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The Long Run Impact of Biofuels on Food Prices

by

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Abstract

More than 40% of US corn is now used to produce biofuels, which are used as substitutes for gasoline in transportation. Biofuels have been blamed universally for past increases in world food prices, and many studies have shown that these energy mandates in the US and EU may have a large (30-60%) impact on food prices. In this paper, we use a partial equilibrium framework to show that demand-side effects - in the form of population growth and income-driven preferences for meat and dairy products rather than cereals - may play as much of a role in raising food prices as biofuel policy. By specifying a Ricardian model with differential land quality, we find that a significant amount of new land will be converted to farming, which is likely to cause a modest increase in food prices. However, biofuels may *increase* aggregate world carbon emissions, due to leakage from lower oil prices and conversion of pasture and forest land for farming.

Keywords: Clean Energy, Food Demand, Land Quality, Renewable Fuel Standards, Transportation

JEL Codes: Q24, Q32, Q42

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1. Introduction

Biofuels are providing an ever larger share of transport fuels, even though they have been universally attacked for not being a "green" alternative to gasoline. In the United States, about 10% of gasoline now comes from corn and this share is expected to rise three-fold in the near future if the Renewable Fuel Standard (RFS) is extended. The European Union, India and China have aggressive biofuel mandates as well. Studies that have modeled the effect of these policies on food prices predict large increases, and have been supported by the run-up in commodity prices in recent years. For example, the International Food Policy Research Institute (Rosegrant *et al.,*2008) suggests that prices of certain crops may rise by up to 70% by 2020.[2]

In this paper, we examine the long-run effects of US and EU biofuel policy in a dynamic, partial equilibrium setting.[3] Our approach is unique in two respects. It is common knowledge that as poor countries develop, their diets change in fundamental ways. In particular, they eat less cereal and more animal protein in the form of meat and dairy products.[4] This fact is important because producing meat and dairy uses more land than growing corn.[5] Coupled with global increases in population, these demand shifts should cause an increase in food prices even without any biofuel policy. Second, many studies assume a fixed supply of land. There is plenty of land in the world, although of varying quality for food production. Sustained food price increases will cause new land

[2] Other studies have also found a significant impact, although not to the same degree. For example, Roberts and Schlenker (2013) use weather-induced yield shocks to estimate the supply and demand for calories and conclude that energy mandates may trigger a rise in world food prices by 20-30%. Hausman, Auffhammer and Berck (2012) use structural vector auto-regression to examine the impact of biofuel production in the U.S. on corn prices. They find that one third of corn price increases during 2006-08 (which rose by 28%) can be attributed to the US biofuel mandate. Their short-run estimates are consistent with our prediction that in the long-run, the impacts may be significantly lower. This is because higher food prices are likely to trigger supply side responses only with a time lag, especially if significant land conversion were to occur.

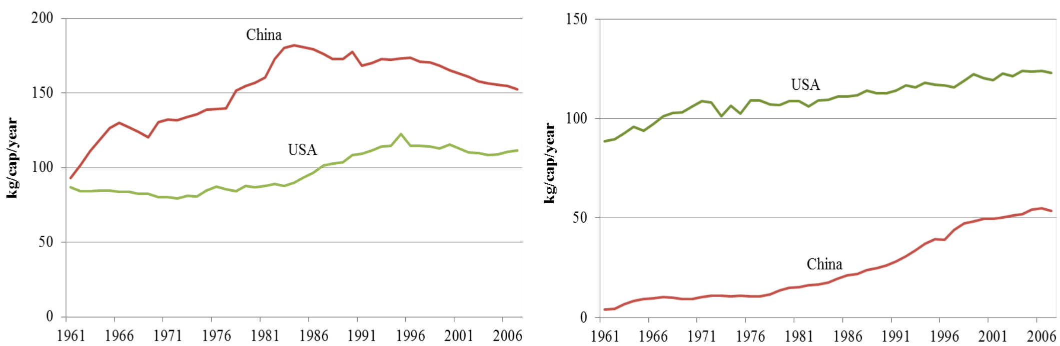
[3] Both have imposed large biofuel mandates. Other nations such as China and India have also announced biofuel mandates but their implementation is still in progress. We discuss them later in the paper.

[4] For instance, aggregate meat consumption in China has increased 33 times in the last 50 years, yet its population has only doubled (Roberts and Schlenker 2013).

[5] On average, eight kilos of cereals produce one kilo of beef and three kilos of cereals produce one kilo of pork.

to be brought under farming, but as we move down the Ricardian land quality gradient, costs will rise, which may in turn put an upward pressure on prices.[6] The model we develop in this paper explicitly accounts for the above effects in a dynamic setting where we allow for a rising supply curve of crude oil.[7]

Fig.1 shows the disparity in meat and cereal consumption in the United States and China. Chinese per capita meat consumption is about half of the US, but cereal consumption is much higher. These gaps are expected to narrow significantly in the near future as the Chinese diet gets an increasing share of its calories from animal protein.[8] Income-induced changes in dietary preferences have been largely ignored in previous economic studies. Our results show that about half the predicted rise in food prices may be due to changes in diet.



(a) Cereal consumption (b) Meat consumption

Figure 1: Per capita cereal and meat consumption in China and US, 1965-2007

Source: FAOSTAT. Note: Chinese cereal consumption excludes grain converted to meat.

[6] Significant amounts of new land is currently being converted for farming (Tyner, 2012).

[7] Hertel, Tyner and Birur (2010) use a general equilibrium trade model (GTAP) to explore the impact of biofuels production on world agricultural markets, specifically focusing on US/EU mandatory blending and its effects on individual countries. They use disaggregated data on world land quality. However, their static framework does not account for changes in food preferences. Reilly and Paltsev (2009) also develop a static energy model that does not account for heterogeneity in land quality.

[8] Although we use China as an example, the trend holds for other countries as well. For example, per capita meat and dairy consumption in developed nations is about four times higher than in developing countries.

Since our main premise is that the pressure on food prices will lead to more land conversion, the model we propose explicitly accounts for the distribution of land by quality. We use data from the US Department of Agriculture (USDA) which classifies land by soil quality, location, production cost and current use as in pasture or forest. With increased use of biofuels, oil prices will fall, which will lead to leakage in the form of higher oil use by countries with no biofuel policy. We endogenously determine the world price of crude oil and the extent of this spatial leakage.[9] We show that biofuel policy may reduce direct carbon emissions (from combustion of fossil fuels) in the mandating countries but it is largely offset by an increase in emissions elsewhere. However, indirect emissions (from land use) go up because of the conversion of pasture and forest land, mainly in the developing countries. Aggregate global greenhouse gas emissions from the US and EU biofuel mandates actually show a small increase.

The main message of the paper is that demand shifts may have as much of a role in the rise of food prices as biofuel policy.[10] Moreover, this price increase may be significantly lower because of supply side adjustments in the form of an increase in the extensive margin. We obtain these results with assumptions of modest growth rates in the productivity of land and in the energy sector. General equilibrium effects of these policies, which we do not consider, may further diminish the price impact of biofuel mandates. By the same token, models that do not account for supply side effects of rising food prices will tend to find large impacts.

[9] Unlike other studies that determine crude oil use in a static setting.
[10] Additional biofuel mandates imposed by China and India also have a surprisingly small effect on food prices.

Section 2 describes the underlying theoretical model. Section 3 reports the data used in the calibration. Section 4 reports results and in section 5 we discuss sensitivity analysis. Section 6 concludes the paper. The Appendix provides data on the parameters used in the model.

2. The Model

In this section, we present the detailed theoretical structure of the calibration model used to estimate food prices. Consider a dynamic, partial equilibrium economy in which three goods, namely cereals, meat and transport energy are produced and consumed in five regions respectively denoted by r (the United States, EU, other High Income Countries, Medium Income Countries and Low Income Countries). Time is denoted by subscript t. The regional consumption of these goods is denoted by $q_{rc}(t), q_{rm}(t)$ and $q_{re}(t)$ where c, m and e denote cereals, meat and energy, respectively. Each region faces a downward-sloping inverse demand function denoted by $D_{rc}^{-1}(q_{rc}(t),t), D_{rm}^{-1}(q_{rm}(t),t)$ and $D_{re}^{-1}(q_{re}(t),t)$, respectively. Within each region, demand for a good is independent of the demand for other goods. Regional demands for the three consumption goods (cereals, meat and transport energy) are modeled by means of Cobb-Douglas demand functions, which shift exogenously over time because of changes in population, income and consumer preferences over meat and cereals. Benefits from consumption are measured in dollars by the Marshallian surplus, i.e., the area under the inverse demand curve.[11]

Land is used to supply food and biofuels. It is available in three qualities denoted by $n = \{High,\ Medium,\ Low\}$ with *High* being the highest quality. The acreage of land quality n in

[11] The structure of the model is similar to that adopted by Chakravorty, Roumasset and Tse (1997) for a single region, and by other studies as well (e.g., Sohngen, Mendelsohn and Sedjo (1999), Fischer and Newell (2008) and Crago and Khanna (2014)). Nordhaus (1973) pioneered this approach by assuming independent demand functions for the US transport, commercial and residential energy sectors.

region r devoted to cereals, meat or biofuel production at any time t is given by $L^n_{rc}(t), L^n_{rm}(t)$ and by $L^n_{rb}(t)$, respectively, where we denote the different land uses by $j = \{c, m, b\}$. Let $\sum_j L^n_{rj}(t)$ be the total acreage in use j for land quality n at any time t and $\overline{L}^n_r$ be the initial land area by quality available for cultivation. Aggregate land under the three crops cannot exceed the endowment of land, hence $\sum_j L^n_{rj}(t) = L^n_r(t) \le \overline{L}^n_r$, for all j. Let new land brought under cultivation at any time t be denoted by $l^n_r(t)$, i.e., $\dot{L}^n_r(t) = l^n_r(t)$, where dot denotes the time derivative. The variable $l^n_r(t)$ may be negative if land is taken out of production: here we only allow new land to be brought under cultivation.[12] The regional total cost of bringing new land into cultivation is increasing and convex as a function of aggregate land cultivated in the region, but linear in the amount of new land used at any given instant – this cost is given by $c_r(L^n_r)l^n_r$ where we assume that $\frac{\partial c_r}{\partial L^n_r} > 0, \frac{\partial^2 c_r}{\partial L^{n2}_r} > 0.$ Additional land brought under production is likely to be located in remote locations. Thus, the greater is the land area already under cultivation, the higher the unit cost of bringing new land into farming within a given quality.

Let the yield for land quality n allocated to use j be given by k^n_{rj}.[13] Yields are higher on higher quality land.[14] Then the output of food or biofuel energy at any time t is given by $\sum_n k^n_{rj} L^n_{rj}$.

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[12] Allowing land to be taken out of production will make the optimization program complicated. When we run our calibration model, this variable is never zero before the year 2100 except in the US (where land conversion is small in any case, as we see later in the paper) and is never zero in any region after the year 2100 because population keeps increasing and diets trend toward more meat and dairy consumption, which is land intensive. However, if food prices fall because of exogenous technological change, some land may go out of production in the distant future, but that is beyond the scope of our analysis.
[13] In the calibration model, crops are transformed into end-use commodities (cereals, meat and biofuels) by means of a coefficient of transformation (crops into commodities) and a cost of transformation, both linear. Their values are reported in the Appendix.
[14] See Appendix Tables A5 and A6.

Regional production costs are a function of output and assumed to be rising and convex, i.e., more area under cereals, meat or biofuel production implies a higher cost of production, given by $w_{rj}(\sum_n k_{rj}^n L_{rj}^n)$.

Oil is a nonrenewable resource and we assume a single integrated "bathtub" world oil market as in Nordhaus (2009). Let $\overline{X}$ be the initial world stock of oil that is used only for transportation, $X(t)$ be the cumulative stock of oil extracted until date t and $x_r(t)$ the regional rate of consumption so that $\dot{X}(t) = \sum_r x_r(t)$. The unit extraction cost of oil is increasing and convex with the cumulative amount of oil extracted, denoted by $g(X)$. Thus total cost of extraction is $g(X)\sum_r x_r(t)$. Crude oil is transformed into gasoline by applying a coefficient of transformation ω_r so that total production of gasoline is $q_{gr} = \omega_r x_r$, where $'g'$ stands for gasoline.[15] Transport fuel is produced from combining gasoline (derived from crude oil) and biofuels in a convex linear combination using a CES specification, given by $q_{re} = \pi_r \left[\mu_{rg} q_{rg}^{\frac{\sigma_r - 1}{\sigma_r}} + (1 - \mu_{rg}) q_{rb}^{\frac{\sigma_r - 1}{\sigma_r}} \right]^{\frac{\sigma_r}{\sigma_r - 1}}$ where q_{re} is the production of transport fuel, π_r is a constant, q_{rg}, q_{rb} the quantities consumed of gasoline and biofuel, μ_{rg} is the share of oil and $(1 - \mu_{rg})$ is the share of biofuels in transport fuel, σ_r is the regional elasticity of substitution.

We assume frictionless trade of food commodities and biofuels across regions. Then we can write the net export demand (regional production net of consumption) for cereals, meat and biofuels as

[15] We include the cost of refining crude oil into gasoline, described in the Appendix.

$\left(\sum_n k_{rc}^n L_{rc}^n - q_{rc}\right)$, $\left(\sum_n k_{rm}^n L_{rm}^n - q_{rm}\right)$ and $\left(\sum_n k_{rb}^n L_{rb}^n - q_{rb}\right)$, respectively. Transport fuel is not traded but blended and consumed domestically.

Given the exogenous shift in demand from population growth and changes in preferences over meat and cereals driven by an increase in GDP per capita, the social planner maximizes net discounted surplus across regions and over time using a discount rate $\rho > 0$. (S)he chooses the regional acreage allocated to food and biofuel production, the amount of new land brought under cultivation, the quantity of each food and energy used and the quantity of gasoline used at each time t in each region r. Note that we do not include the externality cost of carbon emissions from energy or land use in this program. Later, we exogenously impose the mandates on biofuel production by region (the US and the EU) and solve for the constrained solution.[16] The optimization problem is written as

$$\underset{L_{nj}^r,\, q_j^r,\, l_n^r,\, x^r}{Max} \int_0^\infty \left\{ e^{-\rho t} \left[\sum_r \left(\int_0^{q_{rj}} D_{rj}^{-1}(q_{rj}, t) dq_{rj} - \sum_n c_r\ (L_r^n) l_r^n - \sum_j w_{rj} (\sum_n k_{rj}^n L_{rj}^n) \right) - g(X) \sum_r x^r \right] \right\} dt \quad (1)$$

subject to:

$$\sum_j L_{rj}^n = L_r^n \le \bar{L}_r^n, \forall n \quad (2)$$

$$\dot{L}_r^n(t) = l_r^n(t), \forall n \quad (3)$$

$$\dot{X}(t) = \sum_r x_r(t) \quad (4)$$

$$q_{re} = \pi_r \left[\mu_{rg} q_{rg}^{\frac{\sigma_r - 1}{\sigma_r}} + (1 - \mu_{rg}) q_{rb}^{\frac{\sigma_r - 1}{\sigma_r}} \right]^{\frac{\sigma_r - 1}{\sigma_r}} \quad (5)$$

$$\sum_r \left(\sum_n k_{rj}^n L_{rj}^n - q_{rj} \right) = 0 \quad (6)$$

---

[16] In both the unconstrained and constrained models, we compute the aggregate carbon emissions from each program.

where $q_{rg} = \omega_r x_r$. The corresponding generalized Lagrangian can be written as:

$$L = \sum_r \left(\int_0^{q_{rj}} D_{rj}^{-1}(q_{rj}, \mathrm{t}) dq_{rj} - \sum_n c_r \ (L_r^n) l_r^n - \sum_j w_{rj} (\sum_n k_{rj}^n L_{rj}^n) \right)$$
$$-g(X) \sum_r x^r + \sum_r \sum_n \left[\beta_r^n (L_r^n - \sum_j L_{rj}^n) + \theta_r^n l_r^n \right] - \lambda \sum_r x_r$$
$$+ \sum_j \left[\nu_j \left(\sum_r \left(\sum_n k_{rj}^n L_{rj}^n - q_{rj} \right) \right) \right]$$

where β_r^n is the multiplier associated with the static land constraint (2), θ_r^n and λ are multipliers associated with the two dynamic equations (3) and (4), and ν_j represents the world price of traded goods (cereals, meat and biofuels). We get the following first order conditions:

$$k_{rj}^n (\nu_j - w_{rj}') - \beta_r^n \le 0 (= 0 \text{ if } L_{rj}^n > 0), j = \{c, m, b\} \tag{7}$$

$$p_{rj} - \nu_j \le 0 (= 0 \text{ if } q_{rj} > 0), j = \{c, m\} \tag{8}$$

$$p_{re} \frac{\partial q_{re}}{\partial q_{rb}} - \nu_b \le 0 (= 0 \text{ if } q_{rb} > 0) \tag{9}$$

$$\theta_r^n - c_r \ (L_r^n) \le 0 (= 0 \text{ if } l_{rn} > 0) \tag{10}$$

$$p_{re} \frac{\partial q_{re}}{\partial q_{rg}} - g(X) - \lambda \le 0 (= 0 \text{ if } q_{rg} > 0). \tag{11}$$

Finally, the dynamics of the co-state variables is given as

$$\dot{\lambda}(t) = \rho \lambda + g'(X) \sum_r x_r \tag{12}$$

$$\dot{\theta}_r^n(t) = \rho \theta_r^n + c_r' \ (L_r^n) l_r^n - \beta_r^n. \tag{13}$$

This is a standard optimization problem with a concave objective function since the demand functions are downward sloping and costs are linear or convex. The constraints are linear. We can thus obtain a unique, interior solution.[17]

[17] For an analytical solution to a much simpler but similar problem, see Chakravorty, Magne and Moreaux (2008).

Conditions (7) suggest that the cultivated land in each region is allocated either to cereals, meat and energy production until the price (v_j) equals the sum of the production cost plus the shadow value of the land constraint, given by β_r^n. Equation (8) suggests that the regional price of cereals and meat (p_j^r) equals its world price (v_j). Equation (9) suggests that the price of biofuels in each region (p_e^r), weighted by the term $\left(\frac{\partial q_{re}}{\partial q_{rb}}\right)$ equals its world price (v_b). Equation (10) indicates that the marginal cost of land conversion equals the dynamic shadow value of the stock of land θ_n^r. Equation (11) states that the regional price of gasoline (p_{re}) weighted by $\left(\frac{\partial q_{re}}{\partial q_{rg}}\right)$ equals its cost augmented by the scarcity rent λ. Conditions (12) and (13) give the dynamic path of the two co-state variables λ and θ_r^n.

According to equations (9) and (11), consumption of biofuel and gasoline are respectively given by $p_{re}\frac{\partial q_{re}}{\partial q_{rb}} = w_{rb}{}' + \frac{\beta_r^n}{k_{rb}^n}$ and $p_{re}\frac{\partial q_{re}}{\partial q_{rg}} = g(X) + \lambda$. Hence the weighted marginal costs of biofuels and gasoline are equal. A positive quantity of land is allocated to the production of cereals, meat and energy. Obviously, rents will be higher on higher quality land. An increase in the demand for energy will induce a shift of acreage from food to energy and hence drive up the price of food, as well as bring more land into cultivation, potentially of a lower quality.

The biofuel mandate is imposed in the model by requiring a minimum level of consumption of biofuels in transportation at each date until the year 2022. Define the regional mandate in time T as $\underline{q}_{rb}(T)$, which implies that biofuel use must not be lower than this level at date T. This constraint can be written as $\left(q_{rb}(T) - \underline{q}_{rb}(T)\right) \geq 0$. This will lead to an additional term

$\tau_r\left(q_{rb}(T)-\underline{q}_{rb}(T)\right)$ in the generalized Lagrangian. The new condition for allocating land to biofuel (modified equations (7) and (9)) will be $k_{rb}^n\left(p_{re}\dfrac{\partial q_{re}}{\partial q_{rb}}-w_{rb}^{'}+\tau_r\right)-\beta_r^n\le 0,(=0\,\text{if}\,L_{rb}^n>0)$ for all n.

The shadow price τ_r can be interpreted as the implicit subsidy to biofuels that bridges the gap between the marginal costs of gasoline and biofuel. It is of course region-specific. The European mandate is a proportional measure, which prescribes a minimum percent of biofuel in the transport fuel mix. This restriction is implemented in the model by writing $\dfrac{q_{rb}(T)}{q_{re}(T)}\ge\underline{s}(T)$ where $\underline{s}(T)$ is the mandated minimum share of biofuels in transport at time T.

Even though the optimization program abstracts from valuing externalities from carbon emissions, it is important to find out whether carbon emissions decline due to the imposition of the biofuel mandate.[18] 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 biofuel emissions occur mainly at the production stage. 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. In the Appendix we detail the assumptions used to compute regional carbon emissions with and without the biofuel mandate.

3. Calibration of the Model

In this section, we discuss calibration of the model presented above. We aggregate the countries into three groups as stated earlier, using data on gross national product per capita (World Bank 2010). These are High, Medium and Low Income Countries (HICs, MICs and LICs). Since our

[18] Chakravorty and Hubert (2013) analyze the impact of a carbon tax on the transportation sector in the US.

study focuses specifically on US and EU biofuel mandates, the HICs are further divided into three groups - the US, EU and Other HICs. There are five regions in all. Table 1 shows average per capita income by region. The MICs consist of fast growing economies such as China and India that are likely to account for a significant share of future world energy demand as well as large biofuel producers like Brazil, Indonesia and Malaysia. The LICs are mainly nations from Africa.

Table 1. Classification of regions by income (US$)

Regions	GDP per capita	Major countries
US	46,405	-
EU	30,741	-
Other HICs	36,240	Canada, Japan
MICs	5,708	China, India, Brazil, Indonesia, Malaysia
LICs	1,061	Mostly African countries

Notes: Per capita GDP in 2007 dollars, PPP adjusted. *Source*: World Bank (2010)

***Specification of Demand*.** We can now describe the three consumption goods - cereals, meat and dairy products, and transport energy - in more detail. Cereals include all grains, starches, sugar and sweeteners and oil crops. Meat and dairy include all meat products and dairy such as milk and butter. For convenience, we call this group "meat." We separate cereals from meat because their demands are subject to exogenous income shocks as specified below. Meat production is also more land intensive than cereals. As mentioned above, transport energy is supplied by gasoline and biofuels. Cereals, meat and biofuels compete for land that is already under farming as well as new land, which is currently under grassland or forest cover.[19]

Regional demand $D_{rj}(P_{rj},t)$ for good j takes the form

$$D_{rj}(P_{rj},t) = A_{rj}P_{rj}^{\alpha_{rj}}y_r(t)^{\beta_{rj}(t)}N_r(t) \tag{14}$$

[19] Obviously, many other commodities can be included for a more disaggregated analysis, but we want to keep the model tractable so that the effects of biofuel policy on land use are transparent.

where $P_{rj}(t)$ is the output price of good j at time t in dollars, α_{rj} is the regional own-price elasticity and $\beta_{rj}(t)$ the regional income elasticity for good j which varies exogenously with per capita income reflecting changes in food preferences; $y_r(t)$ is regional per capita income, $N_r(t)$ is regional population at time t and A_{rj} is the constant demand parameter for good j, which we calibrate to reproduce the base-year demand for final commodities for each region. The constant demand parameters are reported in Appendix Table A1.[20] The demand function in (14) can be thought of as the demand for a representative individual times the population of the region. Individual demand is a function of the price of the good and income given by GDP per capita.

As incomes rise, we expect to observe increased per capita consumption of meat relative to the consumption of cereals, as noted in numerous studies (e.g., Keyzer *et al.* 2007). We model this shift towards animal protein by using income elasticities for food that are higher at lower levels of per capita income. Specifically, income elasticities for the US, EU and other HICs are taken to be stationary in the model since dietary preferences as well as income in these regions are not expected to change significantly over time, at least relative to developing countries. However, they are likely to vary in the MICs and LICs due to the larger increase in per capita incomes. The higher the income, the lower is the income elasticity. All price and income elasticities are specific to each food commodity (e.g., meat, cereals) and taken from GTAP (Hertel *et al.*, 2008) as described in the Appendix (Tables A1-A3).[21]

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[20] Independence of demand for meat and cereals has been assumed in other studies, see Rosegrant et al. (2001) and Hertel, Tyner and Birur (2010).

[21] Note that not all developing countries have exhibited as large a growth in meat consumption as China. For example, a third of Indians are vegetarian and a change in their incomes may not lead to dietary effects of the same magnitude. Moreover, beef and pork are more land-intensive than chicken, the latter being more popular in countries like India. The distribution of income may also affect this behavior. If it is regressive, the effect on diets may be limited.

We account for regional disparities in the growth of population. While the population of high income nations (including the US and EU) is expected to be fairly stable over the next century, that of middle income countries is predicted to rise by about 40% by 2050 and more than double for lower income countries (United Nations Population Division, 2010). Demand is also impacted by per capita income in each region, which is assumed to increase steadily over time but at a decreasing rate, as in several studies (e.g., Nordhaus and Boyer 2000). Again, regional differences are recognized, with the highest growth rates in MICs and LICs.[22]

Land Endowment and Productivity The initial global endowment of agricultural land is 1.5 billion hectares (FAOSTAT). The regional distribution of land quality is not even, as is evident from Figure 2, which shows land endowments based on climate and soil characteristics.[23] Most good land is located in higher income countries, but Brazil and India also have sizeable endowments of high quality land. Initial endowment for each of the three land qualities can be divided into land already under cultivation and fallow land.[24] As shown in Table 2, more than half of the agricultural land in the HICs (US, EU and Others) is classified as high quality, while the corresponding shares are roughly a third for MICs and LICs, respectively. Most land of medium and low quality is currently fallow in the form of grasslands and forests, and located in MICs and LICs. Note from Table 2 that there is no high quality land available for new production. Future expansion must

[22] Initial population levels and projections for future growth are taken from the United Nations Population Division (2010). Both world food and energy demands are expected to grow significantly until about 2050, especially in the MICs and LICs. By 2050, the current population of 6.8 billion people is predicted to reach nine billion. Beyond that time, population growth is expected to slow, with a net increase of one billion people between 2050 and 2100.

[23] Many factors such as irrigation and climate change can affect land quality. For instance, investment in irrigation can improve the productivity of land. In northern regions like Canada and Russia higher temperatures may cause an expansion of land suitable for agricultural production; hence, area under medium and low qualities may increase in the future. The net effect of these factors on the productivity of new land is unclear and left for future work. However, we do allow for increasing productivity of land over time (see below).

[24] See Appendix for details on land classification. According to FAO (2008a), an additional 1.5 billion hectares of fallow lands could be brought under crop production in the future. This is approximately equal to the total land area already under cultivation.

occur only on lower quality lands. Brazil alone has 25% of all available lands in the MICs and is the biggest producer of biofuels after the US.

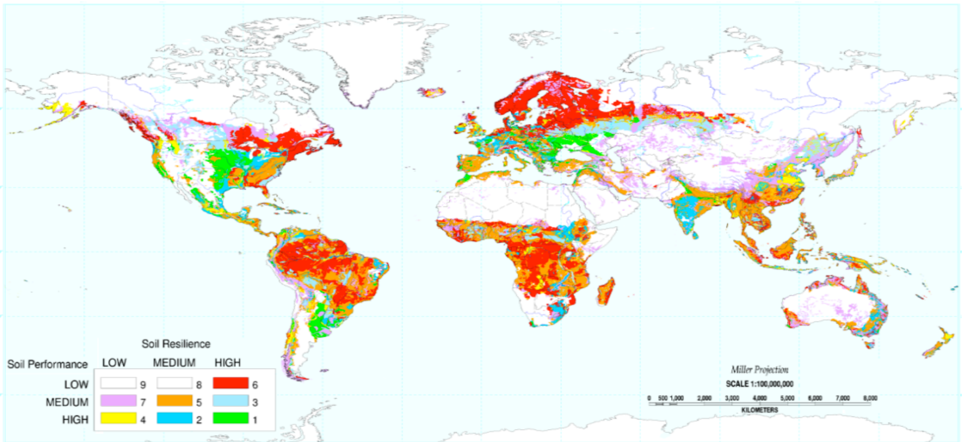

Figure 2. Distribution of land quality

Source: U.S. Department of Agriculture, (Eswaran *et al.* 2003 p.121). *Notes:* Land quality is defined along two dimensions: soil performance and soil resilience. Soil performance refers to the suitability of soil for agricultural production; soil resilience is the ability of land to recover from a state of degradation. Land quality 1 is the highest quality and 9 the lowest. In our model, we ignore category 7 through 9 which are unsuitable for agricultural production and aggregate the rest into three qualities (categories 1 and 2 become *High* quality land, 2 and 3 *Medium* quality land and 5 and 6, *Low* quality land).

As in Gouel and Hertel (2006), the unit cost of accessing new land in a region increases with land conversion. This can be written as

$$c_r(L_r^n) = \phi_{1r} - \phi_{2r} \log\left(\frac{\bar{L}_r^n - L_r^n}{\bar{L}_r^n}\right) \tag{15}$$

where $\bar{L}_r^n$ is the initial endowment of quality *n*, so that $\bar{L}_r^n - L_r^n(t)$ is the fallow land available at date *t,* ϕ_{1r} and ϕ_{2r} are model parameters, positive in value (calibrated from data) and assumed to be the same across land quality but varying by region (see Appendix Table A4).[25]

[25] Intuitively, ϕ_{1r} is the cost of converting the first unit land to farming. Conversion costs increase without bound as the stock of fallow land declines, since the log of the bracketed term is negative.

Table 2. Land currently in farming and endowment of fallow land

	Land quality	US	EU	Other HICs	MICs	LICs	World
Land already under Agriculture (million ha)	*High*	100	100	25	300	150	675
	Medium	48	32	20	250	250	590
	Low	30	11	20	243	44	350
Land available for farming (incl. fallow lands) (million ha)	*High*	0	0	0	0	0	0
	Medium	11	8	21	300	300	640
	Low	11	8	21	500	500	1040

Sources: Eswaran *et al.* (2003), FAO (2008a), Fischer and Shah (2010).

Improvements in agricultural productivity are exogenous and allowed to vary by region and land quality (see Appendix Table A5). All regions are assumed to exhibit increasing productivity over time, mainly because of the adoption of biotechnology (e.g., high-yielding crop varieties), access to irrigation and pest management. However, the rate of technical progress is higher in MICs and LICs because their current yields, conditional on land quality, are low due to a lag in adopting modern farming practices (FAO 2008a). The rate of technical progress is also likely to be lower for the lowest land quality. Biophysical limitations such as topography and climate reduce the efficiency of high-yielding technologies and tend to slow their adoption in low quality lands, as pointed out by Fischer *et al*. (2002).

The production cost for product j (e.g. cereal, meat or biofuel) for a given region is

$$w_{rj}(t) = \eta_{1r}\left(\sum_n k_{rj}^n L_{rj}^n(t)\right)^{\eta_{2r}} \tag{16}$$

where the term inside brackets is the aggregate production over all land qualities in the region and η_{1r} and η_{2r} are regional cost parameters.[26] For food and biofuels, we distinguish between production and processing costs. All crops need to be packaged and processed, and if they are converted to biofuels, the refining costs are significant. For cereals and meat, we use the GTAP 5 database, which provides sectoral processing costs by country (see Appendix Table A7). Processing costs for biofuels are discussed below.

The Energy Sector Transportation energy q_e is produced from gasoline and biofuels in a convex linear combination using a CES specification. For biofuels we model both land using (First Generation biofuels) and newer technologies that are less land-using (Second Generation), the latter are described in more detail below. First and second generation biofuels are treated as perfect substitutes, but with different unit costs, as in many other studies (Chen *et al.* 2012). We use estimates of the elasticity of substitution made by Hertel, Tyner and Byrur (2010). We calibrate the constant parameter in the CES production function to reproduce the base-year production of blending fuel (see Appendix Table A8 for details).[27]

For crude oil reserves, both conventional and unconventional oils (e.g., shale) are included. According to IEA (2011), around 60% of crude oil is used by the transportation sector. From the estimated oil reserves in 2010, we compute the initial stock of oil available for transportation as 153 trillion gallons (3.6 trillion barrels, World Energy Council 2010). The unit cost of oil depends on the cumulative quantity of oil extracted (as in Nordhaus and Boyer 2000) and can be written as

[26] The calibration procedure for this equation is explained in the Appendix and regional cost parameters are reported in Table A6.
[27] Transport fuel production is in billion gallons, which is transformed into Vehicles Miles Traveled (VMT) using the coefficients reported in Table A9.

$$g(X(t)) = \varphi_1 + \varphi_2 \left\{ \frac{X(t)}{\bar{X}} \right\}^{\varphi_3} \tag{17}$$

where $X(t) = \sum_t \sum_r x^r(t)$ is the cumulative oil extracted at time t, $\bar{X}$ is the initial stock of crude oil, φ_1 is the initial extraction cost and $(\varphi_1 + \varphi_2)$ is the unit cost of extraction of the last unit of oil. The parameters φ_1, φ_2 and φ_3 are obtained from Chakravorty *et al.* (2012). The initial extraction cost of oil is around \$20 per barrel (or \$0.50 per gallon) and costs can rise to \$260 per barrel (or \$6.50 per gallon) close to exhaustion (see Appendix Table A10). At these high prices, unconventional oils become competitive.

For each region, we consider a representative fuel: gasoline for the US and diesel for the EU.[28] We further simplify by considering a representative first generation biofuel for each region. This assumption is reasonable because there is only one type of biofuel that dominates in each region. For example, 94% of biofuel production in the US is ethanol from corn, while 76% of EU production is biodiesel from rapeseed. Brazil, the largest ethanol producer among MICs, uses sugarcane. Hence, sugarcane is used as the representative crop for MICs. In the LICs, 90% of biofuels are produced from cassava, although it amounts to less than 1% of global production.[29] Table 3 shows the representative crop for each region and its processing cost in the model base year.[30] Note the significant difference in costs across crops. These costs are assumed to decline by around 1% a year (Hamelinck and Faaij 2006) mainly due to a decrease in processing costs.[31]

[28] Gasoline represents more than three-quarters of US transport fuel use while diesel accounts for about 60% in the EU (World Resources Institute 2010). The coefficients of transformation of oil into gasoline and into diesel are reported in the Appendix.
[29] Energy yield data for first-generation biofuels is reported in Appendix Table A11.
[30] The total cost of biofuels is the sum of the production and processing costs plus rent to land net the value of by-products. Note that production costs depend on what type of land is being used and in which geographical region, and land rent is endogenous. By-products may have significant value since only part of the plant (the fruit or the grain) is

Table 3. Unit processing costs of first generation biofuels

	US	EU	Other HICs	MICs	LICs
Feedstock	Corn (94%)	Rapeseed (76%)	Corn (96%)	Sugar-cane (84%)	Cassava (99%)
Cost ($/gallon)	1.01	1.55	1.10	0.94	1.30

Sources: FAO (2008a); Eisentraut (2010); *Notes*: The numbers in parentheses represent the percentage of first-generation biofuels produced from the representative crop in the base year, 2007 (e.g., corn).

We model a US tax credit of 46 cents/gallon, consisting of both state and federal credits (de Gorter and Just 2010), which is removed from the model in year 2010, as done in other studies (Chen *et al.* 2012). EU states have tax credits on biodiesel ranging from 41-81 cents (Kojima *et al.* 2007). We include an average tax credit of 60 cents for the EU as a whole.

Second gen biofuels can be divided into three categories depending on the fuel source: crops, agricultural and non-agricultural residue. They currently account for only about 0.1% of total biofuel production although the market share may increase with a reduction in costs and improved fuel performance and reliability of the conversion process. Compared to first gen fuels, they emit less greenhouse gases and are less land consuming. Among several second gen biofuels, we model the one that has the highest potential to be commercially viable in the near future, namely cellulosic ethanol (from *miscanthus*, which is a type of perennial grass that produces biofuel) in the US and biomass-to-liquid (BTL) fuel in the EU (IEA 2009b). Their energy yields are much higher than for first gen biofuels. In the US, 800 gallons of ethanol (first gen) are obtained by cultivating one hectare of corn, while 2,000 gallons of ethanol (second gen) can be produced from ligno-cellulosic biomass (Khanna 2008). In EU, around 1,000 gallons/ha can be obtained from BTL, but only 400 gallons/ha are obtained from first gen biofuels.

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used to produce first-generation biofuels. For instance, crushed bean "cake" (animal feed) and glycerine are by-products of biodiesel that can be sold separately. The costs shown in table represent about 50% of the total cost of production.

[31] Except for cassava, for which we have no data.

Second gen fuels are more costly to produce. The processing cost of cellulosic ethanol is \$3.00 per gallon while first gen corn ethanol currently costs about \$1.01 per gallon and ethanol from sugar cane costs \$0.94.[32] The processing cost of BTL diesel is \$3.35 per gallon - twice that of first gen biodiesel. However, technological progress is expected to gradually narrow these cost differentials and by about 2030, the per gallon processing costs of second gen biofuels and BTL diesel are projected to be \$1.09 and \$1.40, respectively.[33] Finally, second gen fuels enjoy a subsidy of \$1.01 per gallon in the US (Tyner 2012), which is also accounted for in the model.

US and EU mandates The US mandate sets the domestic target for biofuels at nine billion gallons annually by 2008, increasing to 36 billion gallons by 2022.[34] The bill specifies the use of first and second gen biofuels (respectively, corn ethanol and advanced biofuels) as shown in Figure 3. The former is scheduled to increase steadily from the current annual level of 11 to 15 billion gallons by 2015. The bill requires an increase in the consumption of “advanced” biofuels (or second generation biofuels) from near zero to 21 billion gallons per year in 2022. In the EU, the mandate requires a minimum biofuels share of 10% in transport fuel by 2020. Unlike the US, the EU has no regulation on the use of second gen fuels.

[32] For second generation biofuels, processing is more costly than for first-generation biofuels and production costs plus land rent account for about 65% of the total cost.

[33] Second generation biofuels costs are assumed to decrease by 2% per year. All data on production costs are from IEA (2009b).

[34] It is not clear whether the mandates will be imposed beyond 2022 but in our model, we assume that they will be extended until 2050. In fact ethanol use in the US has already hit the 10% “blending wall” imposed by Clean Air regulations which must be relaxed for further increases in biofuel consumption. We abstract from distinguishing between the three categories of advanced biofuels in the US mandate. Of the 21 billion of second gen biofuels mandated, 4 billion gallons are low emission biofuels that can be met by biofuels other than cellulosic, such as sugarcane ethanol imported from Brazil. Another billion gallons may be met by biodiesel, which is used mainly for trucks. In this study, we assume that the entire target for advanced biofuels has to be met by cellulosic ethanol.

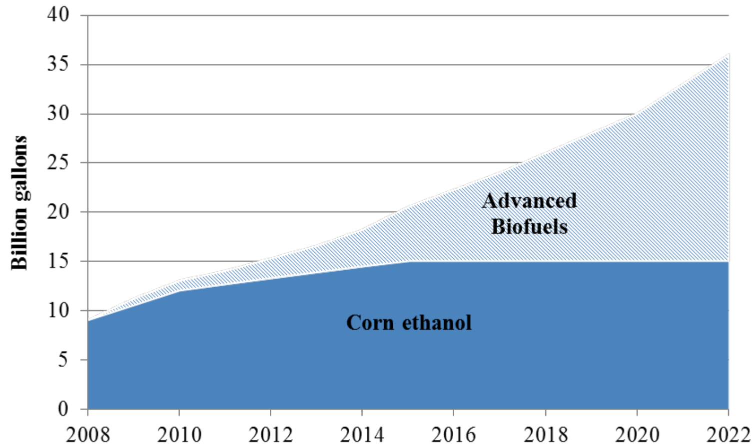

Figure 3. US biofuel mandate

Carbon emissions The model accounts for direct carbon emissions from fossil fuel consumption in transportation and indirect carbon emissions induced by the conversion of new land into agriculture. Carbon from biofuel use is mainly emitted during production and hence is crop-specific. Considering only direct emissions, displacing gasoline by corn ethanol reduces emissions by 35%; 70% if displaced by ethanol from sugarcane. Second-generation biofuels reduce carbon by 80% compared to gasoline (Chen *et al.* 2012).[35] Conversion of land for farming also releases carbon into the atmosphere.[36] Using Searchinger *et al.* (2008), we assume that the carbon released is 300 and 500 tons of CO_2e (CO_2 equivalent) per hectare respectively for medium and low quality land, immediately after land conversion. This is because medium quality land has more pasture and less forests than low quality land, and pastures emit less carbon.[37]

[35] Carbon emissions from gasoline and representative biofuels are reported in the Appendix (Table A12).
[36] This is a gradual process. For forests, it may also depend on the final use of forest products. However, we assume that all carbon is released immediately following land-use change, an assumption also made in other well-known studies (e.g., Searchinger, *et al.* 2008).
[37] There have been recent studies (see Hertel *et al.,* 2010) which suggest that the emissions from indirect land use change are likely to be somewhat smaller than those assumed by Searchinger. However, given that significant land use change occurs both in our base model and the one under regulation, these new estimates are unlikely to affect the central conclusions of our paper. Emission levels may change, not the net effect of biofuel regulation.

Trade among regions Although we assume frictionless trading in crude oil and food commodities between countries, in reality, there are significant trade barriers in agriculture, but given the level of aggregation in our model, it is difficult to model agricultural tariffs, which are mostly commodity-specific (sugar, wheat, etc.). However, we do model US and EU tariffs on biofuels. The US ethanol policy includes a per-unit tariff of $0.54 per gallon and a 2.5% *ad valorem* tariff (Yacobucci and Schnepf, 2007). The EU specifies a 6.5% *ad valorem* tariff on biofuel imports (Kojima *et al*. 2007). After 2012, US trade tariffs are removed from the model to match current policy (The Economist, 2012).

The discount rate is assumed to be 2% as is standard in such analyses (Nordhaus and Boyer 2000). We simulate the model over 200 years (2007-2207) in steps of five, to keep the runs tractable. It is calibrated for the base year 2007. The theoretical framework is defined as an infinite horizon problem. However, for tractability, we use a finite approximation in the form of a long time horizon (2007-2207) to ensure that the dynamic rent of oil is positive. This does not really affect the period we are mainly interested in, which is roughly the next decade. We follow Sohngen and Mendelsohn (2003) by assuming that exogenous parameters like population and income do not change significantly after 2100.

Model validation It is not possible to test model predictions over a long time horizon because biofuel mandates have been imposed only recently. However, as shown in Fig.4, the model does track the US gasoline consumption quite closely from 2000 to 2007.[38] The average difference between observed and projected values is systematically around 3%. The model predicts the annual

[38] Note that we only impose biofuel mandates in our model so the gasoline consumption is determined endogenously.

average increase in food prices from 2000 to 2013 at 9%.[39] According to the FAO, food prices grew at an annual rate of 7.5% during this period. The model solution suggests that around 19 million hectares of new land are converted for farming from 2000 to 2009. According to FAOSTAT, 21 million hectares of land were brought into cultivation during this period. These indicators suggest that the model performs reasonably well in predicting the impact of the mandates on different variables of interest.

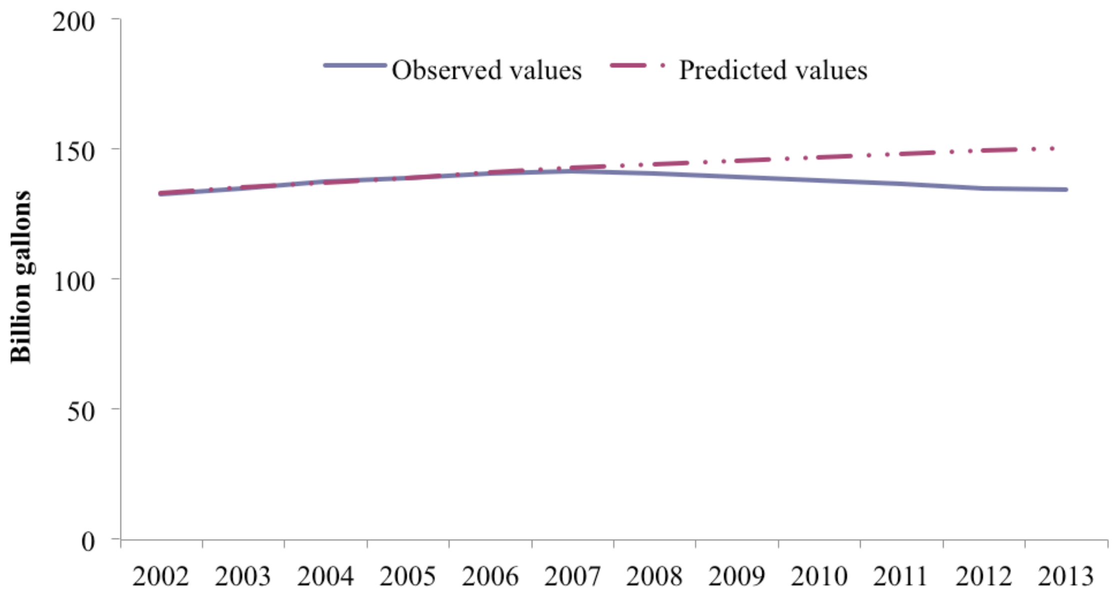

Figure 4: Model prediction vs actual US oil consumption from 2000 to 2013

Source: Consumption figures are from EIA (2014). *Notes*: The difference between observed and predicted values is higher after 2008 since US gasoline consumption fell during the recession 2008-2013. Of course, our partial equilibrium model does not capture short-run macro-economic fluctuations.

4. Simulation Results

We first state the scenarios modeled in the paper and then describe the results. In the *Baseline case* (model BASE), we assume that there are no energy mandates and both first and second gen fuels are available. This is the unconstrained model described before and serves as the counterfactual.

[39] Our world food price is the average of cereal and meat prices weighted by the share of each commodity in total food consumption. In general, it is hard to accurately predict food prices in the short run, because of weather-related variability (droughts such as the one that occurred in Australia in 2008 or Russia in 2010), currency fluctuations and other macroeconomic phenomena.

The idea is to see how substitution into biofuels takes place in the absence of any clean energy regulation. In the *Regulatory Scenario* (model REG), US/EU mandatory blending policies, as described earlier, are imposed. The key results are as follows:[40]

1. Effect of biofuel mandates on food prices. We find that the effect of the mandates on food prices is significant, but not huge (see REG in Table 4). With no energy mandates, food prices rise by about 15%, which is purely from changes in population and consumption patterns (see BASE). [41] With energy mandates, they go up by 32% (see REG). Thus, the additional increase in 2022 from energy regulation is about 17%.[42] This is much smaller than what most other studies predict (Rosegrant *et al.* 2008, Roberts and Schlenker 2012).[43]

Figure 5 shows the time trend in food prices under the two regimes. Note that prices increase both with and without regulation.[44] The substantial increase in food demand in MICs and LICs

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[40] Our results are time sensitive but to streamline the discussion, we mostly focus on the year 2022. In the more distant future (say around 2050 and beyond), rising energy prices and a slowdown in demand growth makes biofuels economical, even without any supporting mandates. Mandates become somewhat redundant by then. Given the lack of space, we do not discuss what happens in 2050 and beyond.

[41] The model is calibrated to track real food prices in 2007. Cereal and meat prices for that year for the BASE case are \$218 and \$1,964 per ton. Observed prices in 2007 were \$250 and \$2,262, respectively (World Bank 2010). The small difference can be explained by our calibration method, which is based on quantities not prices.

[42] Since the model is dynamic, the initial values are endogenous, hence the starting prices in 2007 are not exactly equal (Table 4).

[43] In general, it is difficult to compare outcomes from different models, but Rosegrant *et al.* (2008) predict prices of specific crops such as oilseeds, maize and sugar rising by 20-70% in 2020, which are generally much higher than in our case. Roberts and Schlenker (2013) project that 5% of world caloric production would be used for ethanol production due to the US mandate. As a result, world food prices in their model rise by 30%. These studies assume energy equivalence between gasoline and biofuels, i.e., one gallon of gasoline is equivalent to one gallon of biofuel. We account for the fact that one gallon of ethanol yields about a third less energy than gasoline, as in Chen *et al.* (2012).

[44] Although real food prices have declined in the past four decades, the potential for both acreage expansion and intensification of agriculture through improved technologies is expected to be lower than in the past (Ruttan 2002). From 1960 to 2000, crop yields have more than doubled (FAO 2003). However, over the next five decades, yields are expected to increase by only about 50%, see data presented in Appendix (Table A5). However, yields may also respond to higher food prices, an effect we do not capture here. That will imply a smaller impact of energy mandates on food prices.

accompanied by a change in dietary preferences raises the demand for land, which drives up its opportunity cost. Without energy regulation, meat consumption in these two regions increases by

Table 4. World food, biofuel and gasoline prices (in 2007 Dollars)

		BASE	REG
Weighted food price ($/ton)	2007	557	564
	2022	639 (15%)	746 (32%)
Biofuel price ($/gallon)	2007	2.14	2.18
	2022	1.97	2.19
Crude oil price ($/barrel)	2007	105	106
	2022	121	119

Notes: Weighted food price is the average of cereal and meat prices weighted by the share of each commodity in total food consumption. The numbers in brackets represent the percentage change in prices between 2007 and 2022. Our predictions for crude oil prices are quite close to the US Department of Energy (EIA 2010, p.28) reference projection of $115/barrel in 2022: see their 'High and Low Oil Price' range.

8% (for MICs) and 34% (for LICs) between 2007 and 2022, with the latter starting from a smaller base. The consumption of cereals remains stable. Since more land is used per kilogram of meat produced, the overall effect is increased pressure on land. Food prices decline over time as the effect of the mandates wear off.[45] This is mainly because population growth levels off and yields increase due to technological improvements in agriculture.

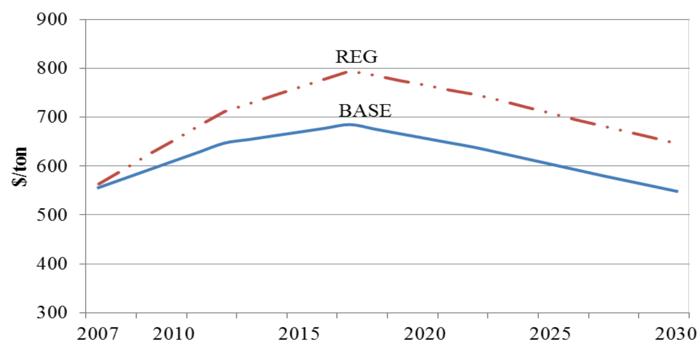

Figure 5. World weighted food prices

Notes: The baseline model is in blue and the regulated model in red. The weighted food price is the average of cereal and meat prices weighted by the share of each commodity in total food consumption.

[45] The increase in price due to regulation is about 6% in the year 2100.

2. *Demand growth causes most of the land conversion, nearly all of it in developing countries.* Table 5 shows that the really big increases in land use occur even without mandates: in the MICs, 119 million ha (=912-793) are brought under production between 2007 and 2022 without any mandates (see BASE). This is about two thirds of all the cultivated land currently in production in the US. No new land (including land available under the US Conservation Reserve Program is brought under cultivation in the US due to higher conversion costs than in MICs. With the mandates, MICs bring another 74 (=986-912) million hectares under farming. Food production in the US/EU declines but rises in the MICs. Overall, the mandates increase aggregate land area in agriculture, because of conversion of new land.

Table 5. Land allocation to food and energy production (in million ha)

		US		EU		MICs	
		BASE	**REG**	**BASE**	**REG**	**BASE**	**REG**
Land under food production	2007	166	167	138	136	789	789
	2022	166	107	137	129	905	980
Land under biofuel production	2007	12	11	5	7	4	4
	2022	12	71	6	14	7	6
Total cultivated land	2007	178	178	143	143	793	793
	2022	178	178	143	143	912	986

Notes: Land allocation in Other HICs and LICs are similar across the two models.

Fig.6 shows land use for food and fuel. Note that in the US about 60 million ha – a third of all farmland – is moved from food to fuel production, but no new land is added (Fig.6a).[46] However, the MICs convert a significant amount of land, irrespective of the energy mandates (Fig.6b).[47] Both first and second gen biofuel production increases sharply under the US mandate. US food production declines by almost 27% as a result of the energy mandates (not shown). US food exports go down by more than 80% (from 75 to 13 million tons). This is because land is shifted out

[46] It is important to note that there are other sources of second gen biofuels that are less land-consuming, such as corn stower and forest products, which can affect these land conversion estimates significantly. They may lead to a lower rise in food prices than predicted in the paper.

[47] We do not show the EU case because the change in acreage is small.

of food to produce biofuels for domestic consumption. Imports of first gen biofuels more than double.

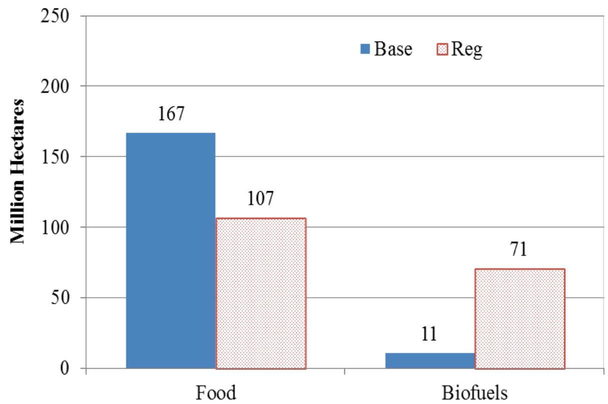

Fig. 6(a). Land allocation in US: land is shifted out from food to fuel

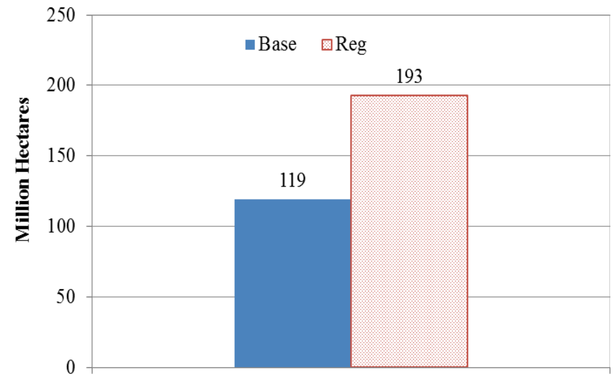

Fig. 6(b) Land conversion in MICs

Figure 6. Land allocation under Base and REG (year 2022)

Note: An area larger than current US farmland is cleared in the MICs but most of it is due to demand growth not biofuel policy

3. *Mandates lead to big increases in biofuel production, earlier in time.* Without regulation, biofuel consumption in the EU and US in 2022 is around 2 and 8 billion gallons, and accounts for 3% and 5.5% of fuel consumption, respectively. This is much lower than what is prescribed by the mandates. Fig.7 shows consumption with and without the mandates (BASE, REG). The mandatory blending policy requires an additional 30 billion gallons of biofuels in 2022 compared to the unregulated case, mostly in the US.[48] The US target is much more ambitious than the EU target. It binds until 2040 (see panels a and b), and yields a bigger gap in consumption with and without the mandate than in the EU.

As seen from Fig. 7(a) and 7(c), first gen fuels decline in use without a mandate for several years before becoming economical in response to rising energy prices. After 2030, their use increases

[48] Global biofuels production under the baseline scenario is 18 billion gallons in 2022.

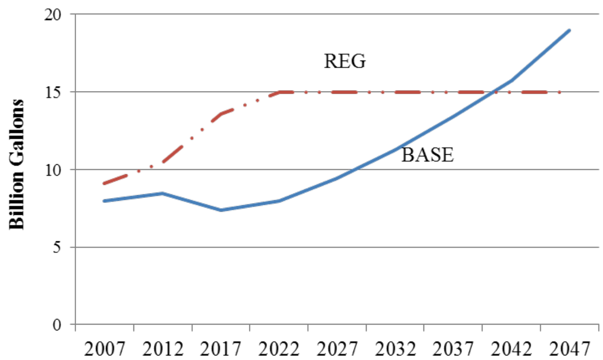

Fig. 7(a) US first gen biofuel use

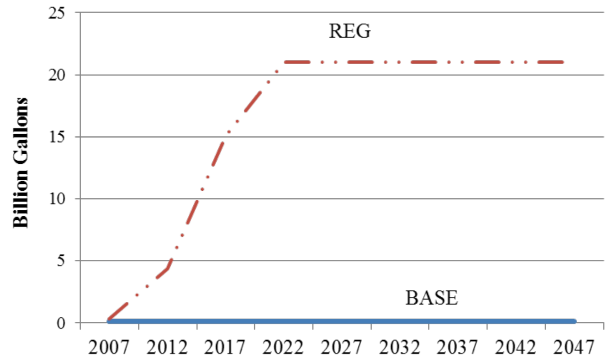

Fig. 7(b) US second gen biofuel us

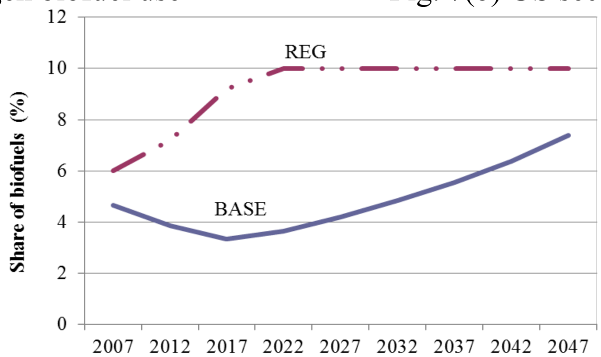

Fig. 7(c) Share of biofuels in transport in EU

Figure 7. US and EU biofuel use (with and without mandates)

Note: The EU mandate is defined as a share.

even without a mandate. In the absence of regulation, the global share of oil in transport steadily decreases from 95% in 2007 to 84% in 2050. The share of biofuels increases, mainly due to an increase in the market share of first gen fuels. With no regulation, second gen biofuels are not economically viable by 2022 in the US whereas they are adopted by 2017 in the EU. This is due to lower unit costs in the EU. The production of first gen fuels, however, does show a more rapid growth after 2030, mainly because of a reduced demand for land (see Fig.7a and 7c).

With no regulation, annual world production of biofuels is constant at about 20 billion gallons until 2020, before increasing to 96 billion in 2050 (not shown).[49] The stagnation until 2020 is due to a rapid increase in the opportunity cost of land, caused by the growing demand for food. Indeed, land rents double in the US and EU during this period. Beyond 2020 however, food demand levels off, and so do land rents. The scarcity rent of oil continues to increase, making gasoline more expensive and biofuels economically feasible (Fig. 7).

4. Mandates reduce crude oil prices and cause significant leakage and direct emissions. The primary goal of biofuel regulation is to reduce direct emissions from the energy sector. US emissions fall by less than 1% and EU emissions by about 1.5% (see Table 6).[50] The switch towards less carbon intensive energy is partially offset by the rise in the demand for the blended fuel. The mandates, while increasing the consumption of biofuels in the US/EU, increase oil consumption and reduce biofuel use elsewhere. This occurs because of terms of trade effects – the mandate lowers the world price of oil (see Table 4). In 2022 the price of oil is about 1% lower, while the price of biofuels increases by 11% with mandatory blending. The net effect is that biofuel consumption outside the US and EU goes down by 20% in 2022, most of it in MIC countries. Oil use in the rest of the world goes up by 1%.[51]

Globally, annual direct emissions of carbon decrease by about 0.5%. Although the US/EU consume a significant share of global transportation energy - 53% in 2007, which declines to 28%

[49] Although the first gen biofuels consumption goes beyond that in REG as shown in Fig 7(a), the total consumption of biofuels (sum of first-and-second gen biofuels) is larger under the REG. Under the BASE scenario, the consumption of second gen biofuels is nil since they are not competitive.
[50] Observed average carbon emissions for previous years are close to our model predictions. The former are 1.7, 0.9 and 5.8 tons of CO_2e for the US, EU and World in 2007, very similar to our base figures shown in Table (IEA, 2009c).
[51] We only discuss spatial leakage while other models have studied inter-temporal leakage (e.g., see Fischer and Salant, 2011) and inter-sectoral leakage (Fullerton and Heutel, 2010).

in 2050 – the decline in emissions in these two regions is mostly offset by spatial leakage. The net effect of mandatory blending policies on global direct emissions is small (Table 6).

Table 6. Direct carbon emissions in billion tons of CO_2e (REG)

	US	EU	World
2007	1.85	0.83	5.1
2022	1.95 (-0.9%)	0.81(-1.5%)	6.30 (-0.5%)

Note: We compute carbon emissions in terms of CO_2e (CO_2 equivalent), which includes other greenhouse gases such as nitrogen dioxide and methane. Numbers in parenthesis represent the percentage change of carbon emissions compared to BASE model, which is not shown.

5. Indirect carbon emissions increase. Biofuel mandates lead to an *increase* in indirect global emissions (see Fig.8). The mandates increase total emissions in most years relative to the unregulated (BASE) case, which to a large degree is due to land conversion. Total emissions (direct and indirect) also increase in the near term (see Fig.8). Since we track the amount and quality of land that is converted for agriculture, we can compute indirect emissions from land use. Regardless of whether biofuel mandates are imposed in our model, the increased demand for food and energy causes large-scale land conversion. The mandates only accelerate this process. In 2022, indirect carbon emissions increase by 60% (or 4.4 billion tons of CO_2e), all of it from non-regulated countries, which is much larger than the annual savings from regulation in the mandated countries (0.01 billion tons). In aggregate, carbon emissions increase by about 4.4 billion tons of CO_2e due to mandatory blending (see Fig. 8).

6. Welfare declines in the non-regulated countries. We compute the regional gains and losses in aggregate consumer and producer surplus for the food and energy commodities as a result of the mandates. Medium and low-income countries experience the largest loss in welfare with mandatory blending. However, the US experiences a slight *increase* in welfare. These results are

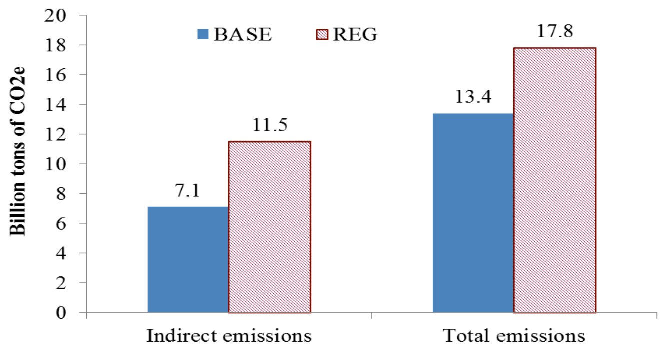

Figure 8. Biofuel mandates do not reduce carbon emissions
Notes: Shown for 2022. Total emissions are the sum of direct and indirect emissions.

primarily driven by changes in surplus from agriculture. The mandates increase biofuel production, which causes an increase in the opportunity cost of land, which in turn drives up the price of agricultural commodities (both food and energy). This has a significant positive impact on surplus in the US agricultural sector, which is one of the stated goals of the mandate (see de Gorter and Just 2010).

Since we do not explicitly account for externalities, the global welfare effect of introducing mandatory blending is negative – welfare declines when the model is constrained. In the MICs and LICs - countries where a large share of income is allocated to food consumption - consumers are more sensitive to changes in food prices. As a result, the loss in welfare of food consumers exceeds the gain to food producers (from higher food prices). Note however, that we do not include the benefits from reduced carbon emissions in the mandated nations or elsewhere, which are likely to be significant because carbon is a global pollutant. On the other hand, higher emissions in other nations due to terms of trade effects will cause environmental damages and will likely decrease aggregate welfare.

5. Sensitivity Analysis

There is uncertainty regarding the values of several key parameters used in the empirical analysis. These include the stock of oil and its cost of extraction, the conversion cost of fallow land and yield parameters for crops. In this section, we investigate the sensitivity of our results to changes in these parameters.[52] We also impose biofuel mandates in two of the largest energy consuming nations, China and India, to check how food prices may be impacted if they too implement their announced mandates. Finally, we check how assumptions regarding the scarcity of crude oil, the interest rate and income-based dietary preferences affect our analysis.

Model Sensitivity to Parameter Values Our strategy is to shock both models (REG and BASE) with the following changes: (1) 50% lower conversion cost for fallow lands, (2) 50% increase in oil stock and (3) a 10% increase in agricultural yields because of adoption of biotechnology.[53] Land conversion costs are important because they represent a situation in which governments may relax regulatory policies or subsidize conversion of land into agriculture. We consider the case of abundant oil, in response to the fact that historically, reserve estimates have been biased downwards.[54] For (3), we model the adoption of genetically modified foods that may raise agricultural yields through introduction of new cropping varieties that are plant and disease resistant and do well in arid environments (FAO 2008b).[55] We assume a reasonable across-the-

[52] Because of a lack of space, we are unable to show all our sensitivity results. We discuss only the most significant ones.
[53] An increase in the cost of extraction of oil is not considered, but would have a similar effect as a reduction in the initial stock of oil since both would raise energy prices. Preliminary runs suggest that the model is not sensitive to the cost of extraction.
[54] For example, recent discoveries of cheap shale oil and gas have made biofuels less economically attractive, according to the IEA (IEA, 2013).
[55] The adoption of Genetically Modified Organisms (GMOs) can help biofuel production by increasing the production of biomass per unit of land as well as the conversion of biomass to first or second gen biofuels (FAO 2008b).

board increase in agricultural yields of 10% relative to the models described earlier.[56] To keep it simple, this increase in yields is assumed uniform across land qualities and regions and affects production of food and biofuels.

Table 7 reports the percent change in the outcome variables under REG relative to BASE when specific parameters are changed. We are interested in changes in the difference between the two models, i.e., for any given row, column entries that deviate significantly from the first column. For instance, when the cost of land conversion declines, food price increases are smaller, which is intuitive. More land will be converted and hence the impact on the food market is lower. With abundant oil, the price of oil is lower, making biofuels less competitive even in the base model. Thus, the net effect of regulation is larger on food prices, than with the initial parameters. This leads to a larger decrease in direct emissions in the regulated regions (US and EU). Finally, higher adoption of biotech leads to less land conversion in the BASE model (by about 50%) so that when the mandate is imposed, the additional land conversion is significant, and we get a large impact on indirect carbon emissions.[57]

EU, Chinese and Indian Mandates, Scarcity of Oil and Stationary Dietary Preferences Before examining the effects of Chinese and Indian mandates, we investigate the effects of the EU mandate without the US policy. Since EU transport fuel consumption is about half that of the US,

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[56] According to the Council of Biotechnology Information (2008), adoption of GMOs contributed to a 15% increase in US crop yields during 2002-07. Due to a lack of data for other countries, we apply this rate of increase across the board.

[57] It may be useful to comment on how the BASE model (the one without regulation) itself responds to changes in the above parameters. The most important observation is that when the conversion cost of new land decreases, direct emissions decline, because more biofuel is used. Less food is consumed but greater biofuel use leads to more land conversion. Other factors have similar qualitative effects on the model without regulation, but less in magnitude. Detailed results for this case are not shown but can be obtained from the authors.

Table 7. Sensitivity analysis: Percentage change of key variables in REG relative to BASE (year 2022)

		Initial Parameter Values	(1) Lower land conversion cost	(2) Higher Oil Stock	(3) Higher Adoption of Biotech
Food price		17	14.1	22	11.84
Biofuel price		10	8.6	30	8.1
Gasoline price		-1	-1.4	-1.5	-1.1
US food exports		-82	-85	-84	-61
US biofuel imports		89	66	150	15
Aggr. acreage		4	4.5	4.38	4.9
Direct emissions	US	-1	-0.5	-3	-1.9
	EU	-2	-1.15	-0.63	1
	World	-1	-0.3	0.65	-1.2
Indirect emissions		61	42	61	169
Total emissions		32	27	30	51

Note: All figures are percent changes in the variable in the REG model over the BASE model

the former has a small effect on prices. The increase in food price is only 1.5%. World direct carbon emissions are almost constant (-0.11%) under the only EU policy, while EU emissions go down by 1.2%. The additional land area required to meet the EU target is smaller and indirect carbon emissions increase by 9%.[58] Now consider the case of China and India, the two most populous countries, imposing domestic biofuel mandates.[59] We assume that these two nations impose a mandate requiring the share of biofuels in transportation to rise linearly to at least 10% by 2022. Imposing these mandates increases biofuel consumption in the MICs from 10 billion gallons under REG to 24 billion.[60] However, terms of trade effects are smaller in this case because these two large countries use more biofuels. Global oil consumption goes down by less than 1%, with

[58] It may be of interest to deduce from our model how the EU mandate affects prices and emissions, given the US mandate. We can compare a case in which only the US mandate is imposed and then compare the outcome with REG in which both mandates are in effect. Since EU gasoline consumption is about half of the US, the change in biofuel consumption is small, which reduces the impact of the EU mandate. The increase in food price is about 2%. World direct carbon emissions are almost constant (-0.17%), and the indirect carbon emissions only increase by 9%.
[59] The number of vehicles in China is expected to increase from 30 to 225 million by the year 2025, and in India from 15 to 125 million (IEA 2009a). Currently, biofuels supply less than 1% of transportation fuel in these countries.
[60] Here China and India are still modeled as part of the group of MICs. To calculate the minimum biofuel standard that meets the China-India target, we get gasoline consumption projections from the Energy Information Administration (EIA 2013).

little change in direct carbon emissions in the MICs. What is interesting is that instead of moving land away from food to fuel production, farmers from MICs, which are land abundant, bring new land under cultivation (another 10 million hectares). As a result, indirect emissions rise to 13 million tons. Still, world food prices rise by only 1% beyond the impacts from US and EU mandates.

We estimate the effects of three other key assumptions in the model. First, we suppose that the price of oil remains constant over the entire period at $105/barrel, the initial crude oil price in our model. Without a mandate, world use of biofuels decreases because of constant oil prices. US biofuel use drops from 8 to 2 billion gallons in 2022, and second gen fuels are never adopted. With the mandate, indirect carbon emissions increase by about 60% compared to the BASE model (both with cheap oil). About 85 million hectares of new land are brought under cultivation because of energy regulation. This is 10 million hectares more than when oil prices rise due to scarcity. With cheap oil, biofuel use is low without mandates and increases sharply with them. Now, imposing the mandate has a bigger effect on food prices, which increase by 30%. Recall that food prices increased by about 17% when oil prices were allowed to increase due to scarcity. The mandates induce higher land conversion to energy and less to food. The subsidy required to meet the US targets is almost 1.5 times larger than under the REG model.

We also examine the sensitivity of the outcome variables to a change in the social discount rate from 2 to 5 percent. A rise in the discount rate leads to a faster extraction of the oil stock. Therefore, one would expect biofuel consumption to decline in the BASE case. Indeed, it decreases from 9 to 4 billion gallons in 2022. Regulated first gen biofuel use is the same under both discount rates, equal to 15 billion gallons. As a result, world food prices increase by 21% due to adoption of the US biofuel mandate (compared to BASE) instead of 17% in the base case. A higher discount rate means a lower oil price, which actually increases domestic emissions in the US, as well as global emissions due to leakage, by a few percentage points.

To see the effect on food prices if no second gen mandate was specified in the US, we do a model run in which both first and second gen biofuels can be used to meet mandatory blending specifications, but there is no requirement on the share of second gen fuels. We find that second gen fuels are too costly and will not be produced without a mandate. With the mandate, 21 billion gallons are produced. Without mandates on second generation biofuels, food prices in 2022 go up by 40% from the base year 2007: in that case land-using first gen fuels supply most of the biofuel. One may expect more food to be produced when second gen fuels which are less land-intensive, are mandated. However, land rents decline, and US food exports double under second gen fuels, albeit from a low base. In summary, the mandate on second gen biofuels helps reduce imports, but does not release land for more food production in the US since second generation biofuels are domestically produced.

Finally, we examine what happens when food preferences are assumed constant, i.e., there is no income-driven preference for meat and dairy products. We fix income elasticities for meat and cereal in the MICs and LICs at levels similar to the US and EU. This means that people in developing countries are assumed to have the same elasticities towards meat and cereals as in developed nations, but at their lower consumption levels. As a result, their meat consumption increases far less rapidly with income than before. To compare, note that per capita meat consumption goes up by 8% in MICs and by 34% in LICs from 2007 to 2022 when preferences change exogenously as in the previous runs. With stationary preferences, meat consumption is almost constant. Food prices *decrease* by about 9% in the same period, compared to a 15% increase in the BASE model (see Table 4). Since land rents fall, more biofuels are produced. For instance in the US, an additional five billion gallons are produced compared to the BASE case, reaching 11 billion gallons in 2022. Food prices are higher under regulation by 7% compared to no regulation, when preferences are assumed stationary. To meet their biofuel targets, the US and EU import less biofuels from MIC countries. MIC nations, in turn, convert less land to farming.[61]

6. Concluding Remarks

We model the dynamic effects of biofuel mandates in the US and EU by combining three elements, which have not been considered together in previous studies - income-driven dietary preferences, differences in land quality and a limited endowment of oil. We find that modeling land supply leads to price impacts of the energy mandates that are generally lower than in most studies. Secondly, demand side effects that include expected changes in dietary preferences account for half of these price effects, the remaining coming from mandates. Third, even mandates adopted by big developing countries China and India do not produce large price effects, although more land is converted into farming.

Our results suggest that dietary changes towards increased meat and dairy consumption may have an important role in the projected growth of food prices. For example, if diets were kept constant, food prices would actually *fall* over time (9%) without energy regulation, and with biofuel mandates, they will rise by only 7% in year 2022, less than what other studies predict. The upshot

[61] We also do a sensitivity run with a higher elasticity of substitution (doubling the base value). This assumption may be realistic if the vehicle fleet is mainly composed of Flex Fuel Vehicles. Biofuel consumption is lower than in the model with initial parameters. Hence, the increase in biofuel production required to meet the biofuel target is higher than under a lower elasticity of substitution. The net effect of biofuel policy is significant - food prices increase by 24%.

of these results is that the effect of energy policies that divert corn from food to fuel can be mitigated by supply side adjustments such as land conversion. However, indirect carbon emissions will be significant, leading to no net reduction in greenhouse gas emissions, one of the primary stated goals of biofuel policy. In fact, annual aggregate emissions are almost invariant with respect to assumptions about the crude oil market. If crude oil supplies are assumed scarce, more biofuels are used, leading to low direct emissions but high indirect emissions from land conversion. If crude oil is assumed abundant, less biofuel is used, causing high direct emissions and low indirect emissions. Thus, biofuel mandates may not reduce aggregate emissions, unless new technologies such as genetically modified crops are widely used.

The model is simple and can be extended in many directions. The general equilibrium effects of the energy mandate are not studied. For example, converting new land into farming may induce labor migration into these areas, which may in turn shift the regional demand curves for food and energy. Alternatively, energy price changes may trigger technological change, which may further reduce the impacts of regulation. For instance, high fuel prices may lead to the increased adoption of fuel-efficient cars and reduce fuel use, including biofuels. Higher meat prices may lead to changes in the livestock industry, such as a shift from ranching to intensive feedlot operations, which will mitigate the effect of food price shocks. Learning effects, that are a result of market share, especially for new technologies like second generation biofuels, may also be quite significant. Finally, it is not clear how other countries will react to the mandates in choosing their own energy and agricultural policies. Strategic interactions could be modeled explicitly in future work. Increases in food prices, whether from demand effects or energy policies, may lead to increased efficiency in agriculture, through irrigation, better seeds and other inputs. Our model assumes exogenous rates of technological change, not linked to prices. Price effects may further strengthen the supply response discussed in the paper.

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Appendix: Data Used in Calibration

Here we describe the model assumptions and data in more detail. The model is a discrete-time, non-linear dynamic programming problem, and was solved using GAMS software. It runs for the period 2007-2207. The reference year for model calibration is thus 2007. Because of the leveling off of population and elasticity parameters, the solution does not change significantly after year 2100. To reduce computational time, we program the model in time steps of 5 years.

Calibration of Demand Demand is specified by condition (14). Cereals include all grains, starches, sugar and sweeteners and oil crops. Meat includes all meat and dairy products such as milk and butter. The constant demand parameter A_{rj} is product and region-specific. It is calculated to reproduce the base year global demand for each product by using $A_{rj} = \frac{D_{rj}(P_{rj},t)}{P_{rj}^{\alpha_{rj}} y_r(t)^{\beta_{rj}(t)} N_r(t)}$ from (14). 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).[62] All the data needed to calculate the constant demand parameters is shown in Table A1. 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 from FAOSTAT. While per capita consumption for the 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 transport fuel is obtained by

[62] 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 (14), the constant parameter A_{rj} is calculated as 0.4212. Other demand parameters are computed similarly.

aggregating the fuel demand for diesel-powered and gasoline-powered cars for each region. For the US, EU, MICs and LICs, this data is 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. Transport 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 taken from Chakravorty *et al.* (2012).[63]

Price and income elasticities for cereals, meat and transport 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. 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 A1.

Exogenous Growth of Demand Demand for food commodities and transport fuel depend upon the growth in per capita income and population. Data on growth rates for per capita income are from

[63] To ensure that the area under the demand curve is bounded, we define an arbitrary limit price for each final good and the corresponding quantity demanded at these prices. The limit price is 10,000 dollars per ton for food commodities and 10,000 dollars per vehicle miles traveled for transport energy. The net surplus is the area between the limit price and the market price. Our results are not sensitive to these values.

Nordhaus and Boyer (2000) and population data for each region is from the UN Population Division (2010). Table A2 shows the level of per capita income and population by region in 2007 and 2050. Since we calibrate our model in time steps of five years, annual growth rates of population and per capita income are constant within each five-year period. Demand for food and fuel are in billion tons and billion miles driven.

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 commodities by region.[64] We thus make some adjustments in the calibration of demand given by (14). First, the change in food preferences is driven by the rise in per capita income. As a result, we consider 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 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 A3 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.

[64] Cranfield *et al.* (2002) estimate consumer demand 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 aggregating preferences over cereals and meat.

Table A1. Demand parameters in base year (2007)

		US	EU	Other HICs	MICs	LICs
Per capita income *(y_r)*	($)	46,405	30,741	36,240	5,708	1,060
Population *(N_r)*	(million)	301	496	303	4,755	765
Per capita demand $\left(\frac{D_{rj}}{N_r}\right)$	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 $\left(P_{rj}\right)$	Cereals ($/ton)	250	250	250	250	250
	Meat ($/ton)	2,260	2,260	2,260	2,260	2,260
	Fuel ($/VMT)	0.14	0.23	0.19	0.19	0.19
Income elasticity $\left(\beta_{rj}\right)$	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 $\left(\alpha_{rj}\right)$	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 $\left(A_{rj}\right)$	Cereals	0.4212	0.3786	0.3527	0.0037	0.0081
	Meat	0.0054	0.0082	0.0286	0.0038	0.0068
	Fuel	0.2060	0.8524	0.2747	0.0957	0.0006

Notes: 1) The letters in parenthesis refer to the regional demand function (equation (14)). 2) 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. *Sources:* Per capita income is from World Bank (2010); Population is from UN Population Division (2010); Per capita demand for cereals and for meat are from FAOSTAT, per capita demand for fuel is from World Resources Institute (2010); World cereal and meat prices are weighted average prices computed from World Bank (2011) data; 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); Price and income elasticities are from Hertel et al. (2008).

Table A2. Population and per capita income in 2007 and 2050

	Population (million)		**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. *Source:* UN Population Division (2010); Initial per capita income is from World Bank (2010), per capita income in 2050 is calculated by using growth rates from Nordhaus (2010).

Table A3. Changes in income elasticities for food commodities 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	+ 0.90
LICs	2007	1,061	+ 0.65	+ 1.30
	2050	**4,000**	**+ 0.59**	**+ 1.20**

Sources: Initial per capita income is from World Bank (2010), per capita income in 2050 is calculated by using the growth rates from Nordhaus (2010); Initial elasticities are from Hertel *et al.* (2008), elasticities in 2050 are from authors' calculations.

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 quality I being the most productive. Three criteria are used, namely, land quality, soil resilience and soil performance. Land quality is defined as the ability to perform its function of sustainable agricultural production. This is measured by the length of the growing season, e.g., the period of a year when the crop can be grown. Soil resilience is the ability to revert to a near original production level after it is degraded. Soil performance measures the capacity to produce under moderate level of inputs in the form of conservation technology, fertilizers and pest control. We disregard land qualities unsuitable for agricultural production, i.e., categories VII to IX. We aggregate the remaining six (I through VI) into three land qualities. Category I and II are grouped as *High* quality, III and IV are *Medium* and V and VI are *Low* quality. We thus have three land qualities indexed by n=*{High, Medium, Low}*. High land quality benefits from a long growing season and soil of high quality. Medium quality land has a shorter growing season due to water stress or excessive temperature variance. Low quality land faces numerous production constraints like water stress.

Forests under plantations or under legislative protection and natural forests are not included in the model. These lands are termed "inaccessible" by Gouel and Hertel (2006) and equal 820 million ha; approximately half of the total land available for farming (see Table 2). The parameters for land conversion costs (see equation 15) are reported in Table A4. They are assumed to be the same across land qualities but varying by region.

Total supply is the product of land supplied times its yield, as discussed earlier.[65] We need to obtain yield data by land quality for each final demand. Each land quality covers a group of countries and FAOSTAT gives crop yields for each country. Eswaran *et al*. (2003) have data on the volume of land by land quality in each region. We match Eswaran *et al.* (2003) and FAOSTAT data by country to get the yield per unit land in each region and the corresponding volume of land available.

Table A4. Cost Parameters for Land Conversion

	ϕ_{1r}	ϕ_{2r}
USA	234	245
MICs	38	42
LICs	83	126

Source: Gouel and Hertel (2006). *Notes*: For MICs (LICs) we adopt their figures for Latin America (Rest of the World).

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 quality and region. These values are presented in Table A5. 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), for all regions.[66] The

[65] Since our model is coded in time steps of five years and harvests are annual, we multiply annual production by five.
[66] Other models make similar assumptions (e.g., Rosegrant *et al.* 2001).

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.

Table A5. Food Crop Yields by Land Quality and Region

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

Source: Yields per land quality are adapted from FAOSTAT and Eswaran *et al.* (2003); average annual growth rates are adapted from Rosegrant *et al.* (2001).

Production costs of crops are taken from 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. Using equation (16), we can recover the cost parameters by using total production costs and volume. They are reported in Table A6. Production costs are the same for each use j but they differ by region, as shown in the table. The cost of processing food crops into cereals and meat is reported in Table A7.

Table A6. Crop production cost parameters by region

	US	EU	Other HICs	MICs	LICs
η_{1r}	1.15	1.15	1.15	1.35	1.25
η_{2r}	1.50	1.55	1.50	1.75	1.80

Source: GTAP 5 Database.

Table A7. 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.

The parameter π_r is region-specific and calibrated from the relation

$$q_{re} = \pi_r \left[\mu_{rg} q_{rg}^{\frac{\sigma_r - 1}{\sigma_r}} + (1-\mu_{rg}) q_{rb}^{\frac{\sigma_r - 1}{\sigma_r}} \right]^{\frac{\sigma_r}{\sigma_r - 1}}$$

. For each region, we choose the value of σ_r to reproduce the base year production of transport fuel.[67] Table A8 presents the data used for the base year (2007) and the computed values of π_r. In the table, transport fuel use equals the sum of fuel consumption for gasoline and diesel cars.[68] To calculate biofuel consumption, we only consider first-generation biofuels since the actual consumption of second generation biofuels is negligible. Transport fuel is in billion gallons and is converted into MegaJoules (MJ) using the coefficients reported in Table A9 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).[69]

Data on crude oil stocks is taken from the World Energy Council (World Energy Council 2010) and reported in Table A10. Oil is also an input in sectors other than transportation, such as in

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[67] The parameter π_r is calculated to reproduce the base year transport fuel production as

$$\pi_r = \frac{q_{re}}{\left[\mu_{rg} q_{rg}^{\frac{\sigma_r - 1}{\sigma_r}} + (1-\mu_{rg}) q_{rb}^{\frac{\sigma_r - 1}{\sigma_r}} \right]^{\frac{\sigma_r}{\sigma_r - 1}}}$$

. We use the observed base year value for the production of transport fuel (q_{re}), oil consumption (q_{rg}), consumption of first gen biofuel (q_{rb}), the observed share of oil in transport fuel $\left(\mu_{rg} = \frac{q_{rg}}{q_{re}}\right)$ and the elasticity of substitution (σ_r). These values are reported in Table A10.

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

[69] 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.

Table A8. Energy supply parameters by region for base year (2007)

	US	EU	Others HICs	MICs	LICs
Transport fuel use q_{re} (bln gal)	152	80	46	144	7
Gasoline use q_{rg} (bln gal)	134	62	26	130	8
Biofuel use q_{rb} (bln gal)	7	3	2	5	0,5
Share of gasoline in fuel μ_{rg}	0.90	0.96	0.97	0.96	0.98
Elasticity of substitution σ_r	2	1.65	2	1.85	1.85
Constant π_r	1.332	1.388	1.090	1.065	0.774

Notes: gal=gallons, *Sources:* Transport fuel use (World Resources Institute 2010); Biofuel use (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 A9. 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)

chemicals and heating. Studies suggest that around 60% of oil consumption occurs in transportation (IEA 2011). We thus consider 60% of total oil reserves as the initial stock available for transport.[70]

Table A10. 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.[71] One gallon of oil produces 0.47 gallons of gasoline or 0.25 gallons of diesel.[72] We use the term "gasoline" for all petroleum products. The

[70] 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.
[71] For other regions, the representative fuel is gasoline.
[72] Conversion rates between oil and oil products may vary based on crude oil quality and refinery characteristics: we abstract from regional differences in crude oil and product quality.

cost of converting oil into gasoline is the same across different regions and equals $0.46 per gallon (Chakravorty *et al.* 2012). This cost is assumed to decrease annually by 0.5%.

Biofuels are produced from specific crops in each region (see Table 3), e.g., sugar cane in MICs and rapeseed in the EU. For each land quality, 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 by quality is reported in Table A11.

Table A11. Yield and representative crop for first generation biofuels

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

Source: FAO (2008a); 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 lands of different quality. 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 biomass whereas 1,000 gallons per hectare are produced from Biomass-to-liquids (BTL).

Carbon emissions Emissions are measured in tons of CO_2 equivalent units, or CO_2e) released per unit of gasoline consumed. The figures used in the model are shown in Table A12. Let z_r^n be the amount of carbon sequestered per unit of land of quality *n* brought into production in region *r*. Then, aggregate indirect carbon emissions by region are given by $z_r^n l_r^n$ where l_r^n is the acreage of land of quality *n* brought into cultivation. Indirect emissions depend on whether forests or grasslands are converted for farming - one hectare of forest releases 604 tons of CO_2e while grasslands emit 75 tons (Searchinger *et al.* 2008).[73] For each land quality 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 the land of medium quality is under pasture (45% under forest), thus indirect emissions from converting one hectare of medium quality land is 313 (=(0.55)75+0.45(604)) tons of CO_2e per hectare.[74] Land of low quality in MICs consists of 84% forest, so emissions are 519 tons CO_2e/ha. The corresponding figures for LICs are 323 tons (medium quality) and 530 tons (low quality). In the LICs, 47% of medium quality land is under forests and 53% under pasture; and 86% of low quality land is under forest and 14% under pasture. High quality land is already under cultivation so there are no additional emissions from new conversion.

Table A12. 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 sugarcane 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.

[73] 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), see *http://www.sciencemag.org/content/suppl/2008/02/06/1151861.DC1/Searchinger.SOM.pdf.* Other studies such as Tyner *et al*. (2010) also use the same assumptions.

[74] 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.