Consequential Life Cycle Assessment of Policy Vulnerability to Price Effects

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Keywords:

emissions
energy
environmental policy
industrial ecology
life cycle assessment (LCA)
partial equilibrium

Summary

The application of life cycle assessment (LCA) in a policy context highlights the need for a "consequential" LCA (CLCA), which differs from an "attributional" LCA (ALCA). Although CLCA offers some advantages over ALCA, such as a capacity to account for emissions resulting from both substitution and price effects, it entails additional assumptions and cost and may yield estimates that are more uncertain (e.g., estimates of impact of biofuel policies on greenhouse gas [GHG] emissions). We illustrate how a CLCA that relies on simple partial equilibrium models could provide important insights on the direction and magnitude of price effects while limiting the complexity of CLCA. We describe how such a CLCA, when applied early in the policy life cycle, could help identify policy formulations that reduce the magnitude of adverse price effects relative to the beneficial substitution effect on emissions because—as the experience with biofuel regulations indicates—regulating price effects is costly and controversial. We conclude that the salient contribution of CLCA in the policy process might lie in warning policy makers about the vulnerabilities in a policy with regard to environmental impact and to help modify potentially counterproductive formulations rather than in deriving the precise estimates for uncertain variables, such as the life cycle GHG intensity of product or average indirect emissions.

Introduction

The debate about the environmental impact of biofuel policies has brought into focus the use of life cycle assessment (LCA) for public decision making. Whereas supply-chain–focused analyses of life cycle greenhouse gas (GHG) emissions suggest that biofuels are less GHG intensive relative to fossil fuel substitutes (de Carvalho 1998; Sheehan et al. 2000; Farrell et al. 2006; Edwards et al. 2008; Huo et al. 2009; Liska et al. 2009), economic analyses predict that GHG emissions may increase over the next several decades as a result of biofuel policies (Searchinger et al. 2008; Hertel et al. 2010; Bento et al. 2011; Laborde 2011; Dumortier et al. 2011; Overmars et al. 2011; Rajagopal and Plevin 2013). This suggests that extrapolating differences in the average supply chain emission intensity of two products in order to predict the future impact of adopting the cleaner of the two products might be misleading. Even preceding the biofuel debate, researchers had recognized limitations of supply-chain–focused LCA as a decision aid and had argued for distinguishing such an LCA, which is sometimes referred to as "*attributional*" LCA (ALCA), from a "*consequential*" LCA (CLCA), which is considered more suitable in a decision-making context (Curran et al. 2005; Delucchi 2005; Finnveden et al. 2009; Earles and Halog 2011; Weidema 2011).

There is a growing body of literature that highlights the differences between ALCA and CLCA. Ekvall and Weidema (2004) suggest that ALCA generally relies on data on average performance or impact, whereas CLCA requires data on marginal changes. Depending on the type of marginal data, CLCA can be used to model the short- or long-run effects (Eriksson et al. 2007). In this article, we focus on the following conceptual distinction between ALCA and CLCA and discuss

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DOI: 10.1111/jiec.12058

Volume 00, Number 0

how CLCA may be employed in the policy process. Whereas ALCA focuses on the vertical dependencies in a product's supply chain, CLCA's strength is in modeling the horizontal linkages at each vertical step in the supply chain. By horizontal linkages, we refer to the competition for a good in alternative applications. For instance, whereas an ALCA of ethanol will account for the relationship of the corn industry to the biorefining industry, the relationship of the biorefining industry to the market of transportation fuels, and so on, CLCA recognizes the competition of corn with other crops (e.g., soybean, wheat, and so on) for farm land, the competition of the biorefining industry with food and livestock industries for corn, the competition of biorefining with oil refining sectors in the fuel market, and so on. Because of such linkages, a shock to any one sector will lead to adjustments in the sectors it is linked to directly (i.e., sectors in the vertical chain) and sectors that are indirectly linked because of competition. CLCA accounts for the transmission of such shocks both vertically and horizontally. For instance, consider a policy such as a corn ethanol mandate. A corn ethanol mandate will increase the demand for corn and therefore increase the price of corn. This will cause corn consumers to substitute away from corn and toward, say, soybean and also reduce total food consumption. At the same time, the increase in corn price will induce farmers to expand corn production at the expense of other crops. This may lead to further adjustments in each of the affected crop markets. Increasing ethanol supply also reduces the demand for gasoline, which, in turn, affects the demand for crude oil. These interlinkages give rise to what is referred to as *feedback* effects or *indirect* effects in the LCA literature. We simply refer to them as *price effects*. The role of price effects in LCA has been illustrated for several products and services other than biofuels, including electricity production (Mattsson et al. 2003), milk production (Thomassen et al. 2008), waste management (Ekvall et al. 2007), fuel cell vehicles (Sandén and Karlström 2007), lead-free solders (Ekvall and Andrae 2006), and land use (Kløverpris et al. 2010).

Accounting of emissions resulting from price effects is an advantage of CLCA relative to ALCA, which, however, entails additional cost. It requires data on behavioral and economic parameters, such as the price elasticity of supply and demand in the sectors directly and indirectly related to the final sector of interest, and so on. One also needs to determine whether a partial equilibrium or general equilibrium analysis is appropriate and whether the model is to be regional, national or global in scope. A general equilibrium framework is theoretically consistent, but also intensive in data requirements and effort. The greater the level of regional and sectoral disaggregation, the larger will be the data requirements. A partial equilibrium (PE) model focusing on one or a few economic sectors of interest is a simpler alternative, but not theoretically complete. In the absence of standard guidelines for performing CLCA, differences between studies resulting from the modeling framework (partial versus general equilibrium), the level of regional and sectoral disaggregation, the computational tools, different data assumptions despite using a common computational tool, and so on, have tended to yield estimates that are more uncertain, when compared to estimates from studies based on ALCA. The estimates of GHG benefits of biofuels is a case in point (Plevin et al. 2010; Dumortier et al. 2011; Rajagopal and Plevin 2013). This presents a challenge for analysts, especially when policy makers or regulators demand a point estimate for choosing a standard or to determine whether a firm is in compliance, as is the case under the U.S. Renewable Fuel Standard (RFS) and California Low Carbon Fuel Standard.

These challenges notwithstanding, in the absence of globally consistent action against global problems, such as global climate change, a life cycle approach is essential if policy makers are to avoid potentially counterproductive, albeit well-intentioned, unilateral policies, such as renewable energy policies, emission performance standards, and so on. In the case of renewable energy, such policies may be rationalized based on other criteria, such as improvements in the terms of trade (Huang et al. 2013), supporting infant industries (Nemet 2012), demonstrating leadership (Schreurs 2008), and so on. The aim of this article is to analyze the role of CLCA in designing energy and environmental policies. To this end, we describe a general approach to CLCA that can yield useful insights about how price effects may manifest themselves in different markets and also identify the sectors that are likely to have a large unintended impact on emissions as a result of a partial policy. This can help analysts focus their attention on modeling a few sectors in detail while excluding others, thereby limiting the complexity of CLCA. We discuss how such a CLCA, when applied early in the policy life cycle, can help identify vulnerabilities in a proposed policy and suggest alternative policy formulations that reduce those risks.

Several studies have analyzed different economic modeling approaches for incorporating price effects in LCA (see the article by Earles and Halog 2011 for a review of these studies). The contribution of this article is to derive general conclusions about the direction of price effects and changes in consumption in different sectors of the economy in response to a shock to one sector. We derive insights that are robust to the choice of modeling approach, whether it is single-market PE, multimarket PE, or general equilibrium. The rest of the article is organized as follows. We first illustrate, using simple PE models, how one can derive, to a first order of approximation, emissions resulting from price effects one market at a time, which are then to be aggregated to derive the change in total emissions (section on *A partial equilibrium consequential life cycle assessment of biofuel policies*). We then extend those insights to a more general multimarket PE framework with multiple interconnected sectors (section on *A general multimarket partial equilibrium consequential life cycle assessment*). We describe how one can predict the direction of impact of price effects in different sectors depending on how they are related to the final sector of interest. Given the recent experience with regulations on emissions resulting from price effects of biofuel policies, which are complex and controversial, we conclude by discussing how CLCA can be utilized to identify potentially harmful policies early in the policy process and to modify the policy formulations (section on *Implications for use of life cycle assessment in policy settings*). For the sake of clarity, we focus on GHG emissions as the environmental burden of interest. However, the findings extend to any number of different environmental burdens.

A Partial Equilibrium Consequential Life Cycle Assessment of Biofuel Policies

We analyze a policy that increases the demand for a good. We describe the effects of this policy on a downstream sector, which consumes this good, on upstream sectors producing the necessary inputs for producing of the good, and a sector that competes for inputs. We first describe the effects conceptually and derive analytical expressions and follow this with numerical simulation. For illustrative purposes only, we use a corn ethanol mandate as the policy under consideration and consider gasoline as the substitute to corn ethanol. We also assume that the mandate is binding, which means that the target level of consumption would not be achieved in the absence of the policy. For mathematical clarity and without loss of generality, we illustrate the effects in a single-region context. The intuition extends easily to a model with multiple regions involved in trade and an arbitrary number of sectors, but the algebraic expressions become unwieldy.

Output Market

We consider the market for gasoline fuel. Let, subscripts g, e, and f denote gasoline, ethanol, and the blended fuel, respectively, p and q denote fuel price and fuel quantity, respectively, $S_i(p) = q_i, i \in \{e, g\}$ denotes the fuel supply function, and $D(p) = q$ denotes the fuel demand function. The fuel market equilibrium is defined by the following system of equations (1) and (2):

$$S_g(p_g) + \bar{q}_e = D(p_f) \tag{1}$$

$$p_f(S_g(p_g) + \bar{q}_e) = p_g S_g(p_g) + \bar{q}_e S_e^{-1}(\bar{q}_e) \tag{2}$$

Equation (1) is a fuel market clearing condition, which states that total supply of fuels (with ethanol adjusted for energy equivalence relative to gasoline) equals demand for gasoline. Equation (2) states that the price of ethanol-blended gasoline is a weighted average of the price of gasoline and ethanol. For a given quantity of ethanol, $\bar{q}_e$, the system of two equations can be solved for p_f and p_g.

One approach to analyze the effect of an exogenous shock to the quantity of ethanol is to conduct a comparative static analysis of the system of equations. Completely differentiating the two equations with respect to p, p_g, and $\bar{q}_e$, and eliminating the dp terms from the two equations, we get equation (3):

$$dq_g = \underbrace{\left[-\frac{b - d + ce}{a - d + cf}\right]}_{\Delta} d\bar{q}_e \tag{3}$$

where $a = (1-\alpha)\frac{\partial S_g^{-1}(q_g)}{dq_g} \geq 0$, $b = \alpha\frac{\partial S_e^{-1}(q_e)}{dq_e} \geq 0$, $c = S_e^{-1}(q_e) - S_g^{-1}(q_g) \geq 0$, $d = \frac{\partial D^{-1}(q)}{dq} \leq 0$, $e = \alpha(1-\alpha)/q_e \geq 0$, $f = -\alpha^2/q_e \leq 0$, and $\alpha = \frac{\bar{q}_e}{S_g(p_g)+\bar{q}_e} \in [0, 1]$.

Equation (3) is the relationship between the equilibrium change in quantities of gasoline and ethanol. Because $a - d + cf \geq 0$ and $b - d + ce \geq 0$, $\Delta \leq 0$ and therefore dq_f and $d\bar{q}_e$ have the opposite sign. In other words, increasing the stringency of ethanol mandates clearly reduces gasoline consumption.[1]

The change in emissions resulting from the replacement of gasoline with ethanol and assuming fixed ALCA emission intensities, z_g and z_e, respectively, is shown by equation (4):

$$\begin{aligned} dZ_{fuel} &= z_e d\bar{q}_e + z_g dq_g \\ &= \underbrace{(z_e - z_g)d\bar{q}_e}_{dZ_{ALCA}} + \underbrace{z_g(d\bar{q}_e + dq_g)}_{dZ_{ifue}} \end{aligned} \tag{4}$$

If $dq_g = -d\bar{q}_e$, $dZ_{fuel} = dZ_{lca}$, which is the change in emissions based only on direct life cycle emission intensity and $dZ_{ifue} = 0$. Otherwise, as shown by equation (5):

$$dZ_{ifue} = z_g(d\bar{q}_e + dq_g) = z_g \underbrace{\left(1 - \frac{b - d + ce}{a - d + cf}\right)}_{\leq 0 \text{ or } \geq 0} d\bar{q}_e \tag{5}$$

We can verify that if demand is perfectly inelastic, which implies that $d = \frac{\partial D^{-1}(q)}{dq} = \infty$, then by using L'Hospital's rule, as $d \to \infty$, $\Delta \to 1 \Rightarrow \frac{dq_g}{d\bar{q}_e} \to -1$. In other words, if demand is perfectly inelastic, then $d\bar{q}_e + dq_g = 0$, that is, ethanol leads to one-to-one replacement of gasoline, which implies $dZ_{ifue} = 0$. Otherwise, $dZ_{ifue} < 0$ or > 0.

Input Market

We now illustrate the effect of the shock on the input-producing sectors. For the sake of clarity, we consider two upstream markets only, namely, the land market and agricultural commodity market, and analyze these markets in a single-region context. The intuition extends easily to an arbitrary number of upstream activities and regions. We also assume that the demand for land is solely for crop production and that there is only one crop, namely, corn, which can be used as food or transport fuel. The crop market clearing condition is defined by equation (6):

$$S_c(p_c) = D_{c,F}(p_c) + D_{c,B} \tag{6}$$

where subscripts c and l denote crop and land, respectively, subscripts F and B denote food and biofuel, respectively, and $S(\cdot)$ and $D(\cdot)$ denote supply and demand functions, respectively.

To analyze the effect of a shock $dD_{c,B}$ to corn demand, we again perform comparative static analysis of the system of equations above. Completely differentiating the two equations with respect to p, p_g, and $D_{c,B}$, we get equation (7):

$$\frac{\partial S_c}{\partial p_c} dp_c = \frac{\partial D_{c,F}}{\partial p_c} dp_c + dD_{c,B} \tag{7}$$

Using the definition of the own price elasticity of supply for commodity i with respect to its price, $\varepsilon_i = \frac{\partial Q_i}{\partial p_i}\frac{p_i^0}{Q_i^0}$ (superscript 0 denotes the initial state) and substituting the gradients in equation (7) with elasticities, and solving for dp_c we get equation (8):

$$\frac{dp_c}{p_c^0} = \frac{dD_{c,B}}{S_c^0\varepsilon_c^s - D_{c,F}^0\varepsilon_c^d} = 0 \tag{8}$$

The net change in corn supply is shown by equation (9):

$$dS_c = S_c^0\varepsilon_c^s\frac{dp_c}{p_c^0} = \frac{S_c^0\varepsilon_c^s}{S_c^0\varepsilon_c^s - D_{c,F}^0\varepsilon_c^d}dD_{c,B} \geq 0 \tag{9}$$

A positive ethanol demand shock will increase the price of corn and increase the total supply of corn.

Economic theory suggests that an increase in output price will lead to both a more intensive use of inputs, which increases productivity of existing farm land (the intensive margin effect) and also leads to expansion of crop acreage (the extensive margin effect). The relative importance of the intensive and extensive margin effects in increasing supply is a question for empirical research and a topic of debate among economists (Keeney and Hertel 2009; Roberts and Schlenker 2010; Berry 2011). Zilberman and colleagues 2011 argue that the history of development of agriculture suggests these margins are dynamic and unstable and are dependent on government policies over the long run. For illustrative purposes, we assume it is constant. If β is the share of the extensive margin in the total increase in corn supply, and assuming the average productivity of land on the extensive margin is y, the increase in acreage dS_l for an increase dS_c in supply can be calculated as $dS_l = \beta\frac{dS_c}{y}$. If z_l is the emissions per unit area of land on the extensive margin that is converted from nonfarm use to farm use, the increase in emissions associated with increase in land use is shown by equation (10):

$$dZ_{luc} = z_l dS_l = z_l\beta\frac{dS_c}{y} \tag{10}$$

Assuming a fixed-proportion relationship between corn input and ethanol output, a given corn ethanol shock, $d\bar{q}_e$, translates in a given shock to corn demand. If η is the ethanol yield per unit of corn, then equation (11) follows:

$$dD_{c,B} = \frac{d\bar{q}_e}{\eta} \tag{11}$$

Substituting equations (9) and (11) in (10), we get equation (12):

$$dZ_{luc} = z_l\frac{\beta}{y}\left[\frac{S_c^0\varepsilon_c^s}{S_c^0\varepsilon_c^s - D_{c,F}^0\varepsilon_c^d}\right]\frac{d\bar{q}_e}{\eta} \tag{12}$$

We can verify that if the supply of corn is perfectly inelastic, that is, $\varepsilon_c^s = 0$, then $dS_l = 0$ and therefore $dZ_{luc} = 0$.

If z_c is the emission intensity associated with crop production, then the change in emissions resulting from the change in food consumption is given by equation (13):

$$\begin{aligned} dZ_{food} &= z_c dD_{c,F} = z_c\varepsilon_c^d D_{c,F}^0\frac{dp_c}{p_c^0} \\ &= z_c\frac{\varepsilon_c^d D_{c,F}^0}{S_c^0\varepsilon_c^s - D_{c,F}^0\varepsilon_c^d}\frac{d\bar{q}_e}{\eta} \end{aligned} \tag{13}$$

If $\frac{dp_c}{p_c^0} \geq 0$, then $dD_{c,F} \leq 0$ and, consequently, $dZ_c \leq 0$. Therefore, an ethanol mandate reduces food consumption, which contributes to a reduction in GHG emissions. If corn demand for food consumption is perfectly inelastic, that is, $\varepsilon_c^d = 0$, then $dD_{c,F} = 0$. In other words, there is no change in corn use for food consumption and therefore $dZ_c = 0$.

Combining the different price effects we can write equation (14):

$$\begin{aligned} dZ_{\mathrm{CLCA}} &= dZ_{fuel} + dZ_{luc} + dZ_{food} \\ &= \underbrace{dZ_{\mathrm{ALCA}}}_{\leq 0} + \underbrace{dZ_{ifue}}_{\leq 0 \text{ or } \geq 0} + \underbrace{dZ_{luc}}_{\geq 0} + \underbrace{dZ_{food}}_{\leq 0} \end{aligned} \tag{14}$$

Equation (14) depicts the difference between ALCA and CLCA predictions of the impact of replacing gasoline with corn ethanol. The nature of impact of price effect in different markets suggests that predictions based only on ALCA may be biased either up- or downward.

Substituting equations (4), (12), and (13) in equation (14) we get equation (15):

$$\begin{aligned} dZ_{\mathrm{CLCA}} = &\underbrace{(z_e - z_g)d\bar{q}_e}_{dZ_{\mathrm{ALCA}}} + z_g(1+\Delta)d\bar{q}_e \\ &+ \left(z_l\frac{\beta}{y}\varepsilon_c^s S_c^0 + z_c\varepsilon_c^d D_{c,F}^0\right)\left[\frac{1}{S_c^0\varepsilon_c^s - D_{c,F}^0\varepsilon_c^d}\right]\frac{d\bar{q}_e}{\eta} \end{aligned} \tag{15}$$

See equation (3) for the definition of Δ. It should be pointed out that we have assumed that the price effects do not affect the emission intensities, namely, z_g, z_e, z_c, and z_l. In reality, ALCA emission intensities may themselves also be endogenous.

Numerical Illustration

We perform a numerical simulation to illustrate which parameters may cause CLCA to differ from ALCA and also identify directions in which the system boundary may need to be expanded. In ex ante analysis of policies, the stringency of a policy is also a decision variable. The magnitude of the policy shock will determine the magnitude of price effects. We therefore simulate three different levels of the mandate, namely, 25%, 100%, and 200% increase in ethanol consumption relative to a base year, chosen as 2007, and illustrate the sensitivity to policy stringency. Also, the more stringent the target, the longer the policy horizon tends to be. However, our model is static and does not include an explicit representation of the time duration over which a policy target is realized. We overcome this limitation of our model by choosing (and subjectively so) different values for the model parameters, depending on the magnitude of

Table 1 Assumed range of values for model parameters for comparison of CLCA and ALCA estimates of change in emissions resulting from an increase in ethanol consumption

Model parameters	*Short run*	*Medium run* [a]	*Long run* [a]
Elasticity of gasoline demand (ε_f^d)	(–0.08, –0.03) [b]	150%	200%
Elasticity of gasoline supply (ε_g^s)	(0.05, 0.15) [c]	150%	200%
Elasticity of ethanol supply (ε_e^s)	(0.5, 1.0) [d]	150%	200%
Elasticity of corn supply (ε_c^s)	(0.08, 0.13) [e]	150%	200%
Elasticity of corn demand (for food) ($\varepsilon_{c,f}^d$)	(–0.08, –0.05) [f]	150%	200%
Average ALCA GHG intensity of gasoline (z_g) (gCO_2-eq/MJ) [g]	(86, 94) [h]	100.5%	101%
Average ALCA GHG intensity of corn ethanol (z_e) (gCO_2-eq/MJ)	(60, 70) [i]	97.5%	95%
Average conversion efficiency of corn to ethanol (η) (liter/tonne)	(387, 417) [j]	105%	110%
Annualized land conversion emissions (z_l) (tonnes CO_2-eq/hectare/year)	(3.7, 16) [k]	97.5%	95%
Average marginal corn yield per hectare (y) (tonnes/hectare)	(8.8, 10) [l]	102%	104%
Share of extensive margin for corn (β)	(0.3, 0.7) [m]	100%	100%
Average ALCA GHG intensity of corn (z_c) ($kgCO_2$-eq/hectare) [n]	(2,600, 2,800) [o]	102%	104%
Policy shock (% increase in ethanol use)	25%	100%	200%

Notes: Table shows different assumed values for three different levels of policy shock.
[a]Medium- and long-run values are obtained by scaling the short-run values by the factors shown in the corresponding columns, and these were chosen subjectively.
[b]Based on range reported by Hughes and colleagues (2008).
[c]Imputed based on range for oil supply elasticity reported by Greene (2010).
[d]Subjective values based on the order or magnitude used in previous studies (Holland et al. 2009; Rajagopal and Plevin 2013) for long run.
[e, f] Based on range reported by Roberts and Schlenker (2010).
[g]g = grams; MJ = megajoule.
[h]A mean value estimated based on range reported by Venkatesh and colleagues (2011).
[i]Mean value assumed by Rajagopal and Plevin (2013).
[j]Corresponds to the range of (2.6, 2.8) gallons per bushel.
[k]Corresponds to the range of (140, 160) bushels per acre.
[l]Based on values in the GTAP database for global average pasture land conversion emissions of 110 tonnes of CO_2-eq/hectare and global average forest conversion emissions of 490 tonnes of CO_2-eq/hectare and amortization of these values over 30 years without any discounting to get the annual average emissions from land use.
[m]An assumption that 40% of the increase in supply is achieved by expanding the area planted to corn.
[n]kg = kilograms.
[o] EBAMM model of Farrell and colleagues (2006) reports of 2,700 kg CO_2-eq/hectare of corn production.
CLCA = consequential life cycle assessment; ALCA = attributional life cycle assessment; GHG = greenhouse gas; CO_2-eq = carbon dioxide equivalent.

shock. Albeit subjective in magnitude, the direction of scaling is based on theoretical considerations or empirical observations. For instance, we assume that the magnitude of price elasticity and technical efficiencies increase with time. Table 1 shows the assumed range of values for the model inputs for the short run, which are used for the 25% shock. For the medium and long run, we scale the short-run values by the factors shown, which, to reiterate, are subjective. We use the medium- and long-run values for the simulations involving a 100% and 200% increase in ethanol consumption. The base-year value for prices and quantities consumed are listed in Table 2.

Table 3 reports the change in price, quantity, and emissions when each input parameter assumes the mean value of its chosen range. Ethanol consumption increases, whereas gasoline consumption declines, in response to the mandate. However, the price of blended fuel declines, and so total fuel consumption increases. Total corn consumption increases, whereas corn consumption as food declines. With respect to emissions, because the ALCA emission intensity of corn is less than that of gasoline, a one-to-one replacement of gasoline with corn (adjusting for energy equivalence) implies emissions will decline and hence $\Delta Z_{ALCA} < 0$. The change in emissions resulting solely from the change in total quantity of fuel consumed, ΔZ_{IFUE}, is positive as a consequence of the increase in total fuel consumption and offsets the pure substitution effect, represented by ΔZ_{ALCA}. The increase in corn production contributes to positive land-use change emissions, ΔZ_{LUC}. Our simulations highlight yet another indirect effect, namely, that as a result of the reduction in corn use for food consumption, this effect counteracts the indirect land-use change (ILUC) effect. It should be pointed out that both indirect fuel-use effect (IFUE) and food consumption effect have received little attention in the debate on indirect emissions of biofuels. Figure 1 plots the relationship between policy stringency and the change in emissions. It suggests that the relationship between ΔZ_{CLCA} and policy stringency is nonlinear and supports our hypothesis that the sign of ΔZ_{CLCA} is uncertain.

Sensitivity Analysis

We now describe a sensitivity analysis in which we vary one parameter at a time while holding all the other parameters at

Table 2 Base-year (2007) values used in simulation

Input	*Value*
Ethanol consumption ($\bar{q}_e^0$) (billion liters)	25
Gasoline consumption (S_g^0) (billion liters)	523
Ethanol price (p_e^0) ($ [a] /liter)	0.59
Gasoline price (p_g^0) ($/liter)	0.73
Blended fuel price (p_f^0) ($/liter)	0.62
Corn use as ethanol ($D_{c,E}^0$) (million tonnes)	41
Corn use as food ($D_{c,F}^0$) (million tonnes)	290
Total corn use (S_c^0) (million tonnes)	330

[a]$ refers to U.S. dollars.

their mean value and calculate a variable as shown by equation (16):

$$R = \frac{\Delta Z_{CLCA}}{\Delta Z_{ALCA}} \tag{16}$$

$R > 0$ implies that both ALCA and CLCA suggest the same direction of impact on emissions. Because $\Delta Z_{ALCA} < 0$, this implies that indirect emissions do not result in a net increase in emissions. $R < 0$ implies that indirect emissions result in a net increase in emissions. Because we perform a local sensitivity analysis by varying one parameter at a time, and because varying any one parameter among corn yield, y, the ALCA emission intensity of corn production, z_c, and the parameter denoting the efficiency of conversion of corn to ethanol, η, will affect the ALCA emission intensity of ethanol, z_e, we exclude these parameters from the sensitivity analysis. We divide the chosen range for each input into ten equally spaced intervals and calculate R 11 times for each parameter. We then compute a pairwise linear correlation between R and each parameter, which is shown in figure 2.

It should be pointed out that the relative strength of the correlation depends on the range chosen for each parameter. For the chosen range of inputs, emission intensity of marginal land has the largest impact on R and is negatively correlated with R. This suggests the importance of limiting expansion of agriculture and preventing expansion into carbon-rich lands. Elasticity of gasoline supply is next most strongly and positively correlated with R. Because an ethanol mandate lowers the price of gasoline, the higher the elasticity of gasoline supply, the greater the reduction in supply of gasoline. This implies lower emissions resulting from IFUE. The share of the extensive margin is negatively correlated with R because the higher the share for the extensive margin in the increase in corn production, the higher the LUC emissions. ALCA emission intensity of ethanol

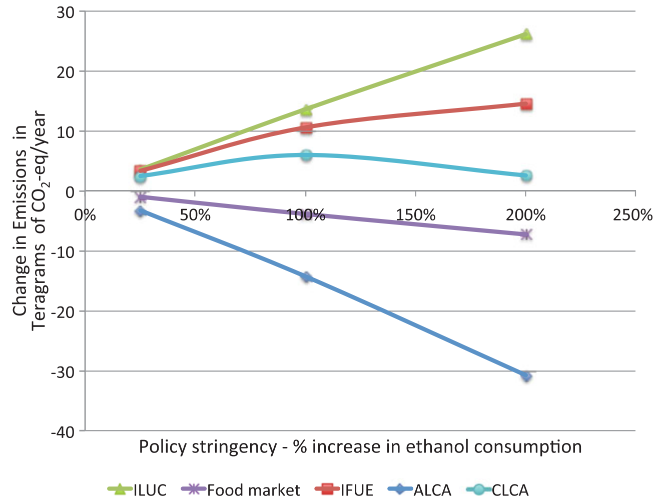

Figure 1 Relationship between magnitude of policy shock and the various sources of change in emissions when each input parameter assumes the mean value in the chosen range. ILUC = indirect land-use change; IFUE = indirect fuel-use effect; ALCA = attributional life cycle assessment; CLCA = consequential life cycle assessment, which, here, is the sum of ALCA, ILUC, IFUE, and food market effects on emissions.

Table 3 Results for simulation when each input parameter assumes the mean value of its range

Policy shock (% change in ethanol use)	*25%*	*100%*	*200%*
Change in ethanol consumption (billion liters)	6.2 (25%)	24.6 (100%)	49.2 (200%)
Change in gasoline consumption (billion liters)	−3 (−0.6%)	−12.8 (−2.5%)	−28 (−5.3%)
Change in consumption of blended fuel (billion liters)	1.1 (0.2%)	3.6 (0.7%)	5 (0.9%)
Change in price of blended fuel ($ [a] /liter)	−0.03 (−3.8%)	−0.1 (−8.2%)	−0.1 (−8.4%)
Change in quantity of corn for food (million tonnes)	−3.6 (−1.2%)	−14.2 (−4.9%)	−27.8 (−9.6%)
Total change in corn consumption (million tonnes)	6.6 (2%)	26 (7.9%)	51 (15.4%)
Change in emissions (Δ Z) in teragrams CO_2-eq/yr			
ΔZ_{ALCA}	−3.3 (100%)	−14.3 (100%)	−30.8 (100%)
ΔZ resulting from IFUE	3.2 (−98.4%)	10.5 (−73.8%)	14.5 (−47.2%)
ΔZ resulting from LUC	3.5 (−107.2%)	13.6 (−95%)	26.1 (−84.8%)
ΔZ resulting from change in food consumption	−1 (31.4%)	−3.9 (27.2%)	−7.3 (23.7%)
Total change in emissions ΔZ_{CLCA}	2.4 (−74.2%)	6 (−41.7%)	2.5 (−8.3%)

Note: Numbers in parentheses denote the percentage change relative to base year for consumption and price. For emissions, they denote the change relative to change in emissions implied by ALCA. Emissions are reported in units of teragrams of CO_2/yr.
[a]$ refers to U.S. dollars.
CO_2-eq/yr = carbon dioxide equivalent per year; IFUE = indirect fuel-use effect; LUC = land-use change.

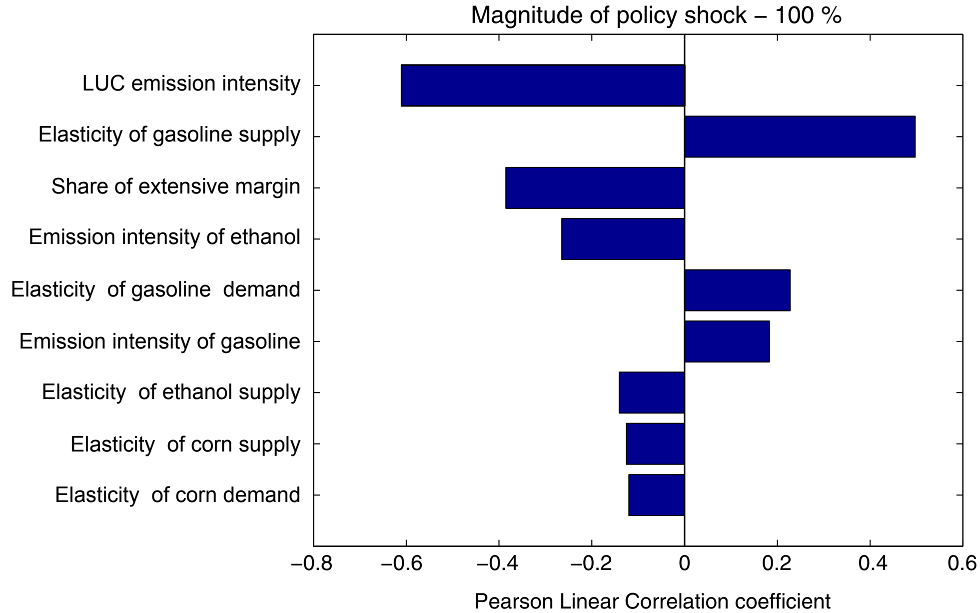

Figure 2 Pairwise linear correlation coefficient between $R = \frac{\Delta Z_{CLCA}}{\Delta Z_{ALCA}}$ and the different input parameters obtained by varying one parameter at a time. Results shown are for a policy shock involving doubling of ethanol consumption relative to base year.

is negatively correlated with R because ΔZ_{ALCA}, which is negative, increases (the magnitude of ΔZ_{ALCA} decreases) and therefore R decreases. Elasticity of gasoline demand is positively correlated with R. This, however, needs careful interpretation. Because elasticity of demand is a negative quantity, a positive correlation means that as magnitude of elasticity of demand decreases, R increases. This is because of the fact that if the ethanol mandate lowers the price of ethanol-gasoline blend, then the more inelastic the demand for fuel, the smaller will be the rebound in gasoline consumption and hence the smaller will be the magnitude of the IFUE effect, which is positive (i.e., contributes to additional emissions). As a result, the difference between ΔZ_{CLCA} and ΔZ_{ALCA} decreases and R increases. However, if the ethanol mandate raises the price of ethanol-gasoline blend, then the more elastic the demand for fuel, the greater the reduction in total fuel consumption will be, and hence the smaller the magnitude of the IFUE effect will be, but which is now negative (i.e., contributes to emission reduction). In this case, the correlation between elasticity of demand and R will be negative. For the range of inputs in table 1, we find that the ethanol mandates always lower the price of ethanol-gasoline blend and hence find a positive correlation between elasticity of demand. This is attributable to the high elasticity of ethanol supply. When we assume a highly inelastic supply of ethanol (e.g., a value in the range 0.05 to 0.1), the model predicts that a doubling of ethanol consumption increases the price of ethanol-gasoline blend and that the elasticity of gasoline demand is negatively correlated with R in such cases. ALCA emission intensity of gasoline is positively correlated with R because ΔZ_{ALCA}, which is negative, increases (the magnitude of ΔZ_{ALCA} decreases) and therefore R decreases. Elasticity of ethanol supply is negatively correlated with R. The higher the elasticity of supply of ethanol, the larger (smaller) the decrease (increase) in price of ethanol-gasoline blend, which implies a higher level of total fuel consumption and IFUE emissions and hence a smaller value of R. Elasticity of corn supply is negatively correlated with R. Because the mandate increases demand for corn, a higher elasticity of supply leads to a greater net increase in corn output and land-use change, which implies higher emissions and therefore a smaller value of R. Elasticity of corn demand is also negatively correlated with R. The higher the elasticity of demand (i.e., the smaller the value of demand elasticity, which is a negative quantity), the smaller the increase in price for a given elasticity of supply and a given demand shock is, and hence the smaller the net increase in corn output is, which implies lower emissions and therefore a higher value of R.

We found similar correlations for both the smaller shock (25% increase in ethanol) and the larger shock (200% increase in ethanol). In fact, with the exception of the correlation between R and the elasticity of fuel demand, the sign of the correlation we find in figure 2 is true for any range of inputs of all parameters. Further, we also performed a Monte Carlo experiment simulating the model for 5,000 different randomly chosen combinations of values for the inputs and found the same type of correlation between output and inputs (see figure 3 for results of this experiment).

The PE analysis provides some new and general insights. The sensitivity to policy stringency, which, ex ante to policy adoption, is a decision variable, reveals a nonmonotonic relationship with emissions. The analysis also shows how various technical and behavioral economic parameters, such as emission intensity, price elasticities, and so on, affect CLCA. It also reveals the role of uncertainty in model parameters. For instance, it shows how the elasticity of fuel demand differs from other parameters in its relationship to total emissions and how

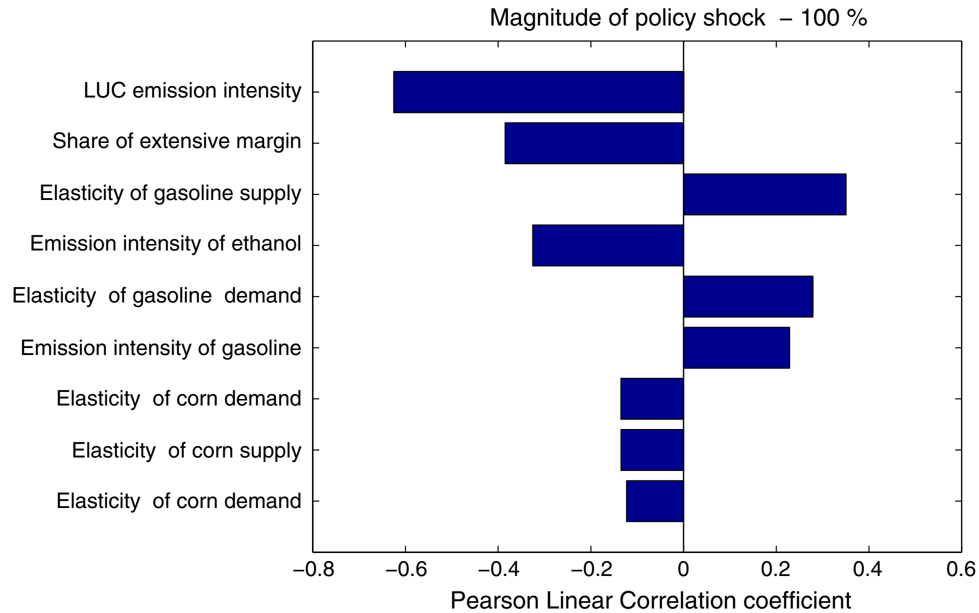

Figure 3 Pairwise linear correlation coefficient between $R = \frac{\Delta Z_{CLCA}}{\Delta Z_{ALCA}}$ and the different input parameters obtained through a Monte Carlo simulation involving 5,000 randomly chosen combinations of inputs. All inputs are assumed uniformly distributed within the range shown in table 1. Results shown are for a policy shock involving doubling of ethanol consumption relative to base year.

the supply function of ethanol may determine whether total fuel consumption increases or decreases.

A General Multimarket Partial Equilibrium Consequential Life Cycle Assessment

Above, we illustrated price effects in different markets using a PE analysis one market at a time without considering interlinkages between different markets. For instance, we assumed that corn supply and corn demand are both unaffected by the price of other crops, land, energy, and so on. Similarly, we also assumed that the ethanol supply and ethanol demand are also unaffected by the price of corn. We now describe a more general multimarket framework with multiple interconnected markets and describe how a shock to one market affects consumption and therefore emissions in every other sector. Figure 4 is a schematic representation of such a multimarket framework. Consider a policy that mandates an increase in consumption of the good M, which we refer to as the "*main*" good. This policy will cause consumption of M to increase and the substitute to main good(s), denoted S, to decrease. Correspondingly, the price of M increases, whereas that of S decreases. Total consumption of the services provided by M and S, denoted $M + S$, may either increase or decrease. In our numerical example, consumption of ethanol-blended gasoline increased as a consequence of the decline in the price of blended fuel. However, this need not always be the case. The price of blended product (or the average price in the market for $M + S$) can increase, in which case aggregate consumption $M + S$ can decline. Higher levels of consumption of the costly technology will lead to lower total consumption.

Consumption of intermediate inputs that are associated with production of the main final good M, but not with production of the substitute final good S, increases with increase in consumption of M. These are denoted as I_M (corn, in our example). Consumption of goods that compete with M for inputs declines. These are denoted as $I_M C$ (corn for food consumption, in our case). Consumption of intermediate inputs that are associated with production of the substitute final good, but not with the production of the main good, decreases because of decline in consumption of S. These are denoted as I_S (e.g., crude oil, which is an input to gasoline). Consumption of goods that depend on intermediate inputs I_S, declines because of a decline in the consumption of I_S. These are denoted as $I_S C$ (e.g., diesel, which is a product of oil refining). Consumption of intermediate inputs that are common inputs to the production of different goods may either increase or decrease. These are denoted I_C (e.g., energy in the form of process heat, electricity, or fuel for machinery).

Consumption in the sectors associated with the production of the intermediate input (I_M) to the main good M, but not associated with substitute to main good S, also increases. These are denoted as I_{IM}. However, consumption of I_{IM} in competing applications, denoted as $I_{IM}C$, declines. Consumption in the sectors associated with the production of the intermediate input (I_S) to the substitute good S, but not associated with the main good M, declines. These are denoted as I_{IS}. As a consequence, consumption of I_{IS} in competing applications, denoted as $I_{IS}C$, also declines. The above insights can be extended to an arbitrary number of up- and downstream activities.

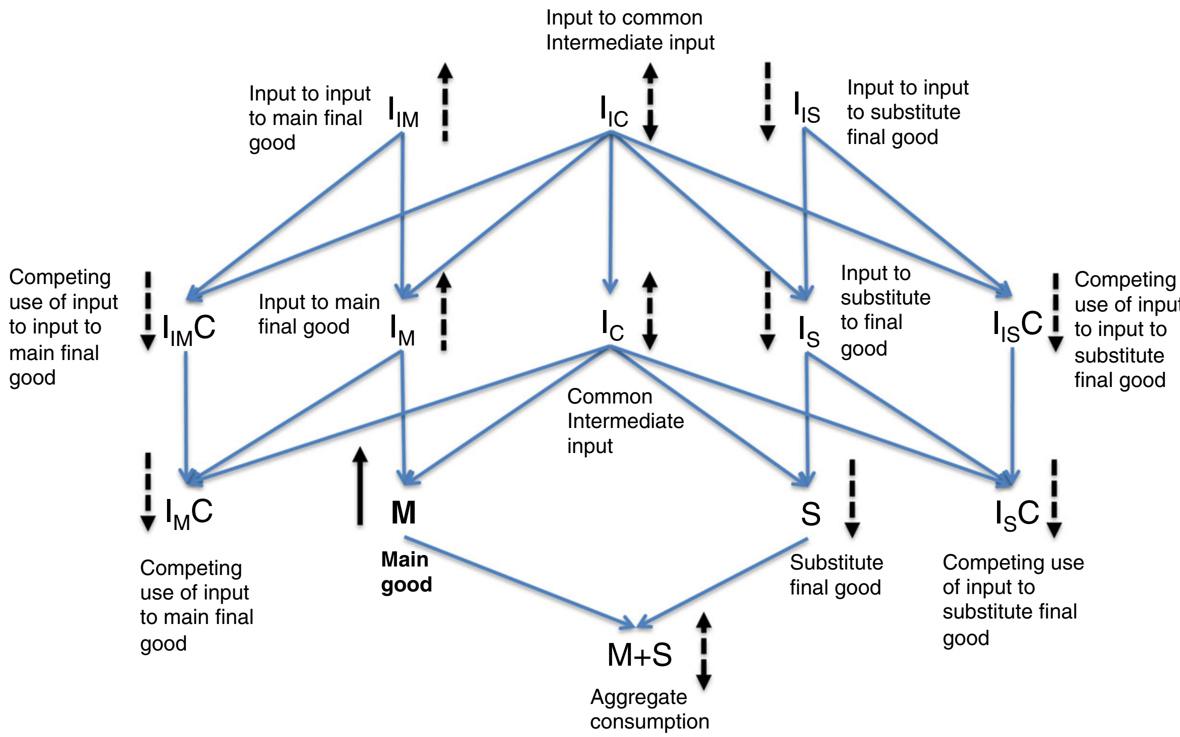

Figure 4 A multimarket framework showing the impact of a positive demand shock to good M (shown by solid arrow) on consumption in the market for other goods. Upward arrows indicate a net positive impact on consumption of a good; a downward arrow indicates a net negative impact on consumption. A bidirectional arrow indicates that the direction of impact is ambiguous.

Emissions associated with a sector will either increase or decrease depending on whether that sector experiences a net increase or decrease in consumption. The aggregate effect may be either an increase or decrease in global emissions. Whereas an ALCA-based comparison would suggest a decrease in emissions because of substitution of a dirty with a clean good, CLCA would suggest an ambiguous effect on emissions. We generalize the findings from the numerical example. Table 4 shows the effect of a change in a given parameter on the ratio $\frac{\Delta Z_{CLCA}}{\Delta Z_{ALCA}}$, *ceteris paribus*. As the difference between the ALCA emission intensities of the main good and the substitute good increases (by either an decrease in the ALCA emission intensity of the cleaner good or an increase in the ALCA emission intensity of the dirtier good), the magnitude of the pure substitution effect increases relative to the price effects and therefore the difference between CLCA and ALCA decreases (or R increases). The relationship between the elasticity of demand for the service provided by the final product and its substitute, denoted by $M + S$ and R, is ambiguous. It depends on the impact of shock on the price in the market for $M + S$ (see the discussion in the section on *Sensitivity analysis* on the elasticity of demand for gasoline). A higher elasticity of supply of final product M also implies a smaller price effect, and therefore the difference between CLCA and ALCA decreases or R decreases. A higher elasticity of demand for inputs to the main final product I_M in a competing use to M (denoted by I_MC) implies a smaller net increase in the consumption of I_M and hence a smaller difference between CLCA and ALCA (or R increases). A higher elasticity of supply of input I_M to the final product M implies a larger increase in the supply of the I_M, and therefore the difference between CLCA and ALCA increases (or R decreases). A higher elasticity of supply of the substitutes S to the final product implies a smaller rebound in the consumption of substitutes

Table 4 Effect of a change in a given parameter on the ratio $R = \frac{\Delta Z_{CLCA}}{\Delta Z_{ALCA}}$, *ceteris paribus*

Parameter		*R*
ALCA emission intensity of main good M	↑	↓
ALCA emission intensity of substitute to main good S	↑	↑
Elasticity of demand for services provided by main good $M + S$	↑	↕
Elasticity of supply of main good M	↑	↓
Elasticity of supply of substitute to main good S	↑	↑
Elasticity of supply of input to production of main good I_M	↑	↓
Elasticity of supply of input to production of substitute to main good I_S	↑	↑
Elasticity of demand for input to main good in a competing use I_MC	↑	↑
Elasticity of demand for input to substitute good in a competing use I_SC	↑	↑

Note: Up arrow indicates increase, down arrow indicates decrease, and bidirectional arrow indicates increase or decrease.
ALCA = attributional life cycle assessment.

and hence a smaller difference between CLCA and ALCA (or R decreases). A higher elasticity of supply of inputs I_S to the final product also has a similar effect as the elasticity of supply of the substitute S.

Implications for Use of Life Cycle Assessment in Policy Settings

When policies are incomplete, that is, do not cover all sources of pollution and target only a subset of polluting activities, policy makers need to be aware of the risk that leakage of pollution to unregulated markets and regions might result in a policy proving ineffective or even counterproductive (as studies suggest may be the case with biofuels). LCA can play a role in highlighting the susceptibility of partial policies to leakage early in the policy life cycle. When policy makers only seek information about the current life cycle environmental footprint of an industry on average or that for a specific firm, then an ALCA may be adequate. In this role, ALCA can aid in screening potentially beneficial technologies for further consideration. Subsequently, when policy makers are considering a policy intervention to support a specific technology or type of service, say, through a technology mandate or a subsidy, and seek to understand the potential impact of such a policy on future outcomes to an order of magnitude, then a CLCA is the more appropriate type of LCA. In this case, one then needs to identify the appropriate modeling framework (whether partial or general equilibrium) and the level of regional and sectoral detail in the chosen framework. Given that the data requirements, and therefore cost of CLCA, increase with level of detail and that uncertainty may increase, we suggest an iterative approach. One can begin with simple partial equilibrium models focusing on the key processes in the life cycle, which, an ALCA might suggest, are major contributors to the current life cycle performance of the main good and of its substitutes. Sensitivity analysis can be used to identify which parameters cause the predictions of CLCA to diverge from ALCA. This can help to identify parameters that deserve further consideration and more detailed investigation. For instance, our illustration of corn ethanol suggests that in addition to the ALCA emission intensities of corn and gasoline, elasticity of gasoline supply and demand have a strong effect on CLCA estimates. This suggests that one should analyze the fuel market effect in greater detail, say, by incorporating the market for crude oil and the rest of the oil products. A benefit of gradually increasing the complexity of CLCA is that simpler models are more amenable to a systematic sensitivity analysis, when compared to larger models.

The previous literature highlighted several issues concerning reliability of LCA results, which are attributable to reasons such as subjective selection of a single methodology when no single standard exists (e.g., Guinee and Heijungs 2011; Creutzig et al. 2012), uncertainty in model parameters (e.g., Huijbregts 2008; Rajagopal and Plevin 2013), and the instability of model parameters over time as a result of dynamic processes (see Zilberman et al. 2011). Our analysis reveals new dimensions of variability. Although each individual category of indirect emissions exhibits a monotonic relationship with policy stringency, total emissions exhibit a nonmonotonic relationship with policy stringency. This suggests that policies that appear harmful in the short run may prove beneficial in the long run or vice versa or exhibit more-complex relationships.

The recent experience with biofuel regulations highlights another policy challenge relevant to partial policies, that of regulating indirect emissions or emissions resulting from price effects. Regulation involves holding firms or individuals accountable for their actions, and therefore regulating emissions resulting from price effects requires holding individual firms accountable for such emissions. Emissions from the supply chain, the use phase, and the end of life of any given batch of goods are, in principle, traceable and attributable to the actions of a specific firm or individual. Therefore, the estimates of ALCA can, in principle, be a basis for regulating any given firm and for determining its compliance with a given target. However, in a competitive market, no single firm can affect price and so the change in price is a consequence of the exogenous shock to supply or demand. The changes that occur in the various interconnected markets as a result of this shock are not traceable or attributable to the actions of any single firm or group of firms. Yet, the increase in emissions in unregulated markets as a consequence of the policy shock represent real additional externalities and hence are policy relevant. This is a challenge that policy makers face in implementing life-cycle–based policies and a topic of debate (NFA 2008; UCS 2008; Liska and Perrin 2009).

LCA is one among several different analytical or procedural tools, such as cost-benefit analysis, life cycle costing, strategic environmental assessment, and environmental management systems, for analyzing the system-wide impacts of a technology or policy (Finnveden and Moberg 2005; Höjer et al. 2008). However, the complexity of the task of deriving a single best estimate for a random variable, such as the emission intensity of the supply chain or the emissions resulting from price effects, is so complex that any single modeling approach or different approaches combined may either prove inadequate or prove to be an opaque, costly exercise. This is one criticism applicable to the large multimarket or computable general equilibrium–based modeling efforts to estimate the life cycle GHG impacts of biofuels. Norgaard 1986 argues that whereas the tendency for single-valued estimates can be explained given the political use of estimates and projections, the approach is analytically indefensible. Further, a decision as to whether and how to address emissions resulting from price effects is beyond the realm of a tool such as LCA. However, we show that CLCA could help identify policy formulations that mitigate the risk of counterproductive outcomes. For instance, we find that the difference in ALCA emission intensity of corn and gasoline has a significant impact on the ratio of CLCA and ALCA estimates. Therefore, ethanol whose ALCA emission intensity is much lower relative to gasoline, such as the second-generation biofuels from cellulosic feedstock derived from agricultural residues, municipal wastes, or even dedicated energy crops, appear more likely to reduce global emissions. To this end, policies should be designed to promote technologies with a smaller ALCA footprint. For instance, stipulating an upper bound on the ALCA emission intensity of the clean technology and setting this upper bound below a safe limit relative to the ALCA emission intensity of the dirty technology will reduce the likelihood that price effects overwhelm the pure substitution effect. In fact, the U.S. RFS II regulations specify such upper bounds for the emission intensity of the different types of biofuels. However, whether the upper bounds that have been specified are sufficiently stringent is a topic for further research. The higher cost of cleaner biofuels will also lead to lower fuel consumption overall, a benefit, from an environmental perspective, that needs balancing against its socioeconomic impacts.

In conclusion, we find that ALCA and CLCA are complements, rather than substitutes, in the policy process. The salient contribution of CLCA may lie in warning policy makers about the vulnerable aspects of a policy with regard to environmental impact and to help modify potentially counterproductive formulations early in the policy life cycle, rather than as a tool for selection of a single best estimate for uncertain variables, such as the life cycle GHG intensity of product, and so on.

Note

1. To determine the magnitude of change, one can evaluate equation (3) either with respect to the initial state, the final state, or any intermediate state, which will yield different, but approximately equal, results for small disturbances. This is not true for large disturbances. We therefore simply solve the system of equations (1) and (2) to determine the final equilibrium and compute the change between the initial and final state. One can verify that evaluating the comparative static expression at the mid-point of the initial and final states yields a similar result as solving the two equations.

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