Title
Economics of Lifecycle analysis and greenhouse gas regulations

Author
Rajagopal, Deepak

Publication Date
2009

Peer reviewed|Thesis/dissertation

Economics of Lifecycle analysis and greenhouse gas regulations

by

Deepak Rajagopal

B.Tech. (Indian Institute of Technology, Madras) 1999
M.S. (University of Maryland, College Park) 2001

A dissertation submitted in partial satisfaction of the
requirements for the degree of
Doctorate in Philosophy

in

Energy and Resources

in the

GRADUATE DIVISION
of the
UNIVERSITY OF CALIFORNIA, BERKELEY

Committee in charge:
Professor David Zilberman, Chair
Professor Daniel Kammen
Professor David Sunding

Fall 2009

Economics of Lifecycle analysis and greenhouse gas regulations

Abstract

Economics of Lifecycle analysis and greenhouse gas regulations

by

Deepak Rajagopal

Doctorate in Philosophy in Energy and Resources

University of California, Berkeley

Professor David Zilberman, Chair

Interest in alternatives to fossil fuels has risen significantly during the current decade. Although a variety of different alternative technologies have experienced rapid growth, biofuels have emerged as the main alternative transportation fuel. Energy policies in several countries envision blending biofuels with fossil fuels as the main mechanism to increase energy independence and energy security. Climate change policies in several regions are also riding on the same hope for reducing emissions from transportation. The main advantage of biofuels is that they are technically mature, cheaper to produce and more convenient to use relative to other alternative fuels. However, the impact of current biofuels on the environment and on economic welfare, is controversial. In my dissertation I focus on three topics relevant to future energy and climate policies. The first is the economics of lifecycle analysis and its application to the assessment of environmental impact of biofuel policies. The potential of biofuel for reducing greenhouse gas emissions

was brought to the fore by research that relied on the methodology called lifecycle analysis (LCA). Subsequent research however showed that the traditional LCA fails to account for market-mediated effects that will arise when biofuel technologies are scaled up. These effects can increase or decrease emissions at each stage of the lifecycle. I discuss how the LCA will differ depending on the scale, a single firm versus a region and why LCA of the future should be distinguished from LCA of the past. I describe some approaches for extending the LCA methodology so that it can be applied under these different situations. The second topic is the economic impact of biofuels. Biofuels reduce the demand for oil and increase the demand for agricultural goods. To high income countries which tend to be both large importers of oil and large exporters of agricultural goods, this implies two major benefits. One of the one hand it reduces the market power of OPEC (Oil Producing and Exporting Countries), a cartel of nations which is the single largest oil exporting entity in the world, and is an entity considered unreliable. On the other hand, it reduces the demand for domestic farm subsidies. At the same crops comprise a small share of the retail price of food. As a result, the expected negative impact of biofuel was at worst a small increase in the retail price of food. However, the food price inflation in the year 2008 suggests that the negative impact on food consumers was significantly higher than expected and also outweighed the impact fuel consumers. I estimate the effect on biofuels on food and oil prices and compare them to other estimates in the literature and also relate these to prices observed in the real world. The third topic is the economics of greenhouse gas regulations of transportation fuels. Climate change policies such as United Nations' Kyoto protocol, European Union Emission Trading Scheme, and the Regional Greenhouse

Gas Initiative in the US north-east mandate an aggregate emission target, called a cap and allow regulated entities to trade responsibilities for abatement. Furthermore, these policies have generally and sometimes exclusively targeted the electricity and industrial sector for emission reduction. However, the Low carbon fuel standard and Renewable fuel standard are two policies about to be implemented by the State of California and the US federal government, which exclusively target the transportation sector for emission reduction. Furthermore, these regulations mandate emission intensity target for fuels rather than aggregate emission reduction. I compare the cost-effectiveness of these two types of regulations, namely, aggregate emission caps versus emission intensity standards and discuss how prices, output and emissions vary between these two types of policies.

Professor David Zilberman
Dissertation Committee Chair

Contents

List of Figures

List of Tables

Acknowledgments

I would like to thank my committee members for their guidance and support. I am indebted to Professor David Zilberman for his outstanding advising and encouragement. I am also indebted to late Professor. Alex Farrell for motivating my interest on the topic of lifecycle analysis and environmental regulation. I also thank Gal Hochman for the stimulating discussions and collaborating with me on several papers. I thank the Energy Biosciences Institute for providing financial support for undertaking this research and attending several conferences. I thank the Energy Resources Group for providing the platform for my transition from a disciplinary to an interdisciplinary researcher. Finally, I thank my family for their support.

Chapter 1

Introduction

The International Energy Agency predicts that global demand for oil (excluding biofuels) will increase approximately 25% to reach 106 million barrels per day by the year 2030[1]. This scenario embodies the effects of measures and policies in place as of mid-2008 as well as expectation of high prices and slower growth in demand. Crude oil import price is expected to average over $100 per barrell (2007 dollars) between 2008-2015 and rise to $120 by the year 2030. The price is higher because the of bulk of the increase in supply of liquid fuels is expected to come from natural gas (through liquefaction) and oil sands which are costlier than conventional oil. Fuels from these sources are on a lifecycle basis also more carbon-intensive than when those produced conventional crude oil. This obviously does not bode well for efforts to mitigate global climate change[2]. Last but not least, the events of 11^{th} September 2001 have spurred US and other large oil importing countries to seek greater energy security by reducing reliance on oil and energy independence by reducing energy imports.

As a result of these drivers, alternative energy sector has witnessed rapid growth in during the current decade. The world has witnessed a similar rise in demand for alternative energy before, most notably in the aftermath of the OPEC oil embargo which happened in 1973. As spectacular as the rise in investments was then, the following decade witnessed a steep decline in oil prices and a consequent decline in interest in alternative energy[3, 4]. This time however, the geopolitics of oil post 9/11, rapid growth in emerging economies, peak oil concerns, and a new consensus on combating climate change, suggest that current interest is likely to be sustained [5, 6, 7].

Several technologies that have the potential to supply a large share of global energy demand for transportation are either undergoing R&D or already under production today[8]. Liquid biofuels (henceforth referred to simply as biofuels), battery-gasoline hybrid vehicles, plug-in electric cars, compressed natural gas vehicles, and hydrogen fuel cell vehicles are some alternatives to gasoline or diesel-powered automobile technologies. Given the the right economic and policy conditions, such technologies can capture a significant share of the oil market. Today, ethanol (from grains and cane) and biodiesel (from oil seeds) which are called first-generation biofuels represent the single largest alternative to oil in use and comprise about 1% of the global supply of transportation fuels [9]. The emergence of biofuels as the main alternative is attributable to its relative advantage in terms of cost, convenience, and technical maturity of the production process[9]. The agricultural and chemical processes (fermentation or trans-esterification) for production of biofuels and distribution and end-use infrastructure for consuming them are all established.

However, the recent evidence about the performance of biofuels in delivering economic and environmental benefits is controversial [9, 10]. [1]. Recent biofuels have had a small but positive impact on energy security by slowing down the rate of growth in imports of oil. The have also had a similar impact on the price of fuel. Our estimates suggest that the US ethanol mandates lowered gasoline prices by 2%-3%[11]. The impact on greenhouse gas emissions is uncertain. Although initial research suggested that biofuels like corn based ethanol and biodiesel from edible oil seeds can have significantly lower greenhouse gas intensity than their fossil substitutes on a lifecycle basis, a more recent estimate suggests the contrary. While the assumptions employed by the latter are controversial, it estimates emissions which are not considered in a traditional lifecycle assessment (LCA) framework. The next chapter discusses this in more detail. Biofuels have also had unintended adverse impacts. They have been partially responsible for the increase in price of food commodities especially grains and oil seeds. Quantitative estimates of the impact of biofuels on food prices are wide ranging from as low as 3% to as high as 75%[12, 13, 14, 15] . Our own estimates suggest that ethanol raised corn prices between 15% to 30%[11].

Biofuels account only for about 1% of global fuel use for transportation [9]. And yet they have generated significant controversy about their impact on environment and the poor. This notwithstanding, the expectation is that share of biofuels will grow substantially during the next couple of decades. The report by the U.S. Department of Energy and U.S. Department of Agriculture (USDA) concludes that it is possible to replace up to

[1] This pertains more to corn-ethanol and biodiesel which have witnessed rapid growth since the year 2000 and not Brazilian cane ethanol which has been in use since the 1970s

30% of current U.S. gasoline consumption with biofuels by 2030[16]. Approximately 60 countries including 23 developing countries have policies to support the development and commercialization of biofuels [8]. In the US, policies such as the California Low Carbon Fuel Standard (LCFS) and US Energy Independence and Security Act (EISA) mandated Renewable Fuel Standard (RFS) envision that blending clean biofuels with fossil fuels will be the principal mechanism for reducing GHG emissions from transportation. The reason for continued emphasis on biofuels is the promise of second-generation biofuels, namely, biofuels produced from cellulosic-biomass from sources such as agricultural and forestry residues, municipal solid waste and grasses grown on marginal land[16, 17, 18]. Such biofuels are expected to deliver significant GHG benefits while having minimal impact on food supply and the natural habitat. Theoretical estimates of yield, land-intensity and carbon-intensity of these type of biofuels certainly warrant a serious effort to develop such technologies. However, the poor performance of the biofuel policies has not only to do with the inherent nature of the first-generation technology (such as it being based on food crops and low yield per hectare of land) but also the limitations of the method used to ex ante assess the performance of biofuels, namely LCA and also the types of policies used, namely blending mandates and trade barriers against imports of more efficient biofuels. A detailed review of the environmental, economic and policy literature on biofuels can be found in Rajagopal and Zilberman[9] and Rajagopal, Sexton et al.[8].

In my dissertation I focus on three different but interconnected topics. The first is the economics of lifecycle analysis and its application to the assessment of environmental impact of biofuel policies. The potential for biofuel as a GHG mitigation option was brought to the fore by work which relied on a methodology called lifecycle analysis. However it has now emerged that in addition to the several advantages there exist some limitations to this methodology as it exists today as a tool for guiding carbon policies. I identify some of these and describe a framework for overcoming them. The second topic is the economic impact of biofuels. Biofuels reduce the demand for oil and increase the demand for agricultural goods. I estimate the effect on biofuels on food and oil prices and compare them to other estimates in the literature and also relate these to prices observed in the real world. The third topic is the economics of GHG regulations. GHG policies such as United Nations' Kyoto protocol, European Union Emission Trading Scheme (ETS), and the Regional Greenhouse Gas Initiative (RGGI) in the US north-east mandate an aggregate emission target, called a cap and allowed regulated entities (nations, states or firms) to trade responsibilities for abatement. Furthermore, these policies have generally or sometimes exclusively targeted emission reduction in electricity and industrial sector. However the LCFS and RFS which exclusively target emission reduction in the transportation sector, mandate emission intensity target for fuels rather than aggregate emission reduction. I compare the cost-effectiveness of these two types of regulations, namely, aggregate emission caps versus emission intensity standards in the context of transportation fuels. These topics are discussed in chapters two, three and four respectively. A summary of the main contributions of my research and the conclusions is presented in chapter five.

Chapter 2

The role of economics in lifecycle environmental impact assessment

2.1 Motivation for LCA

Emission-control policies have generally been designed to hold polluters responsible only for emissions arising directly from a pollution-generating site. Examples include regulation of smoke stack emissions at an industrial facility and regulation of emissions from the tail-pipe of an automobile. A pollution-generating site was not responsible for emissions associated with the production of inputs it consumes so long as they are produced at another site. For instance a factory manufacturing steel using electricity from the electric grid was not accountable for emissions arising during the production of electricity. If every pollution-generating site within a region is regulated this approach of regulating only on-site emissions is efficient. However if not all polluters within the region are regulated there can be leakage, i.e., increase in emissions from unregulated sites as a result of the policy. In the worst case, pollution (in aggregate or the intensity per unit output) can exceed that prior to regulation. For instance, regulation of GHG emissions in OECD region can lead to an increase in emission from developing countries such as China and India. This will occur since polluting industries are likely to relocate from the former to the latter and to the extent that production in the latter is more pollution intensive aggregate pollution will increase. Even within a region, regulation of emissions from just one set of polluters (say transportation) can lead to increase in emissions from another (say, agriculture). If the emissions are global pollutants like any of the greenhouse gases then the region of interest is the entire world. This suggests that GHG policies should be economy-wide (all sectors) and global. However, for a variety of reasons which are beyond the scope of the discussion here, this is not the case. Several of the emerging GHG legislations such as California's LCFS and the US EPA's RFS are policies exclusively targeting transportation fuels.

It is in this context that lifecycle analysis has emerged as an important tool of environmental impact assessment. Lifecycle analysis or lifecycle assessment is a method for calculating the net flow of materials especially pollutants to the environment during the lifecycle of a product. LCA is a systems approach to evaluating the environmental footprint of products, materials, and processes [19, 20]. The goal behind the development of LCA was to quantify the resource and environmental footprint of a product over its entire lifecycle from raw material extraction, manufacturing, and use till ultimate disposal. By resource footprint we mean the total physical flow of both extractive resources such as materials, energy, water etc. and pollution such as green house gases, criteria air pollutants, toxic chemicals etc. through the various stages of the lifecycle. The lifecycle of the fuel includes several stages, namely, production and/or extraction of the feedstock (say, mining of oil), transportation of the feedstock to the processing facility, processing of feedstock to final product (oil refining), transportation and distribution to end-user, and use of the the final product (tailpipe emissions). For this reason, LCA is also referred to as well-to-wheel analysis or cradle-to-grave analysis. The net emissions estimated via LCA is used to estimate the ultimate environmental impact like global warming, acidification, smog, ozone layer depletion etc. using established scientific relationships between emissions and impact. The idea of regulation based on lifecycle emissions is therefore in principle appealing.

2.2 Literature

2.2.1 LCA methodology

Depending on whether the assessment is for the average ouptut from a region or whether it is done for output produced using a specific combination of technologies two major types of LCA exist today, namely, Economic Input-Output LCA and process-LCA.

Economic Input-Output Lifecycle Analysis (EIO-LCA)

The EIO-LCA approach computes the resource requirements and environmental emissions associated with production of a given value worth of a good, say, $1 million worth of steel or electricity. It does so by tracing out the various economic transactions related to production like manufacturing, transportation, mining and related requirements etc. that would take place in order to produce the given value of the good. This information is derived from the economic input/output table of the economy a concept originally developed by Wassily Leontief. Several countries in the world routinely produce such input/output models. In the US, the Department of Commerce maintains a 491 sector industry input-output model of the US economy i.e., a IO table which has 491 rows and columns. The EIO model is a representation of an economy in which the rows and columns in the table represent the various sectors of the economy and the entries in the tables represent total sales from one sector to others, purchases from one sector, or the amount of purchases from one sector to produce a dollar of output for the sector. This model has been used extensively to calculate the environmental impact of major industrial products like steel, concrete, automotive fuels etc. [19, 20] While simple and intuitive this approach has a few drawbacks. Since it assumes fixed proportions in production (Leontief preferences), it does not allow for substitution between inputs within a given sector. While this is not unreasonable in the short-run it is not good in the longer run and some times even in the short run. For example, even in the short-run farm operations offer scope for substitution between fossil energy and labor or between capital and energy. For example farmers may use less tilling or irrigation and use more land in response to higher energy prices. Such effects cannot be captured in this framework. Fertilizer and energy industries may also switch from gas to coal within the medium term in response to high oil prices or vice versa in response to a carbon pollution tax. Second, since the EIO table is aggregated across the whole economy, it captures the average effect rather than the marginal effects which are more important from a policy stand point. However EIO-LCA will do a good job of predicting the average performance of well established and mature industries like steel and automobile manufacturing.

Process-LCA

The process approach to LCA is based primarily on the standard recommendations of the Society of Environmental Toxicology and Chemistry (SETAC) and emphasizes detailed modeling of each and every process in the production chain (Hendrickson06). For example in the case of biofuel production, process LCA would distinguish between farming with irrigation and without irrigation, between farming with no-till, low-till and regular till, between inorganic and organic farming or between dry-mill and wet-mill fermentation of corn to ethanol etc. This approach is useful when analyzing the environmental impact of emerging products and technologies the effects of which are likely to be marginalized when one deals with industry wide aggregate data. For example, the LCA of cellulosic ethanol or the LCA of gasoline produced from tar sands is difficult to model using the EIO tables because of lack of availability of disaggregated data for the relevant sectors and activities. Process LCA is the technique used in the assessment of biofuels [21, 22, 23, 24].

2.2.2 LCA of biofuels

Early assessments based on process-LCA with a few notable exceptions concluded that on average the major types of biofuels such as cane ethanol produced in Brazil, corn ethanol produced in the US, soy biodiesel produced in the US and rapeseed biodiesel in the EU all had lower GHG intensity compared to gasoline or diesel [25, 22, 26]. However average LCA hides significant heterogeneity in emissions across producers of a given type of biofuel. For instance, the LCA of corn ethanol varies significantly depending on whether ethanol producers use coal or natural gas during the processing corn to ethanol. The GHG intensity of coal-based ethanol is 6% lower than that for gasoline whereas the GHG intensity of gas-based ethanol is 30% lower [27]. Recent research paints a more pessimisstic picture with respect to average emissions. Searchinger et al predict that US ethanol mandates will lead to net increase in GHG emissions relative to gasoline [10]. While the assumptions employed by Searchinger et al. are controversial, it nevertheless addresses a methodological gap in the earlier assessments, namely, the exclusion what have come to be called called indirect emissions. However, both the initial accounting based on process LCA models and the more recent calculations based on economic equilibrium models are complementary to each other. The former focus on what can be termed direct emissions and the latter on indirect emissions. In other words, one could say that traditional LCA is an assessment of direct emissions.

2.3 LCA for policy

2.3.1 Classification of emissions

Depending on the mechanism by which emissions occur they can be classified into two categories, namely, direct and indirect.

1. **Direct emissions**: Direct emissions comprise all emissions associated with production and use of inputs used to produce the final product. These can be further classified as,

(a) **Direct on-site emissions**: These are emissions at the regulated site. For example, if the regulated site is an ethanol biorefinery, then these are emissions from combustion of coal or natural gas used in converting corn or sugarcane to ethanol. From figure 2.1, we can see that for US ethanol corn production, biorefinery emissions comprise 55% of total direct emissions.

(b) **Direct off-site emissions**: These are emissions occuring away from a final regulated site but are directly attributable to the final output. Again, assume the regulated site is an ethanol biorefinery. Ethanol producers use crops produced in farms, which use fertilizers and this leads to emission of nitrous oxide, a potent GHG whose global warming potential is 300 times that of carbon-di-oxide. From figure 2.1 we can see that 45% of the total direct emissions are offsite, largely attributable to use fertilizers in corn production.

2. **Indirect emissions**: Indirect emissions arise from indirect effects, which arise when there is a large shock to an economy. In the context of biofuels, one the main indirect effects is land use change. Demand for biofuel raises demand for farmland, which causes marginal land to enter production, a process which called agricultural extensification. If marginal land is rich in carbon, say pastures or forest land, clearing this land releases carbon stored in the soil and above-ground in the biomass to the atmosphere. Biofuels however may not be directly grown on such lands. Instead biofuels may displace food crops which may then be grown on marginal land. Such emissions are called indirect land use change (ILUC) emissions. Figure 2.2 illustrates the fact that ILUC emerges from the interaction of market

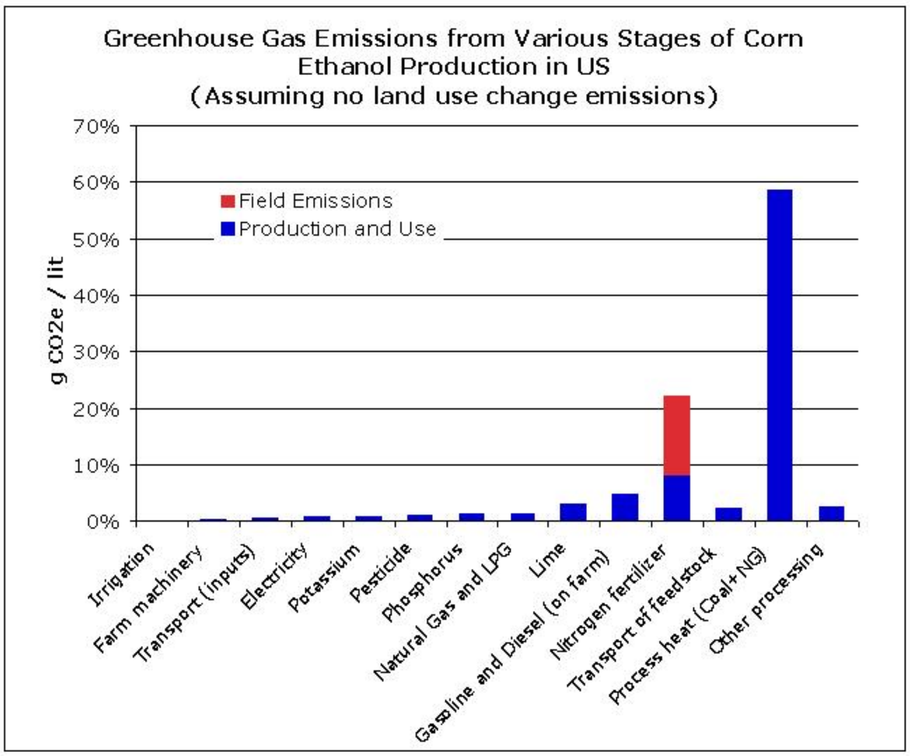


Figure 2.1: Breakdown of direct GHG emissions from production of US corn ethanol

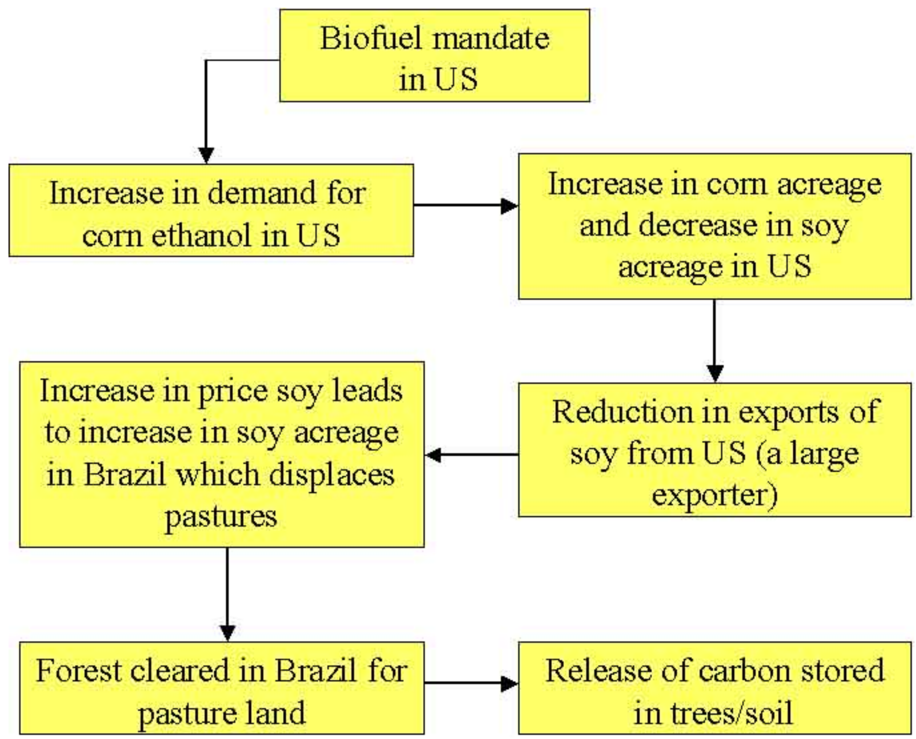


Figure 2.2: One possible chain of events leading to ILUC

for land for various uses (and often across the globe). It is hard to identity all the parcels of land that was or will be converted to farmland because of increase a global increase in crop demand. There are also other indirect effects in the context of biofuels that are important from GHG standpoint, such as the effect on oil markets, on fertilizer markets etc.

2.3.2 Types of LCA from regulatory perspective

Lifecycle estimates will differ depending on the unit of analysis (*firm or micro* and *region or macro*) and the timing of assessment (*ex post* and *ex-ante*).

1. **Ex post micro assessment**: This is an assessment of emissions of a single firm for

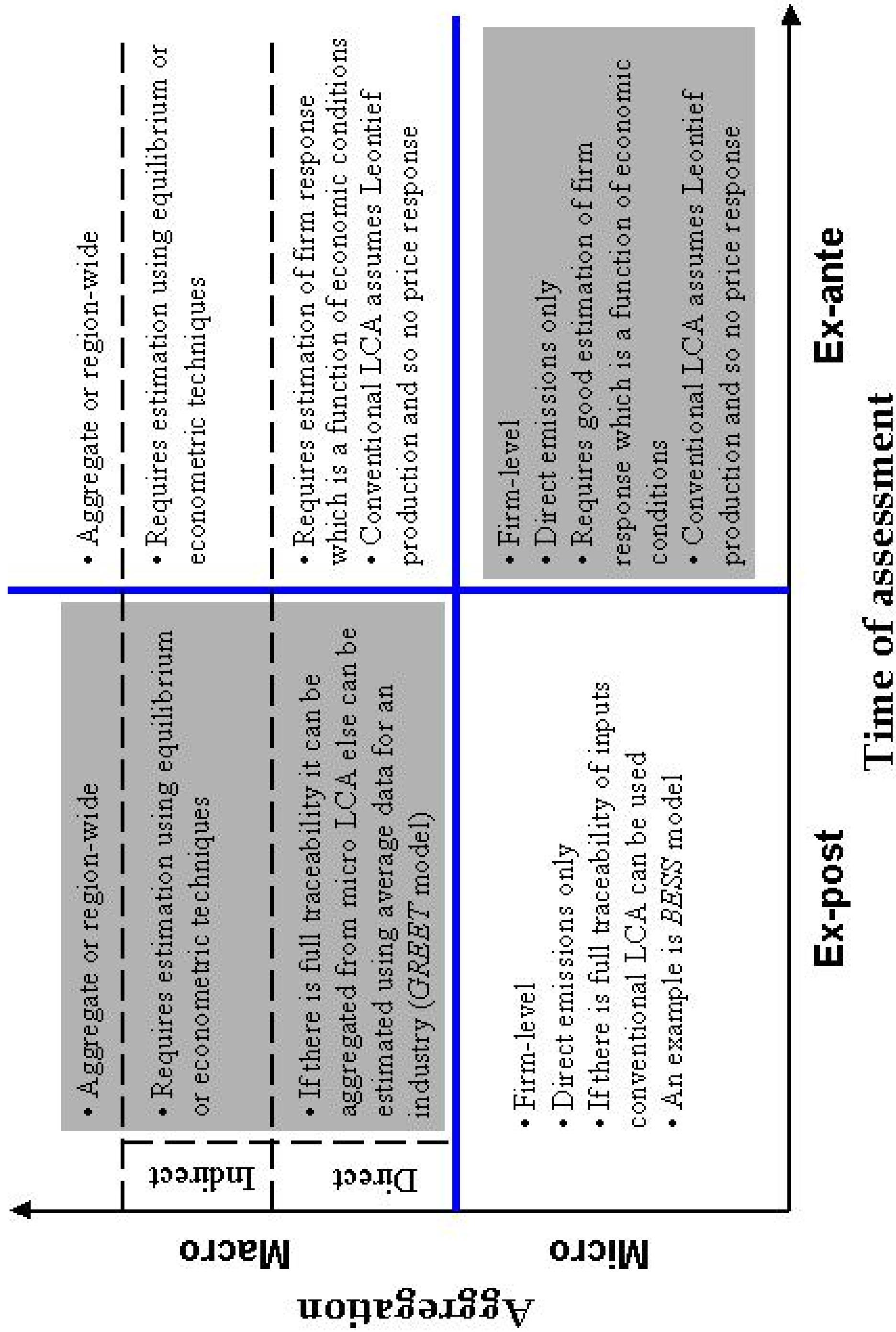


Figure 2.3: Classification of lifecycle estimates

a period in the past. For instance, a biofuel producer operating under an emission permit in the current year may be required to provide a certificate of compliance for renewal of his permit. If there is full traceability simple accounting of the physical inputs and outputs based on conventional process LCA technique is adequate. An implementation of this approach is the BESS model [28]. As explained earlier only direct emissions need to be computed at the firm level while indirect emissions are attributed on average to each firm (see below).

2. **Ex post macro assessment**: This is an ex post impact assessment of a large project such as a regional biofuel mandate. In this case we need to calculate both direct and indirect emissions.

    - **Ex post macro direct emissions**: If there is full traceability of inputs and outputs for each firm, simple aggregation of micro emissions will yield macro emissions. If full information for each firm is not available, an alternative approach is to use industry average values within a process LCA framework to calculate average LCE per unit of biofuel. Aggregate emissions can then be estimated simply by multiplying this by the total quantity of biofuel produced or consumed. An implementation of this approach is the Greenhouse gases, Regulated emissions and Energy use in Transportation (GREET) model [21].

    - **Ex post macro indirect emissions**: The process LCA approach does not incorporate the economic linkages that result in ILUC. There are different possible approaches for estimating ILUC emissions. Section 2.5.3 describes these in more detail. With any approach, the challenge in ex post assessment is in ascribing the appropriate share of total land use change that was observed during the given time interval to biofuels because several other factors including economic growth and weather shocks would have impacted the same. Evidence on ILUC from the recent expansion of biofuel is just beginning to emerge. Higher corn prices are reported to have caused a reduction in acreage enrolled under the conservation reserve program [29]. However, we are not aware of any ex post analysis that tries to rigorously quantify ILUC due to biofuels.

3. **Ex ante micro assessment**: Sometimes a policy-maker may be interested in predicting how different policies affect output and pollution when firms are heterogeneous. Firms' response to policies will differ depending on the time frame under consideration. In the short run, it is reasonable to assume that the production function of a firm is characterized by fixed ratio between the different inputs used in production (such as capital, labor and energy) and possess little flexibility to adjust these ratios in response to change in the relative prices [30]. A reasonable ex-ante estimate then is just the current LCE which can be estimated using process-LCA. However, in the long run, firms can undertake investments that alter the production relationship and therefore the LCE. For example, an ethanol biorefinery may switch from gas to coal based conversion if it expects the relative price of gas to increase substantially enough to justify switching costs. To reiterate, at the firm-level we are concerned only with estimating direct emissions.

4. **Ex ante macro assessment**: Estimating emissions under different future scenarios is often undertaken in policy analysis. For example, a policy-maker may want to the assess the impact of the Energy Policy Act 2006 which mandates the production of 36 billion gallons of biofuel in the US by the year 2022.

    - **Ex ante macro direct emissions**: Estimating the aggregate pollution for an industry, composed of many small firms is a challenging task. However, in the short run aggregation is possible if we assume fixed input output ratios. It has been shown that industry aggregate output and input can be expressed as functions of prices and parameters of the distribution of the input to output ratios across the firms in the industry[31]. It is more challenging to estimate this in the long run. We discuss some methods later.

    - **Ex ante macro indirect emissions**: Ex-ante estimation of indirect emissions requires methods similar to that for ex post assessment with some differences. Unlike ex post assessment, ILUC can be estimated ex-ante while keeping all other factors that influence ILUC at pre-determined levels. Therefore, ILUC can be simulated for a given rate of economic growth and climatic conditions. However, since the future is uncertain, this is in some ways more challenging than ex post assessment.

Current LCA methodology assumes fixed input output ratio in production. This assumption is suitable for ex post accounting of direct emissions or for short-run ex-ante assessment. In the long-run production may occur under conditions that are different technically and economically. Estimating indirect emissions requires a multi-market analysis.

However, estimating indirect emissions is controversial for many reasons, one of which is the method of estimation [32, 33]. In the rest of the paper we describe methods for improving the state-of-the-art in estimation of direct and indirect emissions.

2.3.3 A framework for regulation

Economists have long pointed out that the most efficient mechanism for internalizing pollution externalities is a pollution tax which equals the marginal cost of damage from emissions [34, 35, 36]. A GHG tax provides incentives to shift production away from more GHG-intensive to less GHG-intensive processes in the least-cost manner. However, optimal taxes have proved infeasible because of our inability to accurately estimate marginal social damage. It has also been shown that taxes are the least-cost mechanism to achieve any arbitrary level of emission reduction [34, 37]. However, because of political economic constraints pollution standards (such as an upper-bound on maximum emissions per unit of output) have been preferred over pollution taxes. Hence we focus on GHG standards.

Today, one of the most widely discussed policies for controlling GHG emissions from transportation is a GHG standard for fuels. An emerging legislation is California's Low Fuel Carbon Standard [38]. In this case regulation aims to establish an upper bound for GHG emissions per unit of fuel sold in California. Fuels whose GHG intensity lies below the upper bound will be permitted to be sold in the market. Let f_D^{on} denote the direct onsite emissions, f_D^{off} denote the direct offsite emissions, f_I denote the average indirect emissions, and $\overline{f}$ the upper bound on emissions (all per unit of energy). The upper bound standard requires that each regulated producer satisfy the constraint,

$$f_D^{on} + f_D^{off} + f_I \leq \overline{f} \tag{2.1}$$

But since each regulated site takes the average indirect emissions per unit of energy as given, this effectively implies that each regulated producer ensure that,

$$f_D^{on} + f_D^{off} \leq \overline{f} - f_I \tag{2.2}$$

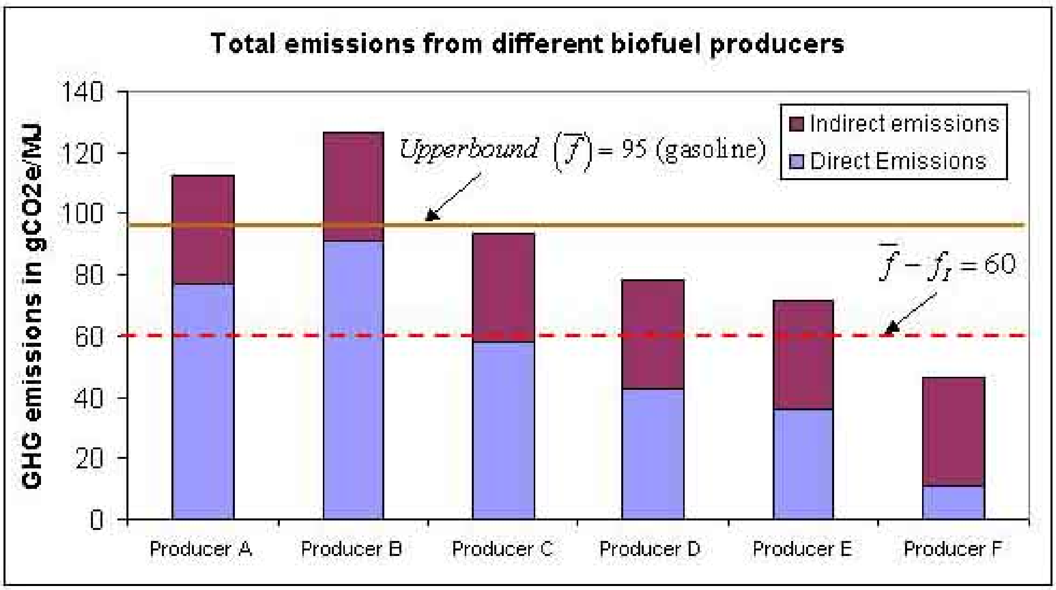
Figure 2.4 shows emissions from ethanol produced under various scenarios of direct emissions relative to the upper bound which is set to equal emissions from gasoline. Indirect emissions are held constant in all these scenarios and assumed as one-third that estimated by Searchinger et. al [10][1]). This shows that only producers of type C through type F will qualify as per the standard. The upper-bound ($\overline{f}$) is fixed by the regulator, and this can be done in a number of ways which we do not discuss here[2]. Instead we focus on methods for estimating f_D^{on}, f_D^{off}, f_I. But before doing so, we classify LCA into different types since the method for estimation varies depending on the type of assessment.

2.4 Sensitivity of lifecycle estimates

Figure 2.1 shows the breakdown of direct emissions from production of corn ethanol in the US. This shows that the conversion of corn to ethanol in the biorefinery and the use

[1]The rationale for this is explained later in the section on estimating ILUC

[2]This framework is also applicable for assessing the impact of an emission-trading scheme on heterogeneous firms. In this case each regulated firm would be required to possess permits for emissions exceeding their quota



A: US corn on average (based on Farrell et. al)
B: Coal based conversion of corn to ethanol all else equal to A
C: Gas based conversion of corn to ethanol all else equal to A
D: Gas based conversion, 39% improvement in corn yield, 25% reduction in energy for processing of corn to ethanol all else equal to A
E: Brazilian Sugarcane ethanol
F: US Switchgrass ethanol

Figure 2.4: Impact of upper bound on different biofuel producers

Table 2.1: Sensitivity of ethanol LCA to fuel mix

	Scenario	kg of CO_2 eq. offset per liter of ethanol	% change over baseline
1	Baseline (Farrell et al *Science* 2006)	0.18	-
2	net GHG displacement if average biorefinery uses only coal based energy	0.09	-50%
3	net GHG displacement if average fertilizer production facility uses only coal based energy	0.07	-61%
4	net GHG displacement if both the average biorefinery and fertilizer producer use only coal	-0.01	-106%
5	net GHG displacement if average biorefinery uses only gas based energy	0.42	133%

of nitrogen fertilizer in corn cultivation are two major sources of GHG emissions from ethanol production. Both these activities are energy intensive and currently depend on coal or natural gas. Estimates suggest that on average biorefineries derive 60% of their energy from coal and 40% from natural gas[3][22]. Farrell et al. [22] also estimate that direct emissions per unit of energy from corn ethanol is on average 20% below that from conventional gasoline [22]. We performed sensitivity analysis of their model to the relative share of of coal and gas use in biorefining and fertilizer production. The results are shown in table 2.1. We find that depending on the value of this share direct emissions may be higher or lower than gasoline. This shows that LCE is sensitive to relative input shares which ultimately is a function of relative prices and other economic parameters. This is the motivation for developing lifecycle indicators as function of prices of inputs instead of just quantities of inputs [39].

[3]Any given biorefinery may use either coal or natural gas. However, averaging across all producers, it appears as that each unit of corn is converted using a mix of coal and natural gas.

2.5 Estimating emissions

With full information about outputs and inputs we can use simple accounting to exactly calculate LCE. However, in the absence of full information we need to estimate LCE. For instance, say we are interested in estimating LCE when the future price of coal increases by 50% relative to natural gas . Economic theory predicts that firms will respond to this change both by using less energy and through interfuel substitution, i.e., using less coal relative to natural gas. The ability to respond depends on several factors such as switching costs and the price elasticity of demand for fuels. These elasticities tend to be higher in the long run compared to the short run. Further elasticity is higher for the industry than for a single firm. Estimating the change in LCE in response to a change relative prices using current LCA is a two step process. First, one has to estimate using an economic model the new input shares in response to the price shock. The modified input shares can then be used in a process LCA model to calculate the modified LCE.

The model we describe below integrates the two steps into a single unified model, one that can simulate the change in LCE as a function of change in economic parameters. In doing so we recognize the relative strengths of the process LCA and the economic models. The former has the benefit of detailed representation of the technology while the latter can predict price response. However, retaining the same level of detail in technology and price variables for all inputs in the lifecycle model is complex and also avoidable for estimation purposes. For instance figure 2.1 shows that biorefining and fertilizer related emissions comprise more than 95% of the total direct emissions from corn ethanol production. Thus small changes in these stages may have a large impact on

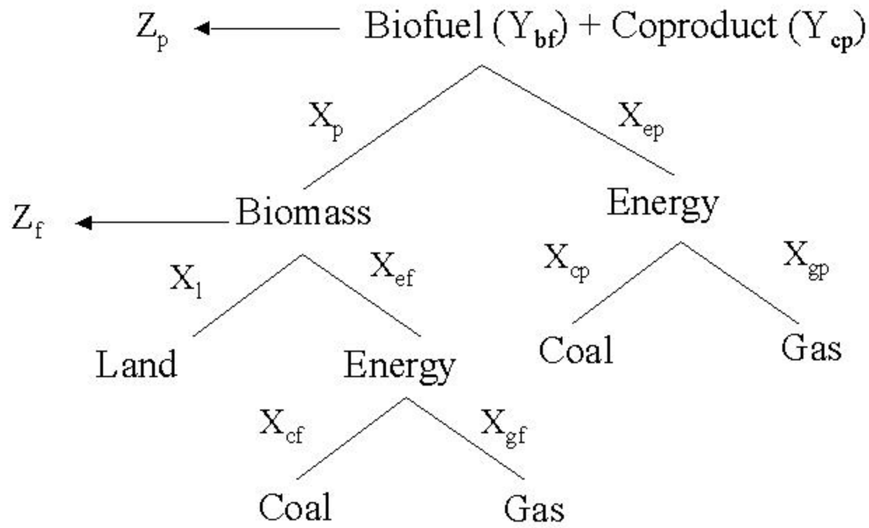


Figure 2.5: A simple model

LCE than large changes at other stages.

2.5.1 Ex-ante estimation of direct micro emissions

We illustrate how LCE can be estimated as an explicit function of input prices. In order to keep the mathematical exposition simple and intuitive, we use a simplified representation of biofuel production (see figure [2.5]). We later generalize the results to a production function with more than two inputs and multiple stages in the lifecycle. Let us assume that ethanol is produced with two inputs namely, corn and energy. Corn is produced using two inputs, land and energy. Finally, energy can be produced from two different sources with different carbon intensities, natural gas and coal. We assume a competitive industry structure where producers take price as given and maximize profit.

Y_{bf} is quantity of biofuel produced, Y_{by} is quantity of co-product produced, X_b

is quantity of biomass required to produce the given quantity of biofuel, X_{ep} is quantity of energy required to convert plant matter to biofuel, X_l is quantity of land to produce the required quantity of plant matter, X_{ef} is quantity of energy embodied in farm inputs other than land, X_{cp}, X_{gp} is quantity of coal and gas required to process biomass into biofuel, X_{cf}, X_{gf} is quantity of coal and gas embodies in farm inputs - notably fertilizer, Z_f is pollution from farm phase, and Z_p is pollution from biorefining or processing phase.

Production function: Let us denote the production relationships as follow,

$Y_{bf} = F_f(X_b, X_e)$

$Y_{by} = F_{cp}(X_b, X_e)$

$X_b = F_b(X_1, X_{ef})$

$X_{ep} = F_e(X_{cp}, X_{gp})$ and $X_{ef} = F_e(X_{cf}, X_{gf})$

$Z_f = G_f(X_{cp}, X_{gp})$

$Z_p = G_p(X_{cf}, X_{gf})$

with, $F_i{}' > 0$, $F_i{}'' < 0$, $G_i{}' > 0$, $G_i{}'' = 0$, (linear pollution function)

Then $\Gamma = Z_f + Z_p$ denotes the total direct emission from processes that yield both biofuel and a co-product. Co-products of current biofuel production find use either as animal feed (distiller's dried grains (DDG) from corn, soybean cake from soybean) or as a source of captive energy (sugarcane bagasse or lignin from cellulose). Therefore, a share of the total emissions should be allocated to the co-product. The total emissions due to corn ethanol can be written as

$$\Gamma_{bf} = (1 - \alpha)Z_f + Z_p \tag{2.3}$$

where, α is the share of emissions allocated to the co-product.[4]

Pollution function: Lets assume pollution arises solely from the use of energy and not other inputs. Assuming that the carbon intensities of coal and natural gas are constants, the pollution function G is linear in the quantity of coal and natural gas consumed at any given stage. Therefore,

$$Z_f = G_f(X_{cf}, X_{gf}) = b_c * X_{cf} + b_g * X_{gf} \tag{2.4}$$

$$Z_p = G_p(X_{cp}, X_{gp}) = b_c * X_{cp} + b_g * X_{gp} \tag{2.5}$$

where b_c, b_g are carbon coefficients for coal and gas respectively. Differentiating Z_f and Z_p with respect to p_i where i ϵ (coal, gas) we get,

$$\frac{\partial Z_f}{\partial p_i} = b_c \frac{\partial X_{cf}}{\partial p_i} + b_g \frac{\partial X_{gf}}{\partial p_i} \tag{2.6}$$

$$\frac{\partial Z_p}{\partial p_i} = b_c \frac{\partial X_{cp}}{\partial p_i} + b_g \frac{\partial X_{gp}}{\partial p_i} \tag{2.7}$$

$$\frac{\partial \Gamma_{bf}}{\partial p_i} = (1-\alpha) \frac{\partial Z_f}{\partial p_i} + \frac{\partial Z_p}{\partial p_i} \tag{2.8}$$

Expressing as elasticities: The change in LCE as a function of change in price of coal p_c is,

$$\frac{\partial \Gamma_{bf}}{\partial p_c} = \frac{1}{p_c}[(1-\alpha)[b_c X_{cf} \epsilon^f_{cc} + b_g X_{gf} \epsilon^f_{gc}] + [b_c X_{cp} \epsilon^p_{cc} + b_g X_{gp} \epsilon^p_{gc}]]$$

Expressing as a elasticity of LCE with respect to price of input,

[4] DDG offsets corn on the margin. Therefore co-product credit is allocated as a share of the emissions associated with corn production. Since 1 bushel of corn (56 lbs) yields about 2.7 gallons of ethanol and 18 lbs of DDG which we assume as equal in value to 18 lbs of corn this implies $\alpha = 18/56 = 0.32$

$$\epsilon_{\Gamma_{bf}} = \frac{1}{\Gamma_{bf}}[(1-\alpha)[b_c X_{cf}\epsilon^f_{cc} + b_g X_{gf}\epsilon^f_{gc}] + [b_c X_{cp}\epsilon^p_{cc} + b_g X_{gp}\epsilon^p_{gc}]]$$

where, ϵ^j_{ki} is the price elasticity of energy source k with respect to energy source i in the j^{th} production process.

Extending this to production using an arbitrary number of inputs and stages,

$$\frac{\partial \Gamma_{bf}}{\partial p_i} = \frac{1}{p_i}\sum_{k=1}^{K} b_k\{(\sum_{j=1}^{J}(X^j_k \epsilon^j_{ki})) - X^{by}_k \epsilon^{by}_{ki})\}$$

where, $i \ \epsilon \ (1..K)$, K is the number of different types of energy sources, and J is the number of different processes in the production tree.

There are a few limitations to this model. By implying instantenous subsitution between inputs in response to change in prices, we have assumed zero switching costs. In reality, producers will respond only if relative prices change more than a certain amount and are expected to remain at levels that provide incentives for switching. This requires modeling price response within a technology adoption framework. However, this assumption may not be completely unrealistic in certain cases. For instance, emerging cellulosic conversion technologies are expected to allow switching between a variety of different feedstock with minor adjustments to feedstock pre-treatment processes. There is a large literature which estimates elasticities of substitution between different types of energy for different sectors of the economy [40, 41, 42]. However, estimating the elasticities for some of the newly emerging industries can prove to be a challenging task.

2.5.2 Ex ante estimation of aggregate direct emissions

The comparative static analysis described applies so long as we can assume the price as exogenous. Certain prices that are exogenous at the firm-level may be endogenous when considered at the aggregate level. However, because biofuels represent a small share of total demand for energy, the prices of coal, natural gas, and electricity can be considered exogenous. With regard to oil or gasoline price, although a large biofuel supply such as a national biofuel mandate will have some impact on oil price, it is yet plausible to assume biofuel producers take oil prices as given[14]. However, with regard to land, a large biofuel project may have significant impact on land prices and hence must be treated as endogenous. If the parameter of interest is endogenous, we need to model producer response using a multi-market framework similar to that for indirect emissions which we discuss next.

2.5.3 Estimation of indirect emissions: ILUC emissions for biofuels

As mentioned earlier estimating indirect emissions requires modeling the linkages between different markets. There are different modeling approaches one can employ. One option is to use an economic input-output(EIO) based LCA model [19]. The EIO framework captures the inter-industry linkages necessary for estimating indirect effects. However, IO framework imposes a Leontief (fixed input share) structure on production and also does not model constraints on avaliable resources such as land and labor. EIO-LCA approach is suitable for ex post assessment than ex ante.

Another option is to use a computable general equilibrium (CGE) model which allows a more flexible production structure (substitution between inputs with different pollution intensities) and also incorporates constraints on resources. [42, 43, 44]. However, like IO models, CGE models require a wealth of data and specification of a number of parameters for representing supply and demand in all the sectors. Often reliable estimates of several parameters may not available and one is forced to base his or her calculations on 'best guesses'. However, if only a limited number of inter-industry interactions are important and if macroeconomic linkages have only second-order importance, then a CGE approach would be inefficient. Far too much time and effort will have to be spent in specifying and calibrating parts of the model, which are not critical to the sectors of interest. A more simple approach can be a multi-market partial equilibrium model focussing on linkages between a small number of markets, which are strongly linked either on the supply side or the demand side [45]. Using the FAPRI model, Searchinger et al. [10] estimate that a 56 billion liter increase over and above the projected US biofuel output by 2015 will cause global agricultural land to expand by 10.6 million hectares. These estimates are however highly controversial [32]. However, equilibrium models are currently the popular approach for estimating ILUC.

A third, even simpler, option is to use statistical techniques to estimate the relationship between agricultural production and agricultural land use. We provide one illustration. Let $L(t)$ denote global agricultural acreage at time t and $Q(t)$ denote global agricultural output at time t. Let $\frac{\delta L}{L}$ denote the percentage change in acreage and $\frac{\delta Q}{Q}$ the percentage change in output during the time interval $(t, t+\delta t)$. We can then estimate a parameter called the elasticity of agricultural acreage with respect to output as $\epsilon_{L/Q} = \frac{\delta L/L}{\delta Q/Q}$. A low value of elasticity of acreage implies increase in production was accompanied by relatively little expansion in acreage with intensification contributing the lion's share of the increase in output. For example, between 1960 and 2007, combined global agricultural output of six major crops (wheat, corn, rice, soybean, sorghum, and cotton) increased

228%, while total acreage under these crops increased only 33%, which implies $\epsilon_{L/Q}$ is 0.14. [5] Rearranging the elasticity expression we get,

$$\delta L = \epsilon_{L/Q}(\frac{L}{Q})\delta Q \tag{2.9}$$

If we are concerned with small changes in output the elasticity of acreage estimated from historical data can be assumed constant and used in the above expression to estimate ILUC (δL). We use this expression to estimate ILUC for the same scenario as that analyzed by Searchinger et al. An increase in ethanol output of 56 billion litres implies increase in corn demand of 140 million tonnes (δQ)[6]. Furthermore, in the year 2006 the combined global acreage of the three major food grains, namely, rice, wheat and corn was about 510 million hectares (L) while combined global production was 1950 million tonnes (Q). Plugging in these values for $\epsilon_{L/Q}, L, Q$ and δQ we estimate ILUC for the scenario analyzed by Searchinger et al. as 5.1 million hectares[7]. Statistical approaches have the advantage of being simple and empirically well grounded. Obviously one can and needs to explore more sophisticated relationships by controlling for factors such as technology, prices, weather and economic growth in the statistical model. There is a rich literature in

[5] Historical data from the US Department of Agriculture database available online at http://www.fas.usda.gov/psdonline/psdhome.aspx.

[6] At a conversion efficiency of 2.7 gallons of ethanol per bushel of corn.

[7] This estimate is conservative, given that we assume the quantity of corn allocated to ethanol is entirely replaced by new supply so that consumption of corn as food remains unchanged. This is unlikely because demand for food is not inelastic and will adjust to higher corn prices. Yet, we find Searchinger et al's estimate of 10.6 million hectares is more than twice ours. However, our estimate may be too optimistic if we consider the relationship between agricultural output and acreage since the year 1990, which suggests an elasticity of 0.36. This suggests ILUC equals 13.2 million hectares. But historical trends may change as policies, market conditions, and biophysical developments can influence how much of future agricultural production occurs, through intensification or through expansion. Adoption of yield-enhancing technologies such as agricultural biotechnology and increase in acreage under irrigation can slow the expansion of agriculture.

agricultural economics which employs econometric techniques to model acreage response to prices and policies which can serve as a useful starting point [46]. The literature on estimation of ILUC is at a rudimentary stage and requires further research.

2.6 Summary

The carbon intensity of conventional fossil fuel say coal, oil or natural gas does not exhibit significant variability across producers. Furthermore, carbon emissions attributable to these fuels is concentrated in the combustion phase of the lifecycle. In contrast for several of the emerging energy sources such as biofuels, batteries and coal-based liquids lifecycle emissions are not concentrated in the combustion phase. Emissions during combustion represent only a share of the total emissions attributable to the production or use of these fuels. Furthermore GHG intensity tends to vary across producers. This coupled with the fact that GHG is a global pollutant and that several of the GHG policies are regional or sectoral in scope, led to the emergence of LCA as an important tool for environmental policy making. LCA has a long and successful tradition as a tool for improving product design and as a tool for show casing social responsibility on the part of private firms. However, relying on current LCA estimates for making decisions about long-term policies is not recommended.

The outcome of LCA is a number such as the average GHG intensity per liter of biofuel produced using a certain crop. The current method of performing LCA is simple and intuitive so long as we are concerned with estimating emissions in the past and in the context of a small (price-taking) region or a single firm. Using this methodology to estimate emissions in the future or in the context of a large region or both is challenging. In using current LCA method for such purposes we are assuming that the production structure is Leontief-type (fixed-proportion). This is not true except in the short-term. When there exist possibilities for substitution between inputs, economic intuition suggests that profit-maximing producers (or utility-maximing consumers) will respond to changes in relative price of different inputs (or goods). Therefore emission intensity of production is a function of prices and should be calculated as such. To this end a partial equilibrium framework to estimate emissions as function of prices has been introduced. This is reasonable when the price changes under question are exogenous. When prices are endogenous, emissions must be estimated using a multi-market or general equilibrium framework. A second assumption implicit in extrapolating current LCA into the future is that there exist no constraints on the factors of production such as land, labor, capital and energy. This is also not true. Increasing output in one sector leads to reallocation of resources across different markets (or simply across different uses, when markets are missing as in the case of goods such as clean air or biodiversity). This is evidenced by the debate on indirect emissions due to land use change induced by large-scale biofuel production. Modeling such changes requires a multi-market equilibrium or general equilibrium framework. Thirdly, LCA is a purely supply side analysis which does not take into account the role of demand. This limitation also can be overcome using an equilibrium framework. Addressing these limitations will allow LCA to become a more reliable tool for policy making. Without doubt, future effort should focus on the role of uncertainty in LCA.

Chapter 3

Economics of biofuels: Impact on food and fuel markets

3.1 Background

Agricultural and fuel commodity prices which had been on upward trend since 2003-2004 peaked during 2008, the year of food and financial crises[47, 48] (see figure 3.1). Interestingly, the period between 2003 and 2008 was also the period during which the production of biofuels such as ethanol and biodiesel grew several fold. During this time global ethanol production from corn and sugar cane more than doubled from 30 billion liters to 65 billion liters while biodiesel production from edible oil seeds such as soybean, oil palm and rapeseed expanded six-fold from 2 billion liters to 12 billion liters[49]. The increase in biofuel demand, which was concentrated in the US and the EU, was driven

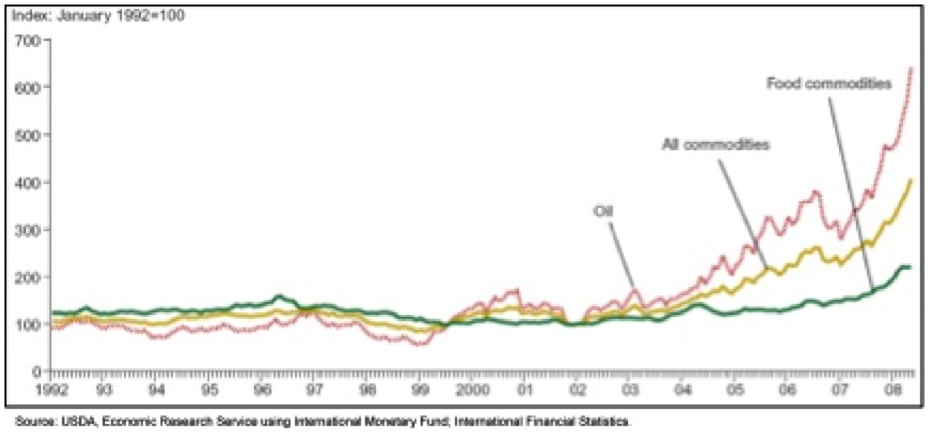


Figure 3.1: Commodity price trends

largely by government mandates and subsidies.[1] This has led to the popular opinion that biofuel policies in the high income countries are the major cause for the run up in food prices and the crisis.

Biofuels reduce the demand for oil and increase the demand for agricultural goods. To high income countries, which tend to be both large importers of oil and large exporters of agricultural goods, this implies a double whammy for the domestic economy. One of the one hand it reduces the market power of the OPEC cartel, a large exporter of oil and a grouping of countries considered politically volatile and hostile to the former's interests. On the other hand, it reduces the demand for domestic farm subsidies. With crops comprising a small share of cost of food in these countries the impact on food consumers will likely be small. To low income countries where crops comprise a major share of cost of food, the fallout of increase in crop prices will be higher. Empirically, however the story is more complex and therefore one may observe a different movement in

[1]Growth in domestic demand in Brazil, a large producer has increased was insignifcant relative to growth in the US, EU and other OECD countries.

prices. The impact of biofuels may be dwarfed or amplified by exogenous shocks to supply and demand. Economic growth, weather and exchange rates fluctuations are example of more traditional shocks to affect demand and supply of food. Under such circumstances one should be cautious in interpreting observed trends as the effect of a single policy or single phenomenon such as expansion of biofuels.

This chapter aims to quantify the contribution of biofuel demand, especially the US ethanol demand, on international crop prices and also on fuel prices. Knowing the effect on crop prices, one can then extrapolate this to the effect on the retail price of food. I first describe a static partial equilibrium model to estimate the effect of ethanol demand on corn and gasoline price in the US. We use this model to simulate the effect of US ethanol demand on the price of corn, soybeans and gasoline. Following this I present a broader review of the literature on the effect of biofuels on food prices. The review reveals the importance of understanding the market for storage to better predict the effect of any large supply or demand shock on commodity prices. The effect of introducing the simplified model of storage into the partial equilibrium model is also illustrated. I conclude by identifying areas for future work.

3.2 Partial equilibrium model with no storage

A stylized model of supply and demand for a crop that has multiple uses, like food and fuel, is shown in figure. Assuming that bioufels are a costlier fuel and no biofuel is consumed in the initial equilibrium, (price P_0 and quantity Q_0) determined by the intersection of total demand (D_{T0}) and supply (S_0). This situation is depicted in figure a. Due to economic growth or due to biofuel policies, demand for biofuel increases, reflected by an upward shift in biofuel demand as shown in figure b. For simplicity, we assume no change in commodity supply in the short run, so the short run equilibrium is determined by the intersection of the new demand, D_{TS}, and supply, S_0. This new equilibrium is characterized by price P_S and quantity Q_S. Crop prices increase and food supply decreases ($Q_{SF} < Q_0$). Total agricultural production may increase ($Q_S > Q_0$). In the long run supply increases, yielding the equilibrium denoted by (P_L, Q_L). This situation is depicted in figure c. In this equilibrium, price is lower than the short run price, and both fuel and food supply are higher than in the short run. Productivity-enhancing technologies like agricultural biotechnology can increase supply without increasing the agricultural land base. The impact of biofuel on gasoline price can be estimated using a similar approach. A model of the oil market with two fuels gasoline and ethanol on the supply side and a demand for transportation fuel is shown in figure. This figure however, shows the effect of biofuel under two different scenarios of elasticity of supply and demand for fuel. Comparing the figure a and b we can see that holding ethanol supply fixed, ethanol has higher impact on price of fuel ($\Delta P_1 > \Delta P_2$) when supply and demand for oil is more inelastic. The single market equilibrium can be extended to multi-market equilibrium with many different crops or fuels which have interlinkages with biofuel crops on the supply or demand side. This can also be extended to include multiple regions.

We develop and simulate one such model to predict the effect of U.S. ethanol production. We consider four commodities, two crops (corn and soybean) and two fuels (gasoline and ethanol), in our model. We consider two regions: the United States and the

Table 3.1: Elasticities used to represent the different scenarios

	Scenarios		
Own price supply elasticities	High	Mid	Low
Corn	0.5	0.4	0.3
Soy	0.5	0.4	0.3
Gas	0.3	0.4	0.5
Own price demand elasticities			
Corn	-0.5	-0.4	-0.3
Soy	-0.5	-0.4	-0.3
Gas	-0.3	-0.4	-0.5

rest of the world (ROW). We assume the own and cross-price elasticities for supply and demand do not vary across these two regions. The equilibrium prices and quantities are then computed under two different scenarios: without biofuel production and with biofuel production at 2007 levels. We report results under three distinct sets of assumptions on price elasticities for crops and for gasoline. These are listed in table 3.1. We consider a high scenario characterized by highly elastic crop markets and an inelastic gasoline market; a low scenario that assumes the oppositea low elasticity for food and an elastic gasoline market; and a mid scenario that assumes moderately elastic markets for both food and gasoline. Biofuel production is shown to have the greatest benefit to consumers in the high scenario. Ethanol demand is assumed inelastic in order to simulate the effect of a mandate. The elasticity assumptions for each scenario are summarized in table 1. Research suggests that gasoline elasticities tend to be less than 0.3 in the short-run. Similarly, for corn and soy, short-run elasticities tend to be less than 0.3. If so, our high scenario provides a conservative estimate of the net consumer benefits from biofuel production. Even long-run gasoline elasticities are less than 0.5. To reduce the complexity

Table 3.2: Price impact of US ethanol consumption under the different scenarios

	Optimistic or high scenario	Intermediate or mid scenario	Pessimisstic or low scenario
Percent change in gasoline price	-2.40%	-1.80%	-1.40%
Percent change in corn price	15%	20%	28%
Percent change in soy price	10%	13%	20%

of simulations and for ease of exposition, we assume fixed cross-price elasticities between corn and soy across all scenarios. In our analysis, we include the impact of biodiesel on the soy market, but we do not estimate the impact of biodiesel production on the diesel market, which further makes our assessment of fuel market benefits conservative. Including the diesel market equilibrium would increase consumer benefits.

The price effects are shown in table 3.2. The model predicts that ethanol consumption in 2007 which was about 6.5 billion gallons of ethanol, increased corn prices between 15% (high scenario) and 28% (low scenario). The price of soy increased between 10% and 20%. At the same time absent ethanol consumption, gasoline prices would be between 2.4% higher (high scenario) and 1.4% higher (low scenario).

Figures 3.2, 3.3, 3.4, 3.5 and 3.6 show the welfare change to various groups. In the mid scenario, we find that gasoline consumers worldwide benefited from 2007 U.S. biofuel production by about US \$31.3 billion because of 1.8% lower gas prices.The total cost to food consumers and to U.S. taxpayers (in the form of subsidy payments), however, was US\$52.8 billion. The net gains to corn and soybean producers was about 27 billion US\$. Thus, under plausible conditions and partial equilibrium analysis, ethanol production is associated with a net benefit worldwide of US\$1.7 billion. Overall, the ROW gained

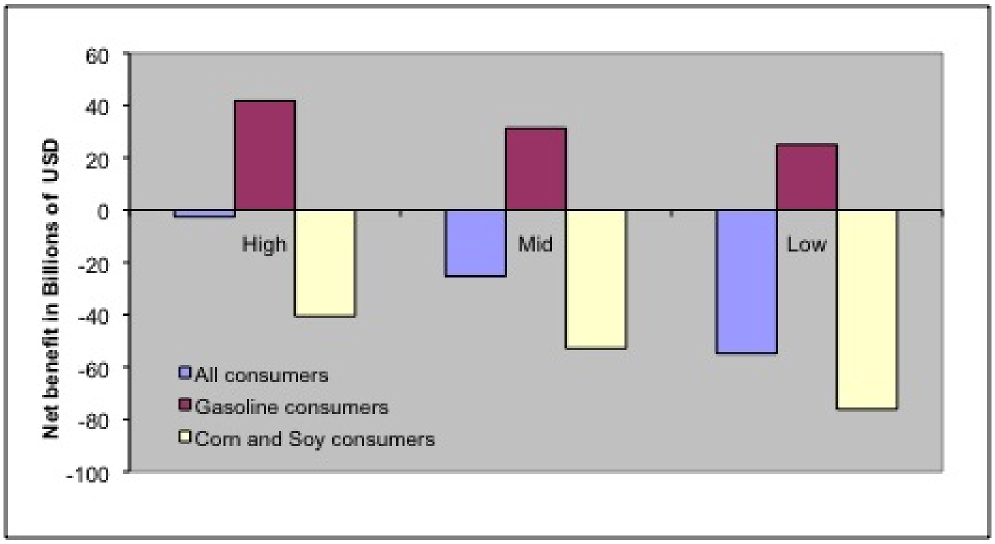


Figure 3.2: Welfare change for all consumers under the three scenarios

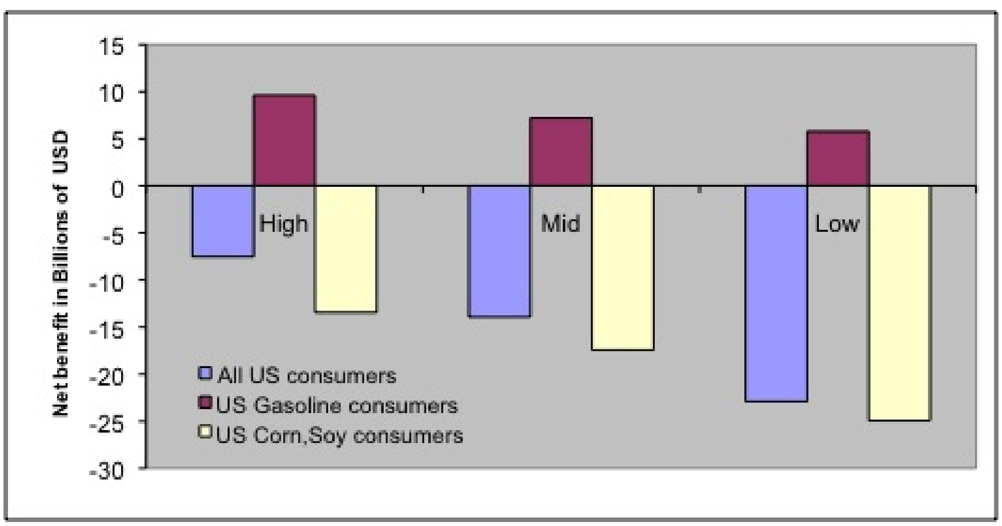


Figure 3.3: Welfare change for US consumers under the three scenarios

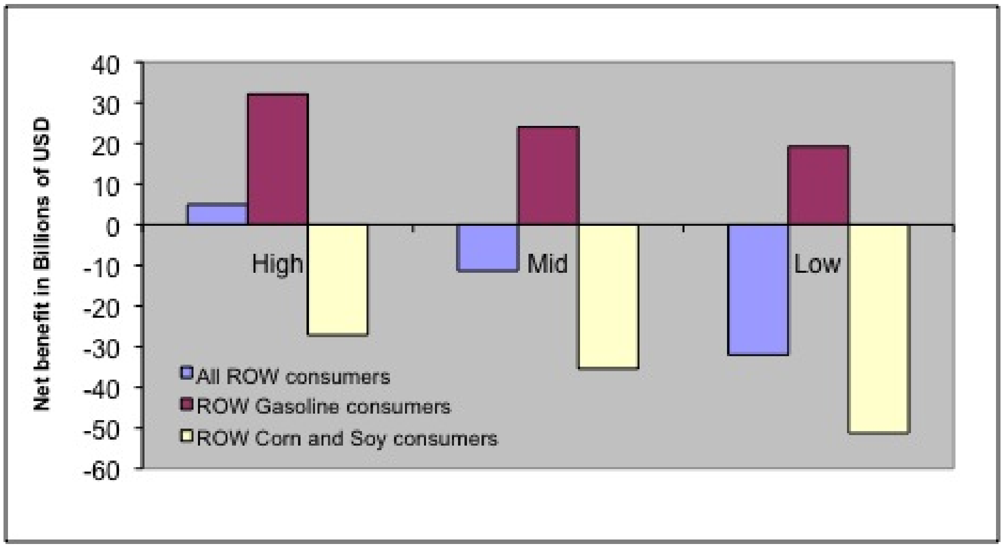


Figure 3.4: Welfare change for ROW consumers under the three scenarios

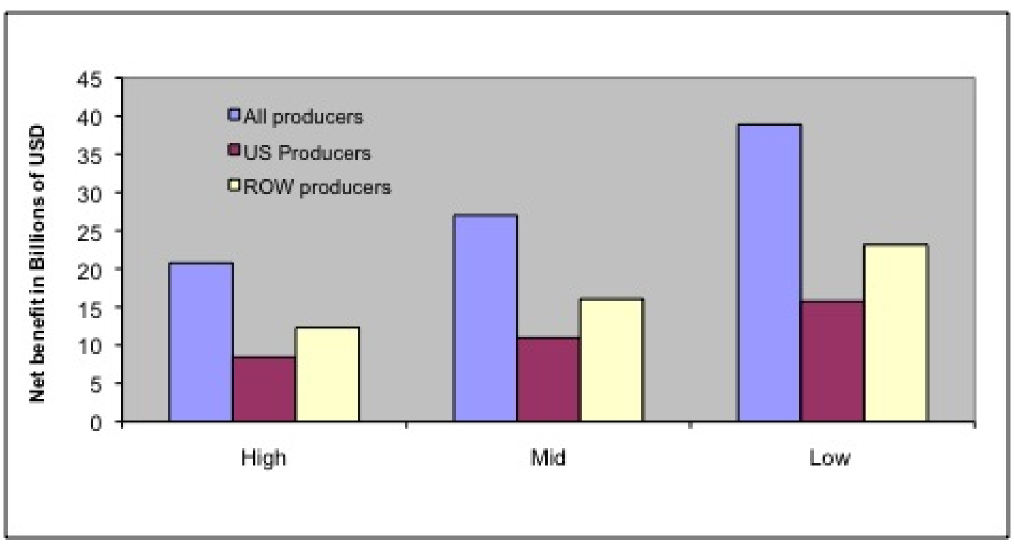


Figure 3.5: Welfare change for all consumers under the three scenarios

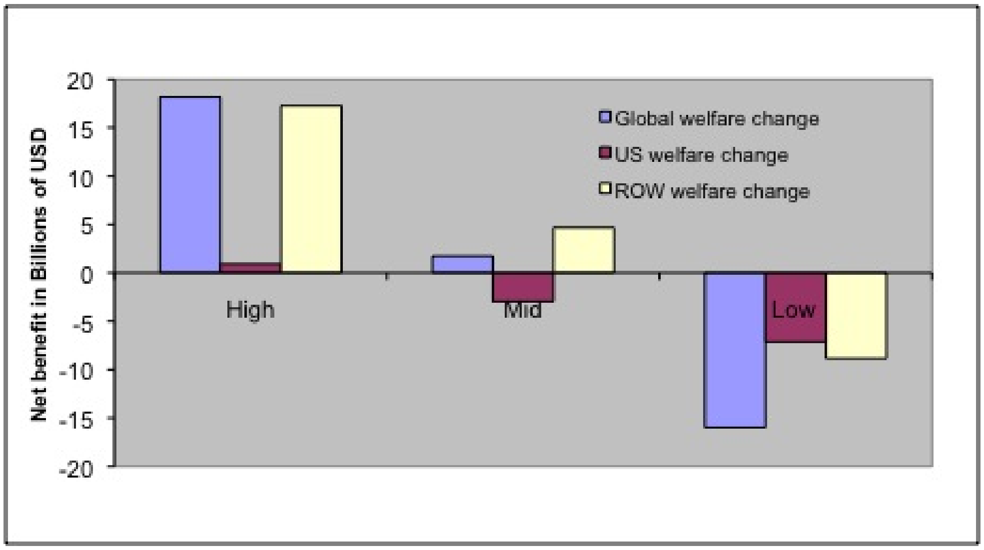


Figure 3.6: Net welfare change due to biofuels under the three scenarios

US$4.7 billion, whereas the U.S. lost US$3 billion (net of taxes). In the United States, under the mid scenario, we find that gasoline consumers gained approximately US$7.2 billion, whereas the total cost to corn and soy consumers was US$17.4 billion, and the cost to taxpayers from the U.S. Volumetric Excise Tax Credit was US$2.2 billion. Higher food prices benefited U.S. corn and soy producers by US$11 billion (the ROW producers gained US$27 billion). For further details on the model the reader should refer [11].

3.3 Review of literature

Between 2007 and 2008, ethanol production in the US by 8%. In contrast it grew 34% between 2006 and 2007. We therefore expect the model described above would a price effect of similar magnitude, around 30% in the worst case (i.e., low scenario) for 2008. However during 2008, the food prices rose much more spectacularly compared to during 2007, to levels not witnessed since the 1970s (in real terms) with serious implication for food security among the poor populations of the world[47]. Several reports and some peer reviewed papers describing the factors responsible for the global food price inflation in 2007 and 2008 have appeared [12, 13, 11, 48]. This literature can be classified under two categories, namely, ex ante assessments and ex post assessments. The latter is the more recent, and explains (in some cases also quantifies) the role of various factors behind the price rise. The former comprises of studies, which began emerging a few years back, and whose objective was to simulate impact of biofuel mandates that were beginning to be put in place, on the price of agricultural commodities in the medium and long-run.

3.3.1 Ex ante assessment

There is a long tradition of use equilibrium techniques to ex ante predict the effects of one or more policies on prices, welfare and a variety of other economic variables[50]. Equilibrium models can be classified as partial equilibrium and general equilibrium models. Partial equilibrium models are essentially a collection of supply and demand equations representing economic behavior of agents in one or more markets of interest. These models have several limitations, such as lack of acknowledgement of the finiteness of resources such as land, labor and capital, no explicit budget constraint on households and no check on conceptual and computation consistency of the model [51]. These limitations can be overcome by using a general equilibrium approach. The main drawback of a computable general equilibrium model is the large data requirements and the high degree of complexity.

Examples of well-known partial equilibrium models include IMPACT, AGLINK/COSIMO, FAPRI, and FASOM.[2] Examples of general equilibrium models include GTAP, LINKAGE and USAGE. [3]. These models were all initially, developed to analyze the impact of domestic agricultural policies and international trade policies. Subsequently these models have found application in the context of GHG and biofuel policies. The predictions of analyzes using some these models is described below.

Partial equilibrium analyses

The International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT) is a partial-equilibrium model that has often been used by the International Food Policy Research Institute (IFPRI) for projecting global food supply food demand and food security to 2020 and beyond. Using this model, Msangi et al. simulate the impact of biofuel under different scenarios on the price of food in different regions [52]. In one of the scenarios, which focused on rapid global growth in biofuel production under conventional conversion technologies, the price for major crops ranges between 30% and 76% by 2020. There is significant increase in malnutrition in many developing country regions with sub-Saharan Africa being the hardest hit. Using the AGLINK and COSIMO models, the OECD predicts the impact of achieving the stated policy targets (as of 2006) for biofuels in several countries [53]. It finds that compared to a situation with unchanged biofuel quantities at their 2004 levels, crop prices could increase by between 2% in the case of oilseeds and almost 60% in the case of sugar by the year 2014.

[2] IMPACT - Model developed by the International Food Policy Research Institute, AGLINK/COSIMO - Model owned by Organization for Economic Cooperation and Development (OECD) and Food and Agricultural Organization (FAO) , FAPRI - Model owned by University of Missouri, and FASOM - Model developed at Texas A&M University

[3] GTAP- Model developed at Purdue University, LINKAGE - The World Bank's model and USAGE - Model developed at Monash University, Australia

General equilibrium analyses

Although there are a number of CGE based assessments of biofuel policies on greenhouse gases, energy price, employment etc only a limited number emphasize the impact on the price of food. Dixon and Osborne use a dynamic CGE model called USAGE to quantify the economy-wide effects of partial replacement of crude petroleum with biofuels in the US. He forecasts the impact of the current biofuel policies on the U.S. economy in 2020[54]. Although there is no direct discussion of the impact of these policies on the global price of food, the model predicts a reduction in agricultural exports and an increase in the export prices. Gohin and Moschini assess the impacts of the European indicative biofuel policy on the EU farm sector with a farm-detailed computable general equilibrium model and predicts positive income effects on farmers in the EU[55]. Birur, Hertel and Tyner use the GTAP-E model to study the impact of six drivers of the biofuel boom, namely, the hike in crude oil prices, replacement of MTBE by ethanol as a gasoline additive in the US, and subsidies for ethanol and biodiesel in the US and EU[44]. They find that between 2001-2006 these drivers were responsible for 9% increase in price of coarse grains in the US, 10% increase in price of oilseeds in the EU-27 region, and 11% for sugarcane in Brazil. Similar impacts were observed on energy-exporting countries in Latin America and sub-saharan Africa.

3.3.2 Ex post assessment

Abbot, Hurt and Tyner through a review of several reports on the food crisis conclude that there are three key drivers of food price increases: the depreciation of the dollar, global changes in production and consumption of key commodities, and the role of biofuels in commodity price increases[12]. They however do not present any quantitative estimate of percentage contribution to the total price rise that is attributable to a specific factor such as biofuel consumption. The Food and Agriculture Organization in its State of Food and Agriculture 2008 report also states that growing demand for biofuels are only among several factors driving increases in agricultural commodity prices. It concludes that ascribing a value to the contribution of biofuels to total price rise is challenging task[48]. An USDA report describing the factors leading the food price rise concludes that the run up in commodity price reflects a trend of slower growth in production and more rapid growth in demand that led to tightening of world balances of grains and oilseeds over the last decade[15]. Biofuels are mentioned as just one in a number of demand-side factors that includes bad weather, depreciation of US dollar, increasing in production costs and government policies in food importing and exporting countries.

Historical data on agricultural commodity prices shows that the price rise of 2008 while unprecedented in magnitude was not unique. Sudden run-ups in food prices were observed between 1971-1974 and between 1994-1996 [47]. While biofuels were unique to the recent crisis, the other factors discussed above were common to one or both the crises. Furthermore, each of the three periods of peak prices have been marked by a below normal ratio of stocks to use. An International Monetary Fund report assessing the impact of rise in food and fuel price on macro-economic indicators such as balance of payments, overall inflation, and poverty, also concludes that biofuels are one among several factors, which coincided to cause the price rise[56]. This report says for rice crop, restrictive trade policies were the major reason for the run up in the prices.

While the reports mentioned above are largely qualitative in nature, there are a few that quantify the effect of biofuel on total price rise. One report, and by far the most pessimistic about the role of biofuels, estimates that biofuels related developments were responsible for 70 to 75% of the price rise between 2002 and 2008[13]. This report uses historical data to estimate the elasticity of world price of agricultural commodities with respect to the price of energy and related inputs to agriculture and with respect to changes in the value of the dollar. Using these elasticities, he estimates that between 2002 and 2007, higher price of energy increased export prices of major U.S. food commodities by about 15-20% points and the depreciating dollar increased food prices by about 20% points. Taken together he argues this translates into a 25 to 30% increase in total price. The author argues that depletion of stocks, shifting for food cropland for production of energy crops, speculative activity and government response in the form of food export bans which caused prices to rise were the consequence of demand for biofuels and hence biofuels explain the remaining 70 to 75% of the increase.

In contrast to the above simple statistical calculation, Rosegrant estimates the effect of biofuels using a simulation-based approach[57]. He simulates the market equilibrium under two different scenarios, namely with and without high fuel demand. For the former he simulates a scenario in which biofuel grows at a rate which was observed between 1990-2000. This is the period before the rapid takeoff in demand for bioethanol. For the latter he simulates actual demand for food crops as a feedstock for biofuel, from the years 2001 through 2007. Based on these simulations he estimates that weighted average grain price increased by an additional 30% under the high biofuel scenario, i.e., the actual situation. The increase was highest for maize (39%) and lower for wheat and rice (22% and 21% respectively). And as described earlier our models estimate that ethanol production in the US in 2007 may have been responsible for a 15% to 28% increase in the world price of maize and 10% to 20% increase in the world price of soy[11].

3.3.3 Summary of literature

Rigorous impact assessment literature is scarce or non-existent. However there is a consistent theme that can be emerges from our review, namely, the depletion of total storage of grains to historically low levels, which have not been witnessed since the 1970s. This was the result of consumption exceeding production in each year for several successive years on account several factors, one of which was biofuel demand. On the demand side, another major factor is rapid economic-growth in emerging economies which increased demand for meat, a highly grain intensive product. On the supply side, bad weather in key grain-producing regions (especially wheat growing regions such as Australia), stagnation of productivity growth (due to under-investment in agricultural research and technology and infrastructure such as irrigation) and increase in production costs (due to high energy prices) have resulted in slow or negative growth in production. Prices spiraled even further as a result of policies such as export bans on grains and import tariffs on non-grain biofuels (especially the US import tariffs on cane ethanol from Brazil) and on account of speculative activity in reaction to such policies. Lastly, the depreciation of the US dollar relative to major world currencies has also been a contributing factor to commodity price increases (Abbott, Hurt et al. 2008; Rosegrant 2008). Historically, when the dollar is weak, commodity prices tend to be higher, and when the dollar is strong, commodity prices tend to be lower. However, with different countries adopting different policies towards biofuels and trade, assessing the country-level impacts of these factors require case-by-case analysis.

In any case with several different factors at play, identifying the contribution of any one factor such as biofuel is a challenging task. The estimates of the impact of biofuels are wide-ranging. The most pessimistic estimate is that suggest about 70 to 75% of the increase in food commodities was attributable to biofuel production where as the more optimistic estimates suggest 30% or lower. With further research no doubt better estimates can be produced. One reason why the optimisitic estimates may be an underestimate is because of a lack of representation of the market for storage in such models. We are not aware of any standard equilibrium models including those mentioned earlier that includes even a simplified representation of storage. The following section discusses the implications of excluding storage and describes one way of modeling the demand storage in a multi-market equilibrium framework.

3.4 Food inventory and biofuels

3.4.1 Recent trends

Historical trends in production, consumption, stock (inventory) and price at the global level for four major crops, namely, maize, wheat, rice and soybeans are shown in figures 3.7, 3.8, 3.9, and 3.10 respectively. Data on inventories was obtained from the United States Department of Agriculture's PSD database while the data on the international

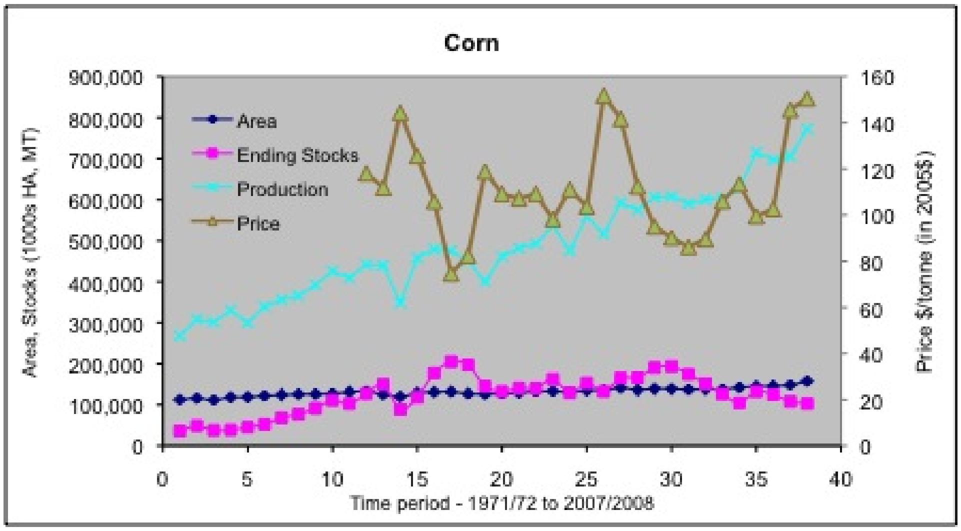


Figure 3.7: Historical data for maize

price was obtained from the IMF Price database on prices of primary commodities.[4] Price data was not available for the years prior to 1980 and hence are not shown. It is immediately apparent from the data that years in which prices increased, the level of inventory declined and viceversa. Years in which a local minimum in inventory levels was reached were also the years in which price reached a local maximum.

3.4.2 Analytical model of storage

For storable goods, the ability to adjust the level of storage (also referred to as inventory or stock) can play a crucial role in maintaining price stability and reducing price volatility when there is a supply or demand shock. During periods of excess of supply, demand from storers protects producers from rapidly descending prices while during period of scarcity, supply from storage protects consumers from rapidly ascending prices. This role of storage however becomes apparent only at times when the ability to increase or

[4] Available online at http://www.fas.usda.gov/psdonline/ and http://www.imf.org/external/np/res/commod/index.asp respectively

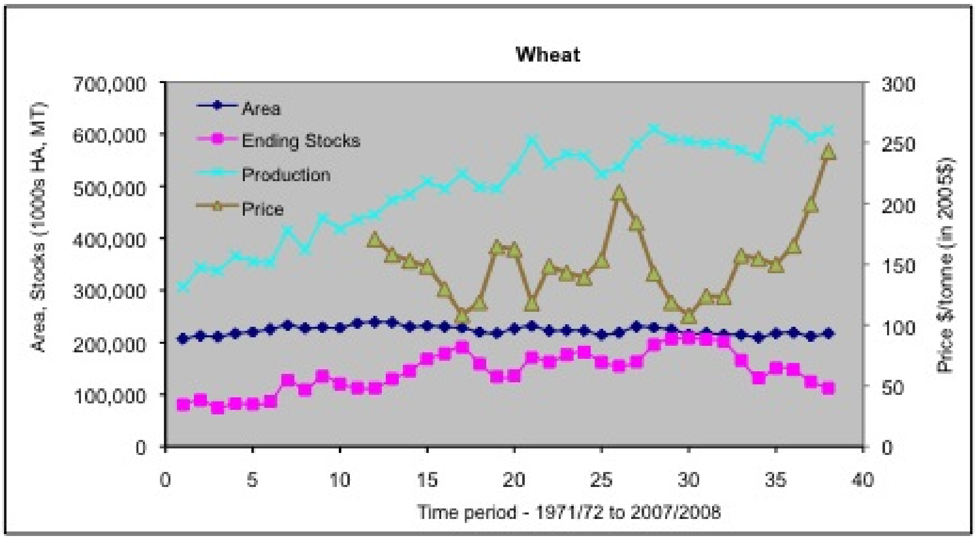


Figure 3.8: Historical data for wheat

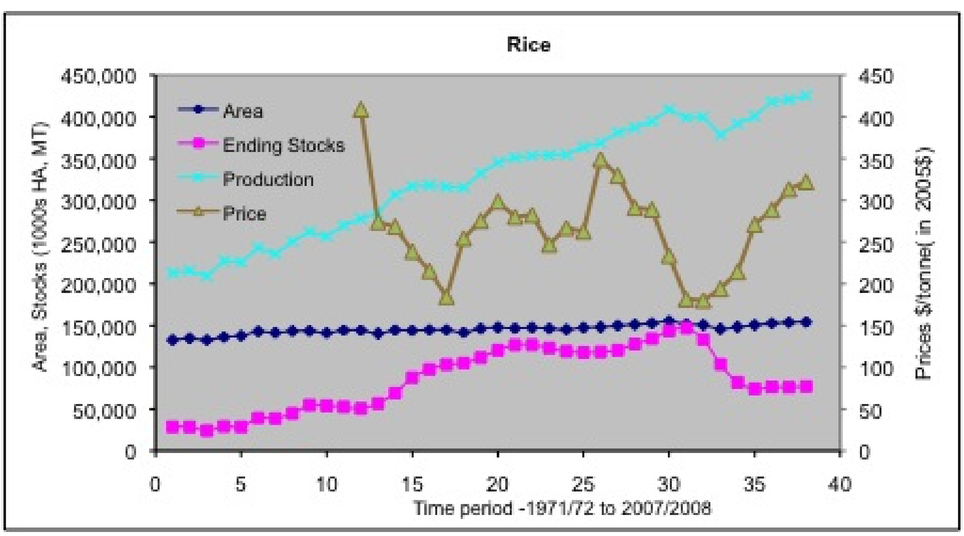


Figure 3.9: Historical data for rice

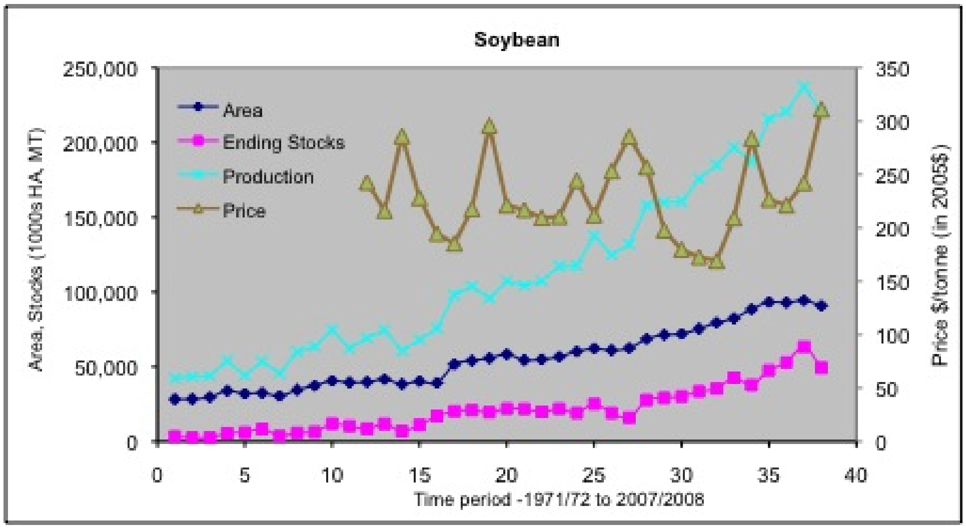


Figure 3.10: Historical data for soybean

decrease storage ceases. The latter occurs when inventory is exhausted. Both crops and fuels are storable good although the nature of storage differs in many ways. Crops can be stored only post-production while cheapest form of storing fuels (fossil fuels in our context) is to not produce them, i.e. leave them in the ground.[5] Fuel production can be adjusted to demand relatively easily by increasing the rate of extraction (assuming there is sufficient slack in refining capacity) whereas agricultural production cannot be given the time involved between planting and harvest.

With storage, equilibrium does not require a price where supply in a given period equals consumption in that period, but a price where supply or harvest (H_t) equals demand (D_t) plus the net change in storage during the current period ΔI_t.

$$H_t = D_t + \Delta I_t$$

[5]Some amount of oil is also stored after extraction such as in the form of Strategic Petroleum Reserves held by the US government.

$\Delta I_t = I_t - I_{t-1}$, the difference in stock at the end of time t and the stock at the end of time t-I. Using this the above equation can be rewritten as,

$$H_t + I_{t-1} = D_t + I_t$$

The left hand side can be called as the total availability A_t, at time time and the right hand side is the sum of demand for consumption and the demand for storage. We can see that the left hand side is not a function of crop price at time t (p_t^c). Planting decisions for harvest at time t need to be made at time t-1. Therefore it is reasonable to assume that supply depends on expected prices for the next period t at time t-1 ($E_{t-1}[p_t^c]$). Likewise I_{t-1} is a function of price in period t-1(p_{t-1}^c) and $E_{t-1}[p_t^c]$. If prices are close to random walks, the current period price is a good forecast for next period's expected price. Therefore $I_t = f(p_t^c)$.

In this chapter we do not focus on the theoretical underpinnings of speculative storage, which is a dynamic and forward-looking decision. Anticipation of future storage decisions affect current ones and these intertemporal links are made more complex by non-negativity constraint on aggregate storage, i.e., one cannot borrow from the future or that storage cannot be negative[58]. Instead we assume that one can estimate an empirically derived storage demand function using historical data on prices and storage, $I_t = I_t(p_t^c, p_{t-1}^c, I_{t-1})$. Consumption demand for crops comprises of demand for food (D_{cf}) and demand for biofuel production (D_{cb}). The demand for food is a function of price of crops t whereas crop demand for biofuels is a function both crop price and the

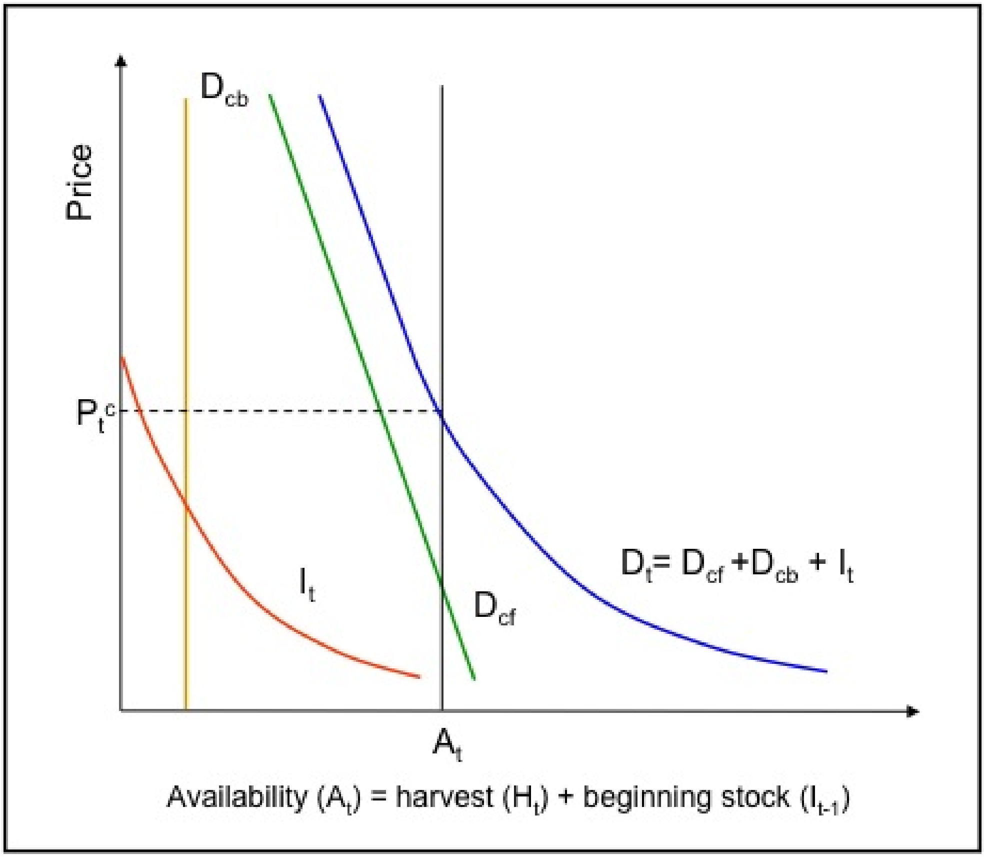


Figure 3.11: Graphical representation of equilibrium with demand for storage

oil price (p_t^o). The equilibrium condition can now be written as

$$H_t + I_{t-1} = D_{cf}(p_t^c) + D_{cb}(p_t^c, p_t^o) + I_t(p_t^c, p_{t-1}^c, I_{t-1})$$

Knowing $H_t, I_{t-1}, p_t^o, p_{t-1}^c$ and the shape of demand functions D_{cf}, one can determine the effect of different levels of biofuel consumption D_{cb} on crop prices. A graphical representation of such an equilibrium is shown in figure 3.11. This model also suggests that for a given quantity of fresh supply from harvest a lower level of beginning stocks will lead to a higher level of prices when demand exceeds harvest. Therefore a fixed biofuel

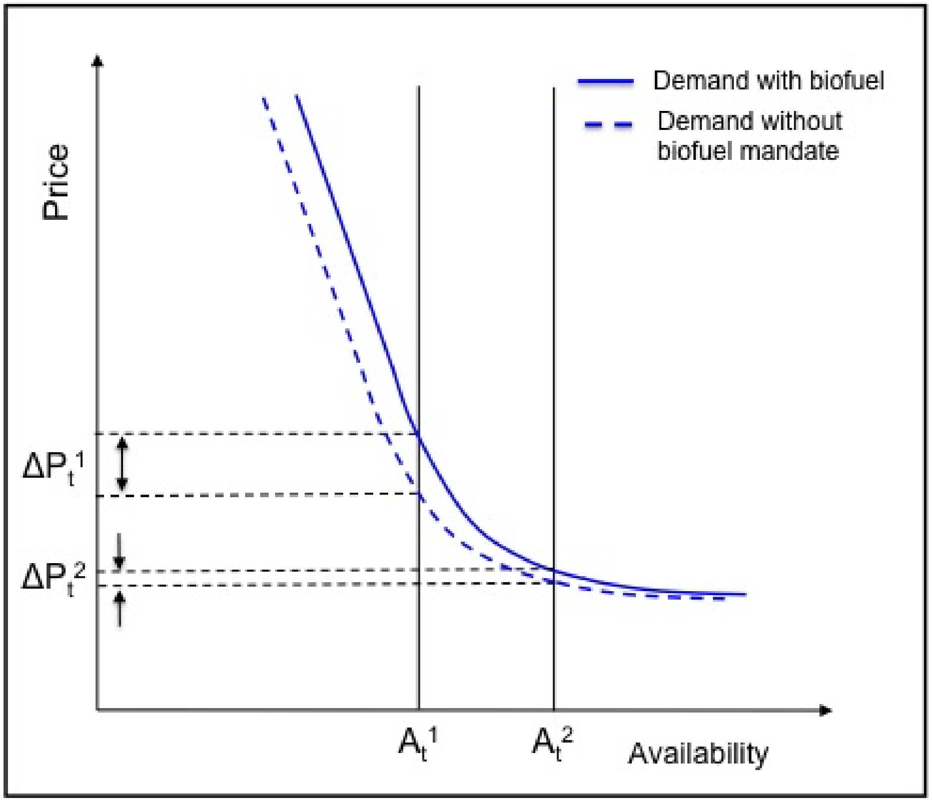


Figure 3.12: Biofuel effect depends on crop availability in a given year

mandate will cause prices to increase more as the level of inventories decline. Therefore changes in price due to biofuels should be estimated taking into account the available level of inventory. Figure 3.12 shows total demand for a crop under two situations, with and without biofuel and the total availability in a given period under two situations, with a high and low level of inventory. We can see that as availability decreases, the impact of a biofuel mandate increases. This also suggests that holding harvested supply constant, a model without the market for storage will overestimate the price effect of biofuel when inventory is large i.e, stocks to use ratio is high relative to a shock due to biofuels compared to one which includes the market for storage. If inventories are low, i.e., stock to use ratio is small, the two models will not differ significantly.

3.4.3 Numerical simulation: Effect of biofuel consumption on crop prices and inventory

Crop demand for food : Let us assume that the demand for crop can be represented as

$$D_{cf} = \beta_0 - \beta_1 p_t^c$$

Assuming an elasticity of demand for food, ϵ_d^{food} and the price, p_0 and quantity of corn q_0 at a given time in the past. Given these parameters we can estimate,

$$\begin{aligned} \beta_1 &= \epsilon_d^{food} \left[\frac{q_0}{p_0} \right] \\ \beta_0 &= q_0 - \beta_1 p_0 \end{aligned}$$

Crop demand for biofuel : Let B denote the quantity of biofuel demanded under a mandate. If γ is the biofuel yield per unit of crop (say, liters per tonne or gallons per tonne), then we can write,

$$\gamma D_{cb} = B$$

For several starch and oilseed based biofuels the co-product of biofuel production is a substitute to the crop itself. If δ is the fraction of crop consumed for biofuel production that is replaced (or returned) to food or feed use, then the effective crop demand for biofuel use is,

$$\frac{\gamma D_{cb}}{1 - \delta} = B$$

Demand for storage : Carter, Rausser and Smith[59] estimate a relationship between prices and inventory as follows,

$$ln\frac{p_t^c}{p_{t-1}^c} = \alpha + \beta ln\left[\frac{I_t}{I_{t-1}}\right] + \mu$$

They estimate $\hat{\alpha}$ and $\hat{\beta}$ for several major crops such as corn, wheat, rice, soybeans, and cotton. Using their estimates for $\hat{\alpha}$ and $\hat{\beta}$ and rearranging their equation, we can predict storage demand in any given year as,

$$I_t(p_t^c) = e^{-\frac{\hat{\alpha}}{\hat{\beta}}}\left[\frac{p_t^c}{p_{t-1}^c}\right]^{\frac{1}{\hat{\beta}}} I_{t-1}$$

Substituting these expressions for D_{cf}, D_{cb} and I_t, and gathering all the terms to one side, we can write the following expression in which the only unknown is the p_{2007}^c,

$$H_t + I_{t-1} - \beta_0 - \beta_1 p_t^c - \frac{1-\delta}{\gamma}B_t - e^{-\frac{\hat{\alpha}}{\hat{\beta}}}\left[\frac{p_t^c}{p_{t-1}^c}\right]^{\frac{1}{\hat{\beta}}} I_{t-1} = 0$$

For calibrating the food demand equation we assume that the elasticity of food demand is -0.2 and we use the international price and global quantity of corn consumed for non-biofuel purposes in 2006. We then use data on ending stocks in 2006 and harvested production in 2007, to predict what the international price of corn would be in the year 2007 with and without biofuel. We compare the price effects for different levels of inventory, namely, the actual level of inventory in 2007 and half the actual level of inventory in 2007. The data and the price estimates are shown in tables 3.3 and 3.4 respectively. The model predicts that biofuel caused corn prices to increase 11% in the

Table 3.3: Input parameters for simulation with storage demand

Parameter	Value	Unit	Description
ϵ_D	0.2		Elasticity of demand for corn for food
p^c_{2006}	123.25	\$/tonne	Average world price of corn in US in 2006
q^{cf}_{2006}	740	million tonne	Quantity of corn consumed in US in 2007
B_{2007}	6.5	billions of gallons	Quantity of ethanol produced in US in 2007
γ	106.3	gallons per tonne	Yield of biofuel per ton of crop
δ	0.32		Share of corn consumed for ethanol replaced by co-product
H_{2007}	705	million tonne	Quantity of corn harvested in US in year 2007
I_{2006}	125	million metric ton	Year ending stock in US in 2006
$\hat{\alpha}$	0.02		from Carter, Rausser and Smith[59]
$\hat{\beta}$	-0.36		from Carter, Rausser and Smith[59]

Table 3.4: Results of simulation with storage

Model predictions under different levels of ending stock in 2006	I_{2006}= \$125/tonne	I_{2006}= \$62.5/tonne
Price of corn in 2007 with biofuel (\$/tonne)	150	165
Price of corn in 2007 without biofuel (\$tonne)	135	140
% increase in price compared to 2006	22%	34%
% increase in price relative to the counterfactual of no biofuel for 2007	11%	18%

actual case and 17% if inventories were half the actual levels in 2007.

3.5 Summary

Biofuels no doubt caused food prices to increase. However there are several other factors one has to contend with before quantifying the effect of biofuels. Economic growth in the developing world caused demand for both food and fuel to increase. Higher fuel prices increased the demand for biofuel beyond levels specified by mandates. Bad weather in key grain exporting regions reduced production at time when demand was growing. These combined with depreciation of the U.S. currency contributed to the recent spike in the price of food. The effect of biofuels on food prices depends on the level of inventory and more accurately, the stocks to use ratio. We have illustrated how an empirically estimated storage demand function can be incorporated into an equilibrium framework to simulate the effect of biofuels on prices. The one-crop, one-region model can be extended without much difficulty to represent the market for multiple crops across multiple regions engaging in trade. This model can also be solved recursively over multiple time periods, to simulate the phenomenon of successive years of declining inventory or declining stocks-to-use ratio. This model will predict that crop price will increase at a faster rate as stocks to use ratio declines. This is envisioned as future work. The empirical challenge is to identify the supply and demand curves for agricultural commodities and fuels. Biofuels improved the welfare of farmers and gasoline consumers. Conservative estimates assuming a competitive oil market suggest biofuels conferred billions of dollars in benefits to oil importing nations.

The situation in both food and fuel markets can be improved through policies that expand supply, for example, enhanced agricultural research and less restrictive regulation of agricultural biotechnology. High prices due to biofuels may provide incentives for innovation in and adoption of productivity-enhancing technologies both in agriculture and energy sectors. Policies can affect the speed, timing, and nature of these technological changes. If mandates are to be used, the level of mandates to should be adjust to the situation in food markets. Shifting to second generation feedstock such as cellulosic biomass will weaken the linkage that has developed because of biofuels between food and fuel markets. Future research should also consider the impact of biofuels on other sectors of the economy including land, water, fertilizer, labor, livestock, food processing, electricity and fuel transportation to name a few.

Chapter 4

Greenhouse gas regulation of fuels: Emission quotas versus emission intensity standards

4.1 Introduction

Some of the major GHG policies implemented till date such as the Kyoto protocol and the EU Emission Trading Scheme (ETS) mandate reduction in aggregate emissions. While the Kyoto mandates national emission reduction targets, the ETS mandates targets for emission reduction for stationary polluting sources such as electric power plants and/or industrial facilities within a specified region. One of the first regulations to exclusively target GHG emissions from transportation is California's Low Carbon Fuel

Standard (LCFS) which mandates a target for GHG intensity of transportation fuels.[1]

Economic theory says that given certain conditions, an unit emission fee equal to the marginal social cost of pollution achieves the first-best (efficient) outcome i.e, attains the optimum level of pollution at least cost[60, 61]. Difficulty in estimating the social cost of pollution leads to the pursuit of cost-effective policies, wherein the goal is to attain a politically chosen target level of pollution[34, 62, 37]. These policies can be implemented either by pricing pollution or by allocating pollution rights. Often instead of choosing a target level of pollution, policy makers choose a target level of pollution intensity i.e, an upper-limit on the quantity of pollution per unit of output. This type of policy is also more generally known as performance-standards. Hence when the pricing approach is infeasible, policy makers can choose from different quantity-based approaches for reducing pollution. However, it appears that performance standards are the preferred form of environmental regulation[63]. Policies such as tail-pipe emission standards, corporate average fuel economy standards, and renewable fuel standards suggest that this is certainly the case for transportation. When damage depends on concentration of pollutant in the ambient environment, performance based standard such as emission intensity standard has optimal properties. When damage depends on aggregate stock of pollution emission this type of policy is sub-optimal.

Being able to predict the effect of different types of policies on variables such as abatement cost, price, output, and pollution is necessary for making good decisions. Furthermore while climate change requires long-term policies, the short-run effect of different

[1] Staff Report: Proposed Regulation to Implement the Low Carbon Fuel Standard - Initial Statement of Reasons (ISOR) Available online at http://www.arb.ca.gov/fuels/lcfs/lcfs.htm

policies on such variables should not be ignored. For costly short-run effects can generate public opposition to replace policies which may be beneficial in the long-term[37]. Hochman and Zilberman[37] compare the effects of two policy tools, namely, an emission tax and an emission standard per unit of output. They find that while as expected, both policies reduce emissions and output; surprisingly enough, taxes may in some cases lead to an increase the emission intensity of output. With carbon taxation continuing to be politically unpopular, we focus our attention on quantity-based policies. Newell and Pizer[64] compare emission regulation and emission-intensity regulation (emission indexed to GDP) of GHG when there is uncertainty in abatement cost and derive conditions under which one is more efficient than the other. Since they focus on economy-wide policies their model abstracts away from the sector-specific characteristics which can affect the relative performance of the two policies as we show in this paper.

Our interest is in comparing emission intensity standard and emission quotas for a sector-specific or product-specific regulation. There is a growing tendency in the case of quantity-based policies to allow trading of pollution rights between regulated entities [65]. The LCFS policy too allows trading of emission credits/permits between firms. However, policies that do not permit trading of pollution rights are also common such as the Clean Air Act standards for toxics. In the model we describe here we assume no trading between firms. While this simplifies the mathematical exposition, it does not however affect the conclusions, which as we explain later hold if trading is permitted. The differences between the two policies stem from a fundamental characteristic of each policy which is not affected by whether trading of pollution rights is allowed or not. We focus on a price-taking region and assume linear technologies i.e., production function is fixed proportion. We focus on the short-run and so we assume that capacity is fixed. We find that an emission quota is more or in the worst case as cost effective as an emission intensity standard for achieving a given level of emission reduction. We also find that aggregate output from the region can be higher or lower than under a quota.

4.2 Model and analytic results

We model the behavior of fuel-producing firms facing environmental regulation. As mentioned above we focus on a price-taking region, with a number of competitive price-taking producers who produce a homogeneous product, transportation fuel. The market price of the finished fuel is p. Firms convert inputs to output in fixed-proportion. Firms are heterogenous, differing in capacity q_i^0 which we assume is fixed, in marginal cost c_i^0 (constant for a given firm), and in the pollution intensity of output γ_i^0. We also assume that $\frac{\partial c_i^0}{\partial \gamma_i} < 0$, $\frac{\partial^2 c_i^0}{\partial \gamma_i^2} > 0$, i.e., cleaner fuels are costlier to produce.Using this notation, profit π_i^0 and pollution Z_i^0 can be expressed as,

$$\begin{aligned} \pi_i^0 &= (p - c_i^0) q_i^0 \\ Z_i^0 &= \gamma_i^0 q_i^0 \end{aligned}$$

A firm can reduce emissions in any of the following ways.

1. *Adopt cleaner inputs*: A firm can reduce emissions by adopting technology that reduces emission intensity (for instance switch to newer vintage that is more efficient)

or adopt cleaner energy as in input (for instance switch from using coal to using natural gas).

2. *Blend with cleaner fuels*: Fuels differing in pollution intensity can be blended to produce a fuel with intermediate level of pollution intensity. In fact policies such as the LCFS and RFS envision that blending gasoline (or diesel) with cleaner biofuels will be the principal mechanism for reducing GHG emissions from transportation.

3. *Cut production*: A firm can reduce its total emissions by simply reducing its output. However, if firms have to reduce the pollution intensity of output then it is not sufficient to merely reduce output.The firm has to consider this in conjunction with one of the options above.

Henceforth we refer to these choices simply as option A, option B and option C respectively.[2] The two types of regulations we consider impose different constraints on firms. An emission intensity standard while limiting the maximum allowable emissions per unit of output, does not restrict the aggregate emissions per facility. The converse is true for an aggregate quota.

The optimization problem of a firm with fixed capacity is,

$$\max_{\Delta\gamma_i,\Delta q_i^*,\Delta q_i} \pi_i = \{\underbrace{p(q_i^0 + \Delta q_i + \Delta q_i^*)}_{\text{Revenue}} - \underbrace{(c_i^0 + \Delta c_i(\Delta\gamma_i))(q_i^0 + \Delta q_i)}_{\text{Production cost}} - \underbrace{(p + c_i^t)\Delta q_i^*}_{\text{Blending cost}}\}$$

subject to the constraint that, the average emission intensity is less than the emission

[2] These options are named such that, option A implies adoption, option B implies blending and option C implies cutting or reducing output.

intensity standard, $\overline{z}$

$$\frac{\gamma_i^0 q_i^0 + \Delta\gamma_i q_i + \gamma_i^* \Delta q_i^*}{q_i^0 + \Delta q_i + \Delta q_i^*} \leq \overline{z}$$

or *subject to the constraint that*, total emissions are below the quota, $\overline{Z_i}$ [3]

$$Z_i^0 + \Delta\gamma_i q_i + \gamma_i^* \Delta q_i^* \leq \overline{Z_i}$$

It is worth pointing out that generally intensity standards are uniform across all firms (not indexed by i) while the emission quotas tend to be firm-specific (indexed by i). Holding output constant, any arbitrary level of emission intensity can be translated into an equivalent level of emissions. Similarly any given level of intensity reduction can be translated into an equivalent level of emission reduction and vice versa. Therefore for any firm i, and producing output q_i^0 before regulation, we can write, $\overline{Z_i} = \overline{z} * q_i^0$ (or $\Delta Z_i = Z_i^0 - \overline{z} * \overline{q_i}$).

The decision variables for the firm are, $\Delta\gamma_i$, the amount by which it lowers emission intensity of its own processes by adopting new technology or by switching fuels (option A), Δq_i^*, the quantity of output it procures from other sites for blending (option B), and Δq_i, the amount by which the firm lowers its own production (option C). Since we assume linear technologies, the firm will choose only of the options to reduce pollution (i.e., corner solution). Therefore the decision variable effectively is the discrete choice of

[3]Equivalently, the constraint under a quota can also be expressed as

$$\Delta\gamma_i q_i + \gamma_i^* \Delta q_i^* \geq \Delta Z_i, \text{ where } \Delta Z_i = Z_i^0 - \overline{Z_i}$$

selecting one among the three options for reducing pollution. The firm will choose the most cost-effective option. We describe the economics of each option below.

- Option A (Adopt): Let us assume that the firm i has K discrete choices to reduce emission intensity, with each choice having constant marginal cost. If choice k, $k \in 1..K_i$ involves a cost Δc_{ik} and reduces emissions intensity by $\Delta\gamma_{ik}$, the average cost (AC) of pollution reduction for the $k^{th} choice$ is,

$$AC_A = min\{\frac{\Delta c_{ik}}{\Delta\gamma_{ik}}\} \text{ k } \in 1..K_i$$

- Option B (Blend): A firm can blend dirty-fuel it produces with a cleaner fuel produced either by itself at a different location (Option B_{own}) or by another firm (Option B_{market}).

Option B_{own}**:** Let c_i^* represent the cost of producing the cleaner fuel with $p - c_i^* > 0$ (the firm earns positive profits on the clean fuel), c_i^t the the cost of transporting it to the site producing the dirty-fuel and γ_i^* the pollution intensity of clean fuel. Let the firm blend the dirty and clean fuels in the ratio $(1 - \alpha)$ and α respectively. The average cost of pollution reduction by blending with clean fuel purchased in the market is,

$$AC_{B_{own}} = \frac{c_i^t}{\gamma_i^0 - \gamma_i^*}$$

Option B_{market}**:** Here we assume the firm purchases the clean fuel at the market price p and transports it at a cost c_i^{t*} to its facility for blending with its fuel.

The pollution intensity of clean fuel is γ_i^* ($\gamma_i^* < \gamma_i^0$). Let the firm blend the dirty and clean fuels in the ratio $(1-\alpha)$ and α respectively. The average cost of pollution reduction by blending with clean fuel purchased in the market is,

$$AC_{B_{market}} = \frac{p + c_i^{t*} - c_i^0}{\gamma_i^0 - \gamma_i^*}$$

Corollary: The average cost of pollution reduction by blending is independent of the blend ratio. (See appendix for detailed derivation).

- Option C (Cut production): Lowering output by one unit lowers pollution by a quantity γ_i^0 and lowers profit by an amount $p - c_i^0$. This implies that average cost of pollution reduction by decreasing output is,

$$AC_C = \frac{p - c_i^0}{\gamma_i^0}$$

Table 4.1 summarizes the cost-effectiveness of each option available to a firm. These support the following propositions.

Proposition 1: Under emission quota, firms will prefer to reduce output rather than blend with cleaner fuels from the market.

Proof: Comparing the average cost of abatement for option B_{market} and option C shown in table 4.1 we can see that,

$$AC_{B_{market}} > AC_C \ \forall \ c_i^t > 0, \ \gamma_i^* > 0 \text{ and } \gamma_i^* < \gamma_i^0$$

Table 4.1: Comparison of a firm's choices for emission reduction when production capacity is fixed

Option	Profit (π_i^1)	Loss in profit per unit of output ($\pi_i^0 - \pi_i^1$)	Emission reduction ($Z_i^1 - Z_i^0$)	Reduction in emission intensity	Average cost of abatement
Adopt (A)	$p - c_{ik} + \Delta c_{ik}$	Δc_{ik}	$\Delta\gamma_{ik}$	$\Delta\gamma_{ik}$	$\frac{\Delta c_{ik}}{\Delta\gamma_{ik}}$
Blend with own clean fuel (B_{own})	$p - [(1-\alpha)c_i + \alpha(c_i^* + c_i^t)]$	αc_i^t	$\alpha(\gamma_i^0 - \gamma_i^*)$	$\alpha(\gamma_i^0 - \gamma_i^*)$	$\frac{c_i^t}{(\gamma_i^0 - \gamma_i^*)}$
Blend with clean fuel from market (B_{market})	$p - [(1-\alpha)c_i + \alpha(p + c_i^{t*})]$	$\alpha(p + c_i^{t*} - c_i^0)$	$\alpha(\gamma_i^0 - \gamma_i^*)$	$\alpha(\gamma_i^0 - \gamma_i^*)$	$\frac{(p + c_i^{t*} - c_i^0)}{(\gamma_i^0 - \gamma_i^*)}$
Cut production (C)	-	$p - c_i^0$	γ_i^0	0	$\frac{p - c_i^0}{\gamma_i^0}$

Consider a more realistic assumption, that cleaner fuel is costlier or that there is positive to cost of physically blending different fuels to produce the final fuel. We can see that this only makes cost of blending option to increase further relative to option C.

Proposition 2: For any given firm, abatement costs under an emission intensity standard is equal to or greater than abatement cost under an emission quota.

Proof:

Case 1: Firm produces both dirty and clean fuels.

The cost of achieving compliance with an emission intensity standard is,

$$C_{ub} = \min\{AC_A, AC_{B_{own}}\}$$

The cost of achieving compliance with a quota is,

$$C_{quota} = \min\{AC_A, AC_{B_{own}}, AC_C\}$$

$$\begin{aligned} \text{If } AC_C &< AC_{B_{own}} \text{ and } AC_C < AC_A \\ \text{then } C_{ub} &> C_{quota} \\ \text{else } C_{ub} &= C_{quota} \end{aligned}$$

This implies that $C_{ub} \geq C_{quota}$

Case 2: Firm produces only dirty fuel

The cost of achieving compliance with an emission intensity standard is,

$$C_{ub} = \min\{AC_A, AC_{B_{market}}\}$$

The cost of achieving compliance with a quota is,

$$C_{quota} = \min\{AC_A, AC_C\}$$

Since $AC_C < AC_{B_{market}}$ this again implies that $C_{ub} \geq C_{quota}$. Therefore an emission intensity standard is costlier or equal at-best to a emission quota for a regulated firm. The intuition behind the proposition is that the choice set under an emission quota has more lower cost options than the choice set under an emission intensity standard.

Lemma: An increase in output price (or equivalently a reduction in cost of an input) increases the cost of abating emissions by reducing output relative to the cost of abating emissions by other means. To the extent that this is true, the inefficiency of an intensity standard relative to a quota will decrease.

Proposition 3: Aggregate output under an emission quota can be higher or lower than that under an intensity standard depending on the cost-effectiveness of reducing emissions by reducing output relative to that through technology adoption and through blending with clean fuels, holding production capacity of firms fixed.

Proof: If technology adoption and blending with clean fuels are both unprofitable

($\pi_i^1(A) < 0$ and $\pi_i^1(B) < 0$) then emission intensity standards will force inefficient firms to exit. However, under an emission quota inefficient firms can reduce output and continue to operate. If the production capacity of firms is fixed (i.e., efficient firms cannot increase output to make up for the reduction in capacity due to exit of inefficient firms), then emission quotas will result in higher output than or at least the same amount of output as under intensity standard.

If technology adoption or blending with clean fuels is not costly enough to force firms to exit ($\pi_i^1(A) > 0$ or $\pi_i^1(B) > 0$), and if lowering output is still the cheapest abatement option ($AC_A > AC_C$ and $AC_B > AC_C$), then emission intensity standard will result in higher output than or at least the same amount of output as under quota. This is because even though reducing output is the cheapest abatement option, firms cannot lower their emission intensity by doing so.

4.3 Numerical example

We illustrate the theoretical model using representative data on cost and emissions for ethanol production in the US (see table 4.3). Ethanol biorefineries use either coal or natural gas as the source of energy for producing ethanol from corn. The GHG intensity of ethanol from produced with coal is higher than that produced with natural gas ($89gCO_2e/l$ and $61gCO_2e/l$ respectively).[4] We consider two policies, an emission intensity standard that requires the GHG intensity of ethanol to be below $75gCO_2e/l$ and a quota that requires a 15.7% reduction in emissions by the coal-producing firm

[4] gCO_2e/l refers to grams of carbon-di-oxide per liter of ethanol.

Table 4.2: Input parameters to the simulation for various scenarios

Scenarios*	**I**	**II**	**III**	**IV**	**V**
Price of ethanol ($/liter)	0.628	0.942	0.628	0.628	0.942
Coal-based ethanol production cost ($/liter)	0.430	0.430	0.430	0.430	0.430
Ethanol transportation cost - rail ($/liter)	0.050	0.050	0.050	0.100	0.075
Ethanol transportation cost - road ($/liter)	0.130	0.130	0.130	0.260	0.195
Energy used in biorefining (MJ/liter)	13.85	13.85	13.85	13.85	13.850
GHG intensity of coal-based corn ethanol in gCO2e/liter	89	89	89	89	89.000
GHG intensity of gas-based corn ethanol in gCO2e/liter	61	61	61	61	61.000
Price of coal energy ($/MJ)	0.0020	0.0020	0.0020	0.0020	0.002
Price of natural gas energy ($/MJ)	0.0105	0.0105	0.0262	0.0105	0.010

* Scenarios are the following,
I: Base case - see appendix for further explanation
II: Ethanol price is 50% higher than base case
III: Natural gas is 2.5X costlier relative to coal than base case
IV: Transportation cost is 2X than base case
V: Ethanol price and transportation cost are 1.5X of base case

Table 4.3: Calculated average cost of abatement in $\$/gCO_2e$ for each option

Scenarios	**I**	**II**	**III**	**IV**	**V**
Option A - Switching from coal to gas	0.0042	0.0042	0.0119	0.0042	0.0042
Option B_own	0.0032	0.0032	0.0032	0.0064	0.0048
Option B_market	0.0103	0.0215	0.0103	0.0135	0.0231
Option C	0.0022	0.0057	0.0022	0.0022	0.0057

Table 4.4: Minimum cost of compliance under each policy

1. Firm produces dirty and clean fuel					
Scenarios	**I**	**II**	**III**	**IV**	**V**
Cost under intensity standard	0.0032	0.0032	0.0032	0.0042	0.0042
Cost under emission quota	0.0022	0.0032	0.0022	0.0022	0.0042
Relative cost of intensity standard	145%	100%	145%	188%	100%
2. Firm produces only dirty fuel					
Cost under intensity standard	0.0042	0.0042	0.0103	0.0042	0.0042
Cost under emission quota	0.0022	0.0042	0.0022	0.0022	0.0042
Relative cost of intensity standard	188%	100%	463%	188%	100%

(assuming no change in firm's output) [5]. Coal-using biorefineries can either switch to natural gas as the source of heat(option A), blend with own cleaner gas-based ethanol, in case it owns such a facility (option B_{own}), blend with gas-based ethanol purchased in market (option B_{market}) or simply reduce output (option C) (see table 4.3). For option A we assume switching is comprised only of difference in fuel cost but no fixed-cost.This is not a realistic assumption. Yet we do so, because our purpose is to only illustrate the model and not to rule out any option. The option chosen by a representative firm under either policy in different economic situations and the least-cost policy given a situation is shown in table 4.3. Table 4.3 shows that firms will incur significantly higher cost under an emission intensity standard policy. We can see that the incentive to blend increases with increase in the fuel price or switching cost. However, fuel price increase will likely raise transportation cost which decreases the incentive to blend. Therefore, the net effect

[5] We can see that if there is no change in output, the two regulations imply the firm's fuel has the same pollution intensity on average($\frac{89-75}{89} = 15.7\%$)

is ambiguous. Comparing scenarios I and II we can see that an increase in output price reduces the incentive to reduce output in order to reduce pollution and thereby decreases the inefficiency of an intensity standard relative to a quota.

4.4 Discussion

For a price-taking region, a more efficient policy is one which imposes lower cost on producers to achieve a given level of emission reduction. Emission quotas impose lower or in the worst case the same cost as emission intensity standards in the short-run (when capacity is fixed). The higher efficiency of quotas stems from the fact it provides firms, the additional option of achieving compliance by lowering output whereas the latter does not. The numerical example illustrates how the abatement cost may differ between the two policies under different economic conditions. Although our application has been in the context of transportation fuels, the result is true for GHG emissions from other products too.

The efficiency gained through the option to reduce output will be higher if there is variability in macro-economic circumstances. During a period of low or negative economic growth (like during the current recession) when producer margins are small (or demand is low), pollution reduction is more easily achieved through lower production (or consumption) without necessarily lowering emission intensity which requires adopting new and costlier technologies. [6] On the other hand, during periods of high economic

[6]Gasoline consumption in the US in the year 2009 is expected to be 7% lower compared to 2007. This represents a reduction of about 10.7 billion gallons of gasoline. If a megajoule of corn ethanol reduces GHG emissions 18% relative to a megajoule of gasoline (ignoring indirect emissions such as that from land use change because of increased corn production), about 88 billion gallons of ethanol would be required to achieve the same amount of GHG reduction that will be achieved simply from reduction in demand.

growth, quotas will serve as a binding cap on aggregate emissions which under an emission intensity regulation may increase due to higher output (or consumption). Thus an emission intensity standard can lead to higher than optimal level of abatement during difficult economic times and an increase in emissions during a good economic times.

Our results hold even when we allow for emission trading (which we have not considered) under either policy. Performance-based standards such as emission intensity standards by definition tend to be uniform across firms. Emission quotas on the other hand tend to be polluter-specific. Often they require that polluters reduce emissions by a certain percentage relative to emissions at a certain time (e.g. reduction targets under Kyoto protocol). While emission trading has come to be accepted in the case of emission quotas, there has been limited experience with market-based emission intensity standards. The program that led to the phase-down of lead in gasoline is an example of market-based performance standard which was highly cost-effective compared to performance-standard which did not allow trading and banking.[7]. Emission trading reduces the inefficiency of both an intensity standard and an emission quota when there is heterogeneity across firms. Irrespective of tradability of pollution rights, firms cannot simply reduce output under an intensity standard. Therefore an emission quota with trading i.e., a cap and trade policy will be more flexible than a performance-standard with trading. Furthermore, provisions such as banking and borrowing of permits will improve the flexibility of both quotas and intensity standards but not make intensity standards more flexible than emission quotas. It can also be shown that an intensity standard that varies with time

This represents about 14-fold increase in ethanol consumption in the US and 7-fold increase in global production of ethanol.

[7]Policies such as CAFE standards for automobile manufacturers and Renewable portfolio standards for electricity also allow either trading or banking or both. But these are not emission policies

will for the same reason be less flexible than an aggregate emission quota that varies with time.

Emission quotas reduce the likelihood of blending of clean and dirty fuels. Blending with clean-fuels if they are already being produced, will reduce the effectiveness of the policy in inducing adoption of cleaner technologies by polluting firm. In the worst case simple blending may result in no real emission reduction compared to the pre-policy situation.[8] The incentive to blend decreases with an increase in the cost of clean fuels or an increase in cost of transporting fuels.

Within the world of emission intensity standards, a lifecycle GHG emission intensity standard applied to the final fuel can be more or less efficient than an emission intensity standard on each intermediate input used of the production chain. Intuitively speaking, in the case of the former, the firm has a potentially larger set of mitigation options to choose from, it can abate emissions either directly or indirectly by purchasing cleaner inputs. In economic terms, firms can on the margin equalize abatement costs across the supply chain. If there are limits on emission intensity at each stage this may not be possible. However, lifecycle based policies can result in no net reduction in lifecycle emission or in the worst case increase lifecycle emissions. For instance, when there is heterogeneity in upstream activities (e.g. pollution associated with farming) and these activities serve multiple markets not all of which are unregulated, (e.g. crops can be sold

[8]There are parallels to be drawn here to auto manufacturers adjusting the mix of small (efficient) and large (inefficient) cars in their fleet, rather than improving the fuel economy of each model in order to comply with CAFE. Furthermore, some manufacturers began producing flex-fuel cars, cars capable of running on $E85$ in addition to gasoline, in order to take advantage of the extra mileage credits provided for such vehicles. Although extra credits for flex-fuel cars was based on on the assumption that these would run on $E85$ 50% of the time; estimates seem to suggest that flex fuel vehicles are run on $E85$ less than 1% of the time.

both in food and fuel markets), a lifecycle based policy may lead to mere reallocation of pollution between regulated (fuel) and unregulated (food) markets. In other words, crops that are less input-intensive (produced from fertile soils with less inputs and high yield) are used by fuel producers while those that are more input-intensive crops are used for food. In the worst-case this may lead to an overall increase in polluting inputs and hence emissions from such activities. In the context of biofuels, this phenomenon is called indirect land use emissions. Determining the net effect of lifecycle based regulations requires a general equilibrium analysis.

In future work we will address some of the limitations of our model. One is exogeneity of prices. If the region implementing the policy is large then there will be price-effects of regulation which cannot be ignored and these effects may vary under different policies. The assumption of fixed capacity is another limitation. While this is reasonable in the short to medium term, addressing climate change requires long term policies. We have also not considered administrative costs which can differ significantly for different types of regulations.

Chapter 5

Conclusion

My dissertation makes contributions to three broad areas which will continue to figure prominently in debates on energy and climate change policies. These are, the use of environmental lifecycle analysis as a basis for regulation, the economic impact of biofuel policies and the economics of different types of GHG regulations of transportation fuels. In this chapter I summarize the contributions made to these areas and present my conclusions.

Biofuels have brought LCA to the forefront of environmental and energy policy debates. More generally, the need for LCA in policy analysis will arise under any of the following situations, namely, when regulation is at the product-level, when lifecycle emissions are not concentrated at the product stage or when emissions are site-specific or producer-specific. This means that LCA is relevant for analyzing the impact of several other emerging technologies such as batteries, oil sands, coal-based liquids and natural gas based liquids. LCA based environmental regulation of products, is essentially a back door way of regulating emissions in unregulated sectors. For instance, LCA based regulation of biofuels, is an indirect way of regulating emissions from agriculture.

A pre-requisite for lifecycle based regulation is that we should be able estimate lifecycle emissions reasonably well and this is a challenging task. The current method of performing LCA is an assessment of the past and not an indicator of the future. This limits its usefulness as a tool for making long term policy decisions. LCA indicators do not merely reflect technical relationships between inputs and outputs but implicit in them is a representation of prevailing economic and policy situation. Therefore as economic and policy conditions change, the production function and therefore pollution function will change. Estimating lifecycle indicators as explicit functions of prices can help us better predict the lifecycle impact in future. For this, traditional LCA models which contain a detailed representation of the production technology should be integrated with decision-theoretic models which can predict how economic agents will respond when incentives change.

Second, for policy purposes, lifecycle emissions based on accounting of emissions attributable to a batch of output from a single firm should be distinguished from lifecycle emissions attributable to the aggregate output of a region. The distinction between the two being what is often referred to as indirect effects and indirect emissions. Such effects arise as a result of the interlinkages between markets either on the product side or the input side or both. Integrating LCA with economic models with representation of these interlinkages such as partial or general equilibrium models will allow us to predict the lifecycle impacts under different types of policies.

Emissions estimated using LCA can be used in conjunction with any type of policy instrument. Both price-based such as emission fee or quantity-based instruments such as emission caps and emission intensity standards (more generally, performance standards) can be implied based on lifecycle emissions. The environmental economics literature on instrument choice focuses largely either on the differences between price-based and quantity-based policies or on the difference between policies which permit trading in pollution rights (market-based) and those which do not allow trading (direct controls). In chapter we focus on a question relating to instrument choice received relatively less attention, namely the difference between emission caps and emission intensity standard. We show that given certain conditions, for climate change mitigation, emission caps will be more efficient and emission intensity standards. This has immediate relevance from a policy stand point. The first two regulations of GHG exclusively from transportation are emission intensity standards. Both Low Carbon Fuel Standard and the Renewable Fuel Standards mandate emission intensity limits for transportation fuels. In contrast, earlier regulations such as the Kyoto protocol, Emission Trading Scheme, and the Regional Greenhouse Gas Initiative mandate emission caps rather than emission intensity limits.

The question of efficiency of different instruments or different types of policies is no doubt important. For GHG emissions, the scope i.e., the reach of the policy is equally if not more important. Even the most efficient level of GHG tax on transportation emission can be inefficient if GHG emissions from agriculture are unregulated. This suggest GHG policies should be economy-wide and target all activities that lead to emissions. That said even the efficient economy-wide domestic tax under autarky can be inefficient when there is international trade. Domestic policies may lead to relocation of polluting activities to regions abroad with higher pollution intensity. This suggests that GHG policies should ideally be both economy-wide and global in scope.

In the interim however, i.e, until climate change policies become global and binding on the obligated parties, LCA can play an important role in designing regional or sectoral policies. The effectiveness of LCA based policies however depends on the accuracy of estimates of lifecycle emissions. The debate about the uncertainty of indirect emissions of biofuels is a case in point. A low but incorrect value for GHG intensity of biofuels can lead to emissions of GHG at a faster rate than fossil fuels. Thus the importance of accurately estimating lifecycle emissions cannot be understated.

Biofuels have a had significant impact on food and fuel markets. Quantifying the contribution of biofuel to the run up in food prices is hard since the food markets experienced several other supply and demand shocks concurrently. The contribution of biofuels better understood by understanding the situation with regard to the inventory and how biofuels impact inventory. We find that the impact of a given quantity of biofuel on food supply will be low or high depending on whether inventory is high or low respectively. While the impact of biofuels on food prices has generated much discussion, the impact of biofuels on fuel markets has gone unnoticed. Our simulations suggest that biofuels have caused fuel prices to decline 1% to 2%. Albeit small in price terms, taking into account the quantity of fuel consumed, which is far higher than the quantity of grains, the impact on the revenue of oil exporting nations. This is a conservative estimate since we assumed a competitive market structure for oil market. Taking into account non-competitive behavior in oil market, one is likely to find that the impact of biofuel is higher. To the extent that reducing oil imports and reducing the market power of OPEC is a major driver for biofuel policies (and this should not be hard to believe since policy makers are likely aware that there exist cheaper ways of decarbonizing the economy than biofuels), this is a welcome impact. That said, subsidizing corn ethanol and taxing cane ethanol is not the most efficient way of achieving this outcome. Broadly speaking, the short-term economic impacts of biofuels will depend on a variety of factors such as the harvest in any given year, the oil price, economic growth, strength of the dollar, and level of inventory. Public acceptance of biofuels should be expected to ebb and flow depending on what it perceives as these short-term impacts. The long-term impacts will depend on factors such as investment in technological change, population and economic growth, climate change, and long-term policies towards energy, agriculture, and the environment. The biofuel policy debate is likely to be an ongoing one in the near future.

In conclusion, addressing climate change requires both immediate measures and a long term commitment to GHG emission reduction. The immediacy constraint has relaxed somewhat due to the economic recession which began in 2008. It is predicted that in 2009 gasoline consumption in the US is likely to be 7% lower compared to that during the year 2007. This translates into a reduction of approximately 10.7 billion gallons of gasoline during 2009. Ignoring indirect emissions from biofuels and assuming that a megajoule of corn ethanol reduces GHG emissions 18% relative to a megajoule of gasoline, this implies that approximately 88 billion gallons of ethanol would be required to achieve the same amount of GHG reduction that will be achieved simply from a fall in demand during 2009. This represents about 14-fold increase in ethanol consumption in the US and 7-fold increase in global production of ethanol during 2008. The impact this would have had on food and land is not hard to imagine. Emissions from other sectors and world wide will also likely decrease or increase at a slower rate on account of the economic slowdown. Policy makers should use this windfall gain to design better policies using the latest knowledge rather than proceed with pre-conceived policies.

This means rethinking biofuel policies that were designed prior to the 2008 when policy makers considered the environmental and economic risk of biofuels to far less than their belief today. The weight of evidence suggests that current generation of biofuels, i.e., ethanol and biodiesel produced from crops used as food, leave a lot to be desired. The positive impact of such fuels on energy security, on fuel consumers and food producers has been outweighed by the negative impact on food consumers and uncertain impact on the environment. The future of biofuels depends on the second generation biofuels from cellulosic sources including agricultural, forestry and municipal wastes. Today, cutting-edge knowledge in genomics and biotechnology, process chemistry, and engineering are being applied to producing novel biofuels from these types of feedstock. If these investments bear fruit, liquid biofuels have the potential to displace a substantial amount of oil over the next few decades, with limited negative impact on food supply and the natural habitat. The food-fuel tradeoffs can be mitigated further through policies which lead to enhanced agricultural research and less restrictive regulation of agricultural biotechnology. Even within the first generation not all biofuels are created equal. The economic and environmental impact varies depending on the type of crop and how and where it is produced and processed. Policies should encourage the adoption of those biofuels with the highest net benefit and least negative impact on the poor. Biofuel policies should be one among a portfolio of policies to reduce pollution that includes pollution taxation, energy efficiency and conservation; integrated planning of land use, zoning and transportation; and other technologies that are tried, tested and deployed to address the problems of climate change and rising energy demand. Taxation of pollutiona theoretically efficient policyis made difficult because of political economy considerations. Nevertheless, pollution taxes should be part of our energy future.

Bibliography

[1] IEA. *World energy outlook*. International Energy Agency and OECD, 2008.

[2] A.R. Brandt and A.E. Farrell. Scraping the bottom of the barrel: greenhouse gas emission consequences of a transition to low-quality and synthetic petroleum resources. *Climatic Change*, 84(3):241–263, 2007.

[3] R.M. Margolis and D.M. Kammen. Underinvestment: The energy technology and R&D policy challenge. *Science*, 285(5428):690, 1999.

[4] G.C. Rausser and M. Papineau. Managing R&D risk in renewable energy. *Department of Agricultural & Resource Economics, UCB*, page 1058, 2008.

[5] Clean technology in the downturn: gathering clouds. *The Economist*, 2008.

[6] M.E. Himmel, S.Y. Ding, D.K. Johnson, W.S. Adney, M.R. Nimlos, J.W. Brady, and T.D. Foust. Biomass recalcitrance: engineering plants and enzymes for biofuels production. *Science*, 315(5813):804, 2007.

[7] UK The Royal Society. *Sustainable biofuels: Prospects and challenges*. The Royal Society, 2008.

[8] D. Rajagopal, S. Sexton, G. Hochman, and D. Zilberman. Recent Developments in Renewable Technologies: R&D Investment in Advanced Biofuels. *Annual Review of Resource Economics*, forthcoming, 2009.

[9] D. Rajagopal and D. Zilberman. Environmental, Economic and Policy Aspects of Biofuels. *Foundations and Trends® in Microeconomics*, 4(5):353–468, 2008.

[10] T. Searchinger, R. Heimlich, RA Houghton, F. Dong, A. Elobeid, J. Fabiosa, S. Tokgoz, D. Hayes, and T.H. Yu. Use of US croplands for biofuels increases greenhouse gases through emissions from land-use change. *Science*, 319(5867):1238, 2008.

[11] D. Rajagopal, S. Sexton, G. Hochman, D. Roland-Holst, and D. Zilberman. Biofuel and the food versus fuel trade-off. *California Agriculture (forthcoming)*, 2009.

[12] P.C. Abbott, C.A. Hurt, and W.E. Tyner. *What's driving food prices?* Farm Foundation, 2008.

[13] D. Mitchell. A note on rising food prices. *The World Bank Development Prospects Group*, 2008.

[14] D. Rajagopal, SE Sexton, D. Roland-Holst, and D. Zilberman. Challenge of biofuel: filling the tank without emptying the stomach. *Environmental Research Letters*, 2(9), 2007.

[15] R. Trostle. Global agricultural supply and demand: factors contributing to the recent increase in food commodity prices. *Outlook Report No. WRS-0801, Economic Research Service, US Department of Agriculture, May*, 2008.

[16] RD Perlack. Biomass as Feedstock for a Bioenergy and Bioproducts Industry: The Technical Feasability of a Billion-Ton Annual Supply. Technical report, ORNL/TM-2005/66, ORNL, 2005.

[17] A.J. Ragauskas, C.K. Williams, B.H. Davison, G. Britovsek, J. Cairney, C.A. Eckert, W.J. Frederick, J.P. Hallett, D.J. Leak, C.L. Liotta, et al. The path forward for biofuels and biomaterials. *Science*, 311(5760):484–489, 2006.

[18] C. Somerville. The billion-ton biofuels vision, 2006.

[19] C. Hendrickson, A. Horvath, S. Joshi, and L. Lave. Economic input-output models for environmental life-cycle assessment. *Environmental Science & Technology*, 32(7):184, 1998.

[20] L.B. Lave, E. Cobas-Flores, C.T. Hendrickson, and F.C. McMichael. Using input-output analysis to estimate economy-wide discharges. *Environmental Science & Technology*, 29(9):420–426, 1995.

[21] M.Q. Wang. GREET 1.5-transportation fuel-cycle model-Vol. 1: methodology, development, use, and results. Technical report, ANL/ESD-39 Volume 1, Argonne National Laboratory, Illinois, USA, 1999.

[22] A.E. Farrell, R.J. Plevin, B.T. Turner, A.D. Jones, M. O'Hare, and D.M. Kammen. Ethanol can contribute to energy and environmental goals. *Science*, 311(5760):506–508, 2006.

[23] D. Pimentel and T.W. Patzek. Ethanol production using corn, switchgrass, and

wood; biodiesel production using soybean and sunflower. *Natural Resources Research*, 14(1):65–76, 2005.

[24] D. Tilman, J. Hill, and C. Lehman. Carbon-negative biofuels from low-input high-diversity grassland biomass, 2006.

[25] I. de Carvalho Macedo. Greenhouse gas emissions and energy balances in bio-ethanol production and utilization in Brazil (1996). *Biomass and Bioenergy*, 14(1):77–81, 1998.

[26] J. Sheehan, V. Camobreco, J. Duffield, H. Shapouri, M. Graboski, and KS Tyson. An overview of biodiesel and petroleum diesel life cycles. Technical report, NREL/TP-580-24772, National Renewable Energy Lab., Golden, Colorado, USA, 2000.

[27] D. Rajagopal, G. Hochman, and D. Zilberman. A simple framework for regulation of biofuels. *Handbook of Bioenergy Economics and Policy*, forthcoming, 2009.

[28] A.J. Liska, H. Yang, V. Bremer, G.E. Erickson, T. Klopfenstein, D.T. Walters, and K.G. Cassman. Life cycle assessment of biofuel greenhouse gas emissions and net energy yields using the BESS model. In *Symposium on Biofuels in Developing Countries: Opportunities and Risks at The 2008 Joint Annual Meeting Celebrating the International Year of the Planet Earth, Oct 5-9, Houston Texas*, 2008.

[29] R. Classen and D. Hellerstein. Conservation reserve program acreage to decline: Will benefits also fall? *Amber Waves*, 6(5), 2008.

[30] L. Johansen. *Production functions: An integration of micro and macro, short run and long run aspects*. North-Holland Publishing Company, Amsterdam, 1972.

[31] H.S. Houthakker. The pareto distribution of the cobb-douglas production function in activity analysis. *Review of Economic Studies*, 23(9):27–31, 1955-56.

[32] Southwestern Biofuels Association. Ag Professors Urge EPA to delay indirect land use GHG regs under RFS *Available online at* http://www.swbiofuels.org/november5.html, 2008.

[33] B. Simmons. Indirect land use letter to governor schwarzenegger *Available online at* http://www.arb.ca.gov/lists/lcfs-lifecycle-ws/74-phd_lcfs_final_feb_2009.pdf, 2009.

[34] W.J. Baumol and W.E. Oates. The use of standards and prices for protection of the environment. *Swedish Journal of Economics, Vol 73, No 1, Mar 1971. P42-54.*, 1971.

[35] W.D. Nordhaus. Optimal greenhouse-gas reductions and tax policy in the "DICE" model. *American Economic Review*, 83(2):313–317, 1993.

[36] C. Fischer and R.G. Newell. Environmental and technology policies for climate mitigation. *Journal of Environmental Economics and Management*, 55(2):142 – 162, 2008.

[37] E. Hochman and D. Zilberman. Examination of environmental policies using production and pollution microparameter distributions. *Econometrica*, 46(4):739–760, 1978.

[38] S.P. Holland, C.R. Knittel, and J.E. Hughes. Greenhouse gas reductions under Low Carbon Fuel Standards? *NBER Working Paper*, 2007.

[39] M.A. Delucchi. Conceptual and methodological issues in lifecycle analyses of transportation fuels. *Working paper UCD-ITS-RR-04-45, Institute of Transportation Studies, University of California, Davis*, 2004.

[40] J.M. Griffin. Inter-fuel substitution possibilities: a translog application to intercountry data. *International Economic Review*, 18(3):755–770, 1977.

[41] CT Jones. A pooled dynamic analysis of interfuel substitution in industrial energy demand by the G-7 countries. *Applied Economics*, 28(7):815–821, 1996.

[42] J.M. Burniaux and T.P. Truong. GTAP-E: An Energy-Environmental Version of the GTAP Model. *GTAP Technical Paper*, 16, 2002.

[43] R. Keeney and T.W. Hertel. The indirect land use impacts of US biofuel policies: The importance of acreage, yield, and bilateral trade responses. Technical report, GTAP Working Paper (forthcoming), Center for Global Trade Analysis, Purdue University, West Lafayette, IN, USA, 2008.

[44] D.K. Birur, T.W. Hertel, and W.E. Tyner. Impact of biofuel production on world agricultural markets: A computable general equilibrium analysis. GTAP Working Paper, presented earlier at the 10 thAnnual Conference on Global Economic Analysis, Purdue University, West Lafayette, IN, USA, 2007.

[45] E. Sadoulet and A. De Janvry. *Quantitative development policy analysis: Exercise solutions*. Johns Hopkins University Press, 1995.

[46] Y. Mundlak, R.C. Butzer, and D.F. Larson. Heterogeneous technology and panel

data: The case of the agricultural production function. *World Bank Policy Research Working Paper Series*, (4536), 2008.

[47] M. Peters, S. Langley, and P. Westcott. Agricultural Commodity Price Spikes in the 1970s and 1990s: Valuable Lessons for Today. *Amber Waves*, 2009.

[48] The State of Food and Agriculture - Biofuels: Prospects, risks and opportunities, author=FAO, journal=Food and Agricultural Organization, year=2008.

[49] E. Martinot and J. Sawin. Renewables Global status report: 2009 Update. *REN21 Renewable Energy Policy Network and Worldwatch Institute*, 2009.

[50] P.B. Dixon and B.R. Parmenter. Computable general equilibrium modelling for policy analysis and forecasting. *Handbook of Computational Economics*, 1:3–85, 1996.

[51] T.W. Hertel. Applied general equilibrium analysis of agricultural and resource policies. *Handbooks in Economics*, 18(2A):1373–1420, 2002.

[52] S. Msangi, T. Sulser, M. Rosegrant, R. Valmonte-Santos, and C. Ringler. Global scenarios for biofuels: impacts and implications. *Farm Policy Journal*, 4(2):1–9, 2007.

[53] M. Lampe. Agricultural market impacts of future growth in the production of biofuels, Working party on Agricultural Policies and Markets, 2006.

[54] PB Dixon, S. Osborne, and MT Rimmer. The economy-wide effects in the United States of Replacing crude petroleum with biomass. *Energy & Environment*, 18(6):709–722, 2007.

[55] A. Gohin and G. Moschini. Impacts of the European biofuel policy on the farm sector: A general equilibrium assessment. *Review of Agricultural Economics*, 30(4):623–641, 2008.

[56] IMF. Food and Fuel PricesRecent Developments,Macroeconomic Impact, and Policy Responses. *Report prepared by the Fiscal Affairs, Policy Development and Review, and Research Departments*, 2008.

[57] M.W. Rosegrant. Biofuels and grain prices: impacts and policy responses. *Testimony for the US Senate Committee on Homeland Security and Governmental Affairs*, 2008.

[58] J.C. Williams and B.D. Wright. *Storage and commodity markets.* Cambridge University Press, 1991.

[59] C. Carter, G. Rausser, and A. Smith. Causes of the food price boom. In *Giannini Foundation Symposium on Causes and Consequences of the Food Price Crisis, Berkeley, CA*, 2008.

[60] A.L. Bovenberg, L.H. Goulder, and National Bureau of Economic Research. *Environmental taxation and regulation.* National Bureau of Economic Research Cambridge, Mass, 2001.

[61] M.L. Cropper and W.E. Oates. Environmental Economics: A Survey. *Journal of Economic Literature*, 30(2):675–740, 1992.

[62] J.M. Buchanan and G. Tullock. Polluters' profits and political response: Direct controls versus Taxes. *American Economic Review*, 65(1):139–147, 1975.

[63] G.E. Helfand. Standards versus standards: the effects of different pollution restrictions. *The American Economic Review*, pages 622–634, 1991.

[64] R.G. Newell and W.A. Pizer. Indexed regulation. *Journal of Environmental Economics and Management*, 56(3):221–233, 2008.

[65] T.H. Tietenberg. *Emissions trading: principles and practice.* Resources for the Future, 2006.

[66] L. Fulton, T. Howes, and J. Hardy. *Biofuels for transport: an international perspective.* OECD, International Energy Agency, 2004.

[67] W.R. Morrow, W.M. Griffin, H.S. Matthews, et al. Modeling switchgrass derived cellulosic ethanol distribution in the United States. *Environ. Sci. Technol*, 40(9):2877–2886, 2006.

Appendix

A. Derivation of average cost of emission reduction by blending

Let the firm blend the dirty and clean fuels in the ratio $(1-\alpha)$ and α respectively. GHG emissions per unit of blend is,

$$\gamma_i^1 = (1-\alpha)\gamma_i^0 + \alpha\gamma_i^*$$

Reduction in GHG emissions with respect to unblended fuel, γ_i^0,

$$\Delta\gamma_B = \gamma_i^0 - \gamma_i^1 = \gamma_i^0 - (1-\alpha)\gamma_i^0 + \alpha\gamma_i^* = \alpha(\gamma_i^0 - \gamma_i^*)$$

Option B_{own}:

The cost of producing one unit of blended fuel,

$$c_i^1 = \underbrace{(1-\alpha)c_i^0}_{\text{production cost of dirty fuel}} + \underbrace{\alpha(c_i^* + c_i^t)}_{\text{production and transport cost of clean fuel}}$$

Incremental cost in selling blend as opposed to selling as separate fuels ,

$$\Delta C_{B_{own}} = c_i^1 - c_i^0 = (1-\alpha)c_i^0 + \alpha(c_i^* + c_i^t) - (1-\alpha)c_i^0 - \alpha c_i^* = \alpha c_i^t$$

$\Rightarrow$ Average cost of reducing GHG emissions by blending own fuels,

$$AC_{B_{own}} = \frac{\Delta C_{B_{own}}}{\Delta\gamma_B} = \frac{\alpha c_i^t}{\alpha(\gamma_i^0 - \gamma_i^*)} = \frac{c_i^t}{\gamma_i^0 - \gamma_i^*}$$

Option B_{market}:

The cost of producing one unit of blended fuel,

$$c_i^1 = \underbrace{(1-\alpha)c_i^0}_{\text{production cost of dirty}} + \underbrace{\alpha(p + c_i^{t*})}_{\text{cost of clean-fuel purchased and transported for blending}}$$

Incremental cost of blend compared to own dirty-fuel,

$$\Delta C_{B_{market}} = c_i^1 - c_i^0 = (1-\alpha)c_i^0 + \alpha(p + c_i^{t*}) - c_i^0 = \alpha(p + c_i^{t*} - c_i^0)$$

$\Rightarrow$ Average cost of reducing GHG emissions by blending own fuel with fuel from market,

$$AC_{B_{market}} = \frac{\Delta C_{B_{market}}}{\Delta \gamma_B} = \frac{\alpha(p + c_i^{t*} - c_i^0)}{\alpha(\gamma_i^0 - \gamma_i^*)} = \frac{p + c_i^{t*} - c_i^0}{\gamma_i^0 - \gamma_i^*}$$

B. Data sources for numerical illustration

1. Price of ethanol $= 0.67 * P_g + 0.5$, where, $P_g(= \$2.8/gallon)$, is the average retail price for regular, conventional (non-reformulated) gasoline in the US in 2007. We assume that ethanol is priced for energy relative to gasoline, 0.67 is the correction for energy content, 0.5 is the 50 cent/gallon is the excise tax credit

2. Coal-based ethanol production cost: OECD estimate for ethanol production cost [66]

3. Ethanol transportation cost by rail: [67]

4. Ethanol transportation cost by road: [67]

5. Energy used in biorefining: EBAMM model estimate

   $http://rael.berkeley.edu/ebamm/$

6. GHG intensity of coal-based corn ethanol: EBAMM model estimate

7. GHG intensity of gas-based corn ethanol: EBAMM model estimate

8. Price of coal energy: average delivered price to industries in US for 2007 $http://www.eia.doe.gov/cneaf/coal/page/acr/table34.html$

9. Price of natural gas energy - average US commercial price in 2007

   $http://tonto.eia.doe.gov/dnav/ng/ng\_pri\_sum\_dcu\_nus\_m.htm$