to grow switchgrass. Milbrandt et al. (2014) examined the potential for rising energy crops including switchgrass on marginal land using crop yield estimates by county, and show that biomass on marginal land could produce about 1.9 PWh (petawatthour) of electricity. They also indicate that high yields of switch grass on marginal land cause production to be more probable in the Eastern States and the North West (reaching more than 8 t/acre in some counties), with very poor performance is expected in the dry West.

Gelfand et al. (2013) estimate that 21 gigaliters of ethanol per year could be generated by growing biomass crops on marginal lands, which is equal to approximately 25% of the 2022 target for cellulosic ethanol under the RFS2 mandate. Schmer et al. (2008) estimate that cellulosic ethanol derived from marginal land switchgrass could produce greenhouse gas (GHG) emissions that on average are about 94% lower than estimated GHG emissions from gasoline.

Choice by a farmer on how to use her land depends on profitability of growing a crop. Profitability depends on opportunity cost of using that land for its other options along with input and output prices. Mooney et al. (2008) studied how switchgrass yield is influenced by seeding and nitrogen fertilization rates in low and intermediate environments, also they studied the economically optimal seeding rate and nitrogen fertilization rate. They show that for an expected stand lifespan of 10 years, production costs changed from \$45 per ton in an ideal production environment to \$70 per ton on marginal lands. Recent US policies on promoting biofuel have created higher demands for biofeedstocks with accompanying price rises. This also improves the profitability of the production of biomass on lower quality, less valuable land.

Ricardo (1817) provides a basic theoretical framework for considering alternative land uses with respect to the quality of the land unit used. By this theory we can explain how increase in demand for advanced biofuel because of RFS and rise in the value of cellulosic biofeedstock will expand the range of land dedicated to these biofeedstock compare to corn. Figure 10 portrays how rise in switchgrass price will lead to low quality land expansion. As shown in the figure, the first section (up to line A) is the high quality land. Grains like corn which need good soil, are profitable on this kind of land. As the quality of land decreases, other biomass which can be produced on low quality land is desirable up until to the point that the marginal costs just equals the marginal value of the product (B). When the price of biomass increases (the dotted line) the biomass production becomes profitable in a wider range of situations. From the left some of the higher quality land previously used in corn might be used and from the right yet lower quality land will be used (to the point C) (Swinton et al. 2011).

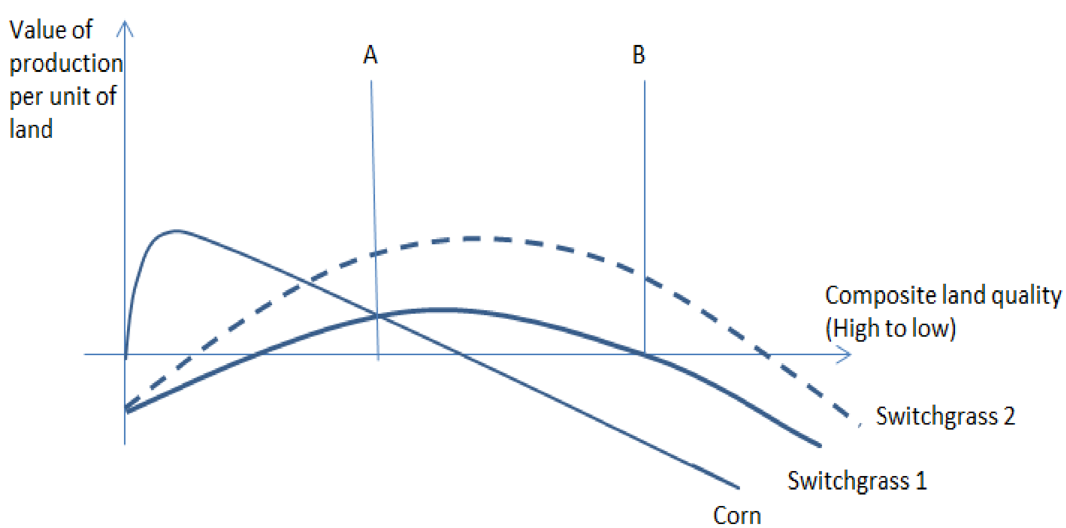

Figure 10. Production net revenue graphed over a continuum of land quality (Barlowe 1986).

Swinton et al. (2011) found that doubling the expected profitability of major crops increase the amount of lands under cultivation by 3.2%. They also concluded that a rise in biomass prices will cause increased land competition in the short term and in turn rises in conventional crop prices.

3.3 Methodology

In this work we use Forest and Agricultural Sector Optimization Model (FASOMGHG) to simulate the effects of growing switchgrass on marginal land. FASOM is a dynamic nonlinear programming, optimization model of US forest and agricultural sector (Beach and McCarl 2010; Lee et al. 2002). The optimization problem maximizes the net present value of overall welfare. The welfare is the sum of consumers' and producers' surplus plus GHG payments. The constraints of the model represent resources such as land and labor and also GHG emissions from the agriculture sector. The model depicts production of crops, livestocks and processed agricultural products in the US.

In FASOM switchgrass is a primary product and cellulosic biofuel is a secondary product. In producing switchgrass the objective function includes cost of production, costs of moving and utilizing the feedstock (hauling and transformation costs) to a point at which it substitute for fossil fuels and also demand coefficients for cellulosic ethanol and biofeedstocks for electricity. Utilization cost is associated with processing variables (McCarl et al. 2005).

For this work, a new crop - "switchgrass- marginal land" - is introduced into the model. The crop budget, cost and yield data for growing switchgrass on marginal land were obtained from the Bio-Based Energy Analysis Group at the University of Tennessee (Yu et al. 2014) in US states where they judged switchgrass could be cultivated on marginal land - Florida, New York, Wisconsin, Georgia, Louisiana, Virginia, Mississippi, Missouri, Texas, South Dakota, Wyoming. In turn "Switchgrass- marginal land" was as assumed a perfect substitute for switchgrass from crop land in producing biofeedstocks for cellulosic ethanol and bioelectricity production although with a higher hauling cost following procedures in (McCarl et al. 2000).

Table 6 presents the blending processing of "Switchgrass- marginal land" into secondary products.

Table 6 Products produced from processing of switchgrass from marginal land.

FASOMGHG name for regional non feed processing alternative	Secondary product manufactured
Switchgrass To Electricity	Tbtus
Switchgrass To Ethanol	Celluslosic Ethanol

The model will be run with the Renewable Fuel Standard mandates at the levels for 2022, with and without switchgrass on marginal land. In this research there are three main scenarios: base, mandatory and voluntary carbon offset markets. Following the discussion from previous chapter the base case is where the carbon price is zero and there is no offset market. The mandatory scenario is where the agriculture sector is entirely covered by the offset program and is paid for offsets but also incurs liabilities if emissions increase. Also the voluntary offset market in this study is where optin producers are only paid for better performance compared to the hybrid baseline. Following our discussion from previous chapter, the hybrid baseline is calculated while providing incentives for biofuel production. Therefore by voluntary program in this study we mean hybrid baseline scenario.

3.4 Results

3.4.1 GHG Effects

Direct effect of substituting biofuels for fossil fuels is offsetting GHG emissions in general. Some argue that growing cellulosic crops on marginal land could provide GHG abatement provided there is not a large release of sequestered carbon “carbon debt” and the switchgrass sequesters more than the native vegetation (Gelfand et al. 2013). However this involves a land use change releasing some carbon plus uses inputs that cause emissions and thus we need the GHG’s life cycle of production plus combustion of biofuels under base model, no marginal land conditions to exceed that when using marginal land (Mitchell, Harmon and O'Connell 2012). This involves changes in soil carbon sequestration, emissions from fertilization and machinery, and emissions from transportation of biofeedstock to the bio refinery.

The total GHG results are compared for cases with and without marginal land in scenarios of this study: base, mandatory and voluntary with hybrid baseline. These results are portrayed in Figure 11. When there is no offset program and the carbon price is zero we find the total GHG net emissions are higher under the scenario with marginal land. The results show that GHGs produced from fuel and fertilizer are higher when we use marginal land compared to no marginal land. But as one can see in Figure 11, under carbon offset programs with 30 $\$CO_2e$ we encounter a higher GHG offset under the mandatory program. The reason is bioelectricity becomes profitable when carbon has value and so switchgrass on marginal land as biofeedstocks is used to contribute to GHG mitigation via bioelectricity.

When the program is voluntary growing switchgrass on marginal land the GHG contribution is not different than that which arises under no marginal land. The total emissions increase with marginal land use due to emissions from fertilizer, fuel, and land conversion carbon debt but this is not enough to eliminate the bioelectricity gains.

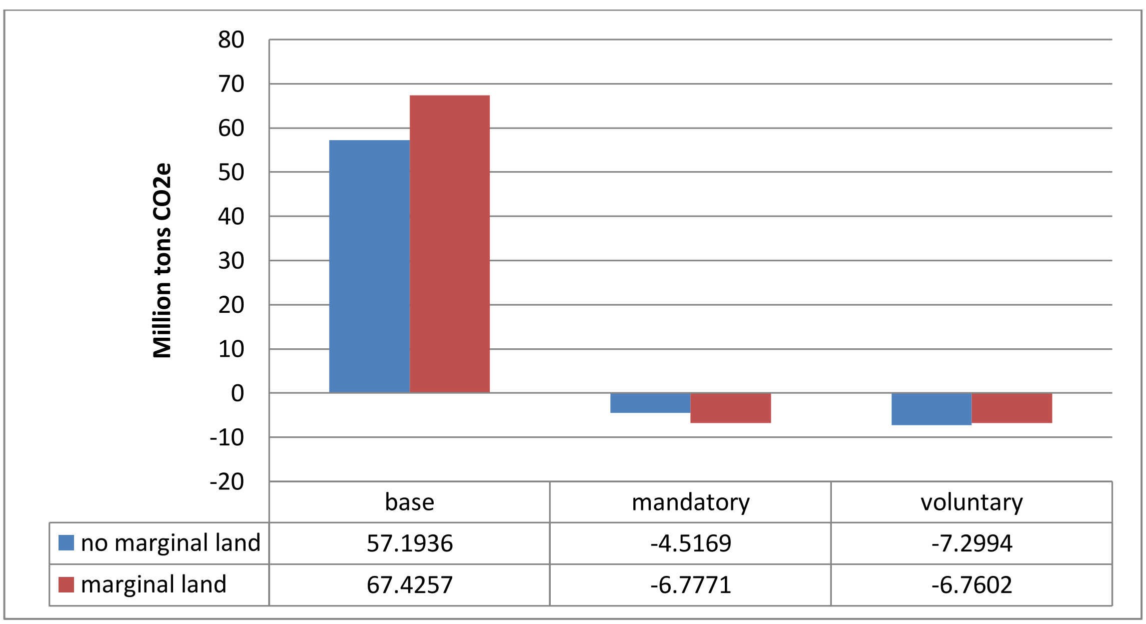

Figure 11. Total GHG annual flux in million tons CO_2 equivalent at 30$ CO_2e.

3.4.2 Production and RFS Mandate Satisfaction

Renewable fuel standard (RFS) called for production and usage of 36 billion gallons of biofuels by 2022 in transportation fuel. Of this, 16 billion gallons is expected to be from cellulosic biofuels. Switchgrass can be converted to cellulosic ethanol fuel and therefore could play an important role in fulfillment of RFS mandates.

A major concern regarding RFS mandates is land competition caused when substituting biofuel feedstocks for conventional food and feed plus the rise in commodity prices (Searchinger et al, 2008). One advantage of growing switchgrass on marginal land is to overcome the competition and production decline/market price increase problem through using the lands inappropriate for crop production. As a result one can see in Figure 12 that by using marginal lands, the acres of conventional land under switchgrass cultivation does not increase from 2015 to 2022, while the RFS requirements on cellulosic biofuel grows from 3 to 16 billion gallons. Thus the RFS requirements are fulfilled from the switchgrass on marginal lands without putting as much pressure on conventional cropland. The relative change in acres of selected conventional crops is shown in

Table 7 for years 2015 to 2025. The results are presenting increase or not significant change in acres under conventional crops production. Although the acres under corn production falls which might be due to less demand for first generation of biofuel. That makes switchgrass to substituting for corn as it is used to produce advanced biofuel.

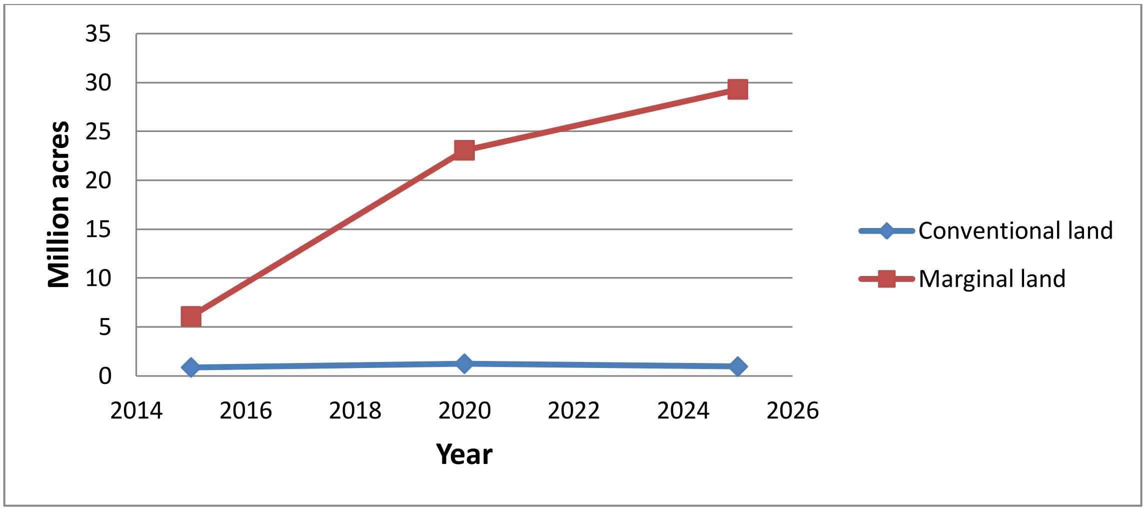

Figure 12. Acres of switchgrass production in voluntary program.

Table 7 Relative changes in million acres of conventional crop production when using marginal land in voluntary program.

	2015	2020	2025
Rice	0.00194	-0.00820	-0.00486
White Wheat	0.00026	0.02675	-0.00041
Hay	0.00030	0.00078	0.00194
Potatoes	0.00623	-0.00229	0.00089
Tomato	0.00315	0.00191	0.00129
Corn	-0.00505	-0.00170	-0.00964

3.4.3 Commodity Price and Welfare Effect

As mentioned in previous section, a major concern regarding RFS mandates to increase biofuel production is the competition over land and accordingly decreases in food and feed production and their price rise. To study the price effect we use the annual price fisher index of all farm products, all live stocks, all processed products, wheat, rice, hay in our model to compare them with and without the marginal land option. The results are presented in Table 8.

The base, no carbon price case shows the availability of marginal lands reduces livestock, wheat and rice prices by 20, 6 and 3 percent respectively compared to the results without marginal land. The livestock price fall is likely due to increases in feedstuff production. As one can see in the same table production of feedstuff such as rice and barely increased by using marginal land. Other feedstuff's production such as hay and wheat decreases.

There is a slight increase in all farm and processed products prices when marginal land is included perhaps due to the fact that marginal lands were providing pasture for cow calf operations and that this requires more intensive livestock feeding. Also farm production decreases so that may also increase the prices. The fall in other farm products could be due to generated income from marginal when it is used for producing switchgrass for bioenergy.

The results of price change when marginal land is included under carbon offset programs are also reported in the Table 8. The price changes are not perceptible as in base case but there is less than 1% increase in mandatory and voluntary programs. Under carbon offset market, switchgrass is mainly used to produce electricity rather than ethanol to be blended in motor fuel, so the effects of RFS on prices still stays.

Table 8 Annual production, price and export index change when marginal land is used in all scenarios compare to no marginal land use.

	Base	Mandatory	Voluntary
All FarmProduction	-0.0022	-0.0027	-0.0028
All FarmPrice	0.0114	0.0028	0.0046
all Farm export	0.0060	-0.0036	-0.0053
AllProcessed production	-0.0027	-0.0004	-0.0004
AllProcessed price	0.0022	0.0060	0.0058
AllProcessed export	-0.0068	-0.0095	-0.0081
AllLivestock production	-0.0054	-0.0002	-0.0002
AllLivestock price	-0.2013	0.0017	0.0041
Wheat production	-0.0091	-0.0056	-0.0055
Wheat price	-0.0665	0.0052	0.0094
Wheat export	0.03441	-0.0027	-0.0039
Rice production	0.0131	0.0002	-0.0008
Rice price	-0.0327	-0.0001	-0.0004
Rice export	0.3119	0.0002	-0.0008
Barley production	0.0335	0.0034	-0.0008
Barley price	0.0638	0.0081	0.0100

Production of switchgrass on marginal lands could encourage economic growth in rural areas and enhance agricultural producer incomes (Jensen et al. 2007).Welfare effects have been studied in this work when using marginal land for switchgrass production. The total welfare increases when using marginal land in all the scenarios, although it is highest in the base case with no offset program. This result is reported in Table 9.

Also the distribution of welfare under base case is depicted in Figure 13. As one can see in this figure the producers' surplus increased significantly. The reason is the added economic profit from using marginal lands. Consumer and total foreign surpluses decrease. The reason is as presented in Table 8, some production indices show decrease and their price indices accordingly show rise. Although the rise in price is slight but it could lower the consumer welfare. Foreign welfare is sum over foreign consumers and producers welfare which is slightly decreasing. Foreign consumers would be worse off because of less US export and higher commodity prices, but this has advantages for foreign producers. In total the loss in foreign consumers' welfare exceeds the gain in foreign producers' surplus. The export indices for all farm and processed products, wheat and rice are also reported in Table 8.

Table 9 Percent change of total welfare increase when marginal land included.

	Base	Mandatory	Voluntary
% Total welfare change	0.0528	0.0047	0.0046

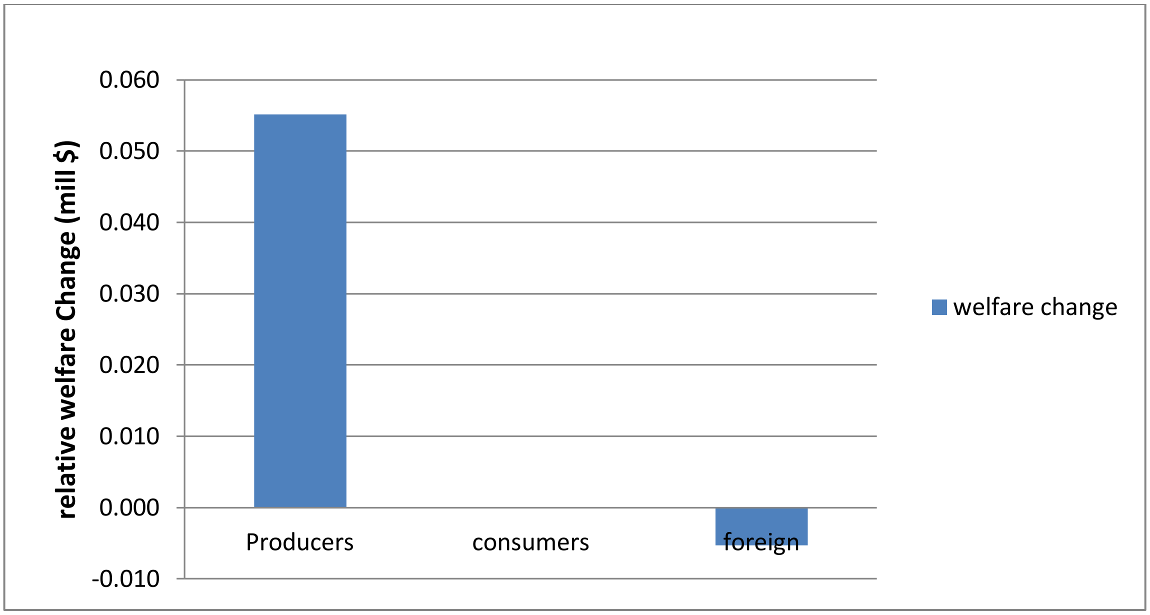

Figure 13. Relative change in welfare distribution in base scenario.

Also the relative welfare distribution with respect to carbon equivalent prices is presented in Figure 14 under the voluntary carbon offset program for 5 and 30 $\$CO_2e$. With marginal land in the model, as the carbon price increases producers' welfare increases and also foreigner's surplus decreases. Also consumer's surplus slightly decreases as the carbon price rises.

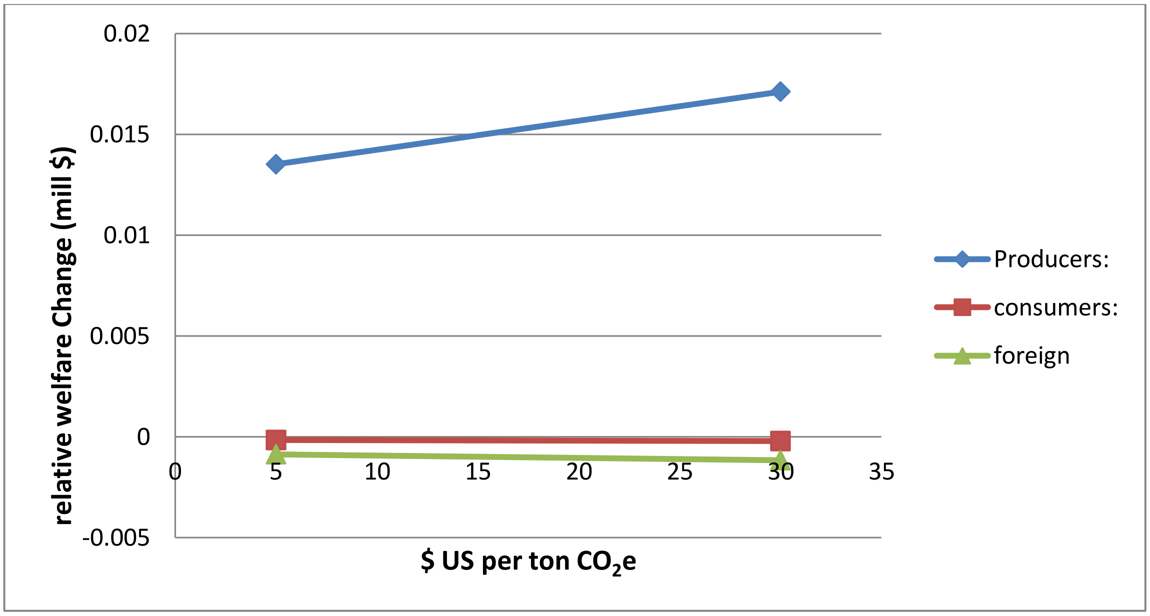

Figure 14. Relative welfare distribution change in voluntary program regarding different CO_2e prices.

3.4.4 Environmental Effects

One challenge regarding conventional biofuel production is that growing crops as a bioenergy feedstock could increase rates of erosion and nutrient runoff. However, studies suggest that growing low-input, perennial grasses as a feedstock would likely reduce such impacts (Campbell et al. 2008; Tilman, Hill and Lehman 2006). Jensn (2007) suggests that Switchgrass can contribute reducing erosion on highly erodable lands, and provide good forage and habitat for native wildlife. Switchgrass could benefit erosion control not only through the presence of vegetative cover on the soil surface, but also with network of fibrous roots in surface layers of soil (Kort, Collins and Ditsch 1998). The results of our study agree that addition of marginal land for switchgrass could help controlling erosion in base scenario. Figure 15 is showing the relative change in erosion when marginal land is included compared to no marginal land.

We also examine the erosion effects under carbon offset programs as well. Mitigation strategies and results and land usage vary with carbon prices. At low carbon prices dominant low cost strategies are those consistent with existing production such as changes in tillage practice, fertilizer application, diet and manure management. At high prices, emission abatements emerge mainly from forestry and biofuels (McCarl and Schneider 2001; Smith et al. 2008). In Figure 15 we portray the erosion results under mandatory and voluntary programs for carbon equivalent prices of 5 and 30 \$ when marginal land is an option. The results indicate that total erosion at higher price (here 30 \$$CO_2$e) will decrease when marginal land is included in the model compare to the same program with no marginal land, but at 5 \$ the overall erosion increases.

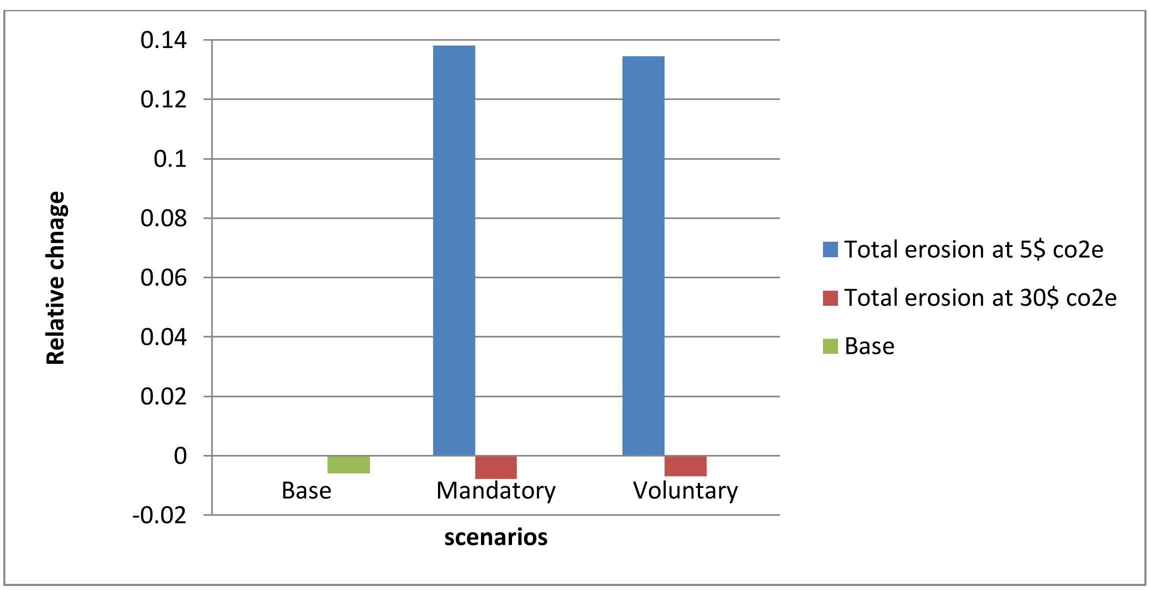

Figure 15. Relative change in erosion with respect to no marginal land in each scenario.

Switchgrass grows in a large portion of the US with low fertilizer applications and high resistance to naturally occurring pests and diseases (Jensen, 2007). The amount of fertilizer switchgrass needs depends on region, yield goal and productive potential of land (Christensen, 2010). Figure 16 and Figure 17 presents the loss in overall Potassium and Nitrogen by including growing switchgrass on marginal land to agricultural sector's lands. The only raise at potassium level is in mandatory program with 30 \$ CO_2e.

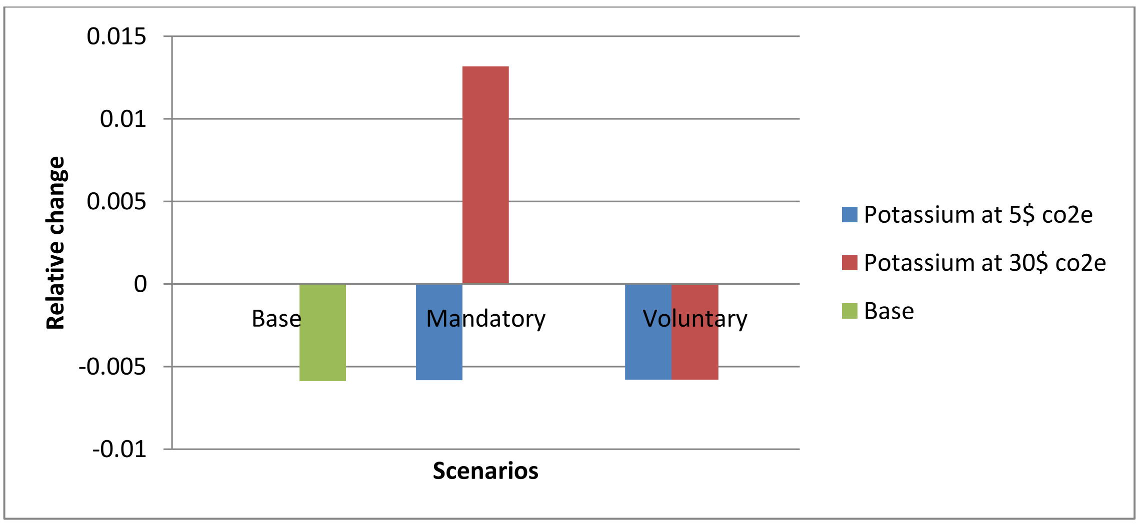

Figure 16. Relative change in potassium with marginal land.

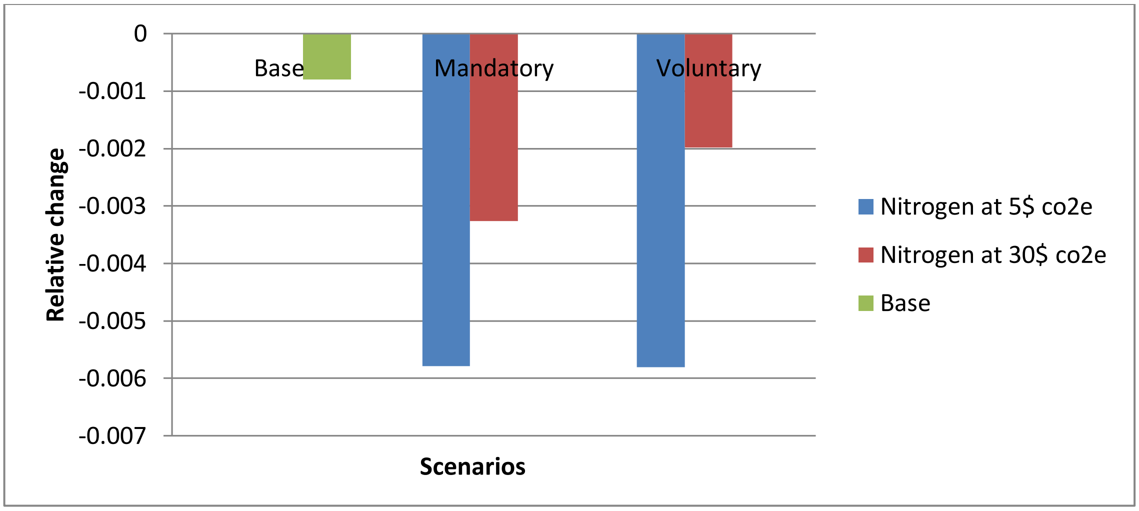

Figure 17. Relative change in nitrogen with marginal land.

3.5 Conclusion

Land competition is a concern when producing large quantities of biofeedstocks to meet RFS mandates. The concern rises due to two reasons: first, Competition for cropland and commodities could lower conventional crop production raising prices and threaten food and feed security. Second conversion of new lands into bioenergy production could worsen climate change effects by emitting carbon stored in soils and vegetation plus emitting GHGs from production process.

Producing biofuel feedstocks on marginal lands could be one solution to the land competition concern. Marginal lands are appropriate for growing some kinds of biomass such switchgrass. In this work we use FASOM-GHG to examine some of the questions regarding market penetration, potential GHG mitigation, price, production, welfare and environmental effects of using marginal land to produce switchgrass.

The net effects of using marginal lands on GHG offsets are complex and dependent on other mitigation practices. Generally the model results show using marginal land increases overall GHG emissions due to emissions from the added fertilizer and fuel consumption on the marginal lands plus no real gain in sequestration. However a different result emerges under carbon offset programs with GHGs reduced somewhat due to a flow of switchgrass into bioelectricity with accompanying offsets relative to coal. This indicates that using marginal land could reduce GHGs if bioelectricity is supported due to its higher carbon offset rates.

We also find that using marginal land for producing cellulosic biofuel takes the pressure off of conventional land use to satisfy the RFS mandate in the absence of carbon prices. Additionally this will help reduce several agricultural product prices although is not true for all agricultural products. Marginal land does not cause agricultural commodity prices to decrease when carbon prices are substantial because this causes use of the marginal land generated switchgrass for electricity production and the pressure remains to meet the RFS2 mandates.

Production on marginal land generally increases profits to agricultural producers. Our welfare study presents a significant increase in producers' surplus. Also total welfare rises under all scenarios of this study when adding marginal land to the model although the loss of ecological services and other amenities is not accounted for.

CHAPTER IV

ON THE DYNAMICS OF PRICE DISCOVERY: ENERGY AND AGRICULTURAL MARKETS WITH AND WITHOUT THE RENEWABLE FUELS MANDATE

4.1 Introduction

Enhancing energy security and reducing greenhouse gas (GHG) emissions are important reasons to promote renewable energy sources such as biofuels. To encourage biofuels, the US government has implemented renewable fuel standards (RFS) regarding the amount of ethanol to be blended into transportation fuel. Ethanol is an oxygen enhancing additive and a replacement for gasoline; therefore its price has a relationship with gasoline and also crude oil. There have been fluctuations in these relationships during past years.

First generation ethanol is what we study in this work and its feedstock is mainly corn. Corn is also the major feed used by the livestock industry. The increase in corn use as a biofeedstock, especially after the ethanol boom that began in 2006 caused competition for land between food and fuel and accordingly food and feed price rises. This also is the source of concerns regarding RFS mandates which requires production of large quantities of biofeedstocks although higher energy prices are also a factor.

The nature of the evolving interdependency between energy and agriculture markets in the US plus the effects of the RFS mandates is the subject of this study. We study the dynamic relationships in and between the real prices of corn, soybeans, cattle, and hogs along with ethanol and the crack ratio (a measures of the refining margin). We do this in a vector autoregression (VAR) framework. Also in this work, the contemporaneous causal flow among the variables is identified using a data determined technique (Bessler and Yang 2003; Mjelde and Bessler 2009). Using directed acyclic graphs to investigate transmitted information among the variables allows us to estimate impulse responses and forecast error variance decomposition from VAR allows comparison to other studies. Also we perform price forecasting taking into account for RFS policies in the model and also blending wall issues.

4.2 Background and Brief Literature Review

Variety of policies has been emerged in US to encouraged biofuel directly or indirectly. One of the major policies in this regard was subsidization of ethanol in the United States, which began with the Energy Policy Act of 1978. Since then, the subsidy has ranged between 40¢ per gallon and 60¢ per gallon of ethanol, and most recently until it was discontinued on December 31, 2011 was 45¢ per gallon (Abbott, Hurt and Tyner 2011). Throughout the last three decades of ethanol production, the subsidy has been a fixed amount per gallon, invariant with oil or corn prices (Tyner and Taheripour 2008).

In 1990, the Clean Air Act was passed, which required vendors of gasoline to have a minimum oxygen percentage in their product because adding oxygen enables the fuel to burn cleaner. Two options for oil industry to meet this requirement was ethanol and methyl tertiary butyl ether (MTBE). MTBE was generally a cheaper alternative than ethanol, but it showed negative environmental consequences and was gradually banned on a state-by-state basis (Birur, Hertel and Tyner 2009).

The 2006 Ban of MTBE, combined with high crude oil price (which climbed to over $100/bbl in 2004) and the ethanol tax credit raised the profitability of ethanol industry particularly beginning in 2004 and 2005. High profit margins from ethanol production in 2004–2007 encouraged rapid investment in the ethanol industry during those years (Tyner et al. 2008). Between 2006 and 2008, the correlation between crude oil and corn prices was strong, in part because ethanol was needed to supply the oxygenate market. After 2008 the oxygenate market was largely saturated, ethanol prices ceased their rapid rise (and corn prices rose significantly), making ethanol production unprofitable in many cases. In 2008-09 and afterward, we see a high correlation (about 0.84 in 2008) between ethanol and corn prices, since the profitability of ethanol production depends on corn price (Abbott, Hurt and Tyner 2011).

On December, 2007, the Energy Independence and Security Act of 2007 (H.R. 6) was signed into law. This legislation amended the Renewable Fuels Standard (RFS) mandating a phase-in for renewable fuel volumes beginning with 9 billion gallons in 2008 and ending at 36 billion gallons in 2022. Growth of corn based ethanol industry in last few years makes corn an energy crop and ties its price partially to energy prices.

Corn is also, an important source of feed for production of livestock, poultry, and dairy products. These uses established a relationship between ethanol and corn price and also the products from corn. Production of biofuels affects the agriculture market in that diversion of land to produce biofeedstocks reduces the supply of other products and as a result there is a likely rise in prices. Alexander and Hurt (2007) suggest that in the long run, food will be able to compete successfully with the use of crops for fuel, but probably with somewhat higher food prices and greater costs of food to consumers.

Several studies in the literature address the interactions of ethanol production and the energy market. For instance, Du and Hayes (2009) calculated the average impact of ethanol production on the gasoline price. Estimation results indicate that, on average, over the whole sample period (2000-2010) the growth in ethanol production reduced wholesale gasoline prices by \$0.25/gallon. Also changes in the price of crude oil were found to have effects on biofuel production and prices. The FAO (2010) finds when crude oil prices increase agricultural commodity markets are affected in two ways. First, crop production costs increase leading to a reduction in supply and a consequent rise in commodity prices. Second, an increase in petroleum-based fuel prices provides an incentive to biofuel producers to expand production, which in turn expands demand for agricultural feedstock crops causing prices to increase. In turn they state that the net impact on commodity markets will depend on the degree of increase in biofuel prices relative to the increase in total crop production cost.

Figure 18 shows the indices of corn, crude oil, ethanol, and gasoline prices since 2000 based on data from the Energy Information Administration (EIA) and USDA. The graph shows these prices have moved together since 2007. In particular before 2007 corn price and crude oil price showed limited responses to each other’s movement, but after this time they show a stronger relationship. The same is true for corn and gasoline.

Gasoline's price has not increased as much as crude oil's price since 2007, the reason could be that crude oil is not the only cost factor in gasoline production.

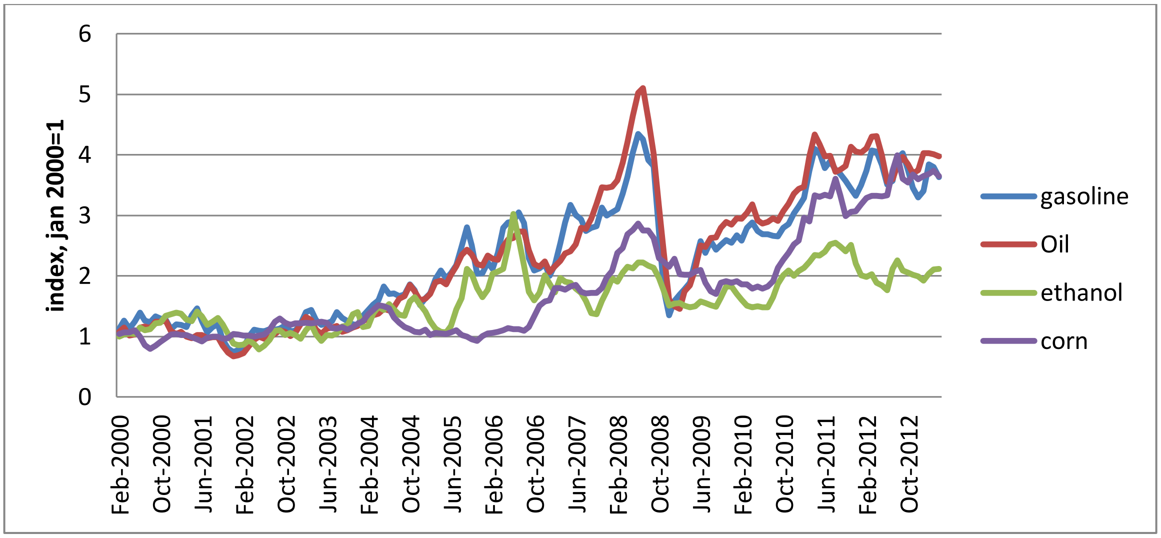

Figure 18. Price index for selected commodities.

Bryant and Outlaw (2006) studied the effect of government policies (RFS and exemption of tax credits) on ethanol production and price by 2012. They conclude that due to powerful market-based incentives the increases in levels of ethanol production would be likely in coming years, even in the absence of government programs. Carter, Rausser and Smith (2012) estimated that corn prices were about 30 percent greater, on average, between 2006 and 2010 than they would have been if ethanol production had remained at 2005 levels with no RFS. Tyner (2010) studied links between agriculture and energy markets and found strong correlation between crude oil and corn prices in

2006-2008 and little link between ethanol and corn prices. But in 2009, when there was ethanol surplus in the market the link between ethanol and corn price was strongest.

In recent years, drops in gasoline usage in US and market (blending wall) limitations to future growth in the blending of biofuel have resulted in a fall in ethanol consumption (Westcott and McPhail 2013). Today Corn ethanol covers 10% of finished motor gasoline in US (E10). E85 (with 70-85% ethanol content) is consumed in limited volumes, and the infrastructure is not prepared to increase this volume. One concern of today's ethanol industry is that we have reached a blending limit known as blending wall. That means reaching the RFS targets for corn ethanol by 2022 will require raising the E10 blend standard for regular vehicles.

4.3 Empirical Methods

4.3.1 Vector Autoregression Model

In this study, we will use Vector autoregression (VAR) model for our analysis. Using this model let us analyze the regularities in the set of variables without imposing any prior restriction is an advantage of VAR (Greene 2003). A VAR can be expressed as:

$$X_t = \sum_{i=1}^{k} \mathrm{B}_i X_{t-i} + CZ_t + u_t$$

Where X_t a (mx1) vector of variables and m is is the number of series. Z_t is a (qx1) vector of strictly exogenous variables. B_i and C are appropriately dimensioned matrices of coefficients. The integers k and t are the number of lags and time indexes, respectively. u_t is the innovation term and it is assumed to be white noise, means E (u_t) = 0. The innovations u_t and u_s are independent for s≠t. Although serially uncorrelated, contemporaneous correlation among the elements of u_t is possible, $\sum = \mathrm{E}(u_t u_t')$ is an (mxm) positive definite matrix.

Contemporaneously correlated innovations could mislead the information one gleans from the vector autoregression (by confounding innovation accounting results). A Choleski factorization is one way to address this issue. In this method, we need to pre multiply the system by lower triangular matrix P^{-1}, such that $P^{-1} \sum P^{-1'} = I$. The problem with this method is that it imposes an ordering through Choleski factorization. Our theory is sometimes not rich enough to suggest which series are exogenous. A Bernanke factorization is another option which allows more general causal flows. Following (Bernanke 1986) one can write the innovations as a linear function of orthogonal innovations:

$e_t = Au_t$

Multiplying matrix A to non-orthogonal innovations, gives orthogonal innovations provides the identified structural VAR. The transformed VAR will thus look as follows:

$$AX_t = \sum_{i=1}^{k} \mathrm{AB}_i X_{t-i} + ACZ_t + Au_t$$

If $AX_t = Y_t$ and $AC = B$, then we can also write the equation in moving average form as follows:

$$Y_t = BZ_t + \sum_{s=0}^{\infty} {}_s e_{t-s}$$

There exist some rules in the literature on number of free parameters to maintain identification (Doan 1993). Compares to Choleski decomposition which imposes a just identified structure, Bernanke allows more flexible identification method based on theory. In this study we will use algorithms of inductive causation (Pearl 2000) with acyclic graphical representations to hold identifying restrictions on matrix A (Awokuse and Bessler 2003).

4.3.2 Directed Acyclic Graphs

We use Directed acyclic graphs; based on graph theory, to explore the causal ordering among the variables of our model. This method finds the causal flow among the variables by using arrows and vertices (Pearl 2000) and statistically inferred information about the probability distribution of the estimated residuals. In other words, it consists of a set of variables and the directed or undirected edges between some of the variables (Pearl 1995). A causal model such as A → B is a directed graph, which means A causes B. It means one can change the value of B by changing the value of A. A directed acyclic graph is a directed graph that contains no directed cyclic paths (Spirtes, Glymour and Scheines 2000). For instance A→B→C→A is a cyclic graph, since we return to the same variable as we start with.

Directed acyclic graphs (DAGS) show the conditional independencies as implied by the recursive product decomposition:

$$\Pr(x_1, x_2, x_3, \dots, x_n) = \prod_{i=1}^{n} \Pr(x_i | pa_i)$$

Here Pr is the probability of the variables $x_1, x_2, x_3, \dots, x_n$ and pa_i is the minimum subset of variables that comes before x_i in causal sense.

Pearl (1995) also suggests the concept of D-separation as a method in DAGS to verify the causal ordering. A variable D-separates two variables when it blocks the information flow between them. One basic pattern of causal relationship is the causal chain (A→B→C). In this chain A and C are dependent unless we condition on B. The other pattern is a causal fork (A← B→C), in which A and C are dependent until we condition on B. Also the last pattern is a causal collider (A→B←C), in this case A and C are independent but are dependent when we condition on B. DAGs infer the causal direction first by testing the correlation between the variables and then by doing a conditional correlation on a third variable and seeing the variables follow any of the above rules of causal ordering.

The Lingam (Linear Non-Gaussian Acyclic Model) algorithm (Shimizu et al. 2006) is used in this study to figure out the causal ordering among the variables. This method is appropriate when at most one of the variable's noises may be Gaussian. Spirtes et al. (2010) explain this method as a system such as:

1) $X = \varepsilon_x$

2) $Y = aX + \varepsilon_y$

3) $Z = bX + \varepsilon_z$

Where a, b and c are the coefficients and ε_x , ε_y , ε_z are independent noises. If we write these equations in reduced forms, we will have:

4) $X = \varepsilon_x$

5) $Y = a\varepsilon_x + \varepsilon_y$

6) $Z = b\varepsilon_x + ac\varepsilon_x + c\varepsilon_y + \varepsilon_z$

LiNGAM algorithm can find the correct matching of coefficients in the Independent Component Analysis (ICA) matrix (Hyvärinen and Oja 2000) and prune away any insignificant coefficients using statistical criteria (Spirtes et al. 2010). A unique DAG will be constructed, since the coefficients are determined for each variable. The required assumptions are: 1) no unmeasured common causes; 2) dependent variable could be explained by a linear equation; 3) relation among variables are not deterministic; 4) i.i.d sampling; 5) Markov condition, which is probability distribution explain one variable is only condition on the variables of direct cause (Spirtes et al. 2010).

4.3.3 Forecasting and Conditional Forecasting

In the literature, using conditional forecasting is an approach to evaluate a policy. It is of interest sometimes to consider the forecast of some variables in the system conditional on some knowledge of the future path of other variables in the system. Sims, Goldfeld and Sachs (1982) address important issues on how to conduct a formal policy analysis.

We can use Vector Autoregression to do policy analysis. Assuming a policy instrument is exogenous; one can view a VAR model's forecasts conditional on different hypothetical values of instrument as capturing the effect of alternative instrument settings on the endogenous variables (Cooley and LeRoy 1985). If we force some values on future path of one variable, this will result in restrictions on the other variables of the system as well. In general forecasting our best guess of future disturbances could be zero, but in conditional forecasting by forcing a value on some variables we cannot assume zero disturbances on other variables. The disturbance is not zero to adapt real values to the required (policy) values.

If we wish to forecast one period ahead conditional on a specific policy, we know the future of policy variable and also the model at the current time. Here is the setup:

$$y_{t+1} = \ _0 e_{t+1} + \ _1 e_t + \ _2 e_{t-1} + \cdots$$

This equation is showing at time t we are predicting for t+1. Since we know the current and past states (history), so we will have:

$$y_{t+1} = \ _0 e_{t+1} + Known$$

Identification of this system depends on the structure imbedded in the matrix $_0$. This structure on $_0$, will communicate the implied path on other variables, in addition to the policy variable whose future values the governmental authority sets. Therefore for this model to be identified, we need sufficient restrictions on $_0$ matrix. For VAR in N variables if we leave more than N(N-1)/2 parameters free (to be estimated) the model is not identified. The restrictions on $_0$, come from theory or inductive causation. We can use the algorithms of inductive causation (communicated through the DAG structure) on the VAR innovations derive the restriction on in contemporaneous time.

4.4 Data

The data used in this study are monthly spanning from January 2000 to April 2013 (160 observations). The period after 2000 is used, since ethanol production has only shown marked increases since 2000. Our data includes corn price (corp), ethanol price (ethp), ethanol production (eprod) and also soybean price, cattle price and hog price (soyp, cattp, hogp) are representatives to show the effects on agricultural market. The agricultural products prices are from the USDA website[1].

In addition we study the Crack ratio (crkr), to show effects of energy market following Du and Hayes (2009) and Knittel and Smith (2012). The crack ratio is a measure of the refining margin. Du and Hayes (2009) define it as the price of gasoline divided by the price of oil. The gasoline price variable is the "total gasoline wholesale/resale price by refiners", which excludes taxes and reflects primarily gasoline prior to blending with ethanol. Crude oil price is the "national average refiner acquisition cost of crude oil".

The energy data and also Ethanol production data were obtained from the U.S. Energy Information Administration (EIA) website. The ethanol price data source is Hart's Oxy-Fuel News. The price data were all deflated by the consumer price index (CPI) drawn from U.S. Bureau of Labor Statistics website. To get the real prices, each price is divided by, CPI in each month/CPI in April 2013. CPI index is from U.S. Bureau of Labor Statistics. Plots of the price series for each market are provided in Figure 19.

4.5 Empirical Results

4.5.1 Stationarity

To choose the best model to describe our time series we need to test for stationarity. Therefore we performed two tests: Dickey–Fuller (DF) and Augmented Dickey–Fuller (ADF) and the results have been shown in Table 10. DF results show that at both critical

[1] www.usda.gov

value ethanol price, crack ratio and hog price are stationary and the rest of variables are non-stationary.

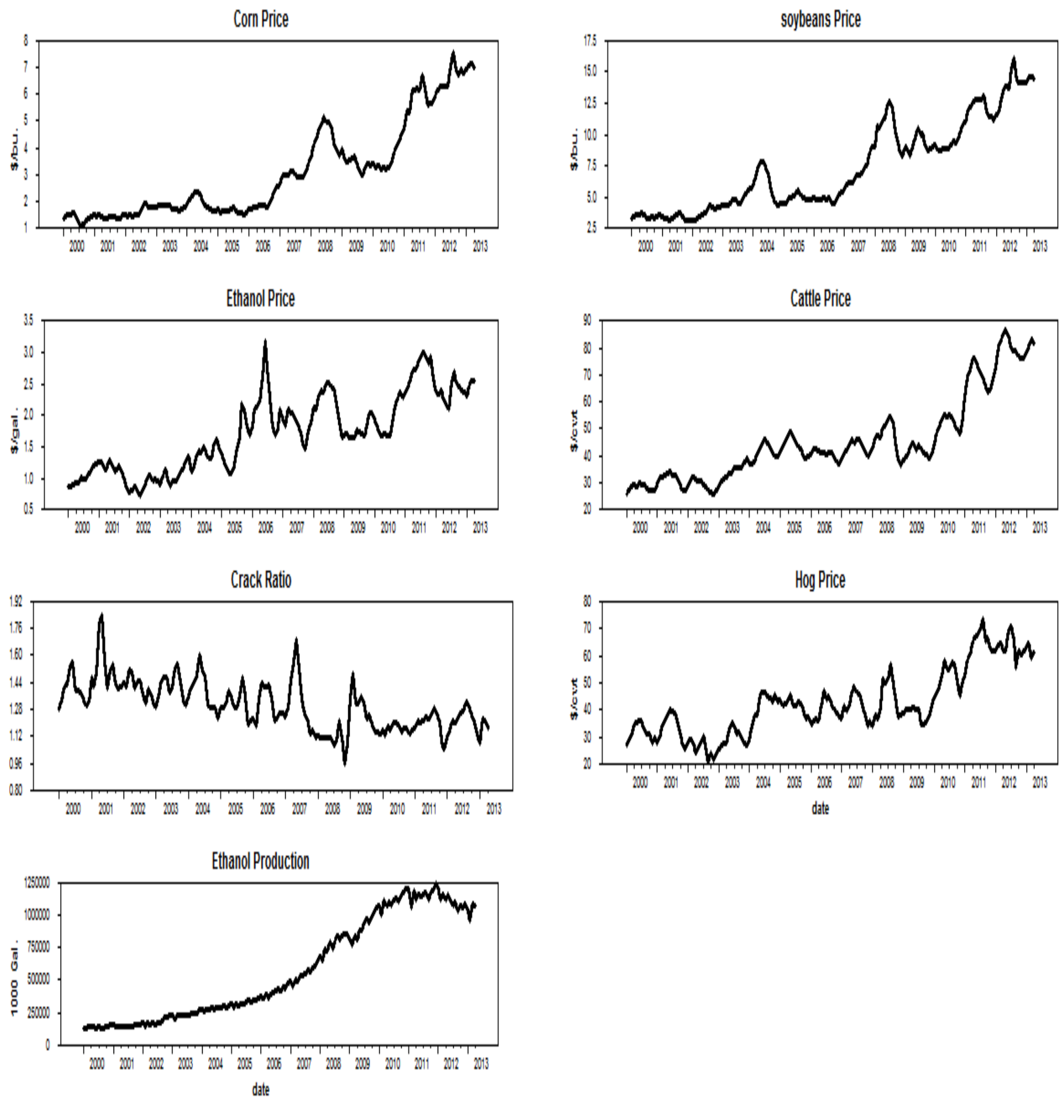

Figure 19. Monthly time series plot of major variables used in model (January2000- April 2013) with all prices expressed in real April, 2013 dollars.

The ADF test indicates that the crack ratio and hog price variables are stationary with 2 and 1 lag respectively. We also find the ethanol price with 2 lags is stationary. The rest of variables are showing non stationary.

Table 10 Dickey–Fuller (DF) and Augmented Dickey–Fuller (ADF) for non-stationary of variables.

Variables	Dickey-Fuller		Augmented Dickey-Fuller		
	Test	Q	Test	K	Q
Corn Price	-0.29	62.23 (0.00)	-0.32	1	60.99 (0.00)
Ethanol Price	-4.31	45.71 (0.12)	-2.84	2	31.18 (0.69)
Crack Ratio	-5.15	70.42 (0.00)	-2.99	2	61.52 (0.00)
Ethanol Production	0.13	667.99 (0.00)	-0.08	1	249.14 (0.00)
Soybeans Price	-1.43	70.78 (0.00)	-1.28	1	38.30 (0.36)
Cattle Price	-2.46	302.88 (0.00)	-2.33	1	81.43 (0.00)
Hog Price	-3.51	76.56 (0.00)	-3.30	1	71.05 (0.00)

The DF test is implemented through an ordinary least squares regression of the first differences of prices on a constant and one lag of the levels of prices (Greene 2003). In ADF test, k lags of dependent variable are included in the regression. The null hypothesis for the test statistic of both tests is the data is non stationary in levels. The null hypothesis is rejected when the observed t-statistics are less than this critical value. The 5% and 10% critical values are (-2.89, -2.58) (Fuller, 1976). ADF regression runs with 12 lags and the chosen lag number (K) is the minimized Schwarz loss metric. Also the Q-statistics is the Lung-Box statistics on the estimated residuals from the test regression. The p-value with respect to each Q-statistics is given in the parenthesis.

4.5.2 Optimal Lag Length

We use Schwarz loss, Akaike loss, Hannan and Quinn's phi measures to determine the optimal length of lags for the VAR model (Table 11). To find the optimal lag we tried these tests for different set of regressions with seasonality, break and lags. We implement the Bai-Parron break test and we choose ethanol production's break at February 2009. The optimal lag length results shows smaller numbers with only seasonality and lags and not break included.

Table 11 VAR optimal lag length determination

Number of lags	Schwarz Information Criterion (SIC)	Hannan and Quinn Information Criterion (HQIC)	Akaike Information Criterion (AIC)
1	14.0694*	12.4485	10.4536
2	14.5285	12.3103*	10.2122
3	15.6201	12.8047	10.6032
4	16.9162	13.5036	10.1988
5	18.0327	14.0229	10.6147
6	19.1616	14.5546	11.0430
7	19.9150	14.7108	10.0959
8	20.8277	15.0263	10.3080
9	21.8751	15.4765	10.6549
10	22.8041	15.8082	10.8833
11	23.4828	15.8898	9.8615
12	23.9342	15.7439	9.6123*

Note: * indicates the most appropriate lag order for the considered model.

The information criteria used to identify the optimal lag length (p) of a VAR process are $AIC = \ln\left(det\widehat{\Omega}_p\right) + p\left(\frac{2n}{T}\right)$,$SIC = \ln\left(det\widehat{\Omega}_p\right) + p\left(\frac{nlnT}{T}\right)$, and $HQIC = \ln\left(det\widehat{\Omega}_p\right) + p\left(\frac{2nln(lnT)}{T}\right)$, where $\widehat{\Omega}_p$ is the maximum likelihood estimate of variance-covariance matrix of Ω, p is the proposed lag length, n is the number of variables, and T is the sample size.

As one can see in this table, Schwarz loss, Hannan and Quinn's phi measures and Akaike loss are minimized at 1, 2 and 10 lags respectively. Smaller lag length seems to be more reasonable for our study, so we need to choose between the one or 2 month lag as idenitified by the Schwarz loss and Hannan and Quinn's phi measures. We will use a two-lag VAR model suggested by Hannan and Quinn's phi measure since the Schwarz loss metric may have a tendency to over-penalize additional regressors compared to the other metrics (Geweke and Meese 1981).

4.5.3 Estimation Results of Two-Lag VAR

The p-values of F-test associated with the null hypothesis of both coefficients of one and two-lagged prices jointly equal to zero at 10% level of statistical significance are given in Table 12. As one can see in the table, all the variables have at least one other significant coefficient in their equation, except for the hog equation. We find the Corn price coefficient is significant in both the ethanol price and ethanol production relations. Also corn price and ethanol production are significant in the crack ratio equation along with the soybean price coefficient. Soybeans, Cattle and hog price coefficients are significant in five of the seven equations. Ethanol price is only significant in the ethanol production equation.

Table 12 P-values associated with F-tests for the null hypothesis of the coefficients on one- and two-lagged prices on each of 7 variables are equal to zero in the two-lagged VAR(2) model estimation results.

dependent variable	**CORP**	**ETHP**	**CRKR**	**EPROD**	**SOYP**	**CATTP**	**HOGP**
CORP	0.000*	0.388	0.075*	0.182	0.621	0.232	0.301
ETHP	0.967	0.000*	0.260	0.013*	0.447	0.829	0.278
CRKR	0.124	0.025*	0.000*	0.379	0.415	0.012*	0.828
EPROD	0.134	0.393	0.033*	0.000*	0.094*	0.317	0.977
SOYP	0.091*	0.861	0.060*	0.046*	0.000*	0.011*	0.209
CATTP	0.005*	0.028*	0.843	0.006*	0.064*	0.000*	0.175
HOGP	0.011*	0.025*	0.223	0.183	0.056*	0.098*	0.000*

* Indicates the p-values below 10% significance level.

4.5.4 Identifying Contemporaneous Structure

We use LiNGAM algorithm to identify the causal structure of the variables in the model. This algorithm is appropriate to use when at most one variable is Gaussian. Therefore, the Normality test is applied before using LiNGAM in this study. A Jarque-Bera test has been applied to the data to determine whether they follow the skewness and kurtosis matching a normal distribution or not. The test statistic is as follows:

$$JB = \frac{n}{6}\left(S^2 + \frac{1}{4}(K-3)^2\right)$$

Where n is the number of observation, S is the sample skewness, and K is the sample kurtosis. The results of the normality test are that we reject the null hypothesis of normality for all the variables except for ethanol price.

Using TETRAD (Scheines and Spirtes 1994) we implement LiNGAM algorithm with prune factor 0.7 to figure out the contemporaneous structure among the seven variables. Figure 20represents the causal structure we find among the variables of our model. As one can see in this figure, energy and agriculture markets are connected through the edge between corn price and ethanol price. The information flow is Corn price causes ethanol price. Corn price also causes the soybean price.

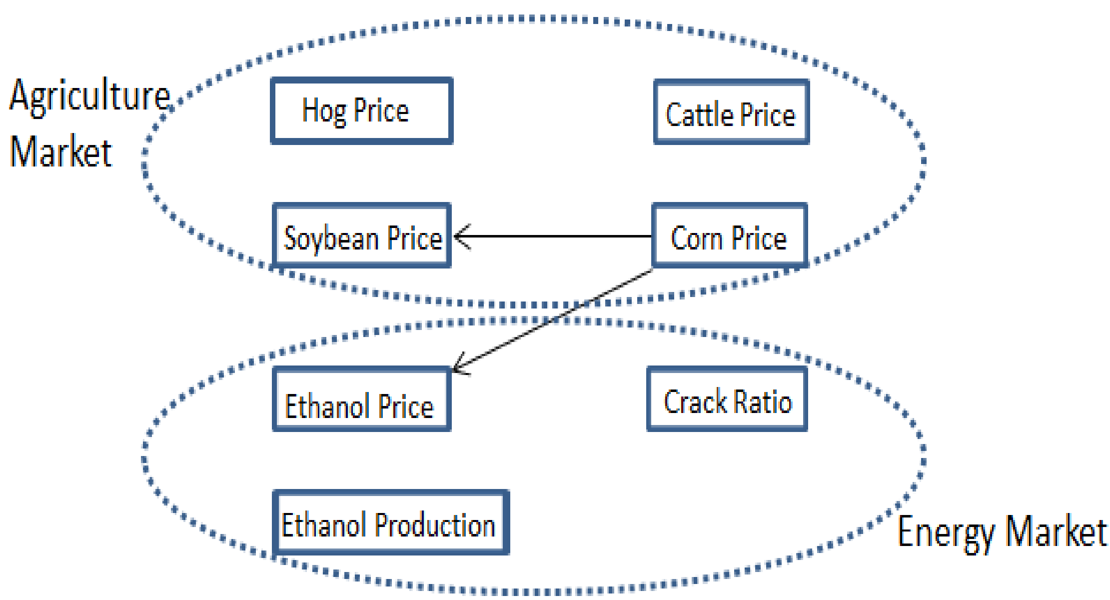

Figure 20 Directed acyclic graph of price interrelationships.

4.5.5 Forecast Error Variance Decomposition

To analyze the effect of each variable on the others in a short and long horizon we performed forecast error variance decomposition. The results of forecast error variance decomposition are reported in Table 13. The time horizon of decompositions is zero (contemporaneous time), 1 month (short horizon), 6 months, 1 year and 3 years ahead (long term). The forecast error variance decomposition suggests that that in contemporaneous time agriculture market prices are all exogenous, except for soybeans where the variation is explained by innovations from corn (39.72%).

Variation of corn price in long horizon is explained mainly by ethanol production and cattle price (11% and 13.3% respectively) and together with other variables they explain 50% of variation in corn price. In the short run, the variations in cattle and hog prices are affected only by corn and soybeans price innovations with the influence of soybeans being higher than that of corn. In the long term ethanol price, ethanol production and crack ratio play a role in explaining cattle and hog prices. For instance, crack ratio and ethanol production explain around 11% and 3.4% of the variation in cattle price respectively.

In the energy market, the crack ratio is showing exogeneity in contemporaneous time and the variations in ethanol price are explained by itself mainly and also by corn price (4.7%). In a 6 months horizon, Variations in ethanol price are explained by crack ratio for about 10%, but this amount decreases in long run (3 years) to about 8.7%. The influence of the crack ratio in explaining ethanol price is higher than the influence of corn price in the longer term. But the immediate effect of corn price on ethanol price is higher than crack ratio. Moreover, although in short run the variables of the model only explain about 9% of the variation in ethanol production but in long term (3years) this number increases to about 75%. The main variables which describe ethanol production variation in long term are crack ratio, cattle and hog prices.

Table 13 Forecast error variance decompositions from two-lag VAR.

Step		CORP	ETHP	CRKR	EPROD	SOYP	CATTP	HOGP
CORP	1	100.0	0.00	0.00	0.00	0.00	0.00	0.00
	2	97.19	0.01	1.34	0.46	0.45	0.26	0.24
	7	79.14	0.48	3.48	1.14	1.00	7.83	6.90
	13	69.30	0.74	2.40	2.58	0.83	13.32	10.80
	37	54.78	3.80	3.09	11.07	1.42	13.32	12.49
ETHP	1	4.71	95.28	0.00	0.00	0.00	0.00	0.00
	2	5.29	92.37	0.00	0.45	0.06	0.47	1.33
	7	2.79	79.96	9.42	0.37	2.08	2.57	2.79
	13	3.43	71.91	9.05	0.36	6.64	5.14	3.43
	37	5.01	66.43	8.79	1.10	8.67	6.49	3.47
CRKR	1	0.00	0.00	100.00	0.00	0.00	0.00	0.00
	2	0.30	0.03	96.77	0.35	1.33	0.03	1.15
	7	0.29	1.99	85.75	0.70	8.12	1.37	1.75
	13	0.41	2.07	81.74	1.37	9.57	2.14	2.67
	37	1.09	1.75	69.35	3.68	8.52	10.88	4.70
EPROD	1	0.00	0.00	0.00	100.00	0.00	0.00	0.00
	2	0.56	1.72	0.98	92.24	1.69	0.93	1.85
	7	0.73	6.62	2.96	69.19	4.79	10.97	4.70
	13	0.39	6.30	6.59	51.03	5.55	19.31	10.79
	37	2.62	2.30	9.91	25.15	2.37	42.79	14.82
SOYP	1	39.72	0.00	0.00	0.00	60.27	0.00	0.00
	2	38.39	0.05	0.55	0.07	60.82	0.00	0.09
	7	34.14	1.43	1.12	0.85	50.08	2.92	9.42
	13	34.50	2.99	1.03	2.68	40.25	4.44	14.09
	37	29.45	3.89	2.97	9.97	30.20	6.75	16.74
CATTP	1	0.00	0.00	0.00	0.00	0.00	100.0	0.00
	2	0.00	0.01	0.07	0.00	2.49	97.16	0.23
	7	0.43	0.04	9.02	0.02	7.45	76.59	6.42
	13	0.90	0.03	11.75	0.19	7.82	69.95	9.33
	37	2.04	0.24	11.36	3.40	10.12	63.84	8.97
HOGP	1	0.00	0.00	0.00	0.00	0.00	0.00	100.0
	2	1.61	0.00	0.09	0.00	0.34	0.11	97.82
	7	2.15	2.30	1.53	0.10	2.22	2.68	88.97
	13	1.72	3.05	1.72	0.12	10.49	7.82	75.05
	37	1.58	2.84	3.32	0.91	16.17	11.20	63.95

4.5.6 Innovation Accounting

We present impulse response functions to analyze the effects of a one-time only shock of one of the series on the other series. These are represented in Figure 21. Horizontal axes on the sub-graphs represent the horizon or number of months after the shock, where we portray 36 months. Vertical axes show the standardized response to the one time shock in each market. The variable's names are labeled at top of the columns. Following (Sims and Zha 1999), we use Monte Carlo to provide confidence bands for impulse responses based on program by (Doan T. 2000).

As one can see in Figure 21, a shock in ethanol production transferred as a positive and long lasting impulse to almost all of the agriculture market commodities' prices (corn, soybeans and cattle). Also in the energy market, a shock in ethanol production has a negative influence on crack ratio, which dampens to zero in the long run. This means an increase in ethanol production decreases the gasoline refining margin and thus the ratio of the gasoline price relative to the crude oil price. Also a shock in ethanol price leads to a negative short term impulse in crack ratio, which dampens to zero in longer term. Increase in ethanol price will decrease the demand for blended fuel and also demand for gasoline. Therefore gasoline price will decrease in short term. But in longer tem this balances with gasoline production and the effects on gasoline price dampens to zero. Therefore ethanol and gasoline in the short run are acting as complementary goods.

The short run negative response of corn price to a one time shock in the crack ratio is likely subject to a similar explanation. An increase in the blended fuel price decreases demand for ethanol and the ethanol price and in turn the corn price. Also we see the ethanol production responds negatively to increase in the crack ratio in short term.

A positive shock in the ethanol price leads to a positive short impulse in the hog price. This rise is likely due to due increased ethanol production with increased corn use and therefore higher effects on the corn prices and in turn increased costs of feeding hogs. The response also transmits to soybeans price with a shock in ethanol production increasing corn use and land/feed competition.

We note also a one-time shock in corn price will lead to short positive impulse to ethanol price, since the ethanol production cost will increase. Also a shock to corn price will lead to positive response of soybeans price. Since soybeans is an important grain for animal feed, it could be a good substitute when price of corn increase. This excess demand will affect the soybeans price to increase, and it gradually dampens to zero.

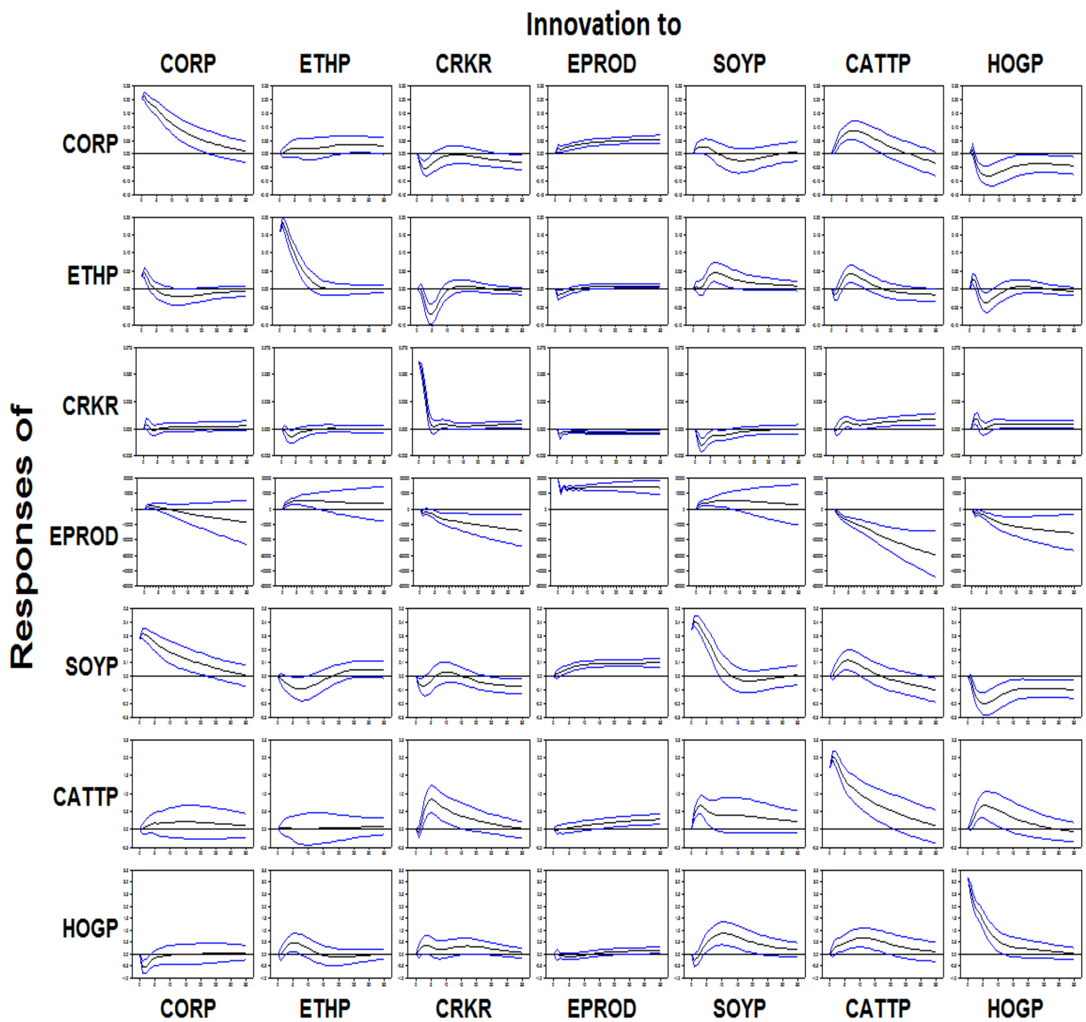

Figure 21. Impulse response functions from innovation of two-lag VAR.

4.5.7 Forecasting and Conditional Forecasting

We constructed forecasts for the prices out to 2022. In our forecasting we took into account the limits imposed by the Renewable Fuel Standards (RFS2) annual amount of ethanol content in blended fuel with gasoline. The 2007 EISA RFS limits corm ethanol to 13.8 and 14 billion in 2013 and 2014 respectively then to 15 billion gallons from 2015 to 2022. The required amount of ethanol blended into fuel is declared yearly, so we calculated monthly amounts using historical monthly shares. Taking the RFS mandated amount of ethanol we construct conditional forecasts. We also consider the case with no mandates and perform unconditional forecast on price series.

Comparing conditional and unconditional forecasts (Figure 22), one can see that all agricultural commodities prices and ethanol price will be higher when we take into account for RFS requirements in our model, except for crack ratio. One can see the forecasting results in the Figure 22. The solid line after Jan 2013 to the end of 2022 is the unconditional forecast and the dotted line is the forecast conditional on RFS policies. The average percent different of conditional forecast compare to unconditional is presented in Table 14. Conditional forecasting gives us an annual average corn price which is 13.3% higher than under the unconditional forecast 2022. This difference is 5.7% for ethanol price and also 12.6% and almost 4% for soybean and cattle prices. By contrast, the conditional forecasts regarding RFS requirements leads to almost a 6% lower crack ratio than when there are no RFS requirements in the model.

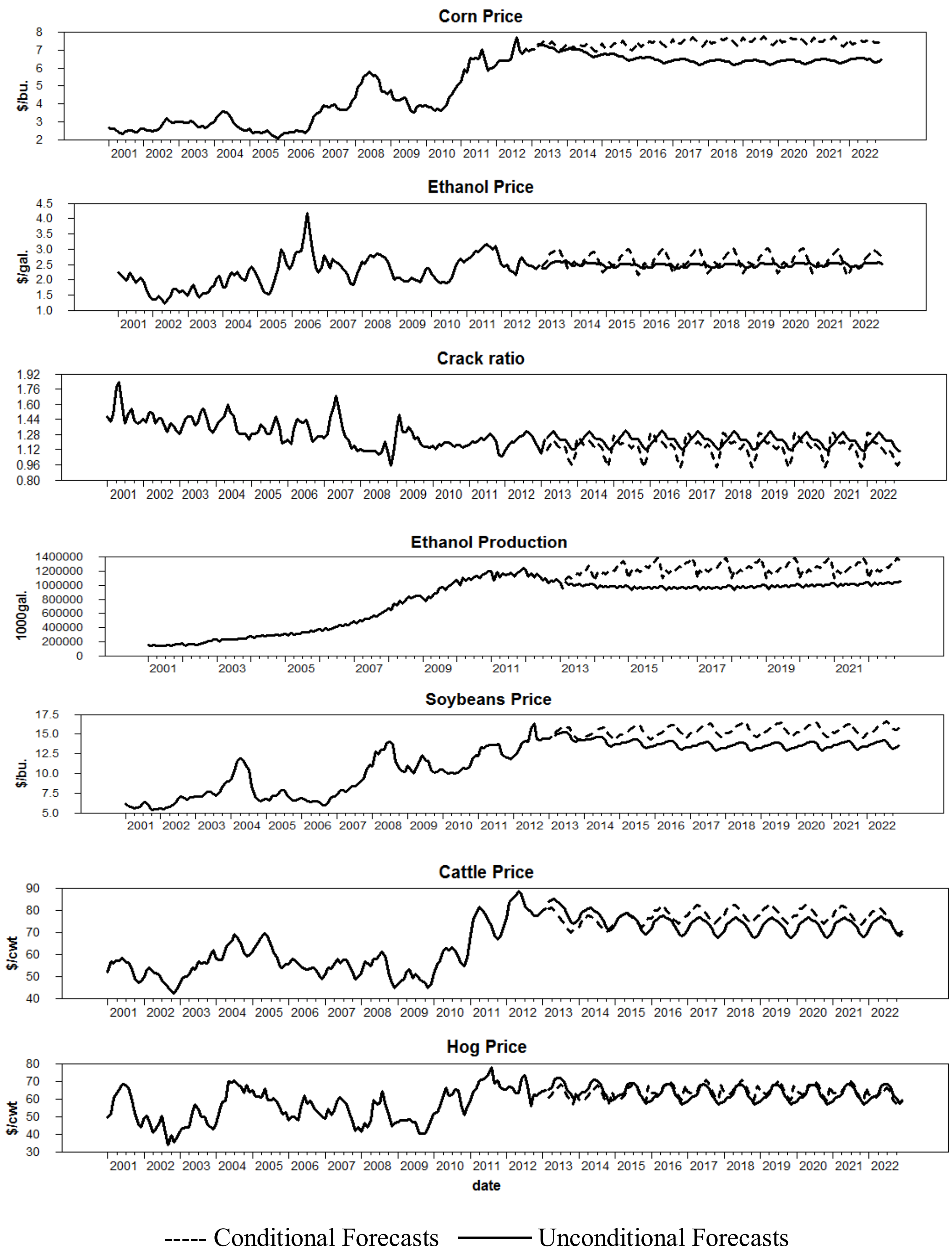

Figure 22. Historical prices plus forecasts to 2022 conditional and unconditional on RFS.

Table 14 Average percent difference in conditional forecasts with respect to unconditional forecasts.

	CORP	ETHP	CRKR	SOYP	CATTP	HOGP
With RFS mandates	13.33	5.73	-5.86	12.06	3.97	1.48
With EIA projection	7.91	3.45	-3.83	7.29	1.88	0.47

In 2013, the blend wall limited ethanol consumption in E10 (motor gasoline contains 10% ethanol) to about 13.3 billion gallons (U.S. Energy Information Administration 2013). For this reason and also constant gasoline consumption of 138 billion gallons as in predictions, ethanol falling short of required amount in the mandate (Westcott and McPhail 2013). This extra requirement of RFS was substituted by blending advanced biofuels in excess of advanced RFS or by using accumulated credits (RINs) (Irwin and Good 2013a). There are two ways to meet EPA requirement and expand the blend wall: 1) increase in domestic gasoline consumption, 2) consumption of E15 or E85 instead of E10 (Irwin and Good 2013b). For this last one to happen we need a lower ethanol price compared to gasoline price since a gallon of E85 contains 75% energy of a same amount of gasoline (Irwin and Good 2013b). On May 7th 2014, Energy Information Administration had released a projection on the amount of ethanol accredited to RFS considering the blending wall (U.S. Energy Information Administration 2014) which is partially different from RFS required amount. One can compare the projection amount with RFS requirement in Table 15. We performed conditional forecasting on prices regarding EIA projection of ethanol amount as well.

Table 15 Ethanol requirement in billion gallons in RFS and EIA projection of credits earned from ethanol.

	RFS requirements	EIA projection
2013	13.8	13.31
2014	14.5	12.73
2015	15	13.59
2016	15	13.65
2017	15	13.84
2018	15	13.91
2019	15	13.95
2020	15	14.06
2021	15	14.12
2022	15	14.37

The rise in average percent forecast with EPA projection is more moderate for corn, ethanol and cattle price compare to the forecast conditional on RFS requirements. This number is also showing almost 2% less decrease for crack ratio which together with less ethanol price increase could make E85 more economically feasible. The results of conditional forecasting are shown in Table 14.

4.6 Concluding Comments

Combining recent advances in causal flows with time series analysis can provide insights of the interactions of energy and agricultural markets. Empirical examination of linkages between these two markets has important policy implications in terms of the consequences on food and energy prices. This study also informs our understanding of the influence of U.S. ethanol policies such as the Renewable Fuel Standard (RFS) mandates on commodity prices in energy and agricultural markets.

This study shows a significant linkage between agricultural and energy market prices mainly transmitted through corn. The results of the directed acyclic graph analysis suggest that, in contemporaneous time, corn price fluctuations cause changes in soybeans and ethanol prices.

Innovation accounting methods are employed to summarize the integration between agriculture and energy markets. Forecast error variance decomposition suggests that ethanol production explains about 10% of the variation in corn and soybeans prices in the longer term. Also corn and soybean price rises have effects on livestock prices through their role as feedstuffs. Corn price and soybeans price together account for about 12 and 18 percent of the changes in cattle and hog prices respectively.

The crack ratio is another important explanatory and reactive factor. Changes in this factor explain about 8.7% of ethanol price changes. After a given positive shock to ethanol production the crack ratio will decrease. Moreover, the implementation of renewable fuel mandates on ethanol will decrease the average gasoline price by 5.8% by 2022. Although this result is similar to Du and Hayes (2012) who believe the effect of an increase in ethanol production is a decrease in gasoline price, a finding unlike that in Knittle and Smith (2012) who found near zero effects.

Furthermore, the result of conditional forecasting taking RFS into account, show the mandatea increased prices for almost all modeled commodities. We also performed a forecasting exercise regarding EIA projection of ethanol accredited for RFS consequences in 2022 as affected by a blending wall issue. The results indicate that blending wall issues cause a smaller increase in ethanol price and also smaller decrease in gasoline price.

CHAPTER V

CONCLUSIONS

Human activities produce greenhouse gases (GHGs) which are a main driver of anthropogenic climate change. Although the main source of GHGs is fossil fuel combustion agriculture produces substantial amounts. Also agriculture could offset GHGs in a number of ways (IPCC, 2014). For instance the agricultural sector is a provider of feedstocks for bioenergy production which is an essential energy option and can reduce GHG net emissions. However mobilizing the mitigation potentials of this sector is not easy and has been of recent interest to researchers and policy makers. This work studies economic implication of some US GHG mitigation policies.

This study mainly considered the following issues:

- Designing a voluntary carbon offset market to deal with additionality and leakage issues and at the same time cost effectiveness of the program.
- Studying economic implications of growing switchgrass on marginal land instead of crop land.
- Examining the price dynamics of energy and agricultural markets and investigating the effect of renewable fuel standards on future prices.

Chapter two of this dissertation examined agricultural sector participation in a voluntary carbon offset market. We showed use of a baseline applicable to market entrants is essential to gain effectiveness in terms of additionality, leakage and program cost. With no baseline, non additional participants enter the program and claim payments without creating additional offsets, and so payments would be higher than additional offsets. We then examine the implications of a per unit baseline where we assign all mitigation activities an amount they must do better than. This baseline works well to overcome non additionality at lower carbon prices but it generates substantially less offsets at higher prices due to its discriminatory effects against bioenergy alternatives that are little used in the without carbon prices case. To improve incentives for doing better in bioenergy related mitigation strategies we suggest a hybrid baseline where for the strategies with small unit levels (like bioenergy and afforestation) in the base situation we pay them if they to do better than the total offset in the base model.

We find that a per unit baseline combined with a hybrid baseline decreases traditional agricultural production and so increases commodity prices and in turn results in higher producers' surplus and lower consumers' surplus. Also we discover the program lowers exports from the US to other countries and decreases foreign surplus. Moreover, we find market forces are likely to increase international production and associated emissions causing leakage.

Chapter 3 of this work studied the economic implications of growing switchgrass on marginal land under RFS requirements. Agronomic advantages of switchgrass make it possible to produce it on marginal lands that are not in crop production reducing land competition between food and energy. We simulate market penetration, potential GHG mitigation, price, production, welfare and environmental effects of using marginal land to produce switchgrass with the FASOM-GHG model.

We find using marginal land in the absence of a carbon market contributes in satisfying RFS cellulosic mandates taking the pressure off of conventional land use. Additionally, this will help reduce several agricultural product prices although is not true for all agricultural products. Livestock prices decrease as some feedstuff production decreases when using marginal land. Under carbon prices we find that the switchgrass produced on marginal land largely goes toward producing electricity and the pressure remains to meet the RFS2 mandates. We also find that because of added fertilizer and fuel consumption, use of marginal land only contributes to GHG reduction when it is used along with higher carbon prices. Growing switchgrass on marginal lands does generate an income increase for producers and an overall increase in total welfare.

In chapter 4, we examine the interdependency between energy and agriculture markets in the US. We use a VAR framework to study the dynamic relationships between the real prices of corn, soybeans, cattle, and hog simultaneously with ethanol and a measure of the refining margin – the crack ratio. We also examine the influence of RFS mandates on these markets.

The results show at contemporaneous time corn price fluctuations cause changes in soybean and ethanol prices. We also fin RFS requirements cause an increase in all prices by 2022 except for crack ratio.

Across the three essays we find that voluntary offset markets, marginal land for biofeedstock production and substituting biofuel for fossil fuels are all policies that could exploit agricultural sector GHG mitigation potentials while they also could be a source of increased income for agricultural producers. But some considerations are important in their success:

- Voluntary carbon offset programs need a baseline to prevent non additionality and leakage and maintain a cost effective program. A per unit baseline appears to be a good choice for most mitigation possibilities but not for ones where baseline use of the mitigation possibility is small. There an approach that permits scale increases is needed,
- While we find growing switchgrass on marginal lands is effective in reducing the food versus fuel competition when a carbon market is not present we find that when a carbon market comes into being that the switchgrass may well be used to produce the higher offsetting bioelectricity without alleviating effects of RFS on prices. We also find that GHG emissions go up unless there are simultaneous carbon market incentives.
- The RFS mandates increase the average ethanol price and decreases gasoline price by 2022.

There are a number of limitations that characterize the work done in this dissertation. Studies with FASOM-GHG use a certain projection of future crop and livestock yields plus international trade and rate of conversion of biofeedstock into biofuels, which could be improved and would affect the results. Also FASOM-GHG assumes rational forward looking decision makers (consumer or producer) which is a strong assumption. Also market power is not considered and all markets are assumed to clear under perfect information. Moreover, loss of ecological services and other amenities are not accounted for in our studies. Also in vector auto regression modeling we just use a selected subset of variables from the agriculture and energy markets. In the real world, there certainly are many other factors that can affect every variable of our study.

Future research could expand the marginal land analysis to consider production of other biofeedstocks on marginal land besides switchgrass. Also for more accurate results of the influence of RFS on prices one could add advanced biofuel next to corn ethanol in the VAR model. Moreover, entering the renewable identification numbers into the model would be helpful since it represents a price of ethanol's credits traded among blending industry.

REFERENCES

Abbott, P.C., C. Hurt and W.E. Tyner. 2011. "What's Driving Food Prices in 2011?" Issue Report. Oak Brook, Ill., Farm Foundation. http://www.farmfoundation.org/news/articlefiles/1742-FoodPrices_web.pdf (accessed May 4, 2014).

Adams, D., R. Alig, B.A. McCarl, et al. 2005. "FASOMGHG Conceptual Structure, and Specification: Documentation." Unpublished, Dept. of Agr. Econ., Texas A&M University, College Station. http://agecon2.tamu.edu/people/faculty/mccarl-bruce/papers/1212FASOMGHG_doc.pdf (accessed June 13, 2014).

Alexander, C. and H. C. 2007. "Biofuels and their Impact on Food Prices." Purdue Extension, ID-346-W. Purdue University, West Lafayette, IN, USA.

Antle, J., S. Capalbo, S. Mooney, E. Elliott, and K. Paustian. 2003. "Spatial Heterogeneity, Contract Design, and the Efficiency of Carbon Sequestration Policies for Agriculture." *Journal of Environmental Economics and Management* 46:231-50.

Awokuse, T.O., and D.A. Bessler. 2003. "Vector Autoregressions, Policy Analysis, and Directed Acyclic Graphs: An Application to the US Economy." *Journal of Applied Economics* 6:1-24.

Babiker, M.H. 2005. "Climate Change Policy, Market Structure, and Carbon Leakage." *Journal of International Economics* 65:421-45.

Barlowe, R. 1986. *Land Resources Economics: The Economics of Real Estate.* Englewood Cliffs, NJ: Prentice-Hall.

Beach, R.H. and B.A. McCarl. 2010. "US Agricultural and Forestry Impacts of the Energy Independence and Security Act: FASOM Results and Model Description." RTI International, 3040. Cornwallis Road Research Triangle Park, NC.

Bernanke, B. 1986. "Alternative Explanations of the Money-Income Correlation." Carnegie-Rochester Conference Series on Public Policy no. 25, North-Holland, Amsterdam.

Berndes, G. 2002. "Bioenergy and Water—the Implications of Large-Scale Bioenergy Production for Water use and Supply." *Global Environmental Change* 12:253-71.

Bernstein, P.M., W.D. Montgomery, and T.F. Rutherford. 1999. "Global Impacts of the Kyoto Agreement: Results from the MS-MRT Model." *Resource and Energy Economics* 21:375-413.

Bessler, D.A., and J. Yang. 2003. "The Structure of Interdependence in International Stock Markets." *Journal of International Money and Finance* 22:261-87.

Birur, D.K., T.W. Hertel, and W.E. Tyner. 2009. "The Biofuels Boom: Implications for World Food Markets." *The Food Economy: Global Issues and Challenges.* 1:61-75.

Bryant, H. and J. Outlaw. 2006. "US Ethanol Production and use Under Alternative Policy Scenarios." Agricultural and Food Policy Center Research Report 06-1, Texas A&M University, College Station.

Bushnell, J.B. 2011. "Adverse Selection and Emissions Offsets." Working Paper, Dept. of Econ., Iowa State University.

Campbell, J.E., D.B. Lobell, R.C. Genova, and C.B. Field. 2008. "The Global Potential of Bioenergy on Abandoned Agriculture Lands." *Environmental Science & Technology* 42:5791-4.

Carter, C., G. Rausser and A. Smith. 2012. "The Effect of the US Ethanol Mandate on Corn Prices." Working paper, Dept. of Agr. Econ., University of California, Davis.

Chazournes, d. and L. Boisson. 1998. "Kyoto Protocol to the United Nations Framework Convention on Climate Change." UN’s Audiovisual Library of International Law, Johannesburg, South Africa. http://untreaty.un.org/cod/avl/ha/kpccc/kpccc.html (accessed June 7, 2014).

Cooley, T.F., and S.F. LeRoy. 1985. "A Theoretical Macroeconometrics: A Critique." *Journal of Monetary Economics* 16:283-308.

Doan T. 2000. "RATS: User's Guide Version 5." Estima, Evanston, Illinois.

Du, X., and D.J. Hayes. 2009. "The Impact of Ethanol Production on US and Regional Gasoline Markets." *Energy Policy* 37:3227-34.

——— 2012. *The Impact of Ethanol Production on US and Regional Gasoline Markets: An Update to 2012.* Iowa State University, Ames, Iowa: Center for Agricultural and Rural Development (CARD).

Fargione, J., J. Hill, D. Tilman, S. Polasky, and P. Hawthorne. 2008. "Land Clearing and the Biofuel Carbon Debt." *Science* 319:1235-8.

Fell, H., and R.D. Morgenstern. 2010. "Alternative Approaches to Cost Containment in a Cap-and-Trade System." *Environmental and Resource Economics* 47:275-97.

Ferraro, P.J. 2008. "Asymmetric Information and Contract Design for Payments for Environmental Services." *Ecological Economics* 65:810-21.

Ferraro, P.J., and S.K. Pattanayak. 2006. "Money for Nothing? A Call for Empirical Evaluation of Biodiversity Conservation Investments." *PLoS Biology* 4:e105.

Field, C., V. Barros, K. Mach and M. Mastrandrea. 2014. "Climate Change 2014: Impacts, Adaptation, and Vulnerability." Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, Press Syndicate of the University of Cambridge, Cambridge, UK.

Florida Farm Bureau Federation. 2009. "Cap and Trade Principles." Agricultural Policy Division, Florida. http://www.floridafarmbureau.org/files/resources/issues/6_09CapandTradePrinciples.pdf (accessed 7 June, 2014).

Gelfand, I., R. Sahajpal, X. Zhang, R.C. Izaurralde, K.L. Gross, and G.P. Robertson. 2013. "Sustainable Bioenergy Production from Marginal Lands in the US Midwest." *Nature* 493:514-7.

——— 2013. "Sustainable Bioenergy Production from Marginal Lands in the US Midwest." *Nature* 493:514-7.

Geweke, J., and R. Meese. 1981. "Estimating Regression Models of Finite but Unknown Order." *Journal of Econometrics* 16:162-9.

Greene, W.H. 2003. *Econometric Analysis.* Englewood Cliffs, NJ: Prentice-Hall.

Heath, L.S., and J.E. Smith. 2000. "An Assessment of Uncertainty in Forest Carbon Budget Projections." *Environmental Science & Policy* 3:73-82.

Hennessy, K., B. Fitzharris, B.C. Bates, et al. 2007. "Climate Change 2007: Impacts, Adaptation and Vulnerability." contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Horowitz, J., and R. Just. 2013. "Economics of Additionality for Environmental Services." *Journal of Environmental Economics and Management* 66.1:105-22.

Hyvärinen, A., and E. Oja. 2000. "Independent Component Analysis: Algorithms and Applications." *Neural Networks* 13:411-30.

Irwin, S. and D. Good. 2013a. "The Ethanol Blend Wall, Biodiesel Production Capacity, and the RFS...Something has to Give." Farmdoc daily, Dept. of agr. Econ., University of Illinois, Urbana- Champaign. http://farmdocdaily.illinois.edu/2013/02/ethanol-blend-wall-biodiesel-RFS.html (accessed April 14, 2014).

———2013b. "Expanding the Ethanol Blend Wall - a Role for E85?" Farmdoc daily, Dept. of agr. Econ., University of Illinois, Urbana- Champaign. http://farmdocdaily.illinois.edu/2013/01/expanding-the-ethanol-blend-wall.html (accessed April 14, 2014).

Jensen, K., C.D. Clark, P. Ellis, B. English, J. Menard, M. Walsh, and de la Torre Ugarte, Daniel. 2007. "Farmer Willingness to Grow Switchgrass for Energy Production." *Biomass and Bioenergy* 31:773-81.

Kim, M., and B.A. McCarl. 2009. "Uncertainty Discounting for Land-Based Carbon Sequestration." *Journal of Agricultural and Applied Economics* 41:1-11.

Knittel, C., and A. Smith,. 2012. "Ethanol Production and Gasoline Prices: A Spurious Correlation." Working Paper, Dept. of Agr. Econ., University of California, Davis.

Kort, J., M. Collins, and D. Ditsch. 1998. "A Review of Soil Erosion Potential Associated with Biomass Crops." *Biomass and Bioenergy* 14:351-9.

Lee, H., B.A. McCarl, and D. Gillig. 2005. "The Dynamic Competitiveness of US Agricultural and Forest Carbon Sequestration." *Canadian Journal of Agricultural Economics/Revue Canadienne D'Agroeconomie* 53:343-57.

Lee, H., B.A. McCarl, U.A. Schneider, and C. Chen. 2007. "Leakage and Comparative Advantage Implications of Agricultural Participation in Greenhouse Gas Emission Mitigation." *Mitigation and Adaptation Strategies for Global Change* 12:471-94.

Mason, C.F. and A.J. Plantinga. 2011. "Contracting for Impure Public Goods: Carbon Offsets and Additionality." No. w16963. National Bureau of Economic Research.

McCarl, B., D. Adams, R. Alig and B. Murray. 2005. "FASOMGHG Conceptual Structure, and Specification: Documentation." Unpublished, Dept. of Agr. Econ., Texas A&M University, College Station. http://agecon2.tamu.edu/people/faculty/mccarl-bruce/papers/1212FASOMGHG_doc.pdf (accessed May 15, 2014).

McCarl, B.A. 2008. "Bioenergy in a Greenhouse Mitigating World." *Choices* 23(1):31-3.

McCarl, B.A., D.M. Adams, R.J. Alig, and J.T. Chmelik. 2000. "Competitiveness of Biomass-fueled Electrical Power Plants." *Annals of Operations Research* 94:37-55.

McCarl, B.A., and U.A. Schneider. 2001. "The Cost of Greenhouse Gas Mitigation in US Agriculture and Forestry." *Science* 294:2481-2.

——— 2000. "US Agriculture's Role in a Greenhouse Gas Emission Mitigation World: An Economic Perspective." *Review of Agricultural Economics* 22:134-59.

McLaughlin, S.B., and L. Adams Kszos. 2005. "Development of Switchgrass (Panicum Virgatum) as a Bioenergy Feedstock in the United States." *Biomass and Bioenergy* 28:515-35.

Metz, B., ed. 2001. "Climate Change 2001: Mitigation." contribution of Working Group III to the third assessment report of the Intergovernmental Panel on Climate Change, Cambridge University Press.

Mezzatesta, M., D.A. Newburn, and R.T. Woodward. 2013. "Additionality and the Adoption of Farm Conservation Practices." *Land Economics* 89:722-42.

Milbrandt, A.R., D.M. Heimiller, A.D. Perry, and C.B. Field. 2014. "Renewable Energy Potential on Marginal Lands in the United States." *Renewable and Sustainable Energy Reviews* 29:473-81.

Mitchell, S.R., M.E. Harmon, and K.E. O'Connell. 2012. "Carbon Debt and Carbon Sequestration Parity in Forest Bioenergy Production." *GCB Bioenergy* 4:818-27.

Mjelde, J.W., and D.A. Bessler. 2009. "Market Integration among Electricity Markets and their Major Fuel Source Markets." *Energy Economics* 31:482-91.

Montero, J. 2000. "Optimal Design of a Phase-in Emissions Trading Program." *Journal of Public Economics* 75:273-91.

Mooney, D.F., R.K. Roberts, B.C. English, D.D. Tyler and J.A. Larson. 2008. "Switchgrass Production in Marginal Environments: A Comparative Economic Analysis Across Four West Tennessee Landscapes." Selected paper presented at the American Agricultural Economics Association Annual Meetings, Orlando, Florida.

Murray, B.C., and J.S. Baker. 2011. "An Output-Based Intensity Approach for Crediting Greenhouse Gas Mitigation in Agriculture: Explanation and Policy Implications." *Greenhouse Gas Measurement and Management* 1:27-36.

Murray, B.C., W.A. Jenkins, J.M. Busch and R.T. Woodward. 2012. "Designing Cap and Trade to Correct for “Imperfect” Offsets." Working Paper, EE 10-03V2, Nicholas Institute, Duke University.

Murray, B.C., B.A. McCarl, and H. Lee. 2004. "Estimating Leakage from Forest Carbon Sequestration Programs." *Land Economics* 80:109-24.

Murray, B.C., B. Sohngen, and M.T. Ross. 2007. "Economic Consequences of Consideration of Permanence, Leakage and Additionality for Soil Carbon Sequestration Projects." *Climatic Change* 80:127-43.

Pattanayak, S.K., and D.T. Butry. 2005. "Spatial Complementarity of Forests and Farms: Accounting for Ecosystem Services." *American Journal of Agricultural Economics* 87:995-1008.

Pearl, J. 1995. "Causal Diagrams for Empirical Research." *Biometrika* 82:669-88.

——— 2000. *Causality: Models, Reasoning and Inference.* Cambridge: MIT press.

Pethig, R. 1976. "Pollution, Welfare, and Environmental Policy in the Theory of Comparative Advantage." *Journal of Environmental Economics and Management* 2:160-9.

Philp, J.C., K. Guy, and R.J. Ritchie. 2013. "Biofuels Development and the Policy Regime." *Trends in Biotechnology* 31:4-6.

Ricardo, D. 1817. *Principles of Political Economy and Taxation.* Harmondsworth, Middlesex: Penguin Books.

Robertson, G.P., S.K. Hamilton, S.J. Del Grosso, and W.J. Parton. 2011. "The Biogeochemistry of Bioenergy Landscapes: Carbon, Nitrogen, and Water Considerations." *Ecological Applications* 21:1055-67.

Runge, C.F., and B. Senauer. 2007. "How Biofuels could Starve the Poor." *Foreign Affairs* 1:41-53.

Scheines, R. and P. Spirtes. 1994. "Tetrad II: Tools for Causal Modeling: User's Manual and Software." Lawrence Erlbaum Associates Inc, Hillsdale, NJ.

Schmer, M.R., K.P. Vogel, R.B. Mitchell, and R.K. Perrin. 2008. "Net Energy of Cellulosic Ethanol from Switchgrass." *Proceedings of the National Academy of Sciences of the United States of America* 105:464-9.

Schneider, U.A., and B.A. McCarl. 2003. "Economic Potential of Biomass Based Fuels for Greenhouse Gas Emission Mitigation." *Environmental and Resource Economics* 24:291-312.

Searchinger, T., R. Heimlich, R.A. Houghton, F. Dong, A. Elobeid, J. Fabiosa, S. Tokgoz, D. Hayes, and T.H. Yu. 2008. "Use of U.S. Croplands for Biofuels Increases Greenhouse Gases through Emissions from Land-use Change." *Science* 319:1238-40.

Segerson, K. 2013. "Voluntary Approaches to Environmental Protection and Resource Management." *Annu.Rev.Resour.Econ.* 5:161-80.

Shimizu, S., P.O. Hoyer, A. Hyvärinen, and A. Kerminen. 2006. "A Linear Non-Gaussian Acyclic Model for Causal Discovery." *The Journal of Machine Learning Research* 7:2003-30.

Shrestha, R.M., and G.R. Timilsina. 2002. "The Additionality Criterion for Identifying Clean Development Mechanism Projects Under the Kyoto Protocol." *Energy Policy* 30:73-9.

Sims, C.A., S.M. Goldfeld, and J.D. Sachs. 1982. "Policy Analysis with Econometric Models." *Brookings Papers on Economic Activity* 1:107-64.

Sims, C.A., and T. Zha. 1999. "Error Bands for Impulse Responses." *Econometrica* 67:1113-55.

Smith, P., D. Martino, Z. Cai, D. Gwary, H. Janzen, P. Kumar, B. McCarl, S. Ogle, F. O'Mara, C. Rice, B. Scholes, O. Sirotenko, M. Howden, T. McAllister, G. Pan, V. Romanenkov, U. Schneider, S. Towprayoon, M. Wattenbach, and J. Smith. 2008. "Greenhouse Gas Mitigation in Agriculture." *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences* 363:789-813.

Spirtes, P., C.N. Glymour, and R. Scheines 2000. *Causation, Prediction, and Search.* Cambridge, MA: MIT press.

Spirtes, P., C. Glymour, R. Scheines, and R. Tillman. 2010. "Automated Search for Causal Relations: Theory and Practice." *In R. Dechter, H. Geffner, &J.Y. Halpern (Eds.), Heuristics, Probability, and Causality: A Tribute to Judea Pearl* 27:467-508.

Swinton, S.M., B.A. Babcock, L.K. James, and V. Bandaru. 2011. "Higher US Crop Prices Trigger Little Area Expansion so Marginal Land for Biofuel Crops is Limited." *Energy Policy* 39:5254-8.

Tilman, D., J. Hill, and C. Lehman. 2006. "Carbon-Negative Biofuels from Low-Input High-Diversity Grassland Biomass." *Science* 314:1598-600.

Tyner, W., F. Dooley, C. Hurt, and J. Quear. 2008. "Ethanol Pricing Issues for 2008." *Industrial Fuels and Power* 1:50-7.

Tyner, W.E. 2010. "The Integration of Energy and Agricultural Markets." *Agricultural Economics* 41:193-201.

Tyner, W., and F. Taheripour. 2008. "Biofuels, Policy Options, and their Implications: Analyses using Partial and General Equilibrium Approaches." *Journal of Agricultural & Food Industrial Organization* 6(2):Article 9.

U.S. Energy Information Administration. 2014. "Annual Energy Outlook." Washington DC, May. http://www.eia.gov/forecasts/aeo/MT_liquidfuels.cfm (accessed 7 June,2014).

———2013. "Short-Term Energy and Summer Fuels Outlook ." Washington DC, April. http://www.eia.gov/forecasts/steo/archives/Apr13.pdf (accessed 7 June, 2014).

Westcott, P. and L. McPhail. 2013. "High RIN Prices Suggest Market Factors Likely to Constrain Future US Ethanol Expansion." Washington DC: U.S. Department of Agriculture, Feed Outlook, August.

Wu, J., and B.A. Babcock. 1996. "Contract Design for the Purchase of Environmental Goods from Agriculture." *American Journal of Agricultural Economics* 78:935-45.

——— 1995. "Optimal Design of a Voluntary Green Payment Program Under Asymmetric Information." *Journal of Agricultural & Resource Economics* 20:316-27.

Yu, T.E., L. He, B.C. English, and J.A. Larson. 2014. "GIS-Based Optimization for Advanced Biofuels Supply Chains: A Case Study in Tennessee." *Lecture Notes in Management Science* 6:217-27.