Does the US Biofuel Mandate Increase Poverty in India?

by

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Abstract

Biofuels have received a lot of attention as a substitute for gasoline in transportation. For instance, more than 10% of US gasoline use now comes from corn ethanol. The US, EU, India and China are major biofuel producers with significant biofuel mandates that require a sharp increase in the portion of transportation fuels that must be produced from land. This policy has been blamed universally for recent increases in food prices. In this paper, we develop a land allocation model to calculate the effect of the US biofuel mandate on the prices of some major food commodities, namely, rice, wheat, sugar and meat and dairy products. Next, using price data and household survey data on food consumption in India, we estimate the own and cross-price elasticities for these commodities. Finally, we compute the first and second order welfare effects of biofuel-induced food prices on households. We show that with perfect pass-through of world prices to the domestic Indian market, the US biofuel mandate alone will lead to about 40 million new poor people in India. With the strong government intervention in the domestic market and imperfect price pass-through, the number goes down to 10 million. The main implication of the paper is that biofuel policies may lead to modest increases in food prices, but may cause a significant increase in poverty in developing countries.

Keywords: Clean Energy, Food Prices, Renewable Fuel Standards, Food Security, Poverty Estimates

JEL Codes: Q24, Q42, O13

This version: November 2011

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1.Introduction

According to a recent issue of The Economist (2010), “by 2050 world grain output will have to rise by half and meat production must double to meet demand. And that cannot easily happen because growth in grain yields is flattening out, and there is little extra farmland….” These problems of yield stagnation and land scarcity are further exacerbated by clean energy policies that promote biofuels such as ethanol from corn and sugarcane. Many countries are actively promoting these renewable fuels to reduce greenhouse gas emissions and as a means of reducing dependence on foreign countries for vital energy supplies. Because of government subsidies, the production of plant-based fuels such as ethanol and biodiesel has grown sharply in recent years.

For instance, about 10% of US gasoline now comes from corn ethanol. It is expected to increase to a nearly 30% share by the year 2022. The US mandate (Energy Independence Security Act, 2007) sets the target for biofuels at 9 billion gallons annually by 2008, increasing to 36 billion gallons by 2022.[2] The bill specifies the use of first and second gen biofuels as shown in Figure 1. The former (corn ethanol) is mandated 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 second gen biofuels from near zero now to 21 billion gallons per year in 2022. In the EU the mandate (European Commission, 2008) requires a minimum share of biofuels of 10% in transportation fuel by 2020. Unlike the US, the EU has no regulation on the use of second gen fuels.

There are several reasons why the use of biofuels has caused concern. First, they use scarce land resources. Growth in biofuel production may well result in a large-scale shift in acreage from food to fuel leading to a reduction in food supplies and increased food prices.[3] In general, most studies predict significant impacts of energy mandates on food prices. For example, Roberts and Schlenker (2010) 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%.[4] Almirall, Aufhammer and Berck (2010) use structural vector auto-regression to examine the

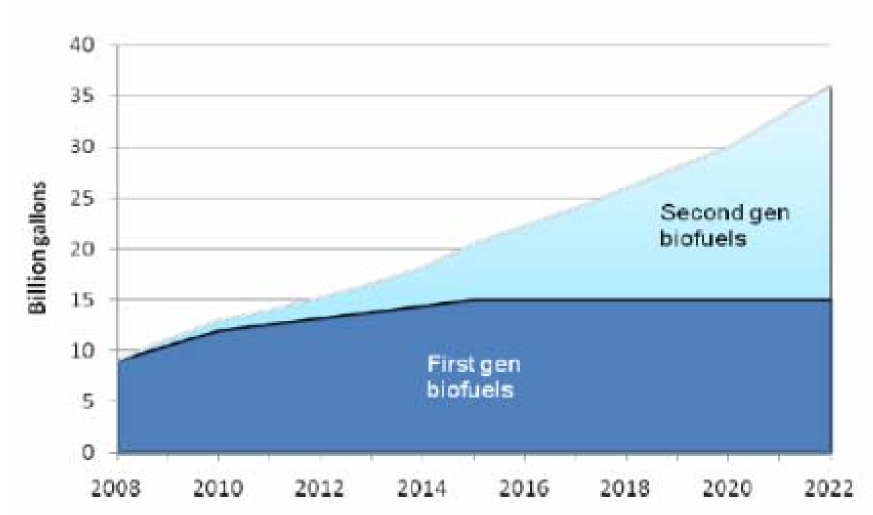
[2] It is not clear whether the mandates will be imposed beyond 2022 but in our model, we assume that they will be extended until 2050. From a political economy point of view, it may be difficult to scale back once biofuels supply 30% or more of transport fuels. In fact ethanol use in the US is close to hitting the 10% “blending wall” imposed by Clean Air regulations which must be relaxed for further increases in biofuel consumption.

[3] A recent study by the International Food Policy Research Institute (Rosegrant *et al.*, 2008) suggests that an aggressive expansion into biofuels will raise the price of certain food commodities by up to 70% by the year 2020.

[4] They acknowledge that “demand growth has accelerated through demand for meat and other animal-based foods, which are highly income elastic.” However, they do not explicitly account for it in their estimation.

impact of biofuel production in the U.S. on corn prices. They conclude that one third of corn price increases from 2006 to 2008 (which rose by 28%) can be attributed to biofuels.[5]

Figure 1. US biofuel mandate



In this paper we do two things. We first estimate a calibrated model of the world energy and food markets where we can impose the biofuel mandates that exist in the US and EU and trace their effects on world biofuel consumption as well as food prices. Second we use the predicted rise in world food prices from this model to estimate distributional impacts on food consumption in Indian households. Our key result is that for certain crops, the price increases from energy mandates may be modest, but their distributional impacts may be regressive with poorer households being impacted the most. Our initial estimates suggest that about 40 million households in India may move from above to below the poverty line. With imperfect price pass-through, which is mostly a result of massive government intervention in food markets in India, the number of the new poor goes down to about 10 million. If other developing countries experience similar effects, the global effect of energy policies may be quite significant and regressive.

[5] Their short-run analysis may well be 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 albeit with a time lag, especially if significant land conversion were to occur.

India is an important country to study because of its high incidence of poverty – about 26% of the people living in rural areas, and 28% in urban areas are below the poverty line.[6] A fifth of the population suffers from malnutrition (FAO 2010). Biofuel production of India has increased from 183 million gallons in 2005 to 285 million gallons in 2009. Approximately 94% of the biofuel produced in India is ethanol (EIA 2011). Blending of biofuels is mandated in 10 states and the current share in transportation is 5% which is expected to rise in the near future.[7] Thus, if developing countries like India and China also impose aggressive domestic biofuel mandates, our estimates suggest that the diversion of arable land from food to energy production (even when new land conversion is accounted for) may cause a significant step back in the fight against poverty (Chen and Ravallion, 2010).

In the rest of the paper, we discuss the global calibration model that estimates the impacts of biofuel mandates in US and EU on food prices in section 2. In section 3, we estimate own and cross-price elasticities for the selected food commodities using household survey data from India and use them to compute changes in welfare among rural and urban households. Section 4 concludes the paper.

2. The calibration model

In our dynamic, partial equilibrium, global economy, three regions (US, India and ROW) consume, supply and trade five food products (rice, wheat, sugar, other crops and meat and dairy).[8] These crops are chosen because they are the most important cereal crops and are most likely to be impacted because of diversion of land to energy production. Other crops include all grains (except rice and wheat), starch crops and oil crops. Meat and dairy products include all meat products and dairy such as milk and butter. These goods compete for land that is already under farming as well as marginal lands, which are currently under grassland or forest cover. Gasoline and biofuels are blended in each region. We thus consider six final consumption goods in the model - namely the five food commodities and energy for transportation.

[6] About 72% of the population lives in rural areas.
[7] Concrete proposals for a biofuel share of 26% of the transport fuel mix exist (Swarup, 2011).
[8] The calibration model described in this section is adapted from Chakravorty et al (2011). They examine the effect of the US and EU biofuel mandates on food prices using an aggregate basket of crops. In order to examine the effect of energy mandates on food crops such as rice and wheat that are important to the Indian diet, we re-calibrate that model for the specific crops described here.

The three crops in our model - rice, wheat and sugar supply 60% of the calories in India (FAOSTAT). It is also important to distinguish crops from meat because the consumption of these two goods is income-sensitive and the latter is more land intensive.[9]

Regional demands (for rice, wheat, sugar, other crops, meat and transportation fuel) are modeled by means of Cobb-Douglas demand functions, which are functions of regional per capita income and population. Thus demand D_l for each final product l takes the form

$$D_l = A_l P_l^{\alpha_l} P_{-l}^{\alpha_{-l}} w^{\beta_l} \ N \tag{1}$$

where P_l is the output price of good l in dollars, P_{-l} is the output price of other goods except good l, α_l is the regional own-price elasticity, α_{-l} is the regional cross-price elasticity, β_l is the income elasticity for good l which changes exogenously with per capita income reflecting changes in food preferences, w is regional per capita income, N is regional population and A_l is the constant demand parameter calibrated from data.[10] As incomes rise, we expect to observe increased per capita consumption of meat products relative to cereals, as noted in numerous studies (e.g., Delgado *et al.* 1998, Keyzer *et al.* 2005). We model this shift towards animal protein by letting income elasticities of food products decline with per capita income (as in Keyzer *et al.* 2005).

Demands are exogenously driven by population and per capita income. Projections of population are taken from United Nations Population Division (UNDP 2010).[11] India's population is expected to increase to around 1.5 billion people in 2025. GDP per capita is non-stationary and is assumed to increase at an exogenous and declining rate. We take US GDP per capita to be increasing at an annual rate of 1.5%, with the rate declining by 0.1% every five years. Indian GDP per capita is assumed to rise annually by 4.5% with a similar rate of decline as in the US.

[9] On average, one hectare of land produces either one ton of meat or three tons of cereals and other crops (Bouwman 1997). There is a large disparity in meat consumption between developed and developing countries, which is expected to narrow over time as incomes converge. Per capita annual consumption of meat in the former is about 300 kg and only 70 kg in the developing world (FAO 2003). This translates to a per capita land requirement for food of 0.353 ha for OECD countries and 0.156 ha for LICs and MICs.

[10] Cross-price elasticities are only defined for food commodities.

[11] The United Nations (UN Population Division, 2010) defines different scenarios for future population projections. We use the medium term scenario.

Total available land area is the sum of current land under agriculture and marginal lands. The initial global endowment of agricultural land is 1.5 billion hectares (FAOSTAT). About 1.6 billion hectares of land are available for conversion to farming (FAO 2008). Since land quality differs across geographical area in both countries, we model this issue explicitly by disaggregating land into three land classes. Each land class (or agro-ecological zones) is based on their climate and soil characteristics. We use the FAO-IIASA database, land class I being the highest land quality (Fischer *et al.* 2002).

Area under crop cultivation can be expanded by converting marginal lands. The initial stock of marginal lands at $t = 0$ is denoted by $L_i^s(0)$. At each period, $l_i^s(t)$ units of marginal land may be brought into cultivation. The corresponding dynamic equation is given by $L_i^S(t) - L_i^S(t-1) = -l_i^S(t)$. The land constraint for each land class at period θ is given by $\sum_j L_i^j(\theta) \le \overline{L} + \sum_{t=0}^{\theta} l_i^s(t)$. In the US, about 170 million hectares (Mha) are under crop cultivation (FAOSTAT). As in Chen et al. (2011), about 10.5 Mha is available for cultivation. In India, 43% of land is under crops (140 Mha), followed by area under forests (67 Mha) and wastelands (72 Mha). The area under food production in India seems to have stabilized over the last decades. This is mainly because conversion of forest land for crop production and other commercial uses is regulated under the Forest Conservation Act of 1980. The country has also implemented a large reforestation program at a rate of 1.32 Mha per year during the period 1980-2005 (Ravindranath *et al.* 2011). In addition, the high population density of nearly 350 persons per sq. km reduces the potential for further expansion of cropland and increased food and fuel production. As a result, we assume that the area under cultivation in India is constant. Most of the 1.6 Mha of marginal lands available in the rest of the world are located in Africa and Latin America (FAO 2008). Forests under plantation or under legislative protection are not included in the model.

The cost of converting marginal lands is assumed to be increasing and convex with respect to the acreage converted. Land is brought into cultivation in the model when the land rent is higher than the cost of conversion. We adopt the same functional form as in Golub *et al.* (2008) given by $C_s = -\psi_1 \ln\left(\frac{L_i^s - l_i^s}{L_i^s}\right) + \psi_2 + \psi_3\left(\frac{l_i^s}{L_i^s}\right)^2$. The parameters are region specific but are not dependent on land class. We assume that once marginal lands are converted, their productivity is the same as from cultivated lands.

Food production is assumed to exhibit constant returns to scale for each land class in the model. Hence, regional food supply is just yield times the land area. Define yield of crop *j* on land class *i* as k_i^j. Then, total production of crop *j* from class *i* is $k_i^j L_i^j$. Improvements in agricultural productivity are allowed to vary by region and land category. All regions exhibit increasing productivity over time, mainly because of the adoption of biotechnology (e.g., high-yielding crop varieties), irrigation and pest management. *Ceteris paribus*, the rate of technical progress is 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 (Fischer *et al*. 2002).

The total cost of food or biofuel production in each region is assumed to be increasing and convex. The higher the production of food and biofuels, the more likely that cultivation moves into lower quality lands (van Kooten and Folmer 2004). Total production cost for product *j* in a given region is defined by

$$C_j\left(\sum_i k_i^j L_i^j\right) = \eta_1\left[\sum_i k_i^j L_i^j\right]^{\eta_2} \tag{3}$$

where $\sum_i k_i^j L_i^j$ is the aggregate output of product *j*, and η_1 and η_2 are regional cost parameters.

Energy in the model is provided by oil as well as biofuels that are land using (often called First Generation biofuels) and newer technologies that are less land-using (Second Generation).[12] The

[12] We transform crude oil into gasoline using a coefficient of transformation equal to 0.48, taken from Chakravorty *et al.* (2010). Thus gasoline is a fixed share of oil. Since other uses of oil are not explicitly considered, the terms "oil" and "gasoline" are often used interchangeably in the paper where convenient.

latter converts parts of the plant other than the fruit or grain into fuels.[13] They currently cost an order of magnitude more than first gen biofuels.

Since 95% of global transportation fuel is provided by crude oil which is a nonrenewable resource, it is reasonable to use a Hotelling framework to model energy supply. Transportation energy q_e is produced from gasoline and biofuels in a convex linear combination using a CES specification, as in Ando *et al.* (2010) given by

$$q_e = \lambda \left[\mu_g q_g^{\frac{\rho-1}{\rho}} + (1-\mu_g)(q_{bf} + q_{bs})^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}} \tag{4}$$

where λ is a constant, μ_g the share of gasoline in transportation energy, ρ the elasticity of substitution, and q_g, q_{bf} and q_{bs} are the respective input demands for gasoline, first gen (generation) and second gen biofuels. The parameters λ and μ_g are calibrated from observed data. As the relative price of gasoline increases, the fuel composition switches towards using less of it.[14] The elasticity of substitution is region-specific and depends upon the technological barriers for displacing gasoline by first gen fuels in each region. We use estimates made by Hertel et al. (2008). As in many other studies, first and second gen biofuels are treated as perfect substitutes.

We define an exogenous world stock of oil and a single integrated “bathtub” world oil market as in Nordhaus (2009). At higher oil prices, new sources such as shale oil reserves become competitive. The stock of oil includes both crude and shale oil stocks. Estimated oil reserves in 2010 serve as the initial stock of oil, which amounts to 179 trillion gallons or 4.26 trillion barrels (WEC 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:

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[13] Examples include cellulosic material and crop residues.

[14] This specification captures the fact that there is still a large technological potential for displacing fossil fuels in passenger transport through blended gasolines such as E85 (85:15 biofuel:gasoline ratio), according to the OECD (2008).

$$C_{oil}(x(\theta)) = \varphi_1 + \varphi_2 \left(\frac{\sum_{t=0}^{\theta} x(t)}{\bar{X}} \right)^{\varphi_3} \tag{5}$$

where $x(\theta)$ is oil used in period θ, $\sum_{t=0}^{\theta} x(t)$ is cumulative oil extracted and $\bar{X}$ is the initial stock of crude oil.

Instead of allowing for the production of different types of first gen fuels in each region, we simplify by considering a representative biofuel for each region. This assumption is reasonable because there is only one type of biofuel that dominates in each region. 94% of production in the US is ethanol from corn (EIA 2011). In India, ethanol is the main biofuel produced and the production of biodiesel remains negligible. The main producer in the ROW region is Brazil where biofuel is produced from sugar cane. Table 1 shows the representative crop for each region and its production cost.[15]

Table 1. Unit cost of first generation biofuels

	US	**India**	**ROW**
Representative crop	Corn	Molasses	Sugar
	(94%)	(76%)	(80%)
Unit cost of production ($/gallon)	1.01	0.55	0.54

Source: Production costs (FAO 2008; Ravindranath *et al.* 2011); *Note*: The numbers in parentheses represent the percentage of first-generation biofuels produced from the representative crop (e.g., corn).

There are many second generation biofuels. We only consider cellulosic ethanol since it has been identified as the most promising second generation biofuel in the US (IEA 2009A). It is produced from miscanthus and switchgrass. Unlike for first gen fuels, we assume that yields are uniform across different land classes since these crops are less demanding in terms of land

[15] By regulation, ethanol cannot be produced from sugarcane in India (Kojima *et al.* 2007). Sugar must be converted to molasses then to ethanol (Ravindranath *et al.* 2011). Molasses are produced from sugarcane juice. One ton of sugar produces 40 kg of molasses which yields 2.5 gallons of ethanol.

quality.[16] Around 2,000 gallons of ethanol per hectare are produced from cellulosic ethanol (IEA 2009). The unit production cost of second generation biofuels is \$3.5 per gallon.[17] In this study, we assume that in India, the production of second generation fuels is zero.

Goods are treated as perfectly homogenous. 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 introduce trade tariffs, which are mostly commodity-specific (sugar, wheat, etc.). However, we do model ethanol tariffs. 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 US mandate (Energy Independence Security Act, 2007) sets the US target for biofuels at 9 billion gallons annually by 2008, increasing to 36 billion gallons by 2022.[18] The bill specifies the use of first and second gen biofuels as shown in Figure 1. The former (corn ethanol) is mandated 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 second gen biofuels from near zero currently to 21 billion gallons per year in 2022.

The government of India has been pursuing biofuel programs for some time in an effort to reduce its dependence on imported oil, which supplies two-thirds of consumption. The share of biofuels is expected to grow from the current share of 5% to 10% and 20% respectively by 2011/2012 (Eisentraut 2010). This goal is clearly out of reach. The target 20% is expected to be met only in 2020.[19]

Two scenarios are defined. In the first one (benchmark scenario), no biofuel policy is implemented. In the second, US and Indian biofuel mandates are introduced in the model. For each scenario, we calculate the food price increase for the different food crops described earlier.

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[16] Some studies show that their yields may differ a bit by location (between the Atlantic region and the southern US, for example).
[17] IEA (2010) defines a range for production costs for cellulosic ethanol between three to five dollars per gallon.
[18] 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 is close to hitting the 10% “blending wall” imposed by Clean Air regulations which must be relaxed for further increases in biofuel consumption.
[19] India is currently the fourth largest producer of ethanol after the US, Brazil and China. Biofuel production will increase significantly because of the projected exponential growth in the number of vehicles from 15 to 125 million (Eisenstraut, 2010).

We maximize the consumer plus producer surplus given regional demand functions for food and energy (denoted by subscript l) where energy may be supplied by gasoline, and first and second generation biofuels. We include the cost of production of food and energy from land (given by C_j), the cost of land conversion (C_s) and the cost of supplying oil (C_{oil}). The choice variables are the consumption of crude oil (x), land of quality i allocated to each use j (L_i^j) and marginal lands brought under cultivation (l_i^s). Endowments include the initial stock of crude oil and land of quality i. The maximization problem where we hide the time and region subscripts (respectively, t and n) can be written as[20]

$$\underset{x, L_i^j, l_i^s}{Max} \sum_{t=0}^{\infty} \left\{ \frac{1}{(1+r)^t} \left[\sum_n \left[\sum_l \int_0^q D_l^{-1} d\theta - \sum_j C_j \left(\sum_i k_i^j L_i^j \right) - C_s \left(\sum_i l_i^s \right) \right] - C_{oil}(x)x \right] \right\} \tag{6}$$

The relative prices of biofuels and gasoline determine their share in the total energy mix. Without the mandates, as energy demand increases over time and oil stocks deplete, the price of gasoline increases (at least over an initial time period) inducing substitution into biofuels. The energy mandates accelerate this substitution process. However, the demand for food also goes up because of population growth and changes in dietary preferences, and this limits the conversion of high quality land from food to energy production. The discount rate is assumed to be 2% as is standard in such analyses (Nordhaus and Boyer 2000). The model is simulated over 200 years (2010-2210) in steps of five, to keep the runs tractable. Year 2010 is the reference year for calibration.

Table 2 reports the rise in food commodity prices in the regulated scenario compared to the benchmark case. Table 3 reports biofuel use and food production in India and in the US under both scenarios in 2015 and 2025. In the absence of any regulation, biofuel use is almost constant in both countries. Due to the mandate, the decrease in food production in India is quite low since ethanol is produced from molasses (a by-product of sugar), not directly from corn.

[20] The complete set of model equations is available from the authors.

Table 2: Increases in Commodity Prices due to Biofuel Mandates (years 2015 and 2025)

	2015 (%)	2025 (%)
Rice	18.5	17.6
Wheat	5.2	6.4
Sugar	2.2	2.1
Meat and Dairy	2.2	4.4
Other Crops	5.4	6.4

Table 3: Biofuel use and food production in India and US (2015 and 2025).

		Biofuel use (million gallons)		**Food production (million tons)**	
	Scenarios	**2015**	**2025**	**2015**	**2025**
India	Benchmark	1,000	1,200	300	500
	Regulation	3,500	6,000	282	480
US	Benchmark	7,800	7,900	535	545
	Regulation	15,000	15,000	514	511

Note: Under the benchmark scenario, there is no biofuel policy. In the regulated case, Indian and US mandates are implemented.

3. Distribution Impacts of Energy Policy: Description of the Data Used

The distributional effects of the above price increases from biofuel mandates are analyzed using the 61st round of the Indian NSS Consumer Expenditure Survey conducted between April 2004 and April 2005. The NSS survey provides detailed information on the quantity and value of goods consumed by each household, and makes a distinction between the amount purchased from the market and that produced in the household farm. There are approximately 500 commodities covered in the survey, ranging from detailed food items to various services. This is one of the most comprehensive and consistent expenditure surveys available for a developing country.

The sample design of the NSS survey is a complex design characterized as two-stage stratified sampling. First, random samples of first stage sampling units (FSU) are selected in each district of a state, where FSUs are defined as *villages* in rural areas and *urban blocks* in urban areas. In the second stage, random samples of households are selected in each FSU according to a number of variables such as region, sub-region and FSU size. The final sample includes 79,298 households in rural areas and

43,346 households in urban areas. Because the survey design is such that every household does not have the same probability of being selected (i.e., simple random sampling), we use the NSS multipliers to recover the population estimates, which are the number of households in the population represented by that household. We also weight the estimates by the household size in order to keep the focus on the individual, rather than on the household.[21]

NSS data records the market activities of each household member, and also the industry and weekly wage income from that activity. Up to five activities are recorded for each person. The household wage income is then the sum of wages from each activity and person. We match these activity-level industry codes to the products that are going to be affected by the biofuel policy according to the calibration model described in the previous section. Wages associated with the growing of rice, wheat, sugarcane, animal farming, as well as 'other food' that includes vegetables and other crops, increase with the change in price. In addition, we allow the wages from services associated with these activities, e.g., harvesting and milling of rice and wheat, to be directly affected by price changes. The industries are chosen to arrive at a welfare estimate that is as conservative as possible. The concordance between commodities and industries is given in the Appendix.

We use monthly time series of food prices in order to analyze the price dynamics of each crop individually. The domestic and world prices are compiled using data from various sources. Domestic prices for rice, wheat, and sugar are obtained from the Indian Ministry of Public Affairs. They reflect average, end-of-month prices across different zones of India.[22] Meat prices are obtained from the Indian Ministry of Agriculture.[23] Exchange rates are taken from the Federal Reserve Bank of India. All world prices are obtained from the World Bank Commodity Price database.[24]

[21] This is common practice in welfare analysis, e.g., see Deaton (2000).
[22] The Ministry of Public Affairs collects information from Northern, Western, Eastern, Northeastern and Southern zones of India. The prices are then averaged to obtain a nationwide price level for each product.
[23] The average meat (mutton) prices are from Hyderabad, Gujarat, Karnataka, Orissa, Maharashtra, Delhi, Tamil Nadu, Uttar Pradesh and West Bengal. The 2010 and 2011 prices are extrapolated using the wholesale price index for meat.
[24] We use Thai 5 percent for rice and US Hard Red Winter (HRW) for wheat, as they provide the longest series.

3. The Effect of Energy Mandates on Households

The biofuel mandates increase the prices of products that are essential to Indian households. Rice, wheat, sugar, meat and dairy constitute about 53 percent of food expenditure in rural India and 49 percent for urban India. Rice is an especially important product with 21 percent and 14 percent of food expenditure in rural and urban areas, respectively.[25] This ratio is negatively associated with overall per capita expenditure of the household, implying that biofuel mandates increase prices of the products that are relatively more important for poorer households.

The food expenditure items are classified as in the previous section: rice, wheat, sugar and meat and dairy.[26] The *other food* category covers items such as fruits and vegetables, and oils and pulses. Tobacco and alcohol are not included in order to maintain consistency with the calibration model. We assume that the own-produced amount is unaffected by the price changes, and we focus mainly on the amount that was purchased from the market. This is plausible because own-produced shares are quite small as seen from the expenditure shares of the purchased and produced amounts for each commodity presented in Table 4. It is clear from the table that the prices of these commodities have increased significantly both in the world market and to a lesser extent, in the domestic market in recent years.

Transmission of World Prices

Before moving to the distributional effects of these price changes, we first analyze the extent to which world prices are transmitted to domestic prices. Domestic policies and trade costs, such as trade barriers and transportation costs, can reduce the transmission of world prices and keep households isolated from increases in world prices. World and domestic prices for rice, wheat, sugar, and meat between January 2005 and May 2011 are presented in Figure 1. The pass-through elasticities are estimated in a single equation framework, similar to the approach used by Campa and Goldberg (2005) and Campa and Minguez (2006). We use the following equation

$$\Delta \ln p_t^d = \sum_k \beta_k \Delta ln p_{t-k}^w + \gamma \Delta \ln(1+\tau_t) + \delta \Delta ln e_t + \varepsilon_t \quad (7)$$

[25] These percentages are estimated using the 61st round of the NSS Consumer Expenditure Survey done in 2004.

[26] The consumption items have the following codes: rice (101-106), wheat (107-114), sugar (269), and meat and dairy (169 and 189).

Table 4: Summary Statistics

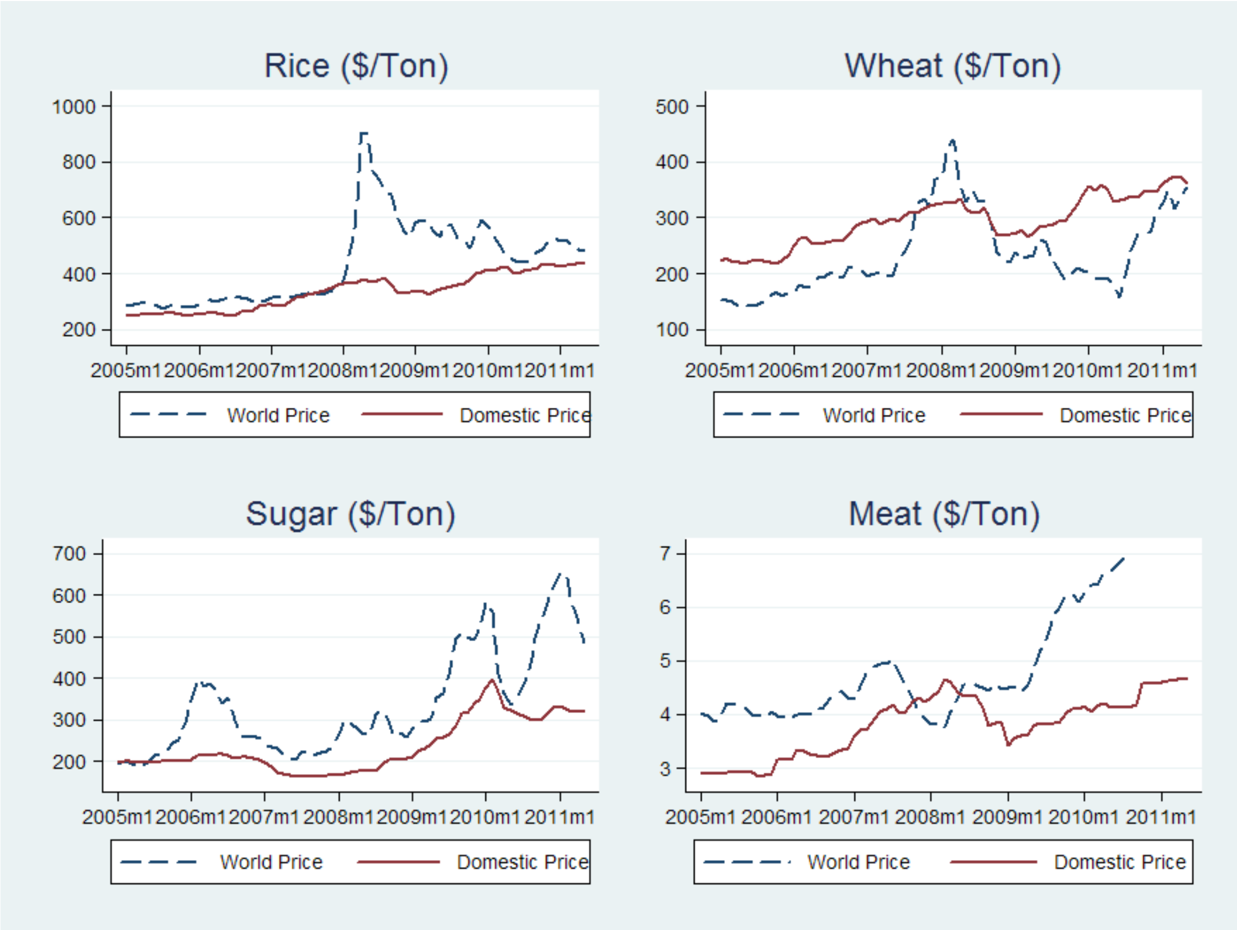
	Rice	Wheat	Sugar	Meat	Other Food
Expenditure Shares (purchased)					
Rural	0.172	0.079	0.058	0.134	0.557
Urban	0.136	0.097	0.037	0.216	0.513
Expenditure Shares (home-produced)					
Rural	0.034	0.018	0.000	0.040	0.019
Urban	0.002	0.002	0.000	0.004	0.002
Price Increase between January 2005- May 2011 (USD,%)					
World	67.74	131.31	151.72	74.33	NA
Domestic	61.86	61.16	64.11	59.16	NA

Notes: Average monthly expenditure shares as a fraction of total expenditures (including non-food) are obtained from the 61st round of NSS Expenditure Survey. Sampling weights are used in estimations. Domestic prices for rice, wheat, and sugar are obtained from the Indian Ministry of Public Affairs. They reflect average end-of-month prices across different zones of India. Meat prices are obtained from the Indian Ministry of Agriculture. Exchange rates are from the Federal Reserve Bank of India. All world prices are obtained from the World Bank Commodity Price database.

where p_t^d represents the domestic price vector expressed in domestic currency for month t; k denotes the set of lags where $k = 0,3,6,9,$ and 12; p_t^w represents the world price, τ_t is the tariff rate of the commodity, e_t is exchange rate, and ε_t is an *i.i.d.* error term at time t. Because it is important to distinguish the long term elasticity from the short-term elasticity, we include the contemporaneous change in world prices, Δlnp_t^w as well as the quarterly lags in the model, Δlnp_{t-k}^w where k denotes the lag for each quarter. The reason for choosing the quarterly lags is the dimensionality problem: it is not possible to estimate a meaningful model with all 12 lags given the length of our series. The short term elasticity for the product is thus given by the coefficient on the contemporaneous price level, β_0. The long-term elasticity captures the effect within one year and is defined as the sum of the coefficients, $\sum_{i=0}^{12} \beta_i$. The results are presented in Table 5.[27]

[27] In the literature, there are various techniques to estimate the transmission elasticity. De Janvry (2010) interprets the ratio of growth rates in domestic and world prices as transmission elasticity. If we follow this approach, we find

Figure 1: Domestic and World Prices for Major Crops in current US Dollars



The estimates suggest that during 2005-2011, changes in sugar and rice prices were significantly transmitted to domestic prices, although the magnitude of the transmission elasticity was small. A one percent increase in the world price of sugar increased domestic prices by 0.219 percent in the short run and 0.383 percent in the long run. The magnitude of the rice transmission elasticity was significant, but smaller in magnitude. The transmission elasticities of meat and wheat were statistically insignificant.

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a 91.3 percent pass-through elasticity for rice. However, this approach does not control for other factors such as exchange rates and trade policy. Another method is to estimate equation (7) in levels instead of differences (e.g. Mundlak 1993; Nicita 2009). We find higher and significant elasticities for all goods using this approach. Augmented Dickey-Fuller tests suggests that the price series are integrated of degree one, and the pass-through coefficients may reflect arbitrary correlation between variables. We thus follow the approach that was used in the exchange rate pass-through literature by Campa and Goldberg (2005) and Campa and Minguez (2006). Further, the Johansen test suggests that we cannot reject the null hypothesis of no cointegration for most of our series. The single equation framework used in these papers is thus suitable for our analysis.

Table 5: Price Transmission Elasticities of World Prices into Domestic Prices

	Short Run	Long Run
Sugar	0.219***^	0.383***^
	(0.043)	[16.40]
Rice	0.057***^	0.181***^
	(0.021)	[7.97]
Wheat	0.008^	0.006^
	(0.035)	[0.01]
Meat	-0.023^	0.056^
	(0.068)	[0.06]

Notes: Elasticity estimates are based on monthly price data between January 2005 and May 2011 and regression of equation (7). Long term elasticities represent price transmission within one year. Standard errors for short run elasticities are reported in parenthesis and F-statistics for long run elastities are reported in brackets. *** denotes p<0.01, **p<0.05 and *p<0.1. ^ indicates that the elasticity is statistically different than 1 at the 1 % level.

Impact on Household Welfare

In order to assess the distributional effects of prices changes, we estimate the effect of the changes in household welfare at different levels of per capita expenditure distribution. The theoretical model used in this paper is based on Deaton (1989), but allowing for modeling household-level responses to price changes based on quadratic Engel curves. Consider the following net expenditure function:

$$B(p,u) = E(p,u) - w(p) \tag{8}$$

where $e(p,u)$ is the expenditure that is required to reach the utility level u and $w(p)$ denotes the wage income of the household. In order to capture the second order consumption effects due to substitution between different goods, we can use a second order Taylor series expansion of $B(p,u)$ around an initial price level p^0 and u^0 written as follows:

$$B(p,u) = B(p^0,u^0) + \sum_i \left(\frac{\partial e}{\partial p_i} - \frac{\partial w_i}{\partial p_i}\right) dp_i + \frac{1}{2}\sum_i \sum_j \left(\frac{\partial^2 e}{\partial p_i \partial p_j}\right) dp_i dp_j \quad (9)$$

Using the envelope theorem, $\partial e/\partial p_i$ is equivalent to the Hicksian demand at the initial price level $h_i(p_i,u) = x_i$. The compensated price elasticity of good i with respect to good j is then $\varepsilon_{ij} = \frac{\partial x_i}{\partial p_j}\frac{p_j}{x_i} = \frac{\partial^2 e}{\partial p_i \partial p_j}\frac{p_j}{x_i}$.The compensating variation, $dB(p,u) = B(p,u) - B(p^0,u^0)$, expresses how much the household needs to be compensated in order to achieve the initial utility level u^0. The negative of this amount is considered a net transfer to the household hence a welfare loss, whereas a positive number indicates that the household is better off, thus experiencing a welfare gain. We can define the compensating variation as a fraction of initial expenditure. Multiplying the right hand side by p_i/p_i , we obtain an expression in terms of elasticities:

$$dlnW = -\frac{dB(p,u)}{e} = -\frac{1}{e}\sum_i \left(x_i p_i - \varepsilon_{w_i} w_i\right)\frac{dp_i}{p_i} - \frac{1}{2e}\sum_i \sum_j \varepsilon_{ij} x_i p_i \frac{dp_i}{p_i}\frac{dp_j}{p_j} \quad (10)$$

where $\varepsilon_{w_i} = \frac{\partial w_i}{\partial p_i}\frac{p_i}{w_i}$ is the elasticity of wage income with respect to the price of good i. Each member of the household contributes to wage income, and each member may be affected by the price change in each good. Therefore, we can express wage incomes as $w = \sum_h w^h$ where $h = 1, \dots, H$ indexes the members of the household. The above equation can be then simplified as:

$$dlnW = -\sum_i \theta_i dlnp_i - \frac{1}{2}\sum_i \sum_j \theta_i \varepsilon_{ij} dlnp_i dlnp_j + \sum_h \sum_i \theta_{w_i}^h \varepsilon_{w_i} dlnp_i \quad (11)$$

where $\theta_i = x_i p_i/e$ is the expenditure share of good i, and $\theta_{w_i}^h = w_h/e$ is the share of wage income in household expenditure contributed by member h. The first term gives the first-order consumption effect by allowing the price increase to reduce household welfare proportional to its budget share. The second term represents the second order consumption effects by incorporating substitutions between consumption items that are induced by price changes. Most components of (11) are data, while the elasticities ε_{ij} have to be estimated using a demand system. The third term represents the changes in wage incomes due to an increase in the price level of good i, multiplied by the wage-price elasticity, ε_w, and the share of wage income in household expenditure, θ_w. Household welfare, in this context, is the sum of the components shown in (11).

Other sources of income, such as remittances, rents and transfers are not likely to be affected by price changes in agricultural products and are thus not incorporated in equation (11). Another potentially important channel, agricultural income is incorporated to the extent that the data allows for it. This is explained in more detail later in the paper.

Equation (11) is a money-metric welfare effect of the price changes that is separately estimated for each household as in Porto (2006), Nicita (2009), Ravallion (1990) and Ural Marchand (2011). The distributional impact of biofuel policy, both through the cost of consumption and income, are then analyzed using a series of nonparametric regressions across the per capita expenditure spectrum.

Consumption Responses

Households are affected by price changes proportional to the expenditure share of the good. The products that are studied in this paper, especially rice, constitute an important part of the budget for a typical Indian household. The expenditure share decreases significantly as we move from poorer to relatively better off households because the budget share of other non-food items, or more expensive calories increases.

The above describes the first-order, short-run impacts of biofuel policy. In the medium to long run, there will be adjustments in the structure of expenditures at the household level. Households will substitute away from crops that are relatively more expensive and move towards cheaper substitutes, thus mitigating the short run adverse effects. Recent literature that analyzes the effect of price changes on household welfare uses first order approximations, not incorporating household responses to price changes (Porto, 2006; Nicita, 2009; Ural Marchand, 2011). However, this would be a significant restriction for the purposes of this paper, as our crops are highly substitutable and the substitution rates are expected to be different in rural and urban areas. More importantly, the global calibration model described earlier in the paper focuses on medium-run adjustments, so we must allow adjustments at the household level in order to maintain temporal consistency.

For these reasons, we estimate a demand system with six goods to obtain the own-price and cross-price elasticities. The six goods are rice, wheat, sugar, meat, other food and non-food. A quadratic demand system is adopted in this paper due to the nonlinear relationship between the expenditure shares of these goods and real expenditure of the household. In particular, we use the QUAIDS model that was developed by Banks et al. (1997). Consider the following equation for the expenditure shares:

$$w_{ih} = \alpha_i + \sum_j \gamma_{ij} lnp_j + \beta_j ln\left(\frac{x_h}{q}\right) + \lambda_i \frac{1}{Q} ln\left(\frac{x_h}{q}\right)^2 + \delta_k X_h + \varepsilon_{ih} \qquad (12)$$

where w_{ih} is the expenditure share of good i for household h, p_j is the price of good j and q is a price matrix that satisfies $lnq = \sum_i \alpha_i lnp_i + \frac{1}{2}\sum_i \sum_j \gamma_{ij}(lnp_i)(lnp_j)$, x_h is the total household expenditure and Q is the Cobb-Douglas price aggregator defined as $Q = \prod_i {p_i}^{\beta_i}$. The budget share w_{ih} is thus defined as a function of prices and real expenditure of the household, x_h/q. As opposed to the AIDS model proposed by Deaton (1980, 1987 and 1990), the QUAIDS specification allows the w_{ih} to be a quadratic function of the real expenditure and estimates quadratic Engel curves. This fits the expenditure structure in the NSS data very well as the coefficients λ_i on the quadratic term turn out highly significant in both rural and urban areas for all goods, with the exception of the demand for sugar in rural areas.

In addition, we extend the method by Banks et al. (1997) by incorporating additional controls, X_h, in the demand system with respective coefficients δ_k for each additional variable k. We control for the household size in order to take into account economies of scale within households, and the percentage share of adults in the households to account for different dietary needs. The NSS data does not ask the household whether or not they are vegetarian, but we include an indicator for the Hindu households in the model which controls the different dietary practices among people with different religious affiliations. Given that the survey is conducted over a one-year period, seasonal differences may be important because of the availability of certain food categories. For this reason, we include an indicator variable that takes the value of one if the household is surveyed in winter months, namely between October and March.[28]

[28] Because this model is estimated as a system of equations, we cannot add a large number of controls without losing consistency and precision. For this reason, we limit the number of controls. Data on the seasonal control is obtained

The NSS Survey asks individuals to report the quantity and the value of consumption for each item. This allows for estimation of unit values of the products for each household. We then average these unit values within each cluster using the sampling weights. The cluster is defined as the first-stage sampling unit (FSU), which is a village in rural areas and an urban block in urban areas. By survey design, households within each FSU are selected randomly, and on average approximately ten households are surveyed within each FSU. In order to obtain unbiased estimates for the demand system, households within each cluster must be subject to the same price level. FSU is the appropriate level of cluster in this case. The one-step larger cluster in which households are randomized is a district in rural areas and a region in urban areas, which may be too large for the same-price assumption to hold.

We need to keep in mind that unit values reflect the quality choice as well as the quantity choice, and thus are imperfect measures of prices. However, we do not observe price levels at the village level, hence we use unit values as a second-best measure. The additional controls for size, the share of adults and religion of the households would partially account for the within-cluster differences across households. However, these controls do not affect the magnitude of the estimates to any significant degree, indicating that households are somewhat homogenous within clusters in terms of their unit values.

The demand system is estimated for urban and rural areas separately using a nonlinear seemingly unrelated regression model. This yields estimates of the coefficients of the demand system, α_i, γ_{ij}, β_j, λ_i and δ_k. In the results that are not reported, δ_k have the expected signs. Hindu households consume significantly more rice and consume less wheat and meat, while their sugar consumption is not statistically different than the rest of the population. Expenditure shares are slightly lower for rice and slightly higher for sugar if the household is surveyed during the winter. Larger households have higher expenditure shares of rice, wheat and sugar, and they have lower expenditure shares of meat. Using the estimated coefficients of α_i, γ_{ij}, β_j and λ_i, the

from the sub-round information. The NSS survey is divided into four sub-rounds each of three months duration (July-September, October-December, January-March and April-June). In each sub-round an equal number of sampling units are surveyed. We control for the winter months by generating an indicator for sub-rounds 2 and 3 in order to account for seasonal variations in the price and availability of different food items. The religion control would take into account different diets to a certain extent. In general, about a third of Indians are vegetarians, while most Muslims, who comprise about 13% of the population, consume mutton as well as poultry and beef.

price elasticities ε_{ij} are computed as defined in Banks et al. (1997). The results are presented in Table 6.

Table 6: QUAIDS Price Elasticities

Rural Areas						
	Rice	Wheat	Sugar	Meat & Dairy	Other Food	Non-Food
Rice	-1.689**	0.281**	0.001***	0.136**	-0.565*	-1.391*
Wheat	0.852**	-1.441***	-0.170***	-0.142**	-0.267*	-0.593*
Sugar	0.318**	-0.212**	-0.618***	-0.107**	0.282*	0.381*
Meat	0.051**	-0.107***	-0.034***	-0.959**	-0.099**	-0.348**
Other Food	0.067**	0.088**	0.051***	-0.034**	-0.578**	0.999*
Non-Food	0.007***	-0.005***	-0.009***	-0.004***	-0.009***	-1.020***
Urban Areas						
	Rice	Wheat	Sugar	Meat & Dairy	Other Food	Non-Food
Rice	-1.865**	0.366**	-0.025***	0.203**	-0.548**	-1.253**
Wheat	0.852**	-1.656***	-0.140***	-0.075**	-0.153**	-0.483**
Sugar	0.164**	-0.302**	-0.510***	-0.093**	0.042**	-0.145**
Meat	0.075***	-0.071***	-0.024***	-1.002***	-0.077**	-0.232**
Other Food	0.050**	0.127***	0.040***	-0.040**	-0.662**	0.828**
Non-Food	0.009***	-0.004***	-0.006***	-0.004***	-0.005***	-0.997***

Notes: Compensated price elasticities are reported. Price of each good is computed from quantity and value of consumption reported by each household. Consumption from own-production is not included. Other food category includes fruits, vegetables, pulses, other cereal, edible oil, spices and beverages. Non-food category includes services, durables and miscellaneous manufacturing products. The six groups together represent the entire household expenditure. *** $p<0.01$, ** $p<0.05$ and * $p<0.1$. The first row represents the quantity effects of an increase in the price of rice.

As expected, own-price elasticities are all negative. These can be seen in the diagonal elements in Table 6 for both rural and urban areas. Cross-price elasticities are positive if the product is a substitute and negative if it is a complement. For each elasticity ε_{ij}, the good i is reported in rows and good j in columns. An effect of a price shock to good *i* can be read row-wise. For example, the first row in rural areas suggests that a 1 percent increase in the price of rice decreases the demand for rice by 1.69 percent and increases the demand for wheat by 0.28 percent, indicating that wheat is a substitute for rice. The second row suggests that an increase in wheat prices leads to a large shift towards rice consumption. A one percent increase in the price of wheat increases the demand for rice by 0.85 percent in both rural and urban areas.

These matrices of compensated price elasticities are then substituted for ε_{ij} into equation (11) to obtain a welfare impact for each household. Therefore, each household is affected by a price change in good i proportional to the budget share of good i, as well as a price change for good j to the extent of substitution between goods i and j. For each household, these effects are aggregated for every combination of goods i and j to arrive at the final estimate of the welfare effect.

In order to analyze the distribution of welfare effects across households with different incomes, we estimate a nonparametric local linear regression. At each point in the expenditure distribution, the following expression is minimized for parameters a and b:

$$\sum_{k}(dlnW_k - a - bx_k)^2 K\left(\frac{x_k - x}{h}\right) \qquad (11)$$

where x_k is the log of per capita expenditure for household k, $K(.)$ is the Epanechnikov kernel function, and h is the bandwidth. For each point in the log per capita expenditure spectrum, this procedure chooses a neighborhood around that point and uses the observations within the neighborhood to obtain a consistent estimate of the average welfare effect for that point. The width of this neighborhood is defined by the bandwidth. As the bandwidth increases, the neighborhood contains a wider segment of the expenditure scale and the estimated line becomes smoother, which is why it is also known as the smoothing parameter.

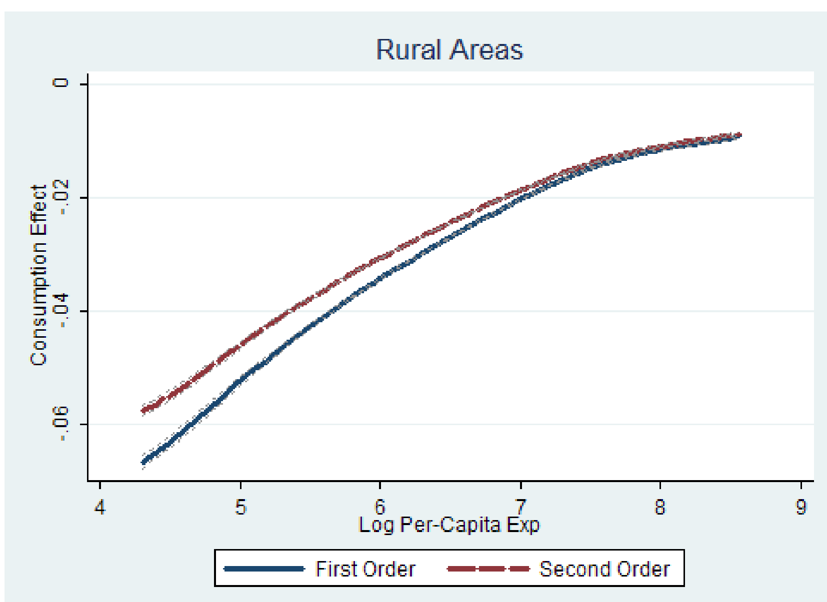
The procedure uses the kernel function to determine the weights while estimating the average welfare effect at each evaluation point. The Epanechnikov kernel function is chosen as it provides the most consistent estimates (Lee and Racine, 2007). This method is used for distributional analysis because it does not require an assumption about the functional form. The shape of the consumption response function over the per-capita expenditure range is determined by the data.

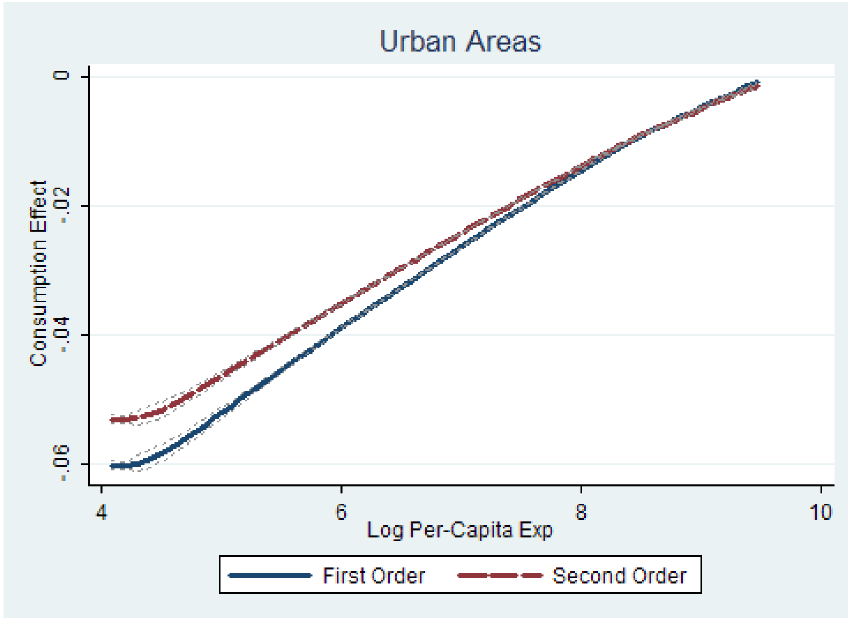
The results are presented in Figure 2 for rural and urban areas. For each household, the x-axis represents the log per capita expenditure and the y-axis shows the percentage increase in the cost of consumption due to the energy mandate. The solid line shows the nonparametric estimates of the average effects at each point of the expenditure scale, which are precisely estimated with very small standard errors.

Clearly, the second-order estimates that incorporate the household responses to price changes are smaller than the first order estimates. As prices increase, households substitute away from more expensive food items towards less expensive ones, thus decreasing the expenditure shares of the items that are highly affected by US biofuel policy. This reduces the consumption effect in both rural and urban areas. The substitution effect is more important for poorer households as the expenditure share of staple goods such as rice and wheat, and food in general, are higher.

The results suggest that poorest households experience the highest absolute welfare loss from the biofuel mandates. The second-order estimate on the left side of the expenditure scale is -5.7 percent and monotonically increases to -0.8 percent in rural areas. In urban areas, the magnitude of the effect is slightly smaller; however, the distribution of the effect possesses a similar shape. The maximum welfare effect was -5.3 percent for the poorest households, and increases to -0.1 percent as we move to the right on the expenditure spectrum.

Figure 2: First and Second Order Consumption Effects





Effect on Income

India is a large producer of agricultural commodities, and approximately three quarters of the population lives in rural areas. Households that are net sellers of agricultural products, as well as wage earners in these industries are expected to benefit from the price increases. Neglecting these effects may lead to a first-order bias in the estimates.

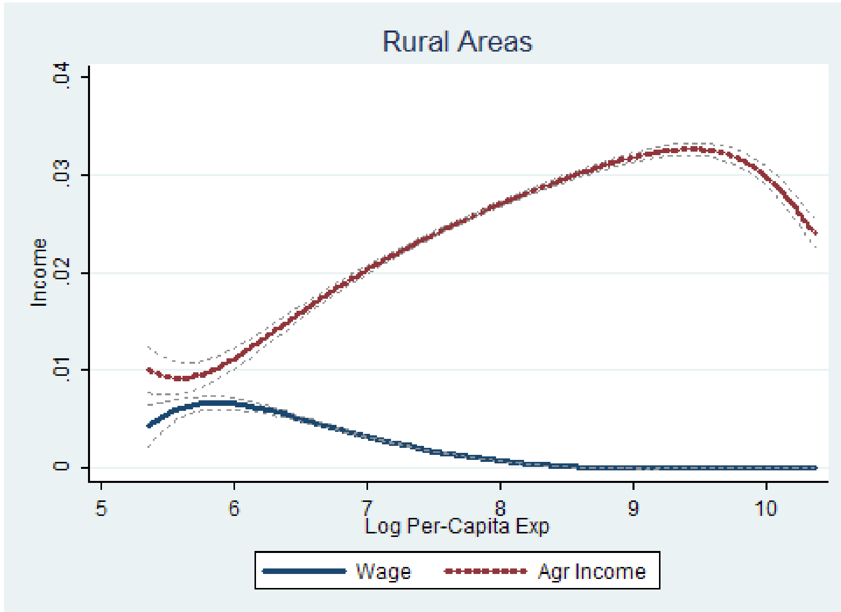
The NSS Employment survey records the industry affiliation of each activity by each individual at 5-digit NIC categories. For each individual, the wages and incomes and the industry code associated with each wage income is given for five activities. There are about 460 thousand observations in the rural areas and 226 thousand observations in urban areas. Approximately 14 percent of individuals in rural areas and 7 percent of individuals in urban areas record more than one activity. We match these activity-specific industry codes to the product categories that are used in the calibration model. The matching is straightforward, and can be seen in the Appendix. Some examples of industries that are matched to the five product categories are the cultivation of cereals, sugarcane, vegetables and animal farming. It is expected that the wages in related services are also affected by the price changes. In order to capture this, we assume wages in agricultural services such as harvesting and irrigation increase by the same magnitude as wages in rice and wheat production. This covers 34.66 percent of the work-age population in rural areas and 5.13 percent in urban areas.

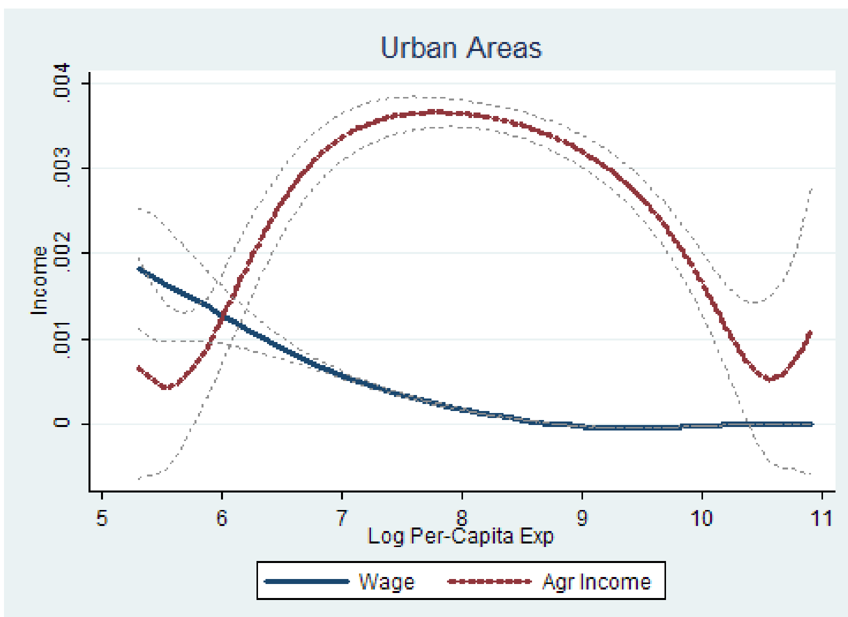
Equation (11) suggests that households will be impacted by price changes proportional to the share of total wage income of all members of the households in total household expenditure. θ_w is therefore directly computed from the data using the total wage of all members and all activities. As in Ferreira et al. (2011), ε_{w_i} is assumed to be unity. That is, price changes are fully transmitted to the wage incomes of individuals who work in these industries. This assumption makes our poverty estimates more conservative as the increase in incomes will make the households better off and partly offset the adverse consumption effects they experience from the price increases. If different members are working in different industries, their wages are differentially impacted by the policy change. In such cases, the weighted average percentage increase in household wage income due to the policy change is used.

As mentioned before, neither the NSS employment survey nor the NSS expenditure survey records information about the production in household farms. This may be an important component of household income, especially for agricultural households. In addition, it is certainly possible that some members of the household are working for wages while others are receiving income from sales of agricultural products. Our focus on agricultural income is on individuals who report that they are employed in one of our industries as a "self-account worker," but report no wages.[29] These individuals are assumed to have received their entire income from sales and profits of agricultural products, and their incomes will be directly affected by the price increase induced by biofuel policy. Once these individuals are identified, they are aggregated at the household level to arrive at the household-level agricultural income. In any case, the absence of data on actual agricultural incomes remains an issue. Using these assumptions, we aim to capture as much of the income effect as possible given the available data. These assumptions are expected to give us an upper bound for the wage and agricultural incomes, and a lower bound for poverty effects for price and wage incomes. The results for wage income and agricultural income are presented in Figure 3.

[29] More specifically, these individuals have the usual status of "self-employed as own-account worker", or "self-employed as employer", their 5-digit industry codes indicate that they are affiliated with production or services in agricultural products, and their wages are zero or missing.

Figure 3: Wages and Agricultural Incomes





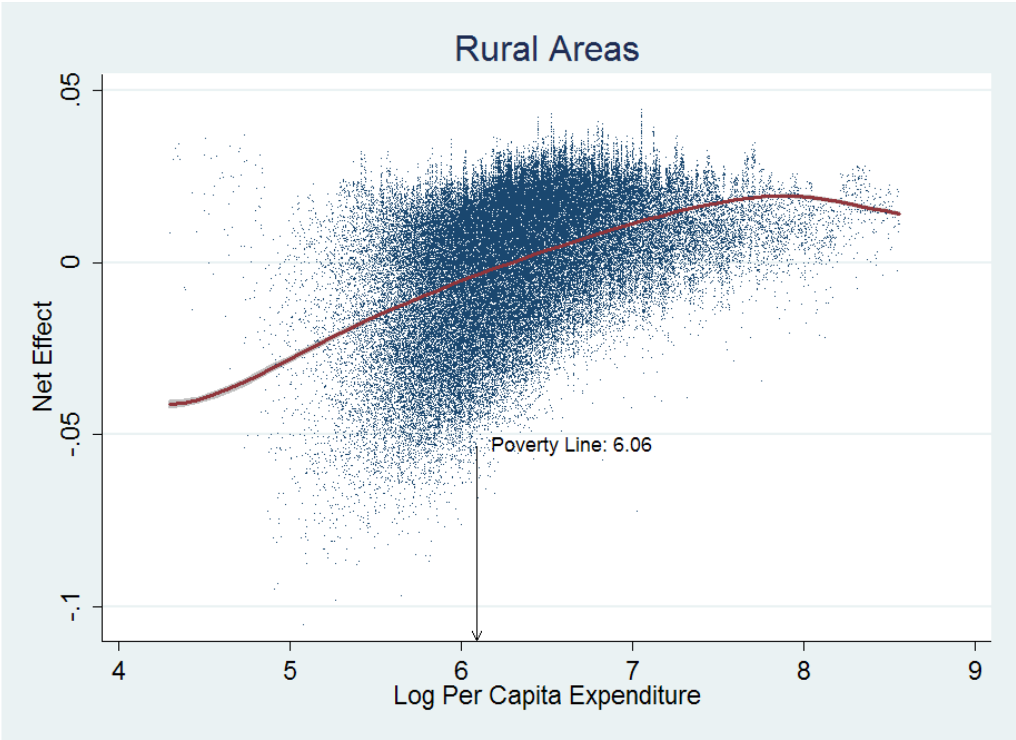
The effect on wage incomes turns out to be pro-poor in both rural and urban areas, due to the fact that the proportion of individuals who earn a wage in agricultural industries is higher at the lower end of the expenditure distribution. The magnitude of the effect is much smaller in urban areas, but it is still pro-poor. The distribution of agricultural incomes, on the other hand, is increasing as we move right on the per capita expenditure scale. Because the proportion of individuals who own land and operate farms is higher among high per-capita expenditure households, this channel has a pro-rich effect. In urban areas, the maximum increase in agricultural incomes is experienced by middle-income households. High-income households in urban areas, for the most part, are affiliated with manufacturing and services, and therefore, the effect on agricultural incomes is relatively small at the right end of the distribution.

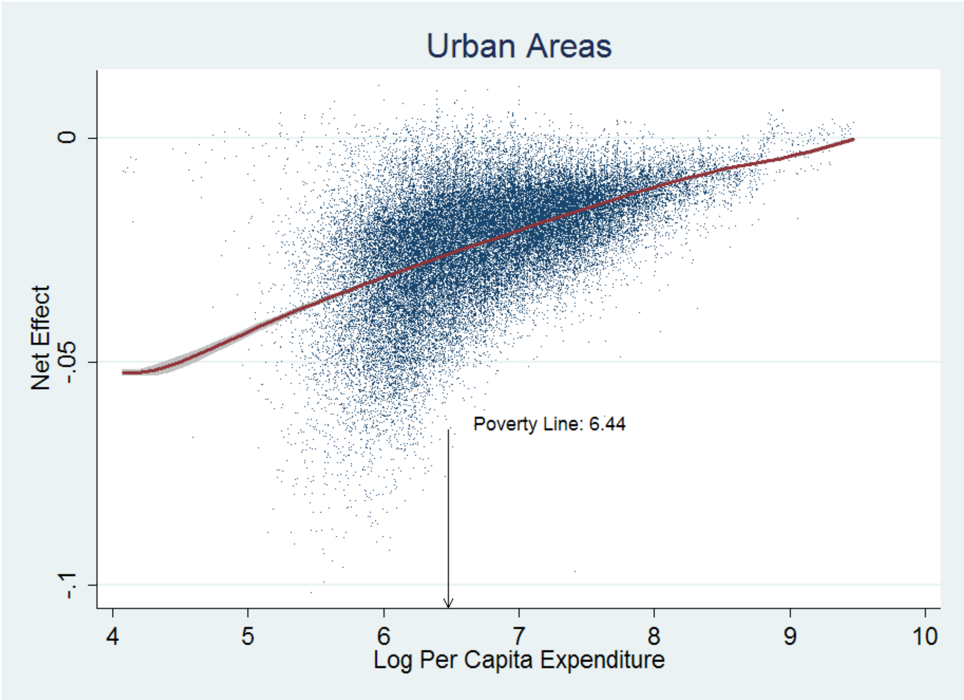
Net Effects

The focus of our analysis is to estimate the impact of biofuel mandates on households through consumption of agricultural products and incomes of individuals. These effects can be analyzed in a unified framework by combining the two channels according to Equation (11). The distributions of these effects across the per capita expenditure distribution are presented in Figure 4. The effect is significantly pro-rich in both rural and urban areas. In rural areas, households that are better off, more specifically, households with per capita expenditure higher than 544 rupees per month, experience a positive welfare effect. These households receive income from agricultural activities, and their income increases due to higher commodity prices induced by US biofuel policy. In addition, there are less impacted through the cost of consumption channel than poorer households. Because they can allocate some expenditure towards non-food items, such as clothing, durables and services, agricultural crops have a smaller share in their total expenditure. As a result, the net effect of biofuel policy on these households is positive. For all the rural households that are below the poverty line, and for the marginal poor that are within 5 percent of the poverty line, the effect is estimated to be negative.

In urban areas, the distribution of the net effect is primarily driven by the cost of consumption because household income from agricultural activities is relatively small. All urban households experience a welfare loss due to higher prices of agricultural commodities, and the negative effect diminishes as we move from poorer to richer households.

Figure 4: Net Effects





Impact on Poverty

The above analysis provides a flexible framework for assessing the potential distributional effects of biofuel mandates. We use these results to estimate the effect of the mandate on poverty in India. The headcount ratio (HCR) or poverty rate is defined as:

$$HCR = \frac{1}{N}\sum_{i=1}^{N} I(x_i \leq z) \tag{13}$$

where N is the total number of individuals, x_i is per capita income and z is the poverty line, $I(.)$ is an indicator function that marks the households for which $x_i \leq z$.

After the policy change, there will be two effects on the poverty rate. First, per capita expenditure of households, x_i, will change due to changes in income and consumption. Second, the poverty line itself will shift to the right because it will cost more to purchase a fixed bundle of goods. The increase in the cost of consumption will, therefore, proportionately move the poverty line upwards. The change in the poverty line is then:

$$dz = \sum_{i} \overline{w}_i dlnp_i + \frac{1}{2}\sum_{i}\sum_{j} \varepsilon_{ij}\overline{w}_i(dlnp_i)(dlnp_j) + + \sum_{h}\sum_{i} \bar{\theta}^h_{w_i}\varepsilon_{w_i}dlnp_i \tag{12}$$

where $\overline{w}_i$ is defined as the average expenditure share, and $\bar{\theta}$ is the share of wage income of the marginal poor whose per capita expenditure is within a 5 percent range of the poverty line (de Janvry and Sadulet, 2010). Here, we use the shares of the marginal poor instead of the entire population because this group is likely to move in and out of poverty with a price change.

The widely used international poverty line, \$1.25 a-day, is converted to Indian Rupees using a 2005 purchasing power parity of Rs 21.6 a day in urban and Rs 14.3 a day in rural areas.[30] A month is assumed to be 30 days. Then, the rural poverty line is 429 rupees and the urban line is 628 rupees. These poverty lines are presented in Figure 2.

The Indian national poverty line is based on a consumption basket that provides a minimum daily calorie intake of 2,400 in rural areas and 2,100 in urban areas. In 2004, the Planning Commission defined this poverty line as 356.3 rupees per day in rural and 538.6 rupees in urban

[30] Purchasing power parity conversions are obtained from the World Bank.

areas. These numbers are significantly lower than the international poverty lines, and thus they translate to a lower poverty rate. In what follows, we distinguish between these two poverty lines.

Table 7 presents the results. The poverty line will increase by dz as a result of the increase in prices. Note that this shift is proportional to the budget share of these consumption items and the elasticity of substitution which governs the rate at which households substitute between different consumption items (equation 12). Our results suggest that the poverty line in rural areas will increase by 4.36 percent and in urban areas by 3.38 percent. Assuming that the expenditure shares of these commodities remain the same, some of the marginal non-poor households will now move below the poverty line due to the increase in the cost of consumption. Therefore, the headcount ratio (HCR) poverty rates will increase proportionately. The increase in prices as a result of the biofuel mandates in the US will move 30.44 million individuals in rural areas and 9.8 million individuals in urban areas below the $1.25 international poverty line. According to the national poverty line, the number of new poor is estimated to be 28.88 million in rural areas and 10.40 million in urban areas. The two estimates are quite similar.

4. Poverty effects with imperfect pass-through

Under heavy policy intervention and market imperfections, the increase in world prices may only partially transmit to the Indian consumer. This was observed during the 2008 spike in world food prices, especially for rice and wheat (see Figure 1). The Indian authorities implemented a series of aggressive policies to prevent these price shocks from being transmitted to domestic prices. The short term policy response to the world food price crisis included (to mention only a few) creation of strategic reserves, releasing government held stocks, raising minimum support prices and export bans (Jones and Kwiecinski, 2010). These policies are costly and not feasible in the long run. For this reason, we consider this scenario as the minimal price transmission given by Table 5 when there is major intervention in the price pass-through mechanism.

Table 7: Poverty Impacts from the US Biofuel Mandate – Full Transmission

	Rural		Urban	
	Initial Values	Effect of the Price Change	Initial Values	Effect of the Price Change
Per Capita Expenditure	587.52	589.45	1194.99	1175.32
Population (millions)	780.44	-	314.15	-
Poverty ($1.25, PPP)				
Poverty Line	429	447.7	628	647.90
Headcount Ratio	39.67	43.57	28.41	31.55
Number of poor (millions)	309.60	340.04	89.25	99.11
New poor (millions)		**30.44**		**9.86**
Total new poor (millions)			**40.30**	
Poverty (National Poverty Line)				
Poverty Line	356.30	370.76	538.6	555.67
Headcount Ratio	24.41	28.11	20.08	22.93
Number of poor (millions)	190.50	219.38	63.08	72.03
New poor (millions)		**28.88**		**8.95**
Total new poor (millions)			**37.83**	

Notes: Estimates are based on the perfect price transmission assumption. PPP-corrected poverty line based on daily expenditure is obtained from the World Bank, and converted to monthly expenditure assuming a 30-day month. Other data on the rural and urban population is obtained from World Development Indicators, based on population in 2010. The effect on the poverty line is estimated using the expenditure share of the marginal poor located within five percent of the poverty line.

Under imperfect price transmission, we repeat the same exercise, but this time we allow the price increases to affect consumption and income of the households to the extent that increases in world prices are conveyed to domestic prices. We use long-term transmission elasticities for rice and wheat presented in Table 5. Under this scenario, domestic prices of sugar and meat will not be affected as their elasticities are insignificant.

With imperfect pass-through, both consumption effects and income effects are smaller. The effect on poverty is estimated to be an 11.06 million increase in the number of poor according to the international poverty line, and an increase of 9.51 million poor people according to the Indian national poverty line.

Table 8: Poverty Impacts from the US Biofuel Mandate – Imperfect Transmission

	Rural		**Urban**	
	Initial Values	**Effect of the Price Change**	**Initial Values**	**Effect of the Price Change**
Per Capita Expenditure	587.52	589.45	1194.99	1175.32
Population (millions)	780.44	-	314.15	-
Poverty ($1.25, PPP)				
Poverty Line	429	438.89	628	639.62
Headcount Ratio	39.67	40.45	28.41	29.99
Number of poor (millions)	309.60	315.69	89.25	94.22
New poor (millions)		**6.09**		**4.97**
Total new poor (millions)		**11.06**		
Poverty (National Poverty Line)				
Poverty Line	356.30	364.52	538.6	548.56
Headcount Ratio	24.41	25.06	20.08	21.48
Number of poor (millions)	190.50	195.61	63.08	67.48
New poor (millions)		**5.11**		**4.40**
Total new poor (millions)		**9.51**		

Notes: Estimates are based on the perfect price transmission assumption. PPP-corrected poverty line based on daily expenditure is obtained from the World Bank, and converted to monthly expenditure assuming a 30-day month. Other data on the rural and urban population is obtained from the World Development indicators, based on the population in 2010. The effect on the poverty line is estimated using the expenditure share of the marginal poor located within five percent of the poverty line.

5. Concluding Remarks

Many countries including the US, EU, China and India have adopted aggressive policies to promote biofuels and reduce their dependence on imported oil. Most of the literature on the effect of biofuel policies has focused on estimating the effect of diverting crops away from food to energy on food prices. In general these models suggest price increases of 30% or more, caused by the diversion of crops from food to fuel. In this paper, we first use a model with differential land quality to estimate the effects of the US energy mandate on the price of selected commodities, namely rice, wheat, sugar and meat and dairy, all of which are important suppliers of nutrition in developing countries. Our framework allows for an increase in land allocation to crops when food prices increase. We show that the effect of clean energy mandates may be in the order of 15-20% for certain crops, but not all.

More importantly, we then use Indian price data to compute the pass-through of these world price increases to the domestic market, and then use household survey data to estimate the own and cross-price elasticities for these food commodities. We can then estimate the welfare effects of energy-induced food prices for India, which is representative of a typical developing country with a significant share of the population below the poverty line. These estimates include both the direct negative impacts of price increases induced by US biofuels policy, and the smaller positive impacts from higher agricultural wages and incomes. The price increases are shown to be regressive, since poorer households spend more of their household budget on these major food groups. The wage effects benefit the poor since a larger proportion of them work as wage labor in the food sector. However the positive income effects mainly accrue to the rural middle and high income groups, who own more of the agricultural assets. Richer urban households tend to own more non-agricultural capital and are less impacted.

With perfect price pass-through to the Indian market, we show that close to 40 million people in India may become poor, mostly in the rural areas. However, if domestic policy prevents the pass through of world prices, then the estimates are much lower, about 10 million. Of course, interventions in the domestic market to prevent the transmission of world prices have significant welfare costs.

The main point of the paper is that the effect of the US biofuel mandate may lead to an increase in the number of poor by about 10-40 million, in one major country. If one considers other developing countries in Asia and Africa, the conclusion from this analysis is that the effect of biofuel policies may be quite significant and regressive, i.e., affecting poorer people the most. We have not taken into account energy mandates adopted by other countries such as the EU, China and India, which may increase these estimates significantly. India already supplies 5% of its transportation fuels from ethanol produced from sugarcane. A more ambitious target of a 15-25% share of transport fuels from land will divert more land from food production and therefore add to the estimates we present. These more ambitious goals are being discussed mainly to reduce dependence on foreign fuel supplies and the promotion of clean energy sources.

Future extensions of this work will involve the addition of an explicit Indian energy mandate to the one imposed by the US. We can also estimate the effect of these clean energy policies on malnutrition among individuals. Each consumption item in the NSS data is hand-matched to its calorie, fat and protein content using the FAO nutritional database. The policy induces a change in the price vector, and therefore alters the consumption structure for each household. Nutritional changes can be estimated by computing the nutritional intake before and after the price change. We can then estimate the number of individuals (if any) that will move below the recommended minimum daily nutritional intake.

References

Banks, J., Blundell, R. and Lewbel, A. (1997), "Quadratic Engel Curves and Consumer Demand," *The Review of Economics and Statistics*, 79(4): 527-539.

Campa, J. M. and Goldberg, L. (2005). "Exchange Rate Pass-Through into Import Prices," *The Review of Economics and Statistics,* 84(7): 679-690.

Campa, J.M. and Minguez, J.M. (2005). "Differences in Exchange Rate Pass-through in Euro Area," *European Economic Review,* 50: 121-145.

Chakravorty, Ujjayant, Marie-Helene Hubert, Michel Moreaux and Linda Nostbakken (2011), "Do Biofuel Mandates Raise Food Prices?" Unpublished manuscript.

Chen,S. and M. Ravallion (2010), "The Developing World is Poorer Than We Thought, But No Less Successful in the Fight Against Poverty, *Quarterly Journal of Economics*, November, 1577-1625.

Chen, X., H. Huang, M. Khanna (2011). Land Use and Greenhouse Gas implications of Biofuels: Role of Technology and Policy. Agricultural and Applied economics Association Meetings, 2011 Annual Meeting, 24-26 July, 2011, Pittsburgh, Pennsylvania.

de Janvry, A. and E. Sadoulet (2010). "The Global Food Crisis and Guatemala: What Crisis and for Whom?" World Development, 38(9), 1328-1339.

Deaton, A. (1987). "Estimation of Own- and Cross-Price Elasticities From Household Survey Data", *Journal of Econometrics*, (36): 7-30.

Deaton, A. (1990). "Price Elasticities from Survey Data: Extensions and Indonesian Results", *Journal of Econometrics*, (44): 281-309.

Deaton, A. and Muellbauer (1980). "An Almost Ideal Demand System", *American Economic Review*, 70(3): 312-326.

EIA (2011). International Energy Statistics. U.S. Energy Information Administration Washington D.C, United-States Lien : http://www.eia.gov/countries/data.cfm

Eisentraut, A. (2010). *Sustainable Production of Second-Generation Biofuels: Potential and perspectives in major economies and developing countries*, OECD/IEA, Paris, France.

FAOSTAT. http://faostat.fao.org/default.aspx?alias=faostat&lang=en, Food and Agricultural Organisation, Rome, Italy.

FAO (2003). *World agriculture towards 2015-2030,* Food and Agriculture Organization, Rome, Italy.

FAO (2008). *The State of Food and Agriculture. Biofuels: Prospects, Risks and Opportunities,* Food and Agricultural Organization, Rome, Italy.

FAO (2010). The State of Food Insecurity in the World: Addressing the protracted crisis. Food and Agricultural Organization, Rome, Italy.

Ferreira, F.H. G., Fruttero, A., Leite, P. and Lucchetti, L. (2011). "Rising Food Prices and Household Welfare: Evidence from Brazil in 2008", *Policy Research Working Paper Series*, No.5652, The World Bank.

Fischer, G., H. Van Velthuisen, M. Shah, and F. Natchtergaele (2002). *Global Agro-ecological Assessment for Agriculture in the 21rst Century: Metholodology and Results*. International Institute for Applied Systems Analysis (IIASA), Laxenburg, Austria; Food and Agricultural Organization, Rome, Italy.

Golub, A., T.W. Hertel, B. Sohnghen (2008). Land-Use Modelling in Recursively-Dynamic GTAP Model. In "*Economic Analysis of Land Use in Global Climate Change Policy"* edited by T. Hertel, S. Rose and R.J.L Tol. Routledge explorations in environmental economics.

IEA (2009). *From 1st to 2nd generation biofuel technologies: An overview of current industry and R&D activities.* International Energy Agency, Paris, France.

Jones, D. and Kwiecinski, A. (2010). "Policy Responses in Emerging Economies to International Agricultural Commodity Price Surges", *OECD Food, Agriculture and Fisheries Working Papers*, No. 34.

Kojima, M., D. Mitchell, and W. Ward. (2007). "Considering Trade Policies for Liquid Biofuels", *World Bank, Energy Sector Management Assistance Program*, Renewable Energy Special report 004/07. http://siteresources.worldbank.org/INTOGMC/Resources/Considering_trade_policies_for_liquid_biofuels.pdf

Li Q., and Racine, S. (2007). Nonparametric Econometrics. Princeton University Press, Princeton, NJ.

Nicita, A. (2009). "The Price Effect of Trade Liberalization: Measuring the Impact on Household Welfare," *Journal of Development Economics*, 89(1): 19-27.

Nordhaus, W.D. (2009). "The Economics of an Integrated World Oil Market," Keynote Address, International Energy Workshop, Venice, Italy, June 17-19, 2009.

OECD (2009). "The Bioeconomy to 2030: designing a policy agenda," Organization of Economic Cooperation and Development, Paris, France.

OECD (2008). "Biofuel Support Policies: An Economic Assessment," Organization of Economic Cooperation and Development, Paris, France.

Porto, G. (2006). "Using Survey Data to Assess the Distributional Effects of Trade Policy", *Journal of International Economics*, 70(1): 140-160.

Rajagopal, D. and D. Zilberman (2007). “Review of Environmental, Economic, and Policy Aspects of Biofuels,” World Bank, Policy Research Working Paper 4341.

Roberts, M. and W. Schlenker (2010). “The U.S. Biofuel Mandate and World Food Prices: An Econometric Analysis of the Demand and Supply of Calories.” NBER Working Paper N°15921.

Ravindranath, N.H, C. S. Lakshmi, R. Manuvie and P. Balachandra. 2011. Biofuels production, and implications for land-use, food production and environment in India, Energy Policy 39(10) 5737-5745.

Rosegrant, M.W., M.S. Paisner, S. Meijer and J. Witcover (2001). *Global Food Projections to 2020: Emerging Trends and Alternative Futures*, International Food Policy Research Institute, Washington DC.

Swarup, Renu (2011). *Bioenergy Programme in India: Current Status and Future Priorities*, October, Department of Biotechnology, Ministry of Science and Technology, New Delhi.

The Economist (2010). *Brazil’s agricultural miracle: How to feed the world*. 26th August 2010. http://www.economist.com/node/16889019?story_id=16889019

UN Population Division (2010). *World Population Prospects: The 2010 Revision*, United Nations, Economic and Social Affairs, Population Division, New York. Available online: http://esa.un.org/unpd/wpp/index.htm

Ural Marchand (2011). Tariff Pass-Through and the Effect of Trade Liberalization on Household Welfare”, mimeo, University of Alberta.

World Energy Council (2010). *2010 Survey of Energy Resources.* London. http://www.worldenergy.org/publications/survey_of_energy_resources_2010/default.asp

Yacobucci, B.D and R. Schnepf (2007). *Ethanol and Biofuels: Agriculture, Infrastructure, and Market Constraints Related to Expanded Production,* Congressional Research Service.

Appendix: Matching between Commodities, Expenditure Categories and Industries

Products	NSS Categories		5-Digit NIC 1998 Categories	
	Codes	Description	Codes	Description
Rice	101, 102	Rice	01111	Growing of food grain crops (cereals and pulses)
	103	Chira	01403	Activities establishing a crop, promoting its growth or protecting it from disease and insects. Transplantation of rice in rice fields.
	104	Khoi, lawa	01404	Harvesting and activities related to harvesting, such as preparation of crop cleaning, trimming, grading, drying.
	105	Muri		
	106	Other rice products		
Wheat	107, 108	Wheat/atta	01111	Growing of food grain crops (cereals and pulses)
	110	Maida	01403	Activities establishing a crop, promoting its growth or protecting it from disease and insects. Transplantation of rice in rice fields.
	111	Suji, rawa		
	112	Sewai, noodles		
	113	Bread: bakery		
	114	Other wheat products		
			01404	Harvesting and activities related to harvesting, such as preparation of crop cleaning, trimming, grading, drying.
Sugar	269	Sugar (sub-total)	01115	Growing of sugarcane or sugar beet
Meat & Dairy	160	Milk: liquid (litre)	01407	Activities to promote propagation, growth and output of animals and to obtain
	161	Baby food	01409	Other agricultural and animal husbandry service activities, n.e.c.
	162	Milk: condensed/ powder	01211	Farming of cattle , sheep, goats, horses, asses, mules and hinnies; dairy farming
	163	Curd	01212	Rearing of goats, production of milk
	164	Ghee	01213	Rearing of sheep; production of shorn wool
	165	Butter	01214	Rearing of horses, camels, mules and other pack animals.
	166	Ice-cream	01221	Raising of pigs and swine
	167	Other milk products	01222	Raising of poultry (including broiler) and other domesticated birds; production of eggs and operation of poultry hatcheries Raising of bees; production of honey
	180	Eggs (no.)	01223	Raising of bees; production of honey
	181	Fish, prawn	01224	Raising of silk worms; production of silk worm cocoons (production of raw silk is classified under class 1711) Farming of rabbits including angora rabbits
	182	Goat meat/mutton	01225	Farming of rabbits including angora rabbits

	183	Beef/ buffalo meat	01229	Other animal farming; production of animal products n.e.c. (Includes: raising in captivity of semi domesticated or wild live animals including birds and reptiles,
	184	Pork	01500	Hunting, trapping and game propagation including related service activities
	185	Chicken	05001	Fishing on commercial basis in ocean, sea and coastal areas
	186	Others: birds, crab, oyster, tortoise, etc.	05002	Fishing on commercial basis in inland waters.
			05003	Gathering of marine materials such as natural pearls, sponges, coral and algae.
			05004	Fish farming, breading and rearing including operations of hatcheries for fin an shell fish
			05005	Service activities related to marine and fresh water fisheries and to operators of
Other Food	115-122	Jowar, bajra, maize, barley, small millets, ragi and other cereal	01112	Growing of oilseeds including peanuts or soya beans
	139	Cereal substitutes: tapioca, jackfruit, etc.	01119	Growing of other crops, n.e.c. (Includes growing of potatoes, jams, sweet
	159	Pulses & pulse products (Sub-total)	01121	Growing, in the open or under cover, of vegetables
	179	Edible oil (sub-total)	01122	Growing of horticultural specialties including: seeds for flowers, fruit or
	229	Vegetables (sub-total)	01131	Growing of coffee or cocoa beans
	249	Fruits (fresh, sub-total)	01132	Growing of tea or mate leaves including the activities of tea factories associated
	259	Fruits (dry, sub-total)	01133	Growing of edible nuts including coconuts
	289	Spices (sub-total)	01134	Growing of fruit: citrus, tropical pome or stone fruit; small fruit such as berries;
	290-293	Tea and coffee	01135	Growing of spice crops including: spice leaves (e.g. bay, thyme, basil); spice
Notes: The categories within NSS and NIC are all subject to the same price shocks as the corresponding product in the first column. The table does not present one-to-one matching between NSS and NIC categories.				