Land Allocation between Food and Energy

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By

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Abstract

Many countries are promoting biofuels as a substitute for scarce oil. This paper develops a model of dynamic land allocation between food and energy and shows how the model can be calibrated using standard optimization techniques. Some possible implications of the trade-offs between food and energy are discussed. Specifically, we show that the effect of mandates is mainly felt through increased land conversion, which increases indirect carbon emissions. Crude oil prices do not decrease significantly because of leakage.

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Introduction

Many countries have adopted biofuel mandates including the United States, the European Union, China and India. These mandates range from imposing a certain minimum volume of biofuels that must be used in the transportation sector to a certain proportion of fuels that must come from biofuels. The US mandate is especially large, since the current mandate which prescribes a certain volume of first generation biofuels (mainly from corn ethanol) has already been met and a larger mandate on second generation biofuels (from cellulosic and other materials) will increase the share of biofuels to about a third of all transport fuels by the year 2022. Fig.1 shows the US mandate over time.

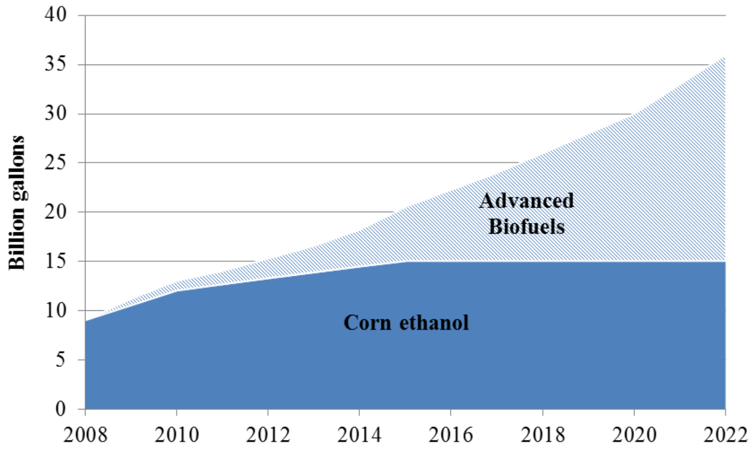

Figure 1. US biofuel mandate

The European Union also has a biofuel mandate which has been scaled back a bit, but nevertheless implies a rising share of biofuels in transport. Other countries such as China and India have also imposed biofuel shares for their transport sectors, although it is somewhat difficult to gauge if their governments will scale back these targets over time. For example, the Indian mandate is aggressive, with a biofuel target of some 20 percent of fuels. However, India is a heavily populated country with relatively little surplus arable land that can be used to grow sugarcane, which is the main crop that supplies biofuels. Either it may have to import fuels from other nations such as Brazil, or grow less food crops – the latter could imply a significant positive impact on the price of food commodities. In both China and India, increased production of food or energy from crops will also mean increased pressure on land and also water resources.

The goal of this paper is two fold. First we develop a simple model of land allocation for food and energy that is dynamic to show the conditions under which land will be allocated between food and energy production. This task is not simple because land allocation for energy is tied to the price of the substitute – crude oil. We model crude oil as a Hotelling type scarce resource. This is a reasonable assumption because crude oil is increasingly becoming scarce as supply shifts to some of the more polluting sources such as the oil sands of Alberta. We show how a constrained social planner imposes a biofuel mandate and derive the necessary conditions for this model. We then discuss how such a framework can be implemented by using secondary data on energy demand and supply. We provide a preview of some key empirical results from this exercise. The purpose of this exercise is to show interested researchers and students how policy analysis can be done by applying a simple theoretical and empirical framework.

The Model

We have simplified the model somewhat so that the basic structure can be revealed. To begin, let us assume only one land quality, one type of biofuel (say, only first generation), one type of food crop, say corn, and one region. Once we understand how the model works, we can see how the framework is implemented to include different land qualities, second generation biofuels, different type of crops and multiple regions.

Let us consider a dynamic, partial equilibrium economy in which only two goods, namely food and energy are produced and consumed. These goods are denoted respectively by q_f and q_e.[2] Concave utility functions for both of these goods are denoted by $U_f(q_f)$ and $U_e(q_e)$ respectively. Land and oil are the two primary factors in this economy. The land area devoted to food or biofuel production (energy) at any time t is given by $L_f(t)$ and $L_e(t)$ respectively. Let $L = \sum_j L_j$ with $j = \{f, e\}$ be the total area cultivated at any time t. Of course, if surplus land is available, new land can be brought under cultivation at any instant, in the model. Let $\bar{L}$ be the initial land area available for cultivation. Thus change in the total land area available under food or energy production equals the new land brought under production for food or energy production, given by $l(t)$. Then $\dot{L}(t) = l(t)$. Note that the variable $l(t)$ may be negative if land is taken out of production: we discuss this case later.[3] Of course, the total land cultivated at any time cannot exceed the aggregate land endowment, $\sum_{j \in \{f,e\}} L_j(t) = L(t) \le \bar{L}$. The total cost of bringing new land into cultivation is increasing and convex, given by $c(L,l)$, where we assume that the cross-partial derivative is zero and the partial derivatives are positive $c_L > 0,\ \ c_l > 0$. The cost of conversion of new land increases because this surplus land may be located in more

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[2] A much simpler, but similar framework which examines land allocation between food and energy can be found in Chakravorty, Magne and Moreaux (2008).

[3] Allowing land to be taken out of production will make the optimization program really complicated, since $l(t)$ may then be positive or negative. When we run our calibration model, this variable is never negative because population keeps increasing and diets trend towards more meat and dairy consumption which is land intensive. Hence we write the program here assuming that we only increase land allocation over time.

remote locations. Thus the greater is the land area already under cultivation, the higher is the unit cost of bringing new land into farming, whether for food or energy production. The conversion cost function is the same whether new land is being used for food or energy.

Let the yield per unit of land be given by k_j. Then the output of food or biofuel energy at any time t is given by $q_j(t) = k_j L_j(t)$. Production costs are a function of output, and assumed to be rising and convex, i.e., more area under food or energy production implies a higher unit cost of production, given by $w_j(q_j)$.

Oil is a nonrenewable resource. Let $\overline{X}$ be the initial stock of oil, $X(t)$ be the cumulative stock of oil extracted at date t and $x(t)$ its rate of consumption so that $\dot{X}(t) = x(t)$. The unit extraction cost of oil is increasing and convex with the cumulated amount of oil extracted. It is denoted by $g(X)$. Thus total cost of extraction becomes $g(X)x$. Consider crude oil and biofuels to be perfect substitutes for now. Then the total energy consumed is given by $x + q_e$.

Assuming a discount rate of $r > 0$, we can write the social planner's objective function as

$$\underset{L_i, l_i, x}{Max} \int_0^\infty \left\{ e^{-rt}[U_e(x+q_e)+U_f(q_f)] - c(L,l) - \sum_j w_j(k_j L_j) - g(X)x \right\} dt, \quad j = \{e, f\} \quad (1)$$

subject to

$$\dot{L}(t) = l(t) \quad (2)$$

$$\dot{X}(t) = x(t) \quad (3)$$

$$\sum_j L_j \leq \overline{L}, \quad X(t) \leq \overline{X} \quad (4)$$

The Hamiltonian can be written as

$$\underset{L_j,l,x}{Max}\, H = U_e(x+q_e) + U_f(q_f) - c(L,l) - w_f(k_f L_f) - w_e(k_e L_e) - g(X)x + \beta(\bar{L} - \sum_j L_j) + \theta l + \lambda x, \quad j \in \{f, e\}$$

where β is the multiplier associated with the static land constraint, and θ and λ are the multipliers associated with the two dynamic equations (2) and (3). We get the following first order conditions

$$k_j(U_j' - w_j') - c_L - \beta \le 0 \quad (= 0 \quad if \quad L_j > 0), \quad j \in \{e, f\} \tag{5}$$

$$c_l(L,l) = \theta \tag{6}$$

$$U_e' \le g(X) - \lambda \quad (= 0 \quad if \quad x > 0), \tag{7}$$

and finally the dynamics of the co-state variables given as follows

$$\dot{\lambda}(t) = r\lambda - g'(X)x \tag{8}$$

$$\dot{\theta}(t) = r\theta - \beta + c_L(L,l).\text{[4]} \tag{9}$$

This is a standard optimization problem with a concave objective function – note that the utility functions are concave and costs are linear or convex. The constraints are linear. Therefore, by imposing appropriate boundary conditions such as Inada conditions on the utility function, we can obtain a unique, interior solution. For reasons of space, we do not solve the model fully here, but for a solution to a problem somewhat similar in spirit, see Chakravorty, Magne and Moreaux (2008). We have abstained from fully specifying the transversality conditions and inequality constraints. But we can provide some intuition. Conditions (5) suggest that the marginal land is allocated either to food and energy production until the price equals the sum of the production and conversion costs, plus the shadow value of the land constraint, given by β. Equation (6) suggests that the marginal cost of land conversion equals the dynamic shadow value of the stock of land, which is θ. The standard Hotelling condition for extraction of oil is given by (7). Note

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[4] We avoid writing out the full set of transversality conditions.

that $\lambda(t)$ is negative, since the stock represents the oil extracted previously. Thus oil prices equal the sum of the extraction cost and scarcity rent. Conditions (8) and (9) give the dynamic path of the two co-state variables $\lambda(t)$ and $\theta(t)$.

In the empirical version of this simple model that is presented in the rest of the paper, we extend the above framework in several dimensions. In order to impose a mandate on biofuel use, we impose a set of additional constraints on the above model. For example, the US mandate requires a minimum level of consumption of biofuels in transportation at each date until the year 2022. Define the mandate in time T as $\underline{q}_e(T)$ which implies that biofuel use must not be lower than this level. Then we can add an additional constraint of the form $q_e(T) \geq \underline{q}_e(T)$. This will lead to an additional constraint in the Hamiltonian above of $+\gamma\left[q_e(T) - \underline{q}_e(T)\right]$. With this change we get an additional term when we differentiate the Hamiltonian with respect to $q_e(T)$. In this fashion a schedule of constraints as in the US mandate, can be imposed. The European mandate is a proportional measure which prescribes a minimum percent of biofuel in the transport fuel mix. This can also be easily implemented in the form of $\frac{q_e(T)}{q_e(T)+x(T)} \geq \underline{s}(T)$ where $\underline{s}(T)$ is the mandated minimum share of biofuels in transport.

Calibration of the Model

Here we describe the empirical model in detail. Notice that all variables are functions of time, but for convenience we omit the time index and the region index when necessary. The model is a discrete-time, non-linear dynamic programming problem and was solved using GAMS software. It runs for the period 2007-2207. Because of the leveling off of population and elasticity parameters, the solution does not change significantly after year 2100. To reduce computational time, the model is programmed in time steps of 5 years. The reference year for model calibration is thus 2007.

Calibration of Demand

Regional demands for three consumption goods - cereals, meat and transportation fuel are modeled by means of Cobb-Douglas demand functions, which are functions of regional per capita income and population.[5] Thus, demand D_i for good i takes the form

$$D_i = A_i P_i^{\alpha_i} w_i^{\beta_i} N \qquad (10)$$

where P_i is the output price of good i in dollars, α_i is the regional own-price elasticity, β_i is the income elasticity for good i which changes exogenously with per capita income reflecting changes in food preferences, w_i is regional per capita income for good i, N is regional population and A_i is the constant demand parameter for good i which is calibrated to reproduce the base-year demand for final products for each region. Demand for food products is in billion tons and demand for fuel is in billion miles.

Cereals include all grains, starches, sugar and sweeteners and oil crops. Meat includes all meat products and dairy such as milk and butter. Demand for blending fuel is the sum of the demand for blending fuel for gasoline-powered car and diesel car. The constant demand parameter A_i is product and region-specific. It is calculated to reproduce the base year global demand for each

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[5] Demand for cereals and meat are assumed to be independent as in other studies (Rosegrant et al. (2001); Hertel, Tyner and Birur (2010)).

product by using $A_i = \frac{D_i}{P_i^{\alpha_i} y_i^{\beta_i} N}$ from (10). That is, we use the regional per capita income, population, demand for each product and the price of the product in the base year (2007).[6]All the data needed to calculate the constant demand parameters is shown in Table 1. Initial per capita income is taken from the World Bank database (World Bank 2010) and population from United Nations Population Division (2010). Per capita demand for cereals and meat are taken from FAOSTAT. While per capita consumption for US and EU is readily available from FAOSTAT, per capita consumption for MICs, Other HICs and LICs is computed by aggregating per capita consumption across countries, weighted by the share of the country's population in the region. Initial per capita demand for transportation fuel is obtained by aggregating fuel for diesel-powered car and gasoline-powered car for each region. For the US, EU, MICs and LICs, this data are readily available from World Resources Institute (2010). However, for Other HICs, they are aggregated from individual country data. Initial prices are domestic or world prices depending on whether the product is traded or not. Since cereals and meat are internationally traded, we use world prices for different types of cereals and meat from World Bank (2011) and calculate their weighted average for the base year. Transportation fuels are consumed and produced domestically so their price is region-specific. US and EU fuel prices are from Davis *et al.* (2011). Other HICs, MICs and HICs fuel prices are world weighted averages from Chakravorty *et al.* (2012).

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[6] For example, for cereal demand in the US in year 2007, US per capita income is \$46,405, population 301 million, per capita demand for cereals is 0.27 tons and the initial price and income demand elasticities are -0.1 and 0.01, respectively. The price for cereals is \$250/ton. From (10), the constant parameter A_l is calculated as 0.4212. Other demand parameters are computed similarly.

Price and income elasticities for cereals, meat and transportation fuel are given by Hertel *et al.* (2008). Regional demand elasticities for the EU, Other HICs, MICs and LICs are aggregated up from individual country demands. To illustrate our procedure, suppose we need to compute the cereal demand for a region with two countries. We use the per capita demand for cereals, the world cereal price, population and price and income elasticities for each country to compute the country demand curve for cereals, which is aggregated up to get the regional demand. Thus, the regional demand elasticity for cereals is the weighted average elasticity where the weight is the share of country consumption in regional consumption. These elasticities are reported in Table 1.

Table 1. Demand parameters in base year (2007)

		US	**EU**	**Other HICs**	**MICs**	**LICs**
Per capita income	($)	46,405	30,741	36,240	5,708	1,060
Population	(millions)	301	496	303	4,755	765
Per capita demand	Cereals (tons/cap/yr)	0.27	0.14	0.22	0.20	0.20
	Meat (tons/cap/yr)	0.40	0.21	0.20	0.07	0.030
	Fuel (VMT/cap/yr)	10,730	3,429	3,219	644	214
Prices	Cereals ($/ton)	250	250	250	250	250
	Meat ($/ton)	2,260	2,260	2,260	2,260	2,260
	Fuel ($/VMT)	0.09	1.12	1.11	1.11	1.11
Income elasticity	Cereals	+0.01	+0.02	+0.03	+0.60	+0.65
	Meat	+0.89	+0.80	+0.85	+0.90	+1.10
	Fuel	+0.90	+0.90	+0.90	+0.99	+1.30
Price elasticity	Cereals	-0.10	-0.12	-0.13	-0.37	-0.40
	Meat	-0.68	-0.65	-0.65	-0.80	-0.80
	Fuel	-0.60	-0.65	-0.65	-0.50	-0.50
Constant	Cereals	0.4212	0.3786	0.3527	0.0037	0.0081
	Meat	0.0054	0.0082	0.0286	0.0038	0.0068
	Fuel	0.1591	0.3375	0.2716	0.1296	0.0263

Notes: 1) Units: per capita income is in 2007 dollars; population in millions; per capita demand for cereals and meat in tons/cap/year; per capita demand for fuel in VMT/cap/year.

Demand for food products and transportation fuel depend upon the growth in per capita income and population. Growth rates of per capita income data are taken from Nordhaus and Boyer (2000); population for each region is from the UN Population Division (2010). Table 2 shows the level of per capita income and population by region in 2007 and 2050. Since our model is calibrated in time steps of five years, annual growth rates of population and per capita income are constant within each five year period.

The AIDADS system (An Implicit Direct Additive Demand System) is the most flexible demand function that takes into account the change in dietary preferences with a rise in the level of income. However, there are no studies that provide the demand parameters for cereal and meat products by region.[7] We thus make some adjustments in the calibration of demand given by (10). First, the change in food preferences is driven by the rise in per capita income. As a result, we consider the per capita income and not the global income (per capita income times population) as in other studies (e-g., Rosegrant *et al.*,2008). Second, we introduce flexibility in food consumption by letting income elasticities vary exogenously with the level of income. These

Table 2. Population and per capita income in 2007 and 2050

	Population (millions)		**Per capita income** ($)	
	2007	2050	2007	2050
US	301	337	46,405	63,765
EU	496	554	30,741	42,241
Other HICs	303	339	36,240	49,798
MICs	4,755	6,661	5,708	16,451
LICs	765	1,791	1,061	3,743
World	6,620	9,682	--	--

Notes: Income is in 2007 dollars.

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[7] Cranfield *et al.* (2002) estimate consumer demand patterns for different groups of products (food, beverages and tobacco, gross rent and fuel, household furnishings and operations and other expenditure) using the AIDADS demand system. Unfortunately, this classification is not useful for our analysis of preferences over cereals and meat.

country-level elasticities are taken from Hertel *et al.* (2008). For each country, we match the per capita income from the World Bank (2010) database to the elasticity for cereals and meat. Table 3 shows the resulting income-based elasticities (see numbers in bold). Per capita income in the LICs in year 2050 is assumed to converge to the per capita income for MICs in year 2007. As a result, LIC income elasticities in year 2050 are similar to MIC income elasticities in 2007.

Table 3. Changes in income elasticities for food products conditional on per capita income

Region	Year	Per capita income ($)	Cereals	Meat
US	2007	46,405	+ 0,01	+ 0,89
	2050	63,765	+ 0,01	+ 0,88
EU	2007	30,741	+ 0,02	+ 0,80
	2050	42,241	+ 0,02	+ 0,79
Other HICs	2007	36,240	+ 0,03	+ 0,85
	2050	49,798	+ 0,03	+ 0,84
MICs	**2007**	**5,708**	**+ 0,60**	**+ 1,01**
	2050	16,451	+ 0,55	+ 0,96
LICs	2007	1,061	+ 0,65	+ 1,30
	2050	**4,000**	**+ 0,59**	**+ 1,20**

Land Quality The USDA database divides the world land area into nine categories based on climate and soil properties and suitability for agricultural production (Eswaran *et al.* 2003) labeled I to IX (see Figure 2), land class I being the most productive. Three criteria are used, namely, land quality, soil resilience and soil performance. Land quality is defined as the ability of the land to perform its function of sustainable agricultural production and enable it to respond to sustainable land management. Soil resilience is the ability of the land to revert to a near original production level after it is degraded. Soil performance is the ability of the land to produce under moderate level of inputs in the form of conversation technology, fertilizers and pest control.

Land classes unsuitable for agricultural production, i.e., categories VII to IX are disregarded in our study. We aggregate the remaining six (I through VI) into three classes. Category I and II are grouped as land class 1, III and IV as class 2, and V and VI as class 3. We thus have three land classes indexed by $n = \{1, 2, 3\}$. Land class 1 benefits from a long growing season and soil of high quality. Class 2 has a shorter growing season due to water stress or excessive temperature variance. Class 3 is the lowest quality and faces numerous constraints like water stress.

As in the theoretical framework, we assume that the cost of bringing new land into production is increasing and convex with the land converted into agricultural use (as in Gouel and Hertel 2006). Land conversion costs in time t can be written as

$$C(t) = \phi_1 - \phi_2 \ln\left(\frac{\bar{L} - L(t)}{\bar{L}}\right) \tag{11}$$

where $\bar{L}$ is the initial endowment of fallow land, so that $\bar{L} - L(t)$ is the fallow land available at date t, ϕ_1 and ϕ_2 are model parameters (calibrated from data) assumed to be the same across land class but varying by region. The parameters for land conversion costs are reported in Table 4. They are assumed to be the same across land classes but varying by region.

Table A4. Cost Parameters for Land Conversion

	ϕ_1	ϕ_2
USA	234	245
MICs	38	42
LICs	83	126

Source: Gouel and Hertel (2006). Notes: Our parameters for MICs (LICs) are their figures for Latin America (Rest of the World).

Food and Energy Production. Total supply is the product of land supplied times its yield, as discussed earlier.[8] We need to obtain yield data by land class for each final demand. Each land class covers a group of countries and FAOSTAT gives crop yields for each country. USDA has data on the volume of land by land class in each region. We thus match USDA and FAOSTAT data by country to get the yield per unit land in each region and the corresponding volume of land available.

Table 5. Food Crop Yields by Land Class and Region

	Land class	**US**	**EU**	**Other HICs**	**MICs**	**LICs**
Initial crop yields (tons/ha)	1	4.0	4.0	3.5	3.5	2.0
	2	2.5	2.0	2.2	1.7	1.0
	3	1.7	1.5	1.7	1.0	0.5
Annual growth in crop yields (%)	1	0.9	0.9	0.9	1.2	1.1
	2	0.7	0.7	0.7	1.0	0.8
	3	0.6	0.6	0.6	0.8	0.7

Source: Yields per land class are adapted from FAOSTAT and USDA; average annual growth rates are adapted from Rosegrant *et al.* (2001).

To calculate yields for food crops (cereals and meat), we use yield data for each crop, namely cereals, starches, sugar and sweeteners and oil crops weighted by their share of production for each land class and region. These values are presented in Table 5.

Food crops can be used directly for food (i.e., cereals) or animal feed that is transformed into meat. We assume that one ton of primary crop produces 0.85 tons of the final food product (FAOSTAT), assumed uniform across regions.[9] The quantity of meat produced from one ton of crop is region-specific and adapted from Bouwman (1997). We use a feed ratio of 0.4 for developed countries (US, EU and Other HICs) and 0.25 for developing countries (MICs and LICs) to account for higher conversion efficiencies in the former.

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[8] Since our model is coded in time steps of five years and harvests are annual, we multiply annual production by the number of time periods (5 years).

[9] Other models make similar assumptions (e.g., Rosegrant *et al.* 2001).

Biofuels are produced from specific crops in each region (see Table 6), e.g., sugar cane in MICs and rapeseed in EU. For each land class we determine the crop-specific biofuel yield by multiplying the yield crop and the conversion coefficient of crop into biofuels (Rajagopal and Zilberman 2007). The representative crop and energy yield for each land class are reported in Table 6.

Table 6. Yield and representative crop for first generation biofuels

		US	**EU**	**Other HICs**	**MICs**	**LICs**
Crop type		Corn	Rapeseed	Corn	Sugar-cane	Cassava
Energy yield	1	820	500	717	1,800	400
per land class	2	512	250	451	874	200
(gallons/ha)	3	250	180	249	514	100

Sources: FAO (2008); FAOSTAT and EIA (2011); Rajagopal and Zilberman (2007).

Information on second gen biofuels is not easily available. Their yields are assumed to be uniform across land class. This assumption is reasonable because second-gen biofuels are less demanding in terms of land quality than first gen biofuels (Khanna 2008). Recall that 2,000 gallons per hectare are produced from ligno-cellulosic whereas 1,000 gallons per hectare are produced from Biomass-to-liquids (BTL).

As described in the theory section, the total cost of food or biofuel production in each region is assumed to be increasing and convex. Since we have different land classes, we model production cost for product j (e.g. cereal, meat or biofuel) for a given region as

$$w_j = \eta_1 (\sum_n k_n^j L_n^j)^{\eta_2} \tag{12}$$

where the term inside brackets is the aggregate production over all land classes (denoted by n) in the region and η_1 and η_2 are regional cost parameters. We can recover the cost parameters by using total production costs and volume. Production costs of crops are taken from the GTAP database 5 for the year 1997, the latest year available, aggregated suitably for the different regions (Other HICs, MICs and LICs). The GTAP database divides the total costs into intermediate inputs, skilled and unskilled labor, capital, land and taxes. Parameters are reported in Table 7. Production costs are same for each use j but they differ by region as shown in the table.

Table 7. Crop production cost parameters by region

	US	EU	Other HICs	MICs	LICs
η_1	1.15	1.15	1.15	1.35	1.25
η_2	1.50	1.55	1.50	1.75	1.80

Source: GTAP 5 Database.

The cost of processing of food crops into cereals and meat is reported in Table A8.

Table 8. Processing costs for food crops by region

	U.S.	E-U	Other HICs	MICs	LICs
Cereals ($/ton)	120	120	120	150	150
Meat ($/ton)	900	900	900	1,200	1,200

Source: GTAP 5 Database.

Transport fuel Fuel is provided by three resources – oil, first gen and second gen biofuels. Data on crude oil stocks are taken from the World Energy Council (World Energy Council 2010) and reported in Table 9. Oil is also an input in sectors other than transportation, such as in chemicals and heating. Studies (IEA 2011) suggest that around 60% of oil consumption occurs in transportation. We thus consider 60% of total oil reserves as the initial stock available for transport.[10]

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[10] By keeping the share of oil in transportation fixed, we ignore possible changes in the share of petroleum that is used in transportation. It is not clear *ex ante* how this share will change as the price of oil increases - it may depend on the availability of substitutes in transport and other uses.

Table 9. Extraction cost of crude oil

Initial stock (trillion gallons)	**Extraction cost in $/gallon**		
	φ_1	φ_2	φ_3
153	0.47	6	5

Sources: Stock (World Energy Council, 2010); Extraction costs (Chakravorty *et al.* 2012)

Oil is converted into gasoline or diesel for transportation use. We consider a representative fuel in each region - gasoline for the US and diesel in the EU.[11] One gallon of oil produces 0.47 gallons of gasoline or 0.25 gallons of diesel.[12] We use the term "gasoline" for all petroleum products in the rest of the paper.

Transportation energy q_e is produced from gasoline and biofuels in a convex linear combination using a CES specification, as in Ando *et al.* (2010) given by

$$q_e = \sigma \left[\mu_g q_g^{\frac{\rho-1}{\rho}} + (1-\mu_g)(q_{bf}+q_{bs})^{\frac{\rho-1}{\rho}}\right]^{\frac{1}{\rho-1}} \tag{13}$$

where q_e is the production of transport fuel, μ_g the share of gasoline, ρ the elasticity of substitution, and q_g, q_{bf} and q_{bs} are the respective input demands for gasoline, first gen and second gen biofuels and σ is a constant. The parameter σ is region-specific and calibrated from equation (13). We substitute for the parameters for each region, and choose the value of σ to reproduce the base year transport fuel production. Table 10 presents the data used in this exercise for the base year (2007) and the computed values of σ. In the table, transport fuel use equals the

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[11] For the other regions, the representative fuel is gasoline.

[12] In the paper, we discuss the sensitivity of our results to change in oil reserve estimates. Conversion rates between oil and products may vary based on crude oil quality and refinery characteristics, but we abstract from regional differences in crude oil and product quality.

sum of fuel consumption for gasoline and diesel cars.[13] To calculate biofuel consumption, we only consider first-generation biofuels since the actual consumption of second generation biofuels is negligible. Blending fuel production is calculated in volume units (billion gallons). It is converted into MegaJoules (MJ) by using the coefficients reported in Table 11 and then into Vehicle Miles Traveled (VMT), the unit of demand in our model. One MJ of transportation energy equals 0.177 VMT for a gasoline-powered car and 0.155 miles for a diesel car (Chen *et al*, 2012).[14]

Table 10. Energy supply parameters by region for base year (2007)

	US	EU	Others HICs	MICs	LICs
Transport fuel use q_e (bln gal)	152	80	46	144	7
Gasoline use q_g (bln gal)	134	62	26	130	8
Biofuel use q_{bf} (bln gal)	7	3	2	5	0,5
Share of gasoline in fuel μ_g	0.90	0.96	0.97	0.96	0.98
Elasticity of substitution ρ	2	1.65	2	1.85	1.85
Constant σ	1,332	1,388	1,090	1,065	0,774

Notes: gal=gallons, *Sources:* Transport fuel consumption (World Resources Institute 2010); Biofuel consumption (EIA 2011) is the sum of ethanol and biodiesel use; Share of gasoline and biofuels in transportation is computed from observed data. Elasticities of substitution are taken from Hertel, Tyner and Birur (2010).

Table 11. Energy content of fuels

	Gasoline	Ethanol	Cellulosic Ethanol	Diesel	Biodiesel	BTL Diesel
Energy content (MJ/gal)	120	80	80	137	120	135

Source: Chen *et al.* (2012)

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[13] We ignore other fuels such as jet fuel and kerosene which together account for about 10% of world transport fuel consumption.

[14] For simplicity we assume that only conventional passenger cars are used. To meet the US target, the share of biofuels in total transportation fuel should exceed 15%; as a result, some conventional cars should be replaced by more efficient Flex Fuel Vehicles (FFVs): for these, one MJ of transportation energy equals 0.216 VMT for a gasoline-powered car and 0.189 for diesel. By not considering the choice of vehicles in our model (as in Bento *et al.*, 2009 and Chen *et al.*, 2012) we may be overestimating the demand for fuel, hence our estimate of the impact on food prices may be biased upward.

Carbon emissions The model tracks direct as well as indirect carbon emissions. Emissions from gasoline are constant across regions, but emissions from first and second gen biofuels are region-specific and depend upon the crop used. Emissions from gasoline occur at the consumption stage, while emissions from biofuels occur at the production stage. Let z_g represent the amount of emissions (measured in tons of CO_2 equivalent units, or CO_2e) released per unit of gasoline consumed, and z_{bf} and z_{bs} are emissions per unit first and second gen biofuels. The figures used in the model are shown in Table 12. Finally, indirect carbon emissions are released by conversion of new land, namely forests and grasslands into food or energy crops. This sequestered carbon is released back into the atmosphere. Let z_n be the amount of carbon sequestered per unit of land of class *n* brought into production. Then, aggregate indirect carbon emissions by region are given by $z_n l_n$.

Indirect emissions depend on whether forests or grasslands are being converted for farming - one hectare of forest releases 604 tons of CO_2e while grasslands emit 75 tons (Searchinger *et al,* 2008).[15] For each land class and region, we weight the acreage converted by the share of new land allocated to each use (grasslands or forests). For instance, in the MICs, 55% of land class 2 is under pasture (45% under forest), thus indirect emissions from converting one hectare of land class 2 are 313 (=0,55*75+0,45*604) tons of CO_2e per hectare.[16] Land class 3 has 84% forest, so emissions are 519 tons CO_2e/ha. The corresponding figures for LICs are 323 tons (land class 2)

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[15] Losses from converting forests and grasslands are assumed to be the same in MICs and LICs. Carbon is sequestered in the soil and vegetation. We assume that 25% of the carbon in the top soil and all the carbon stored in vegetation is released during land conversion. Detailed assumptions behind these numbers are available in the supplementary materials to Searchinger *et al*. (2008) available at: http://www.sciencemag.org/content/suppl/2008/02/06/1151861.DC1/Searchinger.SOM.pdf. Other studies such as Tyner *et al.* (2010) also use these assumptions.

[16] By using this method, we assume that the share of marginal land under forests and grasslands is constant. In our model, the area of marginal land converted into cropland is endogenous; however, we cannot determine if forests or grasslands have been converted.

and 530 tons (class 3). In the LICs, for land class 2.47% is under forests and 53% under pasture; for land class 3.86% is under forest and 14% under pasture.

Table 12. Carbon emissions from gasoline and representative biofuels

	Carbon emissions (kg of CO_2e/gallon)	**Emission reductions relative to gasoline**
Gasoline	3.2	**--**
Corn ethanol	2	35%
Cellulosic ethanol	0.5	83%
Diesel	3.1	--
Rapeseed biodiesel	1.5	50%
BTL diesel	0.5	83%
Sugarcane ethanol	0.8	72%
Cassava ethanol	0.8	72%

Source: Gasoline, corn ethanol and sugar-cane ethanol figures are taken from Ando *et al,* (2010) and Chen *et al,* (2012), *Note:* Carbon emissions from biofuels include emissions from feedstock production and biofuel conversion, distribution and consumption, Feedstock production also emits other greenhouse gases such as nitrogen dioxide and methane; hence, carbon emissions are calculated in terms of CO_2e,

Policy Runs

Figure 2 shows land allocation under the biofuel mandate imposed by the United States and the European Union. When compared with the solution with no mandate, it is clear that the mandate results in new land conversion from 2007 to 2022 to the tune of about 119 million hectares, while without the mandate only 74 million ha are brought into cultivation. That is, the area converted increases by a factor of 1.60 due to the mandate. Note the large increase in land under biofuels in the United States in the year 2022 – about 60 million ha are taken out of food production and moved into biofuel production. However, the aggregate acreage in farming in the US stays the same – even though surplus lands exist, they are not converted due to the relatively high cost of production in the US relative to other countries, especially in the Middle Income category. Of course, if trade restrictions are imposed, domestic production may become economical. One implication of this significant shift in land allocation is that the US ceases to be a major exporter of food crops and becomes a large importer of biofuels.

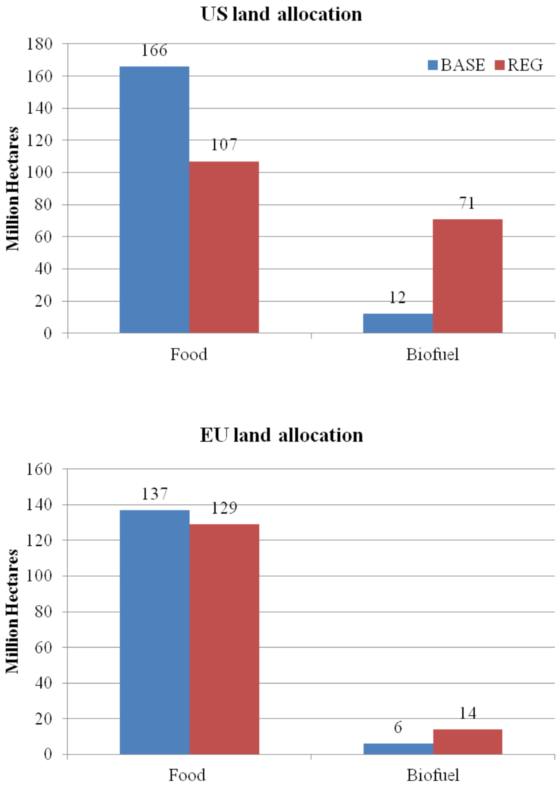

Figure 2. Land allocation under Base and REG (year 2022)

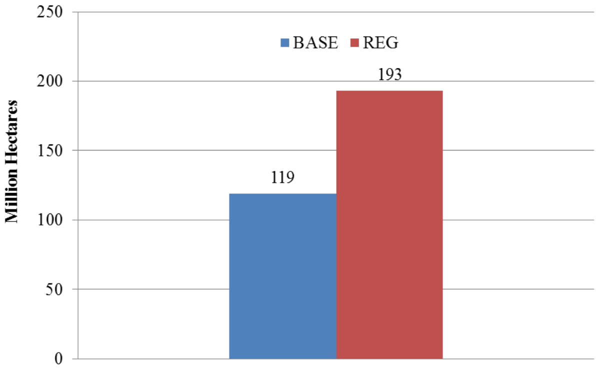

Figure 3. Aggregate land bringing into cultivation from 2007 to 2022 under Base and REG

Even if one of the objectives of biofuel mandate is to curb down carbon emissions in the transportation sector, the carbon footprint of this policy is highly negative. World direct carbon emissions seem not to be impacted by the regulation in the US and EU. Despite the switch towards less carbon intensive fuel, direct carbon emissions in regulated countries increase slightly. Due to the rise in biofuels demand from regulated countries, world biofuels price increases by 11% while oil price declines slightly. As a result, the price of transport energy augments driving up the miles traveled and carbon emissions (see Table 13). Consumers in non-regulated countries respond to energy price change by increasing the share of oil, which leads to slight increase in carbon emissions (see Table 13). The noteworthy increase in carbon emissions comes from the change in land-use. To satisfy the increase in biofuels demand, additional idle lands are bringing into cultivation in MICs countries (see Figure 3). It leads to a jump in indirect carbon emissions by 4.4 billion tons of CO_2e (or by 60%) (see Table 13).

Table 13. Direct and indirect carbon emissions in billion tons of CO_2e (REG)

	Direct carbon emissions			Indirect carbon emissions
	US	EU	World	World
2007	1.85	0.83	5.1	Na
2022	1.95 (-0.9%)	0.81(-1.5%)	6.30 (-0.5%)	11.5 (+60%)

Note: Numbers in parenthesis represent the percentage change of carbon emissions compared to BASE model, which is not shown here. In 2007, indirect carbon emissions are not available in our model since indirect carbon emissions are calculated by taking into account the change in land-use compared to the previous period; 2007 is the base year.

Conclusion

We develop a dynamic model of land allocation of food and fuel sectors to analyze the effects of US and EU policies on world carbon emissions. Biofuel mandates do not meet their objective in terms of carbon emissions. While world direct carbon emissions do not change significantly due to leakage in the non-mandate countries, world indirect carbon emissions increase sharply because of land use changes. Thus biofuel policies may help make countries more self-reliant in their energy consumption, but they do not make a major dent in mitigating the environmental footprint of fossil fuel combustion. Although the model is quite simple yet has many moving parts. An important extension would be to incorporate uncertainty in parameters such as the endowment of oil, productivity of crops and demand growth and perform Monte Carlo estimations to obtain confidence intervals around the predictions. Finally more work could be done to examine the effect of food price increases on household poverty and distributional impacts, in countries with a large number of poor people.

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