The Renewable Fuel Standard: Market and Welfare Effects of Alternative Policy Scenarios

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Abstract

We construct a tractable multi-market equilibrium model designed to evaluate alternative biofuel policies. The model integrates the US agricultural sector with the energy sector, and explicitly consider both US ethanol and biodiesel production. The model provides a careful structural representation of the renewable fuel standard (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 parameterized model is simulated to analyze alternative scenarios, including: repeal of the RFS; projected 2022 RFS mandates; and, optimal (second best) mandates. The results confirm that the current RFS program considerably benefits the agriculture sector, but also leads to overall welfare gains for the United States (mostly via beneficial terms of trade effects). 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*). Constrained optimal mandates would entail more corn-based ethanol and less biodiesel than in both the *status quo* and the projected 2022 scenario.

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1. Introduction

Over the last decade the United States have 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 the impact that this has had on food prices has fueled controversies. Concerns have also been raised about the actual environmental benefits of biofuels, especially vis-à-vis the existence of indirect land use effects. In addition, difficulties exist in meeting the desired targets for biofuel use. Further expansions of the corn-based ethanol industry is constrained by the so-called blend wall, and the development and production of cellulosic biofuel has severely lagged the mandates schedule set out in EISA. Furthermore, the current economic environment of 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 paper we construct a tractable multi-market equilibrium model that is specifically designed 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 production and welfare impacts of these policies. The model improves on many existing models focused exclusively on ethanol (e.g., Cui et al. 2011) by explicitly modeling both US ethanol and biodiesel production. This requires a coherent system representation of the feedstock used in biofuel production. For conventional ethanol, 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), in this paper we assume that further expansions of biodiesel production would have to rely on redirecting vegetable oils from other uses. 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 (e.g., EPA 2016), an economic evaluation of current and prospective US biofuel policies need to consider the interactions between ethanol and biodiesel production. In this paper we propose to do so by developing 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 paper 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 *status quo* level of mandates entails a 40% 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 1.7%. Because the United States are 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 does lead to reduced carbon emission, although we estimate that the monetary value of such reduced emission accounts for only about 20% of the overall welfare effect. Aggregate welfare in the *status quo* is larger than in the "no biofuel policy" scenario by about $4.4 billion. To further improve welfare from the *status quo*, 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 the EPA recent waivers—would lead to sizeable welfare losses relative to the *status quo*.

[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.

2. The RFS: A Brief Overview

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 encompasses 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. To enforce these RVOs the EPA has developed a Renewable Identification Number (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.

[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).

Table 1. Statutory Mandates, EPA Rulings, and 2022 Scenario (billion gallons)

	2015		2016		2017		2022	
	EISA	EPA Final	EISA	EPA Final	EISA	EPA Proposed	EISA	Projected Scenario
Renewable fuel	**20.5**	**16.93**	**22.25**	**18.11**	**24.0**	**18.8**	**36.0**	**20.787**
Advanced biofuel	5.5	2.88	7.25	3.61	9.0	4.0	21.0	5.787
Biodiesel	≥ 1.0	1.73	≥ 1.0	1.90	≥ 1.0	2.00 [a]	≥ 1.0	… [b]
Cellulosic biofuel	3.0	0.123	4.25	0.230	5.5	0.312	16.0	0.787 [c]
Non-cellulosic advanced biofuel	*2.5*	*2.757*	*3*	*3.38*	*3.5*	*3.688*	*5*	*5*
Corn ethanol	*15*	*14.05*	*15*	*14.5*	*15*	*14.8*	*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.

Notes: [a] For biodiesel this 2017 mandate is final (proposed biodiesel mandate for 2018 is 2.1 billion gallons); [b] Biodiesel produced as needed (assumed to be the marginal advanced fuel); [c] Linear trend projection based on 2014-2017 EPA rulings ($R^2 = 0.998$).

Table 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 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 efficiently produced, at present, the implicit mandate for corn-based ethanol can be obtained as the difference between the renewable fuel mandate and the advance biofuel mandate. This is reported in the last row of Table 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 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 1.

The columns labeled "EPA" reflect the agency's exercise of its waiver authority (for 2017 these figures are proposed levels). 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, the EPA is signaling a clear intention to abide by the statutory mandates for the other components of the RFS. For example, for 2017, the implied non-cellulosic advanced biofuel mandate from the proposed rulemaking is actually higher than the implied statutory mandate. 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 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) [4]; 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).[5] The last column of Table 1 constitutes the "2022 scenario" that we will analyze in our counterfactual simulations, along with a few other scenarios discussed below.

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 soybean (including soybean oil and meal);

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[3] Although the biodiesel mandate in 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) meant to reflect the higher energy content of biodiesel (relative to ethanol) (Schnepf and Yacobucci 2013).

[4] Irwin and Good (2015) similarly assume that "…the write down in total advanced biofuels mandate is equivalent to the write down in the cellulosic mandate."

[5] Lade, Lin Lawell and Smith (2016) also find that biodiesel served as the marginal biofuel for RFS compliance in 2013.

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 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 (Schnepf and Yacobucci 2013). Inevitably, the model involves considerable notation; rather than introduce each term separately in the text, for the convenience of the reader the notation used is consolidated in Table A1 in the Appendix.

3.1 Domestic Production

The model represents three domestically produced primary products: corn, soybeans, and crude oil. Concerning the two agricultural products, we conceive of them as arising from an equilibrium allocation of 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. Holding constant (across scenarios) the price of other agricultural products, and the price of inputs used in farming (other than land and energy), the supply functions for corn and soybeans can be represented as:

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

where 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). The parameterization that we employ presumes a quadratic structure for the profit function, such that the supply functions are linear.

The acreage functions $L_i(p_i, p_j)$ are implicitly derived from profit-maximizing land allocation decisions. Hence, the supply functions that we parameterize embed equilibrium conditions in the land market. Because the model will solve for different equilibrium fuel prices across scenarios, the price of energy inputs used in agricultural production cannot be presumed constant. Nonetheless, under the ancillary simplifying condition that energy inputs are used in fixed proportion with land, having accounted for equilibrium in the land market it follows that the supply functions of interest can in fact be 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 $S_R(p_R)$.

Transformation sectors

The refining of crude oil yields gasoline, diesel fuel, and other refined petroleum products. We assume a Leontief (fixed proportions) production technology, such that the production process is represented as follows:

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

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

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

where $x_R \equiv S_R + \overline{S}_R$ is the total supply of crude oil to the US market ($\overline{S}_R$ 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 is represented by the following Leontief production functions:

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

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 valuable byproducts—such as distilled dried grains with soluble—that substitute for corn grain and soybean meal in animal feed (Hoffman and Baker 2011). The endogenously determined animal feed products in our model are corn and soybean meal. To account for the feedback effects on these markets of varying ethanol production (across scenarios), we assume that the quantities of byproducts which substitute for corn and soybean meal used in livestock feed are $\delta_1 \tilde{x}_c$ 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 produced oil and meal. In turns, some of the meal and oil that is domestically produced by the crushing process is exported. Given the assumed 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 and meal 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, and it can meet domestic demand for all other uses. Conversion of soybean oil into biodiesel 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.

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

[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.

Just 2010). Having accounted for their different energy contents, ethanol is considered a perfect substitute for gasoline, and biodiesel a perfect substitute for diesel.[7] 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. The indirect utility function 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. Thus, we are postulating strong (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 green-house gas (GHG) emissions associated with the consumption vector of all energy products (accounting for the fact that biorenewable energy products entail savings on emission).

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 product 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.

[7] As in Cui et al. (2011), the price of gasoline fuel is expressed in dollars per gasoline-energy-equivalent gallon (GEEG), and the price of diesel fuel is expressed in dollars per diesel-energy-equivalent gallon (DEEG).

4. Equilibrium

The equilibrium conditions represent the situation where the United States are 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. But because we calibrate the model to a specific benchmark data year (2015), we want to exactly account for other trade flows that, however, because they are of minor importance, are treated as exogenous in our equilibrium conditions. 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).[8] 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

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

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*).

The market clearing conditions can now be stated as follows:

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

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

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

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

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

$$x_h - X_h = D_h(p_h) \tag{15}$$

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.[9] 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 discussed earlier, that is, the following identities will hold at the equilibrium:

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

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

where ϑ is the coefficient that, as per the RFS regulation, converts biodiesel quantities into ethanol units (e.g., $\vartheta = 1.5$ for traditional biodiesel and $\vartheta = 1.7$ for renewable diesel). 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:

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

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

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

[9] 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 a number of 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 we need to link the price of endogenous fossil fuel inputs (gasoline and diesel), and the price of endogenous renewable fuels (ethanol and biodiesel), with the prices of blended fuels p_{gf} and p_{df}. These relationships need to reflect the fact that gasoline and diesel blends are subject to federal and state taxes (which are 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 relationship must reflect the cost that obligated parties (refiners and blenders) face for complying with the binding mandates, which are mediated by the Renewable Identification Numbers (RIN) prices.

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 in 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. Presuming that the "blend wall" is not binding (as maintained in our model), and 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 ethanol seller 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:

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

Analogously, a seller of 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:

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

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

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

Similarly, for an obligated party who sells only pure fossil-based diesel and buys all needed RINs, the zero-profit condition is:

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

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

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

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

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

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

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

The two terms on the LHS of equation (32) represent the total profit from selling fossil gasoline and fossil diesel on the domestic market, respectively. This profit must pay for the net loss of selling the mandated renewable fuel on the domestic market—that there are such net losses is a necessary implication of the condition that renewable fuel mandates are binding. 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 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 retail 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 of this paper 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 noting that, under the RFS, selling a gallon of fossil gasoline entails the same compliance cost as selling a gallon of fossil diesel. Hence, from (27) and (28) we immediately get the following arbitrage relation between blended fuel prices and the price of fuel inputs:

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

This equation provides the last arbitrage condition required to close the model. 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.

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 Supplementary Material document 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).

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.[10] The purpose of calibration is to choose parameter values for the chosen functional forms of demand and

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

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 soybean $S_c(p_c, p_s)$ and $S_s(p_c, p_s)$; domestic demand functions for corn, soybean meal and soybean oil $D_c(p_c, p_m, p_v)$, $D_m(p_c, p_m, p_v)$, and $D_v(p_c, p_m, p_v)$; foreign import demand functions for corn, soybean meal and soybean oil $\bar{D}_c(p_c)$, $\bar{D}_m(p_m)$, and $\bar{D}_v(p_v)$; domestic supply and foreign export supply functions for crude oil $S_R(p_R)$ and $\bar{S}_R(p_R)$; domestic demand functions for gasoline fuel and diesel fuel $D_{gf}(p_{gf}, p_{df})$ and $D_{df}(p_{gf}, p_{df})$; and, domestic demand function for other refined petroleum products $D_h(p_h)$. All of these functions are postulated to have a linear form.

Table 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.

Elasticities

The elasticity values used to calibrate the model, summarized in Table 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 Supplementary Material document. 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 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).

Tables 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]

Notes. [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 Supplementary Material document for more details.

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 Supplementary Material document 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, the elasticities we use in our baseline 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. We note that this value is also close to the estimated value 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 Supplementary Material document 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.

Technical coefficients

The full set of technical coefficients is reported in Table A2 in the Appendix. The Leontief production coefficient for ethanol production assumes that one bushel of corn yields 2.8 gallons of ethanol, just as in Cui et al. (2011). What we do differently in this paper 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 (Oil Crops Yearbook, USDA), 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.

GHG Emissions and Social Cost

Total GHG emission from transportation fuel and other refined petroleum products is computed as $E = \sum_j q_j E_j$, where q_j denotes the quantity of individual fuel types consumed in the United States, and E_j denotes the corresponding emission rate. These emission rates are reported in Table A3 in the Appendix. The GHG lifecycle emissions rate of fossil gasoline, measured as kg/gallon of carbon dioxide equivalent (CO2e), is taken from Wang et al. (2012). For the other types of fuels, the rates reported in this table account for both the EPA's relative lifecycle GHG emissions rates per energy unit of each fuel,[11] and the different energy content of each fuel. As for GHG emissions rate

[11] The relative lifecycle GHG emissions rates for diesel, corn-ethanol, biodiesel and sugarcane ethanol—when fuels are measured in energy equivalent units—are 100%, 79%, 43%, and 39%,

of other refined petroleum products, the coefficient we computed is based on five major products of this category.[12]

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, 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 $\gamma = \$20/\text{tCO2}$.[13] Due to the uncertainty and controversy regarding this parameter, however, alternative values will be considered in the sensitivity analysis section.

Other Baseline Variables

Data on prices and quantities used to calibrate the model are reported in the Supplementary Material document, which includes sources and calculation methods. Many of these values are also reported in the *status quo* column of Table 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

respectively. 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 A3.

[12] 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.

[13] 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).

the sum of actual net exports and implied net exports from the export of soybeans (as discusser earlier, exporting a bushel of soybeans in the model is equivalent to exporting a fixed-proportion bundle, as per the assumed technological coefficients). The price of biodiesel is also calculated. It turns out that a representative biodiesel price, such as that reported by the USDA,[14] would imply an unreasonably low "core value" for the corresponding RIN price, if one assumed that the biodiesel blending subsidy was 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.[15]

Other variables of interest reported in the *status quo* column of Table 3 also include motor fuel taxes and RIN prices. Concerning motor fuel taxes, we note at this juncture that these taxes, in virtual 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.[16]

[14] 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)

[15] 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.

[16] 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 (this is the average of D6 RIN prices over the period January 2016-May 2016, as reported in "PFL Weekly RIN Recap").

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: current RFS mandate levels (the *status quo*); implementation of the 2022 RFS mandates, with projected adjustments for cellulosic biofuels as discussed in section 2 (Table 1); and, repeal of the RFS (no biofuel policies).[17] In addition to evaluating the above scenarios, because we have an explicit welfare function, the model permits us to characterize optimal biofuel mandates. This scenario presumes that the blend wall is immaterial. Regardless of whether the latter assumption is realistic at present, this scenarios is of interest because it essentially estimates the expected welfare gains that would arrive from sufficient infrastructure investments to eliminate the blend wall (e.g., by promoting the diffusion of E85 gasoline blends). With this scenario, optimal mandates are calculated 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 will allow an estimate of market effects (e.g., prices and equilibrium quantities of agricultural products), 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 Supplementary Material document); net benefits accruing to domestic producers of crude oil; net government tax revenue; and, the monetary value of GHG emission savings.

[17] 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 Supplementary Material document provides the equilibrium conditions for the case when this requirement is binding.

6.1. Results

In Table 3 and Table 4, results pertaining to the various scenarios are reported by column in the following order: *laissez faire*, no biofuel policies, *status quo*, optimal mandates, and 2022 mandates. The top portion of Table 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 current level.[18] 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 (without loss of generality, because the biodiesel mandate is binding in those scenarios). Next, Table 3 reports the equilibrium prices and quantities for all scenarios that are considered. Whereas Table 3 focuses on the market impact of policies in the various scenarios, Table 4 pertains to the computed welfare impacts, which are reported as changes from the "no biofuel policies" scenarios, i.e., the *status quo ante*. 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 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 is the monetary value of the policies' impact on changes in GHG emissions. Because this estimate is dependent on the assumed social cost of carbon emission—a somewhat controversial parameter the value of which is surrounded by considerable uncertainty—this table also reports changes in emissions measured in physical units (tCO2e).

Status Quo, Status Quo Ante, and Laissez Faire

Given the calibration strategy described in the foregoing, the equilibrium variables for the *status quo* column in Table 3 are equal to the 2015 variables' 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 *status quo* is 9.9%, indicating that the blend wall has essentially been

[18] 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).

Table 3. Market Effects of Alternative Policy Scenarios

	Laissez Faire	No Biofuel Policies	*Status Quo*	Optimal Mandates	Year 2022 Mandates
Gasoline fuel tax ($/gallon)		0.449	0.449	0.449	0.449
Diesel fuel tax ($/gallon)		0.516	0.516	0.516	0.516
Biodiesel subsidy ($/gallon)			1.000		
Cellulosic biofuel mandate (billion units)			0.123		0.787
Advanced biofuel mandate (billion units)			2.880	1.626	5.787
Renewable biofuel mandate (billion units)			16.930	20.406	20.787
Corn price ($/bushel)	2.99	2.63	3.68	4.06	3.88
Soybean price ($/bushel)	9.19	9.10	10.10	9.70	11.14
Soybean meal price ($/short ton)	374.88	376.55	368.49	368.83	363.28
Soybean oil price (¢/pound)	22.30	21.12	31.60	28.05	41.83
Crude oil price ($/barrel)	49.94	49.22	48.40	48.27	48.00
Gasoline fuel price ($/GEEG)	2.00	2.32	2.22	2.11	2.30
Diesel fuel price($/DEEG)	1.49	2.09	2.24	2.57	2.12
Gasoline price ($/gallons)	2.00	1.87	1.72	1.58	1.74
Diesel price ($/gallons)	1.49	1.58	1.67	1.97	1.50
Ethanol price ($/gallon)	1.41	1.30	1.61	1.71	1.67
Biodiesel (supply) price ($/gallon)	2.94	2.85	3.65	3.38	4.43
Other refined products' price ($/KEEG)	1.06	1.16	1.26	1.28	1.31
RIN price for ethanol ($/unit)			0.49	0.68	0.50
RIN price for biodiesel ($/unit)			0.73	1.01	1.99
Ethanol quantity (billion gallons) [a]	7.960	4.144	14.140	18.868	15.104
Blending ratio of ethanol (%) [b]	5.440	3.000	9.871	12.819	10.652
Biodiesel quantity (billion gallons) [c]			1.779	1.025	3.275
Gasoline fuel quantity (billion GEEGs)	143.962	136.917	139.051	141.585	137.353
Diesel fuel quantity (billion DEEGs)	48.859	46.991	46.548	45.509	46.900
Other refined products quantity (bn KEEGs)	82.548	79.687	76.476	75.958	74.889
Corn production (billion bushels)	13.586	13.149	14.216	14.844	14.156
Soybean production (billion bushels)	4.046	4.147	3.927	3.766	3.975
Corn demand (billion bushels)	8.123	8.273	7.851	7.675	7.794
Total corn for ethanol (billion bushels)	2.811	1.449	5.158	6.847	5.497
Corn export (billion bushels)	2.766	3.244	1.833	1.316	1.564
Soybean meal demand (million short tons)	47.082	46.522	48.408	48.854	49.042
Soybean meal export (million short tons)	54.905	54.469	56.572	56.483	57.932
Soybean oil demand (billion pounds)	12.753	12.724	12.260	12.670	11.525
Soybean oil for biodiesel (billion bushels)			8.363	2.595	19.803
Soybean oil export (billion pounds)	31.656	32.829	22.421	25.943	12.261
Crude oil domestic supply (billion barrels)	3.477	3.465	3.450	3.448	3.443
Crude oil import (billion barrels)	3.314	3.122	2.907	2.872	2.800

Notes. [a] Includes all ethanol blended into gasoline fuel: cellulosic ethanol, sugarcane ethanol, and corn-based ethanol. [b] Calculated by using physical units (ratio of gallons of ethanol to gallons of gasoline fuel). [c] Includes biodiesel imports and biodiesel from feedstocks other than vegetable oil, as well as biodiesel from vegetable oil.

reached.[19] The no biofuel policies scenario, as noted, presumes that all mandates and biofuel ethanol blending ratio in the *status quo* is 9.9%, indicating that the blend wall has essentially been crude oil price (and refined products prices) is much smaller: the crude oil price is estimated to decline by 1.7%, the gasoline price to decline by 7.8% (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 7%).

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 biofuel policies 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 4, comparing the *status quo* to the no biofuel policies we find that aggregate welfare is improved by the RFS, by $4.4 billion. Some of this positive impact depends on lowering pollution, as emission are reduced by 44 million tCO2e. The magnitude of this reduction is somewhat small, however, at least compared with the pollution reduction due to current motor fuel taxes (comparing the *laissez faire* with the no biofuel policies scenario, motor fuel taxes reduce pollution by 130 million tCO2e). Correspondingly, the monetary value of the reduced emissions attributable to the RFS is also somewhat limited ($0.9 billion, about

[19] The blending ratio is calculated by using physical units as ratio of gallons of all blended ethanol to gallons of gasoline fuel.

Table 4. Welfare Effects of Alternative Policies (changes relative to no biofuel policies)

	Laissez Faire	*Status Quo*	Optimal Mandates	Year 2022 Mandates
Social welfare ($ billion)	1.855	4.430	5.431	0.296
Pollution effect ($ billion) [a]	-2.596	0.873	0.706	1.742
Tax revenue ($ billion)	-86.508	0.174	3.102	1.828
P.S. Agriculture ($ billion) [b]	9.927	17.267	18.665	25.129
P.S. Crude Oil supply ($ billion) [b]	2.521	-2.819	-3.273	-4.207
Efficiency loss from cellulosic biofuel [c]		-0.221		-1.417
C.S. Crop products' demand ($ billion) [d]	-2.987	-9.384	-11.944	-11.911
C.S. Fuel demand ($ billion) [d]	73.845	6.808	7.745	1.359
Gasoline fuel demand ($ billion)	45.196	13.449	29.690	2.727
Diesel fuel demand ($ billion)	28.650	-6.641	-21.946	-1.368
C.S. Other refined products ($ billion) [d]	7.652	-8.267	-9.570	-12.228
Change in GHG emissions (million tCO2e) [a]	129.8	-43.64	-35.29	-87.11

Notes. [a] In the no-biofuel-policies scenario, the GHG emission level is 3,021 million tCO2e, the monetary cost of which is $60.4 billion. [b] P.S. = producer surplus. [c] Compute based on D3 RIN price of $1.80. [d] C.S. = consumer surplus.

20% of the total net welfare gains). Most of the estimated increase in aggregate welfare is ultimately due to the positive impacts that the RFS has on the US terms of trade. Mandates results in increased price of corn and soybean, and a decreased price of crude oil. Because the United States are 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. It is also of some interest to note that, compared with the no biofuel policies 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. The reason 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 externality.[20]

When comparing the *status quo* 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 soybean, noted earlier, the RFS is

[20] Given the assumed emission rates and social cost of carbon, the per-gallon Pigouvian taxes needed to correct the externality would be $0.239 for gasoline, $0.273 for diesel, $0.133 for corn-based ethanol, and $0.109 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).

estimated to increase the sector's producer surplus by $17.3 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.

Year 2022 Mandates

The last column in both Table 3 and Table 4 considers the 2022 RFS scenario, the terms of which were discussed earlier and illustrated in Table 1. The major differences in mandated volumes from the *status quo* values 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 additional pollution reduction relative to the *status quo*. As for welfare measures, however, Table 4 shows overall welfare is considerably lower with the 2022 mandates than in the *status quo*. The increase in crop prices benefit 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 the *status quo*), 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, biodiesel produced from vegetable oil turns out to be a costly way to increase advanced biofuel supply. The projected expansion of the cellulosic biofuel mandate also weighs heavily of 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.

Optimal Mandates

In this second best scenario, we take as given the existing motor fuel taxes and ask what level of mandates would maximize the welfare function. In this process, we also ignore the possible limitations arising from the blend wall. Indeed, one of the motivations for the exercise is precisely to impute a welfare value to the investment that may be required to remove blend wall constraints (such as, for example, an expanded fleet of flex fuel vehicles, and/or a larger network of E85 refueling stations). The grid search method that we implemented identifies an optimal biodiesel mandate of 1.63 billion gallons, zero mandates for cellulosic biofuel, and an overall renewable fuel mandate of 20.4 billion gallons (implying an effective corn-based ethanol mandate of approximately 18.8 billion gallons). Thus, the constrained optimal mandates that we find would envision a 25% 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 the *status quo* and the year 2022 scenario, but the soybean price would decline.

The corn increase results in higher marginal cost of supplying ethanol, and the ethanol price also increases. Consequently, the ethanol RIN price also increases. Table 3 indicates that the biodiesel RIN price also increases with the optimal mandates, relative to the *status quo*, 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 was preserved, the optimal mandates would entail essentially a zero RIN price for biodiesel).[21] These optimal mandates would result in higher emissions than the *status quo*. The overall welfare gains associated with such optimal mandates, relative to the *status quo*, is $1 billion. Again, this can be interpreted as the potential payoff of whatever investments may be

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

required to break down the blend wall. Whether such investments are socially beneficial, of course, would depend on their costs.

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 paper'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 of two experiments. A more comprehensive set of sensitivity analyses are being carried out and will be included in the Supplementary Material document.

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

The appropriate response to the carbon externality, of course, crucially depends on the social cost of carbon. Indeed, as noted earlier, given the assumed \$20/tCO2 social cost of carbon, existing motor fuel taxes exceed the level of Pigouvian taxes that would be required to correct this externality. A higher cost of carbon may change this feature, of course, and also directly impact estimated welfare effects. Hence, we start by considering a higher cost of carbon, specifically \$37.7/tCO2. Given the emission levels in Table A3, with this cost of carbon the implied Pigouvian taxes for fossil gasoline and diesel would be \$0.45/gallon and \$0.514/gallon, respectively, i.e.,

Table 5. Sensitivity Analysis

Market Effects	Higher social cost of carbon ($\gamma = 37.7$)			Pigouvian motor fuel taxes		
	Status Quo	Optimal Mandates	Year 2022 Mandates	*2015 Mandates*	Optimal Mandates	Year 2022 Mandates
Gasoline motor fuel tax ($/gallon)	0.449	0.449	0.449	0.239	0.239	0.239
Diesel motor fuel tax ($/gallon)	0.516	0.516	0.516	0.273	0.273	0.273
Ethanol subsidy ($/gallon)				0.106	0.106	0.106
Biodiesel subsidy ($/gallon)	1.000			0.164	0.164	0.164
Cellulosic biofuel mandate (billion units)	0.123		0.787	0.123		0.787
Advanced biofuel mandate (billion units)	2.880	2.292	5.787	2.880	1.764	5.787
Renewable biofuel mandate (billion units)	16.930	21.292	20.787	16.930	19.230	20.787
Corn price ($/bushel)	3.68	4.12	3.88	3.68	3.95	3.88
Soybean price ($/bushel)	10.10	10.01	11.14	10.10	9.73	11.14
Soybean meal price ($/short ton)	368.49	367.31	363.28	368.49	369.11	363.28
Soybean oil price (¢/pound)	31.60	31.07	41.83	31.60	28.26	41.83
Crude oil price ($/barrel)	48.40	48.17	48.00	48.82	48.77	48.44
Gasoline price ($/gallons)	1.72	1.59	1.74	1.82	1.71	1.85
Diesel price ($/gallons)	1.67	1.91	1.50	1.57	1.80	1.39
Ethanol price ($/gallon)	1.61	1.73	1.67	1.61	1.68	1.67
Biodiesel (supply) price ($/gallon)	3.65	3.61	4.43	3.65	3.39	4.43
RIN price for ethanol ($/unit)	0.49	0.68	0.50	0.25	0.40	0.27
RIN price for biodiesel ($/unit)	0.73	1.19	1.99	1.33	1.02	1.94
Ethanol quantity (billion gallons)	14.140	19.088	15.104	14.140	17.554	15.104
Blending ratio of ethanol (%)	9.871	13.002	10.652	9.701	11.792	10.457
Biodiesel quantity (billion gallons)	1.779	1.469	3.275	1.779	1.117	3.275
Corn production (billion bushels)	14.216	14.819	14.156	14.216	14.683	14.156
Soybean production (billion bushels)	3.927	3.782	3.975	3.927	3.805	3.975
Corn export (billion bushels)	1.833	1.244	1.564	1.833	1.471	1.564
Soybean meal export (million short tons)	56.572	56.880	57.932	56.572	56.410	57.932
Soybean oil export (billion pounds)	22.421	22.945	12.261	22.421	25.740	12.261
Crude oil domestic supply (billion barrels)	3.450	3.446	3.443	3.457	3.457	3.451
Crude oil import (billion barrels)	2.907	2.846	2.800	3.017	3.004	2.917
Welfare Impacts						
Social welfare ($ billion)	5.203	6.204	1.838	1.215	2.000	-2.915
Pollution effect ($ billion)	1.645	1.719	3.284	0.907	0.672	1.709
Tax revenue ($ billion)	0.174	3.033	1.828	-0.373	-0.116	-0.806
P.S. Agriculture ($ billion)	17.267	21.030	25.129	14.303	14.862	22.322
P.S. Crude Oil supply ($ billion)	-2.819	-3.613	-4.207	-2.421	-2.597	-3.732
Efficiency loss from cellulosic biofuel	-0.221		-1.417	-0.221		-1.417
C.S. Crop products' demand ($ billion)	-9.384	-12.659	-11.911	-7.204	-8.913	-9.731
C.S. Fuel demand ($ billion)	6.808	7.234	1.359	3.442	5.824	-0.232
C.S. Other refined products ($ billion)	-8.267	-10.541	-12.228	-7.218	-7.732	-11.029
GHG emissions change (million tCO_2e)	-43.64	-45.60	-87.11	-45.37	-33.61	-85.44

Notes. Welfare Impacts are changes relative to the relevant "no biofuel policies" scenario.

essentially the 2015 benchmark motor fuel taxes. But whereas these tax rates are appropriate for fossil fuels, they are excessive for biofuels (as explained above). The results of this first sensitivity analysis experiment are reported in the first three columns of Table 5. The higher cost of carbon provides a reason for higher "optimal mandates," in particular for slightly higher advance biofuel mandates, than those of Table 3. But the conclusion remains that optimal mandates entail less biodiesel and more corn-based ethanol than both the benchmark 2015 levels and the projected 2022 levels. Concerning welfare, the higher cost of carbon increases the relative importance of the "pollution effect" and increases the estimated positive impact of biofuel policies accordingly. But again, two of the main conclusions from Tables 4 are preserved: the welfare gain from optimal mandates, relative to the *status quo*, is somewhat limited (about $1 billion); and, implementation of the projected 2022 mandate levels considerably worsen overall welfare.

The second sensitivity analysis experiment is meant to isolate the "terms of trade" motive for intervention. Here we return to the baseline value for the cost of carbon, \$20/tCO2, but presume motor fuel taxes that correctly internalize this cost for all fuel types. Given the pollution parameters in Table A3, the required Pigouvian taxes would be \$0.239 for gasoline and \$0.273 for diesel. Given that these taxes are levied on volume of blended gasoline fuel, accounting for both lower pollution and lower energy content of biofuels require subsidies for both ethanol and biodiesel of \$0.106/gallon and \$0.164/gallon, respectively. Although this tax/subsidy scheme internalizes the carbon externality, mandates can still be helpful in order to improve the terms of trade, as discussed above. The results of this experiment are reported in the last three columns of Table 5. Optimal mandates are only marginally changed, relative to the baseline results in Table 3. In particular we find that optimal mandates entail considerably less biodiesel and more corn-based ethanol than the projected 2022 mandate levels. As for welfare effects, we find that the total welfare gains from optimal mandates here amount to \$2 billion (relative to the no biofuel policies scenario). When compared with the corresponding figure of \$5.4 billion reported in Table 4, this suggests that the ability to influence terms of trade via the use of RFS mandates accounts for about 40% of the overall welfare gains attributable to the RFS. As with all previous scenarios, implementation of the 2022 projected mandate levels leads to a large welfare loss, relative to current mandates.

7. Concluding remarks

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 *status quo*). 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 biofuel policies), we find that current biofuel policies increase corn and soybean prices by 40% and 11% , respectively, and also lead to a 1.7% 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 $4.4 billion. As noted above, the impact of RFS policies on the terms of trade is the primary cause for these positive welfare effects. The RFS also leads to lower pollution, but the extent of this positive impact is somewhat limited. Relative to the case with no government policy (*laissez fair*), it turns out that about 75% of GHG emissions reduction that was achieved by policies in place in 2015 can be attributed to motor fuel taxes alone.

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. For example, we find that full implementation of the 2022 mandate levels for advanced biofuels (with realistic targets for cellulosic biofuels, projected from recent EPA rulemakings) would be costly to the United States—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 (assuming the blend wall is not binding) 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). 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 may help to rationalize some of the political economy features of the debate about the future of the RFS.

Appendix

Table A1. Notation

A1.1 – 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)
Δ_c =	Change in corn carryover stocks
Δ_s =	Change in soybean carryover stocks
Δ_m =	Change in soybean meal carryover stocks
Δ_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

A1.2 – 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

A1.3 – Technical coefficients

$\beta_g =$	units of gasoline per unit of crude oil (production coefficient)
$\beta_d =$	units of diesel per unit of crude oil (production coefficient)
$\beta_h =$	units of byproduct (heating oil) per unit of crude oil (production coefficient)
$\alpha_e =$	units of ethanol per unit of corn (production coefficient)
$\alpha_m =$	units of soybean meal per unit of soybean (production coefficient)
$\alpha_v =$	units of soybean oil per unit of soybean (production coefficient)
$\alpha_b =$	units of biodiesel per unit of soybean oil (production coefficient)
$\delta_1 =$	fraction of corn used in ethanol production that is returned as a byproduct that substitutes for corn as livestock feed
$\delta_2 =$	fraction of corn used in ethanol production that is returned as a byproduct that substitutes for soybean meal as livestock feed
$\zeta_e =$	units of GEEG ethanol per unit of raw ethanol (energy conversion coefficient)
$\zeta_b =$	units of DEEG biodiesel per unit of raw biodiesel (energy conversion coefficient)

A1.4 – 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)

A1.4 – 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

Table A2. Technical Coefficients

Parameter	Symbol	Value	Source/explanation
Ethanol production coefficient (gallons/bushel)	α_e	2.8	Eidman (2007)
Ethanol by-product replacing corn in feed, as fraction of corn used for ethanol production	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 production	δ_2	0.003	$\delta_2 = (0.307 \times 0.29)(56/2000)$
Biodiesel production coefficient (gallons/pound)	α_b	0.131	EIA [a]
Soybean meal production coefficient (short tons/bushel)	α_m	0.024	$\alpha_m = 45.1/1{,}873$ [b c]
Soybean oil production coefficient (pounds/bushel)	α_v	11.425	$\alpha_v = 21{,}399/1{,}873$ [c d]
Gasoline heat content (million BTUs/barrel)	ζ_1	5.06	EIA [a]
Diesel heat content (million BTUs/barrel)	ζ_2	5.77	EIA [a]
Ethanol heat content (million BTUs/barrel)	ζ_3	3.558	EIA [a]
Biodiesel heat content (million BTUs/barrel)	ζ_4	5.359	EIA [a]
Ethanol energy equivalent coefficient (GEEG/gallon)	ζ_e	0.703	$\zeta_e = \zeta_3 / \zeta_1$
Biodiesel energy equivalent coefficient (DEEG/gallon)	ζ_b	0.929	$\zeta_b = \zeta_4 / \zeta_2$
Gasoline production coefficient (gallons/barrel)	β_g	21.286	$\beta_g = x_g / x_R$
Diesel production coefficient (gallons/barrel)	β_d	9.115	$\beta_d = x_d / x_R$
Other refined petroleum products production coefficient (KEEG/barrel)	β_h	13.96	Calculated [a e f]
"Equivalence value" of RIN generation for biodiesel	ϑ	1.5	Schnepf & Yacobucci (2013) [g]
Fraction of cellulosic ethanol in cellulosic biofuel	μ_{ce}	0.02, 0.10	Assumed [h]
Required fraction of ethanol as oxygenate	μ_{oxy}	0.03	Assumed

Notes. [a] Corresponds to a conversion factor of 7.65 pounds of soybean oil per gallon of biodiesel. http://www.eia.gov/totalenergy/data/monthly/pdf/sec13.pdf.

[b] http://www.ers.usda.gov/datafiles/Oil_Crops_Yearbook/table3.xls.

[c] http://www.ers.usda.gov/datafiles/Oil_Crops_Yearbook/table4.xls.

[d] http://www.ers.usda.gov/datafiles/Oil_Crops_Yearbook/table5.xls.

[e] In 2015, a 42-US gallon barrel of crude oil provided 6.3% average gains from refining (see table "Refinery Yield" [EIA], http://www.eia.gov/dnav/pet/pet_pnp_pct_dc_nus_pct_m.htm).

[f] Calculated as $\beta_h = (42 \times 1.063 - \beta_g - \beta_d) \times 0.98$, where 0.98 is the weighted average of kerosene energy equivalent coefficient for the other refined petroleum products.

[g] This is the most common "equivalence value" for biodiesel.

[h] For the benchmark 2015 year we set $\mu_{ce} = 0.02$, estimated from EPA's "RIN generation summary" over 2014 and 2015 http://www.epa.gov/fuels-registration-reporting-and-compliance-help/spreadsheet-rin-generation-data-renewable-fuel. For the 2022 scenario, we set $\mu_{ce} = 0.10$, consistent with data and discussion contained in EPA (2016).

Table A3. Emission Rates (kg CO2e/gallon) and Social Marginal Damage

Parameter	Symbol	Value	Source/explanation
GHG emissions rate of gasoline	E_g	11.948	Wang et al. (2012)
GHG emissions rate of diesel	E_d	13.625	$E_g \times 1.0 \times \zeta_2 / \zeta_1$ (EPA 2010) [a]
GHG emissions rate of ethanol	E_e	6.637	$E_g \times 0.79 \times \zeta_3 / \zeta_1$ (EPA 2010) [a]
GHG emissions rate of biodiesel	E_b	5.441	$E_g \times 0.43 \times \zeta_4 / \zeta_1$ (EPA 2010) [a]
GHG emissions rate of sugarcane ethanol	E_{se}	3.277	$E_g \times 0.39 \times \zeta_3 / \zeta_1$ (EPA 2010) [a]
GHG emissions rate of cellulosic biofuel	E_{ce}	3.361	$E_g \times 0.40 \times \zeta_3 / \zeta_1$ [b]
CO_2 emissions rate of other refined petroleum products	E_h	9.410	EIA [c]
Marginal emissions damage ($/t$CO_2$)	γ	20.0	Stern (2007) and Cui et al. (2011)

Notes. [a] Relative life-cycle GHG emissions rates per energy unit relative to gasoline baseline, from Chapter 2.6 of EPA (2010). http://www3.epa.gov/otaq/renewablefuels/420r10006.pdf. See also: Lifecycle Greenhouse Gas Emissions from Biofuels, Compared to their Petroleum Substitutes" (AFDC). http://www.afdc.energy.gov/uploads/data/data_source/10328/ghg_biofuels2.xlsx.

[b] Coefficient of 0.4 is based on the basis that qualifying cellulosic biofuels under RFS must achieve at least a 60% reduction in emissions. http://www.epa.gov/renewable-fuel-standard-program/renewable-fuel-annual-standards.

[c] kg CO2e/KEEG. Weighted average of CO2 emissions rates from table "Carbon Dioxide Emissions Coefficients" (EIA) http://www.eia.gov/environment/emissions/co2_vol_mass.xls and information in FAQ (EIA). http://www.eia.gov/tools/faqs/faq.cfm?id=307&t=11.

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