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Regulation of GHG Emissions from Biofuel Blended Energy

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Abstract: Regulatory agencies are planning to implement policies targeted at mitigating greenhouse gas emissions (GHG)—e.g., low carbon fuel standards and carbon trading. Biofuels are viewed as a path to achieve these goals. Biofuels, however, pose challenges to regulators because their GHG emissions are site-specific (there are regional differences, as well as technical differences) and uncertain. In this article, we propose methodological improvements to existing methods that yield better estimates for biofuel GHG emissions, and reduce uncertainty. We propose to break the net emissions caused by a regulated site, such as an oil refinery, into two parts: direct and indirect emissions. Direct emissions arise both at and away from the final regulated site, but are directly attributable to the final output. Indirect emissions, on the other hand, are comprised of emissions not traceable to a single entity, but which can be computed from aggregate supply and demand, e.g., indirect land use change (ILUC) emissions due to agricultural expansion. The sum of the site-specific direct emissions and the average indirect emissions is, then, compared to the standard, which is constructed given uncertainty. Such a framework can be implemented in practice given existing data and yet allows flexibility given heterogeneity and uncertainty.

Economic forces, as well as demand for energy security, no doubt are providing incentives for producing and blending biofuels as substitute fuel. At the same time in order to tackle global warming, governments are beginning to regulate emissions attributed to energy production and consumption. Biofuels, which are part of the energy production sector, pose additional challenges to regulators, because their GHG emissions not only vary between regions and between the technologies used, but are also uncertain. Biofuels can be produced from a diverse set of feedstock (e.g., corn, sugarcane, cassava) using a diverse set of production technologies; a set of technologies that varies with location and with time. The cultivation and processing of each type of feedstock can be carried out in a variety of ways with widely varying carbon intensities.

The challenge of regulating biofuel is then augmented by uncertainty; primarily, from indirect emissions. Biofuels increase demand for agricultural land, which induces land use changes in regions that substantially affect global carbon sequestration (regions that are also efficient in producing biofuel crops). Furthermore, trade causes land use changes to occur in regions different from the place of production and/or consumption of biofuels. Therefore, regulating biofuels should account for the indirect emissions, if indeed the regulators' goal is to lower, or at least mitigate, carbon emissions.

In this article, we clearly categorize GHG emissions into direct and indirect emissions. We then suggest a site-specific methodology for regulating GHG emissions, a methodology which extends current methods by introducing heterogeneity, as well as accounting for uncertainty and market forces. Specifically, we propose a site-specific method for measuring GHG emissions, and introduce, albeit briefly, a conceptual framework for regulating biofuels using the proposed measures.

2. Calculating emissions

We classify emissions into two categories: Direct and Indirect.

Direct Emissions

Direct emissions comprise all emissions directly related to production of final output (e.g., gasoline or biofuel or a blend). Direct emissions are classified into two sub-categories; namely,

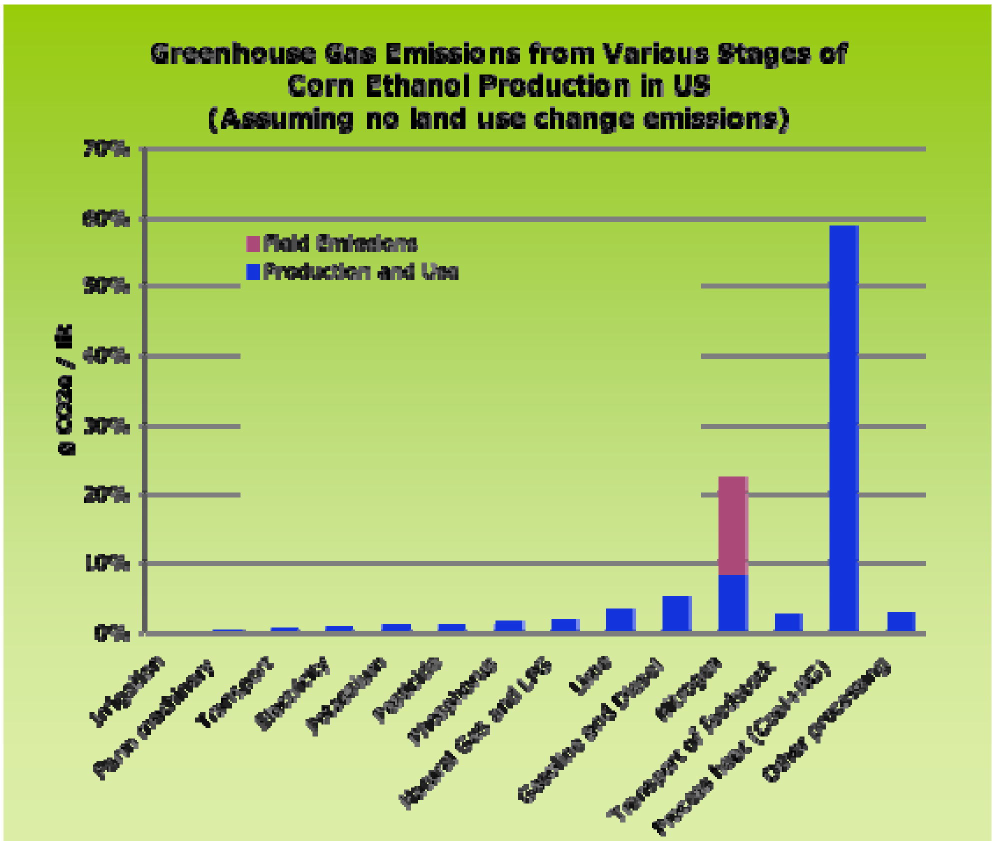
Direct on-site emissions: These are emissions at the regulated site, which are directly related to the production of the final product. For example, if the regulated site is an ethanol biorefinery, then these are emissions from combustion of coal or natural gas used in converting corn or sugarcane to ethanol. Suppose, for instance, that the regulated site is a biorefinery. For US ethanol corn production, direct on-site emissions comprise 55% of total direct emissions (see Fig. 1). Although soil carbon emissions from farming are not included in the figure they are relevant and should be taken into account. This is a source of uncertainty that should be addressed in a regulatory framework.

Direct off-site emissions: These are emissions emanating off-site that are directly attributed to intermediate inputs used to produce the final good. For instance, ethanol producers use crops. Crops use fertilizers, which are a large source of emissions both at the farm site and at the fertilizer production site. From Figure 1 we can see that 45% of the direct emissions are off-site, with fertilizer production and use accounting for a large share of total emissions.

Several studies calculate direct emissions from biofuels, which include both combustion and production. A detailed review of this literature can be found in Rajagopal and Zilberman (2007). Most of these studies use an LCA approach and report a single number. For example, Farrell et al. (2006) calculated that corn ethanol emits 77 grams of carbon-dioxide equivalent emissions (gCO2e) per megajoule (MJ) of energy, while gasoline emits 94 gCO2e per MJ.

Measuring direct emissions using LCA has its strength and weakness. The strength is that LCA allows for comprehensive accounting of all direct on-site and off-site emissions. The weakness is that it reports a number, which represents the emission intensity for a particular combination of inputs (usually assumed equal to the industry's average). For instance, Farrell et al. (2006) assume the ethanol refinery uses a mix of 40 percent coal and 60 percent natural gas to produce the energy required for production of ethanol from corn; the direct on-site emissions are, therefore, appropriately weighted by the average carbon intensity of coal and natural gas. Now an increase in the price of natural gas relative to coal leads the marginal producer to switch to coal, which would increase the fraction of coal and increase GHG emissions. Therefore, current LCA may provide a good description of the present or the past, but have limited ability to predict what happens when economic conditions change. Modeling lifecycle indicators as functions of economic and policy parameters can overcome this limitation. A detailed discussion of price-responsive lifecycle indicators can be found in Rajagopal and Zilberman (2008a). They show that depending on whether an ethanol refinery uses coal instead of natural gas for its energy needs, ceteris paribus, the total direct emissions for corn ethanol equals 91% of net GHG emissions from gasoline (as opposed to 58% when it uses natural gas).

Figure 1: **Lifecycle GHG emissions for us corn ethanol based on ebamm model**



Indirect Emissions

When food or cropland is diverted to biofuel production it will have two types of effects, namely, extensive and intensive effects. GHG emissions that accompany such changes are referred to as indirect emissions. For instance, demand for biofuel raises the price of agricultural commodities, which raises the rent to land, thereby allowing marginal land to enter production, i.e., the extensive effect. Emissions due to the extensive effects arise from (i) conversion of non-agricultural land into farmland (for example, emissions from clearing trees and pastures), and (ii) cultivation on converted land (for example, emissions from use of inputs like fertilizer). On the other hand, higher output prices result in more intensive use of inputs like fertilizers and irrigation on existing farmland, i.e., the intensive effect.

Different from direct emissions, indirect emissions arise from the interaction of aggregate supply and demand, and therefore are not site-specific. Analogous to the idea of a price taking producer, we propose the indirect emissions allocated to a regulated facility equal the average amount of indirect emissions. The average is the total amount of indirect emissions calculated using a multi-market or general equilibrium model, divided by total amount of biofuel produced. The indirect emissions allocated to each site equal this number times the amount of biofuel produced. Given an estimate of indirect land use changes (ILUC) a simple model for calculating total and average indirect emissions is described in the appendix.

The current approach to calculate ILUC is to model the impact of a shock in the form of a biofuel mandate on the demand and supply of land in a partial or general equilibrium framework. Searchinger et al. (2008), using the FAPRI partial equilibrium model of the agricultural sector in conjunction with the global GTAP land database, calculated that producing 56 billion liters of corn ethanol (requiring 140 million tonnes of corn at a corn to ethanol conversion rate of 2.7 gallons of ethanol per bushel of corn) in the US would cause global agricultural acreage to expand by 10.8 million hectares. By allocating this acreage across difference types of land with differing stocks of carbon, they calculate indirect emission from land use change as 106.4 gCO_2e per MJ of ethanol. Similarly, Hertel et al. (2008) use the GTAP general equilibrium model of the world economy to calculate ILUC resulting from the US and EU's biofuel mandates for 2015. Irrespective of whether a partial or general equilibrium model is used, the calculations should accord with empirical evidence. We believe that Searchinger et al.'s (2007) estimates of ILUC are high.

To this end, let $\varepsilon_{L/Q}$ denote the elasticity of acreage with respect to agricultural production, ΔL/L, the percentage change in acreage, and ΔQ/Q, the percentage change in agricultural output, then, $\varepsilon_{L/Q} = \dfrac{\Delta L/L}{\Delta Q/Q}$. Rearranging we get $\Delta L = \varepsilon_{L/Q} \cdot \Delta Q \cdot L/Q$. Between 1950 and 1998, global agricultural output increased 150% while harvested acreage increased only 13%. This implies $\boldsymbol{\varepsilon_{L/Q}}$ is 0.09. In the year 2006 the combined global acreage of the three major food grains, namely rice, wheat, and corn, was about 510 million hectares, i.e., *L,* while combined global production was 1950 million tones, i.e., *Q*. Given these values for $\boldsymbol{\varepsilon_{L/Q}}$, *L* and *Q*, if corn production were to increase by 140 million tonnes (i.e, ΔQ =140) in order to offset the quantity diverted for ethanol (according to equation (1) above, corn acreage will increase 3.3 million hectares. 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 that Searchinger et al.'s estimate is more than three times higher[4].

Low elasticity of acreage implies intensification involving greater input use (fertilizer, water) and adoption of new technologies (better seeds, pesticides, irrigation), which contributed the lion's share of the increase in output in the 20th century. Obviously historical trends may change, but they can be affected by policies, market conditions, and biophysical developments. For example, future agricultural expansion may occur on marginal lands with low yield.

Although the current approach for calculating ILUC is to use equilibrium models, an econometric model can be employed. Given the wide variation in the historical acreage response, point estimates of ILUC do not present a complete picture and a sensitivity analysis of ILUC to various assumptions about prices, technologies and policies in the future should be undertaken.

3. A Target Number and a Framework for Regulation

Current regulations, such as the maximum allowable emission in mechanisms like the low carbon fuel standard (LCFS), aim to establish an upper bound for GHG emissions per unit of biofuel. Searchinger (2007) suggested that the measure of biofuel emissions should include both a direct and indirect effect. Let $\bar{f}$ be the upper bound, which is compared to the emission measure of each site.

For illustration purposes, consider the LCFS, where $\bar{f}$ is the standard, e.g., 94 gCO_2e per MJ. This is the number reported by Farrell et al. for gasoline. Let f_D denote the direct site-specific emissions per unit output and f_I denote the average indirect effect. The sum $f_D + f_I$ represents the overall emissions per unit of biofuel from a given site. To reiterate, f_D is computed using an LCA style approach, whereas f_I is computed using economic equilibrium models.

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[4] Our estimate of ILUC is sensitive to the value of the elasticity of acreage with respect to output $\varepsilon_{L/Q}$. We do acknowledge that our estimate $\varepsilon_{L/Q}$ based on total change in acreage and production between 1950 and 1998 may be optimistic. Disaggregating the data for total acreage and total output for some of the major crops (corn, wheat, rice, soybean, wheat and cotton) shows high variability in $\varepsilon_{L/Q}$ for different crops during different periods. For example, low elasticity (<0.1) for wheat during the green revolution and for cotton after the introduction of biotech but high elasticity (>0.5) at other times when little new innovation was introduced. Furthermore future agricultural expansion may occur on marginal lands where yields may be lower and therefore exhibit $\varepsilon_{L/Q}$. At the same time new technological breakthroughs may deliver higher rate of yield growth. The National Corn Growers Association expects corn yield in the US would increase 20% and reach 175 bushels per acre by 2015. Our aim in any case is not to present a new number for the GHG balance or the land use change but only to point out that there is heterogeneity across locations, feedstocks and technologies and that both direct and indirect effects can be influenced by regulation and economic incentives.

Table 1: Comparison of emissions in different scenarios

	Comparison of gasoline and ethanol*	Direct emissions gCO2e/MJ	Indirect emissionsgCO2e/MJ	Total gCO2e/MJ	% Emissions relative to standard***
	Maximum level of emissions set equal to emissions from marginal gasoline from conventional oil (Farrell et al)	94		94	-
1	US Corn Ethanol today (Direct emissions from Farrell et al. and indirect emissions from Searchinger et al.)	77	106	183	195%
	Corn ethanol scenarios				
2	Corn processing using only coal and Indirect emissions 1/3 rd of Searchinger's estimate**	88	35	123	131%
3	Processing based using only gas and Indirect emissions 1/3 rd of Searchinger's estimate**	61	35	96	103%
	Cellulosic Ethanol scenarios				
4	Direct emissions from Farrel et al. and Indirect emissions from Searchinger et al	11	106	117	125%
5	Direct emissions from Farrel et al. and Indirect emissions 1/3 rd of Searchinger's estimate**	11	35	46	49%

*- comparison is with respect to emissions from marginal gasoline which is assumed to be conventional oil. If marginal gasoline is derived from heavy oil and tar sands then benefits from ethanol increase
** - Scenarios use the assumption that indirect emissions are 1/3rd of Searchinger's estimate
**** - A value greater than one implies total biofuel emissions exceed the standard and a value less than one implies it is below the standard and hence results in GHG savings

Depending on the regulatory framework, the regulated site may have to provide certification showing, $f_D + f_I \leq \overline{f}$ to get a permit. Alternatively, the regulator may need to inspect the site and show that $f_D + f_I > \overline{f}$ to close the site. Since the site takes f_I as given, this effectively requires ensuring that the direct emissions f_D satisfies the constraint, $f_d < \overline{f} - f_I$.

In Table 1 we show emissions from ethanol produced under various scenarios of direct and indirect emissions relative to emissions from gasoline. Current estimates for direct emissions (Farrell et al., 2006) and indirect emissions (Searchinger et al., 2008) imply ethanol is more polluting than gasoline. More interestingly, it suggests that, even if indirect emissions decrease to 1/3rd the amount estimated by Searchinger et al. (2008), corn ethanol still under performs gasoline. Scenarios with indirect emissions equaling 1/3rd of Searchinger et al.'s estimate were chosen because as we explained earlier we expect their estimate of induced land use change to be more than three times larger compared to ours (See Section 2.2). Finally, a scenario involving cellulosic ethanol and low indirect emissions can potentially reduce carbon emissions by 50 percent relative to gasoline (scenario 5).

We now briefly discuss the data required to implement this framework. As regards the setting of an upper bound on emissions from biofuel, one option is to set this relative to the emissions from gasoline, for example, no higher than net GHG emissions from gasoline and reliable estimates of this exist today. As regards on site and offsite direct emissions from biofuel, these can be estimated using the type of data that was used by Farrell et al. (2006) in determining the direct emissions from corn ethanol. Calculation of indirect emissions among other things requires data on the quantity and type of lands that were converted from non-farm use to farm use world-wide and the net change in carbon stored on those parcels of land due to such conversion and these can be obtained from literature. Again this can be calculated using data from GIS based models. It is worth emphasizing that the most accurate estimate we can obtain is total land use change between two points in time. The most challenging aspect however is in ascribing a share of this total change to biofuels after controlling for changes in land use due to other factors such as economic growth and weather shocks.

4. Policy

If the goal is to produce biofuel efficiently, and to minimize carbon emissions and damage to the environment, then the first best policy is a carbon tax and payment for environmental services. Levying a carbon tax shifts production from fossil fuel to biofuel and induces greater supply of clean fuel. It, however, brings on land conversion and a loss of biodiversity. Therefore, a policy to price clean air should be paired with a policy to price environmental services (Hochman et al., 2008). Politically, a carbon tax may not be a viable option. It may not be feasible to levy a tax on a global public bad. A second best policy is the next possibility.

A fuel tax based on LCA is currently proposed by some state and national governments. They are easy to impose because fuel consumption is observable. Different from existing fuel taxes, a second best fuel tax should vary according to fuel types--with dirtier fuels taxed more heavily. LCA could then be used to classify fuels according to their carbon emissions. Such a tax may also account for other local externalities such as traffic congestion. This policy also has a problem of double counting.

An alternative second best solution, which bans biofuel production if it has limited environmental benefit, is LCA thresholds or certification standards. Only biofuels that have sufficient small life cycle emissions can be used. Governments may account toward mandate or offer subsidies only to those biofuels that are certified to meet the desired standards (e.g., the number used to compare the direct and indirect site specific emissions). Note that standards might be different between countries, because local environmental amenities are different. Standards are currently used in the United States.

Because carbon emissions are a global public bad, policy ought to be coordinated between all countries. More specifically, international environmental agreements should account for the cost of deforestation (e.g., destruction of rain forests in Brazil). Landowners do not capture all the benefit from their efforts to preserve the environment. The benefit, in terms of biodiversity and carbon sequestration, accrues to people around the world. Therefore, landowners should be paid for the environmental services their land provides. To this end, an international agreement, which will internalize the negative externalities from fuel production and consumption, needs to be established.

5. Conclusion

Even if a first best GHG tax is imposed on all GHG emitting fuels, so long as there is no tax on emissions from land use, biofuels can result in leakage, i.e., effective GHG emissions due to a blend may be above the level accepted by the regulator. In the absence of carbon tax, the implementation of second best mechanisms such as carbon standards or emission trading will inevitably require calculation of all direct and indirect emissions associated with final output. With this in mind we have outlined a framework that can be applied to the regulation of GHG emissions from energy production. Ours is a hybrid approach that suggests a process LCA type approach for calculation of direct emissions and a market equilibrium approach for calculation of indirect effects. But significant improvements in the methodology for calculating ILUC, as well as ILUC emissions, is required before it is used in regulation. Our framework however is generic and given data on direct and indirect emissions can be implemented in practice and can account for heterogeneity and uncertainty. It can also be extended to the regulation of non-greenhouse gas externalities. An obvious exclusion in this article is a discussion of the monitoring mechanisms for tracing and certifying emissions, the information gaps, and the transaction costs associated with implementing this framework. We hope to address this in future work.

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Appendix: Mathematical model for calculation of indirect emissions

$\Delta\gamma$ To present this notion more precisely, let Q denote the total agricultural output before biofuel, ΔQ_b the quantity of crop allocated for biofuel production, and ΔQ the total increase in output after biofuel[5]. Let, L_0 denote the total land under cultivation before introduction of biofuel, ΔL_0 the change in land under cultivation after introduction of biofuel (i.e., the extensive effect)[6], and ΔL_b the land required to produce the quantity ΔQ_b of biofuel. Let Z_0 and Z_1 denote the change in emissions from agriculture with and without biofuel production and ΔZ denote the total change in agricultural emissions due to introduction of biofuel. ΔZ is broken down into two components, F_D the change in direct agricultural emissions due to production of biofuel and F_I the change in indirect agricultural emissions due to production of biofuel. Let δ denote the average GHG coefficient of new land, γ_0 the average GHG coefficient of farming before biofuel, the change in the average pollution due to farming activities. With this notation, the mathematical model is described below.

Agricultural emissions before biofuel $Z_0 = \gamma_0 L_0$

Agricultural emissions after biofuel, $Z_1 = \gamma_1 L_1 = \delta \Delta L_0 + (\gamma_0 + \Delta\gamma_0)(L_0 + \Delta L_0)$

Change in agricultural emissions, $\Delta Z = Z_1 - Z_0 = \delta \Delta L_0 + \gamma_0 \Delta L_0 + L_0 \Delta\gamma_0$

[5] ΔQ_b is likely to be greater than ΔQ because of the following reasons: (1) Higher prices due to biofuel will depress demand and hence a portion of the diverted crop is never replaced and (2) in certain cases new crops do not have to replace the entire amount because of co-products that can substitute main crop. The gap between ΔQ and ΔQ_b is larger the less elastic the supply of corn and more elastic the demand for food.
[6] This is a function of the price elasticity of supply and demand, price elasticity of productivity and the quantity of biofuel produced.

Breaking down the total change in agricultural emission into direct and indirect changes we write, $\Delta Z = F_D(X_D, \beta_D, \varepsilon_D) + F_I(X_I, \beta_I, \varepsilon_I)$

We write F_D as a function of X_D - a vector denoting the level of technologies and inputs used to produce the final product, β_D - a policy parameter that can be thought of as affecting incentives, and ε_D - a random disturbance term. And so is F_I

The change in direct agricultural emission due to biofuel is $F_D(X_D, \beta_D, \varepsilon_D) = \gamma_0 \Delta L_b$

Therefore, the indirect emissions due to biofuel is then written as $F_I(X_I, \beta_I, \varepsilon_I) = \Delta Z - F_D(X_D, \beta_D, \varepsilon_D) = \delta \Delta L_0 + \gamma_0(\Delta L_0 - \Delta L_b) + L_0 \Delta \gamma_0$

Allocating these total indirect emissions across the total biofuel production, say V, the average indirect land emission per unit of biofuel f_I, is then written as

$$f_I(X_I, \beta_I, \varepsilon_I) = \frac{F_I(X_I, \beta_I, \varepsilon_I)}{V}$$

If we look closely the indirect emissions is comprised of,

$\delta \Delta L_0$ - emissions due to land conversion only (this is what Searchinger et al. and Fargione et al. calculate)

$\gamma_0 \Delta L_0$ - emissions from farming on the newly converted land

$\gamma_0 \Delta L_b$ - emissions during cultivation of the biofuel crop

$L_0 \Delta \gamma_0$ - emissions due to changes in farming practices on pre-existing farm land after the introduction of biofuel