ELSEVIER

Contents lists available at ScienceDirect

Global Environmental Change

journal homepage: www.elsevier.com/locate/gloenvcha



The impact of biofuel-induced food-price inflation on dietary energy demand and dietary greenhouse gas emissions



Noah Scovronick*, Paul Wilkinson

London School of Hygiene and Tropical Medicine, Department of Social and Environmental Health Research, 15-17 Tavistock Place, London, WC1H 9SH, United Kingdom

ARTICLE INFO

Article history:
Received 18 April 2013
Received in revised form 17 September 2013
Accepted 25 September 2013

Keywords:
Biofuel
Food prices
Greenhouse gases
Nutrition
Climate change
Public health

ABSTRACT

Dramatic increases in liquid biofuel production have led to concerns about associated impacts on food prices, with many modeling studies showing significant biofuel-related price inflation. In turn, by changing patterns of food demand, biofuel production may indirectly influence greenhouse gas emissions. We estimated changes to dietary energy (calorie) demand and greenhouse gas emissions embodied in average diets under different biofuel-related food-price scenarios for Brazil, China and the United States, using food-price projections and food-price elasticities. Average energy demand decreased in all countries, from about 40 kcal per person per day in Brazil under a moderate price inflation scenario – a reduction of 1% relative to the (2009) reference scenario – to nearly 300 per day in the United States with high price inflation – almost 8% of reference levels. However, emissions per calorie increased slightly in all three countries. In terms of total greenhouse gas emissions, the results are suggestive of overall reductions only in the United States, where average reductions ranged from about 40 to 110 kg of carbon dioxide equivalent emissions per person per year. In China, the direction of impact is unclear, but the net change is likely to be small. Brazilian results were sensitive to parameter values and the direction and magnitude of impact is therefore uncertain. Despite the uncertainty, even small changes (positive or negative) in individual dietary emissions can produce large changes at the population level, arguing for the inclusion of the dietary pathway in greenhouse gas accounting of liquid biofuels.

© 2013 Elsevier Ltd. All rights reserved.

1. Introduction

Liquid biofuels – comprised mainly of ethanol and biodiesel – are receiving increasing attention as an alternative to fossil fuels in the transport sector. Support for liquid biofuels stems from their potential to help mitigate climate change, improve energy security, and revitalize agricultural economies. Accordingly, there has been a dramatic increase in biofuel production over the past 5–10 years, and strong growth is expected to continue (Organization for Economic Cooperation and Development, 2012).

The rapid expansion of the biofuel sector has led to concerns about possible unintended consequences that may result from further production. Specifically, research has demonstrated that indirect impacts of biofuel expansion may undermine climate change mitigation objectives. Examples include increased emissions that may result from biofuel-induced land-use change (Fargione et al., 2008; Searchinger et al., 2008), or the potential for

biofuels to lower fossil fuel prices and create a 'rebound effect', whereby consumers negate potential greenhouse gas (GHG) gains by returning to fossil fuels (Khanna and Zilberman, 2012).

Another possible consequence of further biofuel production relates to the relationship of biofuels to food prices. Increased linkages between the agriculture and energy markets have stimulated competition for land, feedstock crops and other agricultural resources, which may drive up food prices (FAO, 2008; Runge and Senauer, 2007). Numerous analyses attributed at least part of the food price spikes of 2007/2008 to liquid biofuels (Naylor et al., 2007; Runge and Senauer, 2007; Timilsina and Shrestha, 2010), while many modeling studies of future prices have found a strong influence of biofuel demand into the future (Fischer et al., 2009; Rosegrant et al., 2008; Timilsina et al., 2010; Zilberman et al., 2013).

The price of food affects what people eat (Epstein et al., 2012; French, 2003). Therefore, biofuel-induced changes to food prices have implications for GHG emissions by altering dietary patterns. This emission pathway has so far been explored mainly with regard to how changing food demand influences land-use. However, the production, distribution and storage of food are also responsible for substantial GHG emissions globally, with

^{*} Corresponding author. Tel.: +44 (0)20 7927 2415; fax: +44 (0)20 7927 2701. E-mail addresses: Noah.Scovronick@lshtm.ac.uk (N. Scovronick), Paul.Wilkinson@lshtm.ac.uk (P. Wilkinson).

different foods exhibiting considerably different levels of embodied emissions (Berners-Lee et al., 2012; Carlsson-Kanyama and Gonzalez, 2009; Wallén et al., 2004).

This study explores how biofuels influence GHG emissions by affecting food prices and associated food demand. Specifically, we estimate the embodied emissions in average diets under different biofuel-related food-price scenarios for three countries: Brazil, China and the United States. These countries were chosen because they are major food consumers, have contrasting average diets, and contribute substantially to global GHG emissions; they are also responsible for $\sim\!\!75\%$ of global biofuel production (US Energy Information Administration, 2011). Land-use change is not considered.

2. Methods

The modeling approach was to compare the emissions in average diets under two future (2020) scenarios of biofuel-induced food-price inflation with a reference scenario reflecting dietary emissions in 2009. To isolate the effect of food prices, all other variables were held constant. Therefore, our study can be described as a 'thought experiment' comparing the current world with two future worlds where everything is the same except for food prices and associated food demand.

The model consisted of three steps. First, projections of biofuel-induced food-price inflation in the year 2020 were applied to food-price elasticities to estimate how diets would change in response.

We used estimates of price inflation reported by Rosegrant et al. (2008), which were derived using the IMPACT partial-equilibrium agriculture and trade model. Their study reports the percent difference in world food prices under two biofuel production scenarios compared with a baseline scenario where biofuel production does not increase after 2010. The first scenario, which we refer to as the 'Moderate (price) Inflation' scenario, was based on actual national biofuel plans for future production. The second, referred to as the 'High Inflation' scenario, was based on a much larger increase in production, with corresponding price inflation. Specifically, in 2020, demand for biofuel feedstock in the Moderate and High Inflation scenarios is 165 and 373 megatons higher than in the baseline scenario, respectively. Table 1 presents the level of price inflation for key food groups in each scenario, while Supplementary Section 1 provides more details of the scenario design outlined by Rosegrant et al. (2008).

Other studies have reported slightly different levels of price inflation for similar scenarios (Fischer et al., 2009). Therefore, we conducted Monte Carlo simulations (100,000 simulations) allowing for parameter uncertainty in the price projections by sampling from a normal distribution around the point estimates using a standard deviation of 30% of those estimates. A standard deviation that is proportional to the central estimate is appropriate because although *absolute* levels of price inflation differ somewhat between

Table 1Price differences in 2020 for select food groups under the two price inflation scenarios compared to a baseline of no growth in biofuels after 2010 (Rosegrant et al., 2008). Estimates for food groups are simple averages of more disaggregated projections.

	Moderate inflation (%)	High inflation (%)
Maize	+26.3	+71.8
Other cereals	+8.6	+21.4
Root crops	+7.7	+18.6
Sugarcane	+11.5	+26.6
Oils	+18.1	+44.4
Fruits/vegetables	+2.8	+6.5
Meat	+1.8	+4.1
Livestock products (milk/eggs)	+1.6	+3.8

studies, there are strong qualitative similarities in terms of the *relative* level of price inflation expected for different food groups: high inflation in coarse grains (including maize), followed by other grains, with more modest increases in fruits/vegetables and meat (Fischer et al., 2009; Rosegrant et al., 2008; Timilsina et al., 2010). The proportional standard deviation maintains these rankings, on average, but allows the magnitude of the price inflation to vary.

The difference in prices between the two inflation scenarios and the baseline was applied to recently published, country-specific food-price elasticities to predict the corresponding changes to food demand in each country (Coelho et al., 2010; Hovhannisyan and Gould, 2011; Okrent and Alston, 2011). Food-price elasticities include own-price and cross-price elasticities. An own-price elasticity estimates the percent change in the quantity demanded of a given food resulting from a 1% change in the price of that same food. For example, an own-price elasticity of pork of -0.5 means that a 1% increase in the price of pork will reduce pork demand by 0.5%.

A cross-price elasticity estimates the percent change in the quantity demanded of a given food in response to a 1% change in price of another food; for example, an increase in the price of wheat may increase the demand for rice through substitution. Therefore, by incorporating both own- and cross-price elasticities, our model estimated the spectrum of dietary changes likely to result from a suite of price changes. Price effects were combined additively.

Elasticity figures for China were only available for urban areas, so we assumed they hold for the entire country (Hovhannisyan and Gould, 2011); those for Brazil and the USA were calculated using nationally representative data (Coelho et al., 2010; Okrent and Alston, 2011). Because elasticity values depend on factors such as the estimation technique and the data set, and because not all elasticity values are statistically robust (particularly for cross-price elasticities), we also allowed for uncertainty in the elasticity estimates during the Monte Carlo simulations, again using a normal distribution with a standard deviation of 30% of the estimates.

The output of this first modeling step was the average percent change in demand of each food type. The second step was to apply these changes to data on average food availability in each country, taken from the Food and Agriculture Organization's Food Balance Sheets for 2009 (FAOStat, 2013). Food Balance Sheets estimate the per capita food availability for nearly 100 foods for almost every country in the world, and is the basis of commonly cited measures of food security. We chose to use Food Balance Sheets instead of household survey data for two reasons. First, the data are available for all three countries and are compiled using the same methods. Second, data from household surveys normally measure only food that is actually consumed or at least bought, but a change in food demand would also influence GHG emissions through changes in the amount of food lost in the supply chain or wasted in the household. Food Balance Sheets reveal some of these losses, and has been used in similar analyses for this reason (Berners-Lee et al.,

And last, published estimates (Berners-Lee et al., 2012; Carlsson-Kanyama and Gonzalez, 2009; Wallén et al., 2004) of embodied GHG emissions of different food types were applied to the average diets under each scenario to calculate the difference in average emissions in each of the three countries. The published estimates are for European countries, which were the only studies identified that presented values for a large number of disaggregated food types quantified using a consistent method. The Monte Carlo simulations incorporated uncertainty in the estimates of embodied emissions by sampling from a log-normal distribution (to prevent negative values) using the (geometric) mean and (geometric) standard deviation of the different estimates. To calculate the GHG intensity of diets in the reference scenario,

Download English Version:

https://daneshyari.com/en/article/10505032

Download Persian Version:

https://daneshyari.com/article/10505032

<u>Daneshyari.com</u>