ENVIRONMENTAL POLICY, GREENHOUSE GAS POLLUTING INPUTS, AND LIFECYCLE ANALYSIS

By

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ENVIRONMENTAL POLICY, GREENHOUSE GAS POLLUTING INPUTS, AND LIFECYCLE ANALYSIS

Abstract
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This dissertation consists of three studies that investigate impact of environmental taxes on firms’ technology and entry behaviors, substitution between greenhouse gas (GHG) polluting and nonpolluting inputs in agricultural production, and lifecycle emissions with incorporation of input substitution in production and transportation sectors of biofuel.

The first study examines under which conditions an environmental tax can be used to induce firms to adopt a clean technology and, also, to deter entry. We find that despite facing a polluting incumbent, an entrant might enter the market and acquire a clean technology when the tax is stringent enough and the clean technology is effective in eliminating pollution. A duopoly with two clean firms is socially optimal if the technology cost is low and the environmental damage is sufficiently high. However, if the environmental damage is low, a partially clean duopoly, in which only one firm adopts the green technology, could be socially optimal.

The second study reports meta-regressions of Morishima substitution elasticities between GHG polluting and each of three nonpolluting inputs (labor, land, and capital) in agricultural production. We treat energy, fertilizer, and manure collectively as the “polluting input”. Our results show that each estimated long-run elasticity for the reference case, which is most relevant for assessing GHG emissions through lifecycle analysis, is greater than 1.0 and significantly
different from zero. Predicted long-run elasticities generally remain significantly different from zero at the data means for alternative plausible cases. These findings imply that lifecycle analysis based on fixed proportions production functions could provide grossly inaccurate measures of GHG of biofuel.

The third study develops a lifecycle economic analysis (LCEA) model that integrates input substitution, technology switching, and substitution of biodiesel for diesel into the standard lifecycle analysis (LCA) of biofuel that assumes fixed-proportions production. We use the LCEA model to examine the impacts of a pure carbon tax and a revenue-neutral tax-subsidy policy on lifecycle greenhouse gas emissions from cellulosic ethanol using forest residues as feedstock in Washington State. Our findings document that a standard LCA that assumes fixed input proportions substantially underestimates emission reduction from carbon tax policies.
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CHAPTER ONE
THE IMPACT OF ENVIRONMENTAL TAXES ON FIRMS' TECHNOLOGY AND ENTRY DECISIONS

Abstract

This paper investigates conditions under which the regulator can strategically set an emission fee as a tool to induce firms to adopt a green technology and, also, promote (or hinder) entry deterrence. We consider a market in which a monopolistic incumbent faces the threat of entry, and firms can choose between a dirty and a green technology. Our results show that, despite the fact of facing a polluting incumbent, an entrant might find it profitable to join the market and acquire a clean technology if the environmental tax is stringent enough and the technology is effective eliminating pollution. We also demonstrate that a duopoly, in which all firms acquire green technology, is socially optimal if the technology cost is low and the environmental damage is sufficiently high. However, if the environmental damage is low, a partially clean duopoly (in which only one firm adopts the green technology) is socially optimal under less restrictive conditions on the cost of clean technology.

1.1 Introduction

An increasing concern for the negative effects of pollution has induced governments and firms to consider the adoption of clean technologies (also referred as green technologies).\(^1\)

Environmental regulation in this matter is a keystone tool for the development and acquisition of

\(^1\) For instance, the Clinton administration established the Environmental Technology Initiative in 1993 in order to promote green technology adoption and more competitive businesses.
this type of technology. Hence, the analysis and understanding of policy schemes that promote
the investment in clean technologies are of great importance for the solution of several
environmental problems. For instance, Popp (2002) argues that emission fees can promote the
development of less costly pollution control technologies. Stern (2007) also suggests that carbon
pricing provides incentives to invest in new abatement technologies. However, the setting of
environmental policies could generate several distortions; such as hindering domestic firms’
competitiveness or deterring entry. As a consequence, the regulator should take into account
those effects when designing an optimal regulation. Only few studies, nevertheless, have
analyzed environmental regulation when firms are considering the adoption of a new technology
and, in addition, they face the threat of entry. Hence, our study aims to investigate the role of
regulation in the acquisition of green technology and its effects on market competition.

We study a context in which a regulator sets an environmental tax and an incumbent and
a potential entrant decide their type of technology. Specifically, we consider two different
technologies: an environmentally friendly (green) and a dirty technology. The clean technology
is assumed to have different degrees of effectiveness in reducing pollution. That is, it can
completely or partially reduce emissions. The paper analyzes a four-stage complete information
game. In the first and the second period, the regulator sets an emission tax and the incumbent
responds selecting a type of technology, respectively. In the third period the entrant, after
observing the regulator's and incumbent's action, decides whether to join the market and its
technology. Finally, if entry ensues, both firms compete in a Cournot game; otherwise the
incumbent continues to operate as a monopolist. The coal mining industry is an example that
describes this setting, since it is subject to environmental regulation and often faces the dilemma
of whether to acquire new equipment to make their plants less polluting. Another example is DuPont, one of the most important chemical companies in the market, which also faces stringent environmental regulation and has acquired clean technology in the past years.

We first examine how entry decisions and entrant's technology are affected by the emission tax and the incumbent's type of technology. In particular, if the incumbent keeps its dirty technology and the potential entrant has access to clean technology that can only eliminate less than half of the pollution compared to the dirty technology, emission fees are more likely to deter entry. Hence, an environmental regulation accompanied by an early-stage green technology may help the incumbent to keep its monopolistic position. However, an environmental tax does when the technology available is in an advanced stage of development and, hence, it is able to capture a significant proportion of pollutants. In this case the entrant, despite facing a dirty incumbent, is more likely to join the market and acquire a clean technology.

Entry deterrence is more likely to occur if the incumbent has a green technology and an environmental regulation is in place. Although stringent emission fees can support entry deterrence under certain cases, it does not necessarily induce the entrant to acquire a green technology. In fact, the entrant's decision on whether or not to adopt a clean technology depends on its effectiveness in reducing emissions and, also, its cost. Moreover, we find that the adoption of the green technology by the incumbent hinders the acquisition of such a technology by its

---

2 This industry must comply with, among others, the Clean Air Act, the Clean Water Act, and the Toxic Substances Control Act. In addition, according to IBISWorld analyst, B. Bueno, the industry concentration has increased over the past five years (PRWEB, July 06, 2012).

3 Bloomberg news in January 2011 reported that DuPont invested around $5.8 billion in 2011 acquiring a Denmark-based industrial biotechnology company.
competitor. That is, a potential entrant that has decided to join the market is more likely to adopt a clean technology when it faces a dirty incumbent than otherwise.

We also evaluate social welfare under different contexts of environmental deterioration. Our welfare comparisons suggest that when the environmental damage is sufficiently high and the cost of a partially clean technology is low, the entry of a clean competitor is always welfare improving. Our findings, hence, indicate that the presence of a potential entrant that can be induced by the environmental regulation to acquire a green technology makes the regulator less willing to facilitate the incumbent's entry-deterring practices. In addition, if the environmental damage is relatively low, a partially green duopoly is socially preferred than a completely dirty duopoly. Intuitively, the reduction of the moderate environmental damage by only one green firm compensates the loss in producer surplus due to the cost of adopting a clean technology. Therefore the regulator should evaluate emission fees and, in particular, their effects on the market structure and the acquisition of clean technologies, depending on the environmental damage and the technology's cost.

Studies over the last decades have analyzed firms' incentives to invest in abatement technologies, due to environmental regulations. A well-designed environmental policy can stimulate the adoption of new technologies that reduce marginal emissions or save abatement costs (Porter and van der Linde, 1995; Requate, 2005; Perino and Requate, 2012). Several authors have demonstrated that firms' incentives to adopt clean technology differ across market structures and policy instruments. They have also analyzed the optimal environmental policy scheme that generates the most incentives (see Katsoulacos and Xepapadeas, 1996; Montero, 2002; and Requate and Unold, 2003). A traditional conclusion is that such incentives increase monotonically with regulation stringency (Requate and Unold, 2003). Among different
environmental regulations, it is well known that market-based instruments are preferred by economists and widely implemented in many countries (Requate, 2005). Specifically, emission fees are an effective instrument in providing incentives to acquire a new abatement technology in perfectly competitive markets (Parry, 1998) as well as in oligopolistic markets (Montero, 2002). Similarly, our paper examines how an appropriate emission fee induces firms to adopt a clean technology. However, unlike the previous literature, we focus on an entry-deterrence model rather than markets that do not face entry threats. Our results suggest that stringent emission fees not only could induce the acquisition of green technology but also affect entry decision.

Environmental regulation, in an entry-deterrence game, strategically affects firms' entry decision and, hence, market structure. From the regulator's perspective, environmental policy is a tool that can create barriers to entry. Early studies have examined how a stringent emission quota acts as an effective instrument in leading to cartelization (Buchanan and Tullock, 1975; Maloney and McCormick, 1982; Helland and Matsuno, 2003). An article survey conducted by Heyes (2009) also concludes that environmental regulations help incumbents to discourage entry and thus reduce market competition. However, few papers have analyzed entry deterrence in the case of an emission tax. Schoonbeek and de Vries (2009) examine the effects of emission fees on firms' entry in a complete information context and Espínola-Arredondo and Muñoz-García (2013) analyze a setting of incomplete information. Both studies identify conditions under which the regulator protects a monopolistic market by setting an emission fee that deters entry. However, they consider technology as given. Our paper is not only concerned about the role of emission

\[\text{Mason and Swanson (2002) investigate a model in which the incumbent possesses patents and faces the possibility of entry under a MAC-PSB regulation. They show that a patent-holding incumbent can take advantage of such regulation to deter entry.}\]
fees hindering competition, but also examines firms' technology choices by considering that there is a green technology available to both the incumbent and the entrant. This approach allows us to identify cases in which the regulator sets emission fees that do not support entry deterrence and promote the acquisition of green technology.

The paper is organized as follows. Section 2 describes the model and the structure of the game; section 3 examines the equilibrium of the game and section 4 investigates social welfare under different contexts; section 5 concludes and discusses extensions.

1.2 Model

Consider a market in which there is a monopolistic incumbent (firm 1) and a potential entrant (firm 2). Both firms produce a homogeneous good. The output level of firm $i$ is denoted as $q_i$, where $i = 1, 2$. The inverse demand function is assumed to be $p(Q) = a - bQ$, where $a, b > 0$ and $Q$ is the aggregate output level. If firm 2 decides to enter it must incur a strictly positive fixed entry cost, $F$. For simplicity assume that production is costless.

Two different types of technology are available for both firms: a dirty (D) and a green (G) technology. Each firm can be a “dirty” type or a “green” type based on its technology decision. We assume that firms currently have a dirty technology and, hence, if they adopt a green technology they must pay a fixed cost equal to $S \in \mathbb{R}_+$. Technologies differ in terms of their emissions, which are assumed to be proportional to output levels.\(^5\) In particular, if firm $i$ acquires

\(^5\) Porter and van der Linde (1995) demonstrate that environmental technologies basically have two forms: (1) the type of technology that deals with polluting emissions more efficiently and effectively and thus reduces compliance costs when regulation is imposed; and (2) the technological innovation that not only solves the environmental problem but also improves productivity. We here focus on the first form of technology.
a clean technology its total emission level is $E_i = \theta e q_i$, where $e \in (0, \infty^+)$ and $\theta \in (0, 1)$ describes the efficiency of the new technology in reducing emissions. Specifically, the green technology becomes more efficient with lower values of $\theta$, and it is completely free of pollution when $\theta = 0$. However, if firm $i$ keeps its dirty technology then $\theta = 0$ and $E_i = e q_i$.

Environmental damage, $Env$, is assumed to be a linear function of aggregate emissions, that is $Env = \delta \sum_{i=1,2} E_i$, where $\delta > 0$ captures the environmental deterioration.

The regulator sets a tax rate per unit of emission. In particular, it selects an emission fee $\tau$ that maximizes overall social welfare denoted as $W = PS + CS + T - Env$, where $PS$ and $CS$ are the producer and consumer surplus, respectively, and $T$ is the total tax revenue. Firms' technology choices are influenced by the emission fee. Hence, each firm faces the trade-off between the cost of the tax (which is higher when a firm uses the dirty technology) and the fixed investment in green technology. We solve a four-stage complete information game, in which the time structure is as follows:

- In the first period, the regulator sets an optimal tax.
- In the second period, the incumbent chooses its technology.
- In the third period, the potential entrant decides whether or not to enter and, if it enters, which technology to use.
- In the fourth period, if entry is deterred, the incumbent operates as a monopolist. If entry occurs, however, both firms play a Cournot game.

We derive the subgame-perfect Nash equilibrium. Specifically, in the following sections, we first investigate two different market structures and output levels in the fourth period, we then examine firm 2's decision over entry and technology in the third period. We also discuss the
incumbent's technology choice and, finally, we analyze the first period game by identifying the optimal emission fee as well as the resulting social welfare.

1.3 Subgame Perfect Nash Equilibrium

1.3.1 Fourth stage

Let us first examine the case in which the potential entrant stays out of the market.

1.3.1.1 No entry

If entry does not ensue, firm 1's equilibrium output level is denoted by $q_{1m}^j$, where superscript $m$ represents monopoly and $j = D, G$ is the firm's technology. Table 1-1 describes the equilibrium results for this case.

In order to guarantee that firm 1 produces strictly positive output levels the emission fee must be $\tau < \frac{a}{e}$ if it keeps its dirty technology, and $\tau < \frac{a}{\theta e}$ if firm 1 acquires a green technology.

Note that we consider a nonnegative emission tax all through the paper and thus assume $\tau \geq 0$. It is apparent that imposing an emission tax reduces output levels and profits. However, a green monopolist produces more units than a dirty one and its profits depend on the characteristics of the clean technology $(\theta, S)$.

1.3.1.2 Entry

Let $q_{i}^{d, jk}$ denote the equilibrium output level of firm $i$ when both firms compete. The superscript $d$ denotes a duopoly market and the superscript $jk$ represents the case in which firm 1 (incumbent) chooses technology $j$ and firm 2 (entrant) decides to use technology $k$, where $j, k = \{D, G\}$. Four possible cases can arise $(D, D), (D, G), (G, D)$ and $(G, G)$, in which the first (second)
term denotes the technology choice of firm 1 (firm 2, respectively). We separately analyze two groups according to the technology acquired by firm 1: \([(D, D), (G, G)]\) and \([(G, D), (G, G)]\).

Equilibrium results for the case in which firm 1 uses a dirty technology are presented in Table 1-2, where the left-hand column analyzes the case in which firm 2 keeps its dirty technology, while in the right-hand column it adopts a clean technology.

Table 1-2 shows that the effects of the emission tax on output levels and profits depend on the entrant's technology. While firms produce the same output level when they both use a dirty technology, the entrant's profit is lower than that for the incumbent since it has to incur a fixed entry cost, \(F\). In contrast, if firm 2 acquires a green technology, its output level is higher than that of the incumbent. In addition, if the emission fee increases, the incumbent's output level decreases since \(\frac{dq_{1}^{d,G}}{d\tau} < 0\). However, the effect of environmental taxes on firm 2's output depends on the emission-reducing efficiency of the clean technology, \(\theta\). In particular, when the clean technology is relatively effective eliminating pollution, i.e., \(\theta \leq \frac{1}{2}\), the entrant's output level is positively affected by the emission tax since \(\frac{dq_{2}^{d,G}}{d\tau} > 0\), but if \(\theta > \frac{1}{2}\) then firm 2's output decreases since \(\frac{dq_{2}^{d,G}}{d\tau} < 0\).

Let us now analyze the case in which firm 1 decides to acquire a green technology, i.e., \((G, D)\) and \((G, G)\). Table 1-3 presents the equilibrium results.

Similar intuitions to those in Table 1-2 apply when the incumbent is a green type. That is, if only one firm chooses a green technology (in this case firm 1) then its output level and profit increase in the emission fee when \(\theta\) is sufficiently low, i.e., \(\theta \leq \frac{1}{2}\). However, if both firms acquire a green technology that completely eliminates pollution, i.e., \(\theta = 0\), their profits coincide with
those in a duopoly market with zero marginal costs. But if the technology is partially clean, \( \theta > \frac{1}{2} \), then the emission fee reduces firms' profits whether or not firm 2 acquires green technology. Hence, if the alternative technology is not able to eliminate a relevant amount of pollution, regulation negatively affects profits, even in the case of a green duopoly market.

1.3.2 Third stage

In this stage of the game, firm 2 decides whether or not to enter and its technology type. Firm 2 enters if its profit is nonnegative. In addition, it acquires the technology that generates the highest profit given the emission fee, the incumbent's type, and the characteristics of green technology (\( \theta \) and \( S \)).

1.3.2.1 Firm 2's entry and technology decisions when firm 1 is dirty

Entry is profitable if the net benefit from adopting a type of technology is weakly positive, i.e., \( \max \{ \pi_{2,DD}^d, \pi_{2,DG}^d \} \geq 0 \). In addition, the entrant decides to acquire a green technology if tax savings exceed the cost of the new technology. Hence, firm 2 joins the market and becomes a green type obtaining profits

\[
\pi_{2,DG}^d = \frac{(a-2\tau\theta e + \tau e)^2}{9b} - (F + S),
\]

which are positive if the entry cost satisfies \( F \in (0, \bar{F}_{DG}] \), where \( \bar{F}_{DG} = \frac{(a-2\tau\theta e + \tau e)^2}{9b} - S \). In contrast, if firm 2 enters and keeps its dirty technology, it receives profits

\[
\pi_{2,DD}^d = \frac{(a-\tau e)^2}{9b} - F,
\]

which are positive if \( F \leq \bar{F}_{DD} = \frac{(a-\tau e)^2}{9b} \). Lemma 1 summarizes firm 2's decisions when facing a dirty incumbent.
Lemma 1. When firm 1 is a dirty type and $\tau < \frac{a}{(2-\theta)e}$, firm 2 enters and keeps its dirty technology if entry and technology costs are $F \leq \bar{F}^{DD}$ and $S > \hat{S} \equiv \frac{4\tau\theta(1-\theta)(a-\tau e)}{9b}$, respectively. However, firm 2 adopts the green technology if $F \leq \bar{F}^{DG}$ and $S \leq \hat{S}$. Finally, if $F > \max\{\bar{F}^{DD}, \bar{F}^{DG}\}$, firm 2 does not enter.

Hence, firm 2 enters and acquires a green technology when entry and technology costs are sufficiently low. However, if the clean technology is expensive, the entrant prefers to compete using its dirty technology. We next examine whether the emission fee can affect the market structure by influencing the cutoff of entry costs.

Lemma 2. When firm 1 keeps its dirty technology, an increase in emission taxes facilitates entry, $\frac{d\bar{F}^{DG}}{d\tau} \geq 0$, if firm 2 acquires a relatively efficient green technology, i.e., $\theta \in (0, \frac{1}{2}]$. Otherwise, raising emission taxes could deter entry.

The above lemma indicates that strict emission fees accompanied by a green technology that is sufficiently effective eliminating pollution enlarge the set of entry costs for which firm 2 chooses to join the market and to acquire such technology. However, if the clean technology does not significantly ameliorate pollution, or if firm 2 keeps its dirty technology, high emission fees are likely to deter entry.

1.3.2.2 Firm 2's entry and technology decisions when firm 1 is green

We now analyze firm 2's entry and technology choices when firm 1 adopts a green technology. Similar to the previous discussion, firm 2 decides to enter if profits satisfy

---

6 Note that an emission fee $\tau < \frac{a}{(2-\theta)e}$ guarantees strictly positive output levels.
max\{\pi^d_{2,GD}, \pi^d_{2,GG}\} \geq 0. Firm 2 enters the market and adopts a green technology obtaining profits

\[ \pi^d_{2,GG} = \frac{(a-\tau e)^2}{9b} - (F + S) \geq 0, \]

which require an entry cost \( F \in (0, \bar{F}^GG] \) and \( \bar{F}^GG = \frac{(a-\tau e)^2}{9b} - S \). If, in contrast, firm 2 keeps its dirty technology, its profits are

\[ \pi^d_{2,GD} = \frac{(a+\tau e-2\tau e)^2}{9b} - F \]

which are positive if \( F \leq \bar{F}^GD \equiv \frac{(a+\tau e-2\tau e)^2}{9b} \). The following lemma summarizes our findings.

**Lemma 3.** When firm 1 is a green type and \( \tau < \frac{a}{(2-\theta)e} \), firm 2 enters and keeps its dirty technology if entry and technology costs are \( F \leq \bar{F}^GD \) and \( S > \bar{S} \equiv \frac{4\tau e(1-\theta)(a-\tau e)}{9b} \), respectively. However, firm 2 adopts the green technology if \( F \leq \bar{F}^GG \) and \( S \leq \bar{S} \). Finally, if \( F > \max\{\bar{F}^GD, \bar{F}^GG\} \), firm 2 does not enter.

Therefore, a relatively clean duopoly market structure arises if the cost of the green technology is sufficiently low. Note that firm 2 stays out of the market under larger conditions when it faces a green than a dirty incumbent since \( \bar{F}^DD > \bar{F}^GD \) and \( \bar{F}^DG > \bar{F}^GG \). We next discuss the effect of the emission fee on the entry cost cutoffs.

**Lemma 4.** When firm 1 is a green type, an increase in emission taxes raises entry barriers, i.e., \( \frac{d\bar{F}^GK}{d\tau} < 0 \), regardless of the technology \( K = \{D, G\} \) that firm 2 chooses.

Hence, entry is more likely to be deterred when a green incumbent operates in the market and strict emission fees are in place. If we compare the admissible technology costs for an entrant facing a dirty, \( \hat{S} \), and a green incumbent, \( \bar{S} \), we observe that \( \hat{S} > \bar{S} \). Therefore, the
entrant's decision on technology adoption is also affected by the incumbent's type. That is, the entrant is more willing to pay the fixed cost of acquiring a green technology when the incumbent is dirty than when it is green, since $\hat{S} > \tilde{S}$. Finally, we next investigate the impact of the emission fee on potential entrant's technology adoption.

**Lemma 5.** When firm 1 is a dirty type, firm 2 responds to an increase in emission taxes by adopting a green technology if and only if $\theta \in (0, \frac{2}{3}]$. However, when firm 1 is a green type, firm 2 responds to an increase in emission fees by becoming green if the fee is lower than $\frac{e}{2a}$, independent of $\theta$.

In this case we observe that higher emission fees are more likely to induce the acquisition of green technology by an entrant facing a dirty incumbent if such a technology is able to effectively eliminate pollution (low values of $\theta$). However, if the technology is in a preliminary stage and, as a consequence, its capacity to capture emissions is unsatisfactory then higher emission fees do not necessarily induce the acquisition of this type of technology. In addition, when the incumbent is green, a more stringent environmental tax makes the adoption of green technology more attractive, independent of its capacity to eliminate pollution if the emission fee is lower than $\tau < \frac{e}{2a}$.

1.3.3 Second stage

In the second stage, firm 1 now decides whether or not to acquire a green technology. It is obvious that, without environmental regulation, firms have no incentives to invest in a clean technology. However, it is meaningful to investigate the incumbent's technology choices with regulation and entry threats.
In the absence of entry threats, firm 1 chooses the technology associated with higher profits. In particular, it adopts the clean technology if \( S \leq \bar{S} \), where \( \bar{S} \equiv \frac{\tau e(1-\theta)(2a-\tau e-\tau \theta e)}{4b} \). Since we consider a complete information game, the incumbent can fully anticipate the entrant's responses in the third and the fourth stage. Hence, the incumbent can maintain its monopolistic power acquiring the green technology if \( S \leq \bar{S} \).

If, however, firm 1 foresees that entry can occur then its decision on whether to become a green type coincides with that of the entrant since both firms are symmetric except by the fact that firm 2 has to incur a fixed entry cost \( F \). Specifically, when the incumbent anticipates that the entrant keeps its dirty technology, then it acquires a green technology if \( S \leq \tilde{S} \). In contrast, if it anticipates that the entrant will adopt the green technology, firm 1 also becomes a green type if \( S \leq \bar{S} \). Lemma 6 summarizes the above discussions.

**Lemma 6.** Firm 1's technology choices can be summarized as follows:

- **No entry:** when \( \tau < \frac{a}{e} \) and entry does not occur, \( F > \max\{\bar{F}^{GD}, \bar{F}^{GG}\} \), firm 1 becomes a green type if \( S \leq \bar{S} \);

- **Entry:** when \( \tau < \frac{a}{(2-\theta)e} \) and firm 2 enters keeping its dirty technology, \( F < \bar{F}^{GD} \), firm 1 becomes a green type if \( S \leq \tilde{S} \);

- **Entry:** when \( \tau < \frac{a}{(2-\theta)e} \) and firm 2 enters adopting a green technology, \( F < \bar{F}^{GG} \), firm 1 also becomes a green type if \( S \leq \bar{S} \).

Specifically, an incumbent that does not face the threat of entry acquires a green technology if the emission fee and the technology cost are relatively low. In addition, if the clean technology is effective reducing emission (\( \theta \to 0 \)), then the set of admissible values of \( \bar{S} \) expands and, hence, the incumbent is more likely to acquire the technology. Notice that the effects of
imposing emission fees on firm 1's technology adoption follow the same intuitions discussed in Lemma 5. Let us now examine the impact of entry threats on firm 1's technology choices.

**Lemma 7.** In the absence of entry threats firm 1 acquires a green technology under larger conditions than when it faces a potential entrant if \( \tau < \frac{a}{(9-7\theta)e} \). However, if the emission fee satisfies \( \frac{a}{(9-7\theta)e} \leq \tau < \frac{a}{(2-\theta)e} \), firm 1 acquires the green technology under more restrictive conditions in the absence of entry threats than when it faces a potential dirty entrant.

Hence, if the emission fee is relatively low, the incumbent acquires green technology more often when it does not face the threat of entry than otherwise. However, if the emission fee is sufficiently stringent and firm 1 faces the threat of entry of a dirty firm, the incumbent acquires the green technology under larger conditions than when entry threats are absent.

1.3.4 First Stage

1.3.4.1 Regulator's emission tax choice if firm 1 is dirty

As discussed in lemma 6, the incumbent becomes a dirty type if the cost of green technology is sufficiently high. Specifically, when there is no entry \( S > \bar{S}(\tau^{m,D}) \) evaluated in the optimal emission fee, and when entry ensues \( S > \bar{S}(\tau^{d,DD}) \) and \( S > \bar{S}(\tau^{d,DG}) \) for the case of a dirty and a green entrant, respectively. The following proposition identifies the optimal environmental tax.

**Proposition 1.** The optimal emission fee for a dirty incumbent is

- **No entry:** \( \tau^{m,D} = 2\delta - \frac{a}{e} \) if \( \frac{a}{2e} \leq \delta < \frac{a}{e} \) and firm 2 stays out since \( F > \max\{ P^{DD}(\tau^{m,D}), P^{DG}(\tau^{m,D}) \} \).
Entry \((D, D)\): \(\tau^{d, DD} = \frac{3}{2} \delta - \frac{a}{2e} \) if \(\frac{a}{3e} \leq \delta < \frac{a}{e}\) and firm 2 enters since \(F \leq \bar{F}^{DD}(\tau^{d, DD})\), and does not adopt the green technology, i.e., \(S > \bar{S}(\tau^{d, DD})\).

Entry \((D, G)\): \(\tau^{d, DG} = \frac{6(\theta^2 - \theta + 1)}{(1+\theta)^2} \delta - \frac{a}{(1+\theta)e} \) if \(\delta \leq \bar{\delta}\), where \(\bar{\delta} = \frac{a(1+\theta)}{6e(\theta^2 - \theta + 1)}\) and \(F = \bar{F}^{DD}(\tau^{d, DG})\), but adopts the green technology, i.e., \(S \leq \bar{S}(\tau^{d, DG})\).

The optimal emission fee in the case of a dirty monopolist is lower than that in the case of a dirty duopoly, a result in line of Buchanan (1969), for any environmental damage between \(\frac{a}{2e} \leq \delta < \frac{a}{e}\), and also lower than the emission fee under a partially dirty duopoly, \((D, G)\), for the environmental damage \(\delta \in [\frac{a}{2e}, \bar{\delta}]\).\(^7\) In addition, a partially dirty duopoly faces more stringent emission fees than a completely dirty duopoly if the environmental damage is between \(\frac{a(1+\theta)}{9e(1-\theta)} \leq \delta < \bar{\delta}\).\(^8\)

1.3.4.2 Regulator's emission tax choice if firm 1 is green

We next examine the case in which the incumbent adopts a green technology. Lemma 6 discusses the range of \(S\) for which the incumbent becomes a green type. That is, the incumbent adopts a green technology when entry does not ensue if \(S \leq \bar{S}(\tau^{m, G})\). In addition, if a green (dirty) entrant joins the market, the incumbent acquires green technology if \(S \leq \bar{S}(\tau^{d, GG})\) (\(S \leq \bar{S}(\tau^{d, GG})\)).\(^\gamma\)

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\(^7\) In order to compare the optimal emission fee in cases \((D)\) and \((D, G)\) we first need to identify a range of environmental damage for which these two cases coexist. Specifically, emission fees are supported for any value of the environmental damage between \(\frac{a}{2e} \leq \delta < \bar{\delta}\) since \(\delta < \frac{a}{2e}\) and \(\bar{\delta} < \frac{a}{e}\).

\(^8\) Cases \((D, D)\) and \((D, G)\) coexist when \(\frac{a}{3e} \leq \delta < \bar{\delta}\) (or \(\bar{\delta} < \delta < \bar{\delta}\)) and \(\theta e \in (0, \frac{1}{2})\) (or \(\theta e \in (\frac{1}{2}, 1)\)).
\( \hat{S}(\tau^{d,GD}) \), respectively). The optimal environmental taxes for this case are identified in the following proposition.

**Proposition 2.** The optimal emission fee for a green incumbent is

- No entry: \( \tau^{m,G} = 2\delta - \frac{a}{\theta e} \) if \( \frac{a}{2\theta e} \leq \delta < \frac{a}{\theta e} \) and firm 2 stays out since \( F > \max\{F^{GD}(\tau^{m,G}), F^{GG}(\tau^{m,G})\} \).

- Entry \((G,G)\): \( \tau^{d,GG} = \frac{3}{2} \delta - \frac{a}{3\theta e} \) if \( \frac{a}{3\theta e} \leq \delta < \frac{a}{\theta e} \) and firm 2 enters since \( F \leq \hat{F}(\tau^{d,GG}) \), and adopts the green technology, given that \( S \leq \hat{S}(\tau^{d,GG}) \).

- Entry \((G,D)\): \( \tau^{d,GD} = \frac{6\theta^2-\theta+1}{(1+\theta)^2} \delta - \frac{a}{(1+\theta)e} \) if \( \delta \leq \delta < \overline{\delta} \) and firm 2 enters since \( F \leq \hat{F}(\tau^{d,GD}) \), but keeps its dirty technology, given that, \( S > \hat{S}(\tau^{d,GD}) \).

Let us compare emission fees among different market structures. First, the regulator chooses a lower optimal emission fee in the case of a green monopolist than in the case of a completely (or partially) green duopoly \( ((G,G)\) and \( (G,D)\)). This occurs if the clean technology is not sufficiently efficient eliminating pollution, \( \theta > \frac{1}{2} \), and the environmental damage is between \( \delta \in [\frac{a}{2\theta e}, \delta] \).\(^9\) Second, the optimal emission fee in case \( (G,D) \) is higher than that in case \( (G,G) \) when the green technology is inefficient and the environmental damage is between \( \delta \in [\frac{a}{3\theta e}, \overline{\delta}] \). Finally, the optimal emission tax of a green monopoly is lower than that of a dirty monopoly for any environmental damage \( \frac{a}{2\theta e} \leq \delta < \frac{a}{\theta e} \).

For comparison purposes, we next present Figure 1-1.\(^{10}\) The graphical representation shows the ranking previously discussed for the admissible set of parameter values. Specifically,\(^9\) Cases \((G,G)\) and \((G,D)\) cannot coexist if \( \theta \leq \frac{1}{2} \) since \( \delta \leq \frac{a}{3\theta e} \). When \( \theta > \frac{1}{2} \), the admissible range of \( \delta \) is \( \frac{a}{3\theta e} \leq \delta < \overline{\delta} \) since \( \delta < \frac{a}{3\theta e} \) and \( \overline{\delta} < \frac{a}{\theta e} \). Thus, the admissible range of \( \delta \) for cases \((G),(G,D)\), and \((G,G)\) is \( \delta \in [\frac{a}{2\theta e}, \overline{\delta}] \).

\(^{10}\) For presentation purposes we assume \( \theta = \frac{1}{2} \).
it indicates that the regulation is not urgent when the environmental damage is sufficiently low, that is for any value of $\delta < \frac{a}{3e}$, since in this case the emission fee is zero. For a relatively low environmental damage, $\frac{a}{3e} \leq \delta < \frac{2a}{3e}$, the partially clean market faces the highest emission fee, $\tau^{d,DG}$. However, regulation for a market consisting of two dirty firms, $\tau^{d,DD}$, becomes more stringent under a medium level of environmental damage $\delta \in \left[\frac{2a}{3e}, \frac{a}{e}\right)$ relative to the case of a dirty monopoly, i.e., $\tau^{d,DD} > \tau^{m,D}$. Finally, when emissions have grievous consequences, $\frac{a}{e} \leq \delta < \frac{2a}{e}$, only a green market is supported. In this case, the regulator imposes the highest emission fee on a green duopoly that has a partially clean technology, $\theta = \frac{1}{2}$, since it pollutes more than a green monopoly.

1.4 Welfare Analysis

In order to facilitate our comparisons and make them tractable, we consider a green technology with moderate efficiency level, i.e., $\frac{1}{2}$. This assumption simplifies social welfare analysis while still provides useful intuitions.

**Proposition 3.** The social welfare when firm 1 responds to emission fees by keeping its dirty technology is,

- **No entry:** $W^{m,D} = \frac{(a-e\delta)^2}{2b}$
- **Entry** $(D, D)$: $W^{d,DD} = \frac{(a-e\delta)^2}{2b} - F = W^{m,D} - F$
- **Entry** $(D, G)$: $W^{d,DG} = \frac{3a^2 - 5ae\delta + 3(e\delta)^2}{6b} - (F + S) = W^{m,D} + \frac{ae\delta}{6b} - (F + S)$

Hence, for a given environmental damage $\delta \in \left[\frac{a}{2e}, \frac{a}{e}\right)$, optimal emission fees allow the existence of two market structures: a dirty monopoly $(D)$ and a dirty duopoly $(D, D)$. Our results
indicate that a dirty monopoly generates a higher social welfare than a dirty duopoly. Intuitively, a dirty monopoly and duopoly generate the same social welfare when entry costs are zero. This is due to the fact that emission fees are higher when two dirty firms operate in the market than when there is only one dirty firm. However, if the entry cost is strictly positive, it is socially desirable having a dirty monopoly, since this cost reduces social welfare. Therefore, in this context the regulator could raise entry costs, $F$, to obtain a welfare improvement since outcome $(D)$ occurs under a higher range of $F$ than outcome $(D, D)$.\footnote{Specifically, the case (D) requires $F > F^{*D}$, while the case $(D, D)$ requires $F \leq F^{*DD}$. Notice that $F^{*D} > F^{*DD}$. In addition, $S > S^{*DD}$ supports both cases in terms of the fixed costs for green technology. See the proof of Proposition 3 in the appendix.} In addition, social welfare in outcome $(D, G)$ is always higher than $(D, D)$ for all admissible environmental damages, i.e., $\delta \in \left[\frac{a}{3e}, \frac{2a}{3e}\right]$, for which both emission fees are supported.\footnote{Notice that the condition of fixed entry costs $F \leq F^{*DG}$ supports both case $(D, D)$ and $(D, G)$. Moreover, the requirements for the fixed costs of green technology are compatible when $S^{*DD} < S \leq S^{*DG}$. See the proof of Proposition 3 in the appendix.} In this case, the entry of a green firm is socially desirable. Finally, the social welfare of a partially green duopoly is higher than a dirty monopoly only when both fixed costs ($F$ and $S$) are sufficiently low, that is, $F + S < \frac{ae\delta}{6b}$, and there is a moderate range of the environmental damage $\delta \in \left[\frac{a}{2e}, \frac{2a}{3e}\right]$. Under this context and considering that optimal emission fees cannot be modified, the regulator could help the emergence of $(D, G)$
by reducing fix entry costs or partially subsidizing the clean technology.\(^{13}\) Otherwise, the entry of a green competitor is socially undesirable.

Proposition 4 describes social welfare when the incumbent acquires a green technology.

**Proposition 4.** The social welfare when firm 1 responds to emission fees by acquiring the green technology is,

- **No entry:** \(W^{m,G} = \frac{(2a-e\delta)^2}{8b} - S\)
- **Entry \((G,G)\):** \(W^{d,GG} = \frac{(2a-e\delta)^2}{8b} - (F + 2S) = W^{m,G} - (F + S)\)
- **Entry \((G,D)\):** \(W^{d,GD} = W^{d,DG}\)

Comparing the above welfare levels, we observe that the social welfare under no entry is always higher than that when entry ensues and firm 2 is also a green type for \(\frac{a}{e} \leq \delta < \frac{2a}{e}\).

However, the fixed entry costs that supports a green monopolistic market is always higher than that supporting the green duopolistic market.\(^{14}\) Since optimal emission fees cannot be modified in order to guarantee the emergence of a particular market structure, the regulator could promote, for instance, the existence of a green monopoly market throughout entry costs. That is, making entry more expensive to potential entrants induces the emergence of a green monopoly market given the environmental damage, emissions fees and the cost of technology. Moreover, notice that when the clean technology is moderately efficient, a partially green duopolistic market with

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\(^{13}\) Cases \((D)\) and \((D,G)\) requires \(\max\{S^\text{aD}, S^\text{aDG}\} < S \leq \hat{S}^\text{aDG}\). However, the case \((D)\) always requires higher fixed entry costs since \(\hat{F}^\text{aD} > \hat{F}^{aDG}\). See the proof of Proposition 3 in the appendix.

\(^{14}\) Cases \((G)\) requires \(F > F^\text{aG}\), while the case \((G,G)\) requires \(F \leq F^{aGG}\). Notice that \(\hat{F}^aG > F^{aGG}\). Moreover, the condition of fixed costs for green technology is compatible when \(S \leq \min\{\hat{S}^xG, S^{aGG}\}\). See proof of Proposition 4 in the appendix.
a green incumbent, \((G, D)\), occurs for a relatively low range of the environmental damage. However, a green monopoly or green duopoly are supported only under sufficiently high environmental damage, thus limiting our comparisons.\(^{15}\) We next examine under which conditions the social welfare in the case of a green incumbent is higher than that when the incumbent has a dirty technology.

**Lemma 8.** Social welfare when the incumbent is a green type is higher than when it is dirty under the following conditions:

- **Entry:** \(W^{d,GG} > W^{d,DD}\) for \(\delta \in \left[\frac{2a}{3e}, \frac{a}{e}\right]\), if \(S < \frac{(4a-3e\delta)e\delta}{16b}\).
- **Entry:** \(W^{d,GD} > W^{d,DD}\) for \(\delta \in \left[\frac{a}{3e}, \frac{2a}{3e}\right]\).

Hence, a higher social welfare is obtained under a clean duopoly market, \((G, G)\), than a completely dirty duopoly, \((D, D)\), if the environmental damage is sufficiently high and the clean technology has a low cost. This result suggests that a green market is socially preferred when pollution has disastrous consequences on the environment and, most importantly, an inexpensive moderately clean technology, \(\theta = \frac{1}{2}\), is available to firms. In this case, it is socially optimal to induce the incumbent or both firms to adopt the environmentally friendly technology, if entry is not deterred. Therefore, any complementary policy that expands the set of admissible values of the cost of clean technology, \(S\), would favor the emergence of this type of market. However, if the environmental damage is low, a partially dirty duopoly in which only the incumbent adopts the green technology is socially preferred than two dirty firms in the market.

### 1.5 Conclusion

\(^{15}\) See proof of Proposition 4 in the appendix.
This paper examines under which conditions an emission tax can be used to make firms to adopt a green technology and, also, to deter entry. Our results show that a stringent emission fee does not necessarily induce the entrant to acquire a green technology. The entrant's decision about becoming a green type depends on the efficiency of the clean technology reducing emissions and its cost. In addition, if the entrant has decided to join the market and emission fees are sufficiently high, this firm is more likely to adopt a green technology when there is a dirty incumbent operating in the market than otherwise. Moreover, we find that entry is more plausible to be deterred by a green incumbent when there is a strict emission fee in place.

We also provide comparisons of optimal environmental taxes and social welfare under different contexts. In particular, when the environmental damage is sufficiently low, a partially green duopoly is socially desirable than a dirty duopoly. However, when the environmental damage is relatively high and the green technology cost is sufficiently low, a green duopoly is welfare improving than a dirty duopoly. Our results suggest that the regulator should evaluate emission fees and, in particular, their effects on the market structure and the adoption of environmentally friendly technologies, depending on how severe the environmental damage is. Hence, if the environmental damage is relatively low, emission fees that support entry of a green firm are socially preferred than an environmental tax that hinders entry. However, a severe environmental damage calls for policies that promote a clean monopoly or duopoly market.

Our paper can be extended in different ways. For instance, we assume that the environmentally friendly technology does not affect marginal production costs. However, it may be interesting to analyze a setting in which the green technology not only partially reduces pollution but is also able to modify marginal costs. Moreover, our model does not allow the regulator to be uninformed about the cost of clean technology. However, we should expect to
observe different equilibrium results under a context of incomplete information. Finally, it would be worthwhile to analyze a different game structure in which the incumbent produces in the second and fourth stage of the game and the regulator is able to adjust its regulation if entry ensues.
1.6 Appendix

1.6.1 Strictly Positive Output Levels

Let us analyze the case \((D, G)\). Firm 1’s output level is strictly positive, \(q_{1DG}^d > 0\), if
\[ a + \tau \theta e - 2 \tau e > 0 \]
or
\[ \tau < \frac{a}{(2\theta - 1)e} \text{ where } 2 - \theta > 0 \text{ since } \theta \in (0,1) \]
and firm 2’s output level is strictly positive, \(q_{2DG}^d > 0\), if \(a - 2\tau \theta e + \tau e > 0\) or
\[ \tau < \frac{a}{(2\theta - 1)e} \text{ where } 2\theta - 1 > 0 \text{ if } \theta > \frac{1}{2} \]
However, if \(0 < \theta \leq \frac{1}{2}\), any non-negative emission tax ensures \(q_{2DG}^d > 0\). It is immediate to check that \(\frac{a}{(2\theta - 1)e} < \frac{a}{(2\theta - 1)e}\). Hence, for the case \((D, G)\), the emission tax has to satisfy \(\tau < \frac{a}{(2\theta - 1)e}\) for all \(\theta\). Note that the same conditions are required for the case \((G, D)\).

1.6.2 Proof of Lemma 1

If \(\tau < \frac{a}{(2\theta - 1)e}\) both firms produce strictly positive output levels in cases \((D, D)\) and \((D, G)\).

Firm 2 has incentives to adopt a green technology, when facing a dirty incumbent, if
\[
\pi_{2DG}^d \geq \pi_{2DD}^d
\]
\[
\frac{(a-2\tau \theta e + \tau e)^2}{9b} - (F + S) \geq \frac{(a-\tau e)^2}{9b} - F
\]
\[
S \leq \frac{4\tau e (1-\theta)(a-\tau \theta e)}{9b} \equiv \hat{S}
\]
Hence, firm 2 chooses the green technology and enters if
\[
\pi_{2DG}^d = \frac{(a-2\tau \theta e + \tau e)^2}{9b} - (F + S) \geq 0
\]
\[
F \leq \frac{(a-2\tau \theta e + \tau e)^2}{9b} - S \equiv \bar{F}_{DG}
\]
However, firm 2 prefers the dirty technology if $S > \hat{S}$ and entry occurs if

$$\pi^d_{2,DD} = \frac{(a-\tau e)^2}{9b} - F \geq 0$$

$$F \leq \frac{(a-\tau e)^2}{9b} \equiv \bar{F}_{DD}$$

1.6.3 Proof of Lemma 2

We now check the effect of emission taxes on the entry cost cutoffs.

Case $(D,G)$. $\frac{dF_{DG}}{d\tau} = \frac{2e(a-2\tau\theta e+\tau e)}{9b} (1 - 2\theta)$. Since $\frac{2e(a-2\tau\theta e+\tau e)}{9b} > 0$, then $\frac{dF_{DG}}{d\tau} \geq 0$ if $1 - 2\theta \geq 0$, which is equivalent to $0 < \theta \leq \frac{1}{2}$. However, $\frac{dF_{DG}}{d\tau} < 0$ if $\frac{1}{2} < \theta \leq 1$.

Case $(D,D)$. $\frac{dF_{DD}}{d\tau} = \frac{-2e(a-\tau e)}{9b} < 0$ since $\frac{2e(a-\tau e)}{9b} > 0$.

1.6.4 Proof of Lemma 3

Considering $\tau < \frac{a}{(2-\theta)e}$ and given that the incumbent is a green type, the entrant also chooses the clean technology if

$$\pi^c_{2,GG} \geq \pi^c_{2,GD}$$

$$\frac{(a-\tau\theta e)^2}{9b} - (F + S) \geq \frac{(a+\tau\theta e-2\tau e)^2}{9b} - F$$

$$S \leq \frac{4\tau e(1-\theta)(a-\tau e)}{9b} \equiv \tilde{S}$$

Hence, firm 2 chooses the green technology and enters the market if

$$\pi^d_{2,GG} = \frac{(a-\tau\theta e)^2}{9b} - (F + S) \geq 0$$

$$F \leq \frac{(a-\tau\theta e)^2}{9b} - S \equiv \bar{F}_{GG}$$

However, firm 2 prefers the dirty technology if $S > \hat{S}$. Therefore, entry occurs if
\[ \pi_2^{d,GD} = \frac{(a + \tau e - 2\tau e)^2}{9b} - F \geq 0 \]

\[ F \leq \frac{(a + \tau e - 2\tau e)^2}{9b} \equiv \bar{F}^{GD} \]

1.6.5 Proof of Lemma 4

Case \((G, D)\). \(\frac{d\bar{F}^{GD}}{d\tau} = \frac{2e(a + \tau e - 2\tau e)}{9b} (\theta - 2)\). Since \(\frac{2e(a + \tau e - 2\tau e)}{9b} > 0\) and \(\theta - 2 < 0\).

Similarly, it is straightforward to show that \(\frac{d\bar{F}^{GG}}{d\tau} < 0\).

1.6.6 Proof of Lemma 5

Let us first analyze the case in which the incumbent keeps its dirty technology. Then

\[ \frac{d\bar{S}}{d\tau} = \frac{4e(1-\theta)}{9b} (a - 2\tau \theta e) \] is positive if \(a - 2\tau \theta e \geq 0\) which is equivalent to \(\tau \leq \frac{a}{2\theta e}\). In addition, comparing \(\frac{a}{2\theta e}\) with the cutoff for strictly positive outputs, \(\frac{a}{(2-\theta)e}\), we obtain \(\frac{a}{2\theta e} \geq \frac{a}{(2-\theta)e}\) if \(\theta \in (0, \frac{2}{3}]\). Hence, when \(0 < \theta \leq \frac{2}{3}\) we have that \(\frac{d\bar{S}}{d\tau} \geq 0\) for any \(\tau\) that supports strictly positive outputs. However, if \(\frac{2}{3} < \theta < 1\), the minimum \(\min \left\{ \frac{a}{2\theta e}, \frac{a}{(2-\theta)e} \right\} = \frac{a}{2\theta e}\) and thus \(\frac{d\bar{S}}{d\tau} \geq 0\) if \(\tau \leq \frac{a}{2\theta e}\), whereas

\[ \frac{d\bar{S}}{d\tau} < 0 \] if \(\frac{a}{2\theta e} < \tau < \frac{a}{(2-\theta)e}\).

If the incumbent is a green type, we obtain that \(\frac{d\bar{S}}{d\tau} = \frac{4e(1-\theta)}{9b} (a - 2\tau e) \geq 0\) if \(a - 2\tau e \geq 0\), i.e., \(\tau \leq \frac{a}{2e}\). Since \(\frac{a}{2e} \leq \frac{a}{(2-\theta)e}\), hence, \(\frac{d\bar{S}}{d\tau} \geq 0\) if \(\tau \leq \frac{a}{2e}\), regardless of the efficiency of the green technology, whereas \(\frac{d\bar{S}}{d\tau} < 0\) for \(\frac{a}{2e} < \tau < \frac{a}{(2-\theta)e}\).

1.6.7 Proof of Lemma 6

A monopolist has incentives to adopt a green technology if
In addition, firm 1 becomes green if $S \leq \tilde{S}$, when it anticipates that firm 2 enters and acquires green technology. However, firm 1 adopts the clean technology if $S \leq \check{S}$, when knowing entry can occur and firm 2 is a dirty type.

1.6.8 Proof of Lemma 7

We require that firms produce strictly positive output levels for cases $(D), (G), (D, D)$ and $(G, D)$ in order to compare $\bar{S}, \tilde{S}, \hat{S}$, which is satisfied by $\tau \leq \frac{a}{(2-\theta)e}$. Let us first analyze $\bar{S}$ and $\tilde{S}$.

$$\bar{S} - \tilde{S} = \frac{\tau e (1-\theta)}{36b} (2a - 9\tau \theta e + 7\tau e) > 0$$

which is positive if $2a - 9\tau \theta e + 7\tau e > 0$, or equivalently $\tau < \frac{2a}{(9\theta - 7)e}$. If $9\theta - 7 < 0$ then any $\tau < \frac{a}{(2-\theta)e}$ guarantees that $\bar{S} > \tilde{S}$. If $9\theta - 7 > 0$ then $\tau < \frac{2a}{(9\theta - 7)e}$. However, since $\frac{2a}{(9\theta - 7)e} > \frac{a}{(2-\theta)e}$ then $\bar{S} > \tilde{S}$ for all admissible values of $\tau$. Now we compare $\bar{S}$ and $\hat{S}$.

$$\bar{S} - \hat{S} = \frac{\tau e (1-\theta)}{36b} (2a + 7\tau \theta e - 9\tau e) > 0$$

which is positive if $2a + 7\tau \theta e - 9\tau e > 0$, or equivalently $\tau < \frac{2a}{(9-7\theta)e}$. In addition, $\frac{2a}{(9-7\theta)e} - \frac{a}{(2-\theta)e} = \frac{5a(\theta - 1)}{e(9-7\theta)(2-\theta)} < 0$ and thus $\frac{2a}{(9-7\theta)e} < \frac{a}{(2-\theta)e}$. Therefore, $\bar{S} > \hat{S}$ if $\tau < \frac{2a}{(9-7\theta)e}$, whereas $\bar{S} \leq \hat{S}$ if $\frac{2a}{(9-7\theta)e} \leq \tau < \frac{a}{(2-\theta)e}$.
1.6.9 Proof of Proposition 1

**No Entry.** If firm 2 stays out of the market, the regulator solves the following maximization problem,

\[ W^{m,D} = \pi_1^{m,D} + CS^{m,D} + e(\tau - \delta)q_1^{m,D} \]

In particular, \( \pi_1^{m,D} = \frac{(a-\tau e)^2}{4b} \), \( CS^{m,D} = \frac{(a-\tau e)^2}{8b} \), and \( q_1^{m,D} = \frac{a-\tau e}{2b} \). Then

\[ W^{m,D} = \frac{3(a-\tau e)^2}{8b} + \frac{e(\tau - \delta)(a-\tau e)}{2b}. \]

Hence, the optimal emission fee is \( \tau^{m,D} = 2\delta - \frac{a}{e} \) which is nonnegative if \( \delta \geq \frac{a}{2e} \). In addition, \( q_1^{m,D}(\tau^{m,D}) \) is strictly positive if \( \delta < \frac{a}{e} \) hence, combining both conditions we have \( \frac{a}{2e} \leq \delta < \frac{a}{e} \). Moreover, given lemma 1, firm 2 does not enter if \( F > \max\{\bar{F}^{DD}, \bar{F}^{DG}\} \). Substituting \( \tau^{m,D} \) into \( \bar{F}^{DD} \) and \( \bar{F}^{DG} \), we obtain \( F > \max\left\{\frac{4(a-\delta e)^2}{9b}, \frac{4(e\delta - 2\theta e\delta + a\theta)^2}{9b} - S\right\} \). Finally, firm 1 does not adopt the green technology when \( S > \bar{S}(\tau^{m,D}) = \frac{(1-\theta)(2e\delta - a)(3a - 2e\delta + a\theta - 2\theta e\delta)}{4b} \).

\[ \delta \]

Let us first analyze the case in which firm 2 also chooses to keep its dirty technology.

\[ W^{d,DD} = \pi_1^{d,DD} + \pi_2^{d,DD} + CS^{d,DD} + e(\tau - \delta)(q_1^{d,DD} + q_2^{d,DD}) \]

In particular, \( \pi_1^{d,DD} + \pi_2^{d,DD} = \frac{2(a-\tau e)^2}{9b} - F \), \( CS^{d,DD} = \frac{2(a-\tau e)^2}{9b} \) and \( q_1^{d,DD} + q_2^{d,DD} = \frac{2(a-\tau e)}{3b} \).

Then, social welfare function can be rewritten as

\[ W^{d,DD} = \frac{4(a-\tau e)^2}{9b} + \frac{2e(\tau - \delta)(a-\tau e)}{3b} - F \]

Hence the optimal environmental tax is \( \tau^{d,DD} = \frac{3\delta}{2} - \frac{a}{2e} \) which is positive if \( \delta \geq \frac{a}{3e} \). In addition, \( q_i^{d,DD}(\tau^{d,DD}) \) is positive if \( \delta < \frac{a}{e} \) hence, \( \frac{a}{3e} \leq \delta < \frac{a}{e} \). Moreover, according to lemma 1, firm 2 enters and keeps its dirty technology if \( F \leq \bar{F}^{DD}(\tau^{d,DD}) \) and \( S > \bar{S}(\tau^{d,DD}) \). Given the
optimal emission tax, $\frac{d}{dd}(\tau^d, DD) = \frac{(a-e\delta)^2}{4b}$ and $\dot{S}(\tau^d, DD) = \frac{(1-\theta)(3e\delta-a)(2a+a\theta-3\theta e\delta)}{9b}$. Finally, notice that firm 1 also keeps its dirty technology when $S > \dot{S}(\tau^d, DD)$.

However, if the entrant adopts the green technology the optimal fee solves,

$$W^d, DG = \pi_1^d, DG + \pi_2^d, DG + CS^d, DG + (\tau - \delta)\theta q_1^d, DG + (\tau - \delta)\theta q_2^d, DG$$

In particular, $\pi_1^d, DG + \pi_2^d, DG = \frac{(a+\theta e-2\theta e)^2}{9b} + \frac{(a-2\theta e+\theta e)^2}{9b} - (F + S)$, $CS^d, DG = \frac{(2a-\theta e-\theta e)^2}{18b}$,

$$q_1^d, DG = \frac{a+\theta e-2\theta e}{3b}, q_2^d, DG = \frac{a-2\theta e+\theta e}{3b}.$$ Then social welfare can be expressed as follows,

$$W^d, DG = \frac{(a+\theta e-2\theta e)^2}{9b} + \frac{(a-2\theta e+\theta e)^2}{9b} + \frac{(2a-\theta e-\theta e)^2}{18b} + \frac{e(\tau-\delta)(a+\theta e-2\theta e)}{3b}$$

$$+ \frac{\theta e(\tau-\delta)(a-2\theta e+\theta e)}{3b} - (F + S).$$

Therefore, the optimal emission fee is $\tau^d, DG = \frac{6(\theta^2-\theta+1)}{(1+\theta)^2} \delta - \frac{a}{(1+\theta)e}$, which is nonnegative if $\delta \geq \frac{a(1+\theta)}{6e(\theta^2-\theta+1)} \equiv \delta$. In addition, $q_1^d, DG (\tau^d, DG)$ and $q_2^d, DG (\tau^d, DG)$ are strictly positive when $\delta < \frac{a(1+\theta)}{2e(2-\theta)(\theta^2-\theta+1)} \equiv \delta$. Notice that $\delta < \delta$ is always satisfied.

From lemma 1 and using $\tau^d, DG$, we know that firm 2 enters the market and adopts the green technology if $F \leq \frac{[a+(1-2\theta)H]^2}{9b} - S$, where $H \equiv 6e\delta - \frac{a\theta(a+18e\delta)}{(1+\theta)^2}$, and $S \leq \Delta[a(1 + \theta + 2\theta^2) - 6\theta e\delta(1 - \theta + \theta^2)] = \dot{S}(\tau^d, DG)$, where $\Delta \equiv \frac{4(1-\theta)H}{9b(1+\theta)^2}$. In addition, firm 1 does not become a green type if $S > \dot{S}(\tau^d, DG)$, where $\dot{S}(\tau^d, DG) = \Delta[a(2 + \theta + \theta^2) - 6e\delta(1 - \theta + \theta^2)]$.

1.6.10 Proof of Proposition 2

No Entry. When firm 1 is a monopolist, the regulator selects the optimal emission fee solving.
\[ W^{m,G} = \pi_1^{m,G} + CS^{m,G} + \theta e(\tau - d)q_1^{m,G} \]

In particular, \( \pi_1^{m,G} = \frac{(a-\tau e)^2}{4b} - S \), \( CS^{m,G} = \frac{(a-\tau e)^2}{8b} \), and \( q_1^{m,G} = \frac{a-\tau e}{2b} \). Then, social welfare can be rewritten as,

\[ W^{m,G} = \frac{3(a-\tau e)^2}{8b} + \frac{\theta e(\tau - d)(a-\tau e)}{2b} - S \]

and the optimal emission fee is \( \tau^{m,G} = 2\delta - \frac{a}{\theta e} \). We require \( \frac{a}{2\theta e} \leq \delta < \frac{a}{\theta e} \) to assure \( \tau^{m,G} \geq 0 \) and \( q_1^{m,G} > 0 \). Moreover, firm 1 adopts the green technology if

\[ \bar{S}(\tau^{m,G}) = \frac{(1-\theta)(2\theta e\delta-a)(3a\theta-2\theta e\delta-2\theta^2 e\delta)}{4b\theta^2} \]

From lemma 3, firm 2 does not enter when \( F > \max\{\frac{4(\theta^2 e\delta-2\theta e\delta+a)^2}{9b\theta^2}, \frac{4(a-\theta e)^2}{9b} - S\} \).

**Entry.** We first analyze the case in which both firms adopt the green technology. The regulator solves

\[ W^{d,GG} = \pi_1^{d,GG} + \pi_2^{d,GG} + CS^{d,GG} + \theta e(\tau - \delta)(q_1^{d,GG} + q_2^{d,GG}) \]

In particular, \( \pi_1^{d,GG} + \pi_2^{d,GG} = \frac{2(a-\tau e)^2}{9b} - (2S + F), CS^{d,GG} = \frac{2(a-\tau e)^2}{9b}, q_1^{d,GG} + q_2^{d,GG} = \frac{2(a-\tau e)}{3b} \). Then

\[ W^{d,GG} = \frac{4(a-\tau e)^2}{9b} + \frac{2\theta e(\tau - \delta)(a-\tau e)}{3b} - (2S + F) \]

The optimal emission fee is \( \tau^{d,GG} = \frac{3\delta}{2} - \frac{a}{2\theta e} \), which is nonnegative if \( \delta \geq \frac{a}{3\theta e} \). In addition, \( q_i^{d,GG} (\tau^{d,GG}) > 0 \) when \( \delta < \frac{a}{\theta e} \). According to lemma 3, firm 2 enters being a green type if

\[ F \leq \bar{F}^{GG}(\tau^{d,GG}) = \frac{(a-\theta e\delta)^2}{4b} \]

Moreover, both firms adopt the green technology when \( S \leq \bar{S}(\tau^{d,GG}) = \frac{(1-\theta)(3\theta e\delta-a)(a+2a\theta-3\theta e\delta)}{9b\theta^2} \).
Let us now examine the case in which the entrant keeps its dirty technology. Social welfare is the same as outcome \((D, G)\) and thus the optimal emission tax \(\tau^{d,GD} = \tau^{d,DG} = \frac{6(\theta^2-\theta+1)}{(1+\theta)^2} \delta - \frac{a}{(1+\theta)e}\). In addition, the requirement of the fixed costs of green technology coincides with \((D, G)\). However, the admissible condition of fixed entry costs becomes \(F \leq \frac{[a-(2-\theta)H]^2}{9b}\).

1.6.11 Proof of Proposition 3

We first analyze the cases in which firm 1 is a dirty type.

**No Entry.** Substituting \(\tau^{m,D}(\theta = \frac{1}{2}) = 2\delta - \frac{a}{e}\) into \(W^{m,D}\), we obtain

\[
W^{m,D}(\tau^{m,D}) = \frac{(a-e\delta)^2}{2b}.
\]

In addition, the fixed costs need to satisfy \(F > \bar{F}^{*D} \equiv \max\{\frac{4(a-e\delta)^2}{9b}, a^2 - S\}\) and \(S > \frac{(7a-6e\delta)(2e\delta-a)}{16b}\).

**Entry.** If firm 2 also keeps its dirty technology, the social welfare evaluated at

\[
\tau^{d,DD}(\theta = \frac{1}{2}) = \frac{3\delta}{2} - \frac{a}{2e}
\]

is

\[
W^{d,DD}(\tau^{d,DD}) = \frac{(a-e\delta)^2}{2b} - F = W^{m,D} - F.
\]

Firm 2 enters and keeps its dirty technology if \(F \leq \bar{F}^{*DD} \equiv \frac{(a-e\delta)^2}{4b}\) and \(S > \bar{S}^{*DD} \equiv \frac{(5a-3e\delta)(3e\delta-a)}{36b}\).

We now analyze the case in which firm 2 adopts the green technology. If \(\theta = \frac{1}{2}\), the optimal emission fee becomes \(\tau^{d,DG}(\theta = \frac{1}{2}) = 2\delta - \frac{2a}{3e}\) and requires \(\frac{a}{3e} \leq \delta < \frac{2a}{3e}\). Accordingly, the social welfare is
\[ W^{d,DG}(\tau^{d,DG}) = \frac{3a^2-5ae\delta+3(\epsilon\delta)^2}{6b} - (F + S) = W^{m,D} + \frac{ae\delta}{6b} - (F + S). \]

In addition, firm 2 enters and both firms adopt the green technology when \( F \leq F^{**}_{DG} \equiv \frac{a^2}{9b} - S \) and \( \tilde{S}^{*DG} < S \leq \hat{S}^{*DG} \), where \( \tilde{S}^{*DG} = \frac{4(5a-6e\delta)(3\epsilon\delta-a)}{81b} \), and \( \hat{S}^{*DG} = \frac{4(4a-3e\delta)(3\epsilon\delta-a)}{81b} \).

**Social welfare comparisons.** First, given proposition 1, \( W^{m,D} \) and \( W^{d,DD} \) can be supported if \( \frac{a}{2e} \leq \delta < \frac{a}{e} \). It is straightforward to show that \( W^{m,D} > W^{d,DD} \). In addition,

\[ \tilde{S}^{*D} - \tilde{S}^{*DD} = \frac{-(72(e\delta)^2 - 108ae\delta + 43a^2)}{144b} < 0. \]

Hence, the compatible condition for \( S \) is \( S > \hat{S}^{*DD} \). However, \( F^{**} \) is always higher than \( \tilde{F}^{**} \) due to \( \frac{4(a-e\delta)^2}{9b} > \frac{(a-e\delta)^2}{4b} \).

Next, let us compare \( W^{d,DD} \) and \( W^{d,DG} \). Both cases are supported in \( \frac{a}{3e} \leq \delta < \frac{2a}{3e} \). Moreover,

\[ \hat{S}^{*DD} - \hat{S}^{*DG} = \frac{(35a-69e\delta)(a-3e\delta)}{324b} \]

of which sign depends on the value of \( \delta \). Thus the requirement of \( S \) for both cases is \( \text{max}\{\hat{S}^{*DD}, \hat{S}^{*DG}\} < S \leq \hat{S}^{*DG} \). In addition, the condition for fixed entry costs is \( F \leq \min\{\tilde{F}^{**}, \tilde{F}^{**}\} \). Then

\[ W^{d,DG}(\tau^{d,DG}) - W^{d,DD}(\tau^{d,DD}) = \frac{ae\delta}{6b} - S > 0 \]

if \( S < \frac{ae\delta}{6b} \), which is higher than \( \hat{S}^{*DG} \). Hence, \( W^{d,DG} > W^{d,DD} \) is always satisfied under the set of admissible conditions for \( S \) and \( F \).

Finally, the comparison between \( W^{m,D} \) and \( W^{d,DG} \) requires that \( \frac{a}{2e} \leq \delta < \frac{2a}{3e} \).

\[ W^{d,DG}(\tau^{d,DG}) - W^{m,D}(\tau^{m,D}) = \frac{ae\delta}{6b} - (F + S) > 0 \]
if \( F + S < \frac{ae\delta}{6b} \). The conditions of \( S \) for both cases are compatible, i.e., \( \max\{\tilde{S}^{*D}, \tilde{S}^{*DG}\} < S \leq \tilde{S}^{*DG} \). However, \( \bar{F}^{*D} > \bar{F}^{*DG} \).

1.6.12 Proof of Proposition 4

Now we analyze the cases when firm 1 adopts the green technology and \( \theta = \frac{1}{2} \).

No Entry. When firm 1 operates as a green monopolist, the optimal emission fee is

\[
\tau^{mG}\left(\theta = \frac{1}{2}\right) = 2\delta - \frac{2a}{e},
\]

which requires \( \frac{a}{e} \leq \delta < \frac{2a}{e} \). Hence,

\[
W^{mG}(\tau^{mG}) = \frac{(2a-e\delta)^2}{8b} - S.
\]

From proposition 2, firm 2 stays out if \( F > \bar{F}^{*G} \equiv \max\left\{\frac{(4a-3e\delta)^2}{9b}, \frac{(2a-e\delta)^2}{9b} - S\right\} \), and firm 1 adopts the green technology for all \( S \leq \tilde{S}^{*G} \equiv \frac{(5a-3e\delta)(e\delta-a)}{4b} \).

Entry. Let us now analyze the case in which both firms adopt the green technology. The optimal emission fee becomes

\[
\tau^{d,GG}\left(\theta = \frac{1}{2}\right) = \frac{3\delta}{2} - \frac{a}{e},
\]

which requires \( \frac{2a}{3e} \leq \delta < \frac{2a}{e} \). Therefore,

\[
W^{d,GG}(\tau^{d,GG}) = \frac{(2a-e\delta)^2}{8b} - (F + 2S) = W^{mG} - (F + S).
\]

Moreover, both firms adopt the green technology if \( S \leq \tilde{S}^{*GG} \equiv \frac{(4a-3e\delta)(3e\delta-2a)}{18b} \) and firm 2 enters when \( F \leq \bar{F}^{*GG} \equiv \frac{(2a-e\delta)^2}{16b} - S \).

However, if firm 2 keeps its dirty technology, the optimal emission tax, social welfare, and the condition of fixed costs for green technology are the same as outcome \((D, G)\). In addition, it also requires \( \frac{a}{3e} \leq \delta < \frac{2a}{3e} \). The range of fixed entry costs becomes \( F \leq \bar{F}^{*GD} \equiv \frac{(2a-3e\delta)^2}{9b} \).

Social welfare comparisons. Notice that outcomes \((G)\) and \((G, G)\) require that the environmental damage satisfies \( \frac{a}{e} \leq \delta < \frac{2a}{e} \), while case \((G, D)\) only occurs for a relatively low
range of $d$, i.e., $\frac{a}{3e} \leq \delta < \frac{2a}{3e}$. Therefore it is only meaningful to compare $W^{m,G}$ with $W^{d,GG}$. It is straightforward to show that $W^{m,G} > W^{d,GG}$. In addition,

$$S^* - S^{*GG} = \frac{-(9(e\delta)^2 - 36ae\delta + 29a^2)}{36b} \geq 0,$$

depending on the value of $\delta$. Thus the compatible condition of $S$ is $S < \min\{\tilde{S}^*, \tilde{S}^{*GG}\}$.

However, $\tilde{F}^* > \tilde{F}^{*GG}$.

1.6.13 Proof of Lemma 8

No entry. Comparisons between $W^{m,G}$ and $W^{m,D}$ are not possible since they do not coexist within the range of admissible environmental damage.

Entry. Let us compare $W^{d,GG}$ and $W^{d,DD}$ for all $\delta \in \left[\frac{2a}{3e}, \frac{a}{e}\right)$. The conditions of $F$ that support both cases are $F \leq \min\{\tilde{F}^{*DD}, \tilde{F}^{*GG}\}$. In addition,

$$\tilde{S}^{*GG} - \tilde{S}^{*DD} = \frac{-(9(e\delta)^2 - 18ae\delta + 11a^2)}{36b} < 0.$$

Hence, $S < \tilde{S}^{*GG}$. Comparing social welfare for the two outcomes, we obtain

$$W^{d,GG} - W^{d,DD} = \frac{(2a-e\delta)^2}{8b} - \frac{(a-e\delta)^2}{2b} - 2S > 0$$

if $S < \frac{(4a-3e\delta)e\delta}{16b}$, which is lower than $\tilde{S}^{*GG}$.

Note that we cannot compare $W^{d,GG}$ with $W^{d,GG}$ since they occur in different ranges of $\delta$.

Finally, the comparison between $W^{d,GD}$ and $W^{d,DD}$ coincides with that of $W^{d,DG}$ and $W^{d,DD}$ in the proof of proposition 3.
References


Table 1-1 Output levels and profits under monopoly

<table>
<thead>
<tr>
<th>Firm 1’ type</th>
<th>D</th>
<th>G</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output</td>
<td>$q_{1}^{m,D} = \frac{a-\tau e}{2b}$</td>
<td>$q_{1}^{m,G} = \frac{a-\tau \theta e}{2b}$</td>
</tr>
<tr>
<td>Profit</td>
<td>$\pi_{1}^{m,D} = \frac{(a-\tau e)^2}{4b}$</td>
<td>$\pi_{1}^{m,G} = \frac{(a-\tau \theta e)^2}{4b} - S$</td>
</tr>
</tbody>
</table>
Table 1-2 Output levels and profits under duopoly - Firm 1 keeps its dirty technology

<table>
<thead>
<tr>
<th>Firm 2’s type</th>
<th>D</th>
<th>G</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output$^{16}$</td>
<td>$q_i^{d,DD} = \frac{a-\tau e}{3b}$</td>
<td>$q_1^{d,DD} = \frac{a+\tau e}{3b}$ and</td>
</tr>
<tr>
<td></td>
<td>$\pi_i^{d,DD} = \frac{(a-\tau e)^2}{9b}$</td>
<td>$\pi_1^{d,DD} = \frac{(a+\tau e-2\tau e)^2}{9b}$</td>
</tr>
<tr>
<td>Profit</td>
<td>$\pi_2^{d,DD} = \frac{(a-\tau e)^2}{9b} - F$</td>
<td>$\pi_2^{d,DG} = \frac{(a-2\tau e + \tau e)^2}{9b} - (F + S)$</td>
</tr>
</tbody>
</table>

$^{16}$ If both firms keep their dirty technology, case $(D, D)$, they produce strictly positive output levels if be $\tau < \frac{a}{e}$.

However, when only the entrant acquires green technology, $(D, G)$, it produces a positive amount if $\tau < \frac{a}{(2\theta - 1)e}$ and the dirty incumbent requires $\tau < \frac{a}{(2\theta - 1)e}$. For more details see appendix 1.6.1.
Table 1-3 Output levels and profits under duopoly - Firm 1 adopts a green technology

<table>
<thead>
<tr>
<th>Firm 2’s type</th>
<th>D</th>
<th>G</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Output</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$q_{1,GD}^{d}$</td>
<td>$\frac{a-2\tau \theta e + \tau e}{3b}$ and</td>
<td>$q_{i,GG}^{d} = \frac{a-\tau \theta e}{3b}$</td>
</tr>
<tr>
<td>$q_{2,GD}^{d}$</td>
<td>$\frac{a+\tau \theta e - 2\tau e}{3b}$</td>
<td></td>
</tr>
<tr>
<td><strong>Profit</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\pi_{1,GD}^{d} = \left(\frac{a-2\tau \theta e + \tau e}{9b}\right)^2 - S$</td>
<td>$\pi_{1,GG}^{d} = \left(\frac{a-\tau \theta e}{9b}\right)^2 - S$</td>
<td></td>
</tr>
<tr>
<td>$\pi_{2,GD}^{d} = \left(\frac{a+\tau \theta e - 2\tau e}{9b}\right)^2 - F$</td>
<td>$\pi_{2,GG}^{d} = \left(\frac{a-\tau \theta e}{9b}\right)^2 - (F + S)$</td>
<td></td>
</tr>
</tbody>
</table>

\(^{17}\) In order to ensure strictly positive output levels emission taxes satisfy $\tau < \frac{a}{(2-\theta)e}$ for the case $(G,D)$ and $\tau < \frac{a}{\theta e}$ when both firms acquire the green technology, $(G,G)$.
Figure 1-1 Comparisons between optimal emission fees
CHAPTER TWO

SUBSTITUTION ELASTICITIES BETWEEN GHG POLLUTING AND NONPOLLUTING INPUTS IN AGRICULTURAL PRODUCTION:
A META-REGRESSION

Abstract

This paper reports meta-regressions of substitution elasticities between greenhouse-gas (GHG) polluting and nonpolluting inputs in agricultural production, which is the main feedstock source for biofuel in the U.S. We treat energy, fertilizer, and manure collectively as the “polluting input” and labor, land, and capital as nonpolluting inputs. We estimate meta-regressions for samples of Morishima substitution elasticities for labor, land, and capital vs. the polluting input. Much of the heterogeneity of Morishima elasticities can be explained by type of primal or dual function, functional form, type and observational level of data, input categories, the number of outputs, type of output, time period, and country categories. Each estimated long-run elasticity for the reference case, which is most relevant for assessing GHG emissions through lifecycle analysis, is greater than 1.0 and significantly different from zero. Most predicted long-run elasticities remain significantly different from zero at the data means. These findings imply that lifecycle analysis based on fixed proportions production functions could provide grossly inaccurate measures of GHG of biofuel.

2.1 Introduction

Biofuel has become a major substitute for fossil fuel energy sources. It has important benefits such as decreasing dependence on foreign oil imports, providing additional markets for
agricultural products, and creating job opportunities in rural areas. However, despite its appeal as a renewable energy source, there is ongoing debate whether biofuel alleviates environmental concerns. Some studies conclude that biofuel can mitigate greenhouse gas (GHG) emissions (e.g., Farrell et al., 2006), whereas others find that biofuel may result in nearly as much or even more GHG emissions as petroleum-based fuels (e.g., Solomon, 2010; Fargione et al., 2008; Searchinger et al., 2008).

Measurement of GHG emissions from biofuel is typically examined through lifecycle analysis (LCA). LCA assesses the emissions associated with the entire life of biofuel, from its feedstock production to its end use. An accurate LCA is important for environmental policy decisions. For instance, the U.S. Energy Independence and Security Act (EISA 2007) requires the U.S. Environmental Protection Agency to create and enforce a threshold of lifecycle GHG reduction through use of renewable energy. Previous studies on LCA generally assume fixed-proportions production functions and consequently do not account for any input ratio response to changing market and policy conditions. However, a change in the relative price of an input that generates GHG emissions could induce substitution away from that input and alter emissions and environmental policy consequences (Rajagopal and Zilberman, 2008).

This paper provides empirical evidence on substitutability between GHG-polluting inputs and nonpolluting inputs in agricultural production, which is the main feedstock source for biofuel in the U.S.18 We estimate a meta-regression for samples of elasticities of substitution for

18 Biofuel feedstock can be provided by agricultural crops and cellulosic biomass. In the U.S. very little cellulosic biomass is currently used because of the inadequacy of technology to convert cellulose to fuel, so agricultural crops are the primary source of feedstock. Therefore, in this paper we confine our attention to input substitutability in agricultural feedstock production.
polluting and non-polluting inputs. Our findings have important implications because significant substitutability between polluting and non-polluting inputs may greatly alter lifecycle GHG emissions from renewable energy.

A large number of empirical studies have estimated elasticities of input substitution in agricultural production, but their estimates vary considerably. The research tool, meta-analysis, provides a way to summarize and analyze the scattered empirical outcomes on a certain topic (Glass, 1976). In economics, meta-regression is the most commonly applied method of meta-analysis (e.g., Bateman and Jones, 2003; Bellavance et al., 2009; Bureau et al., 2010). The observations used for the dependent variable are estimates obtained from prior empirical studies. The independent variables are factors expected to be relevant for explaining the heterogeneity of empirical outcomes (Stanley and Jarrell, 1989). Meta-regression can provide a combined estimate as well as identify sources of variation in prior estimates (Nelson and Kennedy, 2009).

In this paper we use meta-regression to investigate substitution elasticities between polluting and non-polluting inputs in agricultural production relevant to biofuel feedstock production.19

Three previous meta-regression articles have addressed substitution elasticities. Boys and Florax (2007) conducted a meta-regression to examine the Allen elasticity of substitution between labor and capital in the agricultural sector. Koetse et al. (2008) focused on the Morishima elasticity of substitution between capital and energy for all industries. Stern (2012) investigated shadow substitution elasticities between oil, coal, gas, and electricity in the whole economy. We differ from the existing literature in three aspects: We examine Morishima elasticities of substitution between GHG-polluting inputs (energy, fertilizer, and manure) and

19 We only consider GHG emission in this paper. Hence, “polluting input” means “GHG-polluting input”.

43
non-polluting inputs (labor, land, and capital) in agricultural production. We include a larger number of primary articles (65) on agricultural production for our meta-regression than do Boys and Florax (2007) which includes 35 papers. And, our estimates of substitution elasticities provide a basis for integrating input substitution into LCA of biofuels for purposes of GHG assessment.

The paper is organized as follows. We address issues associated with the choice and measurement of input substitution elasticities in section 2. We describe the selection process and the characteristics of primary studies in section 3. Section 4 identifies potential sources of heterogeneity in empirical outcomes and explains the choice of independent variables. We next discuss the econometric issues and models in section 5. The results of meta-regression are reported in section 6. Section 7 concludes.

2.2 Choice of Dependent Variables

2.2.1 Elasticity of substitution definition

The elasticity of input substitution, originally introduced by Hicks (1932) for analysis of production with two inputs, measures the relative change in input ratios with respect to a relative change in the marginal rate of technical substitution with output held constant:

$$\sigma_{12} = \frac{d \ln(x_1 / x_2)}{d \ln MRTS_{12}}$$

(1)

Where $\sigma$ is the elasticity of input substitution, $x_i$ represents input $i$, $i = 1, 2$, and $MRTS_{12}$ is the marginal rate of technical substitution between the two inputs.

Three alternative generalizations are identified in the literature when production involves three or more inputs – Allen, Morishima and Shadow elasticities of substitution. The Allen
elasticity of substitution (AES) is a one-price-one-factor elasticity of input \( i \) to the price of input \( j \) with all other prices and output held fixed. It measures the share-weighted relative change in conditional input demand with respect to a change in the price of another input:

\[
\sigma^A_{ij} = \eta_j / S_j
\]  

(2)

where \( \sigma^A_{ij} \) is the AES between inputs \( i \) and \( j \); \( \eta_j \) is the conditional cross-price elasticity of input \( i \) with respect to the price of input \( j \); \( S_j \) is the cost share of input \( j \). The AES is the most commonly reported substitution elasticity and is symmetric, i.e., \( \sigma^A_{ij} = \sigma^A_{ji} \). However, it is also the least useful because it adds no additional information beyond the conditional input demand cross-price elasticity and the input’s cost share (Blackorby and Russell, 1989).

The Morishima elasticity of substitution (MES) is a one-price-two-factor elasticity of the input ratio to the price of input \( j \) with all other prices and output held fixed. It can be written as

\[
\sigma^M_{ij} = \eta_j - \eta_\bar{j}
\]  

(3)

where \( \sigma^M_{ij} \) is the MES between inputs \( i \) and \( j \). It can also be calculated from the AES:

\[
\sigma^M_{ij} = S_j (\sigma^A_{ij} - \sigma^A_{ji})
\]  

(4)

Unlike the AES, the MES is asymmetric, so \( \sigma^M_{ij} \neq \sigma^M_{ji} \).

The shadow elasticity of substitution (SES) is a two-price-two-factor elasticity of the input ratio to the price ratio, so it allows the prices of input \( i \) and \( j \) to change while holding output and all other prices constant. Like the AES, the SES is symmetric. Although it is the
broadest generalization of the two-input elasticity of substitution, it is rarely reported in
empirical studies. 20

Two cost shares are essential for each method of computing the SES from reported
conditional price elasticities, AES, or MES. However, they are seldom reported in empirical
studies. It is sometimes impossible to compute all cost shares from reported data and parameter
estimates, especially for papers estimating functions other than the cost function. 21 Consequently,
we necessarily dismiss the SES as a candidate for our dependent variable because of inadequate
data.

Although the MES is seldom reported in our primary articles, it is a conceptually superior
definition to the AES because it focuses on changes in the input ratio, and it is typically possible
to compute it directly from reported conditional price elasticities or AES. Except for the two
studies that report MES, i.e., Debertin et al. (1990) and Napasintuwong et al. (2005), we convert
whatever elasticities are reported in each study into MES. We use equation (3) to determine MES
for studies that report conditional input price elasticities. For studies that use the translog cost
function and only report AES, it is often feasible to first compute an input cost share and then
use equation (4) to determine MES. For studies that report neither conditional input price
elasticities nor AES, additional computation is required, the specific nature of which depends
both on functional form and type of function (e.g., cost, profit, production) estimated.

2.2.2 Computation of MES based on different functional forms and types of function

20 In our selected studies, only Debertin et al. (1990) report the SES.

21 Stern (2012) investigated shadow substitution elasticities between different types of fuel, but he only included
papers in his meta-regression sample that estimated a translog cost function.
2.2.2.1 Translog cost function

The largest number of empirical studies estimate a translog cost function. For such, the cost share equations can be expressed as (Bingswanger, 1974):

\[ S_j = v_j + \sum_i \gamma_{ij} \ln w_i + \gamma_j \ln Q \]  

(5)

where \( w \) is input price, \( Q \) is the output level, and \( v_j, \gamma_{ij} \) and \( \gamma_j \) are parameters to be estimated. The conditional own- and cross-price input demand elasticities can be expressed, respectively, as:

\[ \eta_{jj} = \gamma_{jj} / S_j + S_j - 1 \]  

(6)

\[ \eta_j = \gamma_{ij} / S_i + S_j \]  

(7)

The AES can be specified directly from these parameters and shares as:

\[ \sigma_{ij}^A = (\gamma_{ij} + S_j^2 - S_j) / S_j^2 = \eta_{ij} / S_j \]  

(8)

\[ \sigma_{ij}^A = \gamma_{ij} / S_j S_j + 1 = \eta_{ij} / S_j \]  

(9)

Parameter estimates are routinely presented in the primary studies but cost shares often are not. The cost shares can be obtained if a study reports the conditional own-price input demand elasticities or the own AES. By rearranging equation (6) or (8), we achieve

\[ S_j^2 - (1 + \eta_{jj})S_j + \gamma_{jj} = 0 \]  

(10)

\[ (1 - \sigma_{jj}^A)S_j^2 - S_j + \gamma_{jj} = 0 \]  

(11)

\footnote{The expressions for the own- and cross-price conditional input demand elasticities and the AES are the same for multiple-output as for single-output models.}
Then we solve for the cost shares subject to the constraints that \( S_j \in (0,1) \) and \( \sum_{j=1}^{n} S_j = 1.23 \).

The conditional input demand elasticities or the AES can then be calculated via equations (6)-(7) or (8)-(9), respectively, and the MES via equation (3) or (4).

2.2.2.2 Generalized Leontief cost function

A typical Generalized Leontief cost function can be specified as (Lopez 1982):

\[
C(w, \mathcal{Q}) = Q \sum_{i} \sum_{j} b_{ij} w_i^{1/2} w_j^{1/2} + Q^2 \sum_{i} \alpha_i w_i
\]

where \( b_{ij} \) and \( \alpha_i \) are parameters to be estimated. The conditional input demand functions are defined as

\[
x_i = \sum_{j} b_{ij} \left( \frac{w_j}{w_i} \right)^{1/2} Q + \alpha_i Q^2
\]

The conditional own- and cross-price input demand elasticities for this cost function can be computed from the parameters as follows:

\[
\eta_{ii} = -\frac{Q}{2x_i} \sum_{j \neq i} b_{ij} \left( \frac{w_j}{w_i} \right)^{1/2}
\]

\[
\eta_{ij} = \frac{Q}{2x_i} b_{ij} \left( \frac{w_j}{w_i} \right)^{1/2}
\]

---

23 If an article also presents AES, cost shares can be further validated by rearranging equation (9):

\[ S_i S_j = \gamma_{ij} I (\sigma_{ij}^4 - 1). \]
Alternatively, as long as a study reports the parameter estimates and the own-price elasticities of conditional input demand, the cross-price elasticities can be solved by

\[ \eta_{ij} = -\frac{\eta_{ij}}{\sum_{j \neq i} b_{ij}}. \]

Then the MES can be obtained via equation (3).

### 2.2.2.3 Profit function – transformation from uncompensated to compensated elasticities

Uncompensated elasticities are often reported (or easily derivable) in studies that estimate a profit function in which both outputs and inputs are treated as variable. To compute the MES, we need to first convert the uncompensated elasticities into compensated elasticities. In addition, the model based on the profit function is often associated with multiple outputs. The compensated elasticities of input demand can be obtained as (Lopez, 1984):

\[ \{ \eta_{ij} \} = \{ \eta_{ij}^u \} - \{ \eta_{im}^u \} \{ \eta_{mn}^u \}^{-1} \{ \eta_{mi}^u \} \]  

(16)

where the subscript \( m \) \((n)\) denotes output \( m \) \((n)\), \( \{ \eta_{ij}^u \} \) is a matrix of uncompensated input demand elasticities with respect to input prices, \( \{ \eta_{im}^u \} \) is a matrix of uncompensated output supply elasticities with respect to output prices, \( \{ \eta_{mn}^u \} \) is a matrix of uncompensated input demand elasticities with respect to output prices, and \( \{ \eta_{mi}^u \} \) is a matrix of uncompensated output supply elasticities with respect to input prices.

Then we can use equation (3) to determine the MES. A study reporting an estimated profit function is included in our meta-sample if all the above uncompensated elasticities are given or can be calculated from information reported in the study.

### 2.2.3 Input classification
In agricultural production, GHG emissions occur mainly from the use of three inputs: energy, nitrogen fertilizer, and manure. In this paper, we treat energy, fertilizer, and manure use as the “polluting input”. The polluting input accounts for nearly all the GHG emissions created through the production of agricultural biofuel feedstock. We include labor \((l)\), land \((d)\), and capital \((k)\) as non-polluting inputs. For one pair of inputs, the MES is asymmetric and its value depends on which input price changes. For purpose of facilitating price regulation \((e.g.,\) a carbon tax) on the polluting input, we are interested in changes in the ratio of a non-polluting input and the polluting input as the price of the polluting input varies. As a result, three MES, denoted as \(\sigma_{op}^M\), are computed and investigated separately in this study, where subscript \(o\) and \(p\), respectively, represent non-polluting inputs \((l, d, \text{ and } k)\) and the polluting input.

The assignment of specific inputs in the empirical models to our input categories is reported in Table 2-1. Two input category classification issues warrant particular explanation.

First, part of the polluting input is frequently aggregated with other inputs. Specifically, energy is

\(^{24}\) There are four types of GHG: carbon dioxide \((\text{CO}_2)\), methane \((\text{CH}_4)\), nitrous oxide \((\text{N}_2\text{O})\), and fluorinated gases. The first three types of GHG pollution occur with agricultural production. Specifically, \(\text{CO}_2\) is generated by the use of electricity, fossil fuel, or oil; \(\text{CH}_4\) is generated from animal manure; \(\text{N}_2\text{O}\) is emitted when nitrogen is added to the soil through the use of synthetic fertilizer and through the breakdown of nitrogen in animal manure and urine \((\text{EPA}, \text{2014})\).

\(^{25}\) All fertilizer is included because the empirical studies rarely treat nitrogen fertilizer as a separate input. Nitrogen is nearly always aggregated with other fertilizers such as phosphorous and potassium. Nitrogen is the major nutrient in fertilizer and accounted for 48 percent of total fertilizer cost during the years 1960 to 2011 \((\text{USDA}, \text{2014b})\).

\(^{26}\) Land can increase GHG through land clearing. In this paper, our primary focus is on U.S. agricultural production, so extensive margin impacts that could be particularly important in developing countries are ignored. Hence, land is treated as a non-polluting input.
reported as a separate input in only 23 percent of the selected studies. It is usually aggregated into materials, intermediate inputs, or other inputs. Additionally, 15 percent of the articles aggregate fertilizer into a chemicals input category. In general, chemicals is an aggregate of fertilizer and pesticides. The expenditure share of fertilizer in the USDA chemicals category averaged 66 fpercent during the period 1960 - 2011 (USDA, 2014a). In terms of manure, 97 percent of the studies aggregate applied manure into the fertilizer category or another input category rather than reporting it as a separate input. Second, nonpolluting input categories in the primary studies are sometimes structured differently from our classification. Labor and capital are sometimes disaggregated into several subcategories. For example, labor is often separated into family labor and hired labor. If family labor is treated as a fixed or quasi-fixed input, we only use the MES between hired labor and the polluting input as the observation in the labor elasticity sample. If both family labor and hired labor are variable inputs, we include the elasticities with respect to family labor and hired labor as two separate observations. Also, land is sometimes aggregated into land and structures, real estate, or even capital. We introduce dummy variables in our meta-regression to control for these input classification issues.

2.3 Meta-Regression Sample

We developed our sample of studies by first searching combinations of keywords anywhere in an article using Google Scholar. The keywords used were “agriculture” or “agricultural” or “corn” or “soybean”, “production”, “elasticity” or “elasticities”, “substitution” or “substitutability”, and “input demand” or “factor demand”. As a complement, we referred to a literature review by Salhofer (2000) and two previous meta-analysis papers: Boys and Florax
(2007) and Koetse et al. (2008). For each selected article, we also checked papers in the reference lists. Finally, we used Econlit and Agricola databases to supplement our search.

Our literature search generated 126 studies. Several sampling restrictions were imposed on the retained articles. Since we need to allow for different substitution elasticities between pairs of inputs, studies estimating only a constant elasticity of substitution functional form were excluded from our sample. An article was dismissed if it did not report the MES and did not provide enough information for calculating it. We also dismissed studies in which the variable inputs were not adequate for our purpose. For example, we ruled out Williams and Shumway (2000) because its variable inputs only included fertilizer, pesticides, and nonchemical materials. Some studies for which the MES could be computed only by using cost shares were dismissed because two or more computed cost shares were out of the range (0,1). The reported results in such studies were suspect. Finally, a paper was excluded if the sample size for its estimation was not provided. After the sampling restrictions were imposed, we were left with 65 primary studies.

The MES can be negative; however, this indicates lack of necessary curvature of the production function for cost minimization. For instance, a negative estimate of $\sigma_{op}^M$ implies substitution from a non-polluting input to the polluting input when the price of the polluting input increases. Alternatively, it can result from a positive own-price conditional demand elasticity, which also is not consistent with cost minimization. Following Koetse et al. (2008), we dismissed negative MES empirical outcomes. This resulted in a sample of 225 estimates from 64

---

27 If only one computed cost share in a study was out of the range (0,1), we used $S_j = 1 - \sum_{i \neq j} S_i$ to approximate it.
studies for $\sigma_{lp}^M$, a sample of 120 estimates from 34 studies for $\sigma_{dp}^M$, and a sample of 262 estimates from 58 studies for $\sigma_{kp}^M$.  

2.4 Independent Variables

2.4.1 Sources of MES variation

All but one of the independent variables included in the meta-regression are dummy variables. They are mostly variables that describe characteristics of the primary studies, such as features of the model and data. We follow three criteria for creating dummy variables. First, we consider common explanatory variables that were used in the three previous meta-regression papers on substitution elasticities: Boys and Florax (2007), Koetse et al. (2008), and Stern (2012). Their variables emphasized function type, functional form, technology, model structure, data characteristics, estimation methods, and measurement of output. Second, we introduce additional dummy variables relevant to elasticities of substitution in biofuel feedstock production. For example, we include variables to deal with classification problems between polluting and non-polluting inputs, data period relative to initiation of biofuel production, and country categories. Finally, we eliminate dummy variables that are both insignificant in the meta-regression and cause severe multicollinearity. Table 2-2 describes the dummy variables and reports the distribution of values for each.

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28 For studies with one or more inputs treated as fixed, only the MES between variable inputs are computed. A dummy variable to indicate it is a short-run elasticity is created as one of the independent variables in the meta-regression.
Function type. Different estimates of substitution elasticities are potentially due to the different function types used in the primary studies (Boys and Florax, 2007; Capalbo, 1988; Burgess, 1975). For example, duality theory documents that substitution elasticities can be equivalently derived mathematically from estimates of production, cost, or profit functions. In practice, the elasticities derived from these three function types are often very different, even when the same data are used. This is because the stochastic assumptions in the estimation equations are not equivalent. In our meta-regression, we create two dummy variables for the function types. A cost function is the primary function from which elasticities of substitution are computed and has a value of zero in both dummy variables.

Functional form. Much evidence from empirical studies shows that estimated elasticities vary across flexible functional forms (e.g., Baffes and Vasavada, 1989; Shumway and Lim, 1993). We introduce a dummy variable for functional forms to distinguish between the translog and alternative functional forms.

Technology. Estimates of elasticities are dependent on assumptions about technological change and returns to scale maintained in the estimation (Koetse et al., 2008). Two dummy variables are generated to distinguish between models that allow for non-neutral technological change and non-constant returns to scale, and those that constrain estimates on either of these dimensions.

Model structure. Dynamic models which take account of sluggish input adjustment typically provide different empirical estimates of substitution elasticities than static models (e.g., Leblanc and Hrubovcak, 1986; Lambert and Gong, 2010). A dummy variable distinguishes between them.
Data characteristics. Koetse et al. (2008) and Stern (2012) found that substitution estimates vary significantly with different types of data series. Two dummy variables are introduced in our meta-regression for data series to distinguish between time series data and either cross-sectional or panel data. The observational unit of data may also impact substitution estimates (Boys and Florax, 2007; Stern 2012) and results in our generating two dummy variables to distinguish between national and either farm-level or regional data.

Estimation method. The meta-regression results of Boys and Florax (2007) found that estimation method had a substantial effect on the substitution estimates. Iterative estimation methods, which are most commonly used in the primary studies, produce empirical results consistent with maximum likelihood estimation. A dummy variable distinguishes between these estimation methods and other techniques.

Measurement of output. Empirical substitution estimates from multiple-output models are often different from those estimated with single-output models, even when other conditions are the same (e.g., Hertel and McKinzie, 1986; Capalbo, 1988). The same is true for studies that examine aggregate agriculture as a single output and those that examine an individual commodity or commodity group (Boys and Florax, 2007). We introduce two dummy variables for the output type to distinguish between single-output models of aggregate agriculture and other output specifications.29

Input classification. We introduce three dummy variables regarding the polluting inputs. A dummy variable equals zero if energy is a separate input and one if not. Similar dummy

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29 Ideally we would specify a dummy variable to have a value of zero if the output is corn or soybean supply and one otherwise. Unfortunately, none of the selected articles examines only corn and/or soybeans.
variables are also created for fertilizer and manure, respectively. Four dummy variables are introduced in the classification of nonpolluting inputs. Two are used to indicate aggregate labor and capital, respectively. The other two indicate whether land is a separate variable or aggregated with buildings and structures or with all capital.

*Time period.* Agricultural products began to be used as a source of biofuel feedstock in the early 1980’s. A temporal dummy variable is created to distinguish models that include data after biofuel feedstock production began and those that only use earlier data. We also include a dummy variable for the time horizon of the estimate. It distinguishes elasticities calculated from models with all inputs treated as variable, defined as a long-run elasticity for our analysis, from those calculated from models with one or more constrained inputs.

*Country classification.* Input substitution elasticity estimates may differ across countries due to different levels of technology development, different relative input costs, and different agricultural product mixes. In order to obtain an elasticity estimate that is representative for the U.S., we generate two dummy variables to distinguish the U.S. from developing countries and from other developed countries.

2.4.2 Publication bias

Publication bias may be caused by refereed publication preferences for selecting statistically significant results and censoring values that are inconsistent with theoretical expectations.\(^\text{30}\) It can pose a problem for any summary of literature, including meta-analysis, if it

\(^{30}\) Heckman two-step method is not applicable for publication bias because it requires a sample containing both published and unpublished effects to estimate the inverse Mills ratio. However, for meta-analysis, we do not observe
tends to disguise the real empirical effects (Sutton et al., 2002; Stanley, 2008). It has been found to exist in areas of empirical economics (e.g., Ashenfelter et al., 1999; Doucouliagos, 2005). In terms of elasticities of input substitution, Stern (2012) points out that the publication bias for elasticities is likely the result of censoring positive own-price demand elasticities, which would cause the average of reported MES estimates to be more positive than it actually is. Therefore, a control for publication bias is essential for an accurate meta-analysis. Following his argument, we correct for publication bias by including the inverse of the square roots of sample size as an independent continuous variable in the meta-regression.

2.5 Econometric Method

2.5.1 Econometric issues

Econometric problems in the meta-regression typically include heteroskedasticity, dependence of observations, and multicollinearity (Florax, 2002; Nelson and Kennedy, 2009; Dalhuisen et al., 2003; Florax et al., 2005).

2.5.1.1 Heteroskedasticity

The Breusch-Pagan test shows that heteroskedasticity cannot be rejected, even at a 1 percent significance level for each case.\textsuperscript{31} Heteroskedasticity can be dealt with in several ways.

\textsuperscript{31} The $\chi^2$ for $\sigma_{lp}^M$, $\sigma_{dp}^M$ and $\sigma_{kp}^M$ are 52.46, 68.64 and 43.08, respectively.
Koetse et al. (2010) document that a weighted least squares approach is preferred to either OLS or a mixed effects model for meta-regression. It is also more robust in the presence of potentially omitted variables. Two weights commonly used in meta-regression are the square roots of sample size and the inverse of standard errors of the estimates. We follow Stern (2012) and Florax et al. (2005) by using the square roots of sample size as the weights. There are two reasons for this selection: (a) like Stern’s SES dependent variable, the MES is also a nonlinear combination of parameter estimates, and (b) the standard errors of many MES estimates are not provided or cannot be computed accurately by information available in the primary studies so use of standard errors is not an option.

2.5.1.2 Dependence of observations

Many primary studies report multiple elasticity estimates, typically for different years or time periods, which implies that the observations are probably correlated. The three meta-analyses of elasticities of substitution (Boys and Florax, 2007; Koetse et al., 2008; and Stern, 2012) all employ models that are silent on potential dependence of observations. Failure to account for correlation across observations from the same study may cause underestimation of standard errors. The correlation across observations in the same study can be accounted for by using a panel data model estimator. The fixed effects panel data model is not suitable for our study because some of our primary studies only report a single elasticity estimate. In this case, the fixed effects model does not improve accuracy of the estimation and also results in severe

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32 Stanley and Rosenberger (2009) argue that the square root of sample size is the more appropriate weight in the weighted least squares approach than the inverse of the standard error when the dependent variable of the meta-analysis is a nonlinear combination of parameter estimates in primary studies.
The Lagrange Multiplier test is conducted for each MES sample to determine whether a random effects panel data estimator should be used. The null hypothesis is that a weighted least squared model without random effects is appropriate. We reject the null hypothesis only for the MES sample of capital. Therefore, a weighted least squares estimator is used for the MES of both labor and land with respect to the polluting input and a random effects panel data estimator is used for the capital-polluting input MES.

2.5.1.3 Multicollinearity

For a meta-analysis comprised of a relatively small number of observations and a large number of dummy variables, multicollinearity among independent variables can be a problem even without using a fixed effects estimator (Dalhuisen et al. 2003; Florax et al. 2005). We compute variance inflation factors (VIF) for each of the MES samples to determine whether multicollinearity seriously inflates our estimate of the variance. If the variance inflation factors (VIF) are less than 5 for all independent variables in an MES model, we keep all variables in the meta-regression. If some are greater than 5, we drop the insignificant independent variable with the highest VIF if the number of significant variables and the goodness of fit (adjusted R-square) increase. We continue this process until there are no insignificant variables with a VIF greater than 5 or until deleting another variable fails to increase both the number of significant variables and the goodness of fit. This results in our excluding dummies for cross sectional data and panel data in the estimation of the MES of land and capital vs. the polluting input. We do not exclude any dummies in the estimation of the MES of labor vs. the polluting input.

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33 Jeppesen et al. (2002) discuss why the random effects model is preferred to the fixed effects model.

34 The $\chi^2$ for $\sigma_{ip}^M$, $\sigma_{dp}^M$, and $\sigma_{kp}^M$ are 0.29, 2.09 and 9.56, respectively.
2.5.2 Econometric model

2.5.2.1 Weighted least squares model

The meta-regression model with correction for publication bias can be specified as (Stanley et al., 2008; Stanley, 2008):

\[
\hat{\sigma}_{op,s}^M = \alpha_{op} + \sum_{r=1}^{R} \beta_{op,r} X_{op,sr} + \beta \left( \frac{1}{\sqrt{n_s}} \right) + \varepsilon_s
\]  

(17)

where \( o = l, d \), \( \hat{\sigma}_{op,s}^M \) is the MES estimate between input \( o \) (labor or land) and the polluting input from the \( s^{th} \) study, \( X_{op,sr} \) is the \( r^{th} \) dummy variables for the \( s^{th} \) study, \( n_s \) is the sample size of the \( s^{th} \) study, \( \varepsilon_s \) is the error term of the \( s^{th} \) study with zero mean and variance \( \tau_s^2 \).

Using the square roots of sample size as the heteroskedasticity weights, the weighted least squares model is:

\[
\tilde{\sigma}_{op,s}^M = \beta + \alpha_{op} \sqrt{n_s} + \sum_{r=1}^{R} \sqrt{n_s} \beta_{op,r} X_{op,sr} + u_s
\]  

(18)

where \( \tilde{\sigma}_{op,s}^M = \sqrt{n_s} \hat{\sigma}_{op,s}^M \) is the weighted MES estimate, and \( u_s = \sqrt{n_s} \varepsilon_s \) is the new error term of the \( s^{th} \) study with zero mean and variance \( \nu_s^2 \).

2.5.2.2 Random effects panel data model

The random effects panel data model with publication bias can be specified as (Jeppesen et al., 2002; Greene 7th edition, p.411):

35 Stanley et al. (2008) estimates a similar model using the standard error instead of sample size to account for publication bias.
\[
\hat{\sigma}_{kp,st}^M = \alpha_{kp,s} + \sum_{r=1}^{R} \beta_{kp,r} X_{kp,str} + \beta \left( \frac{1}{\sqrt{n_s}} \right) + \epsilon_{st} \tag{19}
\]

where \( \hat{\sigma}_{kp,st}^M \) is the \( i^{th} \) MES estimate between capital and the polluting input from the \( s^{th} \) study, \( \alpha_{kp,s} \) is the random heterogeneity specific to the \( s^{th} \) study and is constant across observations from the \( s^{th} \) study, \( E(\alpha_{kp,s}) = 0 \), \( E(\alpha_{kp,s}^2) = \tau_s^2 \), \( E(\alpha_{kp,s}\alpha_{kp,m}) = 0 \) for \( s \neq m \). Due to the heteroskedasticity of the MES sample, we first weight the capital-polluting input dataset by the square root of sample size (Florax et al., 2005). Then the random effects model becomes

\[
\hat{\sigma}_{kp,st}^M = \beta + \alpha_{kp,s} \sqrt{n_s} + \sum_{r=1}^{R} \sqrt{n_r} \beta_{kp,r} X_{kp,str} + u_{st} \tag{20}
\]

where \( \hat{\sigma}_{kp,s}^M = \sqrt{n_s} \hat{\sigma}_{kp,s}^M \) is the weighted MES estimate, and \( u_{st} = \sqrt{n_s} \epsilon_{st} \) is the new error term with zero mean and variance \( \tau^2 \). Since the number of MES estimates that can be calculated between capital and the polluting input is not the same for all primary studies, the data of \( \hat{\sigma}_{kp,st}^M \) constitutes an unbalanced panel data set.

**2.6 Meta-regression results**

Empirical estimates of the meta-regression equations for labor, land, and capital MES relative to the polluting input are reported in Table 2-3. The adjusted \( R^2 \) values range from 0.49 for labor to 0.87 for land, both of which are higher than the mean adjusted \( R^2 \) of 0.44 from 140 meta-analyses reported by Nelson and Kennedy (2009). For the panel data estimation of the capital-polluting input MES, the between \( R^2 \) value is 0.93 and the overall value is 0.68. These goodness of fit measures show that our meta-regression models do a reasonable job of explaining
the variation present in each sample. In our assessment of variables that affect MES estimates, we will use a significance level of 10%.

2.6.1 MES variation

Coefficients of the publication bias correction variable for the MES of labor and land vs. the polluting input are -7.909 and -7.405, respectively. They are significantly different from zero, which implies that prior studies with larger sample sizes produce significantly higher empirical estimates of these MES. The coefficient of publication bias correction for the MES of capital vs. the polluting input is also negative but not statistically significant.

Both dummy variables for function type are negative and statistically significant for the labor elasticity. They imply that the labor-polluting input MES estimates obtained from estimated profit, production, or differential input demand functions are significantly lower than from estimated cost functions. Estimated profit functions give a significantly lower estimate of the capital-polluting input MES than other estimated functions, and production and differential input demand functions give a significantly higher estimate of the land-polluting input MES than estimated cost or profit functions. This provides clear evidence of support for the claim that alternative types of functions yield different empirical outcomes.

Neither alternative functional forms, the imposition of neutral technological change, nor dynamic model structures has a significant effect on any of the MES estimates. Boys and Florax (2007) similarly found that the choice of functional form does not significantly alter the AES between labor and capital. Koetse et al. (2008) also found that the MES between capital and energy is not significantly affected by the inclusion of a non-neutral technical change parameter.
Although found to be insignificant in previous meta-analyses, the imposition of constant returns to scale causes significant positive effects on labor and negative effects on land vs. the polluting input MES estimates. If agricultural production actually exhibits non-constant returns to scale, an empirical study with the imposed misspecification of constant returns to scale gives biased estimates of the MES of labor and land vs. the polluting input.

Data characteristics significantly influence each MES estimate. Our results suggest that the use of cross sectional or panel data rather than time series data significantly reduces the estimates of labor-polluting input MES. This is counter to Koetse et al. (2008) and Stern (2012) who found that using cross sectional or panel data provides higher substitution elasticities. Using state or regional level data significantly raises the estimated MES of labor and capital vs. the polluting input and lowers the MES estimate of land vs. the polluting input. Using farm level data leads to a significantly higher MES estimate of labor and lower estimate of land vs. the polluting input.

Only the MES estimate between land and polluting inputs is significantly affected by the estimation method. It is reduced by choosing estimation methods other than maximum likelihood or iterative methods. This is similar to what Boys and Florax (2007) found for the AES between labor and capital.

A model with multiple outputs leads to significantly higher estimates for the MES of land and capital with respect to the polluting input relative to a single output model. Analyzing a subsector of agriculture rather than aggregate agriculture, however, produces a significantly lower estimate for the land-polluting input MES.

Not including polluting inputs separately in the model significantly affects one or more MES estimates. For example, not treating energy as a separate input significantly lowers the
labor and land vs. polluting input MES. Not treating fertilizer or manure as separate inputs significantly alters the land-polluting input MES.

Disaggregating labor significantly lowers the labor-polluting input MES, and aggregating land with capital significantly lowers both the land and capital vs. polluting input MES. Aggregating land with buildings and structures or disaggregating capital has no significant effect on the respective MES.

Using all pre-1981 data has a significant negative effect on the MES estimate for labor-polluting input and a significant positive effect on the MES estimate for land-polluting input. These coefficients imply that the period during which an agriculture-based biofuel industry has developed has made it easier for labor but harder for land to substitute for the polluting input.

Short-run substitution elasticities estimates for land and capital vs. the polluting input are significantly lower than long-run elasticities. That would be consistent with land and capital inputs adjusting more slowly than labor to long-run equilibrium levels.

The estimated MES between land and the polluting input is significantly higher in developing than in developed countries. The substitutability between land and capital vs. the polluting input is also significantly higher in non-U.S. developed countries than in the U.S. and developing countries.

2.6.2 MES estimates and LCA

Based on our choice of meta-regression explanatory variables, the reference case (i.e., when all dummies are equal to zero) represents a long-run MES between non-polluting inputs for a study that includes aggregate labor, land, and capital as non-polluting input categories and the polluting input of energy, fertilizer, and manure. It is based on a static translog cost function that
permits non-neutral technological change and non-constant returns to scale, treats U.S. aggregate agriculture as a single output, includes post-1981 time series data, and uses a maximum likelihood estimator. It is regarded as the most pertinent case for LCA models. The intercepts of the meta-regression represent the estimated MES of the reference case. They are all greater than 1.0 and significantly different from zero, indicating that substantial substitution potential exists between the polluting and non-polluting inputs in the reference case. Our results also suggest that labor is the best substitute for the polluting input, followed by land and capital. Therefore, if an LCA model is set up based on our reference case, the assumption of fixed-proportion production of biofuel feedstock would lead to a potentially seriously inaccurate measure of GHG emissions.

Three additional sets of MES estimates are presented in Table 2-4. The mean MES is the elasticity evaluated at the means of all explanatory variables. The short-run mean MES is the elasticity evaluated at the means of all variables except for the dummy variable for short-run elasticity, which is set to one. The long-run mean MES is the elasticity evaluated at the means of all variables except short run elasticity, which is set equal to zero. These alternatives are admittedly less relevant to LCA modeling because there are no observations with mean (or nearly mean) values of most dummy variables.

All MES estimates are lower than for the reference case, and those between capital and the polluting input are insignificantly different from zero. Nevertheless, the MES for labor and land vs. the polluting input is significant both at the data means and for the long run with other variables at their mean values. Also, the MES for labor-polluting input is significant for the short run with other variables at their mean values. Consequently, even if the agricultural feedstock production sector in an LCA model is based on cases that differ from our reference case in some
aspects, it would still be necessary to take account of substitutability between some non-polluting inputs and polluting inputs.

These four sets of MES estimates provide a strong implication that LCA models need to allow for input substitution in the production of agricultural feedstocks for biofuel. When an energy-price regulation is imposed or market price ratios change, the change in the quantity of the polluting input used in feedstock production does not follow a fixed-proportions path. LCA models that do not account for input substitutability cannot accurately assess GHG emissions when facing a price change in the polluting input and thus could lead to an inappropriate environmental policy conclusion.

2.7 Conclusions

This paper examines whether the empirical evidence on input substitution in agricultural biofuel feedstock production is sufficiently strong to warrant integration into lifecycle analyses. We estimate Morishima elasticities of substitution of non-polluting inputs with respect to the GHG polluting inputs in agricultural production relevant to biofuel feedstock by using meta-regression procedures. Energy, fertilizer, and manure are collectively treated as the “polluting input” while labor, land, and capital are considered as free of GHG pollution. For the meta-regression, we examined 65 empirical studies that include 225 elasticity estimates for labor, 120 for land, and 262 for capital vs. the polluting input. We estimate separate meta-regression models for each of these three samples. The first two elasticities are estimated by weighted least squares regression and the third by a random effects panel-data estimator.

The results show that much of the heterogeneity of Morishima elasticities of substitution for nonpolluting inputs vs. the polluting input in the primary studies can be explained by type of
primal or dual function, functional form, type and observational level of data, input categories, the number of outputs, type of output, time period, and country categories. The reference case in our meta-regression is regarded as the most relevant case for assessing GHG emissions through lifecycle analysis. It represents a long-run MES between the non-polluting inputs of labor, land, and capital and the polluting input of energy, fertilizer, and manure. It is based on a static translog cost function that permits non-neutral technological change and non-constant returns to scale, treats U.S. aggregate agriculture as a single output, includes post-1981 time series data, and uses a maximum likelihood estimator. It is regarded as the most pertinent case for LCA models of U.S. biofuel feedstocks. Each estimated substitution elasticity for the reference case is greater than one and significantly different from zero. Additionally, mean predicted elasticities imply that long-run input substitutability of labor and land vs. the polluting input might also exist in a wide variety of cases.

These findings imply that when a price regulation (e.g., carbon tax) is imposed on the polluting input, the proportions of non-polluting inputs and the polluting input vary and could have an important effect on GHG emissions. Therefore, lifecycle analyses based on fixed proportion production functions for biofuel feedstocks could lead to an inaccurate measure of GHG emissions from biofuel and thus provide an inappropriate reference for policy makers.
2.8 Appendix: References for Meta-analysis


References


   and Aggregate Technology.” Agricultural Productivity: Measurement and Explanation,
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   79(2): 292-308.
   Researcher 5: 3-8.
   Biofuel Carbon Debt.” Science 319: 1235-1238.
Florax, R. J. C. M. (2002). “Accounting for Dependence among Study Results in Meta-analysis:
   Methodology and Applications to the Valuation and Use of Natural Resources.” Research
   Memorandum 5. Amsterdam: Faculty of Economics and Business Administration, Free
   University.


March, 2014.


Use: United States and Mexico.” American Journal of Agricultural Economics 82(1):
183-199.
Table 2-1 Classification of input categories

<table>
<thead>
<tr>
<th>Input category</th>
<th>Inputs in primary studies that are included in the category</th>
</tr>
</thead>
<tbody>
<tr>
<td>Labor</td>
<td>Family labor, hired labor, human labor, operator labor, self-employed labor, contract labor</td>
</tr>
<tr>
<td>Land</td>
<td>Land, real estate</td>
</tr>
<tr>
<td>Capital</td>
<td>Capital, machinery inputs, animal power, inventories, water, irrigation, tractors, physical capital, durable equipment, buildings and farm produced durables, working capital, plowing services, minor implements, major implements</td>
</tr>
<tr>
<td>Energy, fertilizer and manure</td>
<td>Energy, mechanical energy, chemical energy, fuel and oil, fertilizer and lime, manure, chemicals, agrichemicals, biological inputs</td>
</tr>
</tbody>
</table>
Table 2-2 Descriptions of explanatory variables

<table>
<thead>
<tr>
<th><strong>Dummy variables</strong></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Dummy variable value = 0</td>
<td>Dummy variable value = 1</td>
</tr>
<tr>
<td>$\sigma_{y^M}$</td>
<td>$\sigma_{y^M}$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Function type</strong></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost or other functions</td>
<td>Profit function</td>
</tr>
<tr>
<td>Cost or profit functions</td>
<td>Functions other than cost and profit functions</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Functional form</strong></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Translog functional form</td>
<td>Other functional form</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Technology</strong></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Allows non-neutral technological change</td>
<td>Imposes neutral technological change</td>
</tr>
<tr>
<td>Allows non-constant returns to scale</td>
<td>Imposes constant returns to scale</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Model structure</strong></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Static model</td>
<td>Dynamic model</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Data Characteristics</strong></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Time series or panel data</td>
<td>Cross sectional data</td>
</tr>
<tr>
<td>Time series or cross sectional data</td>
<td>Panel data</td>
</tr>
<tr>
<td>National or farm level</td>
<td>Regional/state level data</td>
</tr>
<tr>
<td>National or regional/state level</td>
<td>Farm level data</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Estimation method</strong></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>MLE</td>
<td>Other types of estimators</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Measurement of output</strong></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Single output</td>
<td>Multiple outputs</td>
</tr>
<tr>
<td>Aggregate agriculture</td>
<td>A subsector of agriculture</td>
</tr>
<tr>
<td>-----------------------</td>
<td>---------------------------</td>
</tr>
</tbody>
</table>

### Input classification

<table>
<thead>
<tr>
<th></th>
<th>Energy is a separate input</th>
<th>Energy is not a separate input</th>
<th>Fertilizer is a separate input</th>
<th>Fertilizer is not a separate input</th>
<th>Manure is a separate input</th>
<th>Manure is not a separate input</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggregate labor</td>
<td>33.3%</td>
<td></td>
<td></td>
<td>93.8%</td>
<td>96.7%</td>
<td>98.5%</td>
</tr>
<tr>
<td>Land</td>
<td></td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Aggregate capital</td>
<td></td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>69.5%</td>
</tr>
<tr>
<td>Land is separated from</td>
<td></td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>20.8%</td>
</tr>
<tr>
<td>capital</td>
<td></td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>14.9%</td>
</tr>
</tbody>
</table>

### Time period

| Includes post-1981     | 59.1%                       | 71.7%                         | 54.2%                         |
| observations           |                             |                               |                               |
| All pre-1981 observations |                           |                               |                               |
| Long run elasticity    | 41.3%                       | 9.2%                          | 37.8%                         |
| Short run elasticity   |                             |                               |                               |

### Country classification

| The U.S. or non-U.S. developed countries | Developing countries | 38.7% | 59.2% | 34.4% |
| The U.S. or developing countries         | Non-U.S. developed countries | 14.2% | 5.8%  | 14.9% |

### Correction for publication bias

| Inverse of square roots of sample size | Mean | 0.157 | 0.158 | 0.152 |
|                                         | Maximum | 0.250 | 0.250 | 0.250 |
|                                         | Minimum | 0.021 | 0.021 | 0.021 |
Table 2-3 Meta-regression results, Morishima elasticities of substitution with respect to polluting input

<table>
<thead>
<tr>
<th></th>
<th>Labor, $\sigma_{ip}^M$</th>
<th>Land, $\sigma_{ip}^M$</th>
<th>Capital, $\sigma_{ip}^M$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>2.977***</td>
<td>1.772***</td>
<td>1.414**</td>
</tr>
<tr>
<td></td>
<td>(0.626)</td>
<td>(0.524)</td>
<td>(0.678)</td>
</tr>
<tr>
<td>Publication bias correction</td>
<td>-7.909***</td>
<td>-7.405***</td>
<td>-1.938</td>
</tr>
<tr>
<td></td>
<td>(2.337)</td>
<td>(1.642)</td>
<td>(2.028)</td>
</tr>
<tr>
<td><strong>Function type</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Profit function</td>
<td>-0.685***</td>
<td>0.155</td>
<td>-0.436**</td>
</tr>
<tr>
<td></td>
<td>(0.200)</td>
<td>(0.266)</td>
<td>(0.253)</td>
</tr>
<tr>
<td>Functions other than cost and profit functions</td>
<td>-1.277***</td>
<td>1.543***</td>
<td>0.044</td>
</tr>
<tr>
<td></td>
<td>(0.246)</td>
<td>(0.266)</td>
<td>(0.367)</td>
</tr>
<tr>
<td><strong>Functional form</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other functional form</td>
<td>0.348</td>
<td>-0.101</td>
<td>0.426</td>
</tr>
<tr>
<td></td>
<td>(0.245)</td>
<td>(0.299)</td>
<td>(0.287)</td>
</tr>
<tr>
<td><strong>Technology</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Neutral technological change</td>
<td>-0.232</td>
<td>-0.030</td>
<td>-0.294</td>
</tr>
<tr>
<td></td>
<td>(0.201)</td>
<td>(0.133)</td>
<td>(0.196)</td>
</tr>
<tr>
<td>Constant returns to scale</td>
<td>1.091***</td>
<td>-0.715***</td>
<td>0.292</td>
</tr>
<tr>
<td></td>
<td>(0.219)</td>
<td>(0.265)</td>
<td>(0.272)</td>
</tr>
<tr>
<td><strong>Model structure</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dynamic model</td>
<td>-0.390</td>
<td>0.360</td>
<td>-0.019</td>
</tr>
<tr>
<td></td>
<td>(0.268)</td>
<td>(0.310)</td>
<td>(0.319)</td>
</tr>
<tr>
<td><strong>Data characteristics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cross sectional data</td>
<td>-1.057***</td>
<td>omitted</td>
<td>omitted</td>
</tr>
<tr>
<td></td>
<td>(0.336)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Panel data</td>
<td>-0.916**</td>
<td>omitted</td>
<td>omitted</td>
</tr>
</tbody>
</table>
Regional/state level data

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>Coefficient</th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1.052***</td>
<td>-0.727***</td>
<td>0.739**</td>
</tr>
<tr>
<td></td>
<td>(0.272)</td>
<td>(0.275)</td>
<td>(0.333)</td>
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Farm level data

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>Coefficient</th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.682**</td>
<td>-1.060**</td>
<td>-0.044</td>
</tr>
<tr>
<td></td>
<td>(0.309)</td>
<td>(0.611)</td>
<td>(0.344)</td>
</tr>
</tbody>
</table>

### Estimation method

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>Coefficient</th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Other types of estimators</td>
<td>-0.054</td>
<td>-1.207***</td>
<td>0.137</td>
</tr>
<tr>
<td></td>
<td>(0.172)</td>
<td>(0.192)</td>
<td>(0.217)</td>
</tr>
</tbody>
</table>

### Output measurement

#### Multiple outputs

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>Coefficient</th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.195</td>
<td>1.741***</td>
<td>0.459**</td>
</tr>
<tr>
<td></td>
<td>(0.175)</td>
<td>(0.165)</td>
<td>(0.191)</td>
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</tbody>
</table>

#### A subsector of agriculture

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>Coefficient</th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-0.001</td>
<td>-0.393***</td>
<td>0.120</td>
</tr>
<tr>
<td></td>
<td>(0.207)</td>
<td>(0.534)</td>
<td>(0.234)</td>
</tr>
</tbody>
</table>

### Input classification

#### Energy is not a separate input

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<thead>
<tr>
<th></th>
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<th>Coefficient</th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-0.283***</td>
<td>-0.299*</td>
<td>-0.183</td>
</tr>
<tr>
<td></td>
<td>(0.166)</td>
<td>(0.157)</td>
<td>(0.201)</td>
</tr>
</tbody>
</table>

#### Fertilizer is not a separate input

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>Coefficient</th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-0.194</td>
<td>-0.733***</td>
<td>-0.119</td>
</tr>
<tr>
<td></td>
<td>(0.163)</td>
<td>(0.208)</td>
<td>(0.288)</td>
</tr>
</tbody>
</table>

#### Manure is a not separate input

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>Coefficient</th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-0.489</td>
<td>0.918*</td>
<td>-0.407</td>
</tr>
<tr>
<td></td>
<td>(0.296)</td>
<td>(0.513)</td>
<td>(0.452)</td>
</tr>
</tbody>
</table>

#### Disaggregate labor

<table>
<thead>
<tr>
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<th>Coefficient</th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-0.492***</td>
<td>-</td>
<td>-</td>
</tr>
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<td></td>
<td>(0.173)</td>
<td></td>
<td></td>
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</tbody>
</table>

#### Real estate/land and structure

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<th>Coefficient</th>
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<tr>
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<td>-</td>
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<td>-</td>
</tr>
<tr>
<td></td>
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<td>(0.271)</td>
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#### Disaggregate capital

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<thead>
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</tr>
</thead>
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<tr>
<td></td>
<td>-</td>
<td>-</td>
<td>0.150</td>
</tr>
<tr>
<td></td>
<td></td>
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<td>(0.290)</td>
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#### Land is included in capital

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<td>-1.369***</td>
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### Time period

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**Country classification**

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Notes: “-” indicates the variable is not used as an explanatory variable in the initial regression, and “omitted” means the variable is eliminated due to multicollinearity; ***, **, * = statistically significant at 1 percent, 5 percent and 10 percent level, respectively; standard errors are in parentheses.
Table 2-4 Predicted mean MES

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<th>Capital, $\sigma_{\sigma_p}^M$</th>
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<tr>
<td>Predicted mean MES</td>
<td>0.718*</td>
<td>0.598*</td>
<td>0.631</td>
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<td></td>
<td>(0.488)</td>
<td>(0.404)</td>
<td>(0.583)</td>
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<tr>
<td>Predicted mean short-run MES</td>
<td>0.684*</td>
<td>0.199</td>
<td>0.309</td>
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<tr>
<td></td>
<td>(0.497)</td>
<td>(0.462)</td>
<td>(0.586)</td>
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<tr>
<td>Predicted mean long-run MES</td>
<td>0.742*</td>
<td>0.638*</td>
<td>0.463</td>
</tr>
<tr>
<td></td>
<td>(0.493)</td>
<td>(0.405)</td>
<td>(0.593)</td>
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</table>

Notes: * = statistically significant at 10 percent for 1-sided test; standard errors are in parentheses.
CHAPTER THREE
LIFECYCLE ECONOMIC ANALYSIS OF CELLULOSIC BIOFUEL FOR
ENVIRONMENTAL POLICY ANALYSIS

Abstract

This paper develops a lifecycle economic analysis (LCEA) model that integrates input substitution, technology switching, and substitution of biodiesel for diesel into the standard lifecycle analysis of biofuel that assumes fixed-proportions production and illustrates that a standard lifecycle analysis that assumes fixed input proportions may substantially underestimate the potential emissions reductions from carbon taxes policies. We use the LCEA model to examine the impacts of a pure carbon tax and a revenue-neutral tax-subsidy policy on lifecycle greenhouse gas emissions from cellulosic ethanol using forest residues as feedstock in Washington State. A pure carbon tax higher than $0.039/kg CO₂ stimulates technology switching from coal to woody biomass in a cellulosic ethanol conversion plant and a pure carbon tax higher than $0.116/kg CO₂ induces substitution of biodiesel for diesel in the feedstock and transportation sectors. Estimated emissions are 36 percent and 52 percent lower, respectively, compared to the standard lifecycle analysis. For a revenue-neutral tax-subsidy policy, technology switching in a conversion plant occurs at a tax on fossil fuels higher than $0.006/kg CO₂ accompanied by a subsidy on renewable fuels higher than $0.023/kg CO₂ reduction, which reduces emissions by 31 percent. Biodiesel substitutes for diesel when the tax exceeds $0.017/kg CO₂ with a subsidy that exceeds $0.065/kg CO₂ reduction, which reduces emissions by 38 percent. Both of these energy substitutions occur at a revenue-neutral tax rate lower than the $0.025/kg CO₂ currently proposed for Washington State by CarbonWA, a nonpartisan grassroots
group developing a 2016 citizens’ ballot measure to reduce human impacts on climate change. The revenue-neutral tax-subsidy policy reduces emissions more effectively than the carbon tax policy for a carbon tax lower than $0.116/kg CO$_2$ because it can stimulate both technology switching and substitution of biodiesel for diesel at relatively low tax rates.

### 3.1 Introduction

Biofuels have become major renewable fuels for transportation. For instance, ethanol made up almost 10 percent of U.S. gasoline consumption by volume in early 2012 (EIA, 2012a). Environmental mandates have promoted the development of biofuels, especially cellulosic biofuels. The Renewable Fuel Standard (RFS) mandates that by 2022 liquid fuel consumed in the United States will include 36 billion gallons of renewable fuel, of which 16 billion gallons will be produced from cellulosic feedstock.

Policy makers and researchers have pursued cellulosic biofuel for its advantages in mitigating lifecycle greenhouse gas (GHG) emissions, which the U.S. Energy Independence and Security Act 2007 defines as the aggregate quantity of all types of GHG emissions related to the full fuel lifecycle. The act requires the U.S. Environmental Protection Agency (EPA) to determine and enforce lifecycle GHG reduction thresholds for renewable fuels. The tool primarily used to assess the lifecycle emissions from fuels is lifecycle analysis (LCA). Recent findings based on LCA suggest that the use of cellulosic feedstocks has clear benefits for mitigating GHG emissions (e.g., Daystar et al., 2012; Bright and Strømman, 2009).

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$^{36}$ The mass values of all types of GHG emissions are adjusted to CO$_2$-equivalent emissions according to their global warming potentials.
Most of the existing work using standard LCA is from the engineering field and generally is limited by the implicit or explicit assumption that inputs are used in fixed-proportions in each stage of the biofuel lifecycle. As a result, the emission estimates from those models are only based on current market conditions and do not account for any response to changing market prices or policy incentives. However, input substitutability is likely to exist in the production of feedstock and biofuel and in their transportation. For example, Liu and Shumway (2014) find substantial substitutability between GHG polluting and non-polluting inputs in agricultural production relevant to biofuel feedstock. Significant substitution potential among different energy sources has also been found (e.g., Serletis et al., 2010; Stern, 2012).

Input substitutability can lead to substantial differences in estimated lifecycle GHG emissions. In particular, when a price regulation (e.g., a carbon tax) is imposed on an input that generates GHG emissions, it could induce substitution away from that input and alter emission measures and environmental policy consequences (Rajagopal and Zilberman, 2008a). Two types of literature integrate input substitution into LCA. One is the literature on land-use change in response to biofuel production (e.g., Fargione et al., 2008; Searchinger et al., 2008). These papers are limited in the way in which economic substitution is formally integrated into LCA. The other is the smaller body of work by Rajagopal and Zilberman (2008a, 2008b), who have begun to formally integrate economic input substitution into LCA in a general economic model of production and biofuel markets. They develop an LCA model that includes production of corn and corn-based ethanol conversion in which producers can change optimal input combinations in response to changes in policy and prices. They derive a functional relationship between input prices and lifecycle emissions and use it to analyze sensitivity of the lifecycle emission estimates
to a carbon tax. Rajagopal et al. (2011) extend their work by accounting for indirect emissions induced in the fuel markets.

This present article develops and applies a lifecycle economic analysis (LCEA) model for biofuel and uses this model to analyze the impact of environmental tax policy on biofuel lifecycle emission levels. The term “economic” in LCEA refers to allowing for economic input substitution into production and transportation sectors in the lifecycle of biofuel. In this model, emission level is a function of optimal quantities of inputs that generate emissions, which are determined by partial equilibrium conditions in each sector. Hence, market conditions are incorporated into the lifecycle emissions. Because lifecycle analysis is concerned with long-run impacts, we also consider technology-switching possibilities of the conversion of biofuel and replacement of diesel with biodiesel in the feedstock and transportation sectors.

Our empirical application of the LCEA model examines the impact of alternative tax policies on the emission estimates of forest-residues-derived ethanol in the state of Washington. We first analyze the effects of a pure carbon tax imposed on each unit of emission, as Rajagopal and Zilberman (2008) did for corn-based ethanol, but our analysis differs from theirs in three aspects. First, we include a transportation sector for both feedstock and cellulosic ethanol delivery and distribution to make the biofuel lifecycle more complete. Second, we use conditional price elasticities of energy input demand to analyze emission changes due to price changes. Input substitution is implicitly captured by conditional price elasticities of input demand. Third, we investigate the carbon-tax levels that can stimulate technology switching (from a base plant that uses coal and natural gas to a new plant that uses woody biomass and natural gas) in the ethanol conversion and changes in energy source in the feedstock and transportation sectors.
We also analyze the impact of an integrated carbon-tax-subsidy policy on the lifecycle emission level of ethanol that is revenue-neutral within the energy sector. It taxes nonrenewable energy sources based on the amount of carbon emitted and uses the tax revenues to subsidize renewable energy sources based on the amount of carbon emissions they save. Galinato and Yoder (2010) previously developed and examined this policy. They simulated optimal taxes and subsidies in the motor fuel and electric power industries and compared welfare gains under different environmental policy settings. Different from their research, we focus on how the revenue-neutral tax-subsidy policy would alter the lifecycle emission of cellulosic biofuel when integrating input substitution and technology switching in the production and transportation sectors. Different levels of taxes and subsidies that satisfy the revenue-neutral constraint are examined. We also provide a comparison with a pure carbon tax on lifecycle emission levels.

This article documents extent to which standard LCA analysis can underestimate the emissions reductions that can follow from emissions tax policies by failing to account for economically-induced input substitution, technology switching, and changes in input energy sources. We discuss the threshold of taxes (or subsidies) that can stimulate these substitutions for the case in which the quantities of different energy sources meet the RFS 2022 mandate rather than solving for optimal taxes (or subsidies) and equilibrium fuel output levels.

Compared with emission estimates based on standard LCA, we find that a pure carbon tax of $0.025/kg CO₂ reduces emissions by 5 percent due to the substitution of clean inputs of labor and capital for carbon-intensive energy inputs in the production and transportation of cellulosic ethanol. At tax rates higher than $0.039/kg CO₂, the cellulosic ethanol conversion plant using coal switches technology to using woody biomass. At this rate, emissions are reduced by 36 percent, of which 9 percent is caused by substitution of labor and capital for energy inputs.
and 27 percent by technology switching. When the tax is greater than $0.116/kg CO₂, biodiesel substitutes totally for diesel as the liquid fuel, resulting in a 52 percent emission reduction from the initial level, including 20 percent from substitution of labor and capital for energy inputs, 27 from technology switching, and 5 percent from replacement of diesel with biodiesel.

A revenue-neutral tax-subsidy policy leads to technology switching in the conversion plant at a tax on fossil fuels higher than $0.006/kg CO₂ when accompanied by a subsidy on renewable fuels higher than $0.023/kg CO₂ reduction. Emissions are 31 percent lower than that of standard LCA, 1 percent from substitution of labor and capital for energy and 30 percent from technology switching. Biodiesel substitutes for diesel when the tax exceeds $0.017/kg CO₂ with a subsidy that exceeds $0.065/kg CO₂ reduction. It reduces emissions by 38 percent: 4 percent due to substitution of labor and capital for energy, 30 percent due to technology switching, and 4 percent due to replacement of diesel with biodiesel. When the revenue-neutral tax rate reaches $0.025/kg CO₂, accompanied by a subsidy of $0.094/kg CO₂ reduction, emissions are reduced by another 1 percentage point due to substitution of labor and capital for energy.³⁷

Cumulative emission reductions resulting from an integrated tax-subsidy policy are greater than those caused by the pure carbon tax at all tax rates until the pure carbon tax rate is high enough (i.e., $0.116/kg CO₂) to stimulate replacement of diesel with biodiesel in the feedstock and transportation sector. This is because the revenue-neutral tax-subsidy policy can

³⁷ This is the tax rate currently proposed for Washington by CarbonWA, a non-partisan grassroots group developing a 2016 revenue-neutral citizen’s ballot measure to reduce human impacts on climate change. The CarbonWA tax proposal is a revenue-neutral tax-subsidy policy approach that imposes carbon tax on fossil fuels consumed in Washington and uses the tax revenues to reduce sales tax, fund the Working Family Rebate, and eliminate the Business and Occupation tax (Carbon Washington 2014).
stimulate both technology switching and replacement of diesel with biodiesel at relatively low tax rates. When the tax exceeds $0.11/6/kg CO₂, the pure carbon tax becomes more effective in reducing emissions than the revenue-neutral policy with the same tax level. When the tax approaches $0.25/kg CO₂, emission reduction caused by the pure carbon tax is 71 percent compared to 68 percent by the revenue-neutral policy.

The rest of the article is organized as follows. Section 2 develops a theoretical LCEA model and assesses the effects of policies. Section 3 presents the LCEA model for ethanol that uses forest residues as feedstocks and discusses the impact of a carbon tax and a revenue-neutral tax-subsidy policy on emissions when input substitution, technology switching, and changes in energy source are accounted for in the ethanol lifecycle. Section 4 concludes.

3.2 Theoretical Foundation of the LCEA Model

In the lifecycle of biofuel, there are three sectors that generate GHG emissions from the use of non-renewable or renewable energy inputs: feedstock production, biofuel conversion, and transportation. The feedstock sector produces feedstock that is purchased by a biofuel conversion sector as an input for processing into biofuel. The transportation sector provides

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38 Lifecycle of biofuel comprise six stages which are absorption of GHG emissions by feedstock growth, production of feedstock, transportation of feedstock to a biofuel plant, conversion to biofuel, transportation of biofuel to end users, and combustion of biofuel (Wang et al., 2007; Neupane et al., 2011; Daystar et al., 2012). An assumption with wide acceptance in the literature is that carbon emissions associated with the direct burning of the biomass are offset by the growth of biomass. Consequently, net emissions from the biofuel lifecycle are only associated with the productive sectors (e.g., Daystar et al., 2012).
services for delivering feedstock to biofuel plants and distributing biofuel to the sites where it is combusted. Figure 3-1 summarizes the relationship between these sectors and emissions.

Our LCEA incorporates input substitution in feedstock production, biofuel conversion, and transportation sectors, as well as technology switching in the biofuel conversion sector and changes in energy source in the feedstock and transportation sectors. LCEA model relaxes the standard LCA assumption of fixed-proportions production in each sector and allows market conditions to guide producers’ choices about the quantities and ratios of inputs used, which are determined by a partial equilibrium analysis of each sector. To describe the LCEA model, we begin from the biofuel conversion and move backward to the feedstock production and transportation sectors.

3.2.1 Biofuel conversion sector

The biofuel conversion sector, indexed by $b$, uses feedstock ($Y_f$, where $f$ indexes feedstock type), a vector of non-renewable and renewable energy inputs ($N^b$), labor ($L^b$), and capital ($K^b$) to produce biofuel. Biofuel output is based on the sectoral production function $Y^b = Y^b(Y_f, N^b, L^b, K^b)$. The production function is increasing and concave in all arguments. Input prices are denoted as $p_f$, $p_N^b$, $p_l$, and $p_k$ for feedstock, energy inputs, labor, and capital, respectively, and are assumed to be exogenous. Assuming a perfectly competitive market and a pre-specified quantity of biofuel, $\bar{Y}^b$, the cost-minimization problem can be expressed as

$$\min_{\{Y_f, N^b, L^b, K^b\}} p_f Y_f + p_N^b N^b + p_l L^b + p_k K^b$$

subject to $Y^b \geq \bar{Y}^b$.

The optimal conditions are
\[ p_f - \lambda^b Y_f^b(Y_f, N^b, L^b, K^b) = 0 \] (1)
\[ p_N^b - \lambda^b Y_N^b(Y_f, N^b, L^b, K^b) = 0 \] (2)
\[ p_l - \lambda^b Y_L^b(Y_f, N^b, L^b, K^b) = 0 \] (3)
\[ p_k - \lambda^b Y_K^b(Y_f, N^b, L^b, K^b) = 0 \] (4)
\[ Y^b = Y^b = \bar{Y}^b, \] (5)

where \( \lambda^b \) is the Lagrange multiplier and subscripts of \( Y^b \) represent partial derivatives (e.g., \( Y^b \)). The demand for feedstock and energy inputs in the biofuel production are determined by the partial equilibrium and denoted as \( Y^f^* (p_f, p_N^b, p_l, p_k, \bar{Y}^b) \) and \( N^b^* (p_f, p_N^b, p_l, p_k, \bar{Y}^b) \), respectively.

3.2.2 Feedstock production sector

Production in feedstock sector \( f \) uses energy inputs, labor, and capital. It is characterized by the sectoral production function \( Y_f = Y_f(N_f, L_f, K_f) \), where \( N_f \) is a vector of non-renewable and renewable energy input quantities. Prices of \( N_f \) are denoted by a vector \( p_N^f \) and are treated as exogenous. Similar to the biofuel sector, the cost-minimization conditions under a competitive market determine the optimal quantities of energy inputs, which are \( N^f^* (p_N^f, p_l, p_k, Y^f^*) \).

3.2.3 Transportation sector

The transportation sector delivers feedstock to biofuel production plants and distributes biofuel to the combustion sector. We assume that the transportation sector uses labor, capital, and energy inputs. The same inputs are used to transport either feedstock or biofuel. The product of distance, \( D \), and quantity transported is treated as the output of transportation. The outputs of transporting biofuel, \( Y^{tb} \), and of transporting feedstock, \( Y^{tf} \), are determined by the sectoral
production functions $Y^{tb} = Y^{tb}(N^{tb}, L^{tb}, K^{tb})$ and $Y^{tf} = Y^{tf}(N^{tf}, L^{tf}, K^{tf})$, respectively, where $N^{tb}$ and $N^{tf}$ are vectors of non-renewable and renewable energy input quantities with corresponding prices $p_i$. For a given distance of delivering feedstock $Y^{f*}$ from its production site to biofuel conversion plant, $D^f$, the output level of transportation of feedstock, $\bar{Y}^{tf}$, is $\bar{D}^f * Y^{f*}$. Then the cost-minimizing quantities of energy inputs are $N^{tf*}(p_N, p_L, p_k, \bar{Y}^{tf})$. For a given distance of distributing biofuel from its conversion plant to end-use site, $D^b$, the optimal quantities of energy inputs are $N^{tb*}(p_N, p_L, p_k, \bar{Y}^{tb})$, where $\bar{Y}^{tb} = \bar{D}^b * \bar{Y}^b$.

3.2.4 Lifecycle carbon emissions

Direct lifecycle emissions are calculated in the LCEA model from the use of energy inputs in the feedstock production, biofuel conversion, and transportation sectors. Assuming the quantity of emissions from the use of each energy input is proportional to the quantity of the energy input, total direct emissions can be specified as

$$E(p_N^b, p_N^f, p^b, p^f, p_k, D^f, D^b, Y^{f*}, \bar{Y}^b, e^i) = \sum_i e^i N^i(p_N^b, p_N^f, p^b, p^f, p_k, D^f, D^b, Y^{f*}, \bar{Y}^b),$$

(6)

where $e^i$ denote vectors of emission factors of the vector of energy inputs in process $i$, and $i = b, f, tb, tf$. Unlike the lifecycle emission estimates in most previous LCA papers that are fixed scalars, equation (6) indicates a relationship between emission levels and market prices for producing a certain amount of biofuel, through their effects on input use, because optimal quantities and proportions of inputs can change when input prices change. This is the defining distinction between standard LCA and LCEA.
We next use this LCEA model to analyze the impact of alternative tax policies on lifecycle emissions from ethanol using forest residues as feedstock.

### 3.3 LCEA Model for Forest-Residue-Derived Ethanol

Cellulosic biomass is a potential feedstock for biofuel in the Pacific Northwest. This region has a comparative disadvantage in using agriculture crops as biofuel feedstocks but does have an abundance of cellulosic biomass in the form of forest residues (Yoder et al., 2010). Forest residue comes from logging, tree thinning, milling, and land clearing. While forest residues can be refined to produce several types of biofuel, we focus on forest-residue-derived ethanol and examine the impact of environmental policies on its lifecycle GHG emissions using the LCEA model.  

#### 3.3.1 Analytical procedures

Liquid fuels, which are required for equipment and truck operation, are energy inputs in the forest residue production sector and in the transportation sector. Diesel is the primary liquid

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39 Indirect emissions from land-use changes in the feedstock sector (Searching et al., 2008) are not considered in this study. The value of forest residues is so low that it is not expected to change optimal commercial timber harvest decisions. Hence, the environmental impacts of land-use change or deforestation due to timber harvest decisions are allocated to the main forestry products like timber and wood pulp (Daystar et al., 2012). Indirect emissions can also come from fuel consumption changes caused by the quantity of biofuel adopted in the fuel market (Rajagopal et al., 2011). We do not consider such impacts but rather conduct our analysis to provide the amount of cellulosic ethanol prescribed by the RFS mandate for 2022.

40 In forest residues production, forestry equipment is used to collect and process forest residues into deliverable sizes. In the transportation sector, a combination truck (tractor and trailer) is used to deliver forest residues and distribute ethanol (Daystar et al., 2012).
fuel used. We also assume the availability of non-cellulosic biodiesel as a perfect substitute for diesel (adjusted for energy content), so that either diesel or biodiesel will be used as the sole liquid fuel. Substituting diesel with biodiesel is assumed to occur when the effective price of diesel per unit of energy becomes higher than the effective price of biodiesel. 

The production of forest residues, transportation of forest residues, and transportation of ethanol allows input substitution among labor, capital, and liquid fuel; these are characterized by the production function $Y^j(N^j_{lf}, L^j, K^j) \forall j = f, tf, tb$, respectively, where the subscript $lf$ represents liquid fuel that can be diesel ($d$) or biodiesel ($bd$). To produce a given amount of ethanol, $\bar{Y}^b$, the cost-minimizing quantities of liquid fuels used in the production of feedstock, transportation of feedstock, and transportation of ethanol are initially $N^j_{lf}^*(p_{lf}, p_l, p_k, \bar{Y}^j) \forall j = f, tf, tb$ without any environmental policy.

The energy required for cellulosic ethanol conversion is similar to that for corn ethanol conversion but with an additional step required to break cellulosic material into simple sugars (Goffman, 2009). Energy inputs used for corn ethanol conversion are typically fossil energy like natural gas and coal or renewable energy like wood chips and corn syrup (Wang et al., 2007). We examine two technological types of ethanol conversion plants based on the energy inputs used. The base plant uses both natural gas and coal as processed energy inputs, while the new plant uses natural gas and woody biomass. Energy and non-energy inputs used in each stage of cellulosic ethanol production and transportation are summarized in Table 3-1.

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41 Because LCA focuses on the long run, we allow perfect substitutability between diesel and biodiesel. This assumes that any short-run limits on substitutability are resolved in the long run. For the remainder of the article we use the term biodiesel to mean non-cellulosic diesel.
Ethanol output for each production plant is based on the production function

\[ Y_x^b(Y^f, N_{ngx}^b, N_x^b, L_x^b, K_x^b), \]

where \( x = c \) or \( wb \) represents a plant using coal (base case) or woody biomass (new case), \( N_{ngx}^b \) is the quantity of natural gas consumed by the plant using energy \( x \), and \( N_x^b \) is the quantity of energy \( x \). We allow substitution between energy inputs and clean inputs of labor and capital and assume (a) the forest feedstock is used in fixed proportion to the aggregate of other inputs; and (b) natural gas and energy, \( x \), are also assumed to be used in fixed proportion in the respective plant.\(^{42}\) Therefore, the optimal quantity of natural gas in both plants is the same and the initial quantity of natural gas to produce a given amount of ethanol can be denoted as \( N_{ng}^{b*}(p_{ng}, p_l, p_k, \bar{Y}^b) \). Then the initial quantity of energy \( x \) is \( N_x^{b*}(p_{ng}, p_l, p_k, \bar{Y}^b) \), where \( N_x^{b*} = a_x N_{ng}^{b*} \) and \( a_x \) denotes a constant proportion of energy \( x \) to natural gas.

The total emission from the production and transportation sectors of cellulosic ethanol using plant \( x \) and fuel \( lf \) is

\(^{42}\) The amount of feedstock required for producing one gallon of cellulosic ethanol depends on conversion methodology (Pimentel and Patzek, 2005; Thomas, 2008; Sims et al., 2010). It will require much improvement in technology to substitute feedstock with other inputs, so we make assumption (a) and focus on the substitution of labor and capital for energy. In the existing literature, estimates for the long-run conditional cross-price elasticities between natural gas and coal for the whole U.S. economy and for the industrial sector include both positive and negative estimates (Jones, 1995; Urga and Walters, 2003; Serletis et al., 2010). Since the positive estimates are very small and the mean of the estimates is negative, we treat the cross-price elasticities as zero, which implies that natural gas and coal are used in fixed proportions. In ethanol conversion, woody biomass can be used as an energy source to substitute for coal (Wang et al., 2007). Because LCA focuses on the long run and we assume that any short-run limits on substitutability of energy inputs are resolved in the long run, we treat woody biomass as a perfect substitute for coal as an energy source in ethanol conversion, i.e., assumption (b).
\begin{equation}
E_{x,lf} = e_{lf} \sum_{j=f,t,fb} N_{lf}^{j*} + e_{ng} N_{ng}^{b*} + e_x N_{x}^{b*},
\end{equation}

which is equivalent to

\begin{equation}
E_{x,lf} = e_{lf} \sum_{j=f,t,fb} N_{lf}^{j*} + (e_{ng} + a_x e_x) N_{ng}^{b*}.
\end{equation}

Emission levels vary as the quantity and composition of energy inputs change in response to market and policy conditions. For a given type of ethanol conversion plant, quantities of energy inputs can change due to changes in relative input prices. The amount of change in emission levels for a given ethanol conversion technology can be expressed by the following equation:

\begin{equation}
\Delta E_{x,lf} = e_{lf} \sum_{j=f,t,fb} \Delta N_{lf}^{j*} + (e_{ng} + a_x e_x) \Delta N_{ng}^{b*}.
\end{equation}

Holding capital and labor prices constant, the changes in quantities of liquid fuel and natural gas due to changes in their prices can be obtained by taking the total differentials:

\begin{equation}
\Delta N_{lf}^{j*} = \frac{\partial N_{lf}^{j*}}{\partial p_{lf}} \Delta p_{lf}
\end{equation}

\begin{equation}
\Delta N_{ng}^{b*} = \frac{\partial N_{ng}^{b*}}{\partial p_{ng}} \Delta p_{ng}.
\end{equation}

Rewriting equations (10) and (11) in terms of conditional input demand price elasticities, we obtain

\begin{equation}
\Delta N_{lf}^{j*} = \epsilon_{lf}^{j} N_{lf}^{j*} \Delta p_{lf}
\end{equation}

\begin{equation}
\Delta N_{ng}^{b*} = \epsilon_{ng}^{b} N_{ng}^{b*} \Delta p_{ng}.
\end{equation}

where \( \epsilon_{lf}^{j} \) is the conditional own-price elasticity of liquid fuel used in sector \( j \) and \( \epsilon_{ng}^{b} \) is the conditional own-price elasticity of natural gas used in ethanol conversion. Substituting equations (12) and (13) into equation (9), we obtain
\[ \Delta E_{x,lf} = e_{lf} \sum_{j=f,tf,tb} \frac{\xi_j}{p_{lf}} \Delta p_{lf} + (e_{ng} + a_x e_x) \frac{e_{ng} N_{ng} b^*_x}{p_{ng}} \Delta p_{ng}, \]  
\[ (14) \]

where \( x = \) coal (c) or woody biomass (wb) and \( lf = \) diesel (d) or biodiesel (bd). This equation indicates that changes to lifecycle carbon emissions when the prices of energy inputs change can be characterized by conditional input demand elasticities. Under the assumption of a fixed-proportions production function implicit in most LCA analyses, conditional input demand elasticities are equal to zero, and emissions remain unchanged even when environmental policies cause changes in energy prices. Instead, non-zero conditional input demand elasticities indicate changes in input ratios and thus the presence of input substitutability as input prices change.

Thus, standard LCA analysis is a special case of this more general LCEA framework.

3.3.1.1 Technology switching and liquid fuel changes

Environmental policy could cause producers using coal in the ethanol plant (base) to switch to woody biomass (new) depending on which technology provides lower long-run cost. For simplicity, we assume that the construction costs for base and new plants are the same. The initial input costs for plants using energy source \( x \) are

\[ C_x = p_{ng} N_{ng} b^*_x + p_x N_{x} b^*_x + p_l L_{x} b^*_x + p_k K_{x} b^*_x, \]  
\[ (15) \]

which is equivalent to

\[ C_x = (p_{ng} + p_x a_x) N_{ng} b^*_x + p_l L_{x} b^*_x + p_k K_{x} b^*_x. \]  
\[ (16) \]

Assuming that quantities of labor and capital used in both plants are the same, the initial input cost difference between the new and base plants in the absence of environmental policy is

\[ \Delta \overline{C} = C_{wb} - C_c = (p_{wb} a_{wb} - p_c a_c) N_{ng} b^*_x. \]  
\[ (17) \]
When environmental policy affects the relative prices of carbon intensive and less carbon intensive energy sources, the cost changes in the new plant and the base plant are as follows:

\[ \Delta C_x = (p'_x a_x + p'_n g)\Delta N_{ng}^{b*} + (\Delta p_x a_x + \Delta p_{ng})N_{ng}^{b*} + p_l \Delta l_x^{b*} + p_k \Delta K_x^{b*}, \tag{18} \]

where \( p'_x \) is the new effective price for energy, \( x \). Effective price includes the tax. Producers initially using the base plant switch to the new plant if the input costs in the new plant are lower than the base plant in the long-run:

\[ C_c + \Delta C_c > C_{wb} + \Delta C_{wb}, \tag{19} \]

which is equivalent to

\[ \Delta C_c - \Delta C_{wb} > \overline{\Delta C}. \tag{20} \]

Assuming changes in quantities of labor and capital are the same for both plant types (i.e., \( \Delta L_c^{b*} = \Delta L_{wb}^{b*} \) and \( \Delta K_c^{b*} = \Delta K_{wb}^{b*} \)) and inserting equation (18) into inequality (20), we have

\[ (p'_c a_c - p'_w b a_{wb})\Delta N_{ng}^{b*} + (\Delta p_c a_c - \Delta p_{wb} a_{wb})N_{ng}^{b*} > \overline{\Delta C}. \tag{21} \]

Inserting equation (13) into inequality (21), we obtain

\[ (p'_c a_c - p'_w b a_{wb})\Delta p_{ng} \frac{e_{ng}^{b*} N_{ng}^{b*}}{p_{ng}} + (\Delta p_c a_c - \Delta p_{wb} a_{wb})N_{ng}^{b*} > \overline{\Delta C}. \tag{22} \]

The emission change caused by the technology switching when keeping diesel as the primary liquid fuel is

\[ \Delta E_{cwb} = (E_{wb,d} + \Delta E_{wb,d}) - (E_{c,d} + \Delta E_{c,d}). \tag{23} \]

Total emission reduction from the initial emission level at the technology switching point is

\[ \Delta E = E_{wb,d} + \Delta E_{wb,d} - E_{c,d}. \tag{24} \]

Additionally, the price of diesel per unit of energy is lower than the price of biodiesel in the absence of any environmental policy. When environmental policy affects relative prices of
diesel and biodiesel, biodiesel substitutes totally for diesel in feedstock production and in transportation of the feedstock and ethanol if

\[
\frac{p_d + \Delta p_d}{HV_d} > \frac{p_{bd} + \Delta p_{bd}}{HV_{bd}},
\]

(25)

where \(HV\) denotes heating values. Emission change caused by replacement of diesel with biodiesel is

\[
\Delta E_{dbd} = (E_{wb, bd} + \Delta E_{wb, bd}) - (E_{wb, d} + \Delta E_{wb, d}).
\]

(26)

Total emission change from the initial level when substituting biodiesel for diesel is

\[
\Delta E = E_{wb, bd} + \Delta E_{wb, bd} - E_{c, d}.
\]

(27)

We next analyze the impact of environmental policy on the cellulosic ethanol lifecycle emissions. In the lifecycle, coal is initially used in the ethanol conversion plant and diesel in the production of feedstock and transportation of feedstock and ethanol. Two policy regimes are considered: a carbon tax and an integrated tax-subsidy policy within the fuel industry. The former refers to a tax that is imposed on each unit of emission. The latter refers to a revenue-neutral tax policy on energy sources with higher carbon intensities and offsetting subsidies on energy sources with lower carbon intensities.

3.3.1.2 Carbon tax

The prices of liquid fuels, natural gas, coal, and woody biomass after imposing the carbon tax are as follows:

\[
p'_h = p_h + \tau e_h \, \forall h = lf, ng, c, wb,
\]

(28)

where \(\tau\) denotes the carbon tax and \(lf\) can be diesel (\(d\)) or biodiesel (\(bd\)). The changes in prices are then
\[ \Delta p_h = \tau e_h \ \forall h = lf, ng, c, wb. \]  

Accounting for equations (28) and (29), equation (14) and inequalities (22) and (25) become, respectively,

\[ \Delta E_{x,lf} = \tau (e_{lf})^2 \sum_{j = f, tf, tb} \frac{\epsilon_{lf}}{p_{lf}} \tau e_{ng}(e_{ng} + a_x e_x) \frac{\epsilon_{ng}^{b*}}{p_{ng}} \]  

\[ \tau e_{ng}(a_c(p_c + \tau e_c) - a_{wb}(p_{wb} + \tau e_{wb})) \frac{\epsilon_{ng}^{b*}}{p_{ng}} + \]  

\[ \tau (e_c a_c - e_{wb} a_{wb}) N_{ng}^{b*} > \Delta C. \]  

3.3.1.3 Revenue-neutral tax-subsidy policy

The integrated revenue-neutral tax-subsidy policy imposes a carbon tax on fossil fuels and uses the tax revenue to subsidize each unit of emission reduction of renewable energy. We consider four types of fossil fuels: coal \((c)\), natural gas \((ng)\), diesel \((d)\), and gasoline \((g)\).

Renewable fuels include woody biomass \((wb)\), biodiesel \((bd)\), non-cellulosic ethanol \((ne)\), and cellulosic ethanol \((ce)\). The integrated tax-subsidy policy changes the prices of fossil fuels with a tax on each unit of CO\(_2\):

\[ p_q' = p_q + \tau e_q \ \forall q = c, ng, d, g. \]  

We assume that the emission reduction of woody biomass is measured by the emission of coal minus the emission of woody biomass based on the setting that woody biomass is used to substitute coal in the new conversion plant. We treat the emission of diesel and gasoline, respectively, as the baseline for measuring the emission reduction of biodiesel and ethanol. Effective prices of renewable fuels then become:
\[ p_{wb}' = p_{wb} + s(e_{wb} - e_c) \]  
\[ p_{bd}' = p_{bd} + s(e_{bd} - e_d) \]  
\[ p_n' = p_n + s(e_n - e_g) \quad \forall n = ne, ce, \]  

where \( s \) represents the subsidy on each unit of emission reduction. The changes in prices are

\[ \Delta p_q = \tau e_q \quad \forall q = c, ng, d, g \]  
\[ \Delta p_{wb} = s(e_{wb} - e_c) \]  
\[ \Delta p_{bd} = s(e_{bd} - e_d) \]  
\[ \Delta p_n = s(e_n - e_g) \quad \forall n = ne, ce. \]

Then inequalities (22) and (25) become, respectively:

\[ \tau e_{ng}(a_c(p_c + \tau e_c) - a_{wb}(p_{wb} + s(e_{wb} - e_c))) \frac{\epsilon_{ng}^h n_{ng}^h}{p_{ng}} + \]  
\[ (\tau e_c a_c - s a_{wb}(e_{wb} - e_c)) N_{ng}^{h*} \epsilon_{ng}^h > \Delta c. \]  
\[ \frac{p_d + \tau e_d}{H V_d} > \frac{p_{bd} + s(e_{bd} - e_d)}{H V_{bd}} \]

The revenue-neutral tax-subsidy instrument ensures that tax receipts equal tax subsidies by satisfying the constraint:

\[ \tau \sum q e_q Y_q + s(e_{wb} - e_c) Y_{wb} + s(e_{bd} - e_d) Y_{bd} + s \sum n(e_n - e_g) Y_n = 0, \]  

where \( Y_q, Y_{bd}, \) and \( Y_n \) represent the total quantities of fuel \( q, bd, \) and \( n, \) respectively, consumed by Washington in the target year of 2022 under a binding RFS mandate. In this equation, the emission factor of cellulosic ethanol is not static because the emission of cellulosic ethanol is changed by taxes and subsidies due to the incorporation of input substitution in its lifecycle.\(^{43}\)

\(^{43}\)We assume the emission factor of all other types of cellulosic ethanol is the same as the emission factor of forest-residue-derived ethanol.
For a given type of conversion technology, \( x \), changes in emission when diesel is used and when biodiesel is used are, respectively,

\[
\Delta E_{x,d} = \tau (e_d)^2 \sum_{s=f, tf, tb} \frac{e_d^s N_d^s}{p_d} + \tau e_{ng} (e_{ng} + a_x e_x) \frac{e_{ng} N_{ng}^b}{p_{ng}} \tag{44}
\]

\[
\Delta E_{x,bd} = s e_{bd} (e_{bd} - e_d) \sum_{s=f, tf, tb} \frac{e_{bd}^s N_{bd}^s}{p_{bd}} + \tau e_{ng} (e_{ng} + a_x e_x) \frac{e_{ng} N_{ng}^b}{p_{ng}} \tag{45}
\]

Accordingly, based on a given amount of forest residues-derived ethanol \( \bar{Y}^b \), the emission factors of ethanol can be dynamically computed depending on the least-cost liquid fuel type and conversion technology type by the following equations:

\[
e_{ce,d} = \frac{(E_{x,d} + \Delta E_{x,d})}{\bar{Y}^b} \tag{46}
\]

\[
e_{ce,bd} = \frac{(E_{x,bd} + \Delta E_{x,bd})}{\bar{Y}^b} \tag{47}
\]

The emission factors of other types of energy are treated as constants.

### 3.3.2 Parameter values

Parameter values used in our analysis are based on the assumption that Washington State will meet the RFS 2022 mandate. For the purpose of this research, we focus on production of cellulosic ethanol from forest residues in Washington. By 2022, the RFS requires the blending of 36 billion gallons of renewable fuel to transportation fuel, 16 billion gallons of which must be from cellulosic materials. We consider the case in which Washington is self-sustaining in its production of cellulosic biofuel. It currently consumes 2 percent of national liquid fuel, so we examine a scenario in which it produces 2 percent of the 2022 RFS mandate for cellulosic biofuel, with half of cellulosic feedstocks coming from the forestry sector and converted into cellulosic ethanol. Under these conditions, Washington would produce 1 percent (160 million gallons) of the U.S. mandate of 16 billion gallons of ethanol using forest residues as feedstock in
2022. The quantity of forest residues required for a given amount of cellulosic ethanol depends on the conversion process. This research does not focus on a particular conversion technology. We use the mean of estimates in the existing literature for the amount of woody biomass required to produce one liter of cellulosic ethanol (Pimentel and Patzek, 2005; Thomas, 2008; Sims et al., 2010). Thus, a gallon of cellulosic ethanol is estimated to require 13.25 dry kilograms of cellulosic feedstock. Based on this estimate, we extrapolate that 2.12 billion dry kilograms of forest residues would be required to produce 160 million gallons of cellulosic ethanol.

Parameter values for price elasticities of energy inputs, initial quantities of energy inputs for producing 160 million gallons of cellulosic ethanol in Washington, energy prices, emission factors, initial energy consumption in Washington State in 2022 if the requirements of RFS 2022 are met, heating value of each energy source, and initial input cost difference between new and base plants are presented in order in Table 3-2. They are based on prior literature. Information on capital and labor is not required for the analysis.

No information is available about input price elasticities for cellulosic ethanol plants. We use the weighted average of long-run conditional own-price elasticities of natural gas in the relevant literature (Jones, 1995; Urga and Walters, 2003; Serletis et al., 2010) as a proxy. No prior estimates exist for conditional own-price elasticities of liquid fuel used in the forestry sector or biodiesel used in transportation. Using the same data used by Liu and Shumway (2014), we obtained a meta-regression estimate of the conditional own-price elasticity of GHG-polluting inputs in agricultural production relevant to biofuel feedstock production. We use this estimate as

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44 Multiple conversion pathways for producing ethanol from cellulosic materials are addressed in the literature. Most use biochemical or thermochemical conversion.

45 The weight on each estimate is equal to the reciprocal of the number of estimates in each paper.
the proxy for the conditional own-price elasticity of liquid fuel used in the forestry sector for biofuel feedstock production. We follow Dahl (2012) for the estimate of the conditional own-price elasticity of diesel in transportation of forest residues and transportation of ethanol and use it as a proxy for the own-price elasticity of biodiesel.

Because data for energy used in cellulosic ethanol conversion plants is also not yet available, we rely on proxies for initial energy requirements by energy source. The conversion process for cellulosic ethanol is similar to that for corn ethanol with the additional step of breaking cellulosic materials into simple sugars (Goffman, 2009). Pimental and Patzek (2005) indicate that the conversion process for wood ethanol uses twice as much electricity as that for corn ethanol. Therefore, we double the quantities of natural gas and coal required for producing one gallon of corn-based ethanol in Wang et al. (2007) as an approximation for cellulosic ethanol produced in the base plant. Then we compute the initial quantities of natural gas and coal required for producing 160 million gallons of cellulosic ethanol. The initial quantity of woody biomass in the new plant is computed based on the relative heating values of coal and woody biomass.

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46 Our elasticity estimate is for the reference case in Liu and Shumway (2014), which is regarded as the most relevant case for LCA models. This model is a long-run conditional input demand price elasticity for the polluting input of energy, fertilizer, and manure with prices of labor, land, and capital included as non-polluting input categories in the estimation equation. It is based on a static translog cost function that permits non-neutral technological change and non-constant returns to scale, treats U.S. aggregate agriculture as a single output, includes post-1981 time series data, and uses a maximum likelihood estimator.
In forest residue input processing, Johnson et al. (2012) estimate that diesel used for loading and processing residues at log landings is 3.83 liters per dry metric ton.\textsuperscript{47} We first extrapolate the initial quantity of diesel required to produce 2.12 billion kilograms of forest residues using their estimate. As an alternative energy source, we compute the initial quantity of biodiesel that can substitute totally for diesel based on the heating values of diesel and biodiesel. Heating values of diesel and biodiesel are the mean of lower and higher heating values of diesel and biodiesel, respectively (DOE 2013).

In transportation, we follow Johnson et al. (2012) and set the average delivery distance from forest to ethanol conversion plant at 145 km. Their analysis indicates that 9.33 liters of diesel is required to transport a metric ton of forest residues this distance. The LCA model of ethanol developed by Daystar et al. (2012) implies that the fuel used for ethanol transportation is 0.19 times as much as for forest residue transportation. We follow this result to extrapolate the initial diesel quantities for the distribution of ethanol and assume an average distribution distance of 145 km. Then the initial quantity of biodiesel that can substitute totally for diesel is computed based on the relative heating values of diesel and biodiesel.

We use 2012 prices of natural gas, coal, woody biomass, and diesel in Washington as proxies for their price estimates in 2022. The average 2012 price of biodiesel on the West Coast is used as a proxy for the 2022 biodiesel price in Washington.\textsuperscript{48}

\textsuperscript{47} Johnson et al. (2012) model production for grinding residues at log landings in the Inland West. This is the most similar case to forest residue collection in Washington available in the existing literature.

\textsuperscript{48} The prices are retail prices. We use 2012 data because this is the latest year for which complete information about both energy price and consumption are available for the state of Washington.
Emission factors are in units of CO$_2$ equivalents. The emission factors of natural gas and coal are obtained from the Energy Information Administration (2013a). The emission factor of woody biomass is proxied by the mean emission of harvesting and transporting one unit (MMBtu) of forest residues using diesel and biodiesel.\textsuperscript{49} We consider only harvesting and transportation emissions of woody biomass since emissions from burning woody biomass are totally offset by emissions absorbed in producing the woody biomass.\textsuperscript{50} We follow Galinato and Yoder (2010) to determine the amount of emission generated per gallon of diesel and biodiesel. Emission factors of gasoline and non-cellulosic ethanol are also required when analyzing emission reductions under the integrated tax-subsidy policy. They are obtained from the Energy Information Administration (2013a) and The Climate Registry (2014), respectively.

We extrapolate the initial total consumption of each energy source in Washington in 2022 in the absence of environmental policy that could impact energy prices. Our estimates are based on the following assumptions: (a) the consumption of non-liquid fuels (coal, natural gas, and woody biomass) will be the same as in 2012; (b) the national use of non-cellulosic and cellulosic biofuel will meet the RFS 2022 mandate and Washington will consume 2 percent of each type of biofuel in 2022; (c) cellulosic biofuel consumed in 2022 in Washington is cellulosic ethanol and the proportion of biodiesel to non-cellulosic ethanol consumed will be the same as the proportion of diesel to gasoline consumed in 2012; (d) the total consumption of diesel and biodiesel will remain the same as in 2012; and (e) the total combined consumption of gasoline, non-cellulosic

\textsuperscript{49} We check the sensitivity of our results by using both the lower bound and the upper bound of emission factors for woody biomass. We find no appreciable differences in the results.

\textsuperscript{50} The emission factor of woody biomass in current literature is often much higher since carbon absorption by woody biomass production is not taken into account (\textit{e.g.}, The Climate Registry, 2014).
ethanol, and cellulosic ethanol will remain the same as in 2012. Based on the assumptions (b) and (c), Washington will use 114, 286, and 320 million gallons of biodiesel, non-cellulosic ethanol, and cellulosic ethanol, respectively. Then the consumption of diesel and gasoline in 2022 are computed by the quantities consumed in 2012 minus the quantities of biodiesel and ethanol (adjusted by energy content), respectively, based on assumptions (d) and (e).

The initial input cost difference between new and base plants in the absence of environmental policy is computed based on input quantities and prices. Assuming that fixed construction costs and labor and capital use are the same for both types of plants, the only difference in costs is the source of energy. Using the quantities and prices of coal and woody biomass discussed before, coal for the base ethanol conversion plant initially costs 9.11 million dollars less than woody biomass in the new plant for producing 160 million gallons of forest-residue-derived ethanol.

3.3.3 Results

By inserting the initial quantities of energy inputs for producing 160 million gallons of cellulosic ethanol and emission factors from Table 3-2 into equation (7), the total amount of CO$_2$ emissions from producing 160 million gallons of cellulosic ethanol in the state of Washington in 2022 is estimated to be 780 million kg when the base ethanol conversion plant is used and diesel is the only liquid fuel used in forest-residue production and transportation and ethanol transportation. Accordingly, the average emission level per gallon (emission factor) of cellulosic ethanol is 4.87 kg. Thus, in the absence of any additional environmental policy, ethanol would

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51 RFS 2022 requires 20 and 16 billion gallons of non-cellulosic and cellulosic biofuels, respectively. The ratio of gasoline to diesel consumption in 2012 was 2.5.
reduce carbon emissions by 19 percent and 15 percent, respectively, when substituted for a comparable amount of energy from gasoline or corn ethanol. Under the assumption of fixed-proportion input combinations, the emission reduction of ethanol stays unchanged under any taxes or subsidies on energy inputs. We next examine emission changes under different tax levels for a pure carbon tax and a revenue-neutral tax-subsidy policy allowing for input substitution, technology switching, and change in energy source.

3.3.3.1 Impact of a carbon tax

Figure 3-2 presents the estimated long-run impacts of a carbon tax on emissions when input substitution is permitted in the Washington state cellulosic ethanol production and transportation sectors (i.e., feedstock production, ethanol conversion, and transportation of feedstock and ethanol). We find that taxes and subsidies that stimulate producers to switch from the base ethanol conversion plant that uses coal to a new plant that uses woody biomass are lower than those that stimulate producers to substitute biodiesel for diesel. Inserting parameter values from Table 3-2 into inequality (31), we find that a carbon tax that exceeds $0.039/kg CO$_2$ can trigger a switch from coal to woody biomass in the ethanol conversion plant. Based on inequality (32) and parameter values in Table 3-2, a carbon tax higher than $0.116/kg CO$_2$ can cause biodiesel to substitute for diesel in the production of forest residues and in the transportation of forest residues and ethanol.

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$52$ Gasoline and corn ethanol have emission factors of 8.90 kg CO$_2$/gallon and 5.75 kg CO$_2$/gallon (EIA, 2013a), respectively. Energy content of gasoline and ethanol is 0.125 and 0.084 MMBtu/gallon, respectively (The Climate Registry, 2014).
For a tax rate less than $0.039/kg CO\(_2\), the change in emissions is caused by substitution of labor and capital for energy (diesel, natural gas, and coal) in each of the ethanol production and transportation stages. It follows line \(a1\) in Figure 3-2. Considering a tax rate of $0.025/kg CO\(_2\), which is equal to the carbon tax rate currently proposed by CarbonWA, input substitution of labor and capital for energy causes the emission level to decrease by 43 million kg (a reduction of 6 percent from the initial level), compared to that estimated by the standard LCA, which assumes fixed-proportions production. Prices of coal and diesel are increased by $2.38/MMBtu and $0.28/gallon, respectively. As the tax rate approaches $0.039/kg, emissions are reduced by 67 million kg (9 percent from initial level) due to the input substitution.

The breakeven price between ethanol conversion technologies that use coal (base) and those that use woody biomass (new) as a primary energy source is reached at the tax rate of $0.039/kg CO\(_2\). At higher rates, the ethanol conversion plant switches technology, from using coal to woody biomass. Emissions are reduced by another 214 million kg (27 percent of initial level) to 499 million kg, 36 percent lower than the initial emission estimates, of which 27 percent is from technology switching and 9 percent is from substitution of labor and capital for diesel, woody biomass, and natural gas. Prices for all types of energy increase, e.g., the prices of coal and diesel are raised by $3.72/MMBtu and $0.44/gallon, respectively.

With carbon tax rates of $0.039–$0.116/kg CO\(_2\), ethanol conversion uses woody biomass and natural gas, and production and transportation of feedstock and ethanol uses diesel as the primary energy input. As the tax rate approaches $0.116/kg CO\(_2\), emissions decrease by an additional 89 million kg due to the substitution of labor and capital for energy inputs (diesel, natural gas, and woody biomass) following line \(a2\) in Figure 3-2. Total emissions are reduced by 370 million kg (a reduction of 47 percent from initial level).
At the tax rate of $0.116/kg CO$_2$, the prices of diesel and biodiesel are increased by $1.32$ and $0.71$ per gallon, respectively. The breakeven price is reached between diesel and biodiesel per unit of energy content. The prices of diesel and biodiesel are $5.40$/gallon and $5.02$/gallon, respectively. Biodiesel substitutes for diesel in the feedstock and transportation sectors, which reduces emissions by another 34 million kg to 376 million kg. Thus, at the tax rate of $0.116$/kg CO$_2$, total emission reduction is 52 percent from the initial level: 5 percent due to replacement of diesel with biodiesel, 27 percent due to technology switching in the conversion plant, and 20 percent due to substitution of labor and capital for energy.

For a carbon tax that exceeds $0.116$/kg CO$_2$, further decreases in emissions are caused by substitution between energy and clean inputs in biofuel production and transportation, following the line $a3$ in Figure 3-2. When the tax rate reaches $0.250$/kg CO$_2$, emissions are reduced to 228 million kg. This is a 70 percent reduction from the initial level, of which nearly 19 percent is caused by further substitution of labor and capital for energy sources compared to the tax rate of $0.116$/kg CO$_2$.

Compared to the findings of Rajagopal and Zilberman (2008a) that integrate input substitution into LCA of corn ethanol, our estimates of emission reductions from cellulosic ethanol due to a carbon tax are much lower. For example, they estimate that a tax rate of $0.005$/kg CO$_2$ can reduce lifecycle emissions of corn ethanol by 21 percent. Our estimated reduction from lifecycle emissions of cellulosic ethanol is about 1 percent. One reason for the big difference is that they treat natural gas and coal used in the ethanol conversion plant as substitutes while we treat them as complements. They also use different sources of prior parameter values because they focus on corn-based ethanol, while we consider forest-residue-derived ethanol.
3.3.3.2 Impact of a revenue-neutral tax-subsidy policy

Figure 3-3 presents the estimated long-run impacts of a revenue-neutral carbon tax-subsidy on emissions when input substitution is permitted in the cellulosic ethanol production and transportation sectors in Washington in 2022. By inserting parameter values from Table 3-2 into constraint (43) and inequality (41) and (42), we find that a very low tax rate of $0.006/kg CO₂ on fossil fuels and a corresponding subsidy of $0.023/kg CO₂ reduction on renewables are sufficient to stimulate the ethanol conversion base plant to switch from coal to the new technology using woody biomass. We also find that biodiesel is an economic substitute for diesel when the tax rate reaches $0.017/kg CO₂ and is associated with a subsidy of $0.065/kg CO₂ reduction.

Up to the tax rate of $0.006/kg CO₂ on fossil fuels, the impact of a revenue-neutral tax-subsidy policy on the emission change is equivalent to that of a carbon tax since there are no renewable fuels initially used in producing and transporting ethanol. The change in emission follows line $b1$ in Figure 3-3. As the tax rate approaches $0.006/kg CO₂ accompanied by a subsidy of $0.024/kg CO₂ reduction, emissions are reduced by 11 million (1.4 percent from the initial) to 769 million kg as a result of substitution between energy inputs of diesel, coal, and natural gas and clean inputs of labor and capital. Prices of coal and diesel increase by $0.57/MMBtu and $0.07/gallon, respectively, and the price of woody biomass is reduced by $2.15/MMBtu. At higher tax-subsidy rates, the ethanol conversion plant switches technology to using woody biomass instead of coal as a primary energy source. The technology switching results in an additional drop of 232 million kg CO₂ (30 percent from initial level) to 537 million kg. At this very low revenue-neutral tax rate, the lifecycle emission level is 31 percent lower than
the initial, with 1 percent stemming from substitution of labor and capital for energy and 30 percent from technology switching.

When the tax rate on fossil fuels is in the range of $0.006 to $0.017/kg CO$_2$, the ethanol conversion plant uses woody biomass and diesel is the only liquid fuel used in the feedstock and transportation sectors. Emissions drop by another 23 million kg to 514 million kg (34 percent reduction from the initial) due to further substitution of labor and capital for energy (line $b_2$ in Figure 3-3).

Biodiesel substitutes for diesel when the tax rate reaches $0.017/kg CO$_2$ and is associated with a subsidy of $0.065/kg CO$_2$ reduction. This tax rate is just two-thirds the revenue-neutral carbon tax rate currently proposed by CarbonWA as a 2016 legislative initiative for Washington. At this tax-subsidy level, the prices of diesel and biodiesel are $4.27/gallon and $3.97/gallon. Emissions are reduced by 28 million kg because biodiesel replaces diesel. Hence, at the point at which biodiesel replaces diesel, total emissions are reduced by 294 million kg to 486 million. This is a 38 percent reduction from the initial level, 4 percent of which is from replacement of diesel with biodiesel, 30 percent from technology switching in the conversion plant, and 4 percent from substitution of labor and capital for energy inputs.

With a revenue-neutral tax rate higher than $0.017/kg CO$_2$ on fossil fuels accompanied by a subsidy higher than 0.065/kg CO$_2$ reduction on renewable energy sources, changes in emissions are due to substitution of labor and capital for natural gas, woody biomass, and biodiesel (line $b_3$). For the revenue-neutral tax rate of $0.025/kg CO$_2$ proposed by CarbonWA, the corresponding subsidy for reduced CO$_2$ emissions by renewable energy sources is $0.096/kg CO$_2$ reduction. Prices of biodiesel and woody biomass are reduced by $0.50/gallon and $8.99/MMBtu, respectively, from their initial prices, while natural gas, coal, and diesel prices
increase by $1.33/MMBtu, $2.38/MMBtu, and $0.28/gallon, respectively, from their initial prices. Emissions drop another 8 million kg to 478 million kg (39 percent from the initial level).

If the tax rate on fossil fuels is increased to $0.250/kg CO\textsubscript{2} associated with a subsidy of $0.927/kg CO\textsubscript{2} reduction on renewables, emissions are reduced by another 227 million kg to 251 million kg due to further substitution of labor and capital for energy. This is a total reduction from the initial level of 68 percent.

3.3.3.3 Comparison of a pure carbon tax and revenue-neutral tax-subsidy policy

Table 3-3 summarizes the changes in emissions just before and after pivotal changes in the carbon tax and revenue-neutral tax-subsidies. The cumulative emission reduction caused by the integrated tax-subsidy policy is greater than that caused by the pure carbon tax at all tax rates until the pure carbon tax rate is high enough to stimulate replacement of diesel with biodiesel in the feedstock and transportation sectors. Up to a tax rate of $0.039/kg CO\textsubscript{2}, emission reductions are much lower with the integrated tax-subsidy policy. After the tax reaches $0.116/kg CO\textsubscript{2}, the degree of substitution between clean inputs (labor and capital) and energy inputs (natural gas, woody biomass, and biodiesel) is greater under the pure tax than under the revenue-neutral tax-subsidy policy. At such high rates, the pure carbon tax becomes more effective than the revenue-neutral tax-subsidy policy. A pure carbon tax of $0.250/kg CO\textsubscript{2} reduces emission levels by 3 percent more than the revenue-neutral policy with the same level of tax. But it should be noted that these are very high tax rates on carbon when judged by current carbon market prices worldwide.\textsuperscript{53}

\textsuperscript{53} Sweden has the highest carbon tax in the world, which is $0.168/kg CO\textsubscript{2} (The Carbon Brief, 2014). Carbon taxes in other countries are much lower (World Bank, 2014).
Allowing for input substitution in ethanol production and transportation, lifecycle emissions are reduced as the carbon tax is increased due to the gradual substitution of clean inputs (labor and capital) for energy, switching ethanol conversion technology from using high GHG-emitting coal to low emitting woody biomass, and changing feedstock and ethanol transportation fuel from high-GHG emitting diesel to low emitting biodiesel. The impact of a tax on carbon emissions is very sensitive to the way in which the tax is implemented. A pure tax on carbon alters the relative prices of non-renewable and renewable energy inputs but raises the prices of both. A tax-subsidy policy that is revenue neutral within the energy sector raises prices of non-renewable energy sources while reducing the prices of renewable energy sources. Therefore, the tax-subsidy policy can stimulate technology switching from using coal to woody biomass in ethanol conversion and replacement of diesel with biodiesel in feedstock and transportation sectors at a much lower tax rate compared with the pure tax. The pure tax reduces emissions by smaller quantities than does the tax-subsidy policy until after the tax rate is high enough (a very high $0.116/kg CO$_2$) to stimulate substituting biodiesel for diesel. Then the emissions are reduced more rapidly under the pure tax because it stimulates a more rapid substitution of labor and capital for energy than does the revenue-neutral tax-subsidy policy.

3.3.3.4 Robustness checks on conditional input demand elasticities in cellulosic ethanol conversion

Emission changes due to input substitution depend on conditional energy input demand price elasticities in the production and transportation of cellulosic ethanol in the LCEA model. Since a prior estimate for the long-run conditional own-price elasticity of natural gas in the cellulosic ethanol conversion sector does not exist, we applied the weighted average of natural
gas elasticity estimates in relevant literature (Jones, 1995; Urga and Walters, 2003; Serletis et al., 2010) in the above analysis. In this robustness check, we examine how the impact of incorporating input substitution into ethanol conversion on emissions would change when using the lowest (-0.24) and highest (-0.66) natural gas demand elasticity estimates in the literature.

Table 3-4 presents total emission reductions from the initial level under the carbon tax policy when using three different conditional own-price elasticities for natural gas in the cellulosic ethanol conversion. Emission reductions are positively related to the natural gas elasticity estimate. For relatively low carbon tax rates, the differences in emission reductions from using different natural gas elasticity estimates are small. The difference between using the lowest and the highest elasticity estimates is 6 percent at tax rates of $0.025 - $0.039/kg CO₂. As the carbon tax rate increases, the difference increases. When the tax rate reaches $0.250/kg CO₂, the differences between using the lowest and highest elasticity estimates under the pure tax policy is 36 percent. The impact of alternative natural gas elasticity estimates under the revenue-neutral tax-subsidy policy is similar. The higher the tax rate, the greater the difference in subsidy and in emission reduction, with the latter reaching 33 percent at a tax rate of $0.250/kg CO₂.

3.4 Conclusions

By failing to allow for economically-induced input substitution and technology adoption, standard lifecycle analyses are likely to underestimate the emissions reductions that may follow from carbon tax and subsidy policies. This paper develops a lifecycle economic analysis model (LCEA) that integrates input substitution and technology switching into the standard lifecycle analysis of biofuel. We use this model to estimate the lifecycle emissions from cellulosic ethanol
that uses forest residues as feedstocks and examine the emission reductions under both a pure carbon tax and a revenue-neutral tax-subsidy policy in the state of Washington for the year 2022.

Compared to emission estimates from a standard lifecycle analysis that assumes fixed-proportions production, a pure carbon tax reduces emissions by 9 percent as it approaches $0.039/kg CO$_2$, at which point it can stimulate cellulosic ethanol conversion plants using coal to switch to woody biomass as a primary energy input, resulting in total emission reductions of 36 percent. Biodiesel substitutes for diesel in the forest residue and transportation sectors when the tax is greater than $0.116/kg CO$_2$, resulting in a 52 percent emission reduction from the initial level.

A revenue-neutral tax-subsidy policy can lead a conversion plant using coal to use woody biomass at the very low tax rate of $0.006/kg CO$_2$ accompanied by a subsidy of $0.023/kg CO$_2$ reduction on renewable fuels. Emissions are reduced by 31 percent from the initial level. Biodiesel replaces diesel when the tax exceeds $0.017/kg CO$_2$ with a subsidy that exceeds $0.065/kg CO$_2$ reduction, which reduce emissions by a total of 38 percent. Both of these energy substitutions occur at a revenue-neutral tax rate lower than the $0.025/kg CO$_2$ currently proposed for Washington State by CarbonWA, a nonpartisan grassroots group developing a 2016 citizens’ ballot measure to reduce human impacts on climate change.

The LCEA model developed in this paper could be extended in many different ways. For instance, we assume a competitive market for cellulosic ethanol. Since the cellulosic ethanol industry is in its infancy, it is possible that in 2022 some market power could be exercised in the biofuel industry. Alternatively, the empirical findings of the LCEA model could be refined by incorporating it into a general equilibrium framework rather than relying on the partial equilibrium analysis used in this paper.
### 3.5 Appendix

<table>
<thead>
<tr>
<th>Notation</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a$</td>
<td>Constant proportion</td>
</tr>
<tr>
<td>$b$</td>
<td>Biofuel sector</td>
</tr>
<tr>
<td>$bd$</td>
<td>Biodiesel</td>
</tr>
<tr>
<td>$c$</td>
<td>Coal</td>
</tr>
<tr>
<td>$ce$</td>
<td>Cellulosic ethanol</td>
</tr>
<tr>
<td>$cwd$</td>
<td>Technology switching (coal to woody biomass)</td>
</tr>
<tr>
<td>$d$</td>
<td>Diesel</td>
</tr>
<tr>
<td>$D$</td>
<td>Distance</td>
</tr>
<tr>
<td>$dbd$</td>
<td>Liquid fuel substitution (diesel to biodiesel)</td>
</tr>
<tr>
<td>$e$</td>
<td>Emission factor</td>
</tr>
<tr>
<td>$E$</td>
<td>Emission level</td>
</tr>
<tr>
<td>$f$</td>
<td>Feedstock sector</td>
</tr>
<tr>
<td>$g$</td>
<td>Gasoline</td>
</tr>
<tr>
<td>$j$</td>
<td>Represents $f, tf, tb$</td>
</tr>
<tr>
<td>$K$</td>
<td>Capital</td>
</tr>
<tr>
<td>$L$</td>
<td>Labor</td>
</tr>
<tr>
<td>$lf$</td>
<td>Liquid fuel ($b$ or $bd$)</td>
</tr>
<tr>
<td>$n$</td>
<td>Represents $be, cbe$</td>
</tr>
<tr>
<td>$N$</td>
<td>Energy input</td>
</tr>
<tr>
<td>$ne$</td>
<td>Non-cellulosic ethanol</td>
</tr>
<tr>
<td>$ng$</td>
<td>Natural gas</td>
</tr>
<tr>
<td>$q$</td>
<td>Represents $c, ng, d, g$</td>
</tr>
<tr>
<td>Symbol</td>
<td>Description</td>
</tr>
<tr>
<td>--------</td>
<td>-------------------------</td>
</tr>
<tr>
<td>$t$</td>
<td>Transportation</td>
</tr>
<tr>
<td>$s$</td>
<td>Subsidy</td>
</tr>
<tr>
<td>$tb$</td>
<td>Transportation of biofuel</td>
</tr>
<tr>
<td>$tf$</td>
<td>Transportation of feedstock</td>
</tr>
<tr>
<td>$wb$</td>
<td>Woody biomass</td>
</tr>
<tr>
<td>$x$</td>
<td>Represents $c$ or $wb$</td>
</tr>
<tr>
<td>$Y$</td>
<td>Quantity</td>
</tr>
<tr>
<td>$\varepsilon$</td>
<td>Conditional price elasticity</td>
</tr>
<tr>
<td>$\tau$</td>
<td>Carbon tax</td>
</tr>
<tr>
<td>*</td>
<td>Cost minimizing level</td>
</tr>
</tbody>
</table>
References


Washington State University Agricultural Research Center Research Bulletin XB1047E.
Table 3-1 Input uses in production and transportation sectors for forest-residues-derived ethanol

<table>
<thead>
<tr>
<th>Production and transportation sectors</th>
<th>Energy inputs</th>
<th>Other inputs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest residues production</td>
<td>Liquid fuels (diesel or biodiesel)</td>
<td>Labor and capital</td>
</tr>
<tr>
<td>Ethanol conversion</td>
<td>Base: natural gas and coal</td>
<td>Labor, capital, and forest residues b</td>
</tr>
<tr>
<td>New: natural gas and woody biomass a</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transportation</td>
<td>Liquid fuels (diesel or biodiesel)</td>
<td>Labor and capital</td>
</tr>
</tbody>
</table>

a. Woody biomass can be used as an alternative energy source to coal in the ethanol conversion process.

b. Forest residues, which are one type of woody biomass, are used as a cellulosic feedstock for producing ethanol.
Table 3-2 Parameter values

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Energy Type</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Energy input demand own-price elasticities</td>
<td>Natural gas in cellulosic ethanol conversion$^a$</td>
<td>−0.41</td>
<td>Million MMBtu</td>
</tr>
<tr>
<td></td>
<td>Fuel (i.e. diesel or biodiesel) in forest residues production</td>
<td>−0.73</td>
<td>Million MMBtu</td>
</tr>
<tr>
<td></td>
<td>Diesel in transportation</td>
<td>−0.07</td>
<td>Million MMBtu</td>
</tr>
<tr>
<td></td>
<td>Biodiesel in transportation</td>
<td>−0.07</td>
<td>Million MMBtu</td>
</tr>
</tbody>
</table>

Initial quantities of energy inputs for producing 160 million gallons of cellulosic ethanol

<p>| Cellulosic ethanol conversion | Natural gas | 8.34 | Million MMBtu |
| Coal in base plant$^b$ | 2.54 | Million MMBtu |
| Woody biomass in new plant$^c$ | 3.61 | Million MMBtu |
| Forest residue production | Diesel or | 2.14 | Million gallons |
| Biodiesel$^d$ | 2.29 | Million gallons |
| Forest residue transportation of 145km | Diesel or | 5.22 | Million gallons |
| Biodiesel | 5.59 | Million gallons |</p>
<table>
<thead>
<tr>
<th>Ethanol transportation of 145km</th>
<th>Diesel or</th>
<th>0.992</th>
<th>Million gallons</th>
</tr>
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<tbody>
<tr>
<td>Biodiesel</td>
<td></td>
<td>1.06</td>
<td>Million gallons</td>
</tr>
<tr>
<td>Prices</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Natural gas</td>
<td></td>
<td>9.00</td>
<td>Dollar/MBBtu</td>
</tr>
<tr>
<td>Coal</td>
<td></td>
<td>2.10</td>
<td>Dollar/MBBtu</td>
</tr>
<tr>
<td>Woody biomass</td>
<td></td>
<td>4.00</td>
<td>Dollar/MBBtu</td>
</tr>
<tr>
<td>Diesel</td>
<td></td>
<td>4.08</td>
<td>Dollar/gallon</td>
</tr>
<tr>
<td>Biodiesel</td>
<td></td>
<td>4.31</td>
<td>Dollar/gallon</td>
</tr>
<tr>
<td>Emission factors</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Natural gas</td>
<td></td>
<td>53.10</td>
<td>Kg/MBBtu</td>
</tr>
<tr>
<td>Coal</td>
<td></td>
<td>95.30</td>
<td>Kg/MBBtu</td>
</tr>
<tr>
<td>Woody biomass</td>
<td></td>
<td>1.61</td>
<td>Kg/MBBtu</td>
</tr>
<tr>
<td>Diesel</td>
<td></td>
<td>11.35</td>
<td>Kg/gallon</td>
</tr>
<tr>
<td>Biodiesel</td>
<td></td>
<td>6.13</td>
<td>Kg/gallon</td>
</tr>
<tr>
<td>Gasoline</td>
<td></td>
<td>8.90</td>
<td>Kg/gallon</td>
</tr>
<tr>
<td>Non-cellulosic ethanol</td>
<td></td>
<td>5.75</td>
<td>Kg/gallon</td>
</tr>
<tr>
<td>Initial total energy consumption in Washington State in 2022 under the</td>
<td>Coal</td>
<td>43</td>
<td>Million MMBtu</td>
</tr>
<tr>
<td>Prices</td>
<td>Natural gas</td>
<td>272</td>
<td>Million MMBtu</td>
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### RFS mandate

<table>
<thead>
<tr>
<th>Fuel Type</th>
<th>Requirement</th>
<th>Unit</th>
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<tr>
<td>Woody biomass</td>
<td>96</td>
<td>Million MMBtu</td>
</tr>
<tr>
<td>Diesel</td>
<td>785</td>
<td>Million gallons</td>
</tr>
<tr>
<td>Biodiesel</td>
<td>114</td>
<td>Million gallons</td>
</tr>
<tr>
<td>Gasoline</td>
<td>2280</td>
<td>Million gallons</td>
</tr>
<tr>
<td>Non-cellulosic ethanol</td>
<td>286</td>
<td>Million gallons</td>
</tr>
<tr>
<td>Cellulosic ethanol</td>
<td>320</td>
<td>Million gallons</td>
</tr>
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### Heating value

<table>
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<tr>
<th>Fuel Type</th>
<th>Heating Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diesel</td>
<td>1.33</td>
<td>MMBtu/gallon</td>
</tr>
<tr>
<td>Biodiesel</td>
<td>1.24</td>
<td>MMBtu/gallon</td>
</tr>
<tr>
<td>Gasoline</td>
<td>0.125</td>
<td>MMBtu/gallon</td>
</tr>
<tr>
<td>Ethanol</td>
<td>0.084</td>
<td>MMBtu/gallon</td>
</tr>
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</table>

### Initial input cost difference for base and new plant

<table>
<thead>
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<th>Cost Difference</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>9.11</td>
<td>Million dollars</td>
</tr>
</tbody>
</table>

---

a. For the conditional own-price elasticity of natural gas, Jones (1995) has two estimates for the industrial sector, Urga and Walters (2003) have three estimates for the industrial sector, and Serletis et al. (2010) have one estimate for the national economy.
b. In 2010, the typical corn ethanol conversion plant used 26,050 Btu of natural gas and 7,950 Btu of coal to produce one gallon of corn ethanol (Wang et al., 2007). We assume that twice this amount is required for one gallon of cellulosic ethanol conversion.

c. The heating value of coal is about 1.42 times that of woody biomass (The Climate Registry, 2014), so we assume that the quantity of woody biomass required is 1.42 times that of coal given that the use of natural gas is constant.

d. The average heating value generated by diesel is about 1.07 times the amount of biodiesel per gallon (DOE, 2013). We extrapolate the quantity of biodiesel by multiplying the quantity of diesel by 1.07.


f. From USDOE (2012). This is the average estimate of biodiesel price on the west coast of the United States in 2012.

g. The heating value of dry woody biomass is 17.48 MMBtu per short ton (The Climate Registry, 2014). It is used to convert CO₂ per kg woody biomass to CO₂ per MMBtu of woody biomass.

### Table 3-3 Emission changes comparison between revenue-neutral tax-subsidy policy and carbon tax policy

<table>
<thead>
<tr>
<th>Taxes (Subsidies)</th>
<th>Revenue-neutral tax-subsidy policy</th>
<th>Carbon tax policy</th>
</tr>
</thead>
<tbody>
<tr>
<td>($/kg)</td>
<td>Emission (million kg)</td>
<td>Emission reduction from initial (%)</td>
</tr>
<tr>
<td>Initial emission</td>
<td>780</td>
<td>1%</td>
</tr>
<tr>
<td>$t = 0.006$</td>
<td>Before wb substitutes c 769</td>
<td>1%</td>
</tr>
<tr>
<td>$(s = 0.023)$</td>
<td>After wb substitutes c 537</td>
<td>31%</td>
</tr>
<tr>
<td>$t = 0.017$</td>
<td>Before bd substitutes d 514</td>
<td>34%</td>
</tr>
<tr>
<td>$(s = 0.065)$</td>
<td>After bd substitutes d 486</td>
<td>38%</td>
</tr>
<tr>
<td>$t = 0.025$</td>
<td>478</td>
<td>39%</td>
</tr>
<tr>
<td>$(s = 0.096)$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$t = 0.039$</td>
<td>464</td>
<td>41%</td>
</tr>
<tr>
<td>$(s = 0.150)$</td>
<td>After wb substitutes c 499</td>
<td>36%</td>
</tr>
<tr>
<td>$t = 0.116$</td>
<td>385</td>
<td>51%</td>
</tr>
<tr>
<td>$(s = 0.440)$</td>
<td>After bd substitutes d 376</td>
<td>52%</td>
</tr>
</tbody>
</table>
\[
\begin{array}{cccc}
\text{\(t = 0.25\)} & 251 & 68\% & 228 & 71\%
\end{array}
\]

\((s = 0.927)\)
Table 3-4 Robustness check on the natural gas conditional own-price elasticity in cellulosic ethanol conversion for alternative carbon tax policies

<table>
<thead>
<tr>
<th>Taxes ($/kg)</th>
<th>Subsidies ($/kg)</th>
<th>Emission reduction from initial (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$ε_{ng}^b = -0.41$</td>
<td>$ε_{ng}^b = -0.24$</td>
</tr>
<tr>
<td>0.025</td>
<td></td>
<td>6%</td>
</tr>
<tr>
<td>0.039</td>
<td></td>
<td>36%</td>
</tr>
<tr>
<td>0.116</td>
<td></td>
<td>52%</td>
</tr>
<tr>
<td>0.250</td>
<td></td>
<td>71%</td>
</tr>
</tbody>
</table>

Pure carbon tax rate

Revenue-neutral tax rate ($/kg)

| 0.006 | 0.02314 | 0.02315 | 0.02312 | 31% | 30% | 32% |
| 0.017 | 0.0654 | 0.0655 | 0.0653 | 38% | 37% | 39% |
| 0.025 | 0.0961 | 0.0963 | 0.0959 | 39% | 38% | 41% |
| 0.250 | 0.9266 | 0.9431 | 0.9033 | 68% | 56% | 89% |
Figure 3-1 Relationship of production and transportation sectors and emissions

Notes: Solid boxes and arrows represent sectors and their flows, respectively; dashed boxes and arrows represent carbon emission sources and their flows, respectively.
Figure 3-2 Estimated impact of a pure carbon tax on lifecycle carbon emissions from Washington cellulosic ethanol production, 2022

Notes: \( a0 \) represents the initial lifecycle carbon emissions when assuming fixed-proportions production and transportation of ethanol.
Figure 3-3 Estimated impact of a revenue-neutral tax subsidy on lifecycle carbon emissions from Washington cellulosic ethanol production, 2022

Notes: $x_1 = 0.006$, $x_2 = 0.017$, and $x_3 = 0.025$; $b_0$ represents the initial lifecycle carbon emissions when assuming of fixed-proportions production and transportation of ethanol.