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Three essays on agricultural and environmental economics

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Three essays on agricultural and environmental economics

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DEDICATION

To my current and future family

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ABSTRACT

This dissertation consists of three essays that explore the effects of biofuel and environmental policies on relevant industries. The first essay focuses on examining the market impacts and welfare consequences of U.S. biofuel policies. The second essay quantifies the U.S. agricultural supply response during the biofuel policy period. The third essay focuses on understanding the performance of a different kind of market-based policies in reducing industry-wide emissions.

The U.S. renewable fuel standard (RFS), initiated in 2005 and extended in 2007, has been rationalized as pursuing, for example, reduction of greenhouse gas emission and reduction of the U.S. dependence on foreign energy sources. While its effects on food prices and actual environmental benefits remain controversial, the first essay constructs a multi-market equilibrium model and assesses the current and future economic effects of the RFS. The model integrates the U.S. agricultural sector with the energy sector and explicitly considers both U.S. ethanol and biodiesel production. The model is parameterized to represent observed 2015 data as *status quo* and then simulated to analyze alternative scenarios. The results confirm that the current RFS program considerably benefits the agricultural sector but also leads to overall welfare gains for the United States. Implementation of projected 2022 mandates, which would require further expansion of biodiesel production, would lead to a considerable welfare loss (relative to the *status quo*).

While the abovementioned analysis relies on elasticities from the literature, the second essay directly quantifies the U.S. corn and soybean dynamic supply response. The RFS has been credited with being one of the main causes of (i) the recent global commodity price increases and

(ii) the spatial changes in prices by affecting local basis nearby biofuel plants. The presence of these two demand-induced price effects provides an ideal opportunity to revisit the econometric analysis of the agricultural supply response. By focusing on recent years (2005-2015), therefore, the acreage and yield responses are estimated by using county-level panel data for the twelve Midwest states. The results indicate that the acreage and yield responses are highly inelastic. With relatively significant cross-price acreage elasticities, when corn and soybean prices move together, the response of the total acreage of these two key crops is very small. This result indicates that the ability of the U.S. corn and soybean production sector to accommodate the demand shock caused by the RFS is limited.

As alternatives to command-and-control-type instruments such as mandates, market-based policies, such as voluntary agreement (VA) and Pigouvian tax, can be used to deal with environmental externalities. Given the increasing use of VAs, the third essay examines the performance of VA, relative to a tax policy and *laissez faire* policy, as a way to reduce environmental pollution. We find that when the market is non-competitive, the VA, relative to other policy options, improves welfare despite suffering from free-riding behavior. It is also found that as consumers value the green good more, the VA increases the number of green firms and provides a less competitive environment for free-riders, who increase the price of regular goods. As a result, the total market under the VA becomes less covered, at some point, than the tax policy. As for implementation, the potential gains from of the VA are attainable provided the regulator's threat is credible and sufficiently strong.

CHAPTER 1

INTRODUCTION

The theme of this dissertation is to analyze the market and welfare effects of agricultural and environmental policies on relevant industries. In the last decade, the U.S. renewable fuel standard (RFS), initiated in 2005 and significantly expanded in 2007, has been one of the most influential agricultural-and-environmental policies in the world. It basically mandates certain amounts of biofuels to be blended into U.S. fossil fuel supply in order to reduce greenhouse gas emissions and to reduce the reliance on foreign energy sources. Having agricultural products as main feedstocks for biofuels, it affects agricultural commodity, energy commodity, and fuel markets. In particular, given that the United States is a large net exporter of agricultural products and a large net importer of crude oil, and that the global commodity markets are pretty competitive, the impact of the RFS is not limited to domestic markets but inevitably extends to foreign markets.

Given its significant influence and complexity, we analyze the impact of RFS by constructing a tractable multi-market competitive equilibrium model suitable to evaluate alternative biofuel policies (Chapter 2). The model integrates the U.S. agricultural sector with the energy sector and it explicitly considers both U.S. ethanol and biodiesel production. The model provides a structural representation of the RFS policies, and it uses the arbitrage conditions defining the core value of renewable identification number (RIN) prices to identify the relevant competitive equilibrium conditions. The model is parameterized, based on elasticities and technical coefficients from the literature, to represent observed 2015 data. The model is simulated to analyze alternative scenarios, including: repeal of the RFS; projected 2022 RFS mandates; and, optimal (second best) mandates.

One of the crucial components for determining the impact of the RFS is the responsiveness of U.S. crop commodity supply in regard to relevant price changes. In particular, corn and soybeans, for each of which the United States produces more than 30% of world consumption, are the main feedstocks under the RFS. Whereas the first essay relies on elasticities from the literature, therefore, we directly quantify the U.S. corn and soybean supply response by exploiting the large exogenous price variations associated with the implementation of the RFS (Chapter 3). To do so, we focus on recent years (2005-2015), when the RFS played a major role, and on the twelve Midwestern states that produce most of the nation's corn and soybeans. Acreage and yield responses are modeled separately, where acreage response is modeled as function of expected per-acre returns that account for both expected price and expected yield. Specifically, we estimate a system of dynamic equations that is consistent with the impact of crop rotation on acreage allocation.

The RFS mainly relies on mandates which are the command-and-control-type policy instrument, market-based policies, such as voluntary agreement (VA) and Pigouvian tax, can also be used to deal with environmental externalities. Given the globally increasing use of VAs, we examine the performance of VAs, relative to a tax policy and *laissez faire* policy (i.e., no policy), as a way to reduce environmental pollution. We consider an oligopolistic market, in which consumers care about the environmental friendliness of firms, and construct three-stage game model to analyze the incentive of participants and free-riders. After determining equilibria, numerical simulations are conducted to check the feasibility of the VA and to compare welfare consequences between alternatives.

CHAPTER 2

RENEWABLE FUEL STANDARD IN COMPETITIVE EQUILIBRIUM: MARKET AND WELFARE EFFECTS

2.1 Introduction

Over the last decade the United States has implemented major policies to promote biofuel use. The key provisions, set forth in the Energy Independence and Security Act (EISA) of 2007, are centered on the so-called Renewable Fuel Standard (RFS) which mandates certain amounts of renewable fuels to be blended into the US transportation fuel supply. These ambitious RFS "mandates" have been rationalized as pursuing a variety of objectives, including reduction of GHG emission and reduction of the US dependence on foreign energy sources (Moschini, Cui and Lapan 2012). Arguably, however, one of their most important impacts has been on agriculture. By sizably expanding demand for some agricultural products (e.g., corn to produce ethanol), the RFS is credited with having contributed substantially to increased commodity prices (Wright 2014; de Gorter, Drabik and Just 2015). These price increases have benefited farmers, and led to large land price increases, but biofuel policies' impact on land use has led to controversies, including the food versus fuel debate (Rosegrant and Msangi 2014) and whether biofuels yield actual net environmental benefits (Searchinger et al. 2008). In addition, development and production of cellulosic biofuel—one of the RFS's signature features—has severely lagged the mandates schedule set out in EISA. Furthermore, the current economic environment of relatively low oil prices, coupled with an unexpectedly strong domestic expansion of fossil fuel production, makes the energy security argument somewhat moot. The RFS remains controversial, and there is considerable interest in a comprehensive assessment of the current and future economic impacts of the RFS (Stock 2015).

In this essay we construct a tractable multi-market competitive equilibrium model suitable to evaluate alternative biofuel policies. The model, which integrates the US agricultural sector with the energy sector, pays particular attention to a careful structural representation of the RFS biofuel support policies, and it is amenable to calibration and simulation to produce theoretically-consistent estimates of the market and welfare impacts of these policies. Unlike previous analyses that focused exclusively on ethanol (e.g., de Gorter and Just 2009, Cui et al. 2011), we develop a model that captures all of the various mandates envisioned by the RFS (Schnepf and Yacobucci 2013). These mandates are enforced by the US Environmental Protection Agency (EPA) via Renewable Identification Numbers (RINs), which are tradeable. A novel contribution of this essay is to show how the arbitrage conditions for RIN prices derived from the behavior of distributors that blend biofuels with fossil fuels, including the RIN price inequalities implied by the hierarchical structure of the RFS mandates, can be embedded in a competitive equilibrium model.

One of the fault lines of the current RFS implementation is the rising role of biodiesel (Irwin and Good 2016). Insofar as biodiesel may be the biofuel of choice to meet the advanced biofuel portion of the RFS mandates, as suggested by recent EPA rulemakings (EPA 2016), an economic evaluation of current and prospective US biofuel policies needs to consider the interactions between US ethanol and biodiesel production. The model we present captures this essential connection by an explicit system representation of the feedstock used in biofuel production. For conventional ethanol produced in the United States, corn is the chosen feedstock in virtually all plants. Biodiesel production, on the other hand, uses a variety of feedstocks, including animal fats, recycled fats (yellow grease) and vegetable oils. The latter are the most important primary input, accounting for about 71% of biodiesel feedstock in 2015, with soybean oil being the most widely used (almost three fourths of all vegetable oils used in biodiesel production). Given the constraints on the availability of other more marginal feedstocks (Brorsen 2015), we assume that further expansions of biodiesel production would have to rely on redirecting vegetable oils from other uses. In this essay, therefore, we develop a structural model of ethanol production from corn and biodiesel production from soybean oil.[1] The model captures the competition of primary agricultural products for scarce land, can trace the impact of biofuel mandates on equilibrium prices at various market levels, and can produce a coherent welfare assessment of the overall impact of RFS mandates.

The topic of this essay is of considerable importance from a policy perspective. Biofuel policies, and the future of the RFS mandates, while likely to remain controversial, have a crucial impact on the agricultural sector (Cui et al. 2011, Pouliot and Babcock 2016). We find that the RFS has indeed proved to be a remarkably effective tool for farm support. Relative to the scenario of no biofuel policies, the 2015 level of mandates entails a 38% increase in corn price and an 11% increase in soybean price. The mandates' impact on energy prices is smaller in absolute terms, with crude oil price decreased by 1.4%. Because the United States is a net importer of crude oil, and a net exporter of corn and soybean products, these terms of trade effects contribute significantly to the finding that, overall, the welfare impact of the RFS has been positive. The RFS impact on reducing carbon emission, on the other hand, turns out to be nil once we account for the leakage effect (due to the induced increase in the rest of the world's fossil fuel consumption). Aggregate welfare at current mandate levels is larger than in the "No RFS" scenario by about \$3.4 billion. To further improve welfare from the 2015 mandate levels,

[1] To keep the analysis tractable we avoid the structural representation of other vegetable oil industries. Insofar as soybean oil is a close substitute for other vegetable oils that can also serve as feedstock for biodiesel production, this simplification would seem to entail little loss of generality.

the model suggests that corn ethanol production should be increased, whereas biodiesel production should be decreased. The additional welfare gains from such constrained optimal mandates, however, are somewhat limited. Finally, implementation of the 2022 RFS statutory mandate levels—adjusted for a projected realistic expansion of cellulosic biofuels, consistent with EPA's recent waivers—would lead to sizeable welfare losses.

2.2 The RFS: Current and Prospective Mandates

The biofuel mandates of the RFS codified by EISA considerably extended the earlier provisions of the 2005 Energy Policy Act (Schnepf and Yacobucci, 2013). This legislation laid out a hierarchical set of quantitative minimum requirements for different types of biofuels, as well as a schedule for these mandates to increase over time, with final mandate levels being reached in 2022. The RFS defines an overall "renewable fuel" mandate, to be met with qualifying biofuels that achieve at least a 20% reduction in greenhouse gas (GHG) emissions (relative to fossil fuel), on a lifecycle basis. Furthermore, the RFS specifies a number of nested mandates as subsets of the overall renewable fuel mandate. The largest sub-component is that of "advanced biofuels." Such biofuels must achieve at least a 50% GHG emission reduction (relative to the conventional fuel) and encompass a variety of biofuels, including sugarcane ethanol and biodiesel (but corn-based ethanol is excluded). A portion of the advanced biofuel mandate is explicitly reserved for biomass-based diesel (biodiesel for short). The largest portion of the advanced biofuel mandate was supposed to be accounted for by cellulosic biofuels, identified as reaching a GHG emission reduction of at least 60% relative to the conventional fuel.

The EPA is responsible for implementing the RFS. To do so, prior to each year the EPA determines the fractional requirements that "obligated parties" (e.g., importers and refiners of fossil fuels) have to meet. These fractional requirements are calculated so that the mandates volumes of biofuel are achieved, given expected demand conditions. The fractional requirements determine the individual parties' renewable volume obligations (RVOs), given their sales of transportation fossil fuel. As noted earlier, these RVOs are enforced via the RIN system.[2] In addition to setting appropriate fractional requirements each year to implement the scheduled RFS mandates, the EPA has had to contend with the essential failure of cellulosic biofuel production: technology and production capacity are nowhere close to permit the fulfillment of the ambitious mandates envisioned by EISA. Hence, in the last several years, the EPA has exercised its waiver authority and drastically reduced the statutory RFS mandates accordingly.

Table 2.1 reports RFS mandate levels for the years 2015-2017, and for year 2022 (when biofuel mandates are supposed to reach their final levels). The columns labeled "EISA" contains the statutory mandates, for the overall renewable fuel and its subcomponents: advanced biofuel, biodiesel and cellulosic biofuel. It is useful to supplement these statutory mandates, reported in the first four rows of Table 2.1, with two additional "implied" mandates. Note that there is no explicit mandate for corn-based ethanol. But given that this biofuel is the most cost-effective, at present, the implicit mandate for corn-based ethanol can be obtained as the difference between the renewable fuel mandate and the advanced biofuel mandate. This is reported in the last row of Table 2.1, which shows that corn-based ethanol is effectively capped by EISA to a maximum of 15 billion gallons (from 2015 onward). Also, a portion of the advanced biofuel mandate, not reserved for cellulosic biofuels, can be met by a variety of biofuels (including sugarcane ethanol

[2] RINs are identifiers assigned to biofuel batches at production. They are "separated" from the physical product when the biofuel is blended with fossil transportation fuel. Such separated RINs can then be used by obligated parties to show compliance. Obligated parties can meet the RIN requirements by buying a sufficient amount of biofuel themselves or, alternatively, by buying separated RINs from other parties (McPhail, Westcott and Lutman, 2011).

and biodiesel). This implied "non-cellulosic advanced" biofuel mandate, computed as the difference between advanced biofuel mandates and cellulosic biofuel mandate, is reported in the second-last row of Table 2.1.

The columns labeled "EPA" reflect the agency's exercise of its waiver authority. It seems clear that the EPA has been systematically and drastically reducing the cellulosic biofuel mandate to levels that are feasible given current capacity, and simultaneously scaling back the overall renewable fuel mandate. At the same time, EPA rulemaking shows a clear intention to abide by the statutory mandates for the other components of the RFS. Also, the EPA is clearly signaling that biodiesel provides the avenue for meeting this non-cellulosic advanced biofuel mandate. The 2017 biodiesel mandate is almost sufficient to satisfy the other advanced biofuel mandates.[3] From these observations, we generated a reasonable projection of how the 2022 statutory mandates may be adjusted, and this is reported in the last column of Table 2.1. This projection assumes that: (i) the non-cellulosic portion of the advanced biofuel mandate (5 billion gallons) will be fully implemented; (ii) the cellulosic biofuel mandate will continue to be scaled down based on available capacity (our projection relies on a linear trend of past EPA rulemakings); and, (iii) the overall renewable fuel mandate will be set so that, given (i) and (ii), the implied corn-ethanol mandate is held at the 15 billion gallons cap. As for biodiesel, our working assumption is that this is the marginal biofuel to meet the advanced biofuel mandate, and so the extrapolation as to its level is not required for the model that we discuss next (the biodiesel mandate, *per se*, is not binding).[4] The last column of Table 2.1 constitutes the "2022

[3] Although the biodiesel mandate is defined in physical volume, when biodiesel is used to meet the advanced biofuel standard, or the overall renewable fuel standard, each gallon is multiplied by an "equivalence value" (either 1.5 or 1.7) (Schnepf and Yacobucci 2013).

[4] Lade, Lin Lawell and Smith (2016) also find that biodiesel served as the marginal biofuel for RFS compliance in 2013. Irwin and Good (2016) derive mandate projections to 2022 very similar to ours.

scenario" that is analyzed in our counterfactual simulations, along with a few other scenarios discussed below.

2.3 The Model

The model consists of the following parts: US supply for corn and soybean, consistent with equilibrium conditions in the land market; US oil supply; transformation sectors that produce ethanol and biodiesel from agricultural crops, and gasoline and diesel from domestic and imported crude oil; imports of crude oil and exports of corn and soybeans (including soybean oil and meal); rest of the world's demands for corn and soybean products imports; US demand for food products, transportation fuels and other fuels. The model allows for the endogeneity of crude oil, corn and soybean product prices, in addition to representing equilibrium in the US markets for food products and transportations fuels. The equilibrium conditions used to close the model are based on a novel representation of the arbitrage conditions for RIN prices.

2.3.1 Domestic production

The model represents three domestically produced primary products: corn, soybeans, and crude oil. Concerning the two agricultural outputs, we conceive of their production as arising from an equilibrium allocation of (finite) land across three alternatives: corn, soybean, and all other uses. Given the purpose of this analysis, in our model it is important to represent not just the responsiveness of the supply of each product of interest to changes in its own price, but also the substitutability between corn and soybean, i.e., the cross-price effects. Consistent with recent work addressing agricultural supply response to price changes induced by the biofuel expansion (e.g., Hendricks et al. 2014, Berry 2011), we postulate both a land allocation response and a yield response. Consequently, the supply functions for corn and soybeans are represented as:

(1) $S_i(p_i, p_j) = y_i(p_i)L_i(p_i, p_j)$, $i, j = c, s$ and $i \neq j$

where p denotes prices and the subscripts c and s indicate corn and soybeans, respectively. Hence, the yield functions $y_i(p_i)$ are presumed to respond to own price only, whereas the acreage allocation functions $L_i(p_i, p_j)$ depend on both corn and soybean prices (which are endogenously determined in the model). Provided the symmetry condition $\partial S_c / \partial p_s = \partial S_s / \partial p_c$ holds, the supply functions $S_c(p_c, p_s)$ and $S_s(p_c, p_s)$ are integrable into an aggregate profit function $\Pi(p_c, p_s)$ and thus satisfy $S_c = \partial \Pi / \partial p_c$ and $S_s = \partial \Pi / \partial p_s$ (by Hotelling's lemma).

As noted, the acreage functions $L_i(p_i, p_j)$ are meant to represent an equilibrium allocation of (finite) land to three alternatives, but we specify them as depending only on the prices of corn and soybeans. Two rationalizations can be invoked for this procedure: the price of the outside option (other uses) is constant; or, these functions should be interpreted as *mutatis mutandi* supply relationships (i.e., allowing for equilibrium response in the markets for products other than corn and soybeans). Computation of the producer surplus, as done in this essay, is possible for either rationalization, although the interpretation of such measure might differ in subtle ways (Thurman 1991). In any case, the price of inputs other than land are held constant (across scenarios), except for energy inputs (because the model will solve for different equilibrium fuel prices across scenarios). Still, under the ancillary simplifying condition that energy inputs are used in fixed proportion with land,[5] it follows that the supply functions of interest can in fact be

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[5] The Appendix provides an explicit justification for this assumption based on Beckman, Borchers and Jones (2013). Note that, whereas this simplifies the representation of the relevant equilibrium conditions, we still can account for

represented simply as depending on the prices of the two commodities (corn and soybeans). The supply of the other domestically produced primary product, crude oil, is written as $S_R(p_R)$.

2.3.1.1 Transformation sectors

The refining of crude oil yields gasoline x_g, diesel x_d, and other refined petroleum products x_h. We assume a Leontief (fixed proportions) production technology:

(2) $$x_g = \beta_g Min\{x_R, z_g\}$$

(3) $$x_d = \beta_d x_g / \beta_g$$

(4) $$x_h = \beta_h x_g / \beta_g$$

where $x_R \equiv S_R + \bar{S}_R$ is the total supply of crude oil to the US market ($\bar{S}_R$ denotes US imports of crude oil), and z_g represents other inputs used in the refining process.

Domestically produced corn has three uses in the model: it can be exported; it can be transformed into ethanol; and it can meet domestic demand for all other uses (e.g., animal feed). Corn-based ethanol production x_e is represented by the following Leontief production functions:

(5) $$x_e = \alpha_e Min\{\tilde{x}_c, z_e\}$$

where $\tilde{x}_c$ is the quantity of corn, and z_e denotes all other inputs, used in ethanol production. We note at this juncture that the model will allow for byproducts—such as distilled dried grains with soluble—that can be valuable as animal feed (Hoffman and Baker 2011). The endogenously determined animal feed products in our model are corn and soybean meal. To account for the

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the impact of changing equilibrium energy prices (across scenarios) in the computation of agricultural producer surplus.

feedback effects on these markets of varying ethanol production (across scenarios), the quantities of byproducts which substitute for corn and soybean meal used in livestock feed are represented as $\delta_1 \tilde{x}_c$ and $\delta_2 \tilde{x}_c$, respectively.

Similarly, domestically produced soybeans have two uses: they can be exported as beans; or, they can be crushed to produce oil and meal. In turn, some of the meal and oil that is domestically produced by the crushing process is exported. Given the constant returns to scale technology in the crushing process, and assuming that there are no particular comparative advantages in this process, without loss of generality we can simplify the model and assume that each bushel of soybeans that is exported is really a fixed-proportion bundle of soybean oil and meal.[6] Hence, we presume that the entire domestic production of soybeans is converted into soybean oil x_v and meal x_m by the following Leontief technology:

(6) $$x_v = \alpha_v Min\{S_s, z_v\}$$

(7) $$x_m = \alpha_m x_v / \alpha_v$$

where S_s is domestic soybean supply, and z_v denotes other variable inputs used in the production of vegetable (soybean) oil. Next, soybean oil can be exported, it can be converted into biodiesel, or it can meet domestic demand for all other uses. Conversion of soybean oil into biodiesel x_b takes place according to this Leontief technology:

(8) $$x_b = \alpha_b Min\{\tilde{x}_v, z_b\}$$

where $\tilde{x}_v$ is quantity of soybean oil, and z_b denotes all other variable inputs, used in the production of biodiesel.

[6] Sobolevsky, Moschini and Lapan (2005) explain why, given the maintained assumptions, the location of soybean processing is undetermined such that the only meaningful trade flows that can be recovered by competitive equilibrium pertain to the factor content of trade.

2.3.2 Demand

For the analysis of various scenarios, the model endogenizes both agricultural product prices and fuel prices. We explicitly model the demand for transportation fuels (gasoline and diesel), as well as the demand for other energy products produced by refining crude oil. Because transportation fuels in our model blend fossil and renewable fuels, it is important to account for their energy content. Our maintained assumption is that consumers ultimately care about miles traveled (de Gorter and Just 2010). Having accounted for their different energy contents, ethanol is considered a perfect substitute for gasoline and biodiesel a perfect substitute for diesel. To permit an internally consistent welfare evaluation of alternative policy scenarios, domestic demand functions are obtained from a quasi-linear utility function for the representative consumer, which is written as:

(9) $$U = I + \Phi(p_{gf}, p_{df}) + \Psi(p_h) + \Theta(p_c, p_m, p_v) - \Lambda(E)$$

where I denotes monetary income which, along with all prices, is expressed in terms of a numeraire good whose price is normalized to one. Subscripts *gf* and *df* here denote gasoline fuel and diesel fuels, respectively (i.e., blends of fossil and renewable fuels). Thus, we are postulating additive separability between transportation fuels, heating oil, and food/feed products. This property assumes that a number of cross-price elasticities are equal to zero. But some critical substitution relations (between food/feed products, and between various fuels) are modeled explicitly. Note also that these preferences include the externality cost of transportation fuel consumption via the term $\Lambda(E)$, where E denotes total world GHG emissions associated with the consumption vector of all energy products (accounting for the fact that biorenewable energy products entail savings on emission).

The foregoing approach of modeling biofuels and fossil fuels as perfect substitutes, once expressed in equivalent energy units, is consistent with other recent studies (e.g., Holland et al. 2015), but some additional discussion may be warranted vis-à-vis the "blend wall" issue. The latter refers to the maximum amount of ethanol that can be sold via the so-called E10 gasoline blend (which contains a maximum of 10% ethanol). As noted by Stock (2015, p. 13) "…this is more accurately not a 'wall' but rather a situation in which additional ethanol must be provided through higher blends." When that is the case, it may be important to represent separately consumers' demand for E10 and E85, the higher-ethanol blend that can be used by flexible fuel vehicles (FFVs) (Anderson 2012, Salvo and Huse 2013). As discussed in more detail below, feasibility of the RFS mandate is not an issue in the benchmark 2015 year, nor for the 2022 scenario. Feasibility may be an issue for the higher ethanol levels of the optimal mandates that we calculate, in which case the putative welfare gains of optimal mandates need to be properly qualified.

Demand functions for corn, soybean oil and soybean meal are written as $D_c(p_c, p_m, p_v)$, $D_v(p_c, p_m, p_v)$, and $D_m(p_c, p_m, p_v)$, respectively, and satisfy $D_c = -\partial\Theta/\partial p_c$, $D_v = -\partial\Theta/\partial p_v$ and $D_m = -\partial\Theta/\partial p_m$. Similarly, domestic demand functions for blended gasoline fuel and blended diesel fuel, $D_{gf}(p_{gf}, p_{df})$ and $D_{df}(p_{gf}, p_{df})$, satisfy $D_{gf} = -\partial\Phi/\partial p_{gf}$ and $D_{df} = -\partial\Phi/\partial p_{df}$. Again, in principle the specification can handle some substitution possibility between gasoline and diesel. Such a possible substitution is however not maintained for non-transportation petroleum products, the demand for which is $D_h(p_h) = -\partial\Psi/\partial p_h$. The actual parameterization of these demand functions will assume a quadratic structure for the functions $\Phi(\cdot)$, $\Psi(\cdot)$ and $\Theta(\cdot)$, such that the implied demands are linear. Demand functions for agricultural products exported to the rest of the world (ROW), written as $\bar{D}_c(p_c)$, $\bar{D}_v(p_v)$ and $\bar{D}_m(p_m)$, are also assumed to be linear. As for the externality cost $\Lambda(\cdot)$, we will assume that the social cost is linear in total carbon emission.

2.4 Equilibrium

The equilibrium conditions represent the situation where the United States is a net importer of crude oil, a net exporter of corn, and a net exporter of soybean oil and meal (as noted earlier, exports of soybeans *per se* are treated as exports of soybean oil and meal). These trade flows are endogenously determined by the equilibrium conditions that solve for the equilibrium prices. To exactly match the data of the benchmark 2015 year, all other trade flows (because they are of minor importance) are treated as exogenous. Similarly, our equilibrium conditions reflect observed stock changes in the benchmark year, although these quantities are treated as exogenous across scenarios.

It is useful to separate the equilibrium conditions that apply in any one scenario into market clearing conditions and arbitrage conditions. The latter arise from the competitive (zero profit) conditions that apply to the transformation sectors (oil refining, soybean crushing and ethanol production), together with the presumed Leontief production functions. Arbitrage conditions also arise because of policy interventions in the biofuel market, as discussed below. Unlike Cui et al. (2011), none of our scenarios considers the possibility of using border measures (i.e., tariffs). Hence, the arbitrage conditions that link domestic and foreign prices are directly maintained in our model. Which market equilibrium conditions apply, however, does depend on which policy tools (e.g., mandates, taxes, subsidies) are in place. Here we present the equilibrium conditions for the case with binding mandates (the *status quo*).

The statutory mandate levels are: x_{rf}^{M} for the overall mandate for renewable fuel, x_{a}^{M} for the advanced biofuel mandate, x_{b}^{M} for the biodiesel mandate, and x_{ce}^{M} for the cellulosic biofuel mandate (following the RFS convention, all of these mandates, except x_{b}^{M}, are measured in ethanol units).[7] These mandates define a hierarchical structure: cellulosic biofuels and biodiesel can be also used to meet the advanced biofuel mandate; and all biofuels can be used to meet the overall renewable fuel mandate (Schnepf and Yacobucci 2013). Consistent with the 2015 benchmark year used to calibrate the *status quo*, there are three binding mandates: x_{rf}^{M}, x_{a}^{M} and x_{ce}^{M}. Specifically, the binding cellulosic biofuel mandate is met with domestic production, which is exogenous to our model. The advanced biofuel mandate is met by imports of sugarcane ethanol, the quantity of which is exogenous, and biodiesel, either domestically produced or imported (domestic biodiesel produced from feedstock other than vegetable oil, and the imported amount of biodiesel, are treated as exogenous). More specifically, the equilibrium conditions that we characterize below pertain to the case where the quantity of biodiesel exceeds that required to meet the biodiesel mandate, i.e., the "marginal" fuel to meet the advanced biofuel mandate is biodiesel. Hence, the biodiesel mandate, *per se*, is not binding. Finally, the presumption is that the marginal biofuel for the total renewable mandate is corn ethanol (recall that there is no specific corn ethanol mandate *per se*).

[7] In the RFS regulation, these fuels are denoted as D6, D5, D4 and D3, respectively.

The market clearing conditions can now be stated as follows:

(10) $$S_c(p_c, p_s) - \Delta_c = D_c(p_c, p_m, p_v) + \bar{D}_c(p_c) + (1-\delta_1)\frac{x_e}{\alpha_e}$$

(11) $$\alpha_m[S_s(p_c, p_s) - \Delta_s] - \Delta_m = D_m(p_c, p_m, p_v) + \bar{D}_m(p_m) - \delta_2\frac{x_e}{\alpha_e}$$

(12) $$\alpha_v[S_s(p_c, p_s) - \Delta_s] - \Delta_v = D_v(p_c, p_m, p_v) + \bar{D}_v(p_v) + \frac{x_b}{\alpha_b}$$

(13) $$x_g - X_g + \zeta_e\left(x_e - X_e + \mu_{ce}x_{ce}^M + M_{se}\right) = D_{gf}(p_{gf}, p_{df})$$

(14) $$x_d - X_d + \zeta_b\left(x_b + M_b + N_b\right) = D_{df}(p_{gf}, p_{df})$$

(15) $$x_h - X_h = D_h(p_h)$$

Equation (10) represents equilibrium in the corn market. The term Δ_c here represents change in year-ending (carryover) stocks. The last term on the right-hand-side (RHS) of equation (10) represents the net amount of corn devoted to the production of ethanol, where the coefficient $(1-\delta_1)$ accounts for the quantity of byproducts from ethanol production that substitute for corn as livestock feed. Equation (11) represents equilibrium in the soybean meal market. In this equation, the terms Δ_s and Δ_m represent variations in stocks for soybeans and soybean meal, respectively, whereas the term $\delta_2 x_e/\alpha_e$ accounts for the quantity of ethanol production byproducts that substitute for soybean meal as animal feed. Equation (12) represents equilibrium in the soybean oil market. In this equation, the term Δ_v represents change in stocks of soybean oil. The last term on the RHS of equation (12) represents the amount of soybean oil that is processed into biodiesel. Equation (13) represents equilibrium in the gasoline fuel market, where X_g denotes exports of unblended gasoline. Note that ethanol from all origins—domestically produced corn-based ethanol x_e, net of export X_e and imports of sugarcane ethanol M_{se}, as well as domestically produced cellulosic ethanol—is blended with gasoline, with everything expressed in gasoline energy equivalent units via the coefficient ζ_e. Because only a very small portion of the cellulosic biofuel mandate is met with cellulosic ethanol, however, only the latter amount (denoted $\mu_{ce} x_{ce}^M$) is presumed blended with transportation fuel.[8] Equation (14) represents equilibrium in the diesel fuel market. Here X_d represents exports of refined diesel, M_b represents imports of biodiesel and N_b represents biodiesel domestically produced with feedstock other than vegetable oil. Finally, equation (15) represents equilibrium in the market for heating oil (the composite third product of refining crude oil).

The quantity of corn ethanol and biodiesel in these market clearing conditions must be consistent with the binding mandates, that is, the following identities will hold at the equilibrium:

$$x_e \equiv x_{rf}^M - x_a^M + X_e \tag{16}$$

$$x_b \equiv \left(x_a^M - x_{ce}^M - M_{se} \right) / \vartheta - M_b - N_b \tag{17}$$

where ϑ is the coefficient that, as per the RFS regulation, converts biodiesel quantities into ethanol units ($\vartheta = 1.5$ for traditional biodiesel). The quantities of petroleum products in these market clearing conditions, on the other hand, must satisfy the postulated production relationships, where the total supply of crude oil to the US refining sector depends on the oil price:

$$x_g \equiv \beta_g \left[S_R(p_R) + \bar{S}_R(p_R) \right] \tag{18}$$

$$x_d \equiv \beta_d \left[S_R(p_R) + \bar{S}_R(p_R) \right] \tag{19}$$

$$x_h \equiv \beta_h \left[S_R(p_R) + \bar{S}_R(p_R) \right] \tag{20}$$

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[8] Most of the current production of cellulosic biofuel takes the form of compressed natural gas and liquefied natural gas derived from biogas (EPA 2016). Note, however, that the full mandate x_{ce}^M is relevant for the purpose of refiners/blenders' cost of compliance with the RFS, as discussed below.

In equilibrium, prices must also satisfy arbitrage relations that reflect the zero-profit conditions implied by competitive equilibrium in constant-returns to scale industries. Specifically:

(21) $\alpha_v p_v + \alpha_m p_m = p_s + w_v$

(22) $\alpha_e p_e + \delta_2 p_m = p_c\left(1 - \delta_1\right) + w_e$

(23) $\alpha_b p_b = p_v + w_b$

(24) $\beta_g p_g + \beta_d p_d + \beta_h p_h = p_R + w_g$

Equation (21) represents the zero profit in soybean crushing (the value of all outputs equal the cost of all inputs). Similarly, equations (22), (23) and (24) represent the zero profit conditions in ethanol production, bio-diesel production and crude oil refining, respectively.

Finally, to close the model, the prices of blended fuels p_{gf} and p_{df} need to be linked to the prices of endogenous fossil fuel inputs (gasoline and diesel) and the prices of endogenous renewable fuels (ethanol and biodiesel). These relationships need to reflect the fact that gasoline and diesel blends are subject to federal and state motor fuel taxes (represented by the per-unit terms t_{gf} and t_{df}), and that biodiesel enjoys a per-unit blending subsidy ℓ_b. More importantly, these arbitrage relationships must reflect the cost that obligated parties (refiners and blenders) face for complying with the binding mandates, which are mediated by RIN prices.

2.4.1. RIN prices and arbitrage/zero profit conditions

Our model is specified in terms of absolute mandate quantities, consistent with the RFS statutory requirements laid out in the EISA legislation. As noted earlier, however, the implementation of these RFS mandates takes the form of "fractional requirements" (determined annually by the EPA) imposed on obligated parties (e.g., importers and refiners). These fractional requirements define how much of each renewable fuel must be blended in the fuel supply for each gallon of refined fossil fuel that is marketed. Obligated parties can meet their RVOs by purchasing renewable fuel themselves, or can show that others have done so by purchasing RINs. In fact, because obligated parties are typically not those who produce and/or blend biofuels in the fuel supply, an active market for RINs has emerged, and the associated RIN prices data can prove useful for empirical analyses (Knittel, Meiselman and Stock 2015, Lade, Lin Lawell and Smith 2016). The purpose of this section is to show explicitly that this, somewhat intricate, RFS enforcement mechanism can be fully rationalized in the context of a model, such as ours, that is specified in terms of absolute mandates.

Let R_{rf}, R_a, R_b and R_{ce} denote the RIN prices for generic renewable fuel (e.g., corn-based ethanol), advanced biofuel, biodiesel and cellulosic biofuel, respectively. The nested nature of the RFS mandates imply that $R_{ce} \geq R_a \geq R_{rf}$, and also that $R_b \geq R_a \geq R_{rf}$. Our working assumption that soybean-oil-based biodiesel is the marginal fuel for the purpose of meeting the advanced biofuel mandate implies that the RIN price of advanced biofuels is equal to that of biodiesel, $R_a = R_b$. Furthermore, the presumption that the marginal biofuel for the total renewable mandate is corn ethanol means that R_{rf} is effectively the RIN price for corn-based ethanol. Next, let the fractional requirements that obligated parties are required to meet for total renewable fuel, advanced biofuel and cellulosic biofuel be represented, respectively, by s_{rf}, s_a and s_{ce}. Then, given the foregoing assumptions on the marginal fuels, it follows that the implicit RFS requirement for corn-based ethanol is $\hat{s}_e = s_{rf} - s_a$, and the implicit RFS standard for biodiesel $\hat{s}_b = s_a - s_{ce}$.

To close the model using the arbitrage conditions from RIN prices, we interpret the latter as representing what has been termed as the "core value" of RINs (McPhail, Westcott and Lutman 2011). In particular, we abstract from the fact that obligated parties can borrow RINs from the next year and/or they can save RINs to be used next year (Lade, Lin Lawell and Smith 2016). These core RIN prices are derived as follows. Given that consumer demand is represented in energy units, a blender can choose to sell one unit of pure ethanol as gasoline fuel and earn $\zeta_e p_{gf}$, upon incurring the motor fuel tax cost t_{gf}. Because the RFS envisions obligations only when using fossil fuels, this strategy does not require the seller to turn in RINs. Hence, the blender would be free to sell the RIN that is "separated" when the unit of ethanol is sold as fuel. The minimum price this agent would accept, at given prices, for one generic renewable fuel RIN therefore is:

(25) $$R_{rf} = p_e + t_{gf} - \zeta_e p_{gf}$$

Analogously, a blender selling one unit of biodiesel can earn $\zeta_b p_{df}$ upon incurring the motor fuel tax cost t_{df}. This strategy would separate ϑ RINs. The minimum price this agent would accept, at given prices, for one biodiesel RIN therefore is:

(26) $$R_b = \frac{p_b - \ell_b + t_{df} - \zeta_b p_{df}}{\vartheta}$$

To make the foregoing operational for the purpose of closing the model, next we consider the demand side for RINs. The zero profit conditions for an obligated party who sells only fossil-based gasoline and/or diesel, and buys all needed RINs, are:

(27) $$p_{gf} - p_g - t_{gf} = \hat{s}_e R_{rf} + \hat{s}_b R_b + s_{ce} R_{ce}$$

(28) $$p_{df} - p_d - t_{df} = \hat{s}_e R_{rf} + \hat{s}_b R_b + s_{ce} R_{ce}$$

These two conditions can be combined to provide the zero-profit condition that must apply to the overall refining/blending industry which, as in Lapan and Moschini (2012), is assumed to be competitive and operating under constant returns to scale. To this end, we need to express the RFS fractional requirements s_i in terms of mandated quantities. Assuming binding mandates x_{rf}^M, x_{ce}^M and x_a^M, and exogenously given trade flows (recall: fossil fuel exports are not subject to the fractional RFS requirement), then

(29) $$s_{ce} = \frac{x_{ce}^M}{x_g + x_d - (X_g + X_d)}$$

(30) $$\hat{s}_e = \frac{x_{rf}^M - x_a^M}{x_g + x_d - (X_g + X_d)}$$

(31) $$\hat{s}_b = \frac{x_a^M - x_{ce}^M}{x_g + x_d - (X_g + X_d)}$$

Using equations (25)-(31), the zero-profit condition for the integrated refining-blending industry can then be written as:

(32) $$\begin{aligned} &(p_{gf} - t_{gf} - p_g)(x_g - X_g) + (p_{df} - t_{df} - p_d)(x_d - X_d) = (p_e + t_{gf} - \zeta_e p_{gf})(x_e - X_e) \\ &\quad + (p_b - \ell_b + t_{df} - \zeta_b p_{df})(x_b + M_b + N_b) + \frac{M_{se}}{\vartheta}\left(p_b - \ell_b + t_{df} - \zeta_b p_{df}\right) + x_{ce}^M R_{ce} \end{aligned}$$

The two terms on the LHS of equation (32) can be interpreted as the industry profit from selling fossil gasoline and fossil diesel, respectively. This profit balances the net industry cost of having to meet the (binding) mandates. Specifically, the first term on the RHS of (32) represents the net loss from selling $(x_e - X_e)$ units of corn-based ethanol; note that the motor fuel tax is levied on the volume of ethanol sold, whereas the revenue portion adjusts the price of (blended) gasoline fuel by the energy content of ethanol. The second term on the RHS represents the net loss from selling $(x_b + M_b + N_b)$ units of biodiesel; in addition to the role of the motor fuel tax and energy content, similar to the case of corn-based ethanol, this term also accounts for the biodiesel blending subsidy. The third term on the RHS represents the cost of marketing the (exogenous amount of) sugarcane ethanol M_{se} . Because this ethanol contributes to meeting the advanced biofuel mandate, and because the marginal fuel for meeting this mandate is biodiesel, then the implicit compliance costs associated with sugarcane ethanol is given by the core value of biodiesel RINs. Finally, the last term of the RHS represents the cost of complying with the cellulosic biofuel mandate (both the quantity mandate x_{ce}^{M} and the corresponding RIN price R_{ce} are exogenous to the model).

Because the model endogenously determines two renewable fuel prices—corn ethanol and biodiesel—the zero-profit condition for the integrated refining-blending industry in equation (32) is not sufficient to close the model (unlike in Cui et al. 2011, for instance). The additional price arbitrage condition is derived by combining equations (27) and (28):

(33) $$p_{gf} - p_g - t_{gf} = p_{df} - p_d - t_{df}$$

This equailibrium price relation embeds a critical implication of the RFS: marketing a gallon of fossil gasoline entails the same compliance cost as marketing a gallon of fossil diesel (i.e., the RHS terms of (27) and (28) are the same). In conclusion, therefore, the equilibrium conditions are given by equations (10)-(24), along with equations (32) and (33). These 17 equations are solved for 17 endogenous variables: p_c, p_s, p_m, p_v, p_R, p_{gf}, p_{df}, p_g, p_d, p_h, p_e, p_b, x_e, x_b, x_g, x_d and x_h.

2.4.2. Equilibrium conditions for other scenarios

Equilibrium conditions for scenarios other than the *status quo* will need to be appropriately adjusted. For example, without binding mandates and with no biodiesel subsidy, the equilibrium conditions would not require the arbitrage relations (32) and (33). Instead, the required arbitrage relations (for an interior solution) would be

(34) $p_g = p_{gf} - t_{gf}$

(35) $p_d = p_{df} - t_{df}$

(36) $p_e = \zeta_e p_{gf} - t_{gf}$

(37) $p_b = \zeta_b p_{df} - t_{df}$

The set of equilibrium conditions for this case would then be given by equations (10)-(15), equations (18)-(24), and equations (34)-(37). These conditions also characterize the *laissez faire* scenario, provided that $t_{gf} = t_{df} = 0$. The Appendix shows how the equilibrium conditions for the case of no RFS mandates can be adjusted to maintain the assumption that some ethanol is likely to be required, even without RFS mandates, as an oxygenate for gasoline fuel to meet desired octane levels (a scenario that we explicitly consider in the policy evaluation section).

2.5 Parameterization

The parameters of the model are calibrated to represent the most recent available consistent benchmark data set (the year 2015), in order to capture current conditions in agricultural and energy markets. Specifically, the data for crop variables are based on the 2014/2015 marketing year, whereas crude oil and fuel variables (fossil and renewable) are based on calendar year 2015.[9] The purpose of calibration is to choose parameter values for the functional forms of demand and supply so that: (a) the equilibrium conditions using the parameterized functions, along with the observed values of exogenous variables, produce the values of endogenous variables actually observed in the 2015 benchmark year; and, (b) the parameterized functions imply elasticity formulae that, once evaluated at the 2015 benchmark data, match assumed elasticity values. The functions that we parameterize are the domestic supply functions for corn and soybeans; the domestic demand functions for corn, soybean meal and soybean oil; the foreign import demand functions for corn, soybean meal and soybean oil; the domestic supply and foreign export supply functions for crude oil; the domestic demand functions for gasoline fuel and diesel fuel; and, the domestic demand function for other refined petroleum products. All of these functions are postulated to be linear.

Table 2.2 reports the assumed elasticity parameters used to calibrate the model, along with a brief description of sources/explanations. The remaining coefficients used to calibrate the model are reported in the Appendix.

2.5.1 Elasticities

The elasticity values used to calibrate the model, summarized in Table 2.2, are based on the literature, whenever possible, or assumed to reflect consensus on their qualitative attributes. A full discussion of sources and elasticity derivations is included in the Appendix. A crucial set of parameters, given the objective of the study, concerns the own and cross-price supply elasticities for corn and soybeans. Given the postulated structure discussed earlier, such

[9] The marketing year runs September to August for corn and soybeans, and October to September for soybean meal and soybean oil.

elasticities reflect both acreage allocation decisions as well as yield response effects: $\eta_{ii} = \eta_{ii}^{L} + \eta_{ii}^{y}$ ($i = c, s$) and $\eta_{ij} = \eta_{ij}^{L}$ ($i = c, s, i \neq j$). For acreage elasticities we use the estimates obtained by Hendricks et al. (2014), which are consistent with previous literature that has highlighted inelastic response. As for yield elasticities, Berry (2011) provides an extensive review of existing empirical evidence. The broad consensus is that virtually all of the crop supply response comes from acreage response, not from yield response. Here we use a set of point estimates for yield response to price from Berry and Schlenker (2011).

The own-price elasticity of domestic corn demand is the same as used by de Gorter and Just (2009) and Cui et al. (2011), and similar values are assumed for soybean oil and meal demands. Cross-price demand elasticities are calculated based on these own-price elasticities and one additional parameter that restrict all of the Allen-Uzawa elasticities of substitution to be the same. Import elasticities for the rest of the world (ROW) notionally reflect both ROW demand and supply responses. To keep the model tractable, we do not explicitly model such underlying functions, nor do we represent cross-price effects. But in the Appendix we develop the structural relations between demand and supply elasticities and the import demand elasticity, and use such relations to guide the choice of our baseline import elasticity values. For soybean products, our baseline elasticities are broadly consistent with those reported by Piggott and Wohlgenant (2002), whereas for corn our ROW import demand is more elastic than that postulated by Cui et al. (2011).

Another crucial set of elasticities relates to fuel markets. A considerable body of literature, succinctly reviewed in Difiglio (2014) and Greene and Liu (2015), has documented that gasoline demand is very inelastic. Indeed, Hughes, Knittel and Sperling (2008) find that it has become more inelastic in recent years. We conservatively assume the elasticity of gasoline demand estimated by Bento et al. (2008), who use a microeconomic model that allows consumers to respond to price changes with both car choice and miles traveled. This value is also close to the estimate obtained, with a completely different methodology, by Coglianese et al. (2016), and actually more elastic than other recent estimates (e.g., Lin and Prince 2013). Consistent with findings in the literature (Dahl 2012, Winebrake et al. 2015) we postulate that the demand for diesel fuel is more inelastic than that for gasoline fuel, while the demand for other refined fuel products is specified as relatively more elastic. Similar to demand elasticities, the consensus is that the crude oil supply elasticity is very inelastic (Difiglio 2014, Greene and Liu 2015). Our baseline parameterization relies on the crude oil supply elasticity used by the US EIA National Energy Modeling System (EIA 2014). As for the ROW export supply of crude oil to the United States, again this reflects both ROW supply and demand responses. Concerning the latter, for the United States our model presumes elasticities of demand for refined products, not crude oil. But using the structural (Leontief) production relations between refined products and crude oil, and the equilibrium arbitrage relation between prices in (24), the Appendix shows that, for the 2015 calibration year, the implied US crude oil demand elasticity is -0.20. If the ROW has a similar demand elasticity, and its crude oil supply elasticity is the same as in the United States, as assumed in EIA (2014), then we can obtain the ROW export supply elasticity value reported in Table 2.2.

2.5.2 Technical coefficients

The full set of technical coefficients is reported in Table A1 in the Appendix. For ethanol, we assume that one bushel of corn yields 2.8 gallons of ethanol, just as in Cui et al. (2011). What we do differently in this essay is provide a more careful account of the byproducts from ethanol production. In particular, we recognize that a variety of such byproducts may be produced, and that their use as animal feed substitutes for both corn and soybean meal (Mumm et al., 2014). This is important in our context, because the quantities and prices of both corn and soybean meal are endogenous in the model. Mumm et al. (2014) conclude that byproducts of ethanol production return 30.7% (in weight) of the corn used as feed equivalent, with 71% of these byproducts replacing corn in animal feed, and the remaining 29% replacing soybean meal. Our calibrated parameters δ_1 and δ_2 maintain these proportions, while adjusting to the units used (bushels for corn and short tons for soybean meal). Production of biodiesel is assumed to require 7.65 pounds of soybean oil per gallon of biodiesel (EIA), and we ignore the byproducts for this process (which have limited value, compared with those arising from ethanol production). The Leontief coefficients for the production of soybean oil and meal by crushing soybeans are obtained from the actual 2015 data for the soybean complex, which shows that 1,873 million bushels of soybeans produced 45.1 million short tons of soybean meal and 21,399 million pounds of soybean oil.

Finally, to represent blended fuels in coherent energy units, for the purpose of modeling demand, the British Thermal Unit (BTU) conversion factors of the various fuels are used (EIA). By using the coefficients ζ_i thus obtained, we are able to express blended gasoline fuel in gasoline energy-equivalent gallon (GEEG) units, as in Cui et al. (2011). By a similar procedure, blended diesel fuel is expressed in diesel energy-equivalent gallon (DEEG) units, and other refined petroleum products are expressed in kerosene energy-equivalent gallon (KEEG) units.

2.5.3 GHG emissions and social cost

Total GHG emission relevant for assessing the alternative biofuel policies scenarios include those associated with US consumption of transportation fuel and other refined petroleum products. But, because we are dealing with a global externality, it is important to account for the induced change in ROW emission induced by the RFS (the so-called leakage effect). Hence, total emission is computed as f $E = \sum_j q_j E_j + \bar{D}_R E_R$, where q_j denotes the quantity of individual fuel types consumed in the United States, E_j denotes the corresponding emission rate, $\bar{D}_R$ is the ROW crude oil consumption, and E_R is the associated emission rate. These (lifecycle) emission rates, measured as kg/gallon of carbon dioxide equivalent (CO2e) and reported in Table A2 in the Appendix, are taken from EPA (2010) and reflect consensus estimates of GHG emission savings provided by biofuels.[10] As for GHG emissions rate of other refined petroleum products, the coefficient we computed is based on five major products of this category.[11]

To translate GHG emission into a social cost, we assume a constant marginal social damage of pollution, and thus write $\Lambda(E) = \gamma E$. Regarding . γ ., the marginal social cost of carbon dioxide emissions, the large body of existing work has produced a bewildering array of estimates (Tol 2009), a reflection of the conceptual and practical complexities of such an endeavor. In addition to the familiar difficulties of choosing the baseline value for this parameter,

[10] The relative lifecycle GHG emissions rates for corn-ethanol, sugarcane ethanol, and biodiesel—when fuels are measured in energy equivalent units—are 79%, 39% and 43%, respectively, compared to corresponding fossil fuel baselines. For cellulosic biofuel, the EPA requires that qualifying products provide at least a 60% emission savings relative to fossil fuels, so we conservatively assumed this limit value in calculating the carbon emission coefficient in Table A2.

[11] These products—aviation gasoline, kerosene-type jet fuel, propane, kerosene and residual fuel oil—account for 52%, by weight, of all other refined petroleum products. Owing to the assumed Leontief technology, the assumed emission rates for refined products can alternatively be expressed per units of crude oil consumption, and this rate is used to compute GHG changes in the ROW.

we also need to address the question of what we intend to measure. Our model is predicated on a US-centered welfare criterion. For internal consistency, therefore, our model suggests that only the carbon-emission implications of US biofuel policies for the US economy are relevant. Hence, we follow Cui et al. (2011), who rationalize the use of a benchmark global social cost of \$80/tCO2, based on the *Stern Review* (Stern 2007), and then apportion this cost based on the share of US share of the world economy to obtain the adopted value of $\gamma =$ \$20/tCO2.[12]

2.5.4 Other baseline variables

Data on prices and quantities used to calibrate the model are reported in the Appendix, which includes sources and calculation methods. Many of these values are also reported in the *status quo* column of Table 2.3 below (given that parameters were correctly calibrated, simulation of the *status quo* reproduces the benchmark variables). For most variables, the data pertains to observed representative values for the benchmark (2015) year, but for some variables the benchmark values are calculated to be consistent with the model. These include gasoline fuel and diesel fuel prices, of course. Also, the reported values for the net export of soybean meal and soybean oil are the sum of actual net exports and implied net exports from the export of soybeans (as discussed earlier). The price of biodiesel is also calculated. It turns out that a representative biodiesel price, such as that reported by the USDA,[13] would imply an unreasonably low "core value" for the corresponding RIN price, if one assumed that the biodiesel blending subsidy was

[12] The US government's estimate for the 2015 social cost of carbon (in 2007 dollars) ranges from \$11/ton of CO2 (when using a 5% discount rate) to \$57/ton of CO2 (when using a 2.5% discount rate), with an additional estimate of \$109/ton of CO2 to represent higher-than-expected impacts of temperature changes (US Government 2013, p. 3).

[13] The average annual biodiesel price for 2015 that we computed from USDA data \$2.83/gallon. (National Weekly Ag Energy Round-Up, USDA Ag Marketing Service, https://usda.mannlib.cornell.edu/usda/ams/LSWAGENERGY.pdf)

fully expected, as maintained in equation (26). But in fact this subsidy was passed into law only on December 18, 2015, although it retroactively applied to the entire 2015 calendar year. The considerable uncertainty surrounding the availability of the biodiesel blending subsidy throughout 2015, as well as contractual arrangements that many market operators put in place to deal with that (Irwin 2015), suggests that it is unwise to use the observed biodiesel price in the context of a model that presumes the certainty of such a subsidy. Therefore, we elected to compute the biodiesel price that would be implied by the observed 2015 RIN prices.[14]

Other variables of interest reported in the *status quo* column of Table 2.3 also include motor fuel taxes and RIN prices. Concerning motor fuel taxes, we note at this juncture that these taxes, in virtually all cases, are levied on volume basis (Schroeder, 2015), a feature that we have maintained in our structural model. For gasoline, the assumed per-unit tax is the sum of the federal tax (¢18.40/gallon) and a weighted average of state taxes (¢26.49/gallon). For diesel, the assumed per-unit tax is the sum of the federal tax (¢24.40/gallon) and a weighted average of state taxes (¢27.24/gallon). The RIN price for ethanol is the 2015 average of D6 RIN prices, whereas for biodiesel it is the average of the 2015 annual averages of D4 and D5 RIN prices ($0.7475 and $0.707, respectively), all from OPIS data.[15]

[14] Computation of this price requires simultaneously solving equations (26), (32) and (33), which also yields the blended fuel prices p_{gf} and p_{df} at the calibration point.

[15] The core value for cellulosic biofuel RINs, used to impute the social cost of (exogenous) cellulosic biofuel mandates, is estimated at $1.80 per unit (from the average of D6 RIN prices, over the relevant period, as reported in "PFL Weekly RIN Recap").

2.6 Market and Welfare Impacts of the RFS: Alternative Scenarios

The model outlined in the foregoing sections is used to evaluate a number of policy scenarios, specifically: 2015 RFS mandate levels (the *status quo*); implementation of the 2022 RFS mandates, with projected adjustments for cellulosic biofuels as discussed in section 2.2 (Table 2.1); and, repeal of biofuel mandate policies (No RFS).[16] In addition to evaluating the above scenarios, because we have an explicit welfare function, the model permits us to characterize optimal biofuel mandates (a second best policy, in this setting), for both biodiesel and corn-based ethanol. Finally, for the purpose of benchmarking the welfare implications of these policies, we also evaluate the *laissez faire* scenario (i.e., no biofuel policies and no taxes on transportation fuels).

For each of these five scenarios the model permits computation of market effects (e.g., prices and equilibrium quantities), as well as an assessment of the welfare impacts. Because of its structure, the model accounts for potential welfare gains accruing to the United States through the impact that alternative biofuel policies can have on the US terms of trade for oil, corn and soybean products. Our welfare calculations also identify important distributional effects by breaking down welfare changes for individual components. We specifically identify net benefits accruing to US consumers, measured as consumer surplus from the integrable system of demand equations derived from the indirect utility function in equation (9); net benefits accruing to the domestic agricultural sector (with aggregate producer surplus consistently calculated as discussed in the Appendix); net benefits accruing to domestic producers of crude oil; net government tax revenue; and, the monetary value of GHG emission savings.

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[16] For this scenario, however, we assume that even without biofuel policies a certain amount of ethanol is used by blenders as a gasoline oxygenate. This is modeled as a technological minimum requirement, which is set at 3% of the blended gasoline fuel. The Appendix provides the equilibrium conditions for the case when this requirement is binding.

2.6.1 Results

In Table 2.3 and Table 2.4, results pertaining to the various scenarios are reported by column in the following order: *laissez faire*, no RFS, 2015 mandates, projected 2022 mandates, and optimal mandates. The top portion of Table 2.3 reports the value of the active policy variables for each scenario. Note that, with the exception of the *laissez faire*, all scenarios envision motor fuel taxes at the baseline level. In addition to the relevant mandates, the *status quo* also includes the $1/gallon biodiesel subsidy (technically, a tax credit). This subsidy is omitted from the optimal mandates and 2022 scenarios (this is without loss of generality, because the biodiesel mandate is binding in those scenarios). Next, Table 2.3 reports the equilibrium prices and quantities for all scenarios that are considered. Whereas Table 2.3 focuses on the market impact of policies in the various scenarios, Table 2.4 pertains to the computed welfare impacts, which are reported as changes from the "No RFS" scenarios, i.e., the *status quo* before biofuel policies. The estimated aggregate welfare effects are decomposed into several subcomponents to describe the distributional impacts of RFS policies (including on domestic agricultural producers, domestic crude oil producers, and consumers). The impacts on consumer surplus in transportation fuel demand is decomposed into changes accruing via gasoline fuel demand and diesel fuel demand (this decomposition is feasible due to the zero substitution possibilities between the two fuel demands).

One of the welfare components in Table 2.4 is the monetary value of the policies' impact on changes in GHG emissions. These emission changes are also reported separately in physical units (tCO2e), and decomposed between those occurring in the United States and in the ROW. The latter accounts for the implication of "leakage," which arises when unilateral efforts to reduce a global externality are thwarted by induced emission elsewhere (Hoel 1991). One of the two main avenues for carbon leakage to occur is via the impacts of policies on terms of trade (Felder and Rutherford 1993). Because the model can trace the impact of the RFS on equilibrium crude oil price, we can account for the leakage effect that arises because the ROW oil consumption responds to changes in crude oil price.[17]

2.6.1.1 *Status Quo*, *Status Quo Ante*, and *Laissez Faire*

Given the calibration strategy described in the foregoing, the values of equilibrium variables for the "2015 mandates" column in Table 2.3 are equal to the 2015 values that were used in calibration, a verification that the intercepts and coefficients of all demand and supply functions are precisely calibrated. The ethanol blending ratio in the calibration data is 9.87%, indicating that the blend wall issue is not a concern in the benchmark year.[18] The "No RFS" scenario, as noted, presumes that all mandates and biodiesel subsidies are repealed. Comparison of this scenario with the "2015 mandates" case provides some insight as to the overall market impacts of the current RFS. The largest impact is on agricultural prices: relative to the *status quo ante* the RFS increase corn price by 38% and the soybean price by 11%. All this notwithstanding the fact that the oxygenate requirement for ethanol (which turns out to bind) entails the use of 4.1 billion gallons of ethanol in the "No RFS" scenario. Because biodiesel biases demand of soybean

[17] The elasticity of the ROW crude oil demand used to estimate the leakage effect is $\bar{\varepsilon}_R = -0.2$. As detailed in the Appendix, this is the demand elasticity that is implied by the model's assumed elasticities for refined petroleum products' demands. This value was also used to rationalize the ROW crude oil export supply elasticity used in the model.

[18] As noted earlier, ethanol blend ratios in excess of 10% would require some biofuel to be sold in higher-ethanol blends such as E85 suitable for FFVs. In a recent intercept survey carried out in five US states, Liao, Pouliot and Babcock (2016) find that about 50% of FFV motorists use E85. At present, approximately 8.3% of the US fleet of gasoline-powered cars and light trucks is accounted for by FFVs (EIA 2016). Because E85 on average contains 74% ethanol, if half of FFV were to be accounted for by this blend, the ethanol "saturation point" would be about 12.2% —provided, of course, that FFV motorists were not constrained by the availability of refueling stations. Liao, Pouliot and Babcock (2016) also find that E85 is sold at a premium relative to E10 (on an energy equivalent basis), so that a higher saturation point could actually be supported if E85 were to be priced more aggressively.

products, the RFS increases soybean oil price by 49% whereas soybean meal price actually declines (by 2%). Not surprisingly, the RSF impact on crude oil price (and refined products prices) is much smaller: the crude oil price is estimated to decline by 1.4%, the gasoline price to decline by 9.5% (the price of diesel and that of other refined petroleum products instead increases—reduced amount of refined crude oil, along with the Leontief technology, result in a relative scarcity of these refined products). The RFS leads to a modest contraction in domestic crude oil production, and a larger decline in imports of crude oil (which drop by about 6%).

The *laissez faire* scenario, in addition to the repeal of the RFS, also envisions dropping all motor fuel taxes. This is not a scenario with realistic policy prospects, of course, but it is of some interest to gain insights into the working of the model. Interestingly, the production of corn-based ethanol in the *laissez faire* is considerably higher than in the "No RFS" scenario (the 3% oxygenate requirement is not binding in *laissez faire*). Correspondingly, the corn price is also considerably higher in the *laissez faire* relative to the "No RFS" scenario. The reason for this effect has to do with the impact of transportation fuel taxes. Consistent with the institutional setup, we have modeled these motor fuel taxes as levied on a volume basis (Schroeder, 2015). And, under the presumption that consumers care about miles traveled, fuel demand accounts for the different energy content of biofuels. Hence, as noted by Cui et al. (2011), motor fuel taxes are inherently biased against fuels (such as biofuels) that have lower energy content than fossil fuels. Conditional on such motor fuel taxes being levied per unit of volume of blended fuel, a subsidy for ethanol (and biodiesel) would actually be required just to level the playing field (vis-à-vis the objectives of a Pigouvian tax).

Turning to the welfare impacts reported in Table 2.4, comparing the 2015 mandates case with the "No RFS" scenario we find that aggregate welfare is improved by biofuel policies, by

$3.4 billion. In the logic of the model, there are two distinct reasons why RFS policies may improve welfare: they can help correct the carbon pollution externality (under the maintained presumption that biofuels are less polluting than fossil fuels); and, because the United States is a large country, they may lead to favorable changes in the US terms of trade. It is immediately apparent from Table 2.4 that no portion of the welfare gain associated with 2015 mandates (relative to the no RFS scenario) can be ascribed to a reduction in the carbon externality. The increased use of biofuels does reduce carbon emission in the United States (by about 29 million tCO2e), but this effect is more than offset by increased ROW emissions caused by the RFS-induced decline in the price of crude oil. Leakage, therefore, turns out to imply that US biofuel policies do not contribute to reducing global emissions. It is important to stress that the effects we are quantifying here are distinct from the indirect land use effects emphasized by other critics of US biofuel policies (e.g., Searchinger et al. 2008). Even abstracting from the latter, we find that leakage via terms of trade effects essentially nullifies the potential environmental gains arising from using (marginally) more environmentally friendly fuels.

When comparing the 2015 mandates with the *status quo ante*, it is apparent that the welfare redistribution effects due to the RFS are large (relative to the overall effects). Agriculture is the big winner. Because of the sizeable increase in the prices of corn and soybeans, noted earlier, the RFS is estimated to increase the sector's producer surplus by $15.9 billion per year. The large increase in land prices that has been observed in recent years (Lence 2014) is certainly consistent with these conclusions. Consumers of gasoline fuel also benefit from the decrease in gasoline price, whereas users of diesel fuels are actually hurt by the RFS (as are the consumers of other refined petroleum products). Overall, therefore, these results suggest that repeal of the RFS would lower domestic welfare, both because of terms of trade effects, and because the resulting excess taxation of biofuels (relative to fossil fuels) would excessively depress biofuel production. It is also of some interest to note that, compared with the no RFS scenario, the *laissez faire* results in higher welfare. This seems counterintuitive, given that the welfare function includes an externality cost, and the *laissez faire* does not have corrective motor fuel taxes. One of the reasons for this outcome is that—given the assumed social cost of carbon—motor fuel taxes are set at a higher level than what would be required to internalize the carbon emission externality.[19]

2.6.1.2 Year 2022 mandates

The second-to-last column in both Table 2.3 and Table 2.4 considers the 2022 RFS scenario, the terms of which were discussed earlier and are illustrated in Table 2.1. The major differences in mandated volumes from 2015 levels is that the implied biodiesel mandate is increased by 84%, whereas the implied corn-ethanol mandate is increased by just 7%. Despite the modest increase in corn ethanol production, the ethanol blending ratio (fraction of ethanol in total gasoline fuel) exceeds 10%, a consequence of the decline in gasoline fuel demand associated with higher gasoline prices. Both corn and soybean prices increase substantially, relative to the *status quo*. The increase in soybean price (10.3%) is larger than the increase in corn price (5.4%), relative to the *status quo*, a consequence of the need to expand biodiesel production to meet the advanced biofuel mandate. This is also reflected in a much higher biodiesel RIN price (again under the assumption of no biodiesel subsidy).

The increased use of both biofuels, combined with an overall decline in gasoline fuel consumption, achieves some pollution reduction (unlike the 2015 mandates case). As for welfare

[19] Given the assumed emission rates and social cost of carbon, the per-gallon Pigouvian taxes needed to correct the externality would be \$0.237 for gasoline, \$0.267 for diesel, \$0.131 for corn-based ethanol, and \$0.106 for biodiesel. Of course, motor fuel taxes can be rationalized in the pursuit of more than just reduction in carbon emissions, such as reducing congestion and other externalities associated with vehicle use (Parry and Small 2005).

measures, however, Table 2.4 shows overall welfare is considerably lower with the 2022 mandates than with 2015 mandates. The increase in crop prices benefits farmers, as the agricultural sector's aggregate producer surplus is highest among the scenarios we have considered. Despite the further improvement in the US terms of trade (in addition to increased prices of agricultural exports we have a decrease in the price of crude oil imports, relative to 2015 mandates), overall welfare declines. This is because these pecuniary effects are offset by the efficiency cost of expanding biofuel production (the supply price of biodiesel is increased by \$0.78 per gallon, and the supply price of ethanol also increases by \$0.06 per gallon). In the end, our model shows that biodiesel produced from vegetable oil turns out to be a costly way to increase biofuel supply. The projected expansion of the cellulosic biofuel mandate also weighs heavily on the welfare impacts of the 2022 mandates scenario. The large excess cost of these biofuels relative to consumer value—captured by the D3 RIN price that we have assumed, based on current market conditions—makes expansion of cellulosic biofuel use particularly onerous.

2.6.1.3 Optimal mandates

One of the advantages of the structural model that we have developed is that we can compute "optimal" mandates. In this second best scenario, we take as given existing motor fuel taxes and ask what level of mandates would maximize the welfare function (Marshallian surplus net of external damages). The grid search method that we implemented identifies an optimal biodiesel mandate of 1.66 billion gallons, zero mandates for cellulosic biofuel, and an overall renewable fuel mandate of 19.4 billion gallons (implying an effective corn-based ethanol mandate of approximately 17.7 billion gallons). Thus, the constrained optimal mandates that we find would envision an 18% expansion of the implied corn-based ethanol mandate, relative to the year 2022 scenario, and a drastic reduction of the advanced biofuel mandate (including zero cellulosic biofuel). The corn price would increase, relative to both 2015 mandates and the year 2022 scenario, but the soybean price would decline.

The corn price increase results in higher marginal cost of supplying ethanol, and the ethanol price also increases. Consequently, the ethanol RIN price also increases. Table 2.3 indicates that the biodiesel RIN price also increases with the optimal mandates, relative to 2015 mandates, despite the fact that soybean oil price is lower. Note, however, that the optimal mandate scenario presumes the elimination of the biodiesel subsidy ($1 per gallon), so that the RIN price in the optimal mandate case reflects the full extent of the marginal cost of biodiesel production in excess of its consumer valuation (if the $1 subsidy were preserved, the optimal mandates would entail essentially a zero RIN price for biodiesel).[20] These optimal mandates would result in higher emissions than with the projected 2022 mandates. The overall welfare gains associated with such optimal mandates, relative to 2015 mandates is $0.9 billion, but relative to the projected 2022 scenario the gains amounts to $5.4 billion. The ethanol blending ratio with optimal mandates turns out to be 12.14%. As discussed earlier (see footnote 18), this blending may be supportable given the current fleet of FFVs, provided FFV motorists were not constrained by the availability of E85 refueling stations. Hence, the welfare gain that we estimate would result from optimally rebalancing RFS mandates can be interpreted as the upper bound of the potential payoff of whatever investments may be required to avoid the blend wall.[21] Whether such investments are socially beneficial, of course, would depend on their costs.

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[20] Similar considerations also pertain to the reported RIN prices for the year 2022 scenario.

[21] As noted by a reviewer, a more accurate assessment would compare the welfare of optimal mandates in table 4 with the welfare of mandate levels that are optimal with a binding blend wall. If we interpret the latter as the optimal mandates conditional on a maximum ethanol blend ratio of 10%, we find that they would produce a welfare change of $4 million (relative to no biofuel policies). Hence, the implied payoff associated with E85 infrastructure

2.6.2 Sensitivity analysis

Inevitably, some of the assumed elasticity values or coefficients used to parameterize the model may be perceived as having a degree of arbitrariness. We note at this juncture that the existing econometric evidence can only be of partial help, both because of the limited number of relevant studies, and because the structure underlying existing econometric estimates may not be entirely consistent with the structure of this essay's model. In any event, sensitivity analysis can be helpful to assess the robustness of the results to alternative parameter values. Here we present the results associated with alternative assumptions concerning the ROW elasticity of crude oil supply to the United States, and the ROW elasticities of demand for US agricultural exports. A more comprehensive set of sensitivity analyses is presented in the Appendix.

In the logic of the model, there are two distinct reasons for RFS policies: to correct the carbon pollution externality (under the presumption that biofuels are less polluting than fossil fuels); and, to exploit the terms of trade. Concerning the first of these objectives, the second best setting of the model needs to account for the fact that existing motor fuel taxes also ameliorate the carbon externality. Furthermore, as noted, insofar as these taxes are levied on a volume basis, they are inherently biased against biofuels (because the latter entail lower pollution effects and have lower energy content). This imbalance can, to a degree, be addressed by RFS mandates because these policy instruments work as a tax on fossil fuel and a subsidy for biofuel (in a revenue neutral fashion, as shown in Lapan and Moschini 2012). And because they tax products (fossil fuels) for which the United States is a net importer, and subsidize domestic use of

investments that would permit achieving the blend ratio of the optimal mandates in tables 3 and 4 would reduce to $0.3 billion.

products (corn and soybean products) for which the United States is a net exporter, RFS mandates can also improve the U.S. terms of trade.

To isolate the contribution of these various elements to the estimated market and welfare effects, Table 2.5 reports counterfactual results for scenarios that postulate the absence of all or part of the terms of trade effects. Specifically, the columns labeled as “no TOT effects” presumes that the ROW excess supply of crude oil, and the ROW excess demand for agricultural products, are infinitely elastic (such that the prices of crude oil, corn, soybean oil and soybean meal are constant at the calibrated values). Under these assumptions, we evaluate both 2022 projected mandates and optimal mandates. Because by assumption there are no terms-of-trade effects here, we find that 2022 projected mandates would entail a large welfare loss (relative to the no RFS scenario) of $11.3 billion, despite the fact that they considerably decrease carbon externality (because there is no leakage in this case). Without terms of trade effects we also find that there is no scope for biofuel policies. Note that, even without terms of trade effects, there remains market failure arguments for intervention (carbon externality and the overtaxing of biofuels by existing motor fuel taxes). But the assumed technological requirement for ethanol use as an oxygenate, which is binding at the optimal solution, make such considerations irrelevant.

The last four columns of table 5 decompose the importance of terms of trade as arising from the crude oil market or from agricultural markets. When there are no crude oil terms of trade, such that the price of crude oil is fixed at the baseline level, we find that 2022 mandate levels still entail considerable welfare loss relative to the no RFS scenario. Optimal mandates for this case are close to those reported in Table 2.3 and lead to a $3.1 billion gain in overall welfare (relative to no RFS). If we do allow crude oil price to adjust, and simply postulate that the ROW demands for US agricultural exports are perfectly elastic, then the last two columns in Table 2.5

indicate large welfare losses associated with 2022 mandates, and minor gains arising from optimal policies (a mere $0.1 billion more than in the no RFS scenario).

The combined evidence of tables 4 and 5 suggests that virtually all of the estimated increase in US aggregate welfare is ultimately due to the positive impacts that the RFS has on the US terms of trade. Mandates result in increased prices of corn and soybean, and a decreased price of crude oil. Because the United States is a net exporter of corn and soybean products (both before and after the RFS), and a net importer of crude oil, these changed terms of trade are beneficial. Furthermore, it seems that the terms of trade effects arising from exports of agricultural commodities dominate the beneficial effects associated with decreased crude oil price (which are also affected by the leakage effect).

2.6.3 Comparison with other studies

Differing methodologies and empirical approaches makes comparison of our results with those of other studies perilous. Concerning market effects of the RFS, though, we note that our estimated agricultural price increases due to the RFS are quite similar to those obtained by Carter, Rausser and Smith (2016). Using a completely different methodology—a structural vector autoregression econometric approach—these authors estimate that the EISA additional 5.5 billion gallons ethanol requirement (relative to those envisioned in the 2005 legislation) caused a 31% long-run increase in corn prices. This is quite consistent with our higher estimate for the 2015 mandate levels (39% corn price increase), but our model traces the effects of a larger mandate level. Our estimated agricultural price increases are smaller than those obtained by Cui et al. (2011), reflecting the implications of a much more elaborate model as well as somewhat more conservative elasticity assumptions. Our model is unique in the existing literature, as noted earlier, as being able to articulate the impact of the RFS on soybean prices, not just corn prices.

Other studies have emphasized that the blend wall can make the RFS more costly. Similar to our study, Meiselman (2016) recognizes the RIN price linkages implied by the hierarchical structure of RFS mandates, but he only considers a closed economy scenario and does not envision supply-side interactions between biodiesel and ethanol production. He finds that increasing the mandate around the blend wall would reduce GHG emission, but this would entail a very high (marginal) social cost ($800/tCO2e). Although we do not have a comparable scenario for this estimate, we note that our projected 2022 mandate levels improve on carbon emission, both relative to 2015 levels and to the no RFS scenario, although welfare declines. The latter conclusion, of course, depends on our assumed social cost of carbon (γ =$20/tCO2e). To investigate how the welfare result is affected by the assumed social cost of carbon, we computed two break-even levels for the γ parameter. We find that a social cost of carbon of $72/tCO2 would make welfare with the 2022 mandates the same as in the “No RFS” scenario, but that it would take a social cost of carbon of $190/tCO2 to make welfare with the 2022 mandates the same as with 2015 mandates.

2.7 Conclusion

This paper analyzes some of the market and welfare impacts of US biofuel support policies under the RFS program. To do so, we have constructed a tractable multi-market model that incorporates biodiesel markets as well as ethanol markets, thereby extending previous work that focused solely on gasoline-ethanol blends. The paper shows how compliance requirements on obligated parties, which are mediated by RIN prices, can be used to identify the relevant zero-profit conditions required to close the model. Within this framework, the model is calibrated to match market data for the 2015 benchmark year. The model can then be solved and simulated to study counterfactual policy scenarios, yielding equilibrium prices, quantities and welfare impacts for each experiment of interest. A first-order impact of the RFS is to divert large amounts of corn and soybean oil to biofuel production. This reduces the amount of these products available for export, and the RFS-induced biofuels production also marginally lowers the US demand for refined fossil fuels. Given that the United States are a net importer of crude oil and net exporter of corn and soybean products, the favorable terms-of-trade effects that arise because of the RFS are quite important in order to assess the resulting welfare impacts. Having endogenized the relevant agricultural and energy markets, the model that we construct offers an ideal tool to assess the overall consequences, from the point of view of the United States, of current RFS policies and alternative paths that may be considered going forward.

The results that we have presented confirm that the current RFS program considerably benefits the agriculture sector. Compared with the *status quo ante* situation (no RFS), we find that current biofuel policies increase corn and soybean prices by 38% and 11% , respectively, and also lead to a 1.4% decline in crude oil price. The welfare gain to the United States that can be imputed to the RFS, in 2015, is estimated at about $3.4 billion. Virtually all of these US welfare gains are due to the impact of RFS policies on the terms of trade. Furthermore, the most relevant effects are those associated with the RFS impacts on the price of key US agricultural exports (corn and soybean products). The RFS net impact on carbon emission is nil in the benchmark year, and minimal with the projected 2022 mandate levels. One of the main reasons for this finding is the leakage effects that arise because of increased consumption of fossil fuels in the ROW due to the RFS-induced decline in crude oil price.

There is considerable uncertainty, and policy debate, concerning future implementation of the RFS. The model that we have developed can be used to assess the market and welfare consequences of alternative paths. We find that full implementation of the EISA statutory 2022 mandate levels (except for the widely expected extensive waiver of cellulosic biofuel mandates) would be costly to the United States. This is because biodiesel, as the marginal fuel of choice to meet the advanced biofuel mandate, does not appear to be an efficient enough tool. Alternatively, if we ask what the optimal mandates levels would be in the context of the model, we find that it would be desirable to expand corn-based ethanol production beyond the 15 billion gallon cap envisioned by the EISA legislation (concomitantly, optimal mandates suggest that a reduction of biodiesel production from current levels is also desirable, and no cellulosic biofuel production). As noted, of course, the viability of such an option may need to deal with the blend wall issue. In any event, relative to 2015 mandate levels, these optimal (second best) mandates produce limited welfare gains. This is because, as documented in the analysis we have presented, it is the impact of the RFS on agricultural terms of trade that is most important. For these effects to remain sizeable, the magnitude of US exports cannot be curtailed too much.

In addition to quantifying the overall welfare gains, the model permits a characterization of the re-distribution effects implied by various scenarios. The magnitudes of such effects are quite large, and the documented impacts—agriculture is the big winner—may help to rationalize some of the political economy features of the debate about the future of the RFS. Although our analysis has been consistently articulated in terms of US welfare, our finding that the predominant welfare impacts are rooted in terms of trade effects suggests that this domestic program has clear “beggar-thy-neighbor” implications. Obligations undertaken within the World Trade Organization (WTO) restrain the ability of the United States to use border policies to shift to other countries some of the costs of its long-standing agricultural support objectives. RFS provisions, while *prima facie* consistent with the national treatment principle of the WTO, are apparently effective at shifting some of their costs on foreign constituencies. The fact that the latter represent mostly consumers of agricultural products adds weight to the food-versus-fuel debate. Finally, our finding that the RFS has minimal impacts on reducing global carbon emissions suggests that, from an international perspective, the scope of biofuel policies to improve global welfare may be extremely limited.

Table 2.1. Statutory Mandates, EPA Final Rulings, and 2022 Scenario (billion gallons)

	2015		2016		2017		2022	
	EISA	EPA	EISA	EPA	EISA	EPA	EISA	Projected
Renewable fuel	**20.5**	**16.93**	**22.25**	**18.11**	**24.0**	**19.28**	**36.0**	**20.787**
Advanced biofuel	5.5	2.88	7.25	3.61	9.0	4.28	21.0	5.787
Biodiesel	≥ 1.0	1.73	≥ 1.0	1.90	≥ 1.0	2.00	≥ 1.0	… [a]
Cellulosic biofuel	3.0	0.123	4.25	0.230	5.5	0.311	16.0	0.787 [b]
Non-cellulosic advanced biofuel	*2.5*	*2.757*	*3*	*3.38*	*3.5*	*3.969*	*5*	*5*
Corn ethanol	*15*	*14.05*	*15*	*14.5*	*15*	*15*	*15*	*15*

Source: Schnepf and Yacobucci (2013) and EPA (2016). All quantities are in ethanol-equivalent gallons except for biodiesel, which are in physical volume.

Note: [a] Biodiesel produced as needed (assumed to be the marginal advanced fuel); [b] Linear trend projection based on 2014-2017 EPA rulings (R^2 = 0.998).

Table 2.2. Elasticities

Parameter	Symbol	Value	Source/explanation
Corn acreage own-price supply elasticity	η_{cc}^{L}	0.29	Hendricks et al. (2014)
Corn acreage cross-price supply elasticity	η_{cs}^{L}	−0.22	Hendricks et al. (2014)
Soybean acreage own-price supply elasticity	η_{ss}^{L}	0.26	Hendricks et al. (2014)
Corn yield own-price elasticity	η_{cc}^{y}	0.05	Berry and Schlenker (2011)
Soybean yield own-price elasticity	η_{ss}^{y}	0.01	Berry and Schlenker (2011)
Domestic demand elasticity of corn	ε_{cc}	−0.20	de Gorter and Just (2009)
Domestic demand elasticity of soybean meal	ε_{mm}	−0.20	Bekkerman et al. (2012) [a]
Domestic demand elasticity of soybean oil	ε_{vv}	−0.20	Bekkerman et al. (2012) [a]
Cross-elasticity of domestic corn demand w.r.t. p_m	ε_{cm}	0.065	Calculated [b, d] ($\varepsilon_{mc} = 0.105$)
Cross-elasticity of domestic corn demand w.r.t. p_v	ε_{cv}	0.014	Calculated [b, d] ($\varepsilon_{vc} = 0.105$)
Cross-elasticity of domestic meal demand w.r.t. p_v	ε_{mv}	0.014	Calculated [b, d] ($\varepsilon_{vm} = 0.065$)
ROW import demand elasticity of corn	$\bar{\varepsilon}_{cc}$	−2.70	Calculated [d]
ROW import demand elasticity of soybean meal	$\bar{\varepsilon}_{mm}$	−1.70	Calculated [d]
ROW import demand elasticity of soybean oil	$\bar{\varepsilon}_{vv}$	−1.40	Calculated [d]
Domestic supply elasticity of crude oil	η_{R}	0.25	EIA (2014)
ROW export supply elasticity of crude oil	$\bar{\chi}_{R}$	4.40	Assumed [d]
Domestic demand elasticity of gasoline fuel	ε_{gg}	−0.35	Bento et al. (2009)
Domestic demand elasticity of diesel fuel	ε_{dd}	−0.15	Assumed [c, d]
Domestic demand elasticity of other refined petroleum products	ε_{hh}	−0.50	Assumed [c, d]

Note: [a] Rounded values. [b] Calculated assuming that all of the Allen-Uzawa elasticities of substitution are the same. [c] Based on Dahl (2012) and Winebrake et al. (2015). [d] See the Appendix for more details.

Table 2.3. Market Effects of Alternative Policy Scenarios

	Laissez Faire	No RFS	2015 Mandates	2022 Mandates	Optimal Mandates
Gasoline motor fuel tax ($/gal.)		0.449	0.449	0.449	0.449
Diesel motor fuel tax ($/gal.)		0.516	0.516	0.516	0.516
Biodiesel subsidy ($/gal.)			1.000		
Cellulosic biofuel mandate (billion units)			0.123	0.787	
Advanced biofuel mandate (billion units)			2.880	5.787	1.661
Renewable biofuel mandate (billion units)			16.930	20.787	19.351
Corn price ($/bu.)	3.05	2.67	3.68	3.88	3.96
Soybean price ($/bu.)	9.21	9.11	10.10	11.14	9.69
Soybean meal price ($/ton)	374.58	376.39	368.49	363.28	369.23
Soybean oil price (¢/lb.)	22.51	21.24	31.60	41.83	27.87
Crude oil price ($/bbl)	49.81	49.10	48.40	48.00	48.33
Gasoline fuel price ($/GEEG)	2.02	2.35	2.22	2.30	2.13
Diesel fuel price($/DEEG)	1.40	1.98	2.23	2.12	2.51
Gasoline price ($/gal.)	2.02	1.90	1.72	1.74	1.60
Diesel price ($/gal.)	1.40	1.47	1.67	1.50	1.92
Ethanol price ($/gal.)	1.42	1.31	1.61	1.67	1.68
Biodiesel (supply) price ($/gal.)	2.95	2.86	3.65	4.43	3.36
Other refined products' price ($/KEEG)	1.08	1.17	1.26	1.31	1.27
RIN price for ethanol ($/unit)			0.49	0.50	0.64
RIN price for biodiesel ($/unit)			0.73	1.99	1.03
Ethanol quantity (billion gal.) [a]	8.251	4.123	14.140	15.167	17.778
Blending ratio of ethanol (%) [b]	5.657	3.000	9.871	10.652	12.140
Biodiesel quantity (billion gal.) [a]	0.686	0.686	1.779	3.275	1.049
Gasoline fuel quantity (billion GEEGs)	143.401	136.220	139.051	137.353	141.166
Diesel fuel quantity (billion DEEGs)	49.169	47.336	46.548	46.900	45.679
Other refined products (billion KEEGs)	82.046	79.239	76.476	74.889	76.186
Corn production (billion bus.)	13.665	13.191	14.216	14.156	14.716
Soybean production (billion bus.)	4.029	4.137	3.927	3.975	3.796
Corn demand (billion bus.)	8.096	8.258	7.851	7.794	7.717
Corn export (billion bus.)	2.680	3.198	1.833	1.564	1.450
Soybean meal demand (million tons)	47.182	46.576	48.408	49.042	48.701
Soybean meal export (million tons)	54.984	54.511	56.572	57.932	56.378
Soybean oil demand (billion lbs.)	12.758	12.727	12.260	11.525	12.651
Soybean oil for biodiesel (billion lbs.)			8.363	19.803	2.774
Soybean oil export (billion lbs.)	31.447	32.716	22.421	12.261	26.124
Crude oil domestic supply (billion bbl)	3.475	3.463	3.450	3.443	3.449
Crude oil import (billion bbl)	3.281	3.092	2.907	2.800	2.888
Crude oil foreign demand (billion bbl)	23.132	23.201	23.268	23.307	23.275

Note: [a] Quantities (from all sources) blended into US fuel supply. [b] Calculated by using physical units (ratio of gallons of ethanol to gallons of gasoline fuel).

Table 2.4. Welfare Effects of Alternative Policies (changes relative "No RFS" scenario)

	Laissez Faire	2015 Mandates	2022 Mandates	Optimal Mandates
Social welfare ($ billion)	**3.112**	**3.421**	**-1.058**	**4.316**
Pollution effect [a]	-1.880	-0.104	0.422	-0.378
Tax revenue	-86.168	0.513	2.168	3.197
P.S. Agriculture [b]	10.278	15.891	23.753	16.209
P.S. Crude oil supply [b]	2.472	-2.425	-3.814	-2.679
Efficiency cost of cellulosic biofuel [c]		-0.221	-1.417	
C.S. Crop products' demand [d]	-3.223	-9.092	-11.619	-10.880
C.S. Fuel demand [d]	74.169	5.953	0.504	6.673
Gasoline fuel demand	45.867	17.800	7.078	31.336
Diesel fuel demand	28.301	-11.848	-6.575	-24.664
C.S. Other refined products [d]	7.464	-7.094	-11.055	-7.825
Change in GHG emissions (million tCO2e) [a]	**94.00**	**5.21**	**-21.09**	**18.91**
Changes in the United States	128.58	-28.84	-74.69	-18.71
Changes in the ROW	-34.58	34.04	53.60	37.62

Notes: [a] In the "No RFS" scenario the GHG emission level is 14,684 [2,976 (US) + 11,709 (ROW)] million tCO2e, the monetary cost of which is $293.7 billion. [b] P.S. = producer surplus. [c] Computed based on a D3 RIN price of $1.80. [d] C.S. = consumer surplus.

Table 2.5. Sensitivity Analysis: Terms-of-Trade (TOT) Effects

	Baseline	No TOT effects		No crude oil TOT		No agricultural TOT	
Policies / Market Effects	2015 Mandates	2022 Mandates	Optimal Mandates	2022 Mandates	Optimal Mandates	2022 Mandates	Optimal Mandates
Gasoline motor fuel tax ($/gal.)	0.449	0.449	0.449	0.449	0.449	0.449	0.449
Diesel motor fuel tax ($/gal.)	0.516	0.516	0.516	0.516	0.516	0.516	0.516
Biodiesel subsidy ($/gal.)	1.000						
Cellulosic biofuel mandate (B units)	0.123	0.787		0.787		0.787	
Advanced biofuel mandate (B units)	2.880	5.787	1.117	5.787	1.322	5.787	1.117
Renewable biofuel mandate (B units)	16.930	20.787	5.159	20.787	17.594	20.787	9.662
Corn price ($/bu.)	**3.68**	**3.68**	**3.68**	3.88	3.82	**3.68**	**3.68**
Soybean price ($/bu.)	**10.10**	**10.10**	**10.10**	11.14	9.50	**10.10**	**10.10**
Soybean meal price ($/ton)	**368.49**	**368.49**	**368.49**	363.28	370.58	**368.49**	**368.49**
Soybean oil price (¢/lb.)	**31.60**	**31.60**	**31.60**	41.83	25.93	**31.60**	**31.60**
Crude oil price ($/bbl)	**48.40**	**48.40**	**48.40**	**48.40**	**48.40**	48.03	48.88
Gasoline price ($/gal.)	1.72	1.76	1.88	1.75	1.63	1.75	1.79
Diesel price ($/gal.)	1.67	1.50	1.44	1.52	1.90	1.48	1.65
Ethanol price ($/gal.)	1.61	1.61	1.61	1.67	1.64	1.61	1.61
Biodiesel (supply) price ($/gal.)	3.65	3.65	3.65	4.43	3.22	3.65	3.65
RIN price for ethanol ($/unit)	0.49	0.44	0.41	0.49	0.59	0.44	0.46
RIN price for biodiesel ($/unit)	0.73	1.47		1.97	0.95	1.48	
Ethanol quantity (B gal.)	14.140	15.167	4.129	15.167	16.360	15.167	8.633
Blending ratio of ethanol (%)	9.877	10.685	3.000	10.703	11.222	10.675	6.140
Biodiesel quantity (B gal.)	1.779	3.275	0.686	3.275	0.823	3.275	0.686
Corn export (billion bu.)	1.833	1.568	4.628	1.564	1.650	1.568	3.370
Soybean meal export (M tons)	56.572	57.421	47.636	57.932	56.026	57.421	51.657
Soybean oil export (B lbs.)	22.421	10.982	30.785	12.261	28.051	10.982	30.785
Crude oil domestic supply (B bbl)	3.450	3.450	3.450	3.450	3.450	3.443	3.458
Crude oil import (B bbl)	2.907	2.797	3.114	2.786	2.922	2.810	3.033
Welfare Impacts (relative to "No RFS")							
Social welfare ($ billion)		-11.268	0.0	-2.883	3.057	-9.522	0.146
Pollution effect		1.549	0.0	1.696	0.358	0.330	-0.191
Tax revenue		2.088	0.0	1.880	2.762	2.364	1.163
P.S. Agriculture		-1.243	0.0	23.276	13.283	-0.797	-1.412
P.S. Crude oil supply		0.0	0.0	0.0	0.0	-3.646	-0.741
Efficiency cost of cellulosic biofuel		-1.417	0.0	-1.417	0.0	-1.417	0.0
C.S. Crop products' demand		0.000	0.0	-11.612	-9.538	0.0	0.0
C.S. Fuel demand		-0.985	0.0	-4.937	3.240	4.219	3.518
C.S. Other refined products		-11.260	0.0	-11.769	-7.048	-10.576	-2.192
GHG emissions change (million tCO2e)		-77.45	0.0	-84.82	-17.90	-16.52	9.55
Changes in the United States		-77.45	0.0	-84.82	-17.90	-67.76	-0.85
Changes in the ROW		0.00	0.0	0.0	0.0	51.24	10.40

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APPENDIX A

SUPPLEMENTARY MATERIALS

A.1 Parameterization of Supply Functions and Computation of Producer Surplus

For the simulation of counterfactual policy scenarios, we will rely on a linear parameterization of the supply functions of corn and soybeans, $q_c = S_c(p_c, p_s)$ and $q_s = S_s(p_c, p_s)$. Specifically, we write:

$$\begin{aligned} q_c &= a_c + a_{cc}p_c + a_{cs}p_s \\ q_s &= a_s + a_{sc}p_c + a_{ss}p_s \end{aligned} \tag{38}$$

where, by symmetry, $a_{cs} = a_{sc}$. Let $\eta_{ij} \equiv (\partial S_i / \partial p_j)(p_j / S_i)$, $i, j = c, s$, denote supply elasticities. If the above linear equations represent the first-order approximation to the true supply equations at a quantity-price point $(\overline{q}, \overline{p})$, then the parameters in (38) can be expressed as $a_{ij} \equiv \eta_{ij}(\overline{q}_i / \overline{p}_j)$, $\forall i, j = c, s$. Because we think of supply response as embedding both a yield response and an acreage response—as represented by $S_i(p_i, p_j) = y_i(p_i)L_i(p_i, p_j)$—then

$$\eta_{ii} = \eta_{ii}^{y} + \eta_{ii}^{L}, \quad i = c, s$$

$$\eta_{ij} = \eta_{ij}^{L}, \qquad i \neq j = c, s$$

where $\eta_{ij}^{L} \equiv (\partial L_i / \partial p_j)(p_j / L_i)$ denote acreage response elasticities and $\eta_{ii}^{y} \equiv (\partial y_i / \partial p_i)(p_i / y_i)$ denote yield response elasticities.

A.1.1 Computation of producer surplus

The system of linear supply equations $S_c(p_c, p_s)$ and $S_s(p_c, p_s)$ parameterized in (38) is consistent with the quadratic profit function:

$$\Pi(p_c, p_s) = a_0 + a_c p_c + a_s p_s + \frac{1}{2}\left(a_{cc} p_c^2 + 2a_{cs} p_c p_s + a_{ss} p_s^2\right)$$

where we have maintained the symmetry condition $a_{cs} = a_{sc}$. Under our working assumption that the use of land for corn and soybean production is derived from a profit maximizing allocation of a fixed overall land L^T over three possible uses—corn, soybeans and everything else—this quadratic profit function measures the aggregate surplus to the agricultural sector. Because land is treated as an allocatable fixed factor, its rental price will of course change as corn and soybean prices change, but returns to land (and to other fixed factors) are of course captured by the profit function. For any two scenarios yielding equilibrium prices (p_c^0, p_s^0) and (p_c^1, p_s^1), the aggregate change in gross producer surplus in the agricultural sector would be computed as

$$\Delta\Pi = \Pi(p_c^1, p_s^1) - \Pi(p_c^0, p_s^0).$$

The underlying presumption, in this procedure, is that all other output and input prices (apart from land, of course) are held constant. Given the nature of our policy scenarios, one set of prices that, strictly speaking, cannot be thought of as constant across scenarios is that of energy inputs used in agriculture, which will likely be affected by changes in the energy prices that are endogenous in the model. To account for this effect on producer surplus in a straightforward way, we assume that energy inputs are used in fixed proportion with land, with the same coefficient across all uses. This implies that changes in energy input prices will not affect land allocation decisions, nor total energy use in agriculture. This assumption is broadly supported by the (limited) empirical evidence available to date. Miranowski (2005) estimated the US agricultural sector energy use in 2002 to be about 1.7 quadrillion BTUs overall, of which about 1.1 quadrillion BTUs was in direct energy use (mostly fuel) and the reminder as indirect energy use (e.g., fertilizers and pesticides). Beckman, Borchers and Jones (2013) show that this energy use level was fairly stationary for the period 2001-2011.

To account for the impact of changes in energy input prices on calculated producer surplus, we focus on direct energy use in agriculture. Because the largest component of direct energy use in agriculture is diesel fuel, we assume that the agricultural energy input price p_{ei} is proportional to the price of diesel fuel p_{df}. Given that, we can express the total amount of energy used in agriculture, denoted E_A, in DEEG units. The energy content of distillate Fuel Oil (15 ppm Sulfur and Under) is 137,381 BTU/gallon. Hence, 1.1 quadrillion BTUs is equivalent to E_A =8.007 billion DEEGs. Changes in energy prices will impact producer surplus (increase in energy prices will drive down land prices, for instance). The “net” producer surplus change can be calculated as:

$$\Delta PS = \Delta\Pi - E_A \Delta p_{df} \ .$$

Note: clearly, a_0 does not matter for this computation, so there is no need to calibrate it.

A.2 Parameterization of Demand Functions

Demand functions are derived from a quadratic parameterization for the sub-utility functions that appear in the indirect utility function of equation (9) in the main text. To illustrate, let $v(p)$ represents one of the sub-utility functions in equation (9) in the main text [e.g., $v(p)$ represents $\Theta(p_c, p_m, p_v)$ or $\Phi(p_{gf}, p_{df})$ or $\Psi(p_h)$]. By Roy’s identity, demand functions then satisfy $x_i = -\partial v/\partial p_i$. If the function $v(p)$ is quadratic, demand functions are linear and can be represented as:

(39) $$x_i = a_i + \sum_{j=1}^{n} b_{ij} p_j \quad , \quad i = 1,2,\ldots,n$$

where, by symmetry, $b_{ij} = b_{ji}$. To ensure the required curvature conditions, the $n \times n$ symmetric matrix $\left[b_{ij} \right]$ needs to be negative definite. The unrestricted system in (39) has $n(3+n)/2$ free parameters.

For calibration purposes, we start with elasticity values, and retrieve the parameters of the demand functions. Marshallian (and Hicksian) elasticities are defined as:

(40) $$\varepsilon_{ij} \equiv b_{ij} \frac{p_j}{x_i}$$

which define the $n \times n$ elasticity matrix $\left[\varepsilon_{ij} \right]$. Although this matrix is not symmetric, it is obvious that, in view of (40), it contains only $n(1+n)/2$ free parameters. To calibrate the parameters of the system in (39) to the (data-defined) point $(\overline{p}, \overline{x})$, where $\overline{p} \equiv (\overline{p}_1, \overline{p}_2, \ldots, \overline{p}_n)$ and $\overline{x} \equiv (\overline{x}_1, \overline{x}_2, \ldots, \overline{x}_n)$, given assumed elasticity values $\overline{\varepsilon}_{ij}$, then

(41) $$b_{ij} = \overline{\varepsilon}_{ij} \frac{\overline{x}_i}{\overline{p}_j} \quad , \quad \forall i,j, \quad j \geq i$$

(42) $$a_j = \overline{x}_j - \sum_{k=1}^{n} b_{jk} \overline{p}_k \quad , \quad j = 1,2,\ldots,n$$

A.2.1 Parsimonious version

The strong separability assumption that is maintained in equation (9) in the main text already implies zero cross-price effects between goods belonging to different groups (e.g., gasoline fuel and soybean oil demands). To put more structure on the substitution possibilities between goods belonging to the same group, we start by recalling the Allen-Uzawa partial elasticities of substitution σ_{ij} (one of the concepts that extend the two-good elasticity of substitution notion to the case of n goods). This elasticity is defined as

$$\sigma_{ij} \equiv \frac{e(p,u) \times \left(\partial^2 e(.) / \partial p_i \partial p_j \right)}{\left(\partial e(.) / \partial p_i \right) \left(\partial e(.) / \partial p_j \right)}$$

where $e(p,u)$ is the expenditure function that is dual to $v(p)$. For our quadratic specification (and given quasilinearity, for which Hicksian and Marshallian demands are identical), then

(43) $$\sigma_{ij} = \frac{e(p,u) \times b_{ij}}{x_i(p) \times x_j(p)} \quad , \quad i \neq j$$

To reduce the number of parameters to be calibrated, we assume that, at the calibration point $(\overline{p}, \overline{x})$, all the elasticity of substitutions are equal to each other, i.e.:

Assumption. $\sigma_{ij} = \sigma_0$, $\forall i \neq j$.

Given this assumption, then from (43) it follows that $b_{ij} \equiv \sigma_0 x_i(p) x_j(p) / e(p,u)$, which implies

(44) $$\varepsilon_{ij}(p) = s_j \sigma_0 , \quad i \neq j$$

where $s_j \equiv p_j x_j(p) / e(p,u)$ denotes the jth good expenditure share. Hence, all off-diagonal coefficients b_{ij}, $j \neq i$, can be computed upon knowledge of the elasticity of substitution σ_0 .

However, rather than picking an arbitrary value σ_0 , it may be more transparent to rely of the notion of "total elasticity". Define total or aggregate demand for the x vector as the fix-weight sum

(45) $$Q(p) \equiv \sum_{i=1}^{n} \overline{p}_i x_i(p)$$

The question posed is how this aggregate quantity changes when the price vector p is scaled by the scalar $k > 0$. This leads to the elasticity of total demand ε_0 , which is defined as follows:

(46) $$\varepsilon_0(p) \equiv \frac{\partial Q(kp)}{\partial k}\frac{k}{Q(kp)}\bigg|_{k=1}$$

Using the definition in (45), and evaluating the result at the calibration point $(\overline{p},\overline{x})$, we find

(47) $$\overline{\varepsilon}_0 = \sum_{i=1}^{n}\overline{s}_i\overline{\varepsilon}_{ii} + \sum_{i=1}^{n}\overline{s}_i\left(\sum_{j\neq i=1}^{n}\overline{\varepsilon}_{ij}\right)$$

where $\overline{s}_i \equiv \dfrac{\overline{p}_i x_i(\overline{p})}{Q(\overline{p})}$ are weights (shares) that satisfy $\sum_i \overline{s}_i = 1$.

Note that, when the goods are substitutes (i.e., $\overline{\varepsilon}_{ij} > 0,\ j \neq i$), as we should presume in our model, then the total elasticity is smaller, in absolute value, than the weighted average of the own-price elasticities of individual demands.

Definition: Let $\lambda \in (0,1]$ define the ratio, at the calibration point, between total elasticity and the weighted average of the own-price elasticities of individual demands. That is, $\lambda \equiv \overline{\varepsilon}_0 \Big/ \sum_{i=1}^{n}\overline{s}_i\overline{\varepsilon}_{ii}$.

Using this definition along with (47) and (44), then:

(48) $$\sigma_0 = \frac{-(1-\lambda)\sum_{i=1}^{n}\overline{s}_i\overline{\varepsilon}_{ii}}{\sum_{i=1}^{n}\overline{s}_i(1-\overline{s}_i)}$$

In conclusion, given $\sigma_{ij} = \sigma_0,\ \forall i \neq j$, all cross-price elasticities can be computed upon the knowledge of the elasticity of substitution, i.e., $\overline{\varepsilon}_{ij} = \overline{s}_j\sigma_0$. Furthermore, if total elasticity is a fraction λ of the weighted average of the own-price elasticities of individual demands, then, having assumed the n own-price elasticities of demand, σ_0 can be calculated from (48). Note that the assumption of zero cross-price elasticities is equivalent to $\lambda = 1$ (which would imply $\sigma_0 = 0$).

A.3 Derivation of the Zero-Profit Condition for the Integrated Refining-Blending Industry

From equation (27) in the main text, and using the RIN prices in equations (25) and (26) of the main text, we obtain:

(49) $$p_{gf} - p_g - t_{gf} = \hat{s}_e\left(p_e + t_{gf} - \zeta_e p_{gf}\right) + \hat{s}_b\left(\frac{(p_b - \ell_b) + t_{df} - \zeta_b p_{df}}{\vartheta}\right) + s_{ce} R_{ce}$$

Next, the RFS fractional requirements s_i can be expressed in terms of the mandated quantities, as per equations (29)-(31) in the main text, to obtain:

(50) $$\begin{aligned}&\left(p_{gf} - p_g - t_{gf}\right)\left(x_g + x_d - (X_g + X_d)\right)\\ &\quad = \left(x_{rf}^M - x_a^M\right)\left(p_e + t_{gf} - \zeta_e p_{gf}\right) + \frac{(x_a^M - x_{ce}^M)}{\vartheta}\left(p_b - \ell_b + t_{df} - \zeta_b p_{df}\right) + x_{ce}^M R_{ce}\end{aligned}.$$

Because equations (27) and (28) in the main text imply the (separate) arbitrage condition (33) in the main text, the left-hand-side of (50) can be represented alternatively as

(51) $$\left(p_{gf} - p_g - t_{gf}\right)\left(x_g - X_g\right) + \left(p_{df} - p_d - t_{df}\right)\left(x_d - X_d\right)$$

Furthermore, with binding mandates, domestic production of ethanol and biodiesel satisfy equations (16) and (17) in the main text, that is:

(52) $$x_e - X_e \equiv x_{rf}^M - x_a^M$$

(53) $$x_b + M_b + N_b \equiv \left(x_a^M - x_{ce}^M - M_{se}\right)/\vartheta$$

Using the relations in (51)-(53), the zero-profit condition (50) can then be represented as in equation (32) of the main text:

$$\begin{aligned}&(p_{gf} - t_{gf} - p_g)(x_g - X_g) + (p_{df} - t_{df} - p_d)(x_d - X_d) = \\ &\quad (p_e + t_{gf} - \zeta_e p_{gf})(x_e - X_e) + (p_b - \ell_b + t_{df} - \zeta_b p_{df})(x_b + M_b + N_b) + \frac{M_{se}}{\vartheta}\left(p_b - \ell_b + t_{df} - \zeta_b p_{df}\right) + x_{ce}^M R_{ce}\end{aligned}$$

A.4 Equilibrium with No RFS Mandates but with a Minimum-Use Requirement for Ethanol as an Oxygenate

This scenario assumes that there are no RFS mandates for biofuels, but that a fraction $\mu_{oxy} \in (0,1)$ of total gasoline fuel needs to be accounted for by ethanol to achieve the desired octane level. Note: this is treated as a technological requirement, not an RFS mandate. Hence, we have $x_e = \left[\mu_{oxy}/(1-\mu_{oxy})\right]\left(x_g - X_g\right) - M_{se} + X_e$. For the case in which this technology requirement is binding, therefore, the equilibrium conditions are as follows.

Market clearing conditions

(54) $$S_c(p_c, p_s) - \Delta_c = D_c(p_c, p_m, p_v) + \bar{D}_c(p_c) + \frac{(1-\delta_1)}{\alpha_e}\left[\frac{\mu_{oxy}}{(1-\mu_{oxy})}(x_g - X_g) - M_{se} + X_e\right]$$

(55) $$\alpha_m\left[S_s(p_c, p_s) - \Delta_s\right] - \Delta_m = D_m(p_c, p_m, p_v) + \bar{D}_m(p_m) - \frac{\delta_2}{\alpha_e}\left[\frac{\mu_{oxy}}{(1-\mu_{oxy})}(x_g - X_g) - M_{se} + X_e\right]$$

(56) $$\alpha_v\left[S_s(p_c, p_s) - \Delta_s\right] - \Delta_v = D_v(p_c, p_m, p_v) + \bar{D}_v(p_v) + \frac{x_b}{\alpha_b}$$

(57) $$x_g - X_g + \zeta_e\left[\frac{\mu_{oxy}}{(1-\mu_{oxy})}(x_g - X_g)\right] = D_{gf}(p_{gf}, p_{df})$$

(58) $$x_d - X_d + \zeta_b(x_b + M_b + N_b) = D_{df}(p_{gf}, p_{df})$$

(59) $$x_h - X_h = D_h(p_h)$$

Production relationships

(60) $$x_g \equiv \beta_g\left[S_R(p_R) + \bar{S}_R(p_R)\right]$$

(61) $$x_g \equiv \beta_g\left[S_R(p_R) + \bar{S}_R(p_R)\right]$$

(62) $x_g \equiv \beta_g \left[S_R(p_R) + \overline{S}_R(p_R) \right]$

Price arbitrage relations (zero-profit conditions)

(63) $\alpha_v p_v + \alpha_m p_m = p_s + w_v$

(64) $\alpha_e p_e + \delta_2 p_m = p_c(1 - \delta_1) + w_e$

(65) $\alpha_b p_b = p_v + w_b$

(66) $\beta_g p_g + \beta_d p_d + \beta_h p_h = p_R + w_g$

(67) $p_d = p_{df} - t_{df}$

(68) $p_b = \zeta_b p_{df} - t_{df}$

Zero-profit condition in ethanol blending sector

(69) $p_{gf}\left((1-\mu_{oxy}) + \zeta_e \mu_{oxy}\right) = \left(p_g + t_{gf}\right)(1-\mu_{oxy}) + \left(p_e + t_{gf}\right)\mu_{oxy}$

Equations (54) to (69) can be solved for 16 endogenous variables—p_c, p_s, p_m, p_v, p_R, p_{gf}, p_{df}, p_g, p_d, p_h, p_e, p_b, x_b, x_g, x_d and x_h—conditional on given exogenous stock changes (Δ_c, Δ_s, Δ_m and Δ_v) and exogenous imports, exports and production (M_b, N_b, M_{se}, X_g, X_d, X_h and X_e).

A.5 Elasticity Relations and Assumptions

A.5.1 Crude oil and refined products

A.5.1.1 Demand elasticities

Our model takes the demand elasticities of refined petroleum products (gasoline, diesel, and "other" fuels) as primitives. A considerable body of literature, succinctly reviewed in Difiglio (2014) and Green and Liu (2015), has documented that these demand functions are very inelastic. Indeed, Hughes, Knittel and Sperling (2008) find that they have become more inelastic in recent years. They estimate a short run elasticity of demand for gasoline to be -0.034. Lin and Prince (2013) similarly find short-run elasticities of that magnitude, and their dynamic models estimate the long-run elasticity of gasoline demand to be -0.239 and -0.265 (with control for variance, and no control, respectively). Clearly, very inelastic demand would translate into larger price swings in our counterfactual simulations. Also, for the scenarios that we consider we intend to provide an intermediate-to-long run evaluation. Hence, we conservatively assume the elasticity of gasoline demand to be -0.35. This is the elasticity value estimated by Bento et al. (2008) with a microeconomic model that allows consumers to respond to price changes with both car choice and miles traveled. We note that this value is also close to the estimated value of -0.37 obtained, with a completely different methodology, by Coglianese et al. (2016). As for diesel fuel, because it is largely used for transportation by heavy duty vehicles, its demand is widely considered to be even more inelastic than gasoline demand. Dahl (2012), in a comprehensive review of a large body of literature, puts the elasticity of US gasoline and diesel fuel demands at -0.30 and -0.07, respectively. Winebrake et al. (2015) find diesel demand elasticity to be essentially zero. Our baseline assumption reflects the consensus that diesel demand is more inelastic than gasoline demand, but again with an eye to intermediate-to-long run interpretation of the model, we postulate the diesel demand elasticity to be -0.15. As for the elasticity of demand for the "other fuels", some components (such as heating oil) are likely to have more elastic demand than gasoline, given the availability of substitutes, whereas other components (such as jet fuels) may be more inelastic. In total, our baseline parameterization presumes that this aggregate is more elastic than gasoline, and we assume this elasticity to be -0.50. In conclusion, therefore, we assume:

$$\varepsilon_{gg} = -0.35 \;,\; \varepsilon_{dd} = -0.15 \;\text{ and }\; \varepsilon_{hh} = -0.50 .$$

On the import side, we parameterize a ROW export supply elasticity that, implicitly, reflects ROW supply and demand elasticities for crude oil. As a preliminary step, therefore, it is of some interest to understand what the foregoing assumptions about US demand for refined fuel products imply for the underlying demand for crude oil. To this end, let Q_i, p_i denote quantity and price of the ith refined product (gasoline, diesel, and other), and Q_R, p_R denote the quantity and price of crude oil. Then, from the assumed Leontief technology, $Q_i = \beta_i Q_R$ ($i = g,d,h$), the price arbitrage relation is $p_R + w_g = \sum_i \beta_i p_i$. Differentiating the latter (working with the fuel inverse demand functions is more convenient in this case) we obtain:

$$\frac{dp_R}{dQ_R} = \sum_i \left(\frac{\beta_i p_i}{Q_i} \right) \left(\frac{dp_i}{dQ_i} \frac{Q_i}{p_i} \right) \beta_i$$

If we define the elasticity of crude oil demand as $\varepsilon_R \equiv \left(\frac{dp_R}{dQ_R} \frac{Q_R}{p_R} \right)^{-1}$, and recall that the refined fuel products' demand elasticities satisfy $\varepsilon_{ii} \equiv \left(\frac{dp_i}{dQ_i} \frac{Q_i}{p_i} \right)^{-1}$ (assuming, as we do, zero cross-price effects), then the relation of interest is:

$$\frac{1}{\varepsilon_R} = \frac{\beta_g p_g}{p_R}\frac{1}{\varepsilon_{gg}} + \frac{\beta_d p_d}{p_R}\frac{1}{\varepsilon_{dd}} + \frac{\beta_h p_h}{p_R}\frac{1}{\varepsilon_{hh}}$$

Using the values of prices at the calibrated 2015 year, the foregoing assumptions about demand elasticities for refined fuel products imply a US crude demand elasticity of $\varepsilon_R = -0.20$, which is very much in line with values discussed in the literature reviewed in the foregoing.

A.5.1.2 Supply elasticities

Similar to demand elasticities, the consensus is that the crude oil supply elasticity is very inelastic—see the literature reviewed by Difiglio (2014) and Green and Liu (2015). For example, Erickson and Lazarus (2014), in evaluating the potential impacts of the proposed Keystone XL pipeline, assume a baseline oil supply elasticity of 0.13. Our baseline adopts the supply elasticity values, for both US and foreign crude oil supply, used by the U.S. EIA National Energy Modeling System (EIA 2014). Hence, we assume $\eta_R = \bar{\eta}_R = 0.25$.

A.5.1.2 ROW export supply elasticity

The export supply of crude oil from the rest of the world (ROW) to the United States is notionally defined as: $X \equiv \bar{S}(p_R) - \bar{D}(p_R)$. Differentiating this identity, and defining the ROW export supply elasticity as $\bar{\chi}_R \equiv \frac{dX}{dp_R}\frac{p_R}{X}$, we find:

$$\bar{\chi}_R \equiv \bar{\eta}_R \frac{\bar{S}}{X} - \bar{\varepsilon}_R \frac{\bar{D}}{X}.$$

We have already assumed that $\bar{\eta}_R = 0.25$. If we further assume that the ROW demand elasticity for crude oil is similar to that of the United States (the implied value for which is $\varepsilon_R = -0.20$, as discussed above), then using quantity values for the calibrated 2015 year we find $\bar{\chi}_R = 4.4$, and this is the assumed value in our baseline parameterization.

A.5.2 Agricultural supply response

Given our postulated supply system, supply elasticities reflect both acreage allocation decisions as well as yield response effects: $\eta_{ii} = \eta_{ii}^L + \eta_{ii}^y$ $(i{=}c,s)$ and $\eta_{ij} = \eta_{ij}^L$ $(i{=}c,s,\ i{\neq}j)$. For acreage elasticities we use the estimates obtained by Hendricks et al. (2014), which are consistent with previous literature that has highlighted inelastic response. In particular, their acreage response elasticities are similar to those estimated by Berry and Schlenker (2011). As for yield elasticities, Berry (2011) provides an extensive review of existing empirical evidence, and strongly criticizes the large yield response elasticity implemented in some CGE models. The broad consensus in the profession is that virtually all of the crop supply response comes from acreage response, not from yield response. The agronomic basis for this perspective is that farmers have limited means to increase yield in response to changes in expected prices (variation in fertilizer use is one of the few tools at their disposal, especially for rainfed agriculture). Somewhat at odds with these conclusions, Miao et al. (2016) find a very large response for corn (elasticity of yield response to price equal to 0.23) and no response for soybean yields. Exactly how one should think of the yield response to price, in the context of our model, is perhaps a moot point. In the long run yield is increasing because of technical change driven by a multitude of factors, including exogenous technological opportunity, as well as input and output prices via the so-called induced innovation hypothesis. Here, it seems appropriate to think of yield response to price over and above such secular trend in yield increases. Having conditioned on such a trend, and using a careful instrumental variables approach, Berry and Schlenker (2011) find that yield response to price is very small in magnitude (and sometime negative). For both corn and soybeans, for all the models they consider, they cannot reject the hypothesis that yield response to price is zero. Here we adopt the point estimates from a set of models reported by Berry and Schlenker (2011), specifically the instrumental variable estimations in columns (1a) and (1b) of their Table 1 (for corn) and Table 2 (for soybean). Taking the average of the two point estimates they report (which differ because of a different specification of the time trend), we put $\eta_{cc}^{y} = 0.05$ and $\eta_{ss}^{y} = 0.01$. Hence, for the supply elasticities we have $\eta_{cc} = 0.29 + 0.05 = 0.34$ and $\eta_{ss} = 0.26 + 0.01 = 0.27$, and, as before, $\eta_{cs} = \eta_{cs}^{L} = -0.22$. The last elasticity, $\eta_{sc} = \eta_{sc}^{L}$ will be computed from the symmetry condition.

A.5.3 Soybean complex

Estimates of domestic demand elasticities for soybean oil and meal are scarce. Piggott and Wohlgenant (2002) used estimates of -0.13 for the elasticity of US meal demand and -0.18 for the elasticity of US soybean oil demand. Drabik, de Gorter and Timilsina (2014) rely on this source for the elasticity of meal demand, but assume a larger value for the elasticity of soybean oil demand. Again, here we are largely thinking of *mutatis mutandi* demand functions (where the price of closely related products, not explicitly included in the parameterization, are allowed to adjust), so an inelastic response is probably sensible. Hence, we assume $\varepsilon_{mm} = -0.20$ and $\varepsilon_{vv} = -0.20$. Because the United States is a net exporter of both soybean meal and oil, we also need to specify the elasticity of import demand by the ROW for these products. Notionally, these import demands are defined as $\bar{M}_m \equiv \bar{D}_m - \bar{S}_m$ for soybean meal and $\bar{M}_v \equiv \bar{D}_v - \bar{S}_v$ for soybean oil. Consider soybean meal first. Defining the import demand elasticity as $\bar{\mu}_m \equiv \dfrac{d\bar{M}_m}{dp_m}\dfrac{p_m}{\bar{M}_m}$, then

$\bar{\mu}_m = \frac{\bar{D}_m}{\bar{M}_m}\bar{\varepsilon}_m - \frac{\bar{S}_m}{\bar{M}_m}\bar{\eta}_m$. The foregoing discussion can provide some guidance as to the responsiveness of the foreign demand functions $\bar{D}_m$ represented by $\bar{\varepsilon}_m$, but import demand functions also reflect the responsiveness of foreign supplies. To account for that, the meal supply elasticity $\bar{\eta}_m$ needs to be defined in terms of the underlying structural representation. Given the ROW supply of soybeans $\bar{S}_s = \bar{S}_s(p_s)$, the meal production technology $\bar{S}_m = \alpha_m \bar{S}_s$, and the arbitrage relation $p_s + w = \alpha_m p_m + \alpha_v p_v$, we find:

$$\bar{\eta}_m \equiv \frac{d\bar{S}_m}{dp_m}\frac{p_m}{\bar{S}_m} = \alpha_m \frac{d\bar{S}_s}{dp_s}\frac{p_s}{\bar{S}_s}\alpha_m \frac{\bar{S}_s}{p_s}\frac{p_m}{\bar{S}_m} \qquad \rightarrow \qquad \bar{\eta}_m = \bar{\eta}_s \frac{\alpha_m p_m}{p_s} .$$

Similarly, for ROW soybean oil, recalling that $\bar{S}_v = \alpha_v \bar{S}_s$, we find $\bar{\eta}_v = \bar{\eta}_s \frac{\alpha_v p_v}{p_s}$. Hence, the ROW import demand elasticities can be represented as:

$$\bar{\mu}_m = \frac{\bar{D}_m}{\bar{M}_m}\bar{\varepsilon}_m - \frac{\bar{S}_m}{\bar{M}_m}\frac{\alpha_m p_m}{p_s}\bar{\eta}_s$$

$$\bar{\mu}_v = \frac{\bar{D}_v}{\bar{M}_v}\bar{\varepsilon}_v - \frac{\bar{S}_v}{\bar{M}_v}\frac{\alpha_v p_v}{p_s}\bar{\eta}_s .$$

If we assume that the ROW soybean supply elasticity is similar to that of the United States, and thus put $\bar{\eta}_s = 0.27$, and that the ROW demand elasticities for meal and oil are also the same as in the United States, then, using the variables' values at the calibrated 2015 year, we find $\bar{\mu}_m = -1.7$ and $\bar{\mu}_v = -1.4$. These are the values we assume in our baseline calculations. Note that these values imply import demand functions that are quite a bit more elastic than in Bekkerman et al. (2012) and Kim et al. (2008), who do not consider the structural representation that we have discussed. Our elasticities are similar to the values reported by Piggott and Wohlgenant (2002), who again find somewhat more inelastic response than we do (although they pursue a structural representation similar to what we have provided, they assume no foreign supply response in their calculations).

A.5.4 Corn market

For the domestic market, the demand elasticity is assumed to be the same as for meal and oil, and thus we assume $\varepsilon_{cc} = -0.20$. As for the ROW import demand for US corn, again we start with the definition $\bar{M}_c \equiv \bar{D}_c - \bar{S}_c$, from which we obtain: $\bar{\mu}_c = \frac{\bar{D}_c}{\bar{M}_c}\bar{\varepsilon}_c - \frac{\bar{S}_c}{\bar{M}_c}\bar{\eta}_c$, where $\bar{\mu}_c \equiv \frac{d\bar{M}_c}{dp_c}\frac{p_c}{\bar{M}_c}$. If we assume that supply and demand responsiveness in the ROW are similar to those in the United States, and thus put $\bar{\varepsilon}_c = -0.2$ and $\bar{\eta}_c = 0.34$, then, with variables' values at the 2015 year, we would obtain $\bar{\mu}_c = -7.5$.

But the foregoing derivation of import demand elasticities ignores the interaction (cross-price) effects between corn and soybeans products, for both demand and supply, which we have modeled explicitly in the United States. Such interaction effects are likely to lower elasticity values for both *mutatis mutandi* demand and supply functions, as suggested by the aggregate analysis of Roberts and Schlenker (2009). Rather than explicitly modeling interactions effects for the ROW as well, we take a shortcut and capture those effects by postulating more inelastic foreign response functions. For example, if we set the ROW demand and supply elasticities to the aggregate levels estimated by Roberts and Schlenker (2009), then using the results of one of their preferred specifications (column 2 in their table 3) we would get $\bar{\eta}_c = 0.0554$ and $\bar{\eta}_s = 0.1337$. With these values, at the 2015 calibration year, we obtain a ROW import demand elasticity for corn of $\bar{\mu}_c = -2.7$. This is the baseline value we assume in our counterfactual simulations. Note that this value is still considerably more elastic than was assumed in Cui et al. (2011).

A.6 Sensitivity Analysis

To investigate the robustness of the baseline results in Tables 3 and 4 in the main text, we carried out five additional sets of sensitivity analysis experiments. For each experiment, a subset of parameters are changed to either one-half of the baseline values or to twice the baseline values.[22] The five sets of experiments, and the associated elasticity values and marginal emissions damage, are presented in Table A1. Selected market and welfare results for each scenario are reported in Tables S2 to S6. Note that, in these tables, alternative elasticity assumptions are reported as having the same *status quo* market effects: this is simply a reflection of the calibration procedure (the parameters corresponding to alternative assumptions are still required to be consistent with the benchmark calibration data). This is not true for welfare effects, of course, because they represent changes from the corresponding counterfactual of "No RFS," which changes as the assumed elasticities change.

In Tables S2 to S6 we have highlighted in yellow the figures that differ from the corresponding baseline estimates by more than 10%. One set of elasticities that seems to affect results the least is that of domestic demands for crop products (experiment A, Table A2). Market effects are also very robust for experiments B, C and E (Tables S3, S4 and S6). Assumptions about ROW elasticities (experiment D, Table A5) are somewhat more consequential for market effects. Not surprisingly, alternative elasticity assumptions also tend to matter more for the

[22] For the cross-elasticities of domestic demand functions for crop products, the less (more) elastic scenarios correspond to a doubling (halving) of the λ parameter. See section A.2 for more details on the relationships between λ, the elasticity of substitution and the cross-elasticities of demand.

"optimal mandates" scenarios than for the "year 2022 mandates" scenarios. Welfare estimates are more sensitive to parameter changes than market estimates. ROW elasticities of demand for U.S. crop products, and the ROW elasticity of crude oil supply to the United States, are especially important for welfare calculations, a reminder of the importance that terms of trade effects play in the analysis. U.S. welfare gains are magnified with inelastic ROW responses (see the "less elastic" columns in Table A5), and are reduced when ROW responses are more elastic (see the "more elastic" columns in Table A5). In particular, the "more elastic" set of elasticities for experiment D are such that the overall welfare gains from U.S. biofuel policies are essentially nil. In any event, we note that welfare gains to U.S. farmers are large in any scenario, and that the welfare outcomes for the "year 2022 mandates" scenarios are worse than the corresponding *status quo* scenarios for all of the sensitivity analysis experiments carried out.

Table A1. Alternative Elasticities/Parameters Used for Sensitivity Analysis Experiments

A. Domestic Elasticities for Crop Products Demands

Elasticity of	Symbol	Baseline	Less	More
US corn demand	ε_{cc}	-0.20	-0.10	-0.40
US soybean meal demand	ε_{mm}	-0.20	-0.10	-0.40
US soybean oil demand	ε_{vv}	-0.20	-0.10	-0.40
Elasticity of substitution parameter	λ	0.5	1.0	0.25
US corn demand w.r.t. p_m	ε_{cm}	0.065	0.00	0.194
US corn demand w.r.t. p_v	ε_{cv}	0.014	0.00	0.042
US soy meal demand w.r.t. p_v	ε_{mv}	0.014	0.00	0.042

B. Domestic Elasticities for Crop Supplies

Elasticity of	Symbol	Baseline	Less	More
US corn acreage supply	η_{cc}^{L}	0.29	0.145	0.58
US corn acreage supply w.r.t. p_s	η_{cs}^{L}	-0.22	-0.11	-0.44
US soybean acreage supply	η_{ss}^{L}	0.26	0.13	0.52
US corn yield supply	η_{cc}^{y}	0.05	0.025	0.10
US soybean yield supply	η_{ss}^{y}	0.01	0.005	0.02

C. Domestic Elasticities for Petroleum Products Demands and Crude Oil Supply

Elasticity of	Symbol	Baseline	Less	More
US gasoline fuel demand	ε_{gg}	-0.35	-0.175	-0.70
US diesel fuel demand	ε_{dd}	-0.15	-0.075	-0.30
US petroleum byproducts demand	ε_{hh}	-0.50	-0.25	-1.00
US crude oil supply	η_{R}	0.25	0.125	0.50

D. ROW Elasticities for Crop Products Import Demands and Crude Oil Export Supply

Elasticity of	Symbol	Baseline	Less	More
ROW corn import demand	$\bar{\varepsilon}_{cc}$	-2.70	-1.35	-5.40
ROW soybean meal import demand	$\bar{\varepsilon}_{mm}$	-1.70	-0.85	-3.40
ROW soybean oil import demand	$\bar{\varepsilon}_{vv}$	-1.40	-0.70	-2.80
ROW crude oil export supply	$\bar{\chi}_{R}$	4.40	2.20	8.80
ROW crude oil demand	$\bar{\varepsilon}_{R}$	-0.20	-0.10	-0.40

E. Marginal Emissions Damages (\$/tCO2): Baseline (γ =20); Smaller (γ =10); Larger (γ =40)

Table A2. Sensitivity Analysis for: A. Domestic Elasticities for Crop Products Demands

	Baseline elasticities			**Less elastic**			**More elastic**		
Market Effects	Year 2015 Mandates	Year 2022 Mandates	Optimal Mandates	Year 2015 Mandates	Year 2022 Mandates	Optimal Mandates	Year 2015 Mandates	Year 2022 Mandates	Optimal Mandates
Cellulosic biofuel mandate (B units)	0.123	0.787		0.123	0.787		0.123	0.787	
Advanced biofuel mandate (B units)	2.880	5.787	1.661	2.880	5.787	1.671	2.880	5.787	1.646
Renewable biofuel mandate (B units)	16.930	20.787	19.351	16.930	20.787	19.144	16.930	20.787	19.735
Corn price ($/bu.)	3.68	3.88	3.96	3.68	3.88	3.97	3.68	3.87	3.96
Soybean price ($/bu.)	10.10	11.14	9.69	10.10	11.14	9.67	10.10	11.15	9.73
Soybean meal price ($/ton)	368.49	363.28	369.23	368.49	361.39	369.09	368.49	366.50	369.58
Soybean oil price (¢/lb.)	31.60	41.83	27.87	31.60	42.18	27.72	31.60	41.23	28.17
Crude oil price ($/bbl)	48.40	48.00	48.33	48.40	48.00	48.34	48.40	48.00	48.31
Gasoline price ($/gal.)	1.72	1.74	1.60	1.72	1.74	1.61	1.72	1.74	1.59
Diesel price ($/gal.)	1.67	1.50	1.92	1.67	1.50	1.91	1.67	1.49	1.94
Ethanol price ($/gal.)	1.61	1.67	1.68	1.61	1.67	1.68	1.61	1.66	1.68
Biodiesel (supply) price ($/gal.)	3.65	4.43	3.36	3.65	4.46	3.35	3.65	4.39	3.39
RIN price for ethanol ($/unit)	0.49	0.50	0.64	0.49	0.50	0.64	0.49	0.49	0.64
RIN price for biodiesel ($/unit)	0.73	1.99	1.03	0.73	2.00	1.03	0.73	1.96	1.04
Ethanol quantity (B gal.)	14.140	15.104	17.778	14.140	15.167	17.561	14.140	15.167	18.177
Blending ratio of ethanol (%)	9.871	10.652	12.140	9.871	10.692	12.005	9.871	10.691	12.388
Biodiesel quantity (B gal.)	1.779	3.275	1.049	1.779	3.275	1.055	1.779	3.275	1.039
Corn production (B bus.)	14.216	14.156	14.716	14.216	14.163	14.725	14.216	14.146	14.697
Soybean production (B bus.)	3.927	3.975	3.796	3.927	3.973	3.793	3.927	3.977	3.802
Corn export (B bus.)	1.833	1.564	1.450	1.833	1.558	1.448	1.833	1.571	1.456
Soybean meal export (M ons)	56.572	57.932	56.378	56.572	58.426	56.417	56.572	57.093	56.288
Soybean oil export (B lbs.)	22.421	12.261	26.124	22.421	11.914	26.280	22.421	12.858	25.826
Crude oil domestic supply (B bbl)	3.450	3.443	3.449	3.450	3.443	3.449	3.450	3.443	3.448
Crude oil import (B bbl)	2.907	2.800	2.888	2.907	2.800	2.890	2.907	2.801	2.883
Social welfare ($ B)	3.421	-1.053	4.316	3.656	-0.924	4.534	3.076	-1.231	4.001
P.S. Agriculture ($ B)	15.891	23.753	16.209	16.424	24.315	16.735	15.050	22.888	15.314
GHG emissions change (M tCO_2e)	5.21	-21.30	18.91	5.13	-21.30	18.34	5.33	-20.75	19.84

Note: Welfare Impacts are changes relative to the relevant "No RFS" scenario. Yellow highlight denotes figures that differ from the corresponding baseline estimates by more than 10%.

Table A3. Sensitivity Analysis for: B. Domestic Elasticities for Crop Supplies

	Baseline elasticities			Less elastic			More elastic		
Market Effects	Year 2015 Mandates	Year 2022 Mandates	Optimal Mandates	Year 2015 Mandates	Year 2022 Mandates	Optimal Mandates	Year 2015 Mandates	Year 2022 Mandates	Optimal Mandates
Cellulosic biofuel mandate (B units)	0.123	0.787		0.123	0.787		0.123	0.787	
Advanced biofuel mandate (B units)	2.880	5.787	1.661	2.880	5.787	1.864	2.880	5.787	1.354
Renewable biofuel mandate (B units)	16.930	20.787	19.351	16.930	20.787	18.716	16.930	20.787	20.102
Corn price ($/bu.)	3.68	3.88	3.96	3.68	3.87	3.97	3.68	3.88	3.93
Soybean price ($/bu.)	10.10	11.14	9.69	10.10	11.21	9.66	10.10	11.05	9.75
Soybean meal price ($/ton)	368.49	363.28	369.23	368.49	364.89	366.58	368.49	360.88	373.75
Soybean oil price (¢/lb.)	31.60	41.83	27.87	31.60	42.04	28.16	31.60	41.52	27.43
Crude oil price ($/bbl)	48.40	48.00	48.33	48.40	48.00	48.34	48.40	48.00	48.31
Gasoline price ($/gal.)	1.72	1.74	1.60	1.72	1.74	1.63	1.72	1.74	1.57
Diesel price ($/gal.)	1.67	1.50	1.92	1.67	1.50	1.87	1.67	1.50	1.99
Ethanol price ($/gal.)	1.61	1.67	1.68	1.61	1.66	1.69	1.61	1.67	1.67
Biodiesel (supply) price ($/gal.)	3.65	4.43	3.36	3.65	4.45	3.39	3.65	4.41	3.33
RIN price for ethanol ($/unit)	0.49	0.50	0.64	0.49	0.49	0.63	0.49	0.50	0.64
RIN price for biodiesel ($/unit)	0.73	1.99	1.03	0.73	2.00	1.08	0.73	1.97	0.96
Ethanol quantity (B gal.)	14.140	15.104	17.778	14.140	15.167	16.940	14.140	15.167	18.836
Blending ratio of ethanol (%)	9.871	10.652	12.140	9.871	10.692	11.626	9.871	10.691	12.778
Biodiesel quantity (B gal.)	1.779	3.275	1.049	1.779	3.275	1.184	1.779	3.275	0.844
Corn production (B bus.)	14.216	14.156	14.716	14.216	14.171	14.473	14.216	14.152	15.083
Soybean production (B bus.)	3.927	3.975	3.796	3.927	3.955	3.859	3.927	4.003	3.700
Corn export (B bus.)	1.833	1.564	1.450	1.833	1.574	1.445	1.833	1.564	1.500
Soybean meal export (M ons)	56.572	57.932	56.378	56.572	57.513	57.072	56.572	58.558	55.200
Soybean oil export (B lbs.)	22.421	12.261	26.124	22.421	12.054	25.839	22.421	12.566	26.565
Crude oil domestic supply (B bbl)	3.450	3.443	3.449	3.450	3.443	3.449	3.450	3.443	3.448
Crude oil import (B bbl)	2.907	2.800	2.888	2.907	2.800	2.892	2.907	2.801	2.884
Social welfare ($ B)	3.421	-1.053	4.316	3.988	-0.403	4.728	2.693	-1.938	3.806
P.S. Agriculture ($ B)	15.891	23.753	16.209	18.012	26.009	18.650	13.392	20.900	12.871
GHG emissions change (M tCO_2e)	5.21	-21.30	18.91	4.98	-21.32	15.56	5.44	-20.81	23.62

Note: Welfare Impacts are changes relative to the relevant "No RFS" scenario. Yellow highlight denotes figures that differ from the corresponding baseline estimates by more than 10%.

Table A4. Sensitivity Analysis for: C. Domestic Elasticities for Petroleum Products Demands and Crude Oil Supply

	Baseline elasticities			**Less elastic**			**More elastic**		
Market Effects	Year 2015 Mandates	Year 2022 Mandates	Optimal Mandates	Year 2015 Mandates	Year 2022 Mandates	Optimal Mandates	Year 2015 Mandates	Year 2022 Mandates	Optimal Mandates
Cellulosic biofuel mandate (B units)	0.123	0.787		0.123	0.787		0.123	0.787	
Advanced biofuel mandate (B units)	2.880	5.787	1.661	2.880	5.787	1.764	2.880	5.787	1.624
Renewable biofuel mandate (B units)	16.930	20.787	19.351	16.930	20.787	20.330	16.930	20.787	18.600
Corn price ($/bu.)	3.68	3.88	3.96	3.68	3.88	4.05	3.68	3.88	3.90
Soybean price ($/bu.)	10.10	11.14	9.69	10.10	11.14	9.76	10.10	11.14	9.66
Soybean meal price ($/ton)	368.49	363.28	369.23	368.49	363.28	368.63	368.49	363.28	369.63
Soybean oil price (¢/lb.)	31.60	41.83	27.87	31.60	41.83	28.60	31.60	41.83	27.49
Crude oil price ($/bbl)	48.40	48.00	48.33	48.40	48.03	48.28	48.40	47.94	48.35
Gasoline price ($/gal.)	1.72	1.74	1.60	1.72	1.80	1.46	1.72	1.71	1.67
Diesel price ($/gal.)	1.67	1.50	1.92	1.67	1.31	2.22	1.67	1.59	1.78
Ethanol price ($/gal.)	1.61	1.67	1.68	1.61	1.67	1.71	1.61	1.67	1.66
Biodiesel (supply) price ($/gal.)	3.65	4.43	3.36	3.65	4.43	3.42	3.65	4.43	3.34
RIN price for ethanol ($/unit)	0.49	0.50	0.64	0.49	0.46	0.75	0.49	0.52	0.58
RIN price for biodiesel ($/unit)	0.73	1.99	1.03	0.73	2.10	0.88	0.73	1.93	1.10
Ethanol quantity (B gal.)	14.140	15.104	17.778	14.140	15.167	18.654	14.140	15.167	17.064
Blending ratio of ethanol (%)	9.871	10.652	12.140	9.871	10.672	12.686	9.871	10.730	11.697
Biodiesel quantity (B gal.)	1.779	3.275	1.049	1.779	3.275	1.117	1.779	3.275	1.024
Corn production (B bus.)	14.216	14.156	14.716	14.216	14.156	14.809	14.216	14.156	14.637
Soybean production (B bus.)	3.927	3.975	3.796	3.927	3.975	3.776	3.927	3.975	3.814
Corn export (B bus.)	1.833	1.564	1.450	1.833	1.564	1.333	1.833	1.564	1.542
Soybean meal export (M ons)	56.572	57.932	56.378	56.572	57.932	56.536	56.572	57.932	56.275
Soybean oil export (B lbs.)	22.421	12.261	26.124	22.421	12.261	25.401	22.421	12.261	26.506
Crude oil domestic supply (B bbl)	3.450	3.443	3.449	3.450	3.447	3.449	3.450	3.434	3.448
Crude oil import (B bbl)	2.907	2.800	2.888	2.907	2.809	2.875	2.907	2.786	2.895
Social welfare ($ B)	3.421	-1.053	4.316	4.922	0.248	6.246	2.620	-1.829	3.317
P.S. Agriculture ($ B)	15.891	23.753	16.209	14.200	23.543	13.568	16.729	23.862	17.077
GHG emissions change (M tCO_2e)	5.21	-21.30	18.91	8.61	-13.00	24.42	-1.59	-37.18	9.49

Note: Welfare Impacts are changes relative to the relevant "No RFS" scenario. Yellow highlight denotes figures that differ from the corresponding baseline estimates by more than 10%.

Table A5. Sensitivity Analysis for: D. ROW Elasticities for Crop Products Import Demands and Crude Oil Export Supply

	Baseline elasticities			**Less elastic**			**More elastic**		
Market Effects	Year 2015 Mandates	Year 2022 Mandates	Optimal Mandates	Year 2015 Mandates	Year 2022 Mandates	Optimal Mandates	Year 2015 Mandates	Year 2022 Mandates	Optimal Mandates
Cellulosic biofuel mandate (B units)	0.123	0.787		0.123	0.787		0.123	0.787	
Advanced biofuel mandate (B units)	2.880	5.787	1.661	2.880	5.787	2.711	2.880	5.787	1.117
Renewable biofuel mandate (B units)	16.930	20.787	19.351	16.930	20.787	24.150	16.930	20.787	15.832
Corn price ($/bu.)	3.68	3.88	3.96	3.68	4.05	4.62	3.68	3.78	3.70
Soybean price ($/bu.)	10.10	11.14	9.69	10.10	11.93	10.69	10.10	10.66	9.69
Soybean meal price ($/ton)	368.49	363.28	369.23	368.49	356.68	370.47	368.49	366.22	369.23
Soybean oil price (¢/lb.)	31.60	41.83	27.87	31.60	50.12	36.33	31.60	37.01	27.83
Crude oil price ($/bbl)	48.40	48.00	48.33	48.40	47.62	47.60	48.40	48.20	48.49
Gasoline price ($/gal.)	1.72	1.74	1.60	1.72	1.73	1.53	1.72	1.75	1.64
Diesel price ($/gal.)	1.67	1.50	1.92	1.67	1.49	1.95	1.67	1.50	1.90
Ethanol price ($/gal.)	1.61	1.67	1.68	1.61	1.72	1.87	1.61	1.64	1.61
Biodiesel (supply) price ($/gal.)	3.65	4.43	3.36	3.65	5.07	4.01	3.65	4.06	3.36
RIN price for ethanol ($/unit)	0.49	0.50	0.64	0.49	0.55	0.84	0.49	0.47	0.55
RIN price for biodiesel ($/unit)	0.73	1.99	1.03	0.73	2.40	1.41	0.73	1.74	
Ethanol quantity (B gal.)	14.140	15.104	17.778	14.140	15.167	21.527	14.140	15.167	14.960
Blending ratio of ethanol (%)	9.871	10.652	12.140	9.871	10.696	14.538	9.871	10.689	10.311
Biodiesel quantity (B gal.)	1.779	3.275	1.049	1.779	3.275	1.749	1.779	3.275	0.686
Corn production (B bus.)	14.216	14.156	14.716	14.216	14.128	15.267	14.216	14.177	14.370
Soybean production (B bus.)	3.927	3.975	3.796	3.927	4.006	3.698	3.927	3.954	3.877
Corn export (B bus.)	1.833	1.564	1.450	1.833	1.587	1.202	1.833	1.556	1.779
Soybean meal export (M ons)	56.572	57.932	56.378	56.572	58.113	56.314	56.572	57.758	56.185
Soybean oil export (B lbs.)	22.421	12.261	26.124	22.421	13.222	20.074	22.421	11.682	29.916
Crude oil domestic supply (B bbl)	3.450	3.443	3.449	3.450	3.436	3.436	3.450	3.446	3.452
Crude oil import (B bbl)	2.907	2.800	2.888	2.907	2.805	2.801	2.907	2.799	2.953
Social welfare ($ B)	3.421	-1.053	4.316	9.501	6.505	11.639	-0.728	-6.041	2.502
P.S. Agriculture ($ B)	15.891	23.753	16.209	25.914	39.201	39.115	8.627	13.250	5.821
GHG emissions change (M tCO_2e)	5.21	-21.30	18.91	5.25	-23.08	13.05	4.71	-20.37	20.57

Note: Welfare Impacts are changes relative to the relevant “No RFS” scenario. Yellow highlight denotes figures that differ from the corresponding baseline estimates by more than 10%.

Table A6. Sensitivity Analysis for: E. Marginal Emissions Damages (γ)

Market Effects	Baseline value			Smaller value			Larger value		
	Year 2015 Mandates	Year 2022 Mandates	Optimal Mandates	Year 2015 Mandates	Year 2022 Mandates	Optimal Mandates	Year 2015 Mandates	Year 2022 Mandates	Optimal Mandates
Cellulosic biofuel mandate (B units)	0.123	0.787		0.123	0.787		0.123	0.787	
Advanced biofuel mandate (B units)	2.880	5.787	1.661	2.880	5.787	1.491	2.880	5.787	2.015
Renewable biofuel mandate (B units)	16.930	20.787	19.351	16.930	20.787	19.444	16.930	20.787	19.150
Corn price ($/bu.)	3.68	3.88	3.96	3.68	3.88	3.98	3.68	3.88	3.93
Soybean price ($/bu.)	10.10	11.14	9.69	10.10	11.14	9.62	10.10	11.14	9.84
Soybean meal price ($/ton)	368.49	363.28	369.23	368.49	363.28	369.48	368.49	363.28	368.72
Soybean oil price (¢/lb.)	31.60	41.83	27.87	31.60	41.83	27.20	31.60	41.83	29.27
Crude oil price ($/bbl)	48.40	48.00	48.33	48.40	48.00	48.33	48.40	48.00	48.31
Gasoline price ($/gal.)	1.72	1.74	1.60	1.72	1.74	1.59	1.72	1.74	1.63
Diesel price ($/gal.)	1.67	1.50	1.92	1.67	1.50	1.95	1.67	1.50	1.86
Ethanol price ($/gal.)	1.61	1.67	1.68	1.61	1.67	1.69	1.61	1.67	1.67
Biodiesel (supply) price ($/gal.)	3.65	4.43	3.36	3.65	4.43	3.31	3.65	4.43	3.47
RIN price for ethanol ($/unit)	0.49	0.50	0.64	0.49	0.50	0.65	0.49	0.50	0.61
RIN price for biodiesel ($/unit)	0.73	1.99	1.03	0.73	1.99	0.98	0.73	1.99	1.14
Ethanol quantity (B gal.)	14.140	15.104	17.778	14.140	15.167	18.041	14.140	15.167	17.223
Blending ratio of ethanol (%)	9.871	10.652	12.140	9.871	10.692	12.294	9.871	10.692	11.813
Biodiesel quantity (B gal.)	1.779	3.275	1.049	1.779	3.275	0.935	1.779	3.275	1.285
Corn production (B bus.)	14.216	14.156	14.716	14.216	14.156	14.759	14.216	14.156	14.626
Soybean production (B bus.)	3.927	3.975	3.796	3.927	3.975	3.784	3.927	3.975	3.822
Corn export (B bus.)	1.833	1.564	1.450	1.833	1.564	1.429	1.833	1.564	1.496
Soybean meal export (M ons)	56.572	57.932	56.378	56.572	57.932	56.313	56.572	57.932	56.512
Soybean oil export (B lbs.)	22.421	12.261	26.124	22.421	12.261	26.791	22.421	12.261	24.737
Crude oil domestic supply (B bbl)	3.450	3.443	3.449	3.450	3.443	3.449	3.450	3.443	3.448
Crude oil import (B bbl)	2.907	2.800	2.888	2.907	2.800	2.889	2.907	2.800	2.884
Social welfare ($ B)	3.421	-1.053	4.316	3.473	-1.268	4.514	3.317	-0.636	3.974
P.S. Agriculture ($ B)	15.891	23.753	16.209	15.891	23.753	15.951	15.891	23.753	16.737
GHG emissions change (M tCO_2e)	5.21	-21.30	18.91	5.21	-21.09	20.66	5.21	-21.09	15.19

Note: Welfare Impacts are changes relative to the relevant "No RFS" scenario. Yellow highlight denotes figures that differ from the corresponding baseline estimates by more than 10%.

A.7 Tables for Parameter Values

Table A7. Technical Coefficients

Parameter	Symbol	Value	Source/explanation
Ethanol production coefficient (gal./bu.)	α_e	2.8	Cui et al. (2011)
Ethanol by-product replacing corn in feed, as fraction of corn used for ethanol	δ_1	0.218	$\delta_1 = 0.307 \times 0.71$
Ethanol by-product replacing soy meal in feed, as fraction of corn used for ethanol	δ_2	0.003	$\delta_2 = (0.307 \times 0.29)(56/2000)$
Biodiesel production coefficient (gal./lb.)	α_b	0.131	EIA [a]
Soybean meal production coefficient (tons/bu.)	α_m	0.024	$\alpha_m = 45.1/1{,}873$ [b]
Soybean oil production coefficient (lbs./bu.)	α_v	11.425	$\alpha_v = 21{,}399/1{,}873$ [b]
Gasoline heat content (mil. BTUs/bbl)	ζ_1	5.06	EIA
Diesel heat content (mil. BTUs/bbl)	ζ_2	5.77	EIA
Ethanol heat content (mil. BTUs/bbl)	ζ_3	3.558	EIA
Biodiesel heat content (mil. BTUs/bbl)	ζ_4	5.359	EIA
Ethanol energy equivalent coefficient (GEEGs/gal.)	ζ_e	0.703	$\zeta_e = \zeta_3 / \zeta_1$
Biodiesel energy equivalent coefficient (DEEGs/gal.)	ζ_b	0.929	$\zeta_b = \zeta_4 / \zeta_2$
Gasoline production coefficient (gal./bbl)	β_g	21.286	$\beta_g = x_g / x_R$
Diesel production coefficient (gal./bbl)	β_d	9.115	$\beta_d = x_d / x_R$
Other refined petroleum products production coefficient (KEEGs/bbl)	β_h	13.96	$\beta_h = (42 \times 1.063 - \beta_g - \beta_d) \times 0.98$ [c]
"Equivalence value" of RIN generation for biodiesel	ϑ	1.5	Schnepf & Yacobucci (2013)
Fraction of cellulosic ethanol in cellulosic biofuel	μ_{ce}	0.02, 0.10	Assumed [d]
Required fraction of ethanol as oxygenate	μ_{oxy}	0.03	Assumed

Note: [a] Corresponds to a conversion factor of 7.65 pounds of soybean oil per gallon of biodiesel.
[b] Data taken from https://www.ers.usda.gov/data-products/oil-crops-yearbook/
[c] The coefficient 1.063 accounts for 6.3% average "refinery yield" gains accrued in 2015, whereas 0.98 is the weighted average of kerosene energy equivalence for petroleum products in this category.
[d] The benchmark value of μ_{ce}=0.02 is estimated from EPA's "RIN generation summary" over 2014-2016. For the 2022 (and optimal mandates) scenarios we set μ_{ce}=0.10, consistent with data and discussion contained in EPA (2016).

Table A8. GHG Emission Rates (kg CO2e/gallon) and Social Marginal Damage

Parameter	Symbol	Value	Source/explanation
Gasoline	E_g	11.831	EPA (2010)
Diesel	E_d	13.327	EPA (2010)
Corn-based Ethanol	E_e	6.572	$E_g \times 0.79 \times \zeta_e$ (EPA 2010) [a]
Sugarcane ethanol	E_{se}	3.245	$E_g \times 0.39 \times \zeta_e$ (EPA 2010) [a]
Cellulosic biofuel	E_{ce}	3.328	$E_g \times 0.40 \times \zeta_e$ [a]
Biodiesel	E_b	5.332	$E_d \times 0.43 \times \zeta_b$ (EPA 2010) [a]
Other refined petroleum products	E_h	9.410	EIA [b]
Crude oil (kg CO2e/bbl)		504.67	Computed from E_g, E_d and E_h
Marginal emissions damage ($/tCO2)	γ	20.0	Stern (2007) and Cui et al. (2011)

Notes. [a] Life-cycle GHG emissions rates per energy unit relative to gasoline and diesel baselines (EPA 2010, Chapter 2.6). [b] Weighted average of CO2 emissions rates from various other refined products (see text).

A.8 Notation Recap

Quantities

$S_c =$	corn production
$S_s =$	soybean production
$x_m =$	total quantity of soybean meal produced (from crushing soybeans)
$x_v =$	total quantity of vegetable (soy) oil produced
$x_e =$	domestic production of corn-based ethanol in natural units (gallons)
$x_b =$	domestic production of biodiesel in natural units (gallons)
$\tilde{x}_c =$	quantity of corn used in ethanol production
$\tilde{x}_v =$	quantity of soybean oil used in biodiesel production
$x_R =$	domestic and foreign oil supply
$x_g =$	gasoline production
$x_d =$	diesel production
$x_h =$	other refined petroleum products
$x_e =$	ethanol production
$x_b =$	biodiesel production
$z_g =$	other variable inputs used in the production of gasoline
$z_v =$	other variable inputs used in the production of vegetable (soybean) oil
$z_e =$	other variable inputs used in the production of ethanol
$z_b =$	other variable inputs used in the production of biodiesel
$x_{ce} =$	domestic production of cellulosic biofuel in natural units (gallons)
$\Delta_c =$	Change in corn carryover stocks
$\Delta_s =$	Change in soybean carryover stocks
$\Delta_m =$	Change in soybean meal carryover stocks
$\Delta_v =$	Change in soybean oil carryover stocks
$X_g =$	Net export of gasoline
$X_d =$	Net export of diesel
$X_h =$	Net export of heating oil
$X_e =$	Net export of corn ethanol
$M_b =$	Net import of biodiesel
$M_{se} =$	Import of sugarcane ethanol
$N_b =$	Biodiesel produced from feedstock other than vegetable oil

Prices

p_R =	price of crude oil
p_g =	price of unblended gasoline
p_d =	price of unblended diesel
p_e =	price of ethanol in natural units ($/gallon)
p_b =	price of biodiesel in natural units ($/gallon)
p_{gf} =	*demand* price of "gasoline fuel" (blended gasoline)
p_{df} =	*demand* price of "diesel fuel" (blended diesel)
p_h =	*demand* price of other refined petroleum products
p_c =	price of corn
p_s =	price of soybeans
p_m =	price of soybean meal
p_v =	price of soybean (vegetable) oil
w_g =	price of other inputs used in the production of gasoline and diesel
w_e =	price of other inputs used in the production of corn ethanol
w_b =	price of other inputs used in the production of bio-diesel
w_v =	price of other inputs used in the production of soybean oil and meal

Technical coefficients

β_g =	units of gasoline per unit of crude oil (production coefficient)
β_d =	units of diesel per unit of crude oil (production coefficient)
β_h =	units of byproduct (heating oil) per unit of crude oil (production coefficient)
α_e =	units of ethanol per unit of corn (production coefficient)
α_m =	units of soybean meal per unit of soybean (production coefficient)
α_v =	units of soybean oil per unit of soybean (production coefficient)
α_b =	units of biodiesel per unit of soybean oil (production coefficient)
δ_1 =	fraction of corn used in ethanol production that is returned as a byproduct that substitutes for corn as livestock feed
δ_2 =	fraction of corn used in ethanol production that is returned as a byproduct that substitutes for soybean meal as livestock feed
ζ_e =	units of GEEG ethanol per unit of raw ethanol (energy conversion coefficient)
ζ_b =	units of DEEG biodiesel per unit of raw biodiesel (energy conversion coefficient)

Policy and RFS variables

t_{gf} =	consumption tax on gasoline fuel
t_{df} =	consumption tax on diesel fuel
ℓ_b=	Blending subsidy for biodiesel
ϑ =	"equivalent value" of RIN generation applicable to biodiesel
R_e =	RIN price for corn ethanol (i.e., renewable fuel D6 RINs), \$/unit
R_b =	RIN price for biodiesel (D4 RINs), \$/unit
R_a =	RIN price for advanced biofuel (D5 RINs), \$/unit
R_{ce} =	RIN price for cellulosic biofuel (D3 RINs), \$/unit
x_{rf}^M=	Total renewable fuel mandate
x_a^M =	Total advanced biofuel mandate (in ethanol units)
x_b^M =	Biodiesel component of the advanced biofuel mandate (in biodiesel units)
x_{ce}^M =	Cellulosic biofuel component of the advance biofuel mandate (in ethanol units)
s_{rf} =	RFS fractional standard for total renewable fuel
s_a =	RFS fractional standard for advanced biofuel
s_b =	RFS fractional standard for biodiesel
s_{ce} =	RFS fractional standard for cellulosic biofuel
γ =	Monetary social cost of GHG emission (\$/tCO2e)

Abbreviations

RFS =	Renewable Fuel Standard
EISA =	Energy Independence and Security Act
ROW =	Rest of the World
GEEG =	gasoline-energy-equivalent gallon
DEEG =	diesel-energy-equivalent gallon
KEEG =	kerosene-energy-equivalent gallon

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CHAPTER 3

U.S. CORN AND SOYBEAN DYNAMIC SUPPLY RESPONSE IN THE RENEWABLE FUEL STANDARD ERA

3.1 Introduction

The Renewable Fuel Standard (RFS), initially established by the 2005 Energy Policy Act, and considerably extended by the 2007 Energy Independence Security Act, has introduced a sizable new source of demand for corn and soybeans to produce ethanol and biodiesel. Ceteris paribus, such an exogenous demand shock would be expected to increase the price of corn and soybeans (Cui et al. 2011), and indeed the RFS is credited with being one of the main causes of the commodity price increases in the last decade (Hochman et al. 2012, Roberts and Schlenker 2013, Wright 2014). In addition to contribution to an overall price increase, the biofuel expansion appears to have affected the spatial distribution of prices. Ethanol plants predominantly located in region with abundant corn supply, and by sourcing the required corn they put upward pressure on the local corn price, thereby significantly affecting the basis (McNew and Griffith 2005; Fatal and Thurman 2014). The likely presence of these two price effects (on the level and the spatial distribution) traceable to a largely exogenous demand shock—the biofuel boom driven by RFS mandates—provides an ideal opportunity to revisit the econometric analysis of supply response, an object of considerable interest in agricultural economics.

The resurgence of interest in the U.S. agricultural supply response is also motivated by the policy implications of the RFS. As noted, the massive expansion of biofuel production in the United States has put considerable upward pressure on commodity prices. A major concern is that, if the U.S. supply response cannot accommodate such an expanded demand, then land elsewhere in the world may be converted to the production of these commodities. This possible indirect land use effect is crucial to evaluate the consequence of the RFS on greenhouse gas emission (e.g., Searchinger et al. 2008, Barr et al. 2011, Berry 2011, Berry and Schlenker 2011, Roberts and Schlendker 2013, Gohin 2014, Babcock 2015, Haile, Kalkuhl, and von Braun, 2016). Hence, major economic policy conclusions hinge on whether the U.S. supply response is elastic or inelastic. Existing studies are less than conclusive, especially with regard to the yield response (Miao, Khanna, and Huang 2016; Hendricks, Smith, and Sumner 2014; Scott 2014).

In this essay, we study the acreage and yield response for U.S. corn and soybeans. For acreage response, the analysis focuses on estimating the short-run and long-run elasticities of supply response, including the cross-price elasticities between corn and soybeans and the cross-acreage dynamic adjustment between them. The cross effects between corn and soybeans is emerging as important parameters because the RFS, with conventional ethanol mandates reached their statutory maximum, is mandating increasing amounts of biodiesel (which increase the demand of vegetable oil and, consequently, of oilseeds) (Moschini, Lapan and Kim 2017). We focus on the rainfed producing regions of the Midwest, specifically counties in the following twelve states: Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakoda, Ohio, South Dakoda, and Wisconsin.[23] The region that we identify is responsible for producing a large share of U.S. output (over the last 10 years it has accounted for 87% of U.S. corn and 83% of U.S. soybean production). This consideration, along with the fact that in this region corn and soybean production account for a very large share of cropland use, suggest that it

[23] These 12 states are categorized together into "Midwest" by U.S. Census Bureau (http://www2.census.gov/geo/docs/maps-data/maps/reg_div.txt), which mainly consists of "Heartland" based on U.S. Farm Resource Regions by U.S. Department of Agriculture (http://www.ers.usda.gov/webdocs/publications/aib760/32489_aib-760_002.pdf).

may be key to understand the acreage substitution between these two crops, which is a specific motive of interest of this study. To try to exploit the spatial price variation arising from the biofuel-induces changes in basis, we use panel data at the county level. Furthermore, the analysis of acreage response relies on data for the period 2005-2015. This period fully exploits the price changes that we presumed are influenced by the exogenous biofuel expansion. Furthermore, focusing on recent data has the advantage of minimizing the impact of unmodeled factors that may not hold constant over a longer period of time. In particular, a thorny issue in modeling agricultural supply response to price concerns the role that (changing) agricultural price and income support policies may have played (Lee and Helmberger 1985, MacIntosh and Shideed 1989). The period that we use for our analysis has the advantage of minimizing such impacts owing to the rarely exercised price support payments (such as loan deficiency, marketing loan gains, and certificates) and the stable direct payments.[24]

To analyze the dynamic behavior of the acreage response system, we include two—own and cross—lagged dependent variables in each of corn and soybean estimation equations. We then use a dynamic panel GMM estimator to avoid the possible bias due to the presence of lagged dependent variables. In addition to regressors that are presumed exogenous, instrumental variables include lagged levels of the dependent variables.

The results from our baseline model suggest that, due to significant cross-crop dynamics between corn and soybeans, the U.S. supply responses for corn and soybeans are larger in the

[24] According to the chart provided by Environment Working Group (https://farm.ewg.org/index.php), for the US corn and soybeans, by and large there are three major subsidy categories that are actually paid since 2005: direct payments, price support payments, and crop insurance premium subsidies (except for counter-cyclical programs in 2005-2006 for corn). It shows that price-support payments are nearly zero from 2006 for corn and from 2005 for soybeans and the direct payments are quite stable since 2005 for both corn and soybeans. But the amount of the crop insurance premium subsidies are still fluctuating over time.

short run than in the long run. Our baseline model estimates the own-price supply elasticities, at the mean point of the data, to be 0.50 for corn and 0.38 for soybeans in the short run (the long-run counterparts are 0.38 and 0.27, respectively). Most of this responsiveness is due to acreage allocation decisions, as we find that the yield supply response to price is minimal. The model also identifies cross-price elasticities, which are found to be relatively large: the cross-price elasticity between corn and soybeans at the mean is estimated to be -0.31, and that between soybeans and corn to be -0.51 in the short run (the long-run counterparts are -0.23 and -0.34, respectively). This also implies that, when corn and soybean per-acre revenues move together, the response of the total acreage of these two key crops is very small. We estimate this total elasticity, at the mean point, to be equal to 0.04 in both the short and long run, which suggest that the ability of the U.S. corn and soybean production sector to accommodate the demand shock due to the RFS is very limited. Our supply elasticities are generally consistent with the recent findings of Hendricks, Smith, and Sumner (2014), but differ somewhat from those reported in Miao, Khanna, and Huang (2016).

3.2 Background

The study of agricultural supply response has traditional decomposed it in terms of acreage response and yield response. Studies of acreage responsiveness have relied on a variety of model specification. Because the agricultural sector can safely be construed as competitive, given suitable aggregation conditions, profit maximization has been relied on theory-consistent models (Chambers and Just 1989; Moore and Negri 1992, Moore, Gollehon, and Carey 1994, Arnade and Kelch 2007, Fezzi and Bateman 2011, Lacroix and Thomas 2011, Laukkanen and Nauges 2014). In these studies, estimation equations are expressed by flexible functional forms such as translog or normalized quadratic, such that the dual approach permits one to maintain the standard restrictions that derive from optimization (homogeneity in prices, symmetry, and adding up). A distinct family of flexible models that represent supply response in terms of acreage shares is the linear logit specifications based on Theil (1969)'s multinomial extension of linear logit model (e.g., Bewley, Young and Colman 1987, Wu and Segerson 1995, Miller and Plantinga 1999, Carpentier and Letort 2014). Alternatively, acreage responsiveness has been approached with more *ad hoc* models, including plain linear specifications (e.g., Morzuch, Weaver and Helmberger 1980, Lee and Helmberger 1985, Shideed and White 1989, Goodwin and Mishra 2006; Arnberg and Hansen 2012, Hausman 2012, de Menezes and Piketty 2012, Miao, Khanna, and Huang 2016). Some of these studies also differentiate between short and long-run behavior, an element of interest in this setting at least since Nerlove (1956) (e.g., Arnberg and Hansen 2012, Hausman 2012, de Menezes and Piketty 2012). The dynamics of supply can be complex once one explicitly accounts for crop rotational effects, with results that depart form the canonical findings of traditional Nerlovian models (Hendricks, Smith and Sumner 2014).

In regard to yield response, the literature often relies on the reduced-form approach using simple parametric specifications, with an emphasis on environmental conditions and technological conditions as main determinants. When trying to assess whether or not prices have a significant impact on yields (conditional on the state of technology), the yield estimating equation may include the crop's own output price (Berry 2011, Berry and Schlenker 2011), both input and own output prices (Miao, Khanna, and Huang 2016), a relative price between input and own output prices (Houck and Gallagher 1976, Choi and Helmberger 1993a), or a relative price between output prices (Goodwin et al. 2012). There have also been efforts to obtain yield elasticities with respect to own and cross-output prices based on dual approaches (Arnade and Kelch 2007, Scott 2013).

The model developed in this essay is consistent with the approach followed in many of the aforementioned studies. The presumption is that farmers maximize expected profit, and that their aggregate decisions at the county level (our unit of observation) can be thought of as that of a representative expected profit maximizer. We explicitly model three land uses: corn, soybeans, and everything else. We assume that the acreage shares, which are a function of the price vector, can be parameterized by a linear function, an assumption that makes the specification of dynamic adjustment tractable and permits the use of standard instrumental variable estimation procedures. Our short-run parameterization maintains the symmetry restrictions of profit maximizations (at the mean), in addition to the homogeneity property and the adding-up condition. Additionally, we maintain symmetry for the dynamic adjustment behavior between corn and soybeans. Our analysis focuses on the 12 Midwestern states have consistently produced both corn and soybeans, and that account for the vast majority of U.S. production.[25] To obtain overall supply elasticities, in addition to acreage response, we separately estimate yield response equations for both corn and soybeans. These equations account for weather variables and the state of technology, as well as the own output price (deflated by input price index).

Table 3.1 provides a preview of some of our results in the context of findings from previous studies. This table focuses on studies that estimated both own and cross price elasticities (as noted earlier, several studies did not do that). Only two of the referenced studies

[25] Because the counties that enter our sample mostly produce both corn and soybeans, we do not need to address the corner solution issue which is one of the main concern in some studies (Moore and Negri 1992, Fezzi and Bateman 2011, Lacroix and Thomas 2011).

estimated both short and long-run elasticities, and the latter are reported with (L). Notwithstanding the difficulty of comparing estimates from studies that differ in scope, data and methods, four observations appear in order. First, in most cases corn and soybeans turn out to be substitutes, in accordance with what one should expect when the jointness arises because of an allocatable fixed input (land). Second, in studies conducted before 2000, roughly speaking, the own- and cross-price elasticities for corn tend to be smaller than equal to those of soybeans, in absolute value, while this feature seems absent in more recent studies. Third, the absolute magnitudes of elasticities are larger after 2000. Lastly, our short- and long-run values are very similar to those in Hendricks, Smith, and Sumner (2014), except for somewhat increased acreage responses for corn both in the short and long terms.

The magnitude of the estimate response of yields to crop prices has been somewhat controversial. Berry and Schlenker (2011), using U.S. state-level data over 1961-2009, argue that the yield price elasticities of US crops are no higher than 0.1. Analyzing years from 1980, Scott (2013) obtains the upper bounds of U.S. corn and soybean yield elasticities as 0.04 and 0.11, respectively, based on his indirect approach. Meanwhile, Goodwin et al. (2012) estimate the yield response with respect to their inter-seasonal price (the average harvest-time futures prices in February) to be in the range 0.19-0.27 (for IN, IL, and IA over 1996-2010). They also find small but significant intra-seasonal yield response (i.e., yield response in early growing season). Miao, Khanna, and Huang (2016), focusing on rainfed counties (east of the 100th meridian) over 1977-2007, obtain a relatively large and statistically significant corn yield price elasticities of 0.23, while the elasticity of soybean yield response at the mean is found to be 0.04 and statistically not significantly different from zero.[26] Our results, discussed later, suggest very small yield price elasticities (0.01 for corn and -0.0004 for soybeans) that are not significantly different from zero.

3.3 The Model

Consider a representative farmer's expected profit maximization problem where land is a fixed but allocatable input. Notionally, the expected output vector can be represented as $\mathbf{q} = \mathbf{l} \cdot \mathbf{y}$, where $\mathbf{q} \equiv (q_1, q_2, \ldots, q_K)$ is the vector of expected outputs, $\mathbf{l} \equiv (l_1, l_2, \ldots, l_K)$ is a vector of acreage allocations and $\mathbf{y} \equiv (y_1, y_2, \ldots, y_K)$ is the vector of expected yield. Our strategy is to estimate acreage and yield responses separately. A given amount of land a (total cropland) is allocated to K crops based on expectations of prices and yield. In addition to land, production is assumed to be constrained by a vector of quasi-fixed factors (or environmental conditions) $\mathbf{z}$. Also, $\tilde{\mathbf{p}}$ denotes the vector of expected output prices, $\tilde{\mathbf{r}}$ denotes the vector of per-acre expected revenues, and $\mathbf{w}$ represents the vector of variable input prices.

3.3.1 Acreage response

For a workable econometric specification, we assume that observed county-level land allocations can be represented in terms of the expected profit maximization problem of a representative farmer.[27] Let $\tilde{s}_{kit}$ denote the acreage share to crop k in county i at time t. We

[26] The soybean elasticity, which they actually do not report in the main text, is calculated based on the coefficient under Model III in Table S1 in the supplementary document.

[27] We assume that the potential bias of aggregated data due to sampling and measurement errors during the data generating process is not correlated with our explanatory variables, following Miller and Plantinga (1999).

consider three agricultural land uses: corn ($k=1$), soybeans ($k=2$), and other crops ($k=3$). As for the input side, given the paucity of detailed information, we represent the effect of input prices with a single price variable w_t. In county i at time t, a representative agent makes allocations of total land a_i to the three crops, based on expected per-acre revenues $\tilde{r}_{kit}$ and a joint cost function:

$$\max_{s_{1it},s_{2it},s_{3it}} \left(s_{1it}\tilde{r}_{1it} + s_{2it}\tilde{r}_{2it} + s_{3it}\tilde{r}_{3it}\right)a_i - \tilde{C}(s_{1it},s_{2it},s_{3it};a_i,w_{it},\mathbf{z}_{it}) \quad s.t. \quad \sum_{k=1}^{3} s_{kit} = 1 .$$

Because the cost function $\tilde{C}(s_{1it},s_{2it},s_{3it};a_i,w_{it},\mathbf{z}_{it})$ is homogeneous of degree one in input prices, the objective function is homogeneous of degree one in $\tilde{r}_{1it}$, $\tilde{r}_{2it}$, $\tilde{r}_{3it}$, and w_t, implying optimal allocations are homogeneous of degree zero in $\tilde{r}_{1it}$, $\tilde{r}_{2it}$, $\tilde{r}_{3it}$, and w_t. The property of homogeneity can be maintained at the outset by expressing monetary variables as ratios (relative to one of variables). We choose the general input price as the deflator, and thus use the following expected per-acre revenues in the equations: $r_{kit} = \tilde{r}_{kit}/w_t$ ($k = 1,2,3$). The cost function $\tilde{C}(s_{1it},s_{2it},s_{3it};a_i,w_{it},\mathbf{z}_{it})$ here captures the motive for acreage diversification (e.g., Carpentier and Letort, 2014). We assume that this cost function homogeneous of degree one in total acreage a_i. Hence, having maintained the price homogeneity condition, and given the acreage constraint ($s_{1it} + s_{2it} + s_{3it} = 1$), the problem can be re-stated as:

$$\max_{s_{1it},s_{2it}} \left((r_{1it} - r_{3it})s_{1it} + (r_{2it} - r_{3it})s_{2it} + r_{3it}\right) - C(s_{1it},s_{2it};\mathbf{z}_{it}) .$$

Solving the optimality conditions, optimal acreage allocations can be written as

(1) $$s^*_{kit} = s_{kit}\left((r_{1it} - r_{3it}),(r_{2it} - r_{3it}),\mathbf{z}_{it}\right) \quad \text{for } k = 1,2 ,$$

for county i in time t (and, of course, and $s^*_{3it} = 1 - s^*_{1it} - s^*_{2it}$).

For the purpose of specifying the econometric model, observed acreage shares can be written as $s_{kit} = s_{kit}^{*} + \varepsilon_{kit}$. Importantly, we permit the conditioning variable $\mathbf{z}_{it}$ to include own and cross lagged shares, s_{1it-1} and s_{2it-1}, thereby providing a vehicle to capture the dynamic effects on acreage allocation implied by crop rotation. The set of conditioning variables also includes environmental variables such as spring water stress (Palmer Indices in March, April and May), denoted $\overline{\mathbf{z}}_{it}$, which may directly affect planting decisions. By postulating a linear functional form for the optimal share functions in equation (1), and by imposing symmetry in per-acre revenues (see Appendix B.1) and symmetry in lagged shares, the acreage allocation equations for corn and soybeans can be written as:

(2) $$s_{1it} = \tilde{\alpha}_{1i} + \beta_{11}(r_{1it} - r_{3it}) + \beta_{12}(r_{2it} - r_{3it}) + \gamma_{11}s_{1it-1} + \gamma_{12}s_{2it-1} + \zeta_1{}'\overline{\mathbf{z}}_{it} + \varepsilon_{1it};$$

(3) $$s_{2it} = \tilde{\alpha}_{2i} + \beta_{12}(r_{1it} - r_{3it}) + \beta_{22}(r_{2it} - r_{3it}) + \gamma_{12}s_{1it-1} + \gamma_{22}s_{2it-1} + \zeta_2{}'\overline{\mathbf{z}}_{it} + \varepsilon_{2it}.$$

To make equations (2) and (3) actually estimable, we further assume that the (normalized) expected per-acre revenue can be expressed as follows:

(4) $$r_{kit} = p_{kit}y_{kit} + v_{ki} \qquad \text{for } k = 1,2,3,$$

where p_{kit} is the expected output price and y_{kit} is the expected yield; v_{ki} is the covariance of realized price and yield for crop k in county i. (Recall that, for two random variables ν_1 and ν_2, $\mathrm{E}[\nu_1\nu_2] = \mathrm{E}[\nu_1]\mathrm{E}[\nu_2] + \mathrm{cov}(\nu_1,\nu_2)$) Note that the county-specific covariance term is assumed to be time-invariant. Also, the expected local (county-specific) price is not observed. Following standard practice, this expected local price can be decomposed as $p_{kit} \equiv \overline{p}_{kt} + \delta_{ki}$, where $\overline{p}_{kt}$ is a national reference expected price (which, as explained later, we measure by the futures price) and δ_{ki} is the expected local basis. For tractability, this county-specific and crop-specific basis is assumed to be time invariant—apart from the effects of the expansion of ethanol plants, which we modeled separately. Denoting the product of the national expected reference price and the local expected yield as $\overline{r}_{kit} \equiv \overline{p}_{kt} y_{kit}$, we can express expected per-acres revenues in equation (4) as follows:

(5) $$r_{kit} = \overline{r}_{kit} + \delta_{ki} y_{kit} + v_{ki} \qquad \text{for } k = 1,2,3 .$$

A stylized fact of agricultural productivity is that expected crop yields have steadily trended upward since the mid 1930s, a reflection of technical progress ultimately due to public and private investments in research and development activities (Alston et al. 2010). Our analytical framework permits us to capture the effect of trending yields on crop allocation decision. As discussed in more detail later, expected yields have a common linear trend and county-specific intercepts, and the estimated expected yields will be fully reflected in the $\overline{r}_{kit}$ regressors. But, given the structure of equation (5), trending yields should also interact with the basis term δ_{ki}, implying the presence of county-specific trend effects. The fact that the terms δ_{ki} are unobserved makes it difficult to identify these local effects. Still, to capture at least the mean of these implied trends, we include a common time trend in each estimating share equations.

One of the motivating factors for this study is that the expansion of biofuel production due to the RFS has represented a major exogenous demand shock that, in the logic of our model, is captured by movements in the expected national price. But it is also important to note that biofuel production has local impacts. In particular, the spread of ethanol plants has created new local centers of corn demand that have the potential to affect the local market. To account for this feature of the problem, we include and "ethanol pressure" variable, denoted E_{it}, in the supply response equations. This variable, the construction of which is detailed later, measure the extent to which a county's corn production is likely to be used locally as the feedstock of ethanol local plants.

In conclusion, therefore, we end up with the following two estimating equations:

(6) $$s_{1it} = \alpha_{1i} + \beta_{11}\pi_{1it} + \beta_{12}\pi_{2it} + \gamma_{11}s_{1it-1} + \gamma_{12}s_{2it-1} + \mu_1 E_{it} + \boldsymbol{\zeta}_1{}'\overline{\mathbf{z}}_{it} + \tau_1 T_t + \varepsilon_{1it};$$

(7) $$s_{2it} = \alpha_{2i} + \beta_{12}\pi_{1it} + \beta_{22}\pi_{2it} + \gamma_{12}s_{1it-1} + \gamma_{22}s_{2it-1} + \mu_2 E_{it} + \boldsymbol{\zeta}_2{}'\overline{\mathbf{z}}_{it} + \tau_2 T_t + \varepsilon_{2it}.$$

where $\pi_{kit} \equiv (\overline{r}_{kit} - \overline{r}_{3it})$, $k = 1,2$ represent relative expected per-acre revenues. The county-specific fixed components of the basis and the covariance between price and yields—beyond those captured by the time trend and ethanol pressure variables—are absorbed by the county-specific intercepts α_{ki}. The system of equations (6) and (7) can be expressed in a vector notation as follows:

(8) $$\mathbf{s}_{it} = \boldsymbol{\alpha}_i + \mathbf{B}\boldsymbol{\pi}_{it} + \boldsymbol{\Gamma}\mathbf{s}_{it-1} + \boldsymbol{\psi}'\mathbf{x}_{it} + \boldsymbol{\varepsilon}_{it}$$

where $\mathbf{s}_{it}$ is the 2×1 vector of shares; $\boldsymbol{\alpha}_i$ is the 2×1 vector of constants; $\boldsymbol{\pi}_{it}$ is the 2×1 vector of relative per-acre revenues; $\mathbf{x}_{it}$ is the 5×1 vector of ethanol pressure, Palmer Indices in March, April and May, and time trend; and

$$\mathbf{B} = \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{12} & \beta_{22} \end{bmatrix} \text{ and } \boldsymbol{\Gamma} = \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{12} & \gamma_{22} \end{bmatrix}.$$

One of our main interests is to understand the dynamic adjustment within the share system and obtain short-run and long-run parameters regarding per-acre revenues. In equation (8) the parameters of the matrix $\mathbf{B}$ determine the short-run acreage elasticities w.r.t. per-acre revenue. The long-run parameters can be obtained by the matrix $(\mathbf{I} - \boldsymbol{\Gamma})^{-1}\mathbf{B}$.

For the acreage model considered, we have three cropland uses and four price-related variables (three per-acre revenues and one input price), thereby having twelve elasticities to estimate for the short run and for the long run, respectively. For short-run elasticities, based on equation (8), we estimate three price-related parameters in a system of two equations, which permit us to estimate directly four of these elasticities (η_{km} for $k = 1,2$ and for $m = 1,2$). The remaining eight elasticities are computed by exploiting the theoretical restrictions for adding-up, symmetry and homogeneity, we are able to calculate the rest of elasticities as follows:

(9) $$\eta_{3k} = -\eta_{1k}\frac{s_1}{s_3} - \eta_{2k}\frac{s_2}{s_3}, \qquad \text{for } k = 1,2,3 \quad \text{(adding-up);}$$

(10) $$\eta_{k3} = \eta_{3k}\frac{s_3}{\overline{r}_k}\frac{\overline{r}_3}{s_k} \qquad \text{for } k = 1,2 \quad \text{(symmetry);}$$

(11) $$\eta_{kw} = -\sum_{\ell=1}^{3}\eta_{k\ell}, \qquad \text{for } k = 1,2,3 \quad \text{(homogeneity),}$$

where η_{kw} means the acreage elasticity for crop k w.r.t. the input price index. Because all elasticities are evaluated at the mean of the relevant variables,[28] the share values used in (9), (10) and (11) are also evaluated at the mean point. A similar procedure is used to computed long run elasticities, based on the long-run estimated coefficients $(\mathbf{I}-\mathbf{\Gamma})^{-1}\mathbf{B}$.

The empirical implementation of this framework has to deal with the problem that the "other crops" aggregate is heterogeneous across counties, both in terms of the types of land uses (other than corn and soybeans) that might be considered by farmers, and the acreage extent of

[28] Perhaps the obvious evaluation point for these elasticities is the mean point of the local per-acre revenues r_{kit}. Because of the unobserved component of the basis and price-yield covariance, however, we evaluate the elasticities at the mean point of the variables $\overline{r}_{kit}$ defined earlier.

these other crops. It is therefore not obvious how the relevant expected per-acre revenue for this aggregate should be constructed. Recognizing the issue in measuring other crop variables, the proxy for the per-acre revenue of other crops that we consider is an index of expected revenues of wheat, alfalfa and sorghum (the three most common crops, other than corn and soybeans, for the set of counties we consider). We simply assume that for the other crop category the covariance term for the expected pre-acre revenue is zero. Details on the constructions of expected per-acre revenue are provided in the data section below. Given this proxy for the expected per-acre revenue of other crops, we construct relative per-acre revenues.

3.3.2 Endogeneity issues

A standard concern in the econometric estimation of supply equations involves identification and the potential problem of endogenous prices. Given the presumption that the large price increases experienced in the period under consideration were triggered by exogenous demand shifts, including the major role played by the gradual implementation of the RFS, we believe that the potential endogeneity problem is not a major concern in our analysis. The remaining subtle issue concerns the futures prices. Since Gardner (1976) suggested to use the futures price as a measure of the expected price, the endogeneity issue has been raised (e.g., Choi and Helmberger 1993b). The rationale of such endogeneity is predicated on the possibility that farmers may be partially aware of forthcoming supply shocks at decision time, thereby changing their planting area accordingly, which in turn may affect futures prices. When the predictable supply shocks are (usually negatively) correlated with decision-time futures prices, omitting such predictable components from the estimating equation induces correlations between the price variable and the error term and thereby causes endogeneity bias.

There have been efforts to deal with the foregoing endogeneity problem. The crux of the matter concerns how predictable weather shocks affect planting decisions, thereby affecting expected price. In the context of an aggregate global caloric supply, it is shown that such endogeneity can be treated by instrumenting price with past weather shocks (Roberts and Schlenker 2013), or simply by including current realized shocks as a proxy for predictable shocks (Hendricks, Janzen, and Smith 2015). In this essay, however, our focus is on U.S. county-level supply behavior, and the logic of the foregoing papers does not seem to apply. Therefore, similar to Hendricks, Smith, and Sumner (2014), we assume that the national expected prices, which are actually future prices, are exogenous.

3.3.3 Estimation

Simple ordinary least-square (OLS) estimators of the system of equation in (8) are known to be problematic because unobserved county-specific heterogeneity tends to be correlated with lagged dependent variables. For example, a severe negative county-specific random shock resulting in a low corn acreage share—given the short time frame of our panel data—may be confounded with the estimated county-specific intercept. Then, including last year's low corn shares in current period corn equation may cause positive correlation between the lagged dependent variable with the county-specific heterogeneity in the error term. As a result, the coefficient of own lagged dependent variable is overestimated (upward bias). Thus we need to control the unobserved county-specific heterogeneity to deal with the endogeneity from the omitted variable bias.

To control for the time-invariant, county-specific unobserved heterogeneity, an immediate option is to use the within-groups estimator (i.e., individual fixed effects estimator) by de-meaning variables (e.g., by introducing county-specific dummy variables). When using the within-groups estimator, however, the coefficient estimates of own lagged dependent variables tend to be biased downward because the error term contains the information of demeaned lagged shares (Nickell 1981). Another way to control the unobserved heterogeneity is to take first differences, which, from equation (8), yields following system:

(12) $\Delta\mathbf{s}_{it} = \mathbf{B}\Delta\boldsymbol{\pi}_{it} + \boldsymbol{\Gamma}\Delta\mathbf{s}_{it-1} + \boldsymbol{\psi}'\Delta\mathbf{x}_{it} + \Delta\boldsymbol{\varepsilon}_{it}$.

Although the county-specific heterogeneity is eliminated without causing the bias identified by Nickell (1981), equation (12) is still subject to correlation between lagged shares and error terms because both have $t-1$ terms: $s_{ki,t-1}$ in $\Delta s_{ki,t-1}$ and $-\varepsilon_{mi,t-1}$ in $\Delta\varepsilon_{mit}$ for $k = 1,2$ and $m = 1,2$. Because the own lagged shares are negatively correlated with corresponding error terms (the case of $k = m$), the OLS estimates on the own lagged shares are biased downward.

Note that for own lagged dependent variables, the level equation OLS estimator and the within-groups estimator are biased in opposite directions, and so are the level equation OLS estimator and the differenced equation OLS estimator. One would expect that a candidate of good estimates on own lagged shares will lie between those bounds, or at least not too higher than the level equation OLS estimator or not too lower than the within-groups estimator (or than the differenced equation OLS estimator). For the cross lagged shares, the direction of bias would be opposite if there are negative cross equation correlations.

To account for the endogeneity in the differenced equation, it has been proposed to instrument endogenous regressors with their lagged values. Anderson and Hsiao (1982) suggest to use one period lagged levels (or differences) as instruments and run two-stage least squares estimator (if there is no serial correlation in error term), where lagging causes loss in observations. Holtz-Eakin, Newey and Rosen (1988) and Arellano and Bond (1991) point out that there will be efficiency gains from the Anderson-Hsiao estimator by utilizing a wider set of available instruments under the GMM framework (called as difference GMM estimator). Specifically, each available lagged level in a time period can constitute an instrument, where other data points are replaced by zeros (hence, no further loss in observations after first differencing). There is a potential weakness of difference GMM such that the lagged levels becomes poor instruments for first differenced variables, especially when the coefficients of lagged variables are close to one (the case of random walk). Given that under certain initial conditions differences can also be instruments to estimate equations in levels, Arellano and Bover (1995) and Blundell and Bond (1998) suggest to estimate equations in levels along with the equations in differences as a system (called as system GMM estimator).[29]

We use the difference GMM estimator. Although the foregoing differenced equation estimators have been developed for single equation models, we can extend them to the two-equation system of interest here. To implement this estimator, we use two types of moment weighting matrices. The first matrix reflects the MA(1) feature of differenced errors and assumes homoscedasticity and no cross equation correlation, resulting in the one-step GMM estimator. The other matrix allows heteroscedasticity and cross-equation correlation by utilizing residuals from the one-step estimator, resulting in the two-step GMM estimator. Whereas two-step estimator improves the efficiency from the one-step estimator in the case of a complicated error

[29] Alternative to those estimators based on first-differencing is the bias-corrected fixed effects estimator (Kiviet 1995, Bun and Carree 2005), which basically estimates the size of bias based on a preliminary GMM estimator and subtract it from fixed effects estimates. Attanasio, Picci and Scorcu (2000) suggest to use such estimator when the number of time periods in the data is large enough. For example, Hausman (2012) applies the bias-corrected within-group estimator to estimate the acreage response in Brazil using data over 1973-2005. Bruno (2005) finds that the bias-corrected within-group estimator outperforms alternative first-differencing estimators when the number of individual groups is small.

structure, it is subject to the downward bias in the computed standard errors, especially in small samples (Arellano and Bond 1991).[30] For comparison purposes, we report both results.

The remaining issue is the choice of instruments. Basically, any lagged level is valid for constructing an instrument as long as it is lagged sufficiently to handle the existing serial correlation in the error term. But this proliferation of possible instruments is unattractive because too many instruments overfit the endogenous variables and in turn preserve the bias (Roodman 2009a). The possible remedies are two-fold (Roodman 2009b): i) collapsing the instrument matrix so that each lag generates only one instrument per endogenous variable, and ii) excluding longer lags from instruments. Both treatments are used for our instruments. To delimit valid lags, we check the serial correlation on the error term by regressing residuals on each of their lags as discussed in Wooldridge (2010, pp. 319-320) (see Drukker 2003 for the test performance). Because the equation is first-differenced, the residual tend to display properties of a MA(1) process. Hence, we expect negative correlation in the first lagged residual, and so to uncover correlation in the levels it is most meaningful to check twice-lagged residuals. For example, if the estimated coefficient of twice-lagged residual is significant, we can infer that there is first order serial correlation in levels, and then for share variables third and higher lagged levels are valid for instruments.

[30] Windmeijer (2005) proposes the correction of this bias, while we do not implement it in this paper.

3.3.4 Yield response

We postulate simple linear equations for yield response following the literature reviewed earlier. To be specific, the expected yield for crop k, county i at time t is modeled as follows:

(13) $y_{kit} = \alpha_{ki}^{y} + \beta_{k}^{y} p_{kit} + \xi_{k}' \omega_{it} + m_{k}(t)$, for $k \in \{c, s\}$,

where ω_{it} includes weather variables (heat and water stress) that are all county and time specific, and $m(t)$ is a trend term that captures exogenous technological progress (either a linear trend, of a more flexible spline with two knots). Note that, consistent with virtually all previous applications, in equation (13) we include only the own expected output price (deflated by general input price). The two corn and soybean yield equations are estimated within and SUR framework, which allows for contemporaneous correlation in their residuals.

3.4 Data

For the analysis we construct two datasets: acreage dataset for 2005-2015, and yield dataset for 1971-2015. The former is based on our desire to focus on supply response in the period of the RFS implementation, as discussed in the introduction. The purpose of estimating the yield response model, on the other hand, is to account for anticipated yield increases in computing expected per-acre returns. Because the underlying technical progress responsible for yield increases is inherently a long-term phenomenon, observations over a sufficiently long period are desirable. Hence, we estimated the yield model over the much longer period 1971-2015. In what follows, we explain how we construct each variable in these datasets. The actually analyzed counties in the 12 Midwestern states are displayed in Figure 3.1, and summary statistics are describes in Table 3.2. All monetary values in Table 3.2 are expressed in their nominal values. For the actual estimation, by construction we consider relative terms normalized by the general input price, as discussed earlier.

3.4.1 Acreage shares

County-level acreage values for corn and soybeans are from the National Agricultural Statistics Service (NASS) of the U.S. Department of Agriculture (USDA) (https://quickstats.nass.usda.gov/). The 12 Midwestern states consists of 1,055 counties with 11,605 data points over the considered 11 years. Focusing on counties which are non-irrigated (i.e., less than 10% irrigation rate as defined in Xu et al. 2013) and in the traditionally delimited rainfed area (i.e., East of 100th meridian) yields 834 counties with 9,174 data points. These NASS/USDA data have missing values, however. Accordingly, we choose to drop counties with more than 1/3 missing values over our 11 years; after this procedure, 686 counties remain with 7,546 data points. Finally, we obtain 6,961 observations, over 686 counties, that have observations on both corn and soybean acreages and that have last year acreage values.[31] Note that during the estimation taking first lag on shares causes loss in observations (besides first differencing). To reduce such data loss, we construct first-lagged shares by filling out 2004 values. Thereby, level equation models based on equation (8) have 6,961 observations, while differenced equation models based on equation (12) have 6,149 observations.

To calculate the share of acreage for considered three crop categories—corn, soybeans, and other—we use total cropland values from Census of Agriculture of USDA. Census values

[31] To be precise, we have 120 data points out of 7,546, which are missing both corn and soybean acreage values. After dropping them, we drop additional 277 data points out of 7,426 because either corn or soybean acreage value is missing. In addition, there are 188 observations do not have previous year acreage values.

are only available at five-year intervals. Furthermore, there are counties for which the sum of corn and soybean acreages from NASS/USDA is greater than the census value for total cropland, in some years, implying negative shares for the "other crops" aggregate. This happens even for recent census years, for which an upward adjustment is applied for original census values to conform to NASS/USDA values (http://www.ers.usda.gov/data-products/major-land-uses/glossary.aspx#cropland).

To resolve these issues we do two things. First, consistent with the presumption that, within a given county, total available cropland is unlikely to have varied over last decade, we postulated a constant county-level total cropland, and we measure it by the maximum among census values recorded over the most recent three censuses (2002, 2007 and 2012). Still, this left 118 observations (out of 7,149) with the "insufficient" cropland problem. For these 118 observations, we manually calculate the total cropland value by summing corn and soybeans acreages, from NASS/USDA source, with the area for all other crops obtained from Cropland Data Layer (CDL) of NASS/USDA (https://www.nass.usda.gov/Research_and_Science/Cropland/SARS1a.php). The CDL is an image of an entire state with a crop or land use classification code corresponding to each pixel, where each pixel is less than one acre in size. Based on the classification we can sort out other crops except for corn and soybeans (See Appendix B.2. for the details about the replacement).

3.4.2. Expected per-acre revenues for corn and soybeans

In order to construct the reduced per-acre revenue variables used in equations (6) and (7) (i.e., $\overline{r}_{kit} \equiv \overline{p}_{kt} y_{kit}$), we construct expected output prices ($\overline{p}_{kt}$) and expected yields (y_{kit}) for corn and soybeans (while constructing an index of expected per-acre revenue for the other crop as explained later). We construct the expected national prices with futures prices. Specifically, for crop $k=1,2$ in year t, $\bar{p}_{kt}=p_{kt}^{f,\tau}$, where $p_{kt}^{f,\tau}$ denotes the futures price, for the first delivery month after harvest, quoted at decision time τ. The relevant delivery months are December for corn and November for soybeans. Daily futures price data are obtained from Quandl (https://www.quandl.com/). We use futures prices with a delivery month of December for corn and with a delivery month of November for soybeans. We average daily closing futures prices over January to March, i.e., before the planting season. The general input price index is approximated by the national price index for all agricultural intermediate goods, from the Economic Research Service (ERS) of USDA. Because the input price index is updated only up to 2013, we keep the 2013 value for 2014 and 2015.

To obtain the expected yield values, we can utilize our yield equation, i.e., equation (13). Given that including or excluding the own expected price provides virtually identical predicted yields (as shown in the results section), we use the model without output prices. Furthermore, to obtain the expected yield that is relevant at farmers' decision time, we consider unconditional mean values for the weather variables. Hence, expected yields are constructed as follows:

(14) $$y_{kit}=\hat{\alpha}_{ik}^{y}+\hat{\xi}_{k}'\bar{\omega}_{i}+\hat{m}_{k}(t), \qquad \text{for } k\in\{c,s\},$$

where $\bar{\omega}_{i}$ is a vector of unconditional mean values for weather variables (1971-2015) for county i; a linear time trend is considered for $\hat{m}_{k}(t)$. Using the obtained expected price and expected yield, we construct the expected per-acre revenue variables for corn and soybeans (2005-2015).

3.4.3 Expected per-acre revenue for other crops

As noted, we consider a proxy for "other crops" per-acre revenue. To be specific, we compute the expected per-acre revenue for other crops as an index of expected revenues for wheat, alfalfa and sorghum. Table B1 in the Appendix documents that wheat, alfalfa and sorghum are in fact the major crops, other than corn and soybeans, for the states considered in this study. The expected wheat price is constructed similarly to the procedure used for corn and soybeans: it uses the wheat futures price (for the December delivery month, quoted at decision time). As for the expected alfalfa and sorghum prices, these are respectively measured by averaging state-level received prices for the months of January to March (as done by Hendricks, Smith, and Sumner 2014). Expected yield is the predicted value from county specific regressions on a linear time trend using NASS/USDA wheat, alfalfa and sorghum yield data.[32] Now, the expected revenues for wheat, alfalfa and sorghum are aggregated in the county-specific index by using acreage in 2010 as weights. Due to the presence of considerable missing values in NASS/USDA acreage data, we alternatively use CDL data to obtain wheat and alfalfa acreage information.[33]

3.4.4 Ethanol pressure, weather and yield variables

The ethanol pressure variable measures the local corn demand of ethanol plants based on the nearby ethanol plant capacity, which causes exogenous demand shifts in the local market. For each year, we construct the county-specific ethanol pressure measure by solving a quadratic cost

[32] Given the states missing price and/or yield data by NASS/USDA, replacements are conducted. For example, the alfalfa price (yield) for IN (every county in MI) is missing, so we used that of IL (average expected value of IN) for this state. Since sorghum price (yield) is available only for IL, KS and MO (counties in IL, IN, IA, KS, MO, NE and SD), the (average expected) values are used for contagious states.

[33] Year 2010 is chosen as base year in order to strike the balance between the accuracy of CDL, which starts to use 30m subgrid from 56m for the entire U.S. since 2010, and the accuracy of predicted wheat yield, for which the wheat yield data is available only up to 2007 by NASS/USDA.

minimization problem. For this variable having its value from zero to one, zero means no contribution from the county production to nearby ethanol plants, while one means full contribution. Since the corn-based ethanol has been the main biofuel for recent years, we focus on the local demand shock for corn (not for soybeans). For the detailed model and computation, refer to Appendix B3.

We consider seven weather variables. Two of them are heat variables, growing degree days (GDD) and excess heat degree days (EDD) in the growing season (June to September), and five are water stress variables: monthly Palmer Z indices for May, June, July, August and September. The definition of these weather variables, and the way they are assembled, follows closely the procedure described in Xu et al. (2013). Briefly, GDD accounts additional beneficial degrees within 10°C and 30°C, while EDD captures additional harmful degrees over 32.2°C. For 1971-2014 we use the compiled daily temperature data from United States Historical Climatology Network (USHCN) of National Oceanic and Atmospheric Administration (NOAA), which is provided in the website of Carbon Dioxide Information Analysis Center (CDIAC) (http://cdiac.ornl.gov/epubs/ndp/ushcn/ushcn.html). But CDIAC no longer provides annual updates after 2014, and we collect temperature data from the Parameter-Elevation Regressions on Independent Slopes Model (PRISM) database only for 2015 (http://prism.oregonstate.edu/). Palmer Z index data are collected using the daily index data from NOAA's National Centers for Environmental Information (NCEI) (https://www.ncdc.noaa.gov/temp-and-precip/drought/historical-palmers/). The index measures the deviation from normal water stress, represented by 0, where -2 or less indicates drought and +5 or more indicates flood conditions. All weather variables have no missing values for 686 counties over 45 years.

County-level yield values for corn and soybeans are obtained from NASS/USDA for 1971 to 2015. We collect yield values for the 686 counties used in the acreage estimation. To run the SUR model we drop data points for which at least one of either corn or soybean yield is missing. After dropping missing data points, we eventually have 28,013 observations for the yield estimation, over 45 years.

3.5 Results

3.5.1 Acreage response

The estimation results under the acreage models—dynamic model 1, dynamic model 2 and static model—are displayed in Table 3.3. All models are based on first differencing as in equation (12). The results under the dynamic model 1 are based on one-step GMM estimator, while those under the dynamic model 2 are based on the two-step GMM estimator. The static model uses the two-step GMM estimator, omitting lagged shares in the equations. All standard errors of estimates are clustered by counties to account for the possible correlated behavior within each county. For comparison purposes we estimate three alternative models—level equation OLS, within-groups, and differenced equation OLS estimators—which are reported in Table B2 in the Appendix.

We assume that the futures price and anticipated yields are exogenous and thus treat the constructed per-acre return variables as exogenous, along with the ethanol pressure variable and spring Palmer indices. Except for acreage shares, therefore, we use regressors in differences as instruments without lagging. Note that the time trend effect is estimated by constant term in differenced equations and constant term is used as instruments too. We find evidence of third- and second-order serial correlations in the error terms for corn and soybean equations, respectively. Hence, we conservatively use fifth or longer lagged levels for endogenous variables—corn and soybean shares—for both equations. By collapsing instrument matrix, we have one instrument per lag per variable, and we choose to use only fifth lagged share levels as instruments, yielding two instruments. Given that there is a trade-off between bias and efficiency in terms of number of instruments in the dynamic panel model (e.g., Hendricks, Janzen and Dhuyvetter 2012), we sacrifice some efficiency by choosing a small number of instruments. This is mainly because adding more share instruments (such as sixth lag of corn share and sixth lag of soybean share) weakens the orthogonality of instruments to error terms, resulting in high Hansen's J statistics. Admittedly, because each of our estimation equations includes two lagged dependent variables, and there is serial correlations in the level equation error terms, the choice of instruments is sensitive and restrictive.[34]

We find that the coefficients for all per-acre revenue variables are significant for both corn and soybean equations, under all models in Table 3.3 (and under all models in Table B2). Especially, the magnitude of these coefficients are almost the same under all dynamic models that control the individual fixed effects (that are, the dynamic models 1 and 2 in Table 3.3, and the dynamic models 4 and 5 in Table B2). This supports the exogeneity of per-acre revenue variables to the idiosyncratic error terms. We also find that those estimates under the static model are larger in absolute term compared to those under the dynamic models. Under the dynamic models 1 and 2, the coefficients of own lagged shares are not significant, while those of cross lagged shares are significant. Although it is less straightforward than the case of single equation

[34] As many applications do, introducing year dummies might reduce the correlation between instruments and errors by controlling any common shocks for all counties in a given year. But it would distort the explanatory power of per-acre revenues that include the futures prices, which are common for all counties.

models, one way to check the validity of those estimates is to compare them with biased estimates. It turns out that the GMM estimates on own lagged shares are lower than the level equation OLS estimates and higher than the differenced equation OLS estimates. The GMM estimates on cross lagged shares are similar to those of the within-groups estimates. Thereby we conclude that the difference GMM estimates are not suffering significantly from finite sample bias. Note that the eigenvalues of the 2×2 full matrix of coefficient estimates of own and cross lagged shares $\hat{\Gamma}$ are (0.052, -0.401) for the dynamic model 1, and (0.162, -0.405) for the dynamic model 2, implying that both are dynamically stable.

The coefficients of the ethanol pressure variable and March-May Palmer indices are also robust across the models. Under dynamic models in Table 3.3 (and Table B2), the increase in ethanol pressure is significantly associated with the increase in corn share, while not significant for soybean share. This supports the idea that since the RFS has been initiated, the proliferation of ethanol plants in some regions of the Midwest has promoted the some further expansion of corn production beyond that attributable to national market conditions. The severe rainfall in March and April is significantly associated with less corn share but with more soybean share, while that in May explains less shares for both. The cross correlation of residuals between corn and soybean equations are -0.16 to -0.28. For both dynamic and static two-step estimators, the overidentification test statistics (Hansen's J statistics) indicate that the null hypothesis of valid instruments is not rejected.

Given the small difference in the magnitude between one-step and two-step estimates, our baseline dynamic model is the one based on the two-step GMM estimator because it might improve efficiency to some degree from the one-step estimator when the error structure is not simple. (A caveat is that the robust standard errors might be biased downward for two-step estimator.) Calculated elasticities based on the dynamic and static two-step GMM estimators, evaluated at the mean point of the data, are reported in Table 3.4. For the dynamic case, the long-run parameters are obtained as discussed in Section 3.1. The residual elasticities are computed as discussed in equations (9), (10) and (11) for the short and long runs. Note that we evaluate the elasticities at the mean for the entire samples. To evaluate the elasticities at the mean point, we ignore the covariance term and basis and evaluate the elasticities at the mean of the expected per-acre revenue. The reported standard errors for elasticities are calculated using the delta method.

Most elasticity values turn out to be quite significant. Under all three cases, all signs accord with expectations, where the adding-up condition results in positive signs of soybean and other acreage elasticities w.r.t. input price. Based on the baseline dynamic model, the corn and soybean own- and cross-elasticities, which are of our main motive of interest, show that both crops have a more elastic response in the short run than in the long run. This is because of the structure of $\hat{\boldsymbol{\Gamma}}$ in the dynamic models in Table 3.3, especially indicating the strong cross-acreage dynamics between corn and soybeans. Note that corn elasticities are larger than those of soybeans in absolute terms. The cross-price elasticities are fairly large in absolute value, relative to the own-price elasticities, indicating that an expansion of corn acreage largely comes at the expense of soybean acreage (and vice versa). The short-run elasticities for corn and soybeans under the static model are larger than the counterparts under the dynamic model.

Given the relatively large magnitude of cross-price elasticities, an interesting question concerns the responsiveness of total acreage allocated to the two crops, corn and soybeans, resulting from a generalized increased in their prices. In addition to these individual elasticities, therefore, we compute a "total" elasticity η_T as follows. Consider scaling the price of both crops by a constant $\kappa > 0$, and represent total acreage share allocated to these two crops as $s_T \equiv s_1(\kappa r_1, \kappa r_2) + s_2(\kappa r_1, \kappa r_2)$. The total elasticity η_T can then be defined as

$$\eta_T \equiv \frac{\partial s_T}{\partial \kappa} \frac{\kappa}{s_T}\bigg|_{\kappa=1}.$$

By taking derivative w.r.t. κ of the individual crop shares, and evaluating at $\kappa = 1$, we can then expressed this total elasticity in terms of the individual elasticities as follows:

$$\eta_T = \frac{s_1}{s_T}(\eta_{11} + \eta_{12}) + \frac{s_2}{s_T}(\eta_{21} + \eta_{22}). \tag{15}$$

This total elasticity is also reported in Table 3.4, and turns out to be 0.04 for both short and long runs under the baseline dynamic model, and 0.03 under the static model. This means that, for instance, a doubling of the real price of both corn and soybeans would result in an expansion of the cropland allocated to these two crops of 4% in the short run and in the long run under the baseline dynamic model. For comparison purposes, when using the long-run elasticity values in Hendricks, Smith and Sumner (2014), the total elasticity is obtained by 0.0025. This is much more restrictive than ours, and it is sensible in that their analysis focuses on the three main states in the corn belt (Illinois, Indiana and Iowa).

Given the estimates of the dynamic parameters $\hat{\mathbf{\Gamma}}$ and the short-run response parameters $\hat{\mathbf{B}}$, we can project cumulated values of response parameters $\mathbf{B}_t$ for each year of t as follows:

$$\mathbf{B}_t = \hat{\mathbf{B}} \times \left(\sum_{\ell=1}^{t} \hat{\mathbf{\Gamma}}^{(\ell-1)} \right) \quad \text{for } t = 1, 2, \ldots, \tag{16}$$

where we assume that the (permanent) changes in per-acre revenues occur at $t = 1$. Figure 3.2 describes the adjustment of elasticities calculated from the projected parameters based on equation (16). All own- and cross-elasticities show radical adjustments in the first period. The values oscillate and then almost converge to the long-run values after just three periods. The resulting total elasticity is stable all the time at the low level.

3.5.2 Yield response

The estimation results for the yield equations, based on equation (13), are displayed in Table 3.5. For the comparison, the results with/without the inclusion of the own output price are both reported. Even for the case without price, the two yield equations are run under the SUR model giving the information of residual correlation. The interpretation of the linear trend coefficient is straightforward. For the model without the inclusion of the own price, Table 3.5 shows exogenous technological change is responsible for a gain of 1.666 bu/acre/year for corn, and 0.431 bu/acre/year for soybeans. The weather variables are strongly significant for both corn and soybean yield and across all specifications. Growing season GDD and EDD show expected signs (positive and negative, respectively). The deviation of water stress is bad for yield during early and late growing season (that is, planting time and harvesting time) but beneficial during the middle of the growing season (July and August). When including own price, columns (3) and (4) in Table 3.5, the explanatory power of weather and trend variables remain the same. The calculated elasticities of yield response w.r.t. own outprice are significant but very small: 0.010 for corn and -0.0004 for soybeans.

We also considered a more flexible specification for the trend variable, a spline with two knots which essentially postulate different linear trend for three sub-periods or the same length (1971-1985, 1986-2000, and 2001-2015). The results are reported in Table B3 in the Appendix. For corn we find an increasing effect of technology-induced yield gains over time. The larger annual yield gain for the last sub-period (2001-2015) is consistent with the positive impact on corn yields due to the adoption of genetically engineered varieties, as documented in Xu et al. (2013). For soybeans, the first and third periods show almost identical annual yield gains, with a small drop for the middle period. The use of a spline trend also affects the estimated coefficients for the yield response to price. The computed elasticities are now -0.063 and 0.021 for corn and soybeans, respectively.

3.6 Conclusion

The RFS is widely credited with contributing significantly to commodity price increases. In addition to providing an exogenous source of new demand for agricultural products, the expansion of ethanol producing plants across the Midwest provided a source of change for historical basis patterns. All this provides an ideal setting to estimate the supply response for corn and soybeans, the major agricultural commodities produced in the United States. This paper estimates the U.S. corn and soybean supply response by focusing on the most recent eleven years (2005-2015), which have been most directly affected by the implementation of the RFS. In addition, in this period the impact of traditional government support programs has been minimal, making it easier to econometrically identify farmers' supply response to price signals. One of the main motive of interest in our analysis is to assess the dynamic supply substitutability between corn and soybeans. Hence, the analysis focused on the 12 Midwestern states of the traditional corn belt, where most counties are typically observed to produce both crops. Acreage and yield responses are modeled separately. Acreage share equations maintain the standard theoretical properties of homogeneity, adding-up and symmetry.

Our results, under the dynamic models that we considered, indicate that the U.S. supply responses for corn and soybeans are larger in the short run than in the long run, and that they are quite inelastic. This outcome is attributed to the strong cross-acreage dynamics related to crop rotation behavior. Combining acreage and yield responses (two-step difference GMM estimates for acreage shares, and SUR estimates for expected yield function with a linear trend), we obtain an estimated own-price supply response (at the mean) of 0.51 for corn and 0.38 for soybeans in the short run (and 0.38 and 0.27 in the long run). Virtually all of the estimated response is attributable to acreage changes. Our estimated elasticities are quite similar to the short-run and long-run elasticities reported by Hendricks, Smith, and Sumner (2014), but smaller than those reported by Miao, Khanna, and Huang (2016).

Cross price elasticities between corn and soybeans turned out to be negative, as expected, and relative large in magnitude in the short run and long run. This means that, when both corn and soybean prices move together, the total acreage allocated to these two crops is very inelastic: in both short and long runs, the relevant total elasticity remains 0.04. This suggest that the ability of the U.S. corn and soybean production sector to accommodate the demand shock due to the RFS is quite limited. These results are consistent with the observation that—while world production has grown in response to commodity price increases—over the eleven years of our study the U.S. share of world production, for both corn and soybeans, has been declining.

Table 3.1. Selected Work for U.S. Corn and Soybean Acreage Elasticities

Work	Region/unit/period	Elasticity of	With respect to Corn price (or revenue)	Soy price (or revenue)
Lee and Helmberger (1985) [a]	IL, IN, IA, OH /state/1948-80	Corn acres	0.12	-0.17
		Soy acres	-0.23	0.35
Shideed and White (1989) [b f]	U.S./nation/1951-86	Corn acres	0.19	-0.10
		Soy acres	-0.18	0.41
		Corn acres	0.26 (L)	-0.15 (L)
		Soy acres	-0.69 (L)	1.58 (L)
Chavas and Holt (1990) [c]	U.S./nation/1954-85	Corn acres	0.07	-0.11
		Soy acres	-0.16	0.06
Orazem and Miranowski [d] (1994)	IA/county/1952-91	Corn acres	0.10	0.02
		Soy acres	0.01	0.33
Miller and Plantinga (1999) [e]	IA/county/1981-94	Corn acres	0.93, 2.35	-1.05, -0.50
		Soy acres	-1.59, 0.55	0.53, 1.76
Arnade and Kelch (2007)	IA/county/1960-99	Corn acres	0.01	-0.04
		Soy acres	-0.03	0.05
Hendricks, Smith, and Sumner (2014) [f]	IL, IN, IA /field/1999-10	Corn acres	0.40	-0.31
		Soy acres	-0.46	0.36
		Corn acres	0.29 (L)	-0.22 (L)
		Soy acres	-0.33 (L)	0.26 (L)
This paper [f]	12 Midwest states /county/2005-15	Corn acres	0.50	-0.31
		Soy acres	-0.51	0.38
		Corn acres	0.38 (L)	-0.23 (L)
		Soy acres	-0.34 (L)	0.27 (L)

Note: [a] Values are based on their free-market regime. [b] Values are based on the results using futures price. [c] Values are w.r.t own and cross revenues instead of prices. [d] Values are based on the results under rational expectations. [e] Numbers are paired with smallest and largest values across values for three counties under their unconditional model. [f] long-run values are denoted by (L).

Table 3.2. Summary Statistics (686 counties)

	Mean	Std. Dev.	Min	Max
Data for acreage equations: 2005-2015 (6,961 observations)				
Acreage share for corn	0.35	0.15	0.005	0.77
Acreage share for soybeans	0.32	0.12	0.004	0.65
Acreage share for other crop	0.33	0.22	0.0005	0.98
Expected revenue for corn ($1000/acre) [a]	0.63	0.20	0.16	1.07
Expected revenue for soybeans ($1000/acre) [a]	0.43	0.14	0.14	0.74
Expected revenue for other crop ($1000/acre) [a]	0.42	0.15	0.10	1.05
Input price index (2010=1)	1.03	0.18	0.73	1.23
Ethanol pressure	0.28	0.38	0	1
Palmer Z index in Mar	-0.21	1.71	-4.25	7.08
Palmer Z index in Apr	0.80	2.18	-4.00	9.04
Palmer Z index in May	0.37	2.14	-4.09	8.76
Data for yield equations: 1971-2015 (29,494 observations)				
Yield for corn (bu/acre)	116	36	7	236
Yield for soybeans (bu/acre)	36	10	4	73
Expected price for corn ($/bu)	2.97	1.06	1.26	5.89
Expected price for soybeans ($/bu)	6.91	2.40	2.87	13.31
Input price index (2010=1)	0.64	0.26	0.21	1.23
GDD in growing season	2,432	324	1,168	3,418
EDD in growing season	37	50	0	494
Palmer Z index in May	0.40	2.21	-4.78	9.35
Palmer Z index in Jun	0.24	2.22	-6.51	9.05
Palmer Z index in Jul	0.47	2.37	-5.69	15.21
Palmer Z index in Aug	0.36	2.19	-5.72	11.69
Palmer Z index in Sep	0.16	2.20	-4.94	15.63

Note: [a] The "expected revenues" are the reduced values ($\bar{p}_k \cdot y_k$), without basis and own covariance terms.

Table 3.3. Estimated Coefficients under Dynamic and Statics Models

	Dynamic model 1: One-step diff GMM		Dynamic model 2: Two-step diff GMM		Static model: Two-step diff GMM	
	Corn	Soy	Corn	Soy	Corn	Soy
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Corn revenue	0.29***	-0.27***	0.29***	-0.27***	0.36***	-0.34***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)
Soy revenue	-0.27***	0.29***	-0.27***	0.29***	-0.34***	0.36***
	(0.007)	(0.009)	(0.007)	(0.009)	(0.007)	(0.008)
Other revenue	-0.02***	-0.03***	-0.03***	-0.02***	-0.01***	-0.03***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.002)	(0.003)
Lagged corn share	-0.13	0.22*	-0.07	0.28**		
	(0.137)	(0.125)	(0.121)	(0.111)		
Lagged soy share	0.22*	-0.22	0.28**	-0.17		
	(0.125)	(0.117)	(0.111)	(0.107)		
Ethanol pressure	0.010***	-0.001	0.008***	-0.003	0.010***	-0.006***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Palmer index in Mar	-0.002***	0.001***	-0.002***	0.001***	-0.003***	0.001***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Palmer index in Apr	-0.002***	0.001***	-0.002***	0.001***	-0.002***	0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Palmer index in May	-0.002***	-0.001***	-0.003***	-0.001***	-0.003***	<-0.001
	(0.0003)	(0.002)	(0.0002)	(0.002)	(0.0001)	(0.0001)
Trend	<-0.001	0.003***	<-0.001	0.003***	<0.001	0.004***
	(0.0006)	(0.0005)	(0.0005)	(0.0004)	(0.0002)	(0.0002)
Cross correlation in residuals	-0.19		-0.16		-0.28	
p-value of Hansen's J statics			0.29		0.49	

Note: Standard errors are in parentheses and clustered by counties. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 3.4. Elasticities at Overall Means

	Corn price	Soy price	Other price	Input price	η_T
DYNAMIC: SHORT-RUN					
Corn acreage	0.50***	-0.31***	-0.03***	-0.15***	
	(0.013)	(0.009)	(0.005)	(0.004)	0.04***
Soy acreage	-0.51***	0.38***	-0.03***	0.16***	(0.006)
	(0.014)	(0.012)	(0.007)	(0.004)	
Other acreage	-0.05***	-0.03***	0.06***	0.02***	–
	(0.009)	(0.007)	(0.010)	(0.003)	
DYNAMIC: LONG-RUN					
Corn acreage	0.38***	-0.23***	-0.04**	-0.10***	
	(0.025)	(0.011)	(0.021)	(0.008)	0.04***
Soy acreage	-0.34***	0.27***	-0.01	0.08***	(0.019)
	(0.024)	(0.014)	(0.013)	(0.021)	
Other acreage	-0.08**	-0.01	0.07**	0.03**	–
	(0.040)	(0.012)	(0.030)	(0.013)	
STATIC					
Corn acreage	0.61***	-0.40***	-0.02***	-0.19***	
	(0.010)	(0.008)	(0.004)	(0.003)	0.03***
Soy acreage	-0.65***	0.48***	-0.04***	0.20***	(0.003)
	(0.013)	(0.010)	(0.004)	(0.004)	
Other acreage	-0.03***	-0.04***	0.06***	0.01***	–
	(0.006)	(0.004)	(0.005)	(0.002)	

Note: Standard errors are obtained by delta method and displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. η_T is the responsiveness of total acreage allocated to corn and soybeans w.r.t. same scaling changes in both prices.

Table 3.5. Estimation Results for Corn and Soybean Yields under SUR Model

	Without price		With price	
	Corn yield	Soy yield	Corn yield	Soy yield
Variables	(1)	(2)	(3)	(4)
Corn price			0.233*	
			(0.120)	
Soy price				-0.001
				(0.016)
Growing degree days	0.008***	0.007***	0.008***	0.007***
	(0.001)	(<0.001)	(0.001)	(<0.001)
Excess degree days	-0.299***	-0.069***	-0.299***	-0.069***
	(0.004)	(0.001)	(0.004)	(0.001)
Palmer index in May	-1.054***	-0.375***	-1.052***	-0.370***
	(0.048)	(0.013)	(0.048)	(0.013)
Palmer index in Jun	-0.484***	-0.181***	-0.503***	-0.190***
	(0.051)	(0.014)	(0.052)	(0.014)
Palmer index in Jul	1.636***	0.188***	1.653***	0.196***
	(0.051)	(0.014)	(0.052)	(0.014)
Palmer index in Aug	0.772***	0.693***	0.770***	0.685***
	(0.050)	(0.014)	(0.050)	(0.014)
Palmer index in Sep	-0.382***	-0.017	-0.375***	-0.017
	(0.050)	(0.014)	(0.050)	(0.014)
Trend	1.666***	0.431***	1.682***	0.442***
	(0.008)	(0.002)	(0.011)	(0.003)
Constant	77.771***	12.452***	74.046***	10.680***
	(3.202)	(0.893)	(3.374)	(0.945)
R^2	0.76	0.76	0.76	0.76
Cross correlation of residuals	0.56		0.56	
Own price elasticity			0.010*	-0.0004
			(0.005)	(0.005)

Note: Standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. For elasticities, standard errors are obtained by delta method.

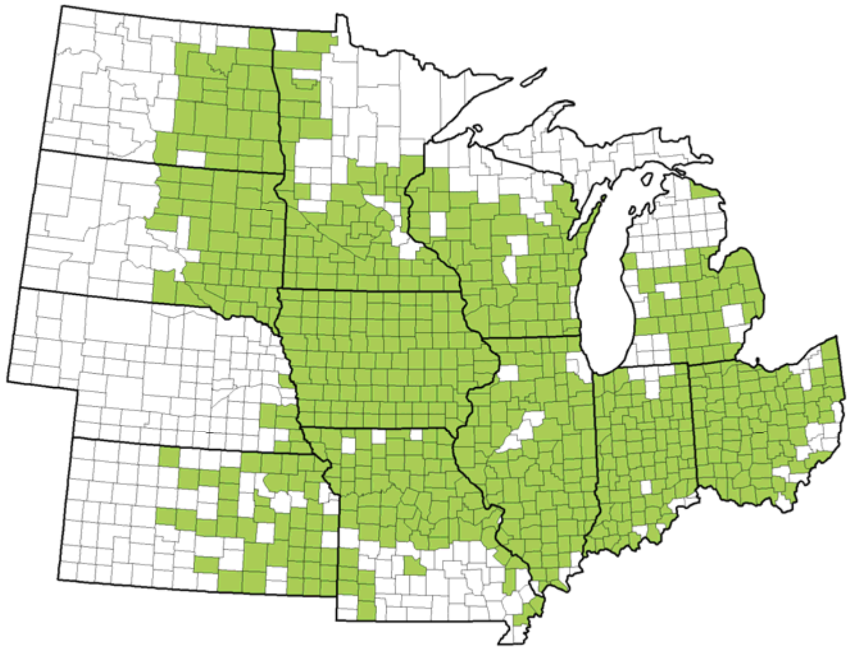

Figure 3.1. The coverage of analysis: 686 counties in 12 Midwestern states

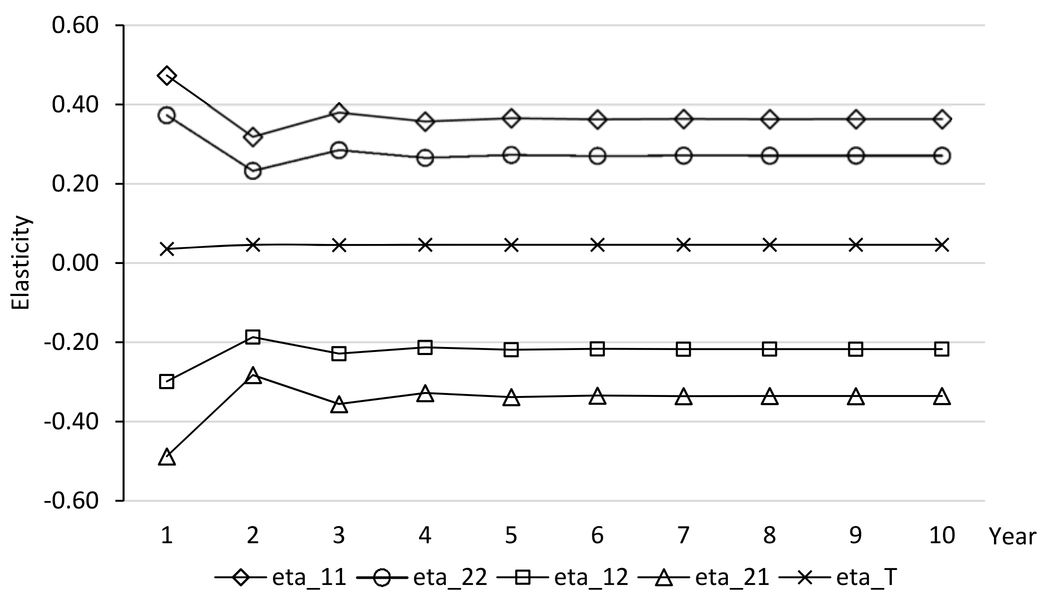

Figure 3.2. Adjustment of Acreage Responses to Changes in Per-Acre Revenues

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APPENDIX B

SUPPLEMENTARY MATERIALS

B.1 Parametric Restrictions

Suppressing subscripts for county and time, we have following supply functions when optimal acreage allocation $l_k(\cdot)$ satisfies the homogeneity of degree zero in its arguments:

$$q_1 = l_1(r_1, r_2, r_3, 1)y_1;$$

$$q_2 = l_2(r_1, r_2, r_3, 1)y_2;$$

$$q_3 = l_3(r_1, r_2, r_3, 1)y_3,$$

where $r_k \equiv p_k y_k + v_k$ is the normalized expected per-acre revenue for crop $k = 1,2,3$. Assume that the covariance term v_k in the expected revenue is constant over time and assume that expected yield is not responding to price (based on our yield estimation results). Then we have following substitution matrix:

$$\begin{pmatrix} \frac{\partial q_1}{\partial p_1} & \frac{\partial q_1}{\partial p_2} & \frac{\partial q_1}{\partial p_3} \\ \frac{\partial q_2}{\partial p_1} & \frac{\partial q_2}{\partial p_2} & \frac{\partial q_2}{\partial p_3} \\ \frac{\partial q_3}{\partial p_1} & \frac{\partial q_3}{\partial p_2} & \frac{\partial q_3}{\partial p_3} \end{pmatrix} = \begin{pmatrix} \frac{\partial l_1}{\partial r_1} y_1^2 & \frac{\partial l_1}{\partial r_2} y_1 y_2 & \frac{\partial l_1}{\partial r_3} y_1 y_3 \\ \frac{\partial l_2}{\partial r_1} y_2 y_1 & \frac{\partial l_2}{\partial r_2} y_2^2 & \frac{\partial l_2}{\partial r_3} y_2 y_3 \\ \frac{\partial l_3}{\partial r_1} y_3 y_1 & \frac{\partial l_3}{\partial r_2} y_3 y_2 & \frac{\partial l_3}{\partial r_3} y_3^2 \end{pmatrix}.$$

After applying the transformation from acreage to optimal share $s_k \equiv l_k / a$ (based on the fixed cropland over the period), we can derive the symmetry restriction for estimation as follows:

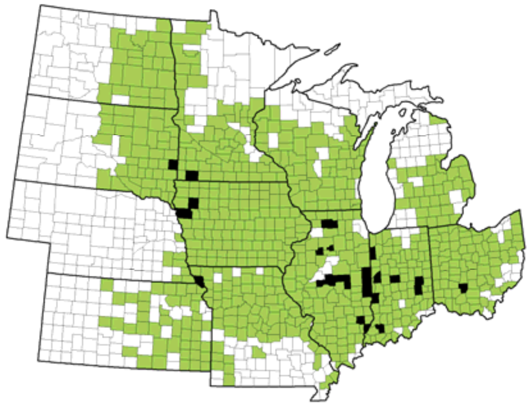
$$\frac{\partial q_1}{\partial p_2} = \frac{\partial q_2}{\partial p_1} \Leftrightarrow \frac{\partial l_1}{\partial r_2} y_1 y_2 = \frac{\partial l_2}{\partial r_1} y_2 y_1 \Leftrightarrow \frac{\partial s_1}{\partial r_2} = \frac{\partial s_2}{\partial r_1} \Leftrightarrow \beta_{12} = \beta_{21}.$$

Other two symmetry restrictions are used in equation (10) for retrieving elasticities.

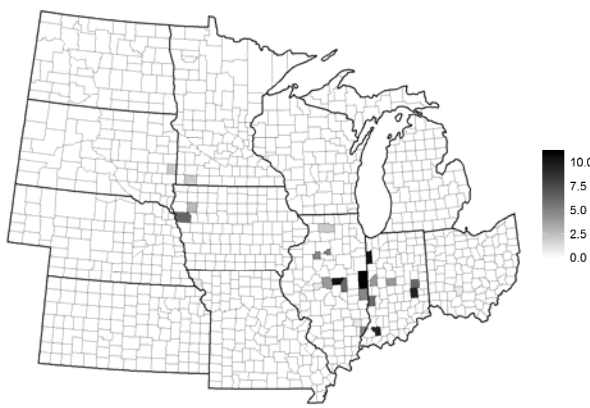
B.2 Replacing Total Cropland Values Using Cropland Data Layer (CDL)

In the CDL webpage, the Metadata section describes the categories of crop and land use in the CDL. The county-level values for the CDL are provided from the FAQ section in the CDL webpage (https://www.nass.usda.gov/Research_and_Science/Cropland/sarsfaqs2.php). Given that the data do not cover our entire data period, we choose to use the values in 2010, from which the sub-grids becomes 30m from 56m, to calculate the ballpark area for other crops. We consider the other crops as all crops except for corn and soybeans, including fallow/idle cropland (where idle cropland includes the area under the conservation reserve program).

There are 118 data points in 24 counties for which the total cropland from NASS survey data is larger than the sum of corn and soybean acreages from the official NASS estimates. Figure B1 describes those counties with dark black, while the panel (b) describes the intensity of having the unmatched data points within the county. In panel (b), the scale from 1 to 11 is described by degree of darkness. For those unmatched points, we first add the CDL other crop acreage to their corn and soybean acreages to obtain a new total cropland. Then we replace the unmatched total cropland values with the new values for those 118 data points. Now, if there are multiple unmatched cases within a county, we choose the largest total cropland and replace others with it. Since we are maintaining the assumption that total available cropland is fixed during the analyzed period, the replacement within county does not affect the estimates as long as the county-specific heterogeneity is controlled.



(a) Unmatched counties



(b) Unmatched observations within counties

Figure B1. Counties having unmatched total cropland values

B.3 Metric for the Local Demand of Ethanol Plants

B.3.1 The model

Notation (ignoring the time subscript t)

N = number of counties

M = number of ethanol plants.

X_i = (expected) corn output of county

K_j = capacity of ethanol plant j

d_{ij} = distance between the centroid of county i and the location of plant j ($d_{ij} > 0$)

x_{ij} = shipment of corn from county i to plant j

E_i = index of ethanol-plant corn demand for county i

Quadratic Programming Formulation

The problem of interest is to source enough output to meet each plant's capacity from the closest source points. The presumption is that there is more than enough total corn, i.e., $\Sigma_{i=1}^{N} X_i \geq \Sigma_{j=1}^{M} K_j$.

Let $c(x_{ij})$ denote the cost of shipping corn from county i to plant j, and we assume that transportation costs are quadratic in the volume shipped, i.e.,

$$c(x_{ij}) = d_{ij} \times \left(x_{ij} + \frac{\gamma}{2} x_{ij}^2 \right), \qquad \gamma > 0.$$

Hence the sourcing of corn for ethanol plants can be formulated as a quadratic programming problem:

$$\min_{\{x_{ij}\}} \sum_{i=1}^{N} \sum_{j=1}^{M} d_{ij} \left(x_{ij} + \frac{\gamma}{2} x_{ij}^2 \right) \qquad \text{s.t.} \qquad \sum_{j=1}^{M} x_{ij} \leq X_i, \ \sum_{i=1}^{N} x_{ij} \geq K_j, \text{ and } x_{ij} \geq 0.$$

Having found the set of shipments $\{\hat{x}_{ij}\}$ that solves the problem, the imputed plant demand for each county is defined as $\hat{x}_i \equiv \Sigma_{j=1}^{M} \hat{x}_{ij}$, and the constraints guarantee that $\hat{x}_i \leq X_i$. Our metric of interest—the intensity of ethanol-plant demand—could then be defined as $E_i \equiv \hat{x}_i / X_i$, where $0 \leq E_i \leq 1$.

Here the solution to this problem is bound to depend on the parameter γ, the value of which is somewhat arbitrary. To calibrate this parameter, we consider the following. There are two contiguous counties for an ethanol plant. Presuming there is enough supply in county 1 for the plant, let x_1 and x_2 denote the shipments from counties 1 and 2 to an ethanol plant (suppressing the plant index), so that the marginal cost of these shipments are

$$mc_1 = d_1(1+\gamma x_1) \text{ and } mc_2 = d_2(1+\gamma x_2).$$

Given that $d_1 < d_2$, the parameter γ will determine the level at which shipments from county 2 become competitive, i.e., $\hat{x}_1$ solves $d_1(1+\gamma \hat{x}_1) = d_2$, implying

$$\gamma \hat{x}_1 = \frac{d_2 - d_1}{d_1}.$$

The RHS measures how further away the centroid of county 2 is from the plant, relative to the distance of the plant from the centroid of county 1. Hence, for a typical plant's capacity-based maximal corn consumption $\tilde{K}$, the parameter γ can be calibrated as

$$\gamma = \frac{\delta}{\tilde{K}},$$

where δ measures how far the second-closest county has to be (relative to the closest county) for the plant capacity to be fully met by the closest county. For example, if $\delta = 5$, then this means that if the second-closest county is less than five times further away relative to the closest county, then both counties will supply corn to the ethanol plant. If however the second-closest county centroid is five times or more further away than the closest county centroid, then the plant will be fully supplied by the closest county. As δ increases, therefore, more counties come into play for a plant, and vice versa.

B.3.2 Data and computation

We consider 170 ethanol plants ($M = 170$), which have ever been operated during 2005-2015. They are all located in the Midwest. For each plant, we then consider nearest twenty counties as potential contributors, for a total of 836 counties analyzed ($N = 836$). Those counties fully cover the 686 counties in our main dataset. For the production level X_i, we use the three year average corn production (2001-2003) by county from NASS/USDA data, and fix the value over entire period (2005-2015) to avoid any possible endogeneity between ethanol pressure and corn production in each year. The annual capacity data for ethanol plants is mainly obtained from the Annual Industry Outlook of Renewable Fuels Association (http://www.ethanolrfa.org/resources/publications/outlook/), and partially from individual websites of biofuel companies. By taking account of the time lag for forming expectation, we calculate the expected ethanol pressure at the decision time in current year based on the last year's capacity information. The haversine distance is calculated from each county to each plant. In regard to the parameter γ, given that the average maximal corn consumption for a plant in 2015 is around 30 million bushels in the dataset, we choose $\delta = 5$ and thereby $\gamma = 1/6$.

Based on those primitive data and parameter values, we solve the above problem using MATLAB and calculate the county-level ethanol pressure. Figure B2 shows the geographic distribution of considered 170 ethanol plants, and Figure B3 describes the calculated ethanol pressure for the 686 counties over the considered period.

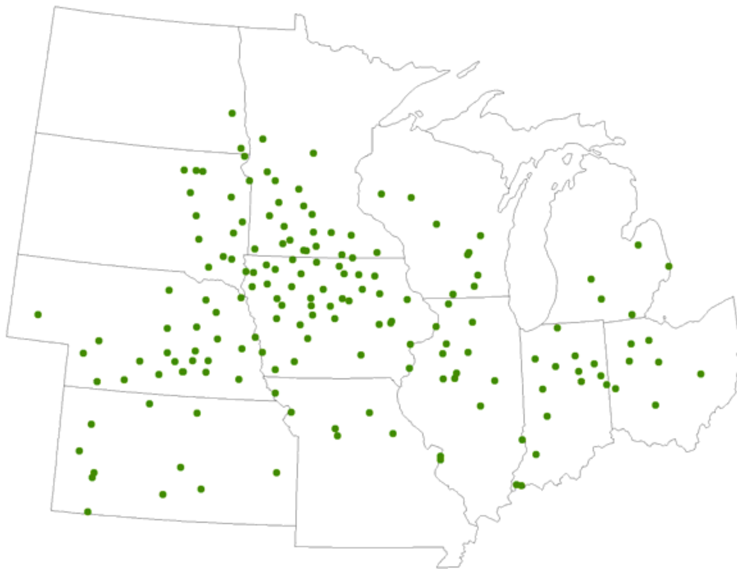


Figure B2. The location of ethanol plants (170 plants)

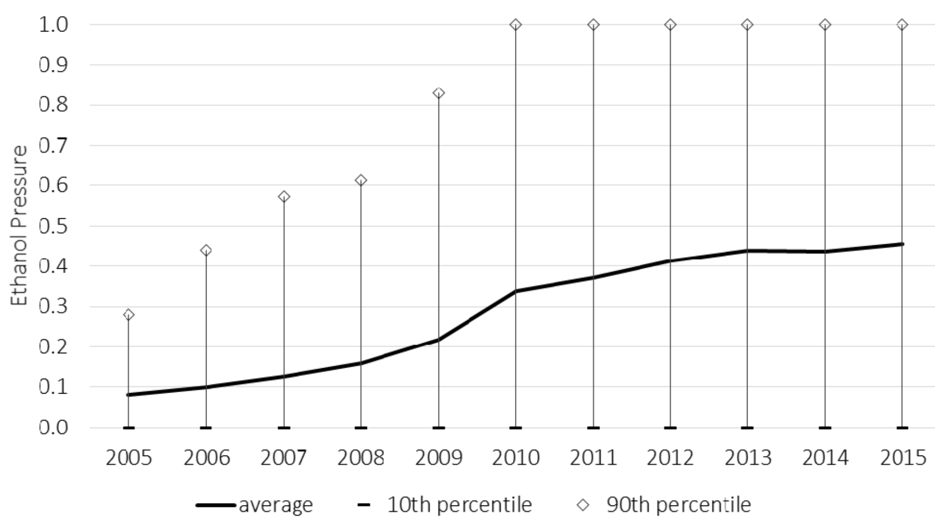


Figure B3. Calculated ethanol pressure for 686 Midwestern counties

B.4 Supplementary Tables

Table B1. Five Major "Other Crops" (% within all crops in 2010 reported in parentheses)

	1st	2nd	3rd	4th	5th
IL	Winter wheat (0.78)	Alfalfa/hay (0.65)	Sweet corn (0.05)	Sorghum (0.05)	Fallow/idle (0.05)
IN	Winter wheat (1.63)	Alfalfa/hay (0.98)	Pop/ornamental corn (0.24)	Fallow/idle (0.03)	Tomatoes (0.03)
IA	Alfalfa/hay (1.75)	Oats (0.22)	Winter wheat (0.01)	Pop/ornamental corn (0.01)	Sod/grass seed (0.01)
KS	Winter wheat (32.77)	Sorghum (7.97)	Alfalfa & hay (2.72)	Fallow/idle (2.56)	Cotton (0.14)
MI	Alfalfa/hay (15.66)	Winter wheat (9.30)	Dry beans (4.04)	Sugarbeets (2.26)	Fallow/idle (1.40)
MN	Spring wheat (7.64)	Alfalfa/hay (2.76)	Sugarbeets (2.31)	Dry beans (0.66)	Sweet corn (0.53)
MO	Winter wheat (3.15)	Cotton (1.09)	Rice (0.49)	Sorghum (0.11)	Fallow/idle (0.07)
NE	Alfalfa/hay (1.44)	Winter wheat (1.23)	Fallow/idle (0.41)	Sorghum (0.01)	Oats (0.01)
ND	Spring wheat (26.11)	Dry beans (5.81)	Alfalfa/hay (3.37)	Sunflower (2.28)	Sugarbeats (1.69)
OH	Winter wheat (7.11)	Alfalfa/ hay (3.57)	Fallow/idle (0.17)	Pop/ornamental corn (0.10)	Oats (0.06)
SD	Alfalfa/hay (16.57)	Spring wheat (6.56)	Winter wheat (4.53)	Sunflower (1.66)	Fallow/idle (0.53)
WI	Alfalfa/hay (25.10)	Winter wheat (20.10)	Oats (2.29)	Dry beans (0.65)	Sweet corn (0.55)

Note: The portion is calculated by "each crop area/total crop area×100" based on Cropland Data Layer dataset for the analyzed 686 counties in 12 states in 2010 (base year for the other crop price index).

Table B2. Estimated Coefficients under Alternative Dynamic Models

	Dynamic model 3: Level OLS		Dynamic model 4: Within-groups		Dynamic model 5: Difference OLS	
	Corn	Soy	Corn	Soy	Corn	Soy
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Corn revenue	0.22*** (0.006)	-0.18*** (0.006)	0.28*** (0.005)	-0.27*** (0.006)	0.30*** (0.005)	-0.28*** (0.005)
Soy revenue	-0.18*** (0.006)	-0.20*** (0.009)	-0.27*** (0.006)	0.31*** (0.007)	-0.28*** (0.005)	0.30*** (0.007)
Other revenue	-0.04*** (0.004)	-0.02*** (0.005)	-0.01*** (0.003)	-0.04*** (0.004)	-0.02*** (0.003)	-0.02*** (0.004)
Lagged corn share	0.94*** (0.003)	0.04*** (0.003)	0.27*** (0.010)	0.24*** (0.007)	-0.25*** (0.010)	0.06*** (0.008)
Lagged soy share	0.04*** (0.003)	-0.95*** (0.004)	0.24*** (0.007)	-0.33*** (0.010)	0.06*** (0.008)	-0.30*** (0.007)
Ethanol pressure	0.004*** (0.001)	<-0.001 (0.001)	0.006*** (0.001)	-0.003* (0.001)	0.008*** (0.002)	-0.003 (0.002)
Palmer index in Mar	-0.005*** (0.0003)	0.002*** (0.0003)	-0.004*** (0.0002)	0.002*** (0.0002)	-0.002*** (0.0001)	0.001*** (0.0001)
Palmer index in Apr	-0.002*** (0.0002)	0.001*** (0.0002)	-0.001*** (0.0001)	<0.001*** (0.0001)	-0.002*** (0.0001)	0.001*** (0.0001)
Palmer index in May	-0.003*** (0.0002)	<-0.001 (0.0002)	-0.003*** (0.0001)	<-0.001 (0.0001)	-0.002*** (0.0001)	<-0.001*** (0.0002)
Trend	-0.002*** (0.0002)	0.002*** (0.0002)	<0.001 (0.0001)	0.002*** (0.0001)	0.001** (0.0004)	0.003*** (0.0003)
Constant	-0.018*** (0.002)	0.029*** (0.002)	0.178*** (0.008)	0.167*** (0.008)		
Cross correlation in residuals	-0.14		-0.13		-0.20	

Note: Standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table B3. Estimation Results for Corn and Soybean Yields under SUR Model Using a Flexible Time Trend

	Without price		With price	
	Corn yield	Soy yield	Corn yield	Soy yield
Variables	(1)	(2)	(3)	(4)
Corn price			-1.507***	
			(0.145)	
Soy price				0.068***
				(0.019)
Growing degree days	0.008***	0.007***	0.007***	0.007***
	(0.001)	(>0.001)	(0.001)	(>0.001)
Over degree days	-0.300***	-0.070***	-0.299***	-0.070***
	(0.004)	(0.001)	(0.004)	(0.001)
Palmer index in May	-1.030***	-0.364***	-1.029***	-0.366***
	(0.048)	(0.013)	(0.048)	(0.013)
Palmer index in Jun	-0.584***	-0.184***	-0.505***	-0.178***
	(0.052)	(0.014)	(0.052)	(0.014)
Palmer index in Jul	1.719***	0.187***	1.649***	0.182***
	(0.050)	(0.014)	(0.050)	(0.014)
Palmer index in Aug	0.762***	0.686***	0.776***	0.692***
	(0.050)	(0.014)	(0.050)	(0.014)
Palmer index in Sep	-0.406***	-0.024*	-0.459***	-0.026*
	(0.049)	(0.014)	(0.050)	(0.014)
Trend 1971-1985	1.457***	0.493***	1.233***	0.478***
	(0.033)	(0.009)	(0.039)	(0.010)
Trend 1986-2000	1.555***	0.362***	1.424***	0.342***
	(0.026)	(0.007)	(0.029)	(0.009)
Trend 2001-2015	2.059***	0.497***	2.111***	0.505***
	(0.030)	(0.009)	(0.031)	(0.009)
Constant	80.693***	11.947***	95.430***	13.266***
	(3.206)	(0.896)	(3.693)	(0.967)
R^2	0.77	0.76	0.77	0.76
Cross correlation of residuals	0.56		0.56	
Own price elasticity			-0.063***	0.021***
			(0.006)	(0.006)

Note: Standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. For elasticities, standard errors are obtained by delta method.

CHAPTER 4

VOLUNTARY AGREEMENTS FOR EMISSION REDUCTION: OLIGOPOLY MARKET WITH GREEN CONSUMERS

4.1 Introduction

Given environmental externalities from firms' production activities, there are uncompensated welfare losses in an economy. Various instruments are used to resolve such externality problems, where their primary goal would be to reduce pollution, thereby improving welfare. With perfect information about environmental damages, a Pigouvian tax would be the most efficient way to achieve the goal. This belongs to economic incentive approaches that—together with tradable permits—offer alternatives to command-and-control type instruments. Another type of instrument related to economic incentives consists of voluntary approaches. Although there are differences in details, voluntary approaches in environmental policies generally rely on commitments of participants to go voluntarily beyond regulation, which has the potential of cost savings on legislation and regulation (Segerson and Miceli 1998; Fleckinger and Glachant 2011).

Voluntary agreements (VAs), by regarding voluntary approaches as a form of agreements, have been used increasingly all around the world. According to the OECD database (http://www2.oecd.org/ecoinst/queries/Default.aspx, accessed April 2017), there are 322 distinguishable VAs in 22 countries, with available data mostly from European countries. In the United States, after the introduction of the Environmental Protection Agency's (EPA) 33/50 program in 1991, there are a growing number of VAs initiated solely by EPA: 28 in 1996, 54 in 1999, and 87 in 2005 (Khanna and Brouhle, 2009, p. 144). According to Carmin et al. (2003), in

United States there are more than 150 VAs, sponsored by the government, industries, and independent third parties (NGOs).

The motivations for firms to participate in VAs are considered mainly two-fold (Lyon and Maxwell 2002; Fleckinger and Glachant 2011): to avoid the threat of an alternative policy (e.g., a tax), and to appeal to consumers who value environmentally-friendly behavior (green consumers). These two motives are accepted as plausible, yet most studies investigate each of them separately. In this essay, we consider both motives together in order to analyze the scope for a VA policy, relative the *laissez faire* (i.e., no policy) and tax policy. To be specific, this essay adds to the previous literature related to multi-firm participation decisions in that oligopolistic product differentiation is embedded in a VA context. This provides a more comprehensive framework to investigate the incentives of firms in their participation behavior and to characterize the feasibility of implementing a VA and its comparable merits relative to other policy options.

Because VAs typically involve a limited number of firms, it is natural to postulate oligopolistic competition. This point has been made by David (2005) who compares tax policy and VA under an oligopolistic setting. But he leaves out the possibility of product differentiation based on consumer preference and also the possibility of firms' free-riding behavior (thereby ending up with full or zero participation). Having postulated the presence of green consumers, we assume that firms operate in an oligopolistic product differentiation setting in the same manner as Bagnoli and Watts (2003). In addition, to incorporate the freeriding behavior, we consider self-enforcing equilibrium in terms of the number of participation under a VA.[35]

To deal with product differentiation and the operation of a VA together, it is assumed that a firm can enhance its environmental performance by adopting a new technology. Furthermore, a VA aiming to reduce industry-wide emissions simply requires firms to use the new technology to join in. This kind of requirement can be found, for example, in the French agreement on treatment of ELVs. Under this VA, the car manufacturers and insurance companies who decided to join in the VA have stated that they only will deal with certified dismantlers. Therefore, a critical mass of dismantlers must be certified so that the volume of ELVs generated by these groups can be handled effectively. Thus, by considering manufacturers and dismantlers as a whole, this is a situation where participants have to adopt facilities for reducing marginal emission rates. It is said that "[c]ertification of the dismantlers is a key element in the success of the EA [environmental agreement] as it provides a means of, largely, excluding free-riders" (EEA, 1998, p. 13; [ ] added). Another example is the Danish agreements on industrial energy efficiency, in which firms get a rebate on their tax payment by committing investments for enhancing their energy efficiency (OECD 2000).

Lyon and Maxwell (2008) distinguish voluntary agreements and public voluntary programs, where the former is based on regulatory threat and the latter is not (but with in-kind subsidy). They categorize US voluntary programs into the latter. As in Fleckinger and Glachant (2011), the VA in this essay is closer to the former which is more frequently used in non-US

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[35] This equilibrium concept was introduced by D'Aspremont et al. (1983) in an effort to explain the stability of cartels. Applications to voluntary environmental agreements include Carraro and Siniscalco (1993), Barrett (1994) and Dawson and Segerson (2008).

region. But even for public voluntary programs in the United States, it might be seen that the threat-based motive is embedded in it as shown empirically by Khanna and Damon (1999) with EPA's Voluntary 33/50 Program.

In addition to the participants' incentive, we consider the regulator's incentive in terms of choosing policy options. We assume the regulator maximizes the social welfare by choosing a policy to implement along with a pursuing emission target, but at the same time she perceives a political cost associated with the use of tax policy, a cost that is avoided with a VA (or in the *laissez faire* situation). In the real world the efficient tax policy is often not chosen (Davis and Knittel 2016), and we conjecture that this reflects policymakers' unwillingness to bear the political cost associated with the use of tax instruments.[36]

Using the proposed structure, we obtain the equilibrium of the game in which the regulator chooses a policy option given subgame-perfect equilibria under the *laissez faire*, VA and tax policy. Through numerical simulations, we find that when the market is non-competitive, the VA, relative to other policy options, improves welfare despite its inefficiency from the presence of free-riding behavior. This advantage wears off as the market becomes more competitive. Our results complement the conclusion in Dawson and Segerson (2008), who focus on the supply side, that a VA is less preferred than a tax policy by a welfare-maximizing regulator due to its inefficiency. The main reason for our results is that when the market is non-competitive, so that the under-production problem prevails, the VA, relative to the tax policy, induces firms to produce more (green) output. Importantly, not all consumers always welcome

[36] While ignored in this paper for simplicity, the target of the VA can be an outcome of negotiation between a regulator and a group of firms. Such situation is dealt with, for example, by Segerson and Miceli (1998), Glachant (2007), Fleckinger and Glachant (2011), and Langpap (2015).

the VA (unlike the argument in David 2005). As the consumers value the green good more, the VA increases the number of green firms and provides a less competitive environment for free-riders, who increase the price of regular goods. As a result, the total market is less covered, at some point, than the tax policy. As to implementation, the potential payoff of the VA is attainable provided the regulator's threat is credible and sufficiently strong. Apart from it (or for the cases of weak threat), a high political cost can make the VA (or *laissez faire*) policy implemented over the tax policy despite its lower potential to affect welfare (similar to the conclusion about non-binding VAs in Glachant 2007).

The chapter is organized as follows. In Section 4.2, we provide a brief background about the major motives for VA participation. Section 4.3 elaborates the model for the analysis of multi-firm product differentiation. In Section 4.4, the equilibrium of the game is analyzed after investigating equilibria under two subgames, such as, product differentiation under tax policy and product differentiation under a proposed VA. Based on reasonably assumed parameter values, numerical simulations are conducted in Section 4.5 to explore the characteristics of equilibrium. Sensitivity analysis provides a more general picture regarding possible policy implementations. Section 4.6 summarizes conclusions.

4.2 Background

In this section we briefly review the literature and evidence about the main two motivations—a regulatory threat and green consumers—for VA participation. Refer to Lyon and Maxwell (2008) for a more general survey of theoretical work and welfare implications in regard to VAs and self-regulation.

Lyon and Maxwell (2002) analyze the increased use of VAs and summarize three motives that corporations can have for regulating themselves: i) cost-cutting, ii) marketing to green consumers who are willing to pay extra for environmentally friendly products, and iii) pre-empting government regulation.[37] Although there are writers supporting the first motive,[38] Lyon and Maxwell point out that the puzzle is why there should be any opportunities for making money by cleaning up, where there is no systematic evidence for this motive empirically. For the second motive, several theoretical studies have been conducted regarding product differentiation, which give clear and coherent insights regarding corporate behavior.[39] Given that the third motive is often investigated by theoretical research, Lyon and Maxwell conclude that there is modest evidence that the threat of future regulation is a significant factor prompting firms to self-regulate. For an example of the empirical evidence, Khanna and Damon (1999) find that compliance under mandatory environmental regulations provides strong incentives for participation under the 33/55 program. Fleckinger and Glachant (2011) also conculde that VA participation is mainly motivated by future threat policies and green preference of consumers, workers and shareholders.

Given that the motives based on a threat policy and green consumers and are compelling, the selected research dealing with the regulatory threat is as follows. With a simple bargaining

[37] Alternatively, Croci (2005, pp. 11-20) enumerates seven specified incentives to participate in VA, including the above three rationales discussed by Lyon and Maxwell (2002).

[38] For example, Smart (1992) mentions 3M's "Pollution Prevention Pays" program that achieves cost saving by reducing its total emissions. In addition, Howarth, Haddad, and Paton (2000) conduct case studies for two EPA's VAs, "Green Light" and "Energy Star Office Products," arguing that those are helpful for saving costs by promoting the adoption of energy efficient technologies by firms.

[39] Despite the lack of clear empirical evidence for the second motive, it is worth investigating further. Börkey et al. (1998) illustrate that the potential benefit of self-regulation is provided by product differentiation, using an example of German "Blue Angel,'' where most of products with this label are more expensive than non-labeled alternative goods.

game situation of one representative firm and regulator, Segerson and Miceli (1998) show that policymakers can induce firms to engage in a VA by a threat of mandatory controls (the "stick approach") as well as by cost-sharing subsidies (the "carrot approach"). Recently, several articles have focused on the interaction among firms, rather than the interaction between one firm and the government under a regulatory threat. David (2005) considers an oligopolistic market to compare tax policy and VAa. Based on full or zero participation outcome, he finds that a VA may be more efficient than taxation in a concentrated industry if pollution is not too damaging and if cheap and efficient abatement technology is available. Dawson and Segerson (2008) develop a multiple-firm model of pollution abatement where an entire industry is faced with possible imposition of an emissions tax if the industry level target is not met. They use the concept of self-enforcing equilibrium to show the existence of equilibrium in which a VA is implemented successfully and to show free-riding behaviors (i.e., not joining in a VA) exist among firms under a successful VA. Similarly, Brau and Carraro (2011) examine the incentive of multiple firms to join in a VA by allowing free-riding behavior, where there are spill-over effects for participants, given a threat of nullifying the VA. McEvoy and Stranlund (2010) investigate consequences of costly enforcement on the ability of VAs in a setting very similar to that of Dawson and Segerson (2008).

The studies on the motive of green consumers are as follows, where most of them focus on product differentiation without modeling a detailed VA structure. Based on the analyses of Gabszewicz and Thiesse (1979) and Shaked and Sutton (1982) regarding vertical product differentiation, Arora and Gangopadhyay (1995) study standard vertical product differentiation under duopoly where a firm's environmental performance is differentiated. They show why some firms voluntarily overcomply with environmental regulation. Under their model, it is found that a minimum standard binding on the dirty firm has the effect of improving the performance of the greener firm. A subsidy obtains the same competitive outcome. The duopolistic vertical differentiation is also dealt with in Bansal and Gangopadhyay (2003), extending the model of Arora and Gangopadhyay (1995), and deriving additional implications that a policy of discriminatory subsidy improves welfare and alleviates total pollution. Given an exogenous division of green and brown consumers, Rodríguez-Ibeas (2007) shows that an increase in the proportion of green consumers is not always good for the environment. In a more general sense, García-Gallego and Georgantzís (2009) analyze the welfare effect of consumers' social consciousness by varying the shape of preference distribution and the market structure. The effect of consumers' awareness about products is also investigated by Brouhle and Khanna (2006) and Brécard (2013) under a model of duopolistic vertical differentiation. Bagnoli and Watts (2003), under a multiple-firm setting, study several vertical differentiation models where environmental friendliness is only partially internalized by consumers. They find that in some but not all cases unregulated competition for green consumers can provide the socially optimal level of the environmental public good.

The previous work has dealt with either the motive of green consumers or the motive of threat policy, but not both together to explain the VA participation behavior. When it comes to the question about the performance of a VA, however, it is hard to pull apart those two motives. Clearly, firms have many ways to differentiate their products vertically in response to green consumers. First, firms can directly put certain labels on their products. According to the Ecolabel Index (http://www.ecolabelindex.com/, accessed April 2017), for example, there are 465 ecolabels in 199 countries and 25 industry sectors, while 203 ecolabels exist in the United States alone. Through VAs, furthermore, firms can label their products officially. With the

Danish agreement on recycling of transport packaging, for example, public access to information is quite easy due to the well-developed 1970 Freedom of Information Act (European Environmental Agency [EEA] 1998, p. 107). In the United States, for example, EPA's VAs, such as ENERGY STAR, WaterSense, and Design for the Environment (now, Safer Choice), have their own labeling policy. Direct listing of participants' performance publicly as in the 33/50 program also makes consumers aware of the performance of firms, causing product differentiation. To sum up, product differentiation is possible either by a firm's own labeling or by joining in a VA.

A regulatory threat—for example, a potential tax policy—is relevant when total emissions in an industry are considered high (even with the existing environmental friendliness for labeling). Given a binding threat, a VA can be initiated to further reduce aggregate emissions in the industry. To illustrate, the VA can take the form of an agreement between the regulator and a group of firms in a relevant industry with an explicit industry-wide target. Examples include the Netherland's KWS 2000 project on reduction of volatile organic compounds (Lévêque and Nadaï 2000); the French agreement on the treatment of end-of-life vehicles (ELVs) (EEA 1998; Lévêque and Nadaï 2000); and the declaration by German industry and trade on global warming prevention (EEA 1998).

All things taken together, the two motives—a regulatory threat and green consumers—coexist for firms that are potential participants in a VA. In this regard, Baron (2011) analyzes a situation where multiple firms in a voluntary organization endogenously decide the "credence" attribute of their products in the presence of consumers valuing the credence and with social pressure from NGOs. It is found that the credence standard is lower with a larger size of organization but higher under social pressure. The model in Baron (2011) simply starts with a fixed division of two groups, firms producing credence goods and firms producing basic goods. In addition, it is assumed that the former group is all in the voluntary organization from the beginning and the latter group is in a perfectly competitive market. In concluding, the author demands future research on several issues, including "the formation and governance of credence organization, including the participation decision of firms" (p. 1337).

Admittedly, the sponsor who initiates a VA is not specified in this essay, whereas the threat of potential tax policy is coming from the regulator. In the United States, for example, VAs are sponsored by government, industries, and third parties. As analyzed by van't Veld and Kotchen (2011), each sponsor might have different characteristics with respect to monitoring ability, capability of using a subsidy or tax, and incentives to control the size of membership. This paper ignores such differences by focusing on the sponsors' goal to reduce industry-wide emissions through the VA. Note that one of the motivations for development of industry-sponsored VAs is actually to avoid, affect, or delay regulation (Carmin et al., 2003). Therefore, whether the target can be met or unmet is the main issue even for the industry sponsor.[40]

4.3 The Model

We consider an industry that consists of N identical firms, each of which produces one of two (differentiated) goods. We assume that N is large enough to have no monopolistic equilibrium in terms of the industry. During the analysis, the integer issue in the number of firms is often ignored for the convenience. For an individual firm i, let C_i be its total costs and E_i be

[40] According to Darnall et al. (2003)'s survey, among 61 VAs that responded from the initial sample of 105 VAs, there are 42 VAs sponsored by government, 9 VAs sponsored by industry, and 10 VAs sponsored by a third party. Ignoring a potential selection bias when receiving responses, government-sponsored VAs are the majority of currently operating VAs.

its total emissions when producing q_i. Now, consider two possible technologies in production and abatement, namely "new" and "old" technologies. Let subscript n and o represent "new" and "old" technologies respectively, and as explained later, they also indicate "green" and "regular" goods (or firms). For firms using new technology, $C_{in} = c_n q_{in}$ and $E_{in} = e_n q_{in}$, while for firms using the old technology, $C_{io} = c_o q_{io}$ and $E_{io} = e_o q_{io}$, where c_n and c_o are the corresponding constant marginal production costs and e_n and e_o are the corresponding constant marginal emission rates with $c_n > c_o$ and $e_n < e_o$.[41] The resulting industry-level emission is $E \equiv \Sigma_{i=1}^{N} E_i$. It is assumed that the product differentiation is possible only in terms of which technology is used in production. Practically, as mentioned in the Introduction, such product differentiation is possible through direct production labeling or indirect information sharing under VAs.

Along with the production structure, the model incorporates the green preference of consumers who care about producers' environmental performance. To be specific, given the firm's ability to differentiate its products based on the technology, consumers are able to distinguish the version of products such as products made by firms using new technology and those made by firms using old technology. Thereby the former is considered as green good (or product made by green firms), while the latter is considered as regular good (or product made by

[41] Bagnoli and Watts (2003) considered binary cost structure regarding two versions of products in two ways: i) different marginal costs with no fixed costs, and ii) same marginal costs with different fixed costs. The former is dealing with c_n for non-linked version of private good and c_ρ for public good that is linked, where the marginal cost for producing private good that is linked with public good is $c_n + c_\rho$ which is greater than that of non-linked version, c_n. The latter is assuming that the cost for producing non-linked version is $c_n + F_n$ while it is $c_n + F_n + F_\rho$ for the linked version. In our model, the former is chosen.

regular firms). Taking into account green preferences, the only channel through which firms can demonstrate their environmental friendliness to green consumers is to use the new technology.

Technically, a unit mass consumers, whose type is denoted by θ , are uniformly distributed over [$\underline{\theta}$, $\overline{\theta}$], where $\underline{\theta}+1=\overline{\theta}$. The value of θ represents the taste of individual consumer. Each consumer buys at most one unit of the product. Specifically, consumer's utility function is written as $U=m+u(y;\theta)$, where m is the common income level, and

$$u(y;\theta)=\begin{cases}0 & \text{if } y=0,\\ \theta(1+s) & \text{if } y=1 \text{ and it is made by the new technology,}\\ \theta & \text{if } y=1 \text{ and it is made by the old technology;}\end{cases}$$

where y is the unit of consumer's purchase; s (>0) captures the additional benefit for consuming a product made by new technology compared to old one. Under this setting, consumers who are willing to pay more for products by the old technology are willing to pay a higher premium when those are produced by the new technology.

Based on the structure of supply and demand sides, we introduce Assumption 1.

Assumption 1. (a) $s\overline{\theta}>c_n-c_o$ and (b) $c_n/(1+s)>c_o$.

Assumption 1(a) means that at least for the consumer who has the highest willingness-to-pay for greenness, the additional benefit by purchasing the greener good exceeds the additional costs for a firm to produce it. Next, Assumption 1(b) implies that the normalized marginal production cost for giving one unit of utility for consumer θ is higher for green good than regular one.

Based on the foregoing structure, the game of interest can be described as follows. The baseline is the *laissez faire* situation (i.e., without any policy). The regulator may wish to reduce the industry-wide emissions up to a certain target by means of policy instruments such as a tax policy or a VA. The emission level which is regarded as appropriate by the regulator can be used as an ex ante regulatory target for a VA policy, or as the basis for setting a tax policy.[42] The regulator's payoff consists of social welfare and a fixed political cost $K\,(\geq 0)$ if a tax policy is implemented.[43] The presence of the political cost decreases the merit of a tax policy for the regulator, thereby making VA (or *laissez faire*) more attractive. The basic structure of the extensive form game is depicted in Figure 4.1 in a somewhat very condensed way. For each payoff matrix, the first element pertains to the regulator and the second pertains to firms.

The whole game consists of three main subgames for no policy (*laissez faire*), tax policy, and VA, respectively. We first consider the tax game where it corresponds to the subgame in which the regulator chooses "Tax policy" in Figure 4.1. Once the regulator decides to go for a tax policy, the following three-stage game is played. In Stage 1, the regulator chooses the tax rate $t\,(\geq 0)$ to meet the desired emission target $\overline{E}^T$. In Stage 2, firms decide which technology to use. In Stage 3, firms engage in quantity competition given the emission tax, where the aggregate emission level is determined accordingly with constant emission rates. We find Nash equilibrium for Stage 3 and in turn Stage 2. Especially for the quantity decision in Stage 3, we focus on symmetric outcomes such that all green firms choose a same level of outputs and all regular firms choose a same level of outputs respectively. This tax game is also a subgame for the

[42] In reality, explicit industry-wide targets are embedded for some VAs, while some VAs do not have such targets (as well as individually assigned ones). Even for the VAs with no explicit targets, however, it can be said that the initiation of them is motivated to pre-empt the regulator's threat policy which might be implemented if no further action is taken.

[43] Introducing a political cost for (tax) regulation is in the same vein as the assumption in for example, Segerson and Miceli (1998), who posit that the VA incurs smaller costs borne by the regulator. Fleckinger and Glachant (2011) also consider that adopting a new regulation is costing for the regulator in terms of spending administrative resources. We simply assume a fixed amount of such cost, which can give us enough intuition in our model. We do not consider uncertainty of threat policy, which is taken care of by a simple probability of passing the legislation in Segerson and Miceli,(1998), Lyon and Maxwell (2003), and Fleckinger and Glachant (2011).

following VA game and its equilibrium outcome is crucial because the severity of the potential emission tax is another motive for firms to join in a VA besides the green consumers. Note that if the regulator chooses the *laissez faire* option, this is equivalent to the case of zero tax rate in the tax game (and $K = 0$).

Next, suppose the regulator chooses to propose the VA with a regulatory threat, which is describes by the subgame in which the regulator chooses "VA" in Figure 4.1. We then consider following three-stage game. In Stage 1, the regulator chooses her regulatory emission target, $\overline{E}^V$. It is also announced that if the participants who adopt the new technology are gathered enough to achieve the target, the VA keeps going forward, otherwise a certain level of tax rate τ (> 0) —a threat tax rate—will be imposed by the end of Stage 2. Thus, there is a possibility that the proposed VA will be cancelled in the middle of the process due to the expectation of its poor performance. In Stage 2, firms decide whether to join a VA. The participating firms in the VA only commits to use the new production technology that causes a higher marginal cost but a lower emission rate per product. The outcome of participation decision in Stage 2 determines the next stage. If there are not enough participants for the target, then the VA becomes ineffective and firms instantaneously face with the tax game based on the announced threat tax rate. If there are enough participants, the VA successfully proceeds to the next stage. In Stage 3, firms do quantity competition in the absence of emission tax and result in the target level of aggregate emissions.

Note that in Stage 2 of the VA game we investigate two compelling settings in terms of the threat tax rate τ (similar to the discussion in David 2005): pre-commitment case in which any τ is credible by firms, and time-consistency case in which only credible threat level is the one that the regulator would impose under the tax policy without any threatening purpose (i.e., $\tau = t$). These two cases provide implications about the credibility of the threat, which is crucial to successfully implement the VA.

We consider Nash equilibrium for Stage 3 in the VA game. Note that the regulator's decision regarding whether to implement the tax policy or not is made in Stage 2. Provided that the VA proceeds to Stage 3, therefore, firms get into quantity competition in the same manner of Stage 3 in the tax game, but with the exemption of the emission tax (or equivalently, with zero tax rate).[44] We focus on symmetric equilibrium such that the quantity levels for green firms are same and those for regular firms are same respectively. Given the quantity decisions and corresponding industry-wide emissions in Stage 3, the regulator in Stage 2 can determine whether the number of participants are sufficient for the target. The potential implementation of the tax policy generates a threat for firms in terms of profit level they will end up with. But through the paper the term "threat" often refers to the tax rate (or the target emission level) which results in such profit level. For the participation decision in Stage 2, we figure out the self-enforcing number of participants which is stable and profitable for all firms given the threat of tax policy.

In our model the considered VA has a very simple form under which firms are required to use a new technology for participation. While not losing the consistent features with the real world examples (as explained in Introduction), such VA has its merits by making the motive for

[44] In Dawson and Segerson (2008), the emission decision, which is separately considered from quantity decision, is made among firms as follows: non-participants (free-riders) choose their emission level without considering the target, and then participants divide the remaining binding target equally among them. Whereas, in this paper the quantity decision is equivalent to the emission decision with constant emission rates. Additionally, given that the VA only requires to use the new technology and that the potential threat policy is implementable in Stage 2, firms do quantity competition, not particularly concerning the emission target, so long as they arrive Stage 3.

participating in it equivalent to the motive for using the new technology which is resulting in product differentiation. Recall that this essay simultaneously considers two motives: green consumers and a regulatory threat. The first motive is embedded in that being a participant in the VA (and self-labeling without any VA) with the new technology is motivated by product differentiation based on green preference on the demand side. Additionally, given that the *laissez faire* industry-wide emission level is considered high, the VA with a binding threat can make more firms use the new technology, thereby having more participants. Thus the second motive is also included.

4.4 Equilibrium

4.4.1. Equilibrium under a tax policy

We first explore the tax game. Let superscript T represent equilibrium outcome under the tax policy. By backward induction, we find equilibrium output schedules for green and regular firms in Stage 3, and subsequently find an equilibrium number of green firms in Stage 2. When figuring out the equilibrium in Stage 3, the number of green firms N_n and the tax rate τ are treated as given from Stage 2 and from Stage 1, respectively. Furthermore, we need to specify the demand functions that two types of firms face with. Taking into account of the symmetry at equilibrium, let p_n and p_o represent the prices of products made by green firms with new technology and by regular firms with old technology respectively.

The surplus of a consumer whose individual preference is θ looks as follows: $\theta + s\theta - p_n$ if she buys a green product or $\theta - p_o$ if she buys a regular product. Then the preference of the consumer who is indifferent between purchasing a green product and a regular product can be expressed by $\theta_n = (p_n - p_o)/s$, while $\theta_o = p_o$ represents that of the consumer who is indifferent between purchasing a regular product and buying nothing. We consider the case of interior solutions where $\underline{\theta} < \theta_o < \theta_n < \overline{\theta}$.

From the classification of consumers, demands for green and regular goods are obtained as follows.

(1) $$Q_n(p_n, p_o) = \overline{\theta} - \frac{p_n - p_o}{s};$$

(2) $$Q_o(p_n, p_o) = \frac{p_n - p_o}{s} - p_o.$$

Note that the market is uncovered as long as $p_o > \underline{\theta}$. The feature of uncovered market enables us to derive inverse demand functions as model imperfect competition à la Cournot.

Considering the division of demand based on greenness of products, firms choose the technology and engage in output competition. Upon the total number of firms in the industry, N, denote the number of firms using the new technology by N_n and that of firms using the old technology by N_o, where $N = N_n + N_o$. After N_n is determined (and N_o is determined accordingly), each of two groups engages in Cournot type competition by choosing output level. From equations (1) and (2), inverse demand functions can be derived for p_n and p_o respectively as follows: $p_n(Q_n, Q_o) = (1+s)\overline{\theta} - (1+s)Q_n - Q_o$ and $p_o(Q_n, Q_o) = \overline{\theta} - Q_n - Q_o$.

Given an emission tax rate t, marginal costs are now $c_n + te_n$ for green firms and $c_o + te_o$ for regular firms. The profits for green firms and regular firms will be then $\pi_n = (p_n - c_n - te_n)q_n$ and $\pi_o = (p_o - c_o - te_o)q_o$. Dropping subscripts for individuality of firms by focusing on symmetric outcomes, first order conditions for a green firm and a regular firm yield following equations:

(3) $0 = p_n(Q_n, Q_o) - c_n - te_n - (1+s)q_n$;

(4) $0 = p_o(Q_n, Q_o) - c_o - te_o - q_o$,

where $Q_n = N_n q_n$ and $Q_o = N_o q_o$. Knowing that $N = N_n + N_o$, we have following equilibrium quantities for individual green and regular firms for given number of green firms and tax rate:

(5) $$q_n^T(N_n, t) = \frac{[1 + s(N - N_n + 1)]\bar{\theta} - (N - N_n + 1)(c_n + te_n) + (N - N_n)(c_o + te_o)}{(1+s)(N+1) + sN_n(N - N_n)};$$

(6) $$q_o^T(N_n, t) = \frac{(1+s)\bar{\theta} + N_n(c_n + te_n) - (1+s)(N_n + 1)(c_o + te_o)}{(1+s)(N+1) + sN_n(N - N_n)}.$$

Consider the range of $N_n \in [0, N]$, now we have following feature for given N_n and $t > 0$

.

Lemma 1. Under Assumption 1, equilibrium individual quantities are always positive.

Proof. See Appendix C.1.

The aggregate (market level) quantities are readily obtained as $Q_n^T(N_n, t) = N_n q_n^T(N_n, t)$ and $Q_o^T(N_n, t) = (N - N_n) q_o^T(N_n, t)$, all positive by Lemma 1. Then the industry-wide emission level under tax policy is $E^T(N_n, t) = e_n Q_n^T(N_n, t) + e_o Q_o^T(N_n, t)$ for given N_n and t . Note that we have following feature for $N_n \in [0, N]$.

Lemma 2. For fixed numbers of green and regular firms, the industry-wide emission level under tax policy decreases in tax rate.

Proof. See Appendix C.2.

The profits for green firms and regular firms under tax policy will be

(7) $\pi_n^T(N_n,t) = \left[p_n^T\left(q_n^T(N_n,t), q_o^T(N_n,t)\right) - c_n - te_n \right] q_n^T(N_n,t)$;

(8) $\pi_o^T(N_n,t) = \left[p_o^T\left(q_n^T(N_n,t), q_o^T(N_n,t)\right) - c_o - te_o \right] q_o^T(N_n,t)$.

Meanwhile, from equations (3) and (4), we get $q_n = (p_n - c_n - te_n)/(1+s)$ and $q_o = p_o - c_o - te_o$. Then, equations (7) and (8) can be alternatively expressed as equations (9) and (10).

(9) $\pi_n^T(N_n,t) = \dfrac{\left[q_n^T(N_n,t)\right]^2}{1+s}$;

(10) $\pi_o^T(N_n,t) = \left[q_o^T(N_n,t)\right]^2$.

Now, firm's technology decision in Stage 2 can be discussed with the obtained equilibrium profits. First of all, under Assumption 1 $q_n^T(N_n,t)$ and $q_o^T(N_n,t)$ are strictly convex for all N_n (Appendix C.3), and so are $\pi_n^T(N_n,t)$ and $\pi_o^T(N_n,t)$, which are resulted from convex monotonic increasing transformations of $q_n^T(N_n,t)$ and $q_o^T(N_n,t)$ as in equations (9) and (10).[45] Next, owing to the presence of multiple firms, Cournot competition feature maintains within each group of firms in a sense that an increase in the number of firms for one group reduces the relative merit of belonging to that group compared to belonging to the other group. Then there is

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[45] Suppose that $q(\cdot)$ is strictly convex and that $f(\cdot)$ is convex and monotonically increasing. Then for v_1 and v_2 in the domain of $q(\cdot)$ and $\lambda \in [0,1]$, $f\left(q\left(\lambda v_1 + (1-\lambda)v_2\right)\right) < f\left(\lambda q(v_1) + (1-\lambda)q(v_2)\right)$ $\leq \lambda f\left(q(v_1)\right) + (1-\lambda) f\left(q(v_2)\right)$. Therefore, $\pi \equiv f(q(\cdot))$ is strictly convex.

at most one intersection between the two equilibrium profit schedules (ignoring the integer issue on the number of firms). First, we can think of two extreme cases which have no intersection: for given t, if $\pi_n^T(N,t) > \pi_o^T(N,t)$, every firm produces green goods of $q_n^T(N,t)$; if $\pi_n^T(0,t) < \pi_o^T(0,t)$, every firm produces regular goods of $q_o^T(0,t)$. For the interior case ($\pi_n^T(N,t) \leq \pi_o^T(N,t)$ and $\pi_n^T(0,t) \geq \pi_o^T(0,t)$), the unique equilibrium number of green firms satisfies the following condition, as in Bagnoli and Watts (2003, p. 431):

(11) $\pi_n^T(N_n^T,t) = \pi_o^T(N_n^T,t)$.

This condition means there is no incentive for firms to deviate from their current technology decision.[46] From equation (11), we can obtain the equilibrium number of green firms $N_n^T(t)$ which is a function of the tax rate imposed in Stage 1.

Remarkably, we can obtain closed-form solutions for the interior case outcome at the equilibrium of this game, which are functions of t such as $N_n^T(t)$, $q_\ell^T(t) \equiv q_\ell^T(N_n^T(t),t)$, $Q_\ell^T(t) \equiv Q_\ell^T(N_n^T(t),t)$, $\pi_\ell^T(t) \equiv \pi_\ell^T(N_n^T(t),t)$ and $E^T(t) \equiv E^T(N_n^T(t),t)$ for $\ell = n,o$. First, we have expressions for aggregate quantities of green and regular goods in the demand side as equations (1) and (2), while Cournot competition yields expressions for aggregate quantities of green and regular goods in the supply side as above. In addition, equation (11) gives us an extra condition so that we can derive explicit solutions for equilibrium outcomes with exogenous parameters

[46] Note that the equality in the condition is guaranteed by ignoring the integer issue in regards to the number of firms. The equilibrium condition, when considering the integer issue, is that i) no green firm has an incentive to be regular unilaterally, i.e., $\pi_n^T(N_n^T,t) \geq \pi_o^T(N_n^T - 1,t)$, and ii) no regular firm has an incentive to be green unilaterally, i.e., $\pi_o^T(N_n^T,t) \geq \pi_n^T(N_n^T + 1,t)$.

(see Appendix C.4 for the detailed derivation). As an example, the explicit expression for the equilibrium number of green firms looks as equation (12):

$$(12)\qquad N_n^T(t) = \frac{\bar{\theta}\left[(1+s)-(1+s)^{0.5}+sN\right]-(1+N)(c_n+te_n)+\left[(1+s)^{0.5}+N\right](c_o+te_o)}{s\bar{\theta}-\left[1-(1+s)^{-0.5}\right](c_n+te_n)-\left[(1+s)^{0.5}-1\right](c_o+te_o)}.$$

With the obtained solutions, furthermore, comparative statics can be conducted as follows.

Lemma 3. At the interior equilibrium in Stage 2 of the tax game, the following comparative statics hold:

(1) the quantity of individual green firm decreases in tax rate;

(2) the quantity of individual regular firm decreases in tax rate;

(3) the profits of individual green firm decrease in tax rate;

(4) the profits of individual regular firm decrease in tax rate;

(5) the aggregate quantity of green firms increases in tax rate;

(6) the aggregate quantity of regular firms decrease in tax rate;

(7) the number of green (regular) firms increases (decreases) in tax rate;

(8) the industry-wide emission level decreases in tax rate.

Proof. See Appendix C.5.

The above results make sense in that, for example, if a higher tax rate is levied, the industry-wide emission level will decrease at equilibrium with a larger number of green firms resulting in an increased aggregate level of green products. Importantly, Lemma 3 holds for tax rates that yield the interior solution for the Stage 2 equilibrium. Regarding boundary cases, we have Lemma 4.

Lemma 4. Given that all firms are regular ($N_n^T = 0$) or given that all firms are green ($N_n^T = N$) in Stage 2 of the tax game, the individual quantity, individual profit, aggregate quantity and resulting industry-wide emission level of firms decrease in tax rate.

Proof. We know that for $N_n^T = 0$, $\partial q_o^T(0,t)/\partial t = -e_o / (1+N) < 0$, while for $N_n^T = N$, $\partial q_n^T(N,t)/\partial t = -e_n / [(1+N)(1+s)] < 0$. By monotonic transformations, the rest holds.

By Lemmas 3 and 4 we can figure that for any level of emission target, which is smaller than the given *laissez faire* emission level, there will be a tax rate which achieves the target. We now define the full range of applicable tax rates as $t \in [0, t_{\max}]$, where $q_n^T(N, t_{\max}) = 0$, i.e., shutting down.

In Stage 1 the regulator imposes a specific level of t . To achieve the target, she sets $t = \bar{t}$ that satisfies $E^T(\bar{t}) = \bar{E}^T$, where the social welfare is maximized. Based on one-to-one relationship implied by Lemma 3(8) and Lemma 4, one can always find out a tax rate that leads to the corresponding target. Actually, the set of feasible emission levels is $E^T \in [0, E^L]$ where $E^T(t_{\max}) = 0$ and $E^L \equiv E^T(0)$. We consider E^L as the baseline level of total emissions in the *laissez faire* case, and N_n^L ($\equiv N_n^T(0)$) as the baseline number of green firms.

The equilibrium in the tax game is summarized in Proposition 1.

Proposition 1. At the equilibrium under tax policy, for the target $\bar{E}^T \in [0, E^L]$,

(1) the regulator imposes tax rate as $t = \bar{t}$;

(2) the number of green firms and regular firms are, respectively,

$$N_n^T = \begin{cases} 0 & \text{if } \pi_n^T(0,\bar{t}) < \pi_o^T(0,\bar{t}) \\ N & \text{if } \pi_n^T(N,\bar{t}) > \pi_o^T(N,\bar{t}) \\ N_n^T(\bar{t}) & \text{otherwise} \end{cases},\ N_o^T = \begin{cases} N & \text{if } \pi_n^T(0,\bar{t}) < \pi_o^T(0,\bar{t}) \\ 0 & \text{if } \pi_n^T(N,\bar{t}) > \pi_o^T(N,\bar{t}) \\ N - N_n^T(\bar{t}) & \text{otherwise} \end{cases};$$

(3) green firms and regular firms, respectively, produce

$$Q_n^T = \begin{cases} 0 & \text{if } \pi_n^T(0,\bar{t}) < \pi_o^T(0,\bar{t}) \\ Q_n^T(N,\bar{t}) & \text{if } \pi_n^T(N,\bar{t}) > \pi_o^T(N,\bar{t}) \\ Q_n^T(\bar{t}) & \text{otherwise} \end{cases},\ Q_o^T = \begin{cases} Q_o^T(0,\bar{t}) & \text{if } \pi_n^T(0,\bar{t}) < \pi_o^T(0,\bar{t}) \\ 0 & \text{if } \pi_n^T(N,\bar{t}) > \pi_o^T(N,\bar{t}) \\ Q_o^T(\bar{t}) & \text{otherwise} \end{cases},$$

having the target exactly met.

4.4.2. Equilibrium under a voluntary agreement

Next, we consider the VA subgame. Let superscript V represent equilibrium outcome under the VA. The equilibrium is checked backward. In Stage 3, given the number of participants (i.e., the number of green firms), firms engage in Cournot competition. The output competition yields exactly same equilibrium quantities as in the tax game with zero tax rate. Interpreting alternatively, it would be the case of no regulatory policy, thereby resulting in pure product differentiation. Thus, we define equilibrium outputs, profits and aggregate emissions in Stage 3 as follows: $q_\ell^V(N_n) \equiv q_\ell^T(N_n, t=0)$, $Q_\ell^V(N_n) \equiv Q_\ell^T(N_n, 0)$, $\pi_\ell^V(N_n) \equiv \pi_\ell^T(N_n, 0)$ for $\ell = n, o$, and $E^V(N_n) \equiv E^T(N_n, 0)$. Noted that unlike the tax policy those equilibrium outcomes under the VA are unchanged with different target levels, given the maintained absence of emission tax.

Assume that the implementation of the VA is considered only when N_n^L is smaller than N. In other words, if all firms are already using the new technology in the *laissez faire* situation, there is no reason to initiate the VA. Under Assumption 1, for the given equilibrium total emissions, we then have following Lemma.

Lemma 5. Under the successfully implemented VA based on a threat policy and green consumers, the total emissions of the oligopolistic industry decrease in the number of participants (i.e., green firms) for $N_n \in [N_n^L, N]$.

Proof. See Appendix C.6.

Lemma 5 holds in that the increase in the total output of green goods leads to the reduction in total industry emissions. Such result is not obvious given the feature of Cournot competition that as the number of participants increases the number of non-participants decreases with a higher level of individual output. By Lemma 5, the target $\bar{E} \in [E^V(N), E^L]$ can be met by increasing the number of participants $N_n \in [N_n^L, N]$. Under the VA, therefore, the number of participants—i.e., green firms—directly plays the key role for meeting the target emission level (while in the tax policy the tax rate determines the number of green firms and in turn the total emissions). Note that as the number of participants increases, the profits of a green firm start to be smaller than those of a regular firm due mainly to the Cournot feature. Thus increasing the number of participants reduces the relative merit of being a participant compared to being a non-participant, and vice versa.

In Stage 2, given the threatened tax rate τ, the number of participants is determined. Suppose that the target emission level is feasible—meaning that it is achievable solely by increasing participants—and call $\tilde{N}_n$ as the minimum number of participants for the target under the VA. In Stage 2 the regulator lets the VA proceed when the target is going to be met, i.e.,

$N_n \geq \tilde{N}_n$. If $N_n < \tilde{N}_n$, however, the announced τ is imposed. For the latter situation, there are two possible cases in terms of the outcome after Stage 2: (a) no participant ($N_n = 0$) and (b) some but not enough participants ($0 < N_n < \tilde{N}_n$). We assume that participants who decided to adopt the new technology in Stage 2 of the VA game cannot reverse their technology choice in the following tax game, implying the agreement is not a cheap talk. After the VA is nullified, for case (a) firms face with the tax game outcome ($N_n = N_n^T(\tau)$). For case (b), profits for a green firm in case (b) are no better than those in case (a). The reason is as follows. In case (b), if $N_n < N_n^T(\tau)$, firms who were non-participants change their technology to the new until $N_n = N_n^T(\tau)$, having the same outcome as in case (a). If $N_n \geq N_n^T(\tau)$, firms who were nonparticipants stick to their old technology which allows higher profits for them but the lower for the green in the comparison to case (a). Assume that when expecting the same profits firms prefer not joining to joining in the going-to-be-nullified VA. Then there is no equilibrium such that firms less than minimum level participate by knowing the target is going to be unmet. As a results, possible equilibrium numbers of participants in Stage 2 lie in $N_n \in \left\{0, [\tilde{N}_n, N]\right\}$.

Now we consider the self-enforcing equilibrium number of participants in Stage 2. Following the discussion in Dawson and Segerson (2008), two conditions should be satisfied: "profitability condition" and "stability condition." For the first condition, it needs to be guaranteed that the participants enjoy a level of profits no less than that without the VA, hence, under the tax policy. The participating firms consist of two types: i) firms who would produce green good even under the tax policy, and ii) firms who would choose old technology if the VA were not initiated. If the profit level for green firms under tax policy is higher than that under the

VA, the number of firms in the second group becomes insufficient, resulting in the nullification of the VA. That the non-participants are always better off compared to the tax outcome makes the profit level of individual green firm pivotal for the VA to proceed to the end of the game, i.e., "successfully implemented." We assume that the VA which is successful is preferred by firms to tax policy when both give same profits. Next, the number of participants is stable if there is no incentive to deviate unilaterally for each group of firms, i.e., no participants want to be a non-participant and no non-participants want to be a participant.

Depending on the threat level—i.e., profit level when the announced tax rate is imposed—the set of N_n that satisfies the profitability condition can be null or not. Figure 4.2 describes the possible situations with different threats (but the same target), where bold line and dots indicate the relevant payoff for a green firm by taking the threatening profit level and possible values of N_n into account. First, in the panel (a), for $\tau = \tau'$ there is no N_n, at which individual green firm is at least as well off as under the tax policy, within $[\tilde{N}_n, N]$. In this case the VA will be nullified with no participants. In panel (b) we consider a severer threat based on $\tau = \tau''(>\tau')$. Then there is a range of N_n, from $\tilde{N}_n$ to N_n at which $\pi_n^V(N_n) = \pi_n^T(\tau'')$, satisfying the profitability condition.

Given the situation as the panel (b) in Figure 4.2, it remains to check the stability condition for the values within $\tilde{N}_n$ to N_n at which $\pi_n^V(N_n) = \pi_n^T(\tau'')$. Note that only $N_n = \tilde{N}_n$ satisfies the stability condition in the sense that at $N_n = \tilde{N}_n$, i) no non-participant (regular firm) has an incentive to change their technology to sell green products (because that would cause a lower level of profits), and ii) no participant (green firm) has an incentive to convert current technology to the old one (which would make the target unmet and thereby trigger the tax policy). For any number of greens firms greater than the minimum requirement, participants are still be able to enjoy a higher profit by becoming a non-participant, hence not stable.

To summarize, the equilibrium number of participants is as follows.

$$N_n^V = \begin{cases} \tilde{N}_n & \text{if } \pi_n^V(\tilde{N}_n) \geq \pi_n^T(\tau) \\ 0 & \text{otherwise} \end{cases}$$

where the positive N_n^V satisfies

(13) $E^V(N_n^V) = \bar{E}^V$.

By Lemma 5 we can obtain the unique positive $N_n^V(\bar{E}^V)$ that satisfies equation (13). To be specific, the nonlinear relationship between positive N_n^V and $\bar{E}^V$ is as follows:

(14) $$\left[N_n^V + \frac{1+s}{s}\frac{\phi-1}{\phi}\right]\left[\frac{\psi + c_n - (1+s)c_o}{s(N-N_n^V)+1+s-\varphi}\right] + \frac{\psi}{\phi}N_n^V = \frac{1+s}{s\phi}(s\bar{\theta} - c_n + c_o - \psi),$$

where $\phi = [e_n + (1+s)e_o]/(e_n + e_o)$ and $\psi = (\bar{E}^V - e_n\bar{\theta})s/(e_n + e_s) + \phi c_o - c_n$ (See Appendix C.7 for the derivation of equation (14)).

4.4.2.1. Credible commitment case

In Stage 1, the regulator proposes the target emission level together with the threat tax rate. Here we first consider the case in which the regulator has commitment power by assuming that the announced threat is credible during the game regardless of its value. Consider the lowest effective threat $\bar{\tau}$ that preserves the profitability and stability for the equilibrium number of participants. Such threat would make both the VA and tax policy equally profitable for the green firm.

(15) $\pi_n^V(N_n^V(\bar{E}^V)) = \pi_n^T(\bar{\tau})$.

Equation (15) describes the relationship between the target and the lowest effective threat under the VA. For given target any potential tax rate higher than or equal to $\bar{\tau}$ yields the same outcome by resulting in no higher threat profits than those under the VA (recall Lemma 3(3)). We simply assume that the regulator announces $\bar{\tau}$ as the potential tax rate in Stage 1.

Now we need to look at the feasibility issue of the target across VA and tax policy. Directly from Lemma 2, if an emission target is attainable via the VA, it could be also met under the tax policy with an appropriate tax rate, but the converse does not necessarily hold. To obtain the feasible set, based on Lemma 5 we define $E_{\min}^V = E^V(N)$, the lower limit of total emissions under the VA. Same as in the tax game, the upper bound of total emissions is the case of *laissez faire*. Then the set of feasible emission targets under the VA is $\bar{E} \in [E_{\min}^V, E^L]$. Figure 4.3 depicts the relationship of feasible sets under the *laissez faire*, VA and tax policy. Once we delimit the feasible target under the VA, we have Lemma 6 regarding the existence of $\bar{\tau}$.

Lemma 6. There is always a tax rate that makes the VA with a feasible target ($\bar{E} \in [E_{\min}^V, E^L]$) strictly profitable for all firms than the tax outcome.

Lemma 6 is followed by Lemmas 1 and 4. Specifically, under the VA for a feasible target the equilibrium profits for a green firm are always positive (by Lemma 1 and equation (9)), while under the tax policy we can find a tax rate that makes the profits equal to zero (by Lemma 4). Thus we can always find $\bar{\tau}$. Now the equilibrium of the VA game based on pre-commitment can be summarized as follows.

Proposition 2. At the equilibrium under the VA with pre-commitment,

(1) the regulator announces the target $\overline{E}^V \in [E^V_{\min}, E^L]$ with the threat tax rate $\tau = \overline{\tau}$;

(2) the equilibrium number of participants is $N^V_n(\overline{E}^V)$ (that of non-participants is $N - N^V_n(\overline{E}^V)$), and the VA is successfully implemented;

(3) participants sell green products of $Q^V_n(\overline{E}^V)$, while non-participants sell regular products of $Q^V_o(\overline{E}^V)$ by having the target exactly met ($E^V(\overline{E}^V) = \overline{E}^V$).

4.4.2.2. Time consistency case

Here we assume that the only credible threat is the tax level that would be imposed under the tax policy, that is $\overline{\tau} = \overline{t}$, while still pursuing $\overline{E}^V$. We have the same set of feasible target under the VA as in Figure 4.3 (feasible means the target can be met by increasing the number of participants), but with an additional issue of whether the VA is implementable or not (as shown in Figure 4.2). For example, if the credible threat is not sufficiently strong, the VA will be nullified with a short of participants, ending up with tax policy game. Thus we have Proposition 3.

Proposition 3. At the equilibrium under the VA with time consistency,

(1) the regulator announces the target $\overline{E}^V \in [\breve{E}_{\min}, E^L)$ with the potential tax rate $\overline{\tau} = \overline{t}$;

(2) the equilibrium number of participants is $N^V_n(\overline{E}^V)$ (that of non-participants is $N - N^V_n(\overline{E}^V)$), and the VA is successfully implemented, provided joining in the VA is profitable; otherwise the tax game outcome revisits;

(3) if VA is successful, participants sell green products of $Q_n^V(\bar{E}^V)$, while non-participants sell regular products of $Q_o^V(\bar{E}^V)$ by having the target exactly met ($E^V(\bar{E}^V) = \bar{E}^V$).

4.4.3 Equilibrium of the game

For a given set of primitive parameter values, the regulator chooses one of the three policy options—*laissez faire*, VA, and tax policy—to maximize his objective function (i.e., the social welfare net of political cost). We sum up the equilibrium of the game in Proposition 4. When welfare levels are equal, assume that *laissez faire*, VA and tax policy are preferred in order.

Proposition 4. There are three potential equilibria based on eleven possible situations for given welfare W^j for $j = L$ (*laissez faire*), V (VA) and T (tax policy) and political cost K:

EQ 1. No policy is implemented (*laissez faire* situation)

if (a) $W^L \geq W^V \geq W^T$, (b) $W^L \geq W^T > W^V$, (c) $W^V > W^L \geq W^T$ with weak threat, (d) $W^T > W^L \geq W^V$ with large K, or (e) $W^V \geq W^T > W^L$ with weak threat and large K;

EQ 2. Tax policy is implemented

if (a) $W^T > W^L \geq W^V$ with small K, (b) $W^T > W^V > W^L$ with small K, or (c) $W^V \geq W^T > W^L$ with weak threat and small K;

EQ 3. VA is implemented

if (a) $W^V > W^L \geq W^T$ with sufficient threat, (b) $W^V \geq W^T > W^L$ with sufficient threat,

or (c) $W^T > W^V > W^L$ with large K;

where in the pre-commitment case the situations of EQ 1(c) and EQ 2(c) would not occur.

4.5 Numerical Simulation and Welfare Analysis

4.5.1 Illustration of equilibrium

The foregoing has shown that, under certain conditions, two alternative instruments, tax policy and VA, are able to achieve the targeted emission level in the industry. Unfortunately, we are unable to provide analytical results to characterize equilibrium outcomes for the VA outcomes. Hence, we resort to numerical simulations to explore the equilibrium characteristics of the two instruments, including their impacts on social welfare.

Consistent with our partial equilibrium framework, social welfare (W) is defined as the sum of producer surplus (PS) and consumer surplus (CS) net of the environmental externality (EX), whereas tax revenue (RV) is added to them for the case of a tax policy. Alternatively, W can be calculated by using equation (16) through considering entire demands net of production and social costs. Recall that the market is uncovered with two threshold values, $\theta_n = (p_n - p_o)/s$ for green goods and $\theta_o = p_o$ for regular goods. Then,

(16) $$W = \int_{\theta_n}^{\bar{\theta}} (1+s)\theta d\theta + \int_{\theta_o}^{\theta_n} \theta d\theta - (c_n Q_n + c_o Q_o) - x(e_n Q_n + e_o Q_o),$$

where $Q_n = \bar{\theta} - \theta_n$ and $Q_o = \theta_n - \theta_o$; x is marginal externality costs from one unit of emission.

In order to illustrate probable equilibrium outcomes including social welfare, specific values of parameters are chosen as in Table 4.1 by preserving internal coherence within the model. First of all, $\overline{\theta}$ is normalized to 1 and thereby $\underline{\theta}$=0 (to determine the degree of heterogeneity between consumers and ensure that the market is uncovered). c_o is set by 0.1 which is appropriate for the Assumption 1. e_o is normalized by 1 so that producing one unit of regular good causes one unit of emission. For features of green goods, c_n is 20 % higher than c_o and e_n is 20 % lower than e_o, reflecting a situation that green goods are less cost-effective but more emission-effective. x is chosen by 0.02 which is 20% of marginal cost of regular good. Note that the difference in production costs between green and regular good, $c_n - c_o$, is 0.02. Then s is chosen by 0.03 which is 1.5 time of the cost difference, thereby satisfying the Assumption 1.[47] N is set by 20 to represent an oligopolistic situation. Based on the assumed parameters and welfare function, we can obtain the following welfare-maximizing targets: $\overline{E}^T$ that maximizes the welfare under the tax policy and $\overline{E}^V$ that maximizes the welfare under the VA, where each maximum level is unique (as either interior or corner solution). For the time being, assume no political cost ($K = 0$).

Table 4.2 describes the outcomes of all terminal nodes in Figure 4.1, based on the assumed parameters in Table 4.1, where only columns (1) to (3) can happen in equilibrium. For display purposes, the equilibrium number of green firms (or participants under the VA) are

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[47] When defining marginal social costs as $c_n + xe_n$ and $c_o + xe_o$, the difference $c_n - c_o + x(e_n - e_o)$ is smaller than $c_n - c_o$ given that $e_n < e_o$ and $x > 0$. Therefore, under Assumption 1 the additional social costs of the green good is also covered by the consumer of highest willingness-to-pay.

rounded after obtaining all the results. First, the resulting industry-wide emissions are lowest under the VA. The social welfare is highest under the VA, followed by the tax policy and the *Laissez faire* case. In the case of pre-commitment, thus, VA is implementable based on the minimum feasible threat that makes the equilibrium profits for a green firm is same under the VA (column 3) and under the threat policy (column 4) (EQ 3(a) in Proposition 4). In the case of time consistency, however, the VA is not implementable because the threat is too weak to make the VA profitable (column 2). Then, if the political cost is insignificant (K <0.000018), the tax policy would be implemented (EQ 2(c) in Proposition 4); if large ($K \geq$0.000018), the *laissez faire* situation would occur (EQ 1(e)).

Other features between tax policy (column 2) and VA (column 3) from Table 4.2 are as follows. In terms of TC, the VA is less efficient than the tax policy in maximizing welfare. This is because under the VA more firms are forced to use the new technology with a higher marginal cost. For CS and PS, the VA generates more surplus than tax policy. Given the non-competitive situation (N=20), the main reason for the higher CS is that there are more total outputs in the market under the VA than the tax policy. Relative to the tax policy, under the VA the segment of the covered market expands for green goods and in turn for total goods (recall that the market coverages for two goods are measured by $Q_n = \overline{\theta} - \theta_n$ and $Q_o = \theta_n - \theta_o$, respectively). Also, the tax exemption under the VA makes PS greater despite of the decrease in prices of both goods. Overall, even after taking RV into account, SW is higher under the VA than under the tax policy, provided the VA is successfully implemented.

4.5.2 Comparative analysis on welfare level

Considering the results in Table 4.2 as a snapshot, further scrutiny is needed for a more general assessment of equilibrium characteristics. In this section we thus conduct comparative analysis. Especially to look at how the maximized welfare behaves, we plot the maximized welfare level when changing one parameter at a time (See Figure C1 in the Appendix C.8). We also plot the market output and price as well as consumer surplus with respect to changes in the additional benefit from purchasing a green good (s) (See Figures C2 in the Appendix C.8). For the comparative analysis, following ranges are considered: $c_o \in [0.095, 0.105]$, $c_n \in [0.115, 0.125]$, $e_o \in [0.95, 1.05]$, $e_n \in [0.75, 0.85]$, $s \in [0.02, 0.04]$,[48] $x \in [0.015, 0.025]$ and $N \in [5, 150]$. The range of N is set to cover more competitive situations, while other ranges are set to have the assumed values in Table 4.1 in the middle. $\overline{\theta}$ is still fixed by 1, and K is ignored which is irrelevant to welfare. Whenever changing a parameter, the welfare-maximizing target and tax rate are recalculated and applied for the outcomes.

It turns out that for both VA and tax policy, the maximized welfare level decreases in c_o, c_n, e_o, e_n, and x.[49] Also it is increasing in s, as expected. The comparative analysis shows that the VA, if it is successful, yields higher welfare than the tax policy with small N, while this is reversed as N becomes large. The reason for this feature is as follows. For a given N, the exemption of the emission tax under the VA has two effects in general: i) in the absence of the

[48] Based on the assumed ranges, the highest difference in social costs between green and regular goods is 0.0285, while the lowest is 0.0025. We set the lower bound of s as 0.02, while setting the upper bound by 0.04 to have the mean as 0.03. This range brings in cases that s is small to cover the gap of social costs between two goods as well as the opposite cases.

[49] Especially for x, we can obtain $\partial W / \partial x = -E$ from equation (16), meaning that the welfare decreases in x and the decrease becomes bigger when the total emissions are heavier.

tax burden, firms produce more outputs in total than the tax policy, yielding higher aggregate CS and PS, and ii) the regulator loses a method to make up the social costs of externality (i.e., no tax revenue). When N is small, the first effect overwhelms the second effect resulting in a higher social welfare under the VA. But as N increases, the market becomes more competitive with more total output. Then the total externality becomes more important than the under-production issue, thereby tax policy performs better in maximizing welfare.

Given that the VA improves welfare partially by increasing overall consumer surplus (in a non-competitive situation), not all consumers always gain from it. Based on more of green firms, the welfare-maximizing VA results in more green goods and less regular goods than the welfare-maximizing tax policy. As a result, the total market can be either more covered or less covered (the former happens in the illustration of Table 4.2). As the consumer's additional benefit (s) increases, however, the welfare-maximizing VA reduces the total output, while the tax policy increases it. As a result, when s is sufficiently large, the total market is less covered and the price of regular goods is higher under the VA than under the tax policy. This is mainly because when maximizing welfare for a higher s, the tax policy lowers the tax burden for all firms in the industry, while the VA directly increases the number of green firms, which exploits the increased willingness-to-pay, while letting free-riders (i.e., non-participants) enjoy the reduced competition with a higher price.

4.5.3 Sensitivity analysis

As a further step to elicit general implications, we conduct a sensitivity analysis which could give us an idea about which cases possibly occur at the equilibrium in the model and what instrument is implemented in order to enhance the social welfare. To do so, each parameter is randomly drawn from a uniform distribution by 10,000 times. Keeping $\bar{\theta}$ as one, the aforementioned ranges of six parameters in the comparative analysis, c_o, e_o, c_n, e_n, s, and x, are considered where their mean values are the assumed values in Table 4.1. For N, we focused on the non-competitive situation by $N \in$ [5, 35], and additionally conduct the same set of simulations except for applying $N \in$ [75, 125] to cover more competitive situations. We assume the political cost is zero during the simulation ($K = 0$). To illustrate the procedure, for each simulation, s is randomly drawn from uniformly distributed range [0.01, 0.05], c_o is drawn from [0.095, 0.105], and so on for remaining parameters. For each vector consisting of drawn values for seven parameters, we check whether the set of drawn values satisfies Assumption 1. If it does not, we consider the drawn vector as an invalid situation. Only for valid cases, we calculate the equilibrium outcomes including the social welfare. Then for each simulation we check which equilibrium occurs under what circumstance.

Table 4.3 reports simulation results when $N \in$ [5, 35] and when $N \in$ [75, 125]. Out of 100,000 simulations, 8,723 cases (10%) are sorted into invalid cases (which do not depend on the level of N, so the same number of invalid cases applies for both ranges of N). For valid cases (90% of 10,000 cases), there are eight possible situations ending up with one of three possible equilibria. (Given that $K = 0$, EQ 1(d), EQ 1(e) and EQ 3(c) in Proposition 4 are excluded). We first look at the case of $N \in$ [5, 35]. In the pre-commitment case the VA is the only policy implemented because it yields highest welfare for all valid cases. Within them, for more than 70% of cases the tax policy yields second highest welfare level (which is the case for the results of Table 4.2). But as long as it is implementable via a credible commitment, the VA will be chosen. Next, if the regulator's commitment power disappears, thereby only the time-consistent threat level is effective, the VA becomes far from an implementable option: only 0.1% of valid cases end up with successful VAs. Instead, for three-fourths of valid cases the tax policy is implemented, and for a fourth no policy is implemented. Thus, even though the VA yields highest welfare in an oligopolistic situation, a strong threat is essential to actually implement it. When examining more competitive situations by $N \in [75, 125]$, the same feature is found. One difference is that there are more cases in which the tax policy yields highest welfare. As noted in the foregoing comparative analysis, this is mainly because in a more competitive market there would be more outputs produced (thereby the merit of the VA decreases) and in turn more emissions, which increases the need for correcting the externality (thereby the *laissez faire* becomes less desirable).

In addition, we can think about the role of the political cost K. To be specific, for the cases of EQ 2(c), in which the tax policy is implemented due to the weak threat under the VA, the number will decrease as K increases, yielding more cases with the *laissez faire* (i.e., the cases move from EQ 2(c) to EQ 1(e)). Then, actually the lowest welfare level among three possible outcomes is achieved. For the cases of EQ 2(b), in which the tax policy is implemented to achieve highest welfare, the number will decrease as K increases and there will be more cases of the VA implemented if the threat is working (i.e., the cases move from EQ 2(b) to EQ 3(c)) or there will be more cases of the *laissez faire* if the treat under the VA is not sufficiently strong (i.e., the cases move from EQ 2(b) to EQ 1(d)). Then, for the pre-commitment case, the VA is going to be the second best option for the regulator who wants to avoid the political cost and has the power to commit. For the time-consistency case, on the other hand, it would be highly likely ending up with the *laissez faire* situation and thereby the industry face with the lowest welfare level among three options.

4.6 Conclusion

This paper analyzes the incentives for firms to participate in a voluntary agreement in the presence of two compelling motives—green consumers and a potential regulatory threat. A voluntary agreement in this essay refers to an environmental agreement initiated to reduce industrywide emissions through the promotion of an environmentally friendly technology. For the sake of simplicity, technologies that firms can use are binary, such as old and new ones. A simple form of voluntary agreement is considered in the sense that being a member only requires using the new (greener) technology. In this setting, choosing the new technology enables firms to differentiate their products as well as to join in the voluntary agreement. Therefore, participation in a VA can be motivated in terms of appealing to green consumers and avoiding the potential tax policy.

Throughout the analysis, we find that a VA can improve welfare over the tax policy in a non-competitive market. This result buttresses the use of VAs in oligopolistic situations, where firms find that being a participant in a VA is another channel to appeal to consumers via product differentiation. But we also find that, because of free-riding behavior, the VA can hurt consumers who have lower willingness-to-pay for green products by leaving them to non-participants. Especially, when consumers' common valuation for a green good rises, the VA, relative to the tax policy, generates more green firms, yielding a less competitive ground for free-riders. Hence, the entire market can be less covered under the VA, although such concentration still gives higher overall consumer surplus.

Despite of the potential merits of VAs under certain circumstances, implementation issues remain, which directly connects to the question of whether the threat policy perceived along with the VA is credible and strong enough to encourage the participation. Not surprisingly, it is found that, if the regulator's commitment is credible regardless of its severity, the VA will be successful whenever it guarantees higher welfare than other policy options. If the regulator is required to be time-consistent, it is almost infeasible to induce enough participants because the threat is weak. Another perspective on the implementation issue—especially for the cases of weak threat—can be obtained from the existence of political costs of regulation, which would arguably be reduced under voluntary approaches. Given that welfare can be best enhanced under the tax policy, the regulator can prefer to implement a policy with smaller costs, which might lead to the VA.

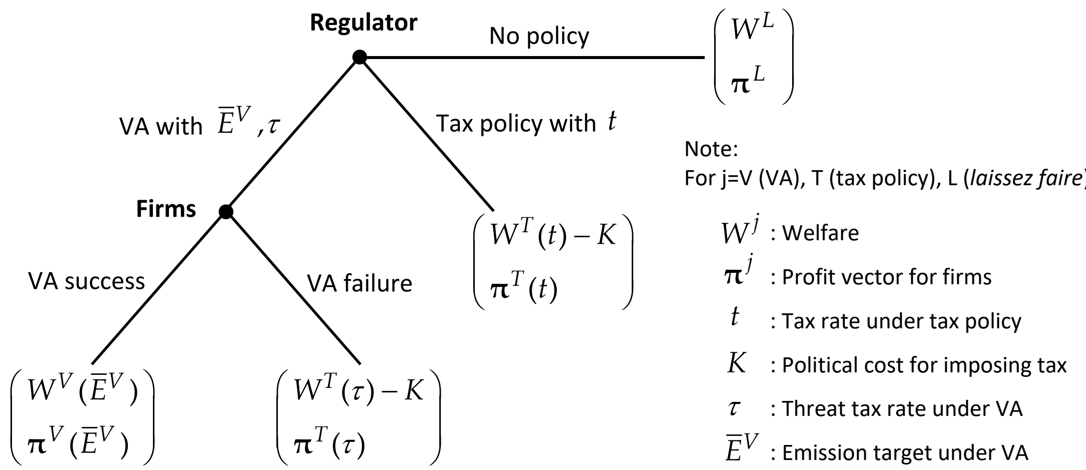

Figure 4.1. The structure of the game

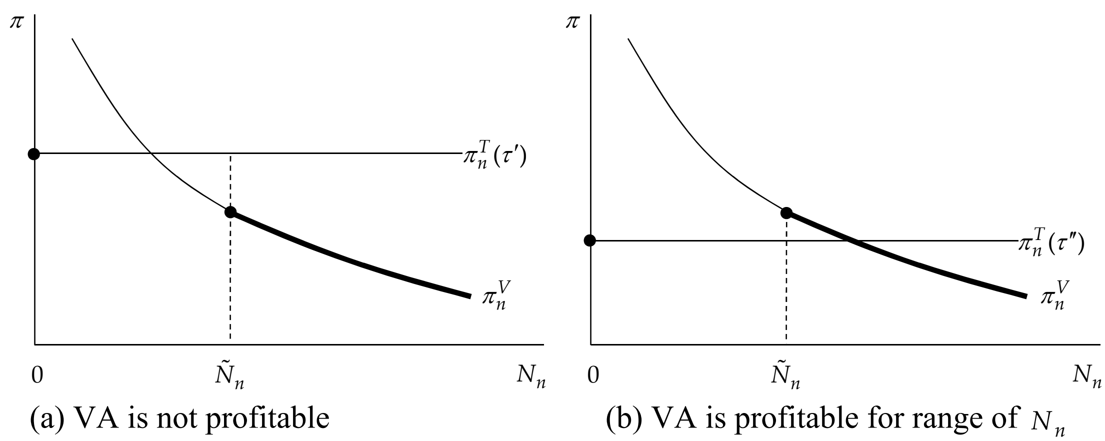

Figure 4.2. Relevant profits for an individual green firm under threats

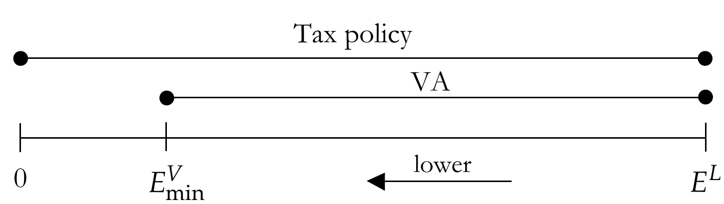

Figure 4.3. The set of feasible target under VA and under tax policy

Table 4.1. Selected Values for Parameters

Parameter	Description	Value
$\bar{\theta}$	Upper bound of uniformly distributed preference ($\underline{\theta} = \bar{\theta} - 1$)	1.00
s	Additional benefit for consuming a green good	0.03
c_o	Marginal cost per regular good	0.10
c_n	Marginal cost per green good	0.12
e_o	Marginal emission per regular good	1.00
e_n	Marginal emission per green good	0.80
x	Marginal externality costs per unit of emission	0.02
$\bar{E}$	Emission target	$\bar{E}^V$ or $\bar{E}^T$
N	Total number of firms in the industry	20

Note: Given the parameters, E^V_{min} =0.6740< $\bar{E}^V$ =0.7650< $\bar{E}^T$ =0.7854< E^L =0.7945.

Table 4.2. Representative Terminal Node Outcomes

	Laissez faire	Tax policy	VA success	VA failure (threat is imposed)
	(1)	(2)	(3)	(4)
N_n	7	8	11	14
q_n	0.0424	0.0423	0.0406	0.0406
q_o	0.0431	0.0429	0.0453	0.0412
Q_n	0.3120	0.3387	0.4484	0.5982
Q_o	0.5450	0.5144	0.4062	0.2178
Q	0.8569	0.8531	0.8547	0.8160
p_n	0.1637	0.1667	0.1619	0.1961
p_o	0.1431	0.1469	0.1453	0.1840
π_n	0.0019	0.0018	0.0017	0.0017
π_o	0.0019	0.0018	0.0021	0.0017
E	0.7945	0.7854	0.7650	0.6963
RV		0.0031		0.0298
EX	0.0159	0.0157	0.0153	0.0139
TC	0.0919	0.0921	0.0944	0.0936
CS	0.3686	0.3656	0.3683	0.3383
PS	0.0371	0.0368	0.0372	0.0340
W	0.3898	0.3899	0.3901	0.3882

Note: For tax policy $\bar{t}$ =0.0040, while the minimum effective threat for VA is $\bar{\tau} = 0.0428$.

Table 4.3. Simulation Results (100,000 draws; 8,723 invalid cases violating Assumption 1)

		$N \in [5, 35]$		$N \in [75, 125]$	
	Implemented Policy	Pre-commitment	Time consistency	Pre-commitment	Time consistency
EQ 1(a)	*Laissez faire*	-	-	-	-
EQ 1(b)	*Laissez faire*	-	-	-	-
EQ 1(c)	*Laissez faire*	-	23,588	-	-
EQ 2(a)	Tax policy	-	-	-	-
EQ 2(b)	Tax policy	-	-	55,200	55,200
EQ 2(c)	Tax policy	-	68,013	-	36,479
EQ 3(a)	VA	23,588	-	-	-
EQ 3(b)	VA	68,139	126	36,527	48
Total valid cases		91,227	91,227	91,227	91,227

Note: Parameters are drawn from following ranges: $\bar{\theta}=1$, $s \in [0.02, 0.04]$, $c_o \in [0.095, 0.105]$, $e_o \in [0.95, 1.05]$, $c_n \in [0.115, 0.125]$, $e_n \in [0.75, 0.85]$, $x \in [0.015, 0.025]$. K is assumed to be zero.

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APPENDIX C

PROOFS AND SUPPLEMENTARY MATERIALS

C.1 Proof of Lemma 1

From Assumption 1, by knowing that $e_n < e_o$, we have following conditions. For $t \geq 0$,

(17) $$\bar{\theta} > \frac{(c_n + te_n) - (c_o + te_o)}{s};$$

(18) $$c_n + te_n > (1+s)(c_o + te_o).$$

From equations (5) and (6), we know that $q_n^T(N_n, t)$ and $q_o^T(N_n, t)$ are all positive if following conditions hold, respectively:

(19) $$\bar{\theta} > \frac{(N - N_n + 1)(c_n + te_n) - (N - N_n)(c_o + te_o)}{1 + s(N - N_n + 1)};$$

(20) $$\bar{\theta} > \frac{-N_n(c_n + te_n) + (1+s)(N_n + 1)(c_o + te_o)}{1+s}.$$

If the right-hand-sides (RHS) of equations (19) and (20) are smaller than that of equation (17) for $N_n \in [0, N]$, then the individual quantities are positive for all N_n under Assumption 1.

The RHS of equations (19) and (20) are decreasing in N_n because the derivatives of them, $[-(c_n + te_n) + (1+s)(c_o + te_o)]/[1 + s(N - N_n) + 1]$ and $[-(c_n + te_n) + (1+s)(c_o + te_o)]/(1+s)$, are all negative for $N_n \in [0, N]$ by equation (18). Therefore, checking end points is enough to figure out whether one RHS is dominantly bigger than the other for $N_n \in [0, N]$ between equations (19) and (20). When $N_n = 0$, the RHS of equations (19) and (20) are $[(N+1)(c_n + te_n) - N(c_o + te_o)]/[1 + s(N+1)]$ and $c_o + te_o$. The former subtracted by the latter is

$(N+1)[(c_n+te_n)-(1+s)(c_o+te_o)]/[1+s(N+1)]$ which is positive by equation (18). When $N_n = N$, the RHS of equations (19) and (20) become $(c_n+te_n)/(1+s)$ and $[-N(c_n+te_n)+(1+s)(N+1)(c_o+te_o)]/(1+s)$. The former subtracted by the latter is $(N+1)[(c_n+te_n)-(1+s)(c_o+te_o)]/(1+s)$ which is positive by equation (18). Therefore, the RHS of equation (19) is greater than that of equation (20) for all N_n. Furthermore, the RHS of equation (19) subtracted by that of equation (17) is $-[(c_n+te_n)-(1+s)(c_o+te_o)]/[s+s^2(N-N_n+1)]$ which is negative for $N_n \in [0,N]$ by equation (18). Hence, the RHS of equation (17) is greater than that of equation (19) for all N_n. As a result, under Assumption 1 equations (19) and (20) are satisfied, meaning that both individual quantities are all positive for all N_n.

C.2 Proof Lemma 2

Under the assumption that $e_n < e_o$ and $s > 0$, we have following partial derivative of $E^T(N_n,t)$ with respect to t for a given N_n:

$$\frac{\partial E^T(N_n,t)}{\partial t} = e_n N_n \frac{\partial q_n^T(N_n,t)}{\partial t} + e_o(N-N_n)\frac{\partial q_o^T(N_n,t)}{\partial t}$$

$$= e_n N_n \frac{-[(N-N_n+1)e_n-(N-N_n)e_o]}{(1+s)(N+1)+sN(N-N_n)} + e_o(N-N_n)\frac{N_n e_n-(1+s)(N_n+1)e_o}{(1+s)(N+1)+sN(N-N_n)}$$

$$< e_n N_n \frac{-[(N-N_n+1)e_n-(N-N_n+1)e_o]}{(1+s)(N+1)+sN(N-N_n)} + e_o(N-N_n)\frac{N_n e_o-(N_n+1)e_o}{(1+s)(N+1)+sN(N-N_n)}$$

$$= e_n N_n \frac{-(N-N_n+1)(e_n-e_o)}{(1+s)(N+1)+sN(N-N_n)} + e_o^2(N-N_n)\frac{-1}{(1+s)(N+1)+sN(N-N_n)} < 0 .$$

C.3 Convexity of Individual Quantities in N_n

The followings are first and second derivatives of $q_n^T(N_n,t)$ and $q_o^T(N_n,t)$ with respect to N_n:

(21) $$\frac{\partial q_n^T(N_n,t)}{\partial N_n} = \frac{-\left[s\bar{\theta} - (c_n + te_n) + (c_o + te_o)\right] - q_n^T(N_n,t)\left[s(N-2N_n)\right]}{(1+s)(N+1) + sN_n(N-N_n)};$$

(22) $$\frac{\partial^2 q_n^T(N_n,t)}{\partial N_n^2} = \frac{-2\dfrac{\partial q_n^T(N_n,t)}{\partial N_n}\left[s(N-2N_n)\right] + 2sq_n^T(N_n,t)}{(1+s)(N+1) + sN_n(N-N_n)};$$

(23) $$\frac{\partial q_o^T(N_n,t)}{\partial N_n} = \frac{\left[(c_n + te_n) - (1+s)(c_o + te_o)\right] - q_o^T(N_n,t)\left[s(N-2N_n)\right]}{(1+s)(N+1) + sN_n(N-N_n)};$$

(24) $$\frac{\partial^2 q_o^T(N_n,t)}{\partial N_n^2} = \frac{-2\dfrac{\partial q_o^T(N_n,t)}{\partial N_n}\left[s(N-2N_n)\right] + 2sq_o^T(N_n,t)}{(1+s)(N+1) + sN_n(N-N_n)}.$$

As we know that $s\bar{\theta} > (c_n + te_n) - (c_o + te_o)$ and $q_n^T(N_n,t) > 0$ under Assumption 1, equation (21) is definitely negative for $N_n \in [0, N/2]$ keeping $s(N-2N_n)$ positive, while its sign is ambiguous for $N_n \in [N/2, N]$. Accordingly, equation (22) is definitely positive for $N_n \in [0, N/2]$, while its sign is ambiguous for $N_n \in [N/2, N]$. Similarly, knowing that $c_n + te_n > (1+s)(c_o + te_o)$ and $q_o^T(N_n,t) > 0$ under Assumption 1, equation (23) is definitely positive for $N_n \in [N/2, N]$ keeping $s(N-2N_n)$ negative, while its sign is ambiguous for $N_n \in [0, N/2]$. Then, equation (24) is definitely positive for $N_n \in [N/2, N]$, while the sign is ambiguous for $N_n \in [0, N/2]$. To sum, based on equations (21) to (24), we cannot be sure about whether the second derivatives of $q_n^T(N_n,t)$ and $q_o^T(N_n,t)$ are positive for $N_n \in [0,N]$. Thus, we further rearrange equations (22) and (24) to find comparable conditions regarding $\bar{\theta}$.

Note that the numerator in equation (22) can be expressed as follows:

$$-2\frac{\partial q_n^T(N_n,t)}{\partial N_n}\left[s(N-2N_n)\right]+2sq_n^T(N_n,t)$$

$$=-2s\left[\frac{-\left[s\bar{\theta}-(c_n+te_n)+(c_o+te_o)\right]-q_n^T(N_n,t)\left[s(N-2N_n)\right]}{\alpha}(N-2N_n)-q_n^T(N_n,t)\right]$$

$$=-2s\frac{-\left[s\bar{\theta}-(c_n+te_n)+(c_o+te_o)\right](N-2N_n)-q_n^T(N_n,t)\beta}{\alpha}$$

$$=-2s\left[\frac{-\left[s\bar{\theta}-(c_n+te_n)+(c_o+te_o)\right](N-2N_n)\alpha}{\alpha^2}-\frac{\left[\left[1+s(N-N_n+1)\right]\bar{\theta}-(N-N_n+1)(c_n+te_n)+(N-N_n)(c_o+te_o)\right]\beta}{\alpha^2}\right]$$

$$=2s\left[\frac{\left[\left[1+s(N-N_n+1)\right]\beta+s(N-2N_n)\gamma\right]\bar{\theta}}{\alpha^2}-\frac{\left[(N-N_n+1)\beta+(N-2N_n)\alpha\right](c_n+te_n)}{\alpha^2}+\frac{\left[(N-N_n)\beta+(N-2N_n)\alpha\right](c_o+te_o)}{\alpha^2}\right]$$

where $\alpha=(1+s)(N+1)+sN_n(N-N_n)>0$ and $\beta=\alpha+s(N-2N_n)^2>0$ for all N_n. The condition for the numerator of equation (22) to be positive, thereby the whole equation to be positive, is:

$$\text{(25)}\qquad \bar{\theta}>\frac{\left[(N-N_n+1)\beta+(N-2N_n)\alpha\right](c_n+te_n)}{\left[1+s(N-N_n+1)\right]\beta+s(N-2N_n)\alpha}-\frac{\left[(N-N_n)\beta+(N-2N_n)\alpha\right](c_o+te_o)}{\left[1+s(N-N_n+1)\right]\beta+s(N-2N_n)\alpha}.$$

For the convexity of the equilibrium quantity of a green firm, all we need to show is that equation (25) holds. Equation (25) describes that $\bar{\theta}$ is greater than the difference between weighted production costs. It can be checked that the denominator of two weights

($[1+s(N-N_n+1)]\beta+s(N-2N_n)\alpha$) is decreasing in N_n because its first derivative with respect to N_n is negative for all N_n (i.e., $-3s[(1+s)+2(N-N_n)+s(N-N_n)(N-N_n+2)]<0$ for $N_n \in [0,N]$). Since the denominator is positive when $N_n = N$ by $(1+s)(1+s+N)$, it is always positive for all N_n. Note that the RHS of equation (25) subtracted by that of equation (17) is $-\beta[(c_n+te_n)-(1+s)(c_o+te_o)]/\{s[[1+s(N-N_n+1)]\beta+s(N-2N_n)\alpha]\}$ which is negative. Therefore, under Assumption 1, the equilibrium quantity of green good in Stage 3 of the tax game is strictly convex in N_n.

Next, the numerator in equation (24) can be expressed as follows:

$$-2\frac{\partial q_o^T(N_n,t)}{\partial N_n}[s(N-2N_n)]+2sq_o^T(N_n,t)>0$$

$$=-2s\left[\frac{[(c_n+te_n)-(1+s)(c_o+te_o)]-q_o^T(N_n,t)[s(N-2N_n)]}{\alpha}(N-2N_n)-q_o^T(N_n,t)\right]$$

$$=-2s\frac{[(c_n+te_n)-(1+s)(c_o+te_o)](N-2N_n)-q_o^T(N_n,t)\beta}{\alpha}$$

$$=-2s\left[\frac{[(c_n+te_n)-(1+s)(c_o+te_o)](2N_n-N)\alpha}{\alpha^2}-\frac{[(1+s)\overline{\theta}+N_n(c_n+te_n)-(1+s)(N_n+1)(c_o+te_o)]\beta}{\alpha^2}\right]$$

$$=-2s\left[\frac{-(1+s)\beta\overline{\theta}}{\alpha^2}+\frac{[(2N_n-N)\alpha-N_n\beta](c_n+te_n)}{\alpha^2}-\frac{(1+s)[(2N_n-N)\alpha-(N_n+1)\beta](c_o+te_o)}{\alpha^2}\right]$$

where $\alpha = (1+s)(N+1) + sN_n(N - N_n) > 0$ and $\beta = \alpha + s(N - 2N_n)^2 > 0$ for all N_n. The condition for the numerator of equation (24) to be positive (thereby the whole equation to be positive) is:

$$(26) \qquad \bar{\theta} > \left[\frac{1}{1+s}\right]\left[\left[\frac{(N-2N_n)\alpha}{\beta} - N_n\right](c_n + te_n) - \left[\frac{(N-2N_n)\alpha}{\beta} - (N_n + 1)\right](c_o + te_o)\right]$$

The equation (26) describes that $\bar{\theta}$ is greater than the difference between weighted production costs. The RHS of equation (26) subtracted by that of equation (17) is

$$(27) \qquad \frac{1}{(1+s)s\beta}\left[s\{(N-2N_n)\alpha - (N_n+1)\beta\} - \beta\right]\left[(c_n + te_n) - (1+s)(c_o + te_o)\right].$$

The term of $s[(N-2N_n)\alpha - (N_n+1)\beta] - \beta$ is decreasing in N_n because its first derivative is negative for all N_n (i.e., $-3s[(1+s) + 2N_n + sN_n(N_n+2)] < 0$ for $N_n \in [0, N]$). When $N_n = 0$, the term becomes $-s(1+s)[(c_n + te_n) - (1+s)(c_o + te_o)]$ which is negative, meaning that the term is negative for all N_n. Then the whole term (27) is negative for all N_n, which implies that under Assumption 1 the Stage 3 equilibrium quantity for a regular firm is strictly convex in N_n.

C.4 Solutions at Equilibrium under Tax policy

We focus on the Stage 2 equilibrium, where all equilibrium outcomes are functions of the equilibrium number of green firm, determined in Stage 2, and the given tax rate. When expressing functions, we drop their arguments for the convenience. Additionally, let $z_n^T \equiv p_n^T - (c_n + te_n)$ and $z_o^T \equiv p_o^T - (c_o + te_o)$.

From the supply side, equations (3), (4), (9) and (10) can be expressed as

$$q_n^T = \frac{p_n^T - (c_n + te_n)}{1+s} = \frac{z_n^T}{1+s}; \qquad q_o^T = p_o^T - (c_o + te_o) = z_o^T;$$

$$\pi_n^T = \frac{\left[p_n^T - (c_n + te_n)\right]^2}{1+s} = \frac{\left[z_n^T\right]^2}{1+s}; \qquad \pi_o^T = \left[p_o^T - (c_o + te_o)\right]^2 = \left[z_o^T\right]^2.$$

For aggregate quantities, we get equations (28) and (29) as follows:

(28) $$Q_n^T = N_n^T q_n^T = N_n^T \frac{z_n^T}{1+s};$$

(29) $$Q_o^T = (N - N_n^T) q_o^T = (N - N_n^T) z_o^T.$$

From the demand side, evaluating at equilibrium, equations (1) and (2) are expressed as

$Q_n^T = \bar{\theta} + p_n^T - p_o^T / s$ and $Q_o^T = p_n^T - p_o^T / s - p_o^T$. Rearranging terms gives the followings:

(30) $$Q_n^T = \frac{s\bar{\theta} + z_o^T - z_n^T + (c_o + te_o) - (c_n + te_n)}{s};$$

(31) $$Q_o^T = \frac{z_n^T - (1+s) z_o^T + c_n + te_n - (1+s)(c_o + te_o)}{s}.$$

Additionally, from equation (11), we have

(32) $$z_n^T = (1+s)^{0.5} z_o^T.$$

Combining equations (28) and (30) and combining equation (29) and (31) yield two equations

where each is a function of z_n^T, z_o^T and N_n^T.

(33) $$N_n^T \frac{z_n^T}{1+s} = \frac{s\bar{\theta} + z_o^T - z_n^T + (c_o + te_o) - (c_n + te_n)}{s};$$

(34) $$(N-N_n^T)z_o^T = \frac{z_n^T - (1+s)z_o^T + (c_n + te_n) - (1+s)(c_o + te_o)}{s}.$$

Utilizing equation (32) in addition to equations (33) and (34), we can figure out expressions for z_n^T and z_o^T. Those expressions consist of only exogenous parameters and tax rate, thereby provide expressions for other variables as follows.

(35) $$q_n^T(t) = \frac{s\bar{\theta} - \left[1-(1+s)^{-0.5}\right](c_n + te_n) - \left[(1+s)^{0.5} - 1\right](c_o + te_o)}{2(1+s) - 2(1+s)^{0.5} + sN};$$

(36) $$q_o^T(t) = \frac{(1+s)^{0.5}s\bar{\theta} - \left[(1+s)^{0.5} - 1\right](c_n + te_n) - \left[(1+s) - (1+s)^{0.5}\right](c_o + te_o)}{2(1+s) - 2(1+s)^{0.5} + sN};$$

$$Q_n^T(t) = \frac{\left[(1+s) - (1+s)^{0.5} + sN\right]\bar{\theta} - (1+N)(c_n + te_n) + \left[(1+s)^{0.5} + N\right](c_o + te_o)}{2(1+s) - 2(1+s)^{0.5} + sN};$$

$$Q_o^T(t) = \frac{\left[(1+s)^{0.5} + N\right](c_n + te_n) - (1+s)(1+N)(c_o + te_o) - (1+s)\left[(1+s)^{0.5} - 1\right]\bar{\theta}}{2(1+s) - 2(1+s)^{0.5} + sN};$$

$$\pi_n^T(t) = (1+s)\left\{\frac{s\bar{\theta} - \left[1-(1+s)^{-0.5}\right](c_n + te_n) - \left[(1+s)^{0.5} - 1\right](c_o + te_o)}{2(1+s) - 2(1+s)^{0.5} + sN}\right\}^2;$$

$$\pi_o^T(t) = \left\{\frac{(1+s)^{0.5}s\bar{\theta} - \left[(1+s)^{0.5} - 1\right](c_n + te_n) - \left[(1+s) - (1+s)^{0.5}\right](c_o + te_o)}{2(1+s) - 2(1+s)^{0.5} + sN}\right\}^2;$$

$$N_n^T(t) = \frac{\bar{\theta}\left[(1+s) - (1+s)^{0.5} + sN\right] - (1+N)(c_n + te_n) + \left[(1+s)^{0.5} + N\right](c_o + te_o)}{s\bar{\theta} - \left[1-(1+s)^{-0.5}\right](c_n + te_n) - \left[(1+s)^{0.5} - 1\right](c_o + te_o)}.$$

C.5 Proof of Lemma 3

L.2(1) $$\frac{\partial q_n^T(t)}{\partial t} = \frac{-\left[1-(1+s)^{-0.5}\right]e_n - \left[(1+s)^{0.5}-1\right]e_o}{2(1+s)-2(1+s)^{0.5}+sN} < 0.$$

($\because$ $1-(1+s)^{-0.5} > 0$, $(1+s)^{0.5}-1 > 0$, and $2(1+s)-2(1+s)^{0.5} > 0$.)

L.2(2) $$\frac{\partial q_o^T(t)}{\partial t} = \frac{-\left[(1+s)^{0.5}-1\right]e_n - \left[(1+s)-(1+s)^{0.5}\right]e_o}{2(1+s)-2(1+s)^{0.5}+sN} < 0$$

($\because$ $(1+s)^{0.5}-1 > 0$, $(1+s)-(1+s)^{0.5} > 0$, and $2(1+s)-2(1+s)^{0.5} > 0$)

L.2(3) $$\frac{\partial Q_n^T(t)}{\partial t} = \frac{-(1+N)e_n + \left[(1+s)^{0.5}+N\right]e_o}{2(1+s)-2(1+s)^{0.5}+sN} > 0.$$

($\because$ Given that $(1+s)^{0.5} > 1$ for all $s > 0$ and $e_o > e_n$, we know that $\frac{e_o}{e_n} > 1 > \frac{(1+N)}{(1+s)^{0.5}+N}$.

Rearranging $\frac{e_o}{e_n} > \frac{(1+N)}{(1+s)^{0.5}+N}$ yields that $-(1+N)e_n + \left[(1+s)^{0.5}+N\right]e_o > 0$.)

L.2(4) $$\frac{\partial Q_o^T(t)}{\partial t} = \frac{\left[(1+s)^{0.5}+N\right]e_n - (1+s)(1+N)e_o}{2(1+s)-2(1+s)^{0.5}+sN} < 0.$$

($\because$ Given that $(1+s)^{0.5}+N < 1+s+N < (1+s)(1+N)$ for all $s > 0$ and $e_o > e_n$, we know

that $\frac{e_o}{e_n} > 1 > \frac{(1+s)^{0.5}+N}{(1+s)(1+N)}$. Rearranging $\frac{e_o}{e_n} > \frac{(1+s)^{0.5}+N}{(1+s)(1+N)}$ yields that

$\left[(1+s)^{0.5}+N\right]e_n - (1+s)(1+N)e_o < 0$.)

L.2(5) $\frac{\partial \pi_n^T(t)}{\partial t} < 0$ ($\because$ π_n^T is monotonically transformed from q_n^T and $\frac{\partial q_n^T(t)}{\partial t} < 0$.)

L.2(6) $\frac{\partial \pi_o^T(\tau)}{\partial \tau} < 0$ ($\because$ π_o^T is monotonically transformed from q_o^T and $\frac{\partial q_o^T(t)}{\partial t} < 0$.)

L.2(7) $$\frac{\partial N_n^T(t)}{\partial t}=\frac{\partial\left(\frac{Q_n^T(t)}{q_n^T(t)}\right)}{\partial t}=\frac{\left(\frac{\partial Q_n^T(t)}{\partial t}\right)q_n^T(t)-Q_n^T\left(\frac{\partial q_n^T(t)}{\partial t}\right)}{\left(q_n^T(t)\right)^2}>0 \ (\because \ \frac{\partial Q_n^T(t)}{\partial t}>0 \text{ and } \frac{\partial q_n^T(t)}{\partial t}<0.)$$

L.2(8) $$\frac{\partial E^T(t)}{\partial t}=e_n\frac{\partial Q_n^T(t)}{\partial t}+e_o\frac{\partial Q_o^T(t)}{\partial t}$$

$$=e_n\frac{-(1+N)e_n+\left[(1+s)^{0.5}+N\right]e_o}{2(1+s)-2(1+s)^{0.5}+sN}+e_o\frac{\left[(1+s)^{0.5}+N\right]e_n-(1+s)(1+N)e_o}{2(1+s)-2(1+s)^{0.5}+sN}$$

$$=-\frac{(1+N)e_n^2-2\left[(1+s)^{0.5}+N\right]e_ne_o+(1+s)(1+N)e_o^2}{2(1+s)-2(1+s)^{0.5}+sN}$$

$$<-\frac{(1+N)e_n^2-2\left[(1+s)^{0.5}+(1+s)^{0.5}N)\right]e_ne_o+(1+s)(1+N)e_o^2}{2(1+s)-2(1+s)^{0.5}+sN}$$

$$=-\frac{\left[(1+N)^{0.5}e_n\right]^2-2\left[(1+s)^{0.5}(1+N)^{0.5}(1+N)^{0.5}\right]e_ne_o+\left[(1+s)^{0.5}(1+N)^{0.5}e_o\right]^2}{2(1+s)-2(1+s)^{0.5}+sN}$$

$$=-\frac{\left[(1+N)^{0.5}e_n-(1+s)^{0.5}(1+N)^{0.5}e_o\right]^2}{2(1+s)-2(1+s)^{0.5}+sN}$$

$$<0.$$

C.6 Proof of Lemma 5

The proof proceeds as follows. First, we show that for a given t the Stage 3 equilibrium total quantity of green firms $Q_n^T(N_n,t)$ is strictly increasing in N_n for $N_n\in[0,N]$. Next, we show that the total output in the industry $Q_n^T(N_n,t)+Q_o^T(N_n,t)$ is strictly decreasing in N_n for $N_n\in[N_n^T(t),N]$, where $N_n^T(t)$ is the (interior) equilibrium number of green firms in Stage 2.

Note that when the total industry output is decreasing in N_n, there will be less industry-wide emissions as N_n increases if the total quantity of green goods, produced at a smaller constant marginal emission rate than regular goods, is increasing. Hence, it is proved that for a given t the industry-wide emission level is decreasing in N_n for $N_n \in [N_n^T(t), N]$. By definition, when applying $t = 0$, the same feature hold under the VA for $N_n \in [N_n^L, N]$, which is the range of interest in the VA game.

The first derivative of the total green output with respect to N_n looks as follows.

$$(37) \qquad \frac{\partial Q_n^T(N_n,t)}{\partial N_n} = \frac{-\left[s\bar{\theta} - (c_n + te_n) + (c_o + te_o)\right]N_n + q_n^T(N_n,t)\left[(1+s)(N+1) + sN_n^2\right]}{(1+s)(N+1) + sN_n(N-N_n)}.$$

For the strictly increasing total green output in N_n, equation (37) should be positive. Using equation (5), we can express equation (37) as follows.

$$(38) \qquad \bar{\theta} > \left[\frac{(N-N_n+1)\gamma - N_n\alpha}{\left[1+s(N-N_n+1)\right]\gamma - sN_n\alpha}\right](c_n + te_n) - \left[\frac{(N-N_n)\gamma - N_n\alpha}{\left[1+s(N-N_n+1)\right]\gamma - sN_n\alpha}\right](c_o + te_o)$$

where $\alpha = (1+s)(N+1) + sN_n(N-N_n) > 0$ and $\gamma = (1+s)(N+1) + sN_n^2 > 0$ for all N_n.

The equation (38) describes that $\bar{\theta}$ is greater than the difference between weighted production costs. We can check that the derivative of the denominator of two weights with respect to N_n is negative (i.e., $-2s(1+s)[N - N_n + 1] < 0$). Then we can conclude that the denominator is positive for all N_n because the denominator is positive when $N_n = N$ (i.e., $(1+s)(1+s+N) > 0$). In addition, the RHS of equation (38) subtracted by that of equation (25) is

$$(39) \qquad \frac{-\left[(1+s)(N+1)(N-N_n) + sN_n(N-N_n)^2\right]\left[(c_n + te_n) - (1+s)(c_o + te_o)\right]}{\left[\{1+s(N-N_n+1)\}\gamma - s\alpha N_n\right]\left[\{1+s(N-N_n+1)\}\beta + s\alpha(N-2N_n)\right]}.$$

For the denominator of term (39), we checked that the first square bracket is positive in the foregoing, and it is shown that the second bracket is positive in Appendix C.3, thereby the denominator is positive for all N_n. Thus, the whole term (39) is negative, implying that the convexity of the individual quantity of green firms in N_n guarantees that equation (37) holds, which proves the total quantity of greens firms is strictly increasing in N_n for $N_n \in [0, N]$.

Next, the first derivative of total output in the industry is as follows.

$$\frac{\partial\left[Q_n^T(N_n,t)+Q_o^T(N_n,t)\right]}{\partial N_n}=\frac{\partial\left[\bar{\theta}-p_o^T(N_n,t)\right]}{\partial N_n} \quad \text{[by equations (1) and (2)]}$$

$$=\frac{\partial\left[\bar{\theta}-(q_o^T(N_n,t)+c_o+te_o)\right]}{\partial N_n} \quad \text{[by equation (4)]}$$

$$=-\frac{\partial q_o^T(N_n,t)}{\partial N_n}.$$

Now showing that the total industry output strictly decreases in N_n is equivalent to showing above expression is negative or $\partial q_o^T(N_n,t)/\partial N_n$ is positive. First, the value of $\partial q_o^T(N_n,t)/\partial N_n$ evaluated at $N_n = N$ is as follows.

$$\left.\frac{\partial q_o^T(N_n,t)}{\partial N_n}\right|_{N_n=N}=\frac{\left[(c_n+te_n)-(1+s)(c_o+te_o)\right]+q_o^T(N,t)sN}{(1+s)(N+1)}.$$

This derivative is positive by equation (18). Also, as shown in Appendix C.3, we know that $q_o^T(N_n,t)$ is strictly convex in N_n. Hence, if it is checked that the first derivative of $q_o^T(N_n,t)$ is positive at a certain value $\breve{N}_n \in [0, N)$, it is also positive for all N_n which is greater than $\breve{N}_n$. In this sense, we check the sign of the first derivative of $q_o^T(N_n,t)$ at $N_n^T(t)$ which is defined by the intersection of the equilibrium quantities of green and regular firms in Stage 2 of the tax game.

$$\left.\frac{\partial q_o^T(N_n,t)}{\partial N_n}\right|_{N_n=N_n^T(t)} = \frac{[(c_n+te_n)-(1+s)(c_o+te_o)]-q_o^T(t)\left[s\left(N-2N_n^T(t)\right)\right]}{(1+s)(N+1)+sN_n^T(t)\left(N-N_n^T(t)\right)}$$

$$= \frac{[(c_n+te_n)-(1+s)(c_o+te_o)]-sq_o^T(t)\left[\frac{Q_o^T(t)}{q_o^T(t)}-\frac{Q_n^T(t)}{q_n^T(t)}\right]}{(1+s)(N+1)+sN_n^T(t)\left(N-N_n^T(t)\right)}$$

$$= \frac{[(c_n+te_n)-(1+s)(c_o+te_o)]-s(1+s)^{0.5}\left[(1+s)^{-0.5}Q_o^T(t)-Q_n^T(t)\right]}{(1+s)(N+1)+sN_n^T(t)\left(N-N_n^T(t)\right)}$$

$$= \frac{(1+s)^{0.5}\left[s\bar{\theta}-[(c_n+te_n)-(c_o+te_o)]\right]}{(1+s)(N+1)+sN_n^T(t)\left(N-N_n^T(t)\right)}$$

$$> 0. \text{ [by equation (17)]}$$

Under Assumption 1, therefore, the first derivative of $q_o^T(N_n,t)$ with respect to N_n is positive at $N_n = N_n^T(t)$ (and we have shown the derivative is also positive at $N_n = N$). Based on the convexity of $q_o^T(N_n,t)$, this implies that $q_o^T(N_n,t)$ strictly increases in N_n for $N_n \in [N_n^T(t),N]$, and in turn $Q_n^T(N_n,t)+Q_o^T(N_n,t)$ strictly decreases in N_n for $N_n \in [N_n^T(t),N]$. As a result, given that $Q_n^T(N_n,t)$ increases in N_n and given that $e_n < e_o$, the total emission level, $E^T(N_n,t) \equiv e_nQ_n^T(N_n,t)+e_oQ_o^T(N_n,t)$, strictly decreases in N_n for $N_n \in [N_n^T(t),N]$ and a given t. By applying $t=0$, we prove that $E^V(N_n)$ strictly decreases in N_n for $N_n \in [N_n^L,N]$ in the VA game.

Strictly speaking, when showing the positive sign of $\partial q_o^T(N_n,t)/\partial N_n$ at $N_n = N_n^T(t)$, we utilize the notion of interior solution $N_n^T(t)$. Thereby the proof holds for $N_n^L = 0$ but it should be the case of an interior solution ($\pi_n^V(0) = \pi_o^V(0)$). The proof simply extends to the boundary situation (e.g., $N_n^L = 0$ as $\pi_n^V(0) < \pi_o^V(0)$), since it is the case that the intersection is made in negative region of N_n so that the sign of $\partial q_o^T(N_n,t)/\partial N_n$ is now positive for $N_n \in [0,N]$.

C.7 Solutions at Equilibrium under VA

In Stage 3 of the VA game, equilibrium schedules are obtained in a same way as Stage 3 in the tax game except that there no emission tax ($t = 0$). Dropping arguments for the convenience, let $z_n^V \equiv p_n^V - c_n$ and $z_o^V \equiv p_o^V - c_o$. Then the counter parts of equations (33) and (34) in the VA game look as follows:

(40) $$N_n^V \frac{z_n^V}{1+s} = \frac{s\bar{\theta} + z_o^V - z_n^V - c_n + c_o}{s};$$

(41) $$(N - N_n^V)z_o^V = \frac{z_n^V - (1+s)z_o^V + c_n - (1+s)c_o}{s}.$$

Additionally, from equation (13) we have following condition.

$$0 = \bar{E} - e_n Q_n^V - e_o Q_o^V$$

$$= \bar{E} - e_n\left(\bar{\theta} + \frac{p_n^V - p_o^V}{s}\right) - e_o\left(\frac{p_n^V - p_o^V}{s} - p_o^V\right)$$

$$= \bar{E} - e_n\bar{\theta} - \frac{e_n + e_o}{s}p_n^V + \frac{e_n + (1+s)e_o}{s}p_o^V$$

$$= \bar{E} - e_n\bar{\theta} - \frac{e_n + e_o}{s}(z_n^V + c_n) + \frac{e_n + (1+s)e_o}{s}(z_o^V + c_o).$$

Then we have following relationship between z_n^V and z_o^V.

(42) $$z_n^V = \frac{e_n + (1+s)e_o}{e_n + e_o}(z_o^V + c_o) + \frac{(\bar{E}^V - e_n\bar{\theta})s}{e_n + e_o} - c_n.$$

Using equation (42), we can express equations (40) and (41) in terms of N_n^V and z_o^V. After rearranging equation (41) for z_o^V, we can find the expression of N_n^V as equation (14) by substituting equation (41) into equation (40). Once N_n^V is obtained, we can find z_n^V and z_o^V, thereby all other equilibrium outcomes can be obtained but not as closed form solutions due to the nonlinearity.

C.8 Supplementary Figures

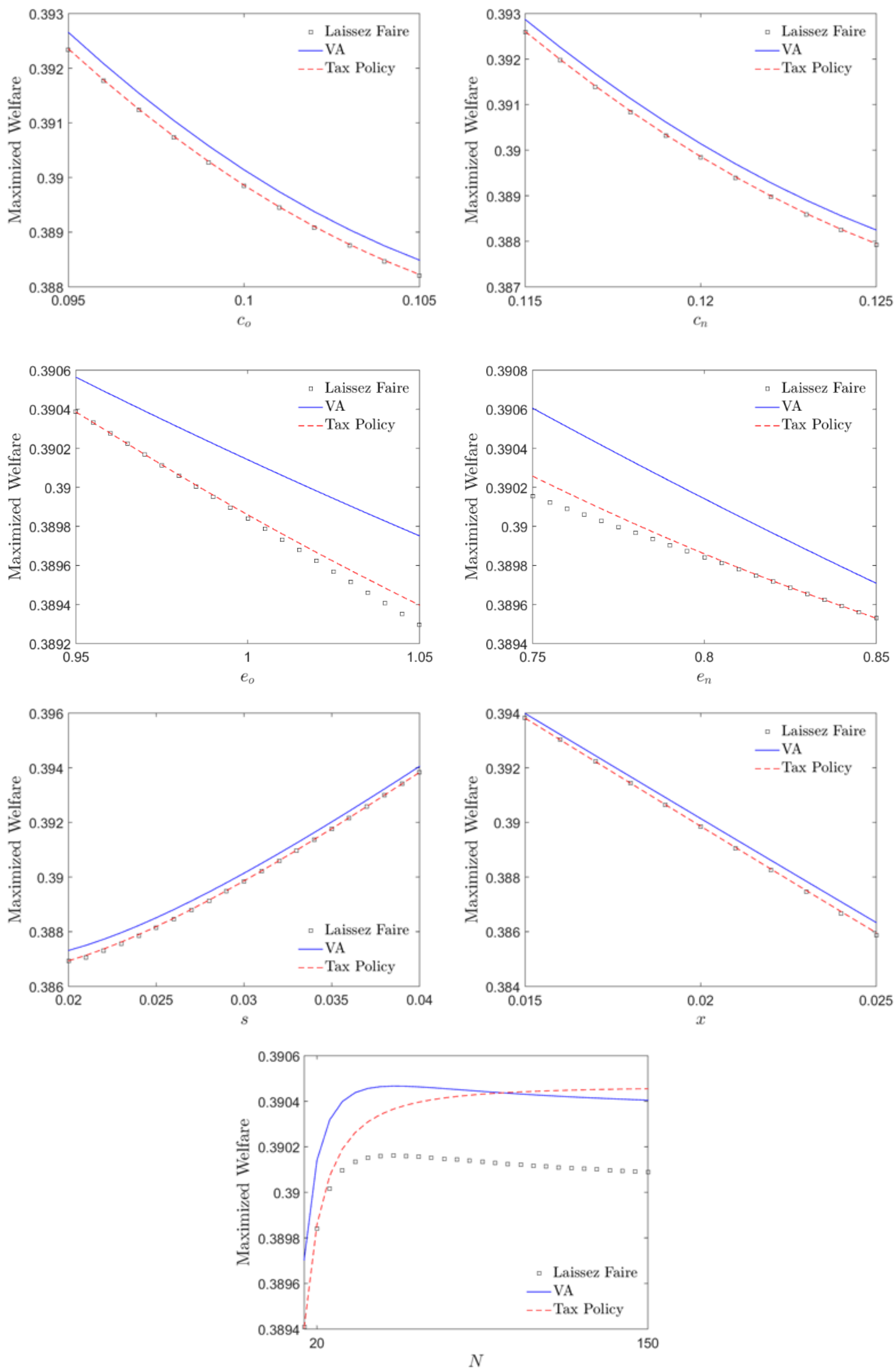
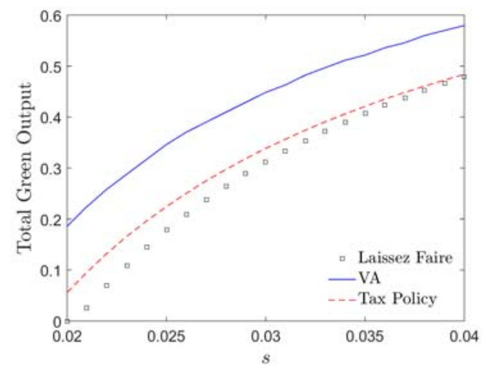
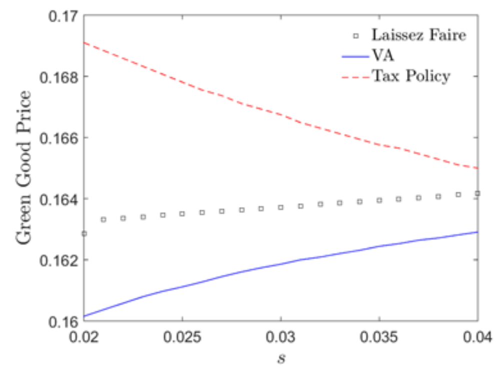


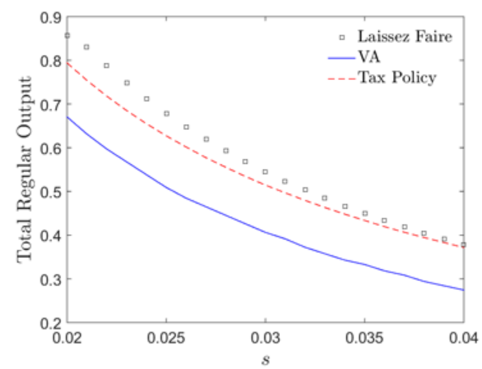
Figure C1. Effects of parameter changes on maximized welfare



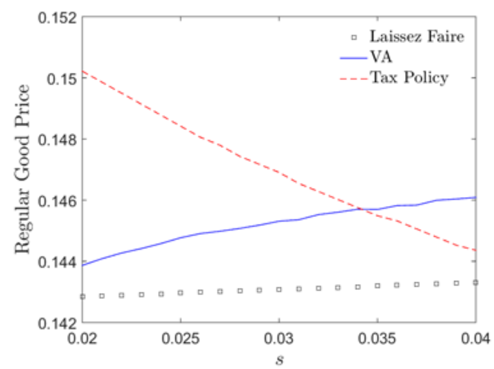
(a) Total green output



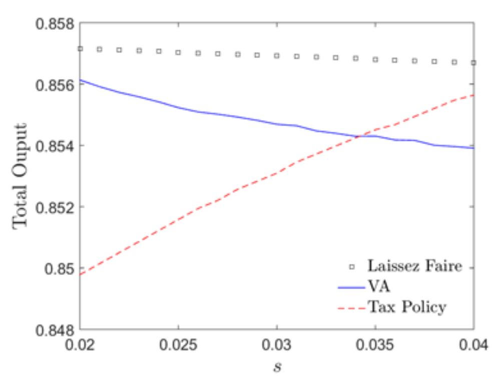
(b) Green good price



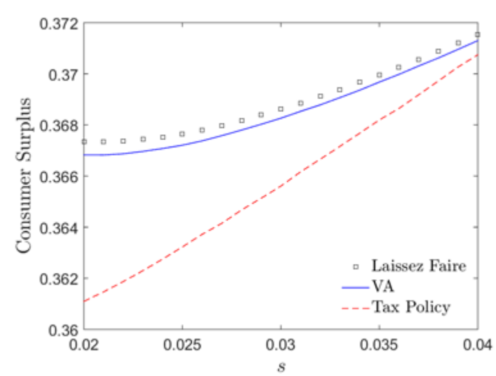
(c) Total regular output



(d) Regular good price



(e) Total output



(f) Consumer surplus

Figure C2. Effects of changes in consumers' additional benefit from a green good (s) on markets

CHAPTER 5

CONCLUSIONS

This dissertation analyzes agricultural and environmental policies that affect the market impacts and resulting welfare in relevant domains. In the first essay, the current and future impact of the U.S. renewable fuel standard (RFS) was analyzed via a multi-market competitive equilibrium model that reflects key features of the markets and RFS. Next, we estimate the U.S. corn and soybean dynamic supply responses, especially focusing on recent years under the RFS, to obtain implications regarding whether the United States is sufficiently responsive to the RFS-induced demand shock on agricultural feedstocks. Lastly, we analyze the performance of voluntary agreements (VAs) relative to other market-based policy options, under an oligopoly market with consumers who care about the greenness of firms.

The results of the first essay confirm that the current RFS program considerably benefits the agriculture sector, but also leads to overall welfare gains for the United States. Virtually all of these US welfare gains are due to the impact of RFS policies on the terms of trade. Furthermore, the most relevant effects are those associated with the RFS impacts on the price of key U.S. agricultural exports (corn and soybean products). Implementation of projected 2022 mandates, which would require further expansion of biodiesel production, would lead to a considerable welfare loss (relative to 2015 mandate levels). Constrained (second-best) optimal mandates would entail more corn-based ethanol and less biodiesel than currently mandated.

The second analysis suggest that U.S. corn and soybean acreage response more in the short run than in the long run, and display the presence of significant cross-acreage dynamics. Cross-price elasticities of acreage responses between corn and soybeans are negative, as expected, and fairly large in absolute value. This implies that when corn and soybean prices move together, the response of total acreage allocated to these two crops is extremely inelastic (0.04 for the short and long run). This suggest that the ability of the U.S. corn and soybean production sector to accommodate the demand shock due to the RFS is limited.

Through the third essay, we find that when the market is non-competitive, the VA, relative to other policy options, improves welfare despite suffering from free-riding behavior. It is also found that as consumers value the green good more, the VA increases the number of green firms and provides a less competitive environment for free-riders, who increase the price of regular goods. As a result, the total market under the VA becomes less covered, at some point, than the tax policy. Regarding implementation, the potential gains from of the VA are attainable provided the regulator's threat is credible and sufficiently strong. If the regulator is required to be time-consistent, it becomes infeasible to induce enough VA participants due to the weak threat.