Centre de Recherche en Économie et Management
Center for Research in Economics and Management

University of Rennes 1

University of Caen Normandie

Working Paper

The effect of the US biofuels mandate on poverty in India

Ujjayant Chakravorty
Department of Economics, Tufts University, USA

Marie-Hélène Hubert
CREM, UMR CNRS 6211, University of Rennes 1, France

Beyza Ural Marchand
University of Alberta, Canada

November 2016 - WP 2016-13

UNIVERSITÉ CAEN NORMANDIE

UNIVERSITÉ DE RENNES 1

The effect of the US biofuels mandate on poverty in India

Ujjayant Chakravorty, Marie-Hélène Hubert and Beyza Ural Marchand*

November, 2016

Abstract

More than 40% of US grain is now used for energy and this share is expected to rise under the current Renewable Fuels Mandate (RFS). There are no studies of the global distributional consequences of this purely domestic policy. Using micro-level survey data, we trace the effect of the RFS on world food prices and their impact on household level consumption and wage impacts in India. We first develop a partial equilibrium model to estimate the effect of the RFS on the price of selected food commodities - rice, wheat, corn, sugar and meat and dairy, which together provide almost 70% of Indian food calories. World prices for these commodities are predicted to rise by 8-16%. Next, we estimate the price pass-through to domestic Indian prices and wage-price elasticities to account for the impact on workers with different skill levels. Poor rural households in India suffer significant consumption losses, which are regressive. However they benefit from wage increases because most of them are employed in agriculture. Urban households also bear the higher cost of food, but do not see a concomitant rise in wage incomes because only a small fraction of them work in food-related industries. Welfare impacts are greater among urban households. However, more poor people in India live in villages, so poverty impacts there are larger in magnitude. We estimate that the RFS leads to about 26 million new poor: 21 million in rural and five million in the urban population, roughly 10 percent of the estimated number of poor people in India today.

Keywords: Biofuels, Distributional effects, Household welfare, Renewable Fuel Standards, Poverty
JEL Codes: D31, O12, Q24, Q42

*Chakravorty: Department of Economics, Tufts University, ujjayant.chakravorty@tufts.edu; Hubert: Department of Economics, University of Rennes 1 (CREM), marie-helene.hubert@univ-rennes1.fr; Ural Marchand: Department of Economics, University of Alberta, beyza.ural@ualberta.ca. We would like to thank the Social Sciences and Humanities Research Council and the French National Research Agency for generous research support, seminar participants at University of California at Berkeley, CESifo Munich, EPA, ETH Zurich, University of Maryland, Ohio State, Paris School of Economics, Resources for the Future, Toulouse School of Economics, Tufts University, Vanderbilt University, Virginia Tech, Wellesley College; and conference participants at the ASSA Annual Meetings, Canadian Economic Association Meetings, European Resource and Environmental Economics Conference, Statistics Norway and the Indian Growth and Development Economics Conference in Delhi. We would like to thank Kyle Emerick for helpful comments and Alausa Waleem for excellent research assistance.

1 Introduction

The United States has been the most aggressive nation in encouraging the use of biofuels in the transportation sector. About 10% of U.S. gasoline now comes from ethanol produced from corn, making it the largest consumer of biofuels in the world. This share is expected to rise several-fold with the advent of second generation biofuels under the Renewable Fuels Standard (RFS) (EPA, 2010).[1] This policy is controversial because it uses scarce land resources that displace food for energy production, leading to an increase in food prices (Rosenthal, 2011). Several studies have attributed past food price shocks in US and world markets to the sharp increase in biofuel production, especially from corn ethanol.[2]

That the RFS induces an increase in the price of food commodities is well established.[3] Given that the US is a major agricultural nation as well as the largest consumer of transport fuels, the distributional effects of this price increase may be significant, and have not been rigorously studied. This is the focus of the present paper. Using micro-level survey data, we estimate the effect of the RFS through consumption and wage impacts among households in India.[4] We use these welfare estimates to compute the effect on poverty.

Our results show that even though the long-run price effects of the RFS on food commodities may be modest relative to what was predicted, the price shocks cause regressive consumption effects and thereby induce significant poverty in a poor, developing country such as India. By our estimates, about 25-26 million people move from above to below the poverty line, the precise figure depending on how well world price shocks percolate into the domestic Indian market.[5] About 20-21 million of these newly poor people live in villages, and the remaining in towns and cities.

We find that consumption effects are regressive, i.e., they are larger among poor households, because they spend a greater share of their budget on food. This is true both for rural and urban households. However wage gains are progressive, especially in rural areas, because a higher share of people work in agriculture related sectors. Urban households do not register large wage gains as only a small share are employed in agriculture. When consumption and wage effects are aggregated, the net effect on welfare

[1] Brazil, the European Union, China and other countries have similar policies that divert corn, sugar cane and other crops from food to energy.

[2] See for example, Mitchell (2008), Rosegrant et al. (2008) and Hausman et al. (2012). They report significant price increases for different food commodities, of the order of 20-70%.

[3] Although there may be differences in the magnitude of price effects, especially in the short and long run.

[4] India is an important country to study because of its high incidence of poverty. According to the multi-dimensional poverty index, which accounts for health, education and living standards, eight Indian states have more poor people than the 26 poorest African states combined (UNDP, 2010). A fifth of the population suffers from malnutrition (FAO, 2010).

[5] The World Bank estimates that 21.2% of the population lives under $1.90-a-day, which corresponds to about 265 million individuals (World Bank, 2016).

is progressive for rural populations and regressive for those residing in towns and cities. However, poverty impacts depend not only on the magnitude of welfare losses but also on the relative share of the population close to the poverty line.[6] Even though the average welfare effects are smaller for rural populations, the poverty impacts are bigger, because a larger population is located near the poverty line.

We study the effect of the RFS in two steps. First, we estimate its effect on the world prices of specific crops which consume a significant acreage and are important to the Indian diet, while aggregating the ones less important.[7] Our calibrated model captures critical dynamic effects such as allowing for new land to be converted to farming when crop prices go up. The goal is to predict price changes that are inclusive of adjustment processes in the world economy. We explicitly model shocks in parameters such as crop yields and food and fuel price elasticities through Monte Carlo simulations that generate a distribution of price effects with corresponding standard errors. We find that the RFS raises long-run food commodity prices in the world market by about 8-16%. These estimates suggest a significant price increase, but modest relative to previous studies.

Next, we use detailed micro-level household data to estimate the effect of food price shocks on Indian households through the cost of consumption and wage incomes. We consider both perfect and imperfect pass-through of world prices to the Indian market. We obtain a distribution of welfare impacts for each household based on the distribution of price shocks from the first stage. We allow for household heterogeneity in terms of expenditure shares, skill levels, income and geographical location. Finally we estimate the number of new poor created as a result of welfare changes and the corresponding price-induced shift in the poverty line.[8]

The study is unique because there are almost no rigorous studies of the global impacts of domestic energy or environmental policies using micro-data. We show that domestic policy decisions of a large economy may have large global welfare impacts.[9] In agricultural and energy markets, where the US produces (and consumes) a sizable share of world supply, these impacts may be significant, as we demonstrate in this paper.[10]

[6] About 67% of India's population lives in rural areas.

[7] We study rice, wheat, sugar and meat and dairy, which together supply about 70% of the calories for the average Indian household.

[8] Although we study the impact of the RFS, the methodology adopted in this paper is fairly general and can be used to study the distributional effects of any policy that causes food price shocks (e.g., agricultural subsidies, trade barriers or natural phenomena such as climate change-induced droughts that affect crop yields).

[9] Leading economists from developing nations such as the Indian Central Bank Governor, Raghuram Rajan, have pointed to the lack of economic studies that analyse the effect of US domestic policy on other nations, especially in the area of monetary policy.

[10] Specifically, there are almost no studies of US energy policy on other nations, using micro-level data that simulates the policy impact on individual households in a representative sample. See Bourguignon et al. (2008) for a careful discussion of top-down models that use macroeconomic policies to study micro-level impacts. A recent study (Bento et al., 2009) focuses on the impact of increased gasoline taxes on gasoline consumption and miles traveled in the US as well as the associated distributional effects across

The main methodological contribution of our paper is in linking a partial equilibrium model of the world food and energy markets to generate predictions of energy policy-induced commodity price shocks, and then using micro-level household data to study the distributional effects of this policy.[11]

In section 2, we outline the calibration model and use Monte Carlo techniques to obtain a distribution of price shocks for selected food commodities induced by the energy mandate. Section 3 discusses the conceptual framework underlying the welfare analysis, the data used and estimates price pass-through elasticities of world to domestic Indian prices. Section 4 shows the welfare estimates. Section 5 concludes the paper. Details of the data used in the estimation are provided in the Appendix.

2 Estimating prices for major food commodities

In this section we calibrate a simple, dynamic partial equilibrium model of the agriculture and transport fuel sectors in order to trace the effect of the US Renewable Fuels Mandate on food prices. This mandate requires the use of biofuels (mainly from corn) in transportation to increase from the current 13 billion gallons to 36 billion by the year 2022 as shown in Figure 1.[12] First we present a toy model which reveals the underlying economic principles, followed by a detailed specification of the calibration model. The goal is to show that the RFS will shift some agricultural land to produce energy, thereby decreasing supply of food crops and increasing their prices. The increase in food commodity prices will lead to new land being brought into cultivation, thereby dampening the price shocks.

2.1 A model of energy and food

Consider a partial equilibrium economy in which two goods are produced — transport energy and food crops. The quantity consumed of each good is denoted respectively by q_e and q_f, where the subscripts e and f denote energy and food crops.[13] Let the downward-sloping inverse demand function for each good by denoted by $D_j^{-1}, j = \{e, f\}$.

households that differ by income, race and other characteristics.

[11] Studies that examine the welfare impacts of price changes, due to trade policy and other macroeconomic shocks, such as Han et al. (2016), Nicita (2009), Porto (2006, 2010), Ural Marchand (2012), Ravallion (1990) and De Janvry and Sadoulet (2010) are deterministic as they consider a single vector of price shocks. We model a stochastic distribution of price shocks which in turn generates a distribution of welfare estimates for each household in the sample.

[12] See e.g., https://www.epa.gov/renewable-fuel-standard-program/program-overview-renewable-fuel-standard-program for the program overview. There is some uncertainty as to how this ambitious mandate will be met by industry, especially in an era of low oil and gas prices, see CBO (2014).

[13] In the empirical model described later, we will distinguish food *crops* from food *commodities*. Demand is expressed in terms of the food commodity, e.g., the rice *crop* is produced on land then converted to rice commodity by applying a coefficient of transformation. In the theoretical model, this distinction is left out for tractability.

Demand is assumed independent of other goods. Transport energy is produced from gasoline or biofuel, which for now are assumed to be perfect substitutes. Food crops and biofuel are produced on land.

Land is assumed to be of uniform quality and may be allocated to energy or food production. Let $L_j(t)$, $j \in \{e, f\}$, be the amount of land dedicated to producing energy and food at any time t. Since we use this model to predict future food prices, we incorporate dynamics with a time subscript. The total land cultivated $L(t)$ is then given by $\sum_{j \in \{e,f\}} L_j(t) = L(t)$. Change in the total land area available under food or energy production equals the new land put to either use, defined by $l(t)$, i.e., $\dot{L}(t) = l(t)$, where dot represents the time derivative. Note that the variable $l(t)$ may be negative if land is taken out of production: here we only allow for new land to be brought under cultivation.

The total cost of bringing new land into cultivation is increasing and convex as a function of aggregate land cultivated, but linear in the amount of new land used at any given instant. It is given by $c(L)l$, where we assume that $c^{'}(L) > 0$ and $c^{''}(L) > 0$. The cost of conversion of new land increases because it is likely to be remotely located and less accessible to markets. Thus the greater is the land area already under cultivation, the higher the unit cost of bringing new land into farming. The conversion cost function is the same whether new land is being used for food or energy.

Crop yield per unit of land for energy or food is denoted by k_j where $j \in \{e, f\}$. Then the output of energy and food crops is given by $q_e = k_e L_e$ and $q_f = k_f L_f$, respectively, where we hide the time subscript.[14] Total production cost is rising and convex with output q_j and is given by $w_j(q_j)$.

The production of transport fuel is given by $k_e L_e + g$ where $k_e L_e$ and g denote production of biofuels and gasoline. Let the unit cost of gasoline be c_g.[15] The RFS is in the form of a quota and can be written as $k_e \bar{L}_e$ where $\bar{L}_e$ is the minimum land area required to meet the imposed target, giving us the constraint $k_e L_e \geq k_e \bar{L}_e$.

Let the social discount rate be r. Then we can write the social planner's objective function as maximization of the discounted Marshallian surplus from energy and food by choosing how much land to plant to food and biofuels and the quantity of gasoline to be used, as follows:

[14] In the calibration model, we allow for production of multiple food and energy crops, as explained below.

[15] Production of crude oil and conversion to gasoline is explicitly modeled in the calibration, described below.

$$Max_{\{L_j,l,g\}} \int_0^{\infty} e^{-rt}\{[\int_0^{k_eL_e+g} D_e^{-1}(\cdot)d\psi + \int_0^{k_fL_f} D_f^{-1}(\cdot)d\gamma]$$
$$-c(L)l - \sum_j w_j(k_jL_j) - c_g g\}dt, \qquad j = \{e, f\} \tag{1}$$

$$\text{subject to} \qquad k_eL_e \geq k_e\bar{L}_e \tag{2}$$
$$\text{and} \qquad \dot{L}(t) = l. \tag{3}$$

The current value Lagrangian can be written as:

$$L = \int_0^{k_eL_e+g} D_e^{-1}(\cdot)d\psi + \int_0^{k_fL_f} D_f^{-1}(\cdot)d\gamma - c(L)l - \sum_{j\in\{f,e\}} w_j(k_jL_j) - c_g g + \theta k_e(L_e - \bar{L}_e) + \lambda l,$$

where θ is the multiplier associated with the mandate (2) and represents the implicit subsidy required to meet it, and λ is the dynamic shadow price of land. The first order conditions, assuming an interior solution, are given by:

$$k_e(p_e + \theta - w_e^{'}) - c'(L)l \ = 0 \tag{4}$$
$$k_f(p_f - w_f^{'}) - c'(L)l \ = 0 \tag{5}$$
$$c(L) \ = \lambda \tag{6}$$
$$p_e - c_g \ = 0 \tag{7}$$
$$\text{and } \dot{\lambda}(t) = r\lambda + c\,'(L)l, \tag{8}$$

along with associated non-negativity constraints, not shown here. Condition (4) suggests that the price of energy (p_e) equals the sum of the marginal cost of biofuel production ($w_e^{'}$) and land conversion plus the subsidy θ induced by the mandate. Equation (5) states that land is allocated to food production until the price of food (p_f) equals the sum of the marginal cost of production ($w_f^{'}$) and conversion cost $c'(L)l$, adjusted by crop yield. The dynamic shadow price of land is equal to the unit cost of conversion from (6). Condition (7) suggests that the price of transport fuel equals the unit cost of gasoline production. Finally (8) relates the rate of change of the land shadow price to the discount rate and marginal cost of land conversion.

We can quickly summarize the main insights from this model. Positive demand shocks will lead to higher prices for food or energy, and induce new land conversion, *ceteris paribus*. A higher price of gasoline will make biofuels relatively economical and trigger an acreage shift from food to energy. Food prices will rise, and new land conversion may occur, exerting downward shift in prices. A larger biofuels mandate will implicitly mean a higher subsidy for biofuel production, increase land under fuel production and lower consumption of the substitute, gasoline.

2.2 Calibration

In this section, we extend the simple framework outlined above to calibrate a model that can trace the effect of the RFS on the price of selected food commodities in the world market. The empirical model described here follows the same optimizing principles we have discussed above, but with extensions that try to capture key features of the world food and energy markets. These include heterogeneity in demand for energy and food in different geographical regions and differences in production costs and in land endowment and quality. The goal is to arrive at realistic long-run predictions for price increases for a set of food commodities that are critical to the Indian diet.

The Renewable Fuel Standard (RFS) sets a minimum use of first generation (ethanol from corn) and advanced biofuels (from cellulosic biomass) as shown in Figure 1. The consumption of first generation fuel equals 15 billion gallons in 2015 (EPA, 2010). Two categories of advanced biofuels are also specified in the mandate - 4 billion gallons of low-carbon biofuels which must exhibit a 50% reduction in greenhouse gas emissions relative to gasoline (only sugarcane ethanol from Brazil can meet this minimum requirement) and 16 billion gallons of second generation biofuels for the year 2022. We consider both types of advanced biofuels in the model.[16]

The price effects are modeled by considering three geographical regions - the United States, India, and the Rest of the World (ROW) - the last region aggregates all other nations. We consider six food commodities - rice, wheat, corn, sugar and "other food" which includes all other crops, and finally, "meat and dairy" considered separately. "Meat and dairy" is not directly produced from land. A portion of the "other crops" and corn are used to feed animals which are then transformed into meat and dairy products. These specific commodities are chosen for two reasons: their importance to the Indian diet and because they use significant land area globally, which makes them especially sensitive to acreage substitution induced by the RFS away from food to energy production.[17] The "other food" category includes all grains other than rice, wheat and corn such as starches and oil crops.[18] We include meat and dairy separately because their production is land-intensive. On average, eight kilograms of cereals produce one kg of beef and three kgs produce one kg of pork. The model assumes frictionless trading across the three regions in the food commodities, crude oil and biofuels. However, transport fuel which is a blend of gasoline and biofuels, is assumed to be produced domestically in each region and is not traded.

[16]Only the one billion gallon mandate for biodiesel that is part of the RFS is not included in our model. Since this is less than 3% of the total mandate, it will likely have a small effect on our results.

[17]Rice, wheat and sugar together supply 60% of all calories in India. They also consume a lot of farmland - according to FAO (2014), rice and corn account for 11% and 12% respectively of world farmland, and wheat another 14%.

[18]These crops are not disaggregated further because they occupy a smaller acreage and are likely to be less important in terms of distributional effects than staples like rice, wheat and corn.

Figure 2 shows a schematic of the calibration model. Land of different qualities is used to grow food crops and biofuels. Gasoline is produced from crude oil. Biofuels and gasoline are substitutes in transport fuel. The six food commodities and transport fuel are characterized by independent demand functions. The time-sensitive biofuel mandate is imposed as a consumption constraint that must be satisfied each year. The model is run for 100 years starting from base year 2012. The discount rate is 2%. All parameters are calibrated to match actual figures for year 2012.

Crop production and costs

Crop yields depend on land quality which varies significantly across geographical regions. Yields can be three times higher on high quality land than on land of low quality (Eswaran et al., 2003). We use the widely used FAO-IIASA database (Fischer et al., 2001) to define three different land qualities based on soil and climate characteristics. Each quality is indexed by n (high, medium, low) with *high* being the most productive.[19] Total land area in the model includes land cultivated in base year 2012 and fallow land that may be brought into cultivation in subsequent periods (see Appendix Table B.1).[20] The unit cost of conversion of land into farming for each land quality and region is taken from Sohngen and Mendelsohn (2003):

$$c_n = \psi_1 - \psi_2 log\left(\frac{\bar{L}_n - L_n}{\bar{L}_n}\right) \tag{9}$$

where $\bar{L}_n$ is the initial area of fallow land of quality n available for cultivation in the base year and L_n is the acreage of quality n already cultivated. Thus, $\bar{L}_n - L_n$ is the residual land available. The smaller this value, the larger is the cost of conversion. Conversion costs go to infinity as available land gets exhausted, since remote locations are prohibitively costly to develop. The parameters ψ_1 and ψ_2 are taken from Gouel and Hertel (2006) and reported in Appendix Table B.2. These parameters are the same for each land class but differ by region. We thus have three conversion cost functions for each region - one for each land quality.

As shown in Figure 2, land is allocated to produce the five food crops and biofuels (first and second generation).[21] We assume linear production, i.e., output is yield times land area. For each land quality, the FAO/IIASA database has information on the acreage under each crop and its yield.[22] The definition of land quality depends on the level of

[19]The database identifies four qualities - very suitable, suitable, moderately suitable and marginally suitable. We have grouped these four into three, by consolidating the two intermediate classes into one, since their yield differences are small.

[20]Protected forests are excluded from the model as in other studies (Golub et al., 2009). For India, we make the plausible assumption that no new land is available for farming (Ravindranath et al., 2011).

[21]First generation biofuels are produced from corn in the US and from sugarcane in India and ROW.

[22]Crop acreage for US and India is readily available from this database. For the ROW region, we

input use such as technology and irrigation. The FAO data gives yield estimates at various levels of inputs - high, medium and low. For each crop and region, we match these yields to actual data from FAO (2014) for base year 2012 and choose the input level that matches the data. For the US, we adopt the yield for "high input" use, and for the other two regions, we choose the yield for "low input use." Crop yields by land quality are reported in the Appendix (see Table B.1). Since the model is dynamic, we allow for exogenous improvements in agricultural productivity specific to region and land quality, detailed in the Appendix.

The total cost of crop production in each region is a function of aggregate regional output and assumed to be increasing and convex. Let j denote the crop produced on any given land, such as rice, wheat, sugar, other food or biofuels. Then the total production cost for crop j in a given region is defined as

$$w_j\left(\sum_n k_n^j L_n^j\right) = \eta_1\left[\sum_n k_n^j L_n^j\right]^{\eta_2} \tag{10}$$

where $\sum_n k_n^j L_n^j$ is the aggregate output of product j, and η_1 and η_2 are regional cost parameters. The data used to estimate this production cost is shown in Appendix Table B.3.

Crops are transformed into six final commodities (rice, wheat, corn, sugar, other food, and meat/dairy) by applying a constant coefficient of transformation, also given in the Appendix. Biofuel supply is region-specific, with a representative fuel for each region. This assumption is reasonable since only one type of first generation biofuel actually dominates in each region. For example, 93% of US production in 2012 was from corn ethanol (EIA, 2014). In India, sugarcane ethanol is the main source of biofuel (Ravindranath et al., 2011). The premier producer in the ROW region is Brazil where ethanol is also produced from sugarcane. Table 1 shows the representative crop for each region, its yield by land quality and production cost.[23] Cellulosic biofuels are assumed to be available in the US alone since it may take a while for them to acquire significant acreage in other regions. As these crops are less demanding in terms of land quality, we assume that their yield is uniform across different qualities. The yield of cellulosic ethanol is assumed to be $2,000$ gallons per hectare and its unit cost \$1.1 per gallon (Chen et al., 2014).

subtract the values for US and India from the total world figure. For wheat, rice, corn and sugar, we can use the data directly. However, to obtain the yield per land class for the category "other crop," we calculate the weighted mean crop yield for grains, roots, tubers, pulses and oil crops where the weight used is the share of each crop in total production in the region.

[23]Output of biofuel per hectare is computed as crop yield times the coefficient of transformation of the crop into biofuel. Production costs include the cost of transforming crop into biofuel net the positive value of any by-products.

Demand for food and transport energy

Demands for each of the six food commodities and for transport fuel are modeled using generalized Cobb-Douglas functions. They are indexed by $i \in$ {rice, wheat, corn, sugar, other food, meat/dairy and transport fuel}. Regional demand D_i for good i is given by

$$D_i = A_i P_i^{\alpha_i} y^{\beta_i} N \tag{11}$$

where P_i is the price of good i (in dollars), α_i and β_i are the regional own-price and income elasticities for good i, y and N are regional per capita income in dollars per capita and population (in billions), and A_i is the constant demand parameter calibrated from data that reproduces the observed demand for the base year (see Appendix Table B.4). We impose exogenous population and GDP per capita projections for each region in order to capture time shifts in demand for food and energy (detailed in Appendix).

Transport energy is supplied by gasoline and biofuel, which are imperfect substitutes. We adopt a CES specification as in Chen et al. (2014) given by

$$q_e = \lambda \left[\mu_g q_g^{\frac{\rho-1}{\rho}} + (1-\mu_g)(q_{bf} + q_{bs})^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}} \tag{12}$$

where q_e is the production of transport fuel in the region, μ_g is the share of gasoline in transport, ρ is the elasticity of substitution, and q_g, q_{bf} and q_{bs} are the respective supplies of gasoline and first and second generation biofuels. The elasticity of substitution depends upon the technological barriers for displacing gasoline by biofuels. Elasticity estimates are from Hertel et al. (2010), and the parameter λ is a constant calibrated to reproduce the base-year production of transport fuel (see Table B.5).

Crude oil supply is modeled as a competitive "bathtub" as in Nordhaus (2009). We posit a rising cost of extraction which captures the fact that with increased extraction, the unit cost of oil rises.[24] As in Nordhaus, the unit extraction cost at any time $\tilde{t}$ is given by

$$c_o(\tilde{t}) = \phi_1 + \phi_2 \left(\frac{\sum_{t=1}^{\tilde{t}} x(t)}{\bar{X}} \right)^{\phi_3} \tag{13}$$

where $x(t)$ represents the quantity of oil extracted at time t and $\sum_{t=1}^{\tilde{t}} x(t)$ the cumulative amount of oil extracted from date t $= 1$ to $t = \tilde{t}$, $\bar{X}$ is the initial amount of oil available, and ϕ_1, ϕ_2 and ϕ_3 are constant parameters. Their values are reported in the Appendix (Table B.6). The parameter ϕ_1 represents the initial unit extraction cost of oil, and

[24]These costs may rise due to depletion effects or the increased cost of environmental regulation of fossil fuels.

$\phi_1 + \phi_2$ the cost of extraction of the last unit. Crude oil is transformed into gasoline, using a conversion coefficient (see Appendix).

We run the model for two cases. In the BASE (baseline) model, biofuels are available but there is no RFS. In the REG (regulation) model, the RFS is imposed.[25] Specifically, we model the RFS by imposing three constraints: (i) the minimum level of consumption of corn ethanol is set at 15 billion gallons in 2015, which can be met through domestic production or imports; (ii) the 4 billion gallons of low carbon biofuels (by 2022) that is met through imports from Brazil, which belongs to ROW (recall that only sugarcane ethanol from Brazil can meet this emissions requirement); and finally cellulosic production is set to increase to 16 billion gallons in 2022.

The global social planner maximizes the discounted consumer plus producer surplus for all regions by choosing the allocation of land to food and biofuels and the consumption of gasoline. The mandate imposes a minimum use of biofuels for each year and causes grains to be diverted from food to energy. This leads to increased acreage in farming in regions that have large endowments of low-cost arable land.[26]

2.3 Effect of the RFS on commodity prices

First we check how well the model reproduces the values of the main variables in the base year (2012). Table 2 reports the observed and predicted values for consumption together with their percentage difference. Most predictions are within a 6% margin of error.

Table 3 shows prices in year 2012 for the six food commodities with and without the RFS.[27] The price effects are modest relative to other studies (Roberts and Schlenker (2013), Hausman et al. (2012)) possibly because of supply-side adjustments built into our model.[28] Wheat prices increase the most followed by "other food" and meat/dairy.[29]

[25] India has also set a target for minimum use of biofuels of 20% by 2017, however, the share of biofuels in transport fuel is less than 5% in 2013 and unlikely to rise sharply. We do not model this policy since the Indian biofuel policy will not likely impact world food and energy markets significantly - India consumes less than 2% of global transport fuel which is small compared to US consumption of about 40%.

[26] Since we have made the model tractable by aggregating countries into three regions, we are unable to say precisely in which country (or countries) land conversion to farming occurs. That would require a more disaggregated framework and may be of limited interest for this study which focuses on the distributional impacts of RFS-induced price changes in one specific country.

[27] We show price estimates for the year 2022 because that is the terminal year for the RFS, and allows the model to make supply side adjustments. Recall that the goal of the paper is to estimate the effect of long-run price shocks on households. Short-run price shocks may be larger. We do not report the price shock on transport fuel because its mean share in household expenditure is 0.3% for rural and 0.6% for urba households: welfare impacts are likely to be small. It is not included in the welfare estimations later in the paper.

[28] Roberts and Schlenker estimate that the US ethanol mandate increased food prices by about 20% with a 95% confidence interval of 14-35%.

[29] There is a shift in acreage away from food to energy production in the US of about 28 million hectares relative to the no mandate case in the year 2022. This represents about 18% of US cropland. Since most

Wheat prices show the largest increase because the US is a major wheat producer. Meat prices increase because of the rise in the price of feed such as corn and soybean, a part of "other crops." Sugar prices are impacted less because it is mostly produced outside the US and can be cultivated in lower quality lands, unlike most grains.

2.4 Sensitivity analysis and Monte Carlo simulations

The parameters of the model may be subject to uncertainty from random shocks or extreme events. In this section we obtain a distribution of price shocks for each of the six commodities using a Monte Carlo technique as in Parry and Small (2005). First, we perform a sensitivity analysis to determine which model parameters affect the prices of our food commodities the most. Specifically, we examine the sensitivity of prices to price and income elasticities of food and fuel, crop yields, extraction cost of crude oil and cost of biofuels (both ethanol and cellulosic) and for the demand parameters: GDP per capita and population. As detailed in the Appendix, commodity prices are most sensitive to food price elasticities and crop yields.

Next, we employ a Monte Carlo method to estimate the combined effect of these two parameters on the price vector. The probability density function for each parameter is assumed to be normal where the mean and standard deviation are shown in Table B.7.[30] The model is run 500 times with independently drawn values from the two selected distributions: price elasticity of food crops and yields. For each draw, we run the model with and without the RFS, i.e., the BASE and REG models. This procedure yields 500 values for the vector of price shocks. The mean and standard errors of the resulting price distributions are presented in Table 5 and the derived distribution of price changes is shown in Figure 3, plotted against the normal distribution. Note that the distributions are unimodal and close to normal, but skewed, especially for sugar, meat and other goods.

3 Estimation of distributional impacts

In this section, we estimate the distributional impacts of the RFS in terms of changes in household welfare caused by the increase in the price of the six food commodities. Following Deaton (1989), the change in household welfare is defined as the negative of the compensation variation as a share of initial household expenditure. That is, the amount households must be compensated in order to have the same utility level they have without the RFS mandate. The increase in commodity prices affects households

of this additional land is released from the acreage in corn and in "other crops," US production of food crops falls by about 32%.

[30] The values of the other parameters is assumed to be known with certainty. As a robustness check, we allowed uncertainty in all parameters by assuming that they follow a normal distribution with mean and standard deviation as shown in Table B.7. Results were quite similar.

primarily through two channels: their cost of consumption and wage incomes. These two effects are estimated with and without the RFS. The welfare impact of the RFS is the percentage gain or loss to households under the RFS relative to the no RFS policy.[31]

Consider the following net expenditure function for a household denoted h:

$$B_h(p,u) = e_h(p,u) - w_h(p) \tag{14}$$

where p is the vector of prices, $e_h(p,u)$ is the expenditure required to reach utility level u and $w_h(p)$ denotes the wage income of the household. A first-order Taylor series expansion of $B_h(p,u)$ around an initial price level p^0 and utility level u^0 and some manipulation yields

$$dB_h(p,u) = B_h(p,u) - B_h(p^0,u^0) = \sum_i \left(\frac{\partial e_h}{\partial p_i} - \frac{\partial w_h}{\partial p_i} \right) dp_i \tag{15}$$

where $dB_h(p,u)$ is the compensation the household needs to achieve the initial utility level u^0. When this term is positive, it is a net transfer, hence a welfare loss for the household. When it is negative, the household is better off, thus experiencing a welfare gain. Define $W_h = -dB_h(p,u)/e_h$ as the compensating variation expressed as a fraction of household initial expenditure.[32] Our estimating equation can then be written as

$$W_h = -\sum_i \theta_{ih} dlnp_i + \sum_m \sum_i \theta^m_{w_{ih}} \varepsilon^s_{w_i} dlnp_i \tag{16}$$

where $\theta_{ih} = x_{ih}p_i/e_h$ is the expenditure share of good i, $\theta^m_{w_{ih}}$ is the share of wage income from production of good i in the household budget contributed by member m and $\varepsilon^s_{w_i}$ is the wage-price elasticity of individual i with skill level s. The first term of (16) gives the direct consumption impact of the price change $dlnp_i$. Households that consume goods $i = 1, ..., n$ will be impacted negatively due to an increase in their cost of consumption. The magnitude of this effect is proportional to the importance of these goods in their budget given by the budget shares θ_{ih}. Expenditure survey data are used to compute these shares for each individual household.

The second component of (16) measures the effect of the price shock on household income, which enters positively in their welfare function. These income changes are

[31] This micro-level approach allows us to obtain distributional and poverty impacts by taking into account household-level heterogeneity in terms of characteristics such as expenditure patterns and factor endowments. The distribution of price shocks generated by the calibration model allows us to derive a corresponding distribution of welfare effects for each household.

[32] We can rewrite condition (15) as $W_h = -\frac{dB_h(p,u)}{e_h} = -\frac{1}{e_h}\sum_i (x_{ih}p_i - \varepsilon_{w_i}w_i)\frac{dp_i}{p_i}$ where x_{ih} is the Hicksian demand for good i by household h and ε_{wi} is the elasticity of wages with respect to the price of good i. By the envelope theorem, $\partial e_h/\partial p_i = x_{ih}$. Each member of the household contributes to household income, which is also affected by the price change. We can express household wage income from good i as $w_{ih} = \sum_m w^m_{ih}$ where $m = 1, ..., M$ represents members of the household.

measured individually for each member m and then aggregated up to the household. Individuals affiliated with industry i with skill level s experience an increase in their wages by the term $\varepsilon^s_{w_i} dlnp_i$ where $dlnp_i$ is the change in price in industry i.[33] The impact of wage income on household net expenditure is then proportional to the contribution of member m to the household budget, given by weight $\theta^m_{w_{ih}}$, which are also computed using the survey data.[34]

3.1 Description of the survey data

We use two nationally representative surveys from the National Sample Survey (NSS) of the Government of India. The NSS Consumer Expenditure Survey is used to estimate the consumption component, and the NSS Employment and Unemployment Survey for the earnings component of household welfare. The 61^{st} and 66^{th} rounds of these surveys, conducted during $2004-2005$ and $2009-2010$ are used.[35] Because the NSS samples rural and urban households separately, we distinguish between rural and urban welfare impacts.

The expenditure survey asks each household the value and quantity consumed for about 500 consumption items during the previous 30-day period.[36] The consumption goods are aggregated into rice, meat, sugar, corn, meat and "other foods" in order to compute expenditure shares for each household (see details in Appendix Table B.10).[37]

The mean household expenditure shares (θ_{ih}) computed from the $2009-2010$ round of the expenditure survey are shown in Table 6. This is our baseline year for the welfare analysis. The distribution of household log per capita expenditure is divided into deciles and the mean shares are shown for both rural and urban households. Note that the budget share for food expenditures is higher for households at the lower end of the distribution.[38] Rural households in the lowest decile spend 13.4% of their budget on rice consumption, decreasing to about 2.7% for those in the highest decile. The distribution of budget shares

[33] Here, the terms *good* and *industry* are used interchangeably. However, we distinguish between the two in the next section. In particular, a good refers to consumption items in the household budget, whereas an industry refers to the individual's primary industry affiliation coded by the 5-digit Indian National Industry Classification (NIC), which includes detailed categories for agricultural goods.

[34] Household-level income data for profits, remittances, rents and transfers is not available and thus not included in our analysis. These effects may be relatively small compared to the direct impacts through cost of consumption and wages. Second order consumption effects are also excluded. In a robustness check, these effects turn out to be quite small when estimated using cross and own-price elasticities from Regmi et al. (2001) and Hertel et al. (2010), respectively.

[35] This is one of the richest micro-level surveys for a developing country as approximately 100,000 households and 460,000 individuals are surveyed in each of the 35 states of the country.

[36] The 66^{th} round reports consumption of meat, fruits, vegetables and spices during a 7-day recall period. These expenditures are adjusted to 30 days.

[37] The definition of food commodities is consistent across the calibration and econometric analysis in the paper. The "other food" category covers fruits, vegetables, starchy foods, other cereals, oil and spices.

[38] As predicted by Engel's law, which states that the budget share of food falls with income, even if food expenditures rise.

for wheat, sugar and "other food" follow a similar trend. We find an inverse-U shape in the distribution of the budget share of meat, indicating that meat consumption increases faster than income in the middle of the distribution.

For the wage income estimates, we use the employment survey, which is an individual-level labor market survey that has information about wages, labor supply, occupation by 5-digit primary industry affiliation codes for each activity, reported according to the Indian National Industry Classification (NIC).[39] The increase in the price of the six commodities affects the earnings of individuals engaged in their production, while the earnings of those not involved stay unchanged.[40]

Table 7 shows the share of individuals within each industry. The Indian NIC classification of industry affiliations of individuals does not distinguish between production of different types of grains (see Appendix Table B.10), so we aggregate rice, wheat, and corn into one category called 'grains'. As expected, a large share of rural individuals is employed in grain production. In the lowest decile, 52.3% of individuals report grain production as their primary industry, decreasing monotonically to nearly 25% in the highest decile. These shares are much smaller and range between 2% and 11.3% among urban individuals.

Consider a scenario with uniform price effects across commodities. In this case, the consumption impacts would be higher (more negative) at the low end of the distribution due to the high budget share of food expenditures. The wage impact would also be higher for poorer households since many of them are in agriculture. The net compensating variation therefore depends on the relative size of these two channels. In terms of rural-urban differences, the consumption impact is expected to be similar between rural and urban households due to their comparable household budget shares, while wage impacts are expected to diverge, with a higher effect among rural households. Note that all households are impacted through the consumption channel, but only some of them are impacted through wages, leading to a larger magnitude of average effects through the former channel. The price effects of the RFS are non-uniform across commodities, which leads to additional variation in distributional impacts across households.

3.2 Pass-through of world prices

An important consideration is the extent to which world prices pass through to domestic Indian prices. India has a history of strong intervention in the form of agricultural subsidies and large-scale government procurement and distribution of food (see

[39] The matching between the NIC codes and the product categories in the consumer expenditure survey is shown in Appendix Table B.10.

[40] We do not measure general equilibrium impacts that arise from factor reallocation across industries. Incorporating these effects on wages involves estimating second-order impacts with cross wage-price elasticities, data for which is unfortunately not available.

Kwiecinski and Jones (2010)). This regulatory environment may restrict the transmission of price shocks from world to domestic markets. Even with no government regulation, price transmission may be low due to other distortions, such as imperfectly competitive producers or retailers, as well as imperfect substitution between imported and domestic goods.

We thus consider both perfect and imperfect pass-through of world prices. For the latter, pass-through elasticities for each commodity are estimated using monthly time-series data. The estimates rely on data for the period 2005-11, as prior data is not available. This period is somewhat unusual because of the spike in commodity prices in 2008, shown in Figure 4, and the resulting aggressive short run response by the Indian government.[41] Due to data limitations, it is not possible to identify the transmission mechanism independently of this policy response. However even though government intervention may have mitigated the effect of world price shocks in the short-run (as is clear from Figure 4), they are distortionary and hence potentially costly in the long run.[42]

The 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.[43] Corn prices are end of month spot prices from the Indian National Commodity and Derivatives Exchange. Meat prices are obtained from the Indian Ministry of Agriculture.[44] Grain prices are defined as the average of rice and wheat prices, as consistent domestic and world prices for grains are not readily available.[45] Exchange rates are obtained from the Federal Reserve Bank of India. All world prices are taken from the World Bank Commodity Price database.[46]

Table 8 shows the summary statistics for price changes for the major commodities between January 2005 and May 2011. Domestic price increases for rice, corn and meat were similar to the changes in world prices, with growth rates of 1.07, 0.8 and 0.84 percent, respectively. However, wheat and sugar prices grew at a slower rate in the domestic market compared to world prices, also seen in Figure 4. Movements in world

[41]India implemented several temporary measures during this time. These include trade policies (export bans, minimum export prices, export taxes and temporary removal of tariffs), increasing minimum support prices, de-listing crops from futures trading, and creating and releasing strategic food reserves. Some of these measures were in effect only for a few months, but they were largely effective in insulating the domestic market from price increases during the crisis (see Kwiecinski and Jones (2010)). Most of these policies were removed eventually.

[42]These costs are not included in our estimates.

[43]The Indian Ministry of Public Affairs collects price data from the Northern, Western, Eastern, Northeastern and Southern zones which are then averaged to obtain a nationwide price level for each commodity.

[44]Average meat (mutton) prices are for 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.

[45]The pass-through elasticity for grains is needed to estimate wage impacts under imperfect pass-though.

[46]For rice prices, the Thai 5% variety is used, as it provides the longest series. US Hard Red Winter (HRW) prices are used for wheat.

prices transmitted only partially to the domestic market, suggesting that pass-through coefficients are likely to vary across commodities and need to be estimated individually.

We estimate the pass-through elasticities using a single equation framework, as in Campa and Goldberg (2005) and Campa and Gonzalez Minguez (2006).[47] The estimating equation is

$$\Delta lnp_t^d = \sum_k \beta_k \Delta lnp_{t-k}^w + \gamma \Delta ln(1+\tau_t) + \delta \Delta lne_t + \varepsilon_t \tag{17}$$

where p_t^d is the domestic price vector expressed in local currency (rupees) for month t; k denotes the set of lags where $k = 0, 3, 6, 9$ and 12; p_t^w is the world price, τ_t is the tariff rate for the commodity, e_t is the exchange rate and ε is an $i.i.d.$ error term at time t. All prices are expressed in nominal terms.[48] Because our goal is to estimate the distributional effects in the long run, we estimate the long-run pass through elasticities by including 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.[49] The short term elasticity is thus given by the coefficient on the contemporaneous price level β_0, while the long-term elasticity $\sum_{i=0}^{12} \beta_i$ is defined as the sum of the coefficients on contemporaneous and lagged prices.

Table 9 shows that the short run transmission of rice price is statistically significant, although the magnitude of the pass-through transmission elasticity is relatively small. A 100% increase in the world price of rice yields a 5.7% increase in the domestic price in the short run. The sugar and corn elasticities are also significant, and larger in magnitude. The pass-through elasticities for meat and wheat are insignificant.

The welfare impacts under imperfect pass-through are estimated by incorporating the long-run pass-through elasticities that are statistically significant. Based on Table 9, world price increases of rice, sugar, and corn are transmitted by 18.1%, 38.3% and 19.7%, respectively, while the changes in wheat and meat prices are not reflected in the domestic market. The predicted price effects from Figure 3 are multiplied by these pass-through

[47]There are other approaches to measuring the pass-through, e.g., De Janvry and Sadoulet (2010) interpret it as the ratio of growth rates in domestic and world prices. Following their approach, we find a 107% pass-through elasticity for rice and 47% for wheat. However, this method does not control for factors such as trade policy shocks. Mundlak and Larson (1992)) estimate a model in levels instead of differences - we find higher and significant elasticities for all commodities using their approach. This is not appropriate in our case, however, since the Augmented Dickey-Fuller tests suggest that the price series are integrated of degree one, and therefore the pass-through coefficients estimated on levels may reflect arbitrary correlation between the series. In addition, the Johansen test suggests that we cannot reject the null hypothesis of no cointegration for most of our series.

[48]The results are similar when all prices are expressed in dollars and the exchange rate variable is dropped. In addition, Granger-Wald tests suggest that there is no reverse causality from domestic prices to world prices for any of the commodities.

[49]Given the length of our data series, it is not possible to consistently estimate the model with all 12 lags, hence we choose quarterly lags.

elasticities prior to the estimation of welfare effects.[50] For perfect pass-through, world prices are assumed to be perfectly transmitted to the domestic market.

3.3 Estimation of wage-price elasticities

The response of wages to price shocks is given by $w = w(p, \gamma)$ where p is the vector of commodity prices and γ is a set of personal characteristics such as education, age, marital status or location. According to the Indian Ministry of Statistics (MOSPI), about 90% of the workforce and 50% of the national product are engaged in the informal economy (MOSPI, 2012). A major advantage of the NSS Employment and Unemployment Survey is that it includes both formal and informal sector labor. Because we aim to estimate the total welfare impacts, the analyses are conducted based on cash and kind weekly wage incomes as reported in the survey. We focus on the working age population between 15 and 65 years old. The sample is also restricted to workers with a principal industry affiliation in one of the six product categories.[51] The model is estimated separately for skilled and unskilled workers, where an unskilled individual is defined as an individual who is illiterate.

The district level unit prices of the products are computed using the two rounds of the expenditure survey by household and product group, and aggregated to the district level using sampling weights. They are merged with the corresponding rounds of the employment survey by district.[52] We estimate the following reduced form wage equation:

$$lnw_{idt} = \alpha + \beta lnp_{dt} + \delta\gamma_{idt} + \mu_{st} + \varepsilon_{idt} \tag{18}$$

where w_{idt} is the wage income of individual i in district d at time t; β is the wage-price elasticity; lnp_{dt} is the employment-weighted (defined below) average price levels in district d at time t and γ_{idt} is a vector of individual characteristics that includes age, age-squared, and indicator variables for male and married workers; μ_{st} is the interaction of state and year fixed effects, and ε_{idt} is an iid error term. To account for the relative size of industries within each district, unit prices are aggregated using shares of employment in each district. These shares are computed for the initial round and kept constant over time to ensure that the results are not driven by changes in industry composition. The unit price can be written as

$$p_{dt} = \sum_i (\chi_{id,2005}) p_{it} \tag{19}$$

[50] For the 'other food' category, the pass-through elasticity is taken as unity.

[51] Following common practice, the 5-digit NIC code for the 'usual principal activity' variable is used as the principal industry affiliation of each individual (Appendix Table B.10).

[52] This approach has been used by Deaton (2000) to exploit the regional variation in prices to estimate systems of demand parameters and by Ravallion (1990) and Porto (2006, 2010) to use consumption surveys to exploit time variation in prices to estimate wage responses. Jacoby (2016) also estimates wage-price elasticities across districts using changes in wages over time.

where $\chi_{id,2005}$ is the employment share of product i in district d in 2005. The standard errors are clustered at the district level to account for within-district correlation.

The endogeneity of price levels in the above equation may bias the elasticity estimates. As in Jacoby (2016) and Mazzolari and Ragusa (2013), we instrument the price variable with an employment-weighted price where the weights are employment shares in all the other districts within the state, i.e.,

$$\bar{p}_{dt} = \sum_i (\chi_{id^-,2005}) p_{it} \tag{20}$$

where $\chi_{id^-,2005}$ is the employment share of product i in 2005 in all districts within the state except the own-district.

Table 10 shows the estimation results where we also report the p-value for the Kleibergen-Paap LM test, which rejects the null hypothesis of underidentification. The F-statistic for the significance of the excluded exogenous variables in the first-stage exceeds the recommended threshold of 10.

The rural wage-price elasticity under IV is estimated to be almost 0.2 for unskilled individuals, and 0.29 for skilled individuals, both statistically significant. For urban workers, only unskilled wages respond significantly to price changes, with an elasticity of 0.2, and the estimate is insignificant for skilled workers. The smaller wage response for rural unskilled workers is plausible given wage rigidities in agricultural sector. Dreze and Mukherjee (1989) in their analyses of rural labor markets in India observe that the standard wage often applies for prolonged periods of time from several months to several years. They observe little seasonality and casual wages are rigid downwards during slack seasons. Supreet (2014) shows that wages in India are rigid, which leads to unemployment once the positive shock dissipates. While the unskilled wage response is similar for rural and urban workers, the insignificant response of skilled wages for urban workers is expected since these workers tend to be affiliated with food manufacturing rather than direct production in the agricultural sector.[53]

[53] As an alternative approach, we use predicted prices to instrument for actual average prices in districts. This is done by allowing the price of each good to increase as predicted by the Monte Carlo results, and then computing the employment-weighted predicted prices for each district. We estimate two versions. First, we use the employment weights in all districts, and second, we exclude the employment weights in the own-district within each state. Table B.9 shows that estimates using weights from all districts are slightly smaller in magnitude for rural households. In particular, the wage elasticity for urban skilled labor is insignificant. On the other hand, if we exclude own-district, the results are similar to our baseline estimates, albeit with slightly larger standard errors. Our preferred specification excludes own-district weights to ensure that endogenous labor demand changes within districts are not causing simultaneity bias by driving both the price measure and the wages.

4 Household welfare and poverty impacts

4.1 Consumption, wages and net welfare

Consumption and wage impacts are shown in Table 11 by per capita expenditure deciles. Under perfect pass-through, the households in the lowest decile suffer a welfare loss of about 6% due to an increase in the cost of consumption. Those in the highest expenditure decile suffer a 4% loss. Losses for urban households are slightly higher. Under imperfect pass-through, all effects decline in magnitude. The poorest households suffer a nearly 4% decline in welfare from consumption - this effect decreases monotonically at higher deciles.

Figure 5 plots the nonparametric local polynomial regression of the household-level consumption impacts on log per capita expenditure. The positive slopes suggest that consumption effects are regressive, i.e., poorer households bear a larger welfare loss. Under imperfect pass-through, the negative effects are muted. Recall that only rice, sugar and corn price shocks are transmitted in this case. The budget share for these items is higher for poorer households, thus imperfect pass-through dampens their price shocks.

Table 11 shows the effect of the price shocks on wage incomes. Under perfect pass-through, the poorest rural households experience a sizable welfare gain of roughly 7%, because a higher share of them are employed in farming. These gains decline sharply with household expenditure - the effect is only 0.15% for the highest decile. Wage gains are smaller for urban households for the same reason, i.e. only a small fraction of them work in food-related industries.

Under imperfect pass-through, the impact on wage incomes is still progressive but smaller, affected only by grain and sugar prices. Rural wage incomes in the lowest decile increase by 1.7%. The impact on urban households is small. Figure 6 shows that the distribution of wage effects has a negative slope for both rural and urban households, suggesting a progressive effect through wages. Both the magnitude and the slope of the wage effect declines under imperfect pass-through, consistent with the lower impacts on price levels.

We can now aggregate consumption and wage income effects in the third panel of Table 11. Net welfare is positive for households in the lowest decile under perfect pass-through of prices, suggesting that the wage effects dominate the higher cost of consumption. Urban households suffer significant welfare losses (more than 6%). Welfare effects are negative in all other cases, although lower under imperfect price pass-through. Figure 7 shows that the welfare effects are markedly different among rural and urban households. They are progressive with a sharp negative slope among rural households, but regressive for urban households. This is because the positive price shocks confer large wage benefits to the rural poor. For the urban poor, the wage benefits are smaller and not enough to offset consumption losses.

4.2 Impact on poverty

The poverty impact is estimated by comparing the number of poor individuals before and after the price change. Let the poverty line be defined by z. Then the poverty rate P is the headcount ratio, i.e., the proportion of population below the poverty line, given by

$$P = \frac{1}{K}\sum_{i=1}^{K} I(x_i \leq z) \tag{21}$$

where K is the total number of individuals, x_i is per capita expenditure of individual i, and $I(\cdot)$ is an indicator function that takes the value 1 for individuals that are below the poverty line, i.e., for whom $x_i \leq z$.

Higher food prices increase wage incomes of individuals who work in industries that are directly affected. This will increase the per capita expenditure of the household in direct proportion to the share of wage income from that industry in the household budget, thereby shifting the welfare distribution upwards. However, the price shock also makes the same basket of goods more costly and therefore shifts the poverty line z to the right.[54] We use the international poverty line (z) of \$1.25 per day which is equivalent to Rs 701.25 per month.[55]

The poverty line is used to partition poor and non-poor individuals prior to the price shock and to identify households that change their poverty status. The households who were marginally poor prior to the price change may no longer be poor if the share of income from affected industries is relatively high. At the same time, the marginally non-poor may become poor if their income share is low. Each household is marked as poor and non-poor before and after the policy change - the change in the poverty rate is estimated as the difference in the poverty rate before and after the price shock. This procedure is repeated for each vector of price shock drawn from the distribution estimated earlier, yielding a mean and standard error of the poverty estimates.

Table 12 shows that the RFS-induced price shocks lead to an increase in poverty, by about 26 million people - out of which 20 million live in rural areas and about six million in towns and cities. This corresponds to a 2.1% increase in the rural poverty rate and a

[54]From (16), this effect is captured by $dz = \sum_i \overline{\theta}_i dlnp_i + \frac{1}{2}\sum_i\sum_j \varepsilon_{ij}\overline{\theta}_i(dlnp_i)(dlnp_j)$ where $\overline{\theta}_i$ is the average expenditure share of the 'marginal poor', which is defined as households within the 5% range of the poverty line as in De Janvry and Sadoulet (2010).

[55]This implies that the 'marginal poor' is a household with per capita expenditure between Rs 666.2 and Rs 736.3, using the 2010 purchasing power parity (PPP) of Rs 18.7 (World Bank Development Indicators). A month is assumed to be 30 days.

1.4% increase in the urban poverty rate.[56] Under imperfect pass through, the figures are quite similar for rural households but smaller for urban residents.

Even though the welfare impact is higher among urban households (Table 11), there is a greater impact on poverty in rural areas. Figure 8 shows the kernel densities of the rural and urban populations relative to the international poverty line. The higher rural population density near the poverty line leads to a higher share falling below the poverty line when the line shifts to the right. Urban households suffer a larger welfare loss, but a smaller number of them are located near the poverty line. This can also be seen by comparing the share of the 'marginal poor'. About 5.5% of rural households have per capita incomes within 5% range of the poverty line, but only 2.9% for urban households. These results highlight the need to study the entire distribution of welfare impacts rather than estimating a single statistic such as the poverty rate.

4.3 Welfare effects by household characteristics

We have focused on the heterogeneity among households in terms of their consumption baskets and income. These sources of variation are expected to be correlated with other characteristics of the household. Certain groups may be more or less impacted due to characteristics such as factor ownership or dietary preferences. Here we dissect the consumption and wage effects across different groups of households using a series of mean comparison tests.[57]

In Table 13, we report factor ownership across households, particularly land and skilled labor. Both landowners and the landless suffer similar consumption impacts, as seen in column (1). However, the wage effects are higher for those who own land, the difference being statistically significant. The effects are similar among urban households. Next we compare the skill level of the household head, where an unskilled individual is defined as someone who is illiterate. As expected, unskilled households experience a larger consumption effect, because they tend to be poorer. However, they see bigger wage gains because they work predominantly in the agriculture sector.

Gender comparisons are made in the third panel.[58] Households with a male head accrue lower consumption impacts and larger wage income gains. Hence overall welfare losses are significantly lower for those with male heads. Religious identity of households may be important to the extent that they are correlated with dietary habits. For example, many Hindus are vegetarians, and tend to consume less animal protein relative to Muslims. Rural Hindu households suffer larger consumption effects, but gain more in wage incomes, with a smaller net welfare loss.

[56]The estimated poverty rate is multiplied by U.N. population projections for 2022 (UNDP, 2015).
[57]We only report the estimates for perfect pass-though.
[58]Approximately 12% of rural households and 14% of urban households have female heads.

5 Concluding remarks

In this paper, we study the effect of the US Renewable Fuels Mandate on household consumption and income in a developing country. We show significant welfare impacts - consumption effects tend to be regressive because the poor spend a larger portion of their expenditure on food. Wage impacts are progressive because the poor are likely to be employed in the agriculture sector and therefore benefit from higher wages. The net effect is progressive for rural populations and regressive for those living in towns and cities, because the latter bear large consumption losses but gain little in wages. However, because a larger number of poor people live in villages, poverty impacts are disproportionately higher for rural households. We estimate that about 25-26 million are likely to become poor as a result of the RFS. These figures are robust to assumptions about the pass-through of world prices to the domestic Indian market.

These impacts may multiply several fold if other countries with rapidly-growing transportation sectors also turn to biofuels as a way of reducing their energy dependence. Some countries such as those of the European Union already have a significant mandate in place, although not as large as the United States mandate. India and China have mandates in the books. In the long-run of course, these price effects may be mitigated by bringing new land under production and technological improvements in farming. However, to the extent that we must use scarce land, water and other resources to produce more food and energy, the supply cost of food commodities is likely to increase, and food price shocks may linger for an extended time period. Other factors such as climatic shifts and droughts may also affect commodity prices and exacerbate these distributional impacts. Even with the Renewable Fuels Mandate, the poverty impacts we report may be much larger if other poor countries such as those in sub-Saharan Africa are included in the analysis.

An important data limitation is that the welfare estimations focus only on wage incomes and consumption, excluding important channels such as agricultural profits. However, including farm profits is unlikely to make a big difference in our estimates because the poor do not own significant assets. We do not take into account general equilibrium impacts driven by factor reallocation across sectors. This requires price data from other sectors, including services such as education and health, data for which is not readily available for a developing country like India. However, the magnitude of the general equilibrium impacts is likely to be small as service sectors are highly regulated in India and they may not be very sensitive to commodity price shocks.

This research can be extended in other directions. The micro-level impacts in India can be compared with that in other countries with significant poor populations to check if the composition of the welfare effects is fundamentally different and idiosyncratic to diet and other cultural factors. For example, societies in which the diet is based on corn or a higher consumption of meat and dairy may be impacted differently. Countries adopt different policies to mitigate the effect of price shocks, which can again be compared to obtain policy insights. Ultimately, these price shocks will affect nutritional intake among individuals and affect the allocation of calories within each household. Each consumption item in the NSS data we have used can be matched to its calorie, fat and protein content using the FAO nutritional database. The price shocks are likely to alter the consumption structure of each household. It may then be possible to estimate the number of individuals that will move below the recommended minimum daily nutritional intake, and isolate the effects on particular segments of the population, such as women and children.

References

Bento, A. M., Goulder, L. H., Jacobsen, M. R., and Von Haefen, R. H. (2009). Distributional and Efficiency Impacts of Increased US Gasoline Taxes. *The American Economic Review*, 99(3):667–699.

Bento, A. M., Klotz, R., and Landry, J. (2015). Are there carbon savings from US biofuel policies? The Critical Importance of Accounting for Leakage in Land and Fuel Markets. *Energy Journal*, 36(3):1276–1289.

Bourguignon, F., Bussolo, M., and Pereira da Silva, L. A. (2008). Introduction: Evaluating the Impact of Macroeconomic Policies on Poverty and Income Distribution. In Bourguignon, F., Bussolo, M., and Pereira da Silva, L. A., editors, *The Impact of Macroeconomic Policies on Poverty and Income Distribution*, pages 1–23. Palgrave MacMillan and the World Bank.

Bouwman, A. (1997). *Long-term scenarios of livestock-crop-land use interactions in developing countries*. Food and Agriculture Organisation, Rome.

British Petroleum (2013). BP Statistical Review of World Energy. June 2013. London: British Petroleum.

Campa, J. and Goldberg, L. (2005). Exchange Rate Pass-through into Import Prices. *Review of Economics and Statistics*, 87(4):679–690.

Campa, J. M. and Gonzalez Minguez, J. M. (2006). Differences in exchange rate pass-through in the euro area. *European Economic Review*, 50(1):121–145.

Carriquiry, M. A., Du, X., and Timilsina, G. R. (2010). Second-Generation Biofuels: Economics and Policies. Policy Research Working Paper, WPS 5406.

CBO (2014). The Renewable Fuel Standard : Issues for 2014 and Beyond. Congressional Budget Offire, Congress of the United States.

Chakravorty, U., Hubert, M.-H., Moreaux, M., and Nøstbakken, L. (2014). The long run impact of biofuels on food prices. CESifo Working Paper: Resource and Environment Economics.

Chakravorty, U., Magne, B., and Moreaux, M. (2012). Resource Use under Climate Stabilization: Can Nuclear Power Provide Clean Energy? *Journal of Public Economic Theory*, 14(2):349–389.

Chen, X., Huang, H., and Khanna, M. (2012). Land-use and greenhouse gas implications of biofuels: role of technology and policy. *Climate Change Economics*, 3(3):1181–1203.

Chen, X., Huang, H., Khanna, M., and Önal, H. (2014). Alternative transportation fuel standards: Welfare effects and climate benefits. *Journal of Environmental Economics and Management*, 67(3):241–257.

De Janvry, A. and Sadoulet, E. (2010). The Global Food Crisis in Guatemala: What Crisis and for Whom? *World Development*, 38(9):1328–1339.

Deaton, A. (1989). Rice Prices and Income Distribution in Thailand: A Non-Parametric Analysis. *Economic Journal*, 99(395):1–37.

Deaton, A. (2000). *The analysis of household surveys: a microeconomic approach to development policy*. Johns Hopkins University Press.

Dimaranan, B., McDougall, R., and Hertel, T. (2007). Behavioral parameters. *GTAP Data Base Documentation*.

Dreze, J. P. and Mukherjee, A. (1989). *Labor Contracts in Rural India: Theories and Evidence*. Macmillan Press.

EIA (2014). International Energy Statistics. U.S. Energy Information Administration Washington D.C, United-States.

EIA (2015). International Energy Outlook, 2014. U.S. Energy Information Administration Washington D.C, United-States.

EPA (2010). Renewable Fuel Standard Program (RFS2) Regulatory Impact Analysis. US Environmental Protection Agency Washington, DC.

Eswaran, H., Beinroth, F. H., and Reich, P. F. (2003). A Global Assessment of Land Quality. *Land quality, agricultural productivity, and food security: biophysical processes and economic choices at local, regional, and global levels*, page 111.

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

FAO (2014). Statistical Databases. Food and Agriculture Organization of the United Nations.

FAO-IIASA (2002). Global Agro-Ecological Zone. Food Agriculture Organization and International Institute for Applied Systems Analysis.

Fischer, G., Shah, M., van Velthuizen, H., and Nachtergaele, F. (2001). Global agro-ecological assessment for agriculture in the 21st century. International Institute for Applied Systems Analysis.

Golub, A., Hertel, T. W., and Sohngen, B. (2009). Land use modelling in a recursively dynamic GTAP framework. *Economic Analysis of Land Use in Global Climate Change Policy*, page 235.

Gouel, C. and Hertel, T. (2006). Introducing Forest Access Cost Functions into a General Equilibrium Model. GTAP Working Research Memorandum.

Han, J., Liu, R., Marchand, B. U., and Zhang, J. (2016). Market structure, imperfect tariff pass-through, and household welfare in urban china. *Journal of International Economics*, 100:220 – 232.

Hausman, C., Auffhammer, M., and Berck, P. (2012). Farm Acreage Shocks and Crop Prices: An SVAR Approach to Understanding the Impacts of Biofuels. *Environmental and Resource Economics*, 53(1):1–20.

Hertel, T., McDougall, R., Narayanan, R., and Aguiar, A. (2007). Behavioral parameters. GTAP Data Base Documentation.

Hertel, T., Tyner, W., and Birur, D. (2010). The global impacts of biofuel mandates. *Energy Journal*, 31(1):75–100.

IEA (2014). *Key world energy statistics*. International Energy Agency.

IEA-ETSAP, I. (2013). Production of Liquid Biofuels, Technology Brief. IEA-ETSAP and IRENA.

Jacoby, H. G. (2016). Food prices, wages, and welfare in rural India. *Economic Inquiry*.

Kwiecinski, A. and Jones, D. (2010). Policy Responses in Emerging Economies to International Agricultural Commodity Price Surges. Organisation for Economic Co-operation and Development (OECD).

Mazzolari, F. and Ragusa, G. (2013). Spillovers from high-skill consumption to low-skill labor markets. *Review of Economics and Statistics*, 95(1):74 – 86.

Mitchell, D. (2008). A note on rising food prices. World Bank, Policy Research Working Paper Series 4682.

Mittal, S. (2006). Structural shift in demand for food: projections for 2020. Indian Council for Research on International Economic Relations (ICRIER).

MOSPI (2012). *Report of the Committee on Unorganised Sector Statistics*. Ministry of Statistics and Programme Implementation.

Muhammad, A., Seale, J. L., Meade, B., and Regmi, A. (2010). International Evidence on Food Consumption Patterns: An Update Using 2005 International Comparison Program Data. *Technical Bulletin, number 125.*

Mundlak, Y. and Larson, D. (1992). On the transmission of world agricultural prices. *The World Bank Economic Review*, 6(3):399–422.

Nicita, A. (2009). The price effect of tariff 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. In *International Energy Workshop*, pages 17–19.

OECD/IEA (2010). Sustainable Production of Second Generation Biofuels: Potential and perspectives in major economies and developing countries. OECD/IEA.

OECD/IEA (2011). Technology Roadmap, Biofuels for Transport. OECD/IEA.

Parry, I. W. and Small, K. A. (2005). Does Britain or the United States have the right gasoline tax? *The American Economic Review*, 95(4):1276–1289.

Paul, S. (2011). Food Preference and Nutrition in India. Working Paper.

Porto, G. (2006). Using survey data to assess the distributional effects of trade policy. *Journal of International Economics*, 70(1):140–160.

Porto, G. (2010). International market access and poverty in argentina. *Review of International Economics*, 18(2):396–407.

Ravallion, M. (1990). Rural Welfare Effects of Food Price Changes under Induced Wage Responses: Theory and Evidence for Bangladesh. *Oxford Economic Papers*, 42(3):574–85.

Ravindranath, N., Sita Lakshmi, C., Manuvie, R., and Balachandra, P. (2011). Biofuel production and implications for land use, food production and environment in India. *Energy Policy*, 39(10):5737–5745.

Regmi, A., Deepak, M., Seale Jr, J., and Bernstein, J. (2001). Cross-country analysis of food consumption patterns. *Changing structure of global food consumption and trade*, pages 14–22.

Regmi, A. and Seale, J. L. (2011). Cross-Price Elasticities of Demand Across 114 Countries. *Technical Bulletin, number 1929.*

Roberts, M. J. and Schlenker, W. (2013). Identifying Supply and Demand Elasticities of Agricultural Commodities: Implications for the US Ethanol Mandate. *American Economic Review*, 103(6):2268–2295.

Rosegrant, M., Zhu, T., Msangi, S., and Sulser, T. (2008). Global scenarios for biofuels: Impacts and implications. *Applied Economic Perspectives and Policy*, 30(3):495–505.

Rosenthal, E. (2011). Rush to use crops as fuel raises food prices and hunger fears. *The New York Times*.

Sohngen, B. and Mendelsohn, R. (2003). An optimal control model of forest carbon sequestration. *American Journal of Agricultural Economics*, 85(2):448–457.

Supreet, K. (2014). Nominal wage rigidity in village labor markets. *National Bureau of Economic Research*, (20770).

UNDP (2010). Human Development Report 2010: The Real Wealth of Nations: Pathways to Human Development. United Nations Development Programme New York, NY, USA.

UNDP (2015). Population Prospects: The 2015 Revision. The Population Division of the Department of Economic and Social Affairs of the UN Secretariat.

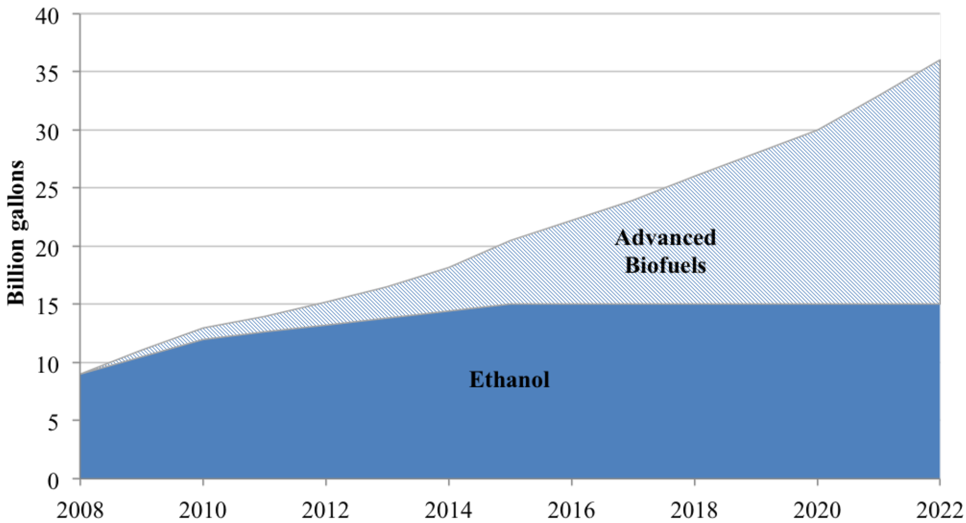
Ural Marchand, B. (2012). Tariff Pass-Through and the Effect of Trade Liberalization on Household Welfare. *Journal of Development Economics*, 99(2):265–281.

World Bank (2015). Commodity Markets Outlook, Prices (Pink Sheet). World Bank.

World Bank (2016). World Databank. World Development Indicators.

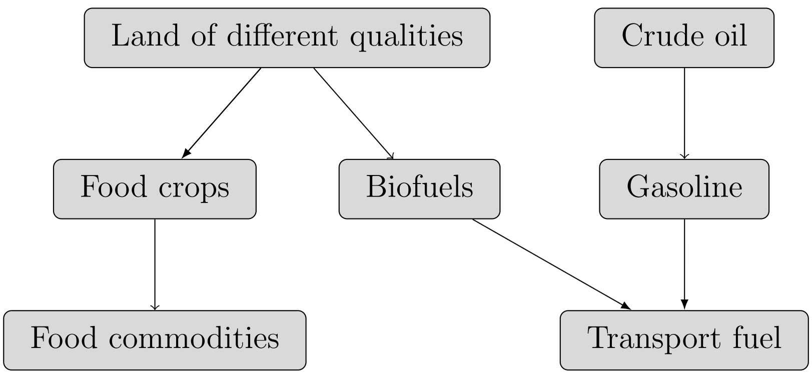
Figures

Figure 1: U.S. renewable fuels mandate



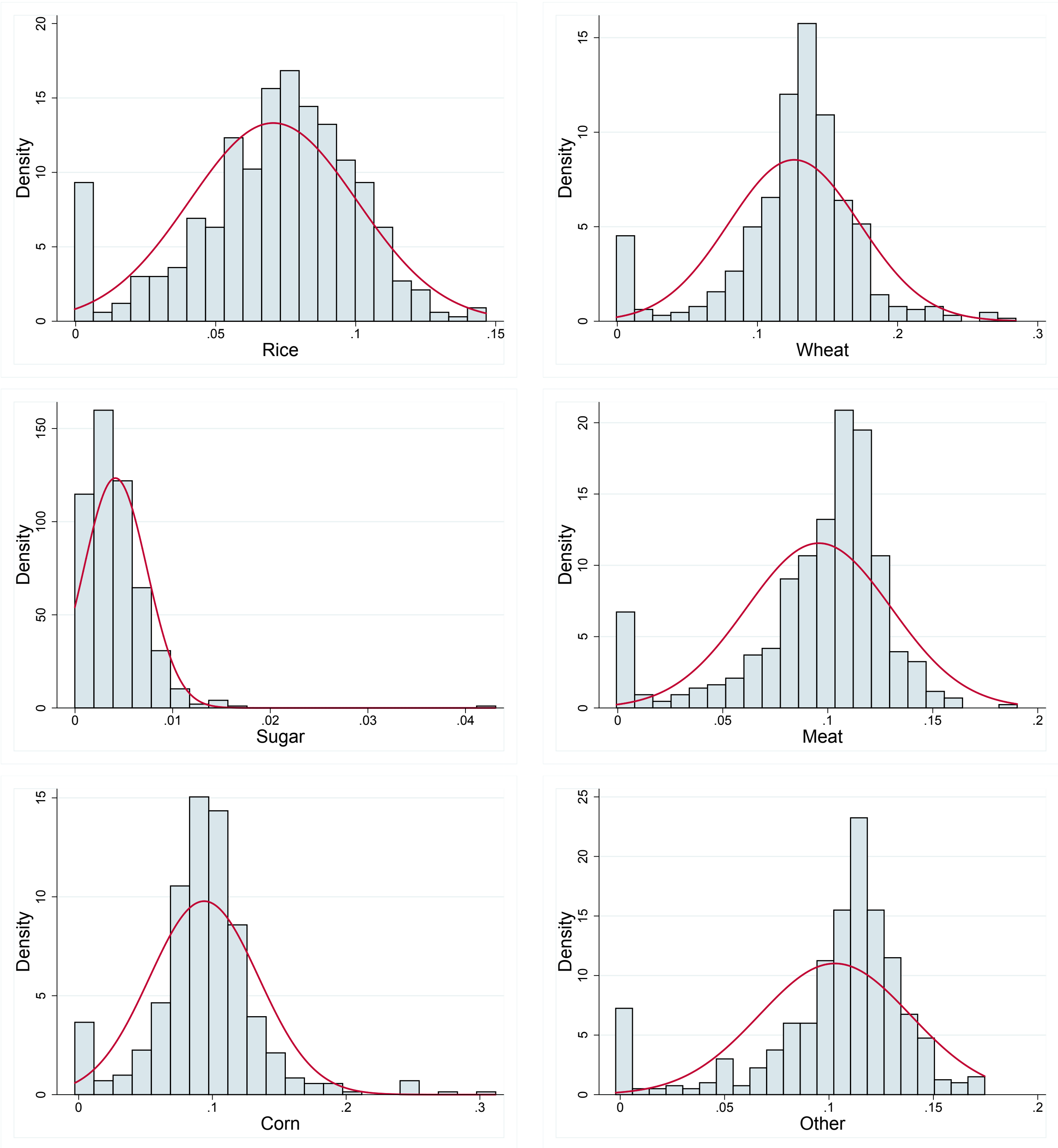
Notes: Beyond 2015, the ethanol mandate is fixed at 15 billion gallons. The rest is advanced biofuels. *Source:* (EPA, 2010)

Figure 2: Schematic of the model with food and energy



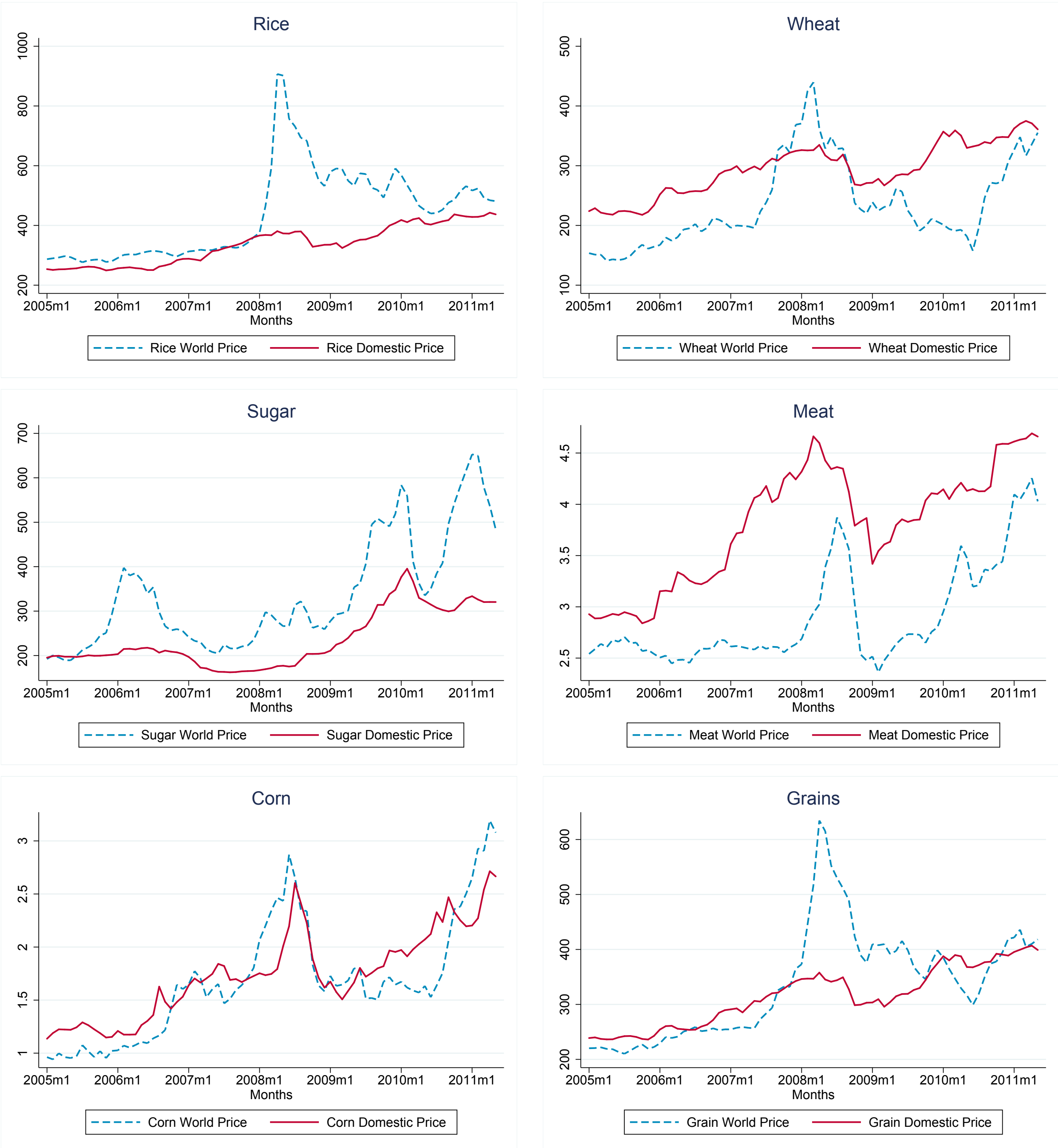
Notes: Land of different qualities is used to produce biofuels or food crops, namely rice, wheat, corn, sugar and 'other crops'. These crops are then transformed into food commodities (rice, wheat, corn, sugar and 'other food'). A portion of 'other crops' and corn goes into 'meat and dairy' production.

Figure 3: Distribution of RFS-induced price shocks



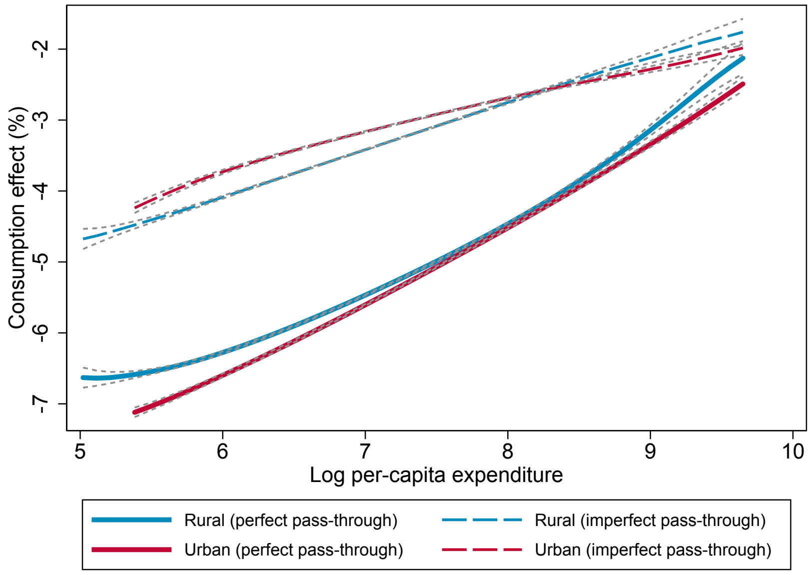
Notes: The graphs show the distribution of price shocks for each commodity from 500 draws from the underlying parameter distributions with and without the RFS. We report values within two standard deviations of the mean, with less than 6 observations outside this range for each commodity. Smooth lines show the normal density.

Figure 4: Domestic and world prices ($) for food commodities



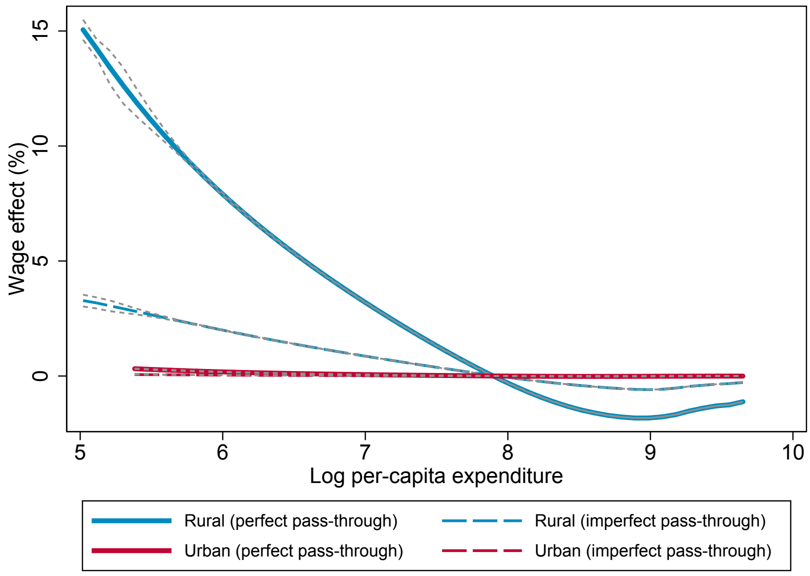
Notes: All prices are in current US dollars. Rice, sugar, wheat and grain prices are in metric tons, while meat and corn prices are in kilogram units. Grains include rice and wheat.

Figure 5: Effect of the price shock on household consumption



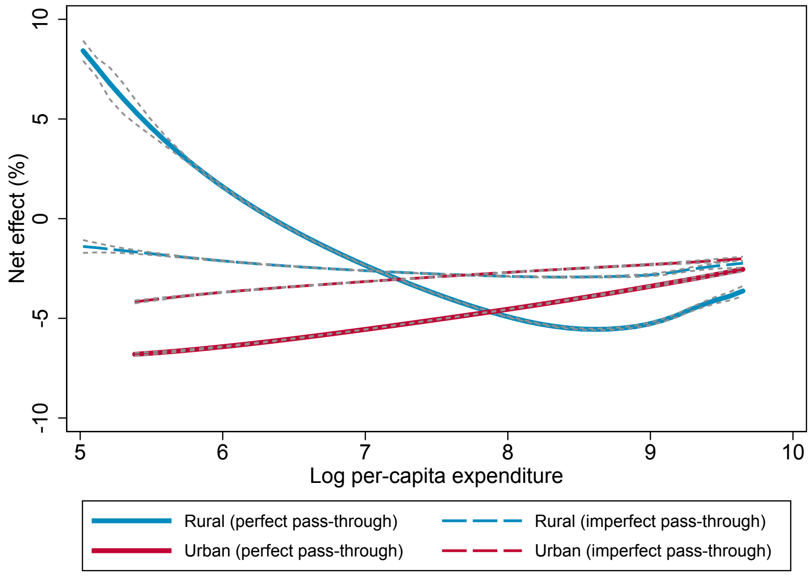
Notes: Local polynomial regression of consumption on log per capita household expenditure.

Figure 6: Effect of the price shock on household wage income



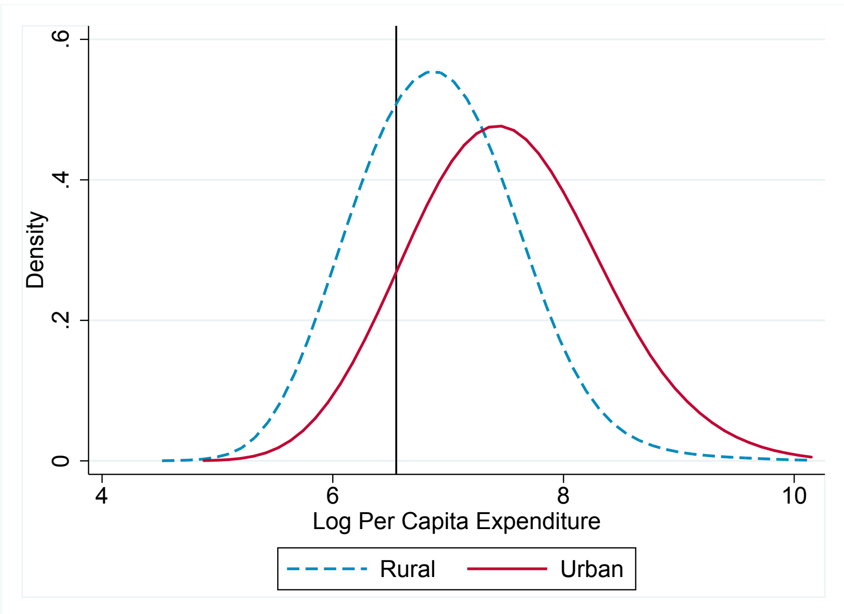
Notes: Local polynomial regression of wage income effects on log per capita household expenditure.

Figure 7: Effect of the price shock on welfare



Notes: Local polynomial regression of net welfare on log per capita household expenditure.

Figure 8: Kernel densities around the poverty line



Notes: Kernel densities over per capita expenditure are shown. The halfwidth kernel of 0.5 and sampling weights are used in density estimation. The vertical line represents the log international poverty line of \$1.25 converted to rupees (i.e. ln(701.25)=6.55).

Tables

Table 1: Cost and yield data for corn ethanol

	US	India	ROW
Representative crop	Corn	Sugarcane	Sugarcane
Share	(93%)	(82%)	(63%)
Unit cost($/gallon)	0.73	1.66	0.63
	Energy yield by land quality (gallons/ha)		
High	876	1,200	1,463
Medium	681	912	1,254
Low	487	790	1,115

Notes: Share denotes production of representative crop in regional biofuel production. The representative crop for ROW is sugarcane - since Brazil is the dominant producer with 47% of ROW production in 2012. Unit costs of production are taken from IEA-ETSAP (2013), OECD/IEA (2011) and Ravindranath et al. (2011).

Table 2: Model validation: consumption of food and fuel in 2012

	US			India			ROW		
	Actual	Predicted	% diff	Actual	Predicted	% diff	Actual	Predicted	% diff
Rice	8.00	8.21	2.64	70.00	74.40	6.27	53.00	54.87	3.54
Wheat	80.00	78.67	-1.66	60.00	57.69	-3.85	65.00	63.56	-2.22
Sugar	60.00	61.42	2.37	23.00	24.38	5.98	22.00	22.57	2.58
Corn	12.00	12.31	2.55	6.00	6.36	6.05	21.00	21.72	3.41
Other food	119.00	120.88	0.74	80.00	81.36	1.70	116.00	117.12	0.96
Meat/Dairy	375.00	383.84	2.08	75.00	77.07	2.77	70.00	71.57	2.24
Fuel	9,250	9,810	-6.1	69	73	6	752	763	1.47

Notes: Consumption units for food in kg/capita and fuel in VMT/capita. Actual values are rounded off. % diff is the percent difference between predicted and actual values. *Sources:* consumption of food commodities: FAO (2014), transport fuel: EIA (2014).

Table 3: Model validation: world food commodity prices in year 2012

	Actual	Model	% diff
Rice	450	462	2.66
Wheat	250	270	8.00
Sugar	450	471	4.66
Corn	250	241	-3.60
Other food	280	271	-3.21
Meat/Dairy	1,960	1,820	-7.14

Notes: % diff represents the percentage difference between predicted and actual values. We report real prices expressed in 2005 US dollars. *Source:* World Bank (2015).

Table 4: Price of food commodities ($/ton) in 2022 with and without the RFS

	Rice	Wheat	Sugar	Meat	Corn	Other food
BASE	514	501	456	2,751	314	400
REG	556	580	458	3,069	345	450
% diff	7.55	15.77	0.40	11.55	9.87	12.50

Notes: BASE refers to the model without RFS, and REG with it. % diff refers to the percentage difference between BASE and REG prices.

Table 5: Mean and standard errors for food commodity prices in year 2022 with and without the RFS

	Rice	Wheat	Sugar	Meat	Corn	Other food
			BASE - without RFS			
Mean	580	579	459	3,245	358	475
	(8.93)	(15.08)	(0.45)	(67.31)	(6.79)	(10.76)
			REG - with RFS			
Mean	627	660	461	3,852	393	530
	(10.22)	(17.44)	(0.42)	(77.66)	(7.56)	(12.35)
			Change in commodity prices (%)			
Mean	7.87	13.19	0.39	9.44	9.89	10.88
	(0.76)	(0.36)	(0.009)	(0.25)	(0.69)	(0.51)

Notes: Standard errors are in parentheses. Estimates obtained from 500 random draws from selected distributions of model parameters, see Appendix for details.

Table 6: Household mean expenditure shares (%) by commodity

	Rural						Urban					
Decile	Rice	Wheat	Sugar	Meat	Corn	Other food	Rice	Wheat	Sugar	Meat	Corn	Other food
1	13.40	6.62	2.20	6.70	0.37	34.13	9.71	8.14	2.52	7.36	0.09	34.02
2	10.83	6.13	2.36	9.49	0.25	33.36	8.88	6.61	2.41	9.59	0.03	32.39
3	9.76	5.04	2.28	11.09	0.26	32.94	8.13	5.93	2.22	10.03	0.04	31.89
4	8.82	4.60	2.29	12.02	0.20	32.12	7.57	5.18	2.13	10.97	0.03	31.22
5	7.92	4.43	2.27	12.93	0.20	30.58	6.85	4.91	2.01	11.63	0.01	29.99
6	7.25	3.89	2.14	12.92	0.10	30.61	6.26	4.26	1.85	11.74	0.01	29.16
7	6.57	3.59	1.98	13.59	0.09	29.84	5.96	3.87	1.67	11.49	0.01	28.36
8	5.66	3.10	1.85	13.45	0.08	28.60	5.01	3.26	1.46	11.01	0.01	28.43
9	4.65	2.62	1.63	12.62	0.03	27.62	4.31	2.75	1.22	10.14	0.01	27.61
10	2.72	1.61	1.02	8.53	0.03	25.70	2.51	1.71	0.76	7.71	0.00	24.22
Overall	7.76	4.16	2.00	11.33	0.16	30.55	6.52	4.66	1.83	10.17	0.02	29.73

Notes: Mean monthly expenditure shares as a fraction of total expenditures are computed from the $2009-2010$ round of the NSS Household Expenditure Survey. Deciles are based on household log per capita expenditures. Sampling weights are used.

Table 7: Employment shares (%) for individuals by commodity

	Rural				Urban			
Decile	Grains	Sugar	Meat	Other food	Grains	Sugar	Meat	Other food
1	52.35	0.45	1.56	3.11	11.29	0.08	1.29	1.26
2	47.34	0.54	1.82	3.17	11.57	0.08	1.52	1.22
3	46.98	0.76	2.32	3.72	11.16	0.18	1.49	1.29
4	45.67	0.76	2.32	3.72	10.24	0.24	1.80	2.77
5	43.50	0.92	2.34	4.24	8.37	0.20	1.85	1.26
6	41.26	1.05	2.66	4.64	7.44	0.06	1.89	1.45
7	39.27	0.88	2.32	5.23	6.09	0.09	1.31	1.21
8	35.03	1.46	2.80	5.72	4.92	0.24	1.67	0.99
9	30.82	1.22	3.56	6.17	3.42	0.16	0.87	1.01
10	25.27	0.68	3.42	6.35	2.08	0.08	0.68	0.68
Overall	40.75	0.87	2.51	4.61	7.66	0.14	1.44	1.31

Notes: Grains denote all grains including rice and wheat: separate NIC codes for rice and wheat are not available. Employment shares as a fraction of total employment (including non-food) are computed from the 66^{st} round of the NSS Employment and Unemployment Survey. Deciles are based on household log per capita expenditures. The matching of the 5-digit NIC affiliation of workers to food categories is shown in Appendix Table B.10. Sampling weights are used in the estimation.

Table 8: Increase in commodity prices (%), 2005-2011

	Rice	Wheat	Sugar	Meat	Corn	Grains
Domestic	72.29	61.16	64.11	59.16	184.62	67.07
World	67.74	131.31	151.72	74.33	219.84	89.90
Ratio	1.07	0.47	0.42	0.80	0.84	0.75

Notes: Ratio represents domestic over world price. The price series are converted to US dollars using exchange rates from the Reserve Bank of India. The period January 2005-May 2011 is the longest available for all commodities. Grains include rice, wheat and corn and its pass-through elasticity is used to compute wage impacts.

Table 9: Estimation of price pass-through elasticities

	Short run (β_1)	Long run ($\sum \beta_i$)
Rice	0.057***	0.181***
	(0.021)	[7.97]
Wheat	0.008	0.006
	(0.035)	[0.01]
Sugar	0.219***	0.383***
	(0.043)	[16.40]
Meat	-0.023	0.056
	(0.068)	[0.06]
Corn	0.280***	0.197***
	(0.093)	[19.66]
Grains	0.069**	0.184**
	(0.024)	[5.62]
N	76	76

Notes: Standard errors for short run elasticities are reported in parenthesis and F-statistics for long-run elasticities are in square brackets. Grains include rice and wheat and its pass-through elasticity is used to compute wage impacts. Only the significant long-run elasticities are incorporated in the estimation. Asterisks denote statistical significance at the 1% ***, 5% ** and 10% * levels.

Table 10: Estimation of wage-price elasticities

	Rural		Urban	
Unskilled	OLS	IV	OLS	IV
Wage-price elasticity	0.141***	0.195**	0.263***	0.204*
	(0.031)	(0.105)	(0.056)	(0.120)
R^2	0.440	0.439	0.521	0.512
N	14,348	14,307	1,291	1,283
Kleibergen-Paap p-value		0.0001		0.0002
First stage F-stat		55.856		15.738
Skilled				
Wage-price elasticity	0.154***	0.289**	0.238***	0.009
	(0.030)	(0.130)	(0.061)	(0.209)
R^2	0.361	0.355	0.424	0.369
N	14,498	14,405	1,749	1,720
Kleibergen-Paap p-value		0.0004		0.0007
First stage F-stat		22.681		14.696

Notes: An unskilled individual is defined as an individual who is illiterate. Estimates based on wage income of individuals and unit prices from the NSS Consumer Expenditure Survey. Employment-weighted price levels are used. All regressions control for age, age-squared, gender, marital status and interaction of state and year fixed effects. Standard errors are clustered at the district level. Asterisks denote statistical significance at the 1% ***, 5% ** and 10% * levels.

Table 11: Effects on consumption, wages and welfare

	Perfect price pass-through				Imperfect price pass-through			
	Rural		Urban		Rural		Urban	
	Mean	SE	Mean	SE	Mean	SE	Mean	SE
Decile				Consumption				
1	-6.030	0.111	-6.321	0.270	-3.955	0.190	-3.631	0.060
2	-5.957	0.109	-6.083	0.250	-3.831	0.183	-3.455	0.057
3	-5.851	0.107	-5.917	0.239	-3.770	0.179	-3.394	0.056
4	-5.724	0.105	-5.787	0.229	-3.665	0.174	-3.317	0.055
5	-5.565	0.102	-5.629	0.216	-3.483	0.165	-3.182	0.053
6	-5.439	0.100	-5.405	0.205	-3.475	0.164	-3.088	0.051
7	-5.334	0.098	-5.211	0.198	-3.379	0.159	-3.001	0.050
8	-5.062	0.093	-5.000	0.188	-3.229	0.152	-2.962	0.049
9	-4.838	0.089	-4.743	0.180	-3.215	0.150	-2.905	0.048
10	-4.038	0.074	-4.316	0.164	-2.573	0.120	-2.764	0.046
Overall	-5.384	0.099	-5.441	0.214	-3.458	0.163	-3.170	0.052
				Wage income				
1	7.030	0.173	0.183	0.139	1.733	0.038	0.034	0.018
2	4.550	0.175	0.104	0.108	1.055	0.039	0.025	0.018
3	3.503	0.171	0.089	0.101	1.112	0.042	0.034	0.018
4	2.975	0.172	0.047	0.125	0.952	0.044	0.013	0.017
5	2.124	0.171	0.019	0.081	0.636	0.044	0.006	0.018
6	1.434	0.169	0.022	0.074	0.392	0.045	0.003	0.008
7	1.239	0.152	0.006	0.047	0.332	0.045	0.001	0.005
8	0.608	0.172	0.009	0.051	0.125	0.046	0.001	0.005
9	0.391	0.176	0.001	0.036	0.086	0.053	0.000	0.007
10	0.145	0.173	0.000	0.011	0.049	0.065	0.000	0.006
Overall	2.400	0.171	0.048	0.077	0.647	0.046	0.012	0.012
				Net welfare				
1	1.000	0.111	-6.138	0.270	-2.222	0.190	-3.597	0.060
2	-1.407	0.109	-5.979	0.250	-2.777	0.183	-3.430	0.057
3	-2.348	0.107	-5.828	0.239	-2.658	0.179	-3.360	0.056
4	-2.748	0.105	-5.740	0.229	-2.713	0.174	-3.304	0.055
5	-3.441	0.102	-5.610	0.216	-2.847	0.165	-3.177	0.053
6	-4.005	0.100	-5.383	0.205	-3.083	0.164	-3.085	0.051
7	-4.095	0.098	-5.205	0.198	-3.047	0.159	-3.000	0.050
8	-4.454	0.093	-4.991	0.188	-3.103	0.152	-2.960	0.049
9	-4.447	0.089	-4.742	0.180	-3.129	0.150	-2.905	0.048
10	-3.893	0.074	-4.316	0.164	-2.524	0.120	-2.764	0.046
Overall	-2.984	0.099	-5.393	0.214	-2.810	0.163	-3.158	0.052

Notes: SE denotes standard errors, estimated through replications based on sampling from the distribution of commodity price shocks.

Table 12: Number of new poor created by the RFS

	Rural		Urban		
	Change in poverty rate	New poor (million)	Change in poverty rate	New poor (million)	Total new poor (million)
Perfect Pass-through:					
Mean	2.052 ***	19.792	1.361***	6.180	25.591
	(0.000)		(0.005)		
Imperfect Pass-through					
Mean	2.175***	20.985	0.829***	3.766	24.751
	(0.005)		(0.001)		

Notes: Standard errors are in parentheses. The $1.25 poverty line is converted to Rupees using 2010 purchasing power parity. The number of new poor is computed using year 2022 United Nations projected population for India of 1.42 billion (UNDP, 2015). Asterisks denote statistical significance at the 1% ***, 5% ** and 10% * levels.

Table 13: Welfare effects by household characteristics

	Rural			Urban		
	Consumption	Wages	Welfare	Consumption	Wages	Welfare
	(1)	(2)	(3)	(4)	(5)	(6)
Land ownership						
Landowner	-5.428	2.833	-2.606	-5.202	0.037	-5.180
	(0.004)	(0.010)	(0.010)	(0.007)	(0.001)	(0.007)
Landless	-5.310	2.287	-3.055	-4.991	0.025	-4.986
	(0.025)	(0.051)	(0.049)	(0.014)	(0.001)	(0.014)
Δ	-0.118***	0.546***	0.450***	-0.211***	0.013***	-0.193***
	(0.021)	(0.050)	(0.047)	(0.015)	(0.001)	(0.014)
t-stat	-5.554	10.996	9.498	-14.365	13.301	-13.477
Skill						
Unskilled	-5.705	3.636	-2.071	-5.848	0.072	-5.779
	(0.007)	(0.021)	(0.020)	(0.014)	(0.001)	(0.014)
Skilled	-5.296	2.437	-2.875	-5.007	0.026	-4.999
	(0.005)	(0.011)	(0.011)	(0.007)	(0.000)	(0.007)
Δ	-0.408***	1.199***	0.804***	-0.841***	0.045***	-0.780***
	(0.009)	(0.022)	(0.021)	(0.017)	(0.001)	(0.016)
t-stat	-43.433	55.667	38.690	-50.388	41.972	-47.855
Gender						
Male	-5.416	2.826	-2.602	-5.133	0.033	-5.115
	(0.005)	(0.011)	(0.010)	(0.007)	(0.000)	(0.007)
Female	-5.476	2.668	-2.828	-5.257	0.039	-5.245
	(0.015)	(0.031)	(0.030)	(0.019)	(0.001)	(0.019)
Δ	0.060***	0.158***	0.226***	0.125***	-0.005***	0.130***
	(0.014)	(0.033)	(0.032)	(0.020)	(0.001)	(0.019)
t-stat	4.210	4.769	7.167	6.387	-4.120	6.814
Religion						
Hindu	-5.460	2.914	-2.555	-5.095	0.034	-5.079
	(0.005)	(0.012)	(0.011)	(0.007)	(0.000)	(0.007)
Islam and other	-5.296	2.450	-2.866	-5.309	0.035	-5.286
	(0.010)	(0.020)	(0.019)	(0.013)	(0.001)	(0.012)
Δ	-0.164***	0.464***	0.311***	0.214***	-0.001	0.208***
	(0.010)	(0.024)	(0.023)	(0.015)	(0.001)	(0.014)
t-stat	-15.671	19.087	13.405	14.450	-1.315	14.369

Notes: Household classification is based on characteristics reported in the 66^{th} round of the NSS Household Expenditure Survey. Gender refers to the gender of the household head. A household is defined as unskilled if the household head is illiterate. t-statistics of the mean comparison tests are reported. Δ denotes the difference in the mean impact. Asterisks denote statistical significance at the 1% ***, 5% ** and 10% * levels.

A Appendix

A.1 Data used in estimation

We use GAMS software to code the calibration model. Here we provide additional data and specifications used in the calibration.

Crop yields, acreage and costs: Table B.1 shows yields and endowment of land for the base year 2012 by land quality and region. Parameters for the cost of converting new land into farming (equation (9)) are reported in Table B.2. Parameters for production costs (equation (10)) are reported in Table B.3. For rice, wheat, sugar and "other crops," we assume that one ton of crop produces 0.85 tons of the final food commodity (FAO, 2014), taken to be uniform across regions. A portion of "other crops" is used as animal feed. The quantity of meat and dairy produced from one ton of "other crops" (called feed ratio) is region-specific and adapted from Bouwman (1997). We use a feed ratio of 0.4 for US and 0.25 for India and ROW.

Regional demands: Regional demands (for rice, wheat, corn, sugar, meat and dairy, other food and transport fuel) are given by equation (11). The constant A_i is calibrated to reproduce demand in the base year and is written as $A_i = D_i/P_i^{\alpha_i} y_i^{\beta_i} N$ using (11). Data used to calibrate A_i is shown in Table B.4. We use estimates from the United Nations (UN Population Division, 2010) based on medium range fertility projections which predict a 2050 world population of 9.3 billion. India's population is expected to increase to about 1.38 billion in 2022. Projections for GDP per capita are from EIA (2015) based on three oil price scenarios: low, high and an intermediate reference case which we adopt for our model.

Energy production: Energy is supplied by a mix of gasoline and biofuels. Transport energy supply q_e is given by equation (12). The parameter λ is a constant calibrated to reproduce base-year production of transport fuel, given by

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

Data used to calibrate λ is reported in Table B.5.

Parameter values used in equation (13) are reported in Table B.6. Data on the initial stock of oil is from British Petroleum (2013). According to IEA (2014), 64% of oil production is used in the transport sector, so we take the initial reserves to be 64% of world oil reserves, i.e., 35.43 trillion gallons. Crude oil is transformed into gasoline: one gallon of oil produces 0.47 gallons of gasoline. The cost of converting oil into gasoline is assumed to be the same across different regions and equals \$0.46/gallon (Chakravorty et al., 2014). Since transport fuel is in energy units, we convert gallons into MegaJoules (MJ). A gallon of gasoline yields 120 MJ of energy; a gallon of ethanol gives 80 MJ. Finally, transport fuel is transformed into Vehicle Miles Traveled (VMT): one MJ of transport energy equals 0.177 VMT for a gasoline-powered car (Chen et al., 2012).

A.2 Sensitivity analysis

We perform sensitivity analysis by shocking the most critical parameters one at a time holding all others at their mean values. To quantify the shock, Parry and Small (2005) assume distributions for the parameters and define a plausible range of parameter values to obtain a 90% confidence interval. In our case, the shock applied to each parameter is the ratio of the standard deviation to the mean. We calculate the mean and standard deviation based on historical data (when available) or from a comprehensive review of the literature.[1] For the parameters crop yield and unit cost of crude oil, we use historical data.[2] The yield for the base year is the mean crop yield, it varies by land quality and region, as reported in Table B.7.[3] The standard deviation of the distribution is computed from regional yield data for the period 1980-2010 obtained from FAO (2014).[4] The base year unit cost of crude oil is the mean for the period 1980-2010 taken from Chakravorty et al. (2012). The standard deviation is calculated from observed data for the same years (World Bank, 2016). For the parameters price elasticity of demand, income elasticity, cost of biofuel, GDP per capita and population, we obtain plausible values from earlier studies. Their mean and standard deviation are reported in Table B.7.[5] The magnitude of the shock applied to each parameter equals the ratio of the standard deviation to the mean expressed as a share and reported in Table B.7. The

[1]To check the robustness of our results, we re-do the sensitivity analysis by applying a +/- 30% shock to the mean value of each parameter. The results did not change significantly.

[2]The main source of uncertainty for crop yields are weather shocks and extreme events such as droughts and hurricanes. For example, after the 2012 drought in the US, average maize yields declined by 25% from their 2011 levels.

[3]This data is readily available for rice, wheat and sugar, both for US and India. For ROW, we net out India and US output from world production. For the "other food" category, we calculate mean yield by dividing total production by acreage planted for each of the three regions.

[4]Since historical data on yield by land class is not available, we cannot compute standard deviations for each land quality. These are taken to be uniform, as shown in Table B.7. In other words, we assume that extreme events affect all land classes equally.

[5]Figures for the US are from Hertel et al. (2007) and Regmi et al. (2001). Both studies estimate the elasticity for two groups of food commodities. The first group includes cereals, sugar and sugar cane, roots and tuber, oils seeds, vegetables and fruits. We use this value as our common elasticity estimate for rice, wheat, sugar and other food. Their second group of food commodities includes meat and dairy which we can adopt directly. Data on price elasticities for India are from Paul (2011), Hertel et al. (2007) and Mittal (2006). For the ROW region, we use elasticity data from Roberts and Schlenker (2013) and Dimaranan et al. (2007) by assuming that their world averages hold for ROW. Roberts and Schlenker (2013) estimate world elasticities for one consolidated commodity group that includes maize, wheat, rice and soybeans, which we use for our four commodities corn, rice, wheat and other food.

model is re-run by replacing each parameter one at a time, keeping the other parameters constant.

Table B.8 reports the results for the sensitivity analysis. The panels show the price estimates and the difference between the regulated (BASE) and unregulated (REG) prices for each parameter shock. In the top panel, we repeat the information from Table 4 to facilitate comparison. The figures in parentheses in the last row for each run is the difference in percentage points between the price shock for that run relative to the model with initial parameter values (top panel). They tell us which parameter has the largest impact on the price shocks from the RFS. For instance, the price of wheat increases with the mandate by 15.8% under the set of initial parameter values (see top panel on left) but with the higher food price elasticity, it increases by 13.3% (second panel). So, the difference is −2.5% points, as noted in the last row. We pick the parameters that affect the price shocks the most. This involves comparison of the vector of price shocks for all five commodities in the the table with some subjective judgment. Rice and wheat are the most important crops, from an acreage as well as consumption standpoint, hence price changes for these two crops matter the most.[6] Using this criteria, we only focus on uncertainty in the two parameters listed in the top of the table, food price elasticity and crop yield.[7]

[6]The effect on sugar prices is generally low, since sugarcane can grow well on lower land qualities, unlike other crops (see Table B.1).

[7]We also ran the two models by shocking the remaining parameters such as income and price elasticity for transport, biofuel cost and population. These shocks did not cause discernible price changes.

B Appendix tables

Table B.1: Endowment of land (million hectares) and crop yields (tons/hectare) by land quality and region

Land quality	Land available	Wheat	Rice	Corn	Sugar	Other crops
			US			
High	60	7.96 (1.50)	7.95 (1.20)	10.80 (1.50)	87 (0.02)	4.50 (1.20)
Medium	80	5.76 (1.50)	5.71 (1.20)	8.14 (1.50)	63 (0.02)	3.50 (1.20)
Low	30	2.90 (1.50)	3.92 (1.20)	5.40 (1.50)	56 (0.02)	2.50 (1.20)
			India			
High	70	4.66 (1.20)	3.58 (1.20)	4.50 (1.30)	80 (0.01)	3.00 (1.20)
Medium	50	2.05 (1.20)	3.13 (1.20)	3.81 (1.30)	61 (0.01)	2.50 (1.20)
Low	10	1.71 (1.20)	2.15 (1.20)	2.14 (1.30)	53 (0.01)	1.50 (1.20)
			ROW			
High	200	3.25 (1.30)	5.60 (1.20)	5.25 (1.20)	71 (0.01)	3.20 (1.50)
Medium	950	2.02 (1.30)	3.36 (1.20)	4.83 (1.20)	61 (0.01)	2.80 (1.50)
Low	950	0.80 (1.30)	2.24 (1.20)	2.97 (1.20)	56 (0.01)	1.50 (1.50)

Source: FAO-IIASA (2002) and FAO (2014). Numbers in parentheses represent the annual growth rate of yield, calculated from historical data.

Table B.2: Parameters for the cost of land conversion

	ψ_1	ψ_2
US	430	431
India	200	200
ROW	26	26

Source: Gouel and Hertel (2006).

Table B.3: Parameters for production cost

	Rice		Wheat		Sugar		Other crops	
	η_1	η_2	η_1	η_2	η_1	η_2	η_1	η_2
U.S.	1.15	1.50	1.15	1.50	1.20	1.55	1.15	1.50
India	1.55	1.80	1.55	1.80	1.55	1.80	1.55	1.80
ROW	1.50	1.75	1.50	1.75	1.50	1.75	1.50	1.75

Source: Chakravorty et al. (2014).

Table B.4: Demand parameters by region and food commodities (base year 2012)

	US	India	ROW
Population *(Billion)*	0.31	1.22	5.36
GDP per capita *($)*	43,210	3,295	10,714
		Rice	
Consumption per capita *(kg)*	8	70	53
Price *($/ton)*	450	450	450
Price elasticity	-0.15	-0.35	-0.20
Income elasticity	0.15	0.57	0.65
Constant A_i	0.004	0.005	0.0004
		Wheat	
Consumption per capita *(kg)*	80	60	65
Price *($/ton)*	250	250	250
Price elasticity	-0.15	-0.35	-0.20
Income elasticity	0.15	0.57	0.65
Constant A_i	0.036	0.004	0.0004
		Corn	
Consumption per capita *(kg)*	12	6	21
Price *($/ton)*	250	250	250
Price elasticity	-0.15	-0.35	-0.20
Income elasticity	0.15	0.57	0.65
Constant A_i	0.005	0.0004	0.00015
		Sugar	
Consumption per capita *(kg)*	60	23	22
Price *($/ton)*	450	450	450
Price elasticity	-0.23	-0.34	-0.25
Income elasticity	0.41	0.71	0.65
Constant A_i	0.003	0.0005	0.0002
		Other food	
Consumption per capita *(kg)*	119	80	116
Price *($/ton)*	280	280	280
Price elasticity	-0.28	- 0.58	-0.30
Income elasticity	0.41	0.71	0.71
Constant A_i	0.007	0.002	0.004
		Meat/dairy	
Consumption per capita *(kg)*	375	75	70
Price *($/ton)*	1,960	1,960	1,960
Price elasticity	-0.28	-0.37	-0.30
Income Elasticity	0.43	0.97	0.77
Constant A_i	0.032	0.00047	0.00053
		Transport fuel	
Consumption per capita *(VMT)*	9,250	69	752
Price *($/VMT)*	0.14	0.23	0.23
Price elasticity	-0.50	-0.21	-0.78
Income Elasticity	1.30	1.30	1.20
Constant A_i	0.003	0.001	0.003

Sources: Consumption figures for food commodities are from FAO (2014); transport fuel: EIA (2014); prices: World Bank (2015); own-price and income elasticities for transport fuel: Parry and Small (2005), Hertel et al. (2007) and Dimaranan et al. (2007); price and income elasticities for food commodities (U.S.) are from Dimaranan et al. (2007), Regmi et al. (2001), Regmi and Seale (2011), Muhammad et al. (2010); price elasticities for food commodities (ROW): Roberts and Schlenker (2013) and from Dimaranan et al. (2007); income elasticities for food commodities (ROW): Dimaranan et al. (2007); price and income elasticities for food commodities (India): Paul (2011), Dimaranan et al. (2007), Regmi et al. (2001), Regmi and Seale (2011); population figures: United Nations Population Division UNDP (2015); and per capita income: EIA (2015).

Table B.5: Parameters for supply of transport fuel (2012)

	US	India	ROW
Transport fuel supply q_e (MJ)	16,400	688	23,150
Gasoline supply q_g (MJ)	15,840	540	22,000
Biofuels supply q_{bf} (MJ)	800	40	1,040
Share of gasoline μ_g	0.90	0.95	0.95
Elasticity of substitution ρ	2	2	2
Constant λ	1.22	1.24	1.37

Notes: MJ: MegaJoules; Production of transport fuel (q_e) equals consumption since transport fuel is not traded; Supply of biofuels (q_{bf}) and gasoline (q_g) are from EIA (2014); the share of gasoline is calculated as the ratio of gasoline (q_g) to transport fuel supply (q_e); elasticities of substitution are from Hertel et al. (2010).

Table B.6: Parameters for extraction cost of crude oil

World reserves (Billion gallons)	ϕ_1	ϕ_2 $/gallon	ϕ_3
35,427	2.50	7.76	15

Source: Oil reserves (British Petroleum (2013) and IEA (2014)); Cost parameters ϕ_1, ϕ_2 and ϕ_3 are from Chakravorty et al. (2012).

Table B.7: Parameter values used in Monte Carlo estimation

	US			*India*			*ROW*		
	Mean	Std. Dev.	Shock(%)	Mean	Std. Dev.	Shock(%)	Mean	Std. Dev.	Shock(%)
				Price elasticity					
Cereals	-0.15	0.022	15	-0.35	0.105	30	-0.20	0.060	30
Sugar	-0.23	0.038	16	-0.34	0.085	25	-0.25	0.065	26
Other food	-0.28	0.038	14	-0.58	0.116	20	-0.30	0.096	32
Meat	-0.28	0.039	14	-0.37	0.140	40	-0.30	0.096	32
Transport	-0.50	0.074	15	-0.21	0.063	30	-0.78	0.026	3
				Income elasticity					
Cereals	0.17	0.021	14	0.57	0.037	6	0.65	0.24	18
Sugar	0.41	0.049	12	0.71	0.001	5	0.71	0.05	8
Other food	0.41	0.042	10	0.71	0.009	13	0.71	0.06	8
Meat	0.43	0.120	28	0.97	0.038	4	0.77	0.07	9
Transport	1.30	0.016	1.2	1.30	0.020	2	1.20	0.12	10
				Crop yield (tons/hectare)					
Rice-H	7.95		12	3.58		13.5	5.60		8.5
Rice-M	5.71	0.936	16	3.13	0.482	15.5	3.36	0.472	14
Rice-L	3.92		24	2.15		22.5	2.24		21
Wheat-H	7.96		3.5	4.66		10	3.25		4
Wheat-M	5.76	0.273	5	2.05	0.439	21	2.02	0.122	6
Wheat-L	3.34		8	1.71		26	0.90		21
Corn-H	10.80		12	4.51		10	5.25		13
Corn-M	8.14	1.329	16	3.81	0.430	21	4.83	0.681	14
Corn-L	5.40		25	2.14		26	2.97		23
Sugar-H	87		5.5	80		9.5	71		6.5
Sugar-M	63	4.706	7.5	61	5.598	11	61	4.563	7.5
Sugar-L	56		8.5	53		21	56		8
Other crops-H	4.5		11	3.00		10	3.2		9
Other crops-M	3.5	13.359	14	2.50	5.970	12	2.80	5.864	11
Other crops-L	2.5		20	1.50		20	1.50		20
				Unit extraction cost of oil ($/barrel)					
Unit Cost	50	7.500	15	50	7.50	15	50	7.500	15
				Unit cost of biofuel ($/gallon)					
Ethanol	0.73	0.025	3.5	0.63	0.02	3	0.63	0.02	3
Cellulosic ethanol	0.99	0.150	15	na	na	na	na	na	na
				Demand parameters in base year					
GDP/capita ($)	43,210	1,022	2.3	3,295	105	3.1	10,714	284	2.5
Population (Billion)	0.31	0.070	2.3	1.22	0.020	1.6	5.36	0.120	2.4

Sources: The magnitude of the shock equals the ratio of standard deviation to mean, as shown. Price elasticities: Regmi et al. (2001), Parry and Small (2005), Dimaranan et al. (2007), Muhammad et al. (2010), Regmi and Seale (2011), Roberts and Schlenker (2013) and Bento et al. (2015) ; Income elasticities: Parry and Small (2005), Dimaranan et al. (2007), Muhammad et al. (2010), Bento et al. (2015); Crop yields: (FAO, 2014); Oil cost: World Bank (2015); Ethanol cost: OECD/IEA (2011) and IEA-ETSAP (2013); Cellulosic ethanol cost: Carriquiry et al. (2010), OECD/IEA (2010), OECD/IEA (2011) and IEA-ETSAP (2013); GDP per capita: EIA (2014); Population: UNDP (2015). *Notes:* Cereals include rice, wheat and corn. Rice-H, Rice-M and Rice-L should be respectively read as: yield of rice on high, medium and low land qualities. The same notation applies for wheat, corn, sugar and other food. The standard deviation is uniform across the different land classes since it is calculated from historical data. Cellulosic ethanol is not produced in India and ROW. Due to a lack on data on land conversion cost, we could not calculate the standard deviation. We assume a shock of 15%.

Table B.8: **Price of food commodities ($/ton) with RFS (REG) and without the RFS (BASE) in 2022: sensitivity to parameters**

	Wheat	Rice	Corn	Sugar	Other food	Meat
			Initial parameter values			
Base	501	514	314	456	400	2,751
REG	580	556	345	458	450	3,069
% diff	15.77	7.55	9.87	0.40	12.50	11.56
			High price elasticity for food			
Base	467	496	301	456	378	2,615
REG	529	530	326	457	418	2,867
% diff	13.27	6.85	8.30	0.22	10.58	9.64
	(-2.50)	(-0.70)	(-1.56)	(-0.22)	(-1.92)	(-1.92)
			High crop yield			
Base	327	422	244	452	288	2,052
REG	375	448	264	454	319	2,246
% diff	14.67	6.16	8.20	0.44	10.76	9.45
	(-1.10)	(-1.39)	(-1.67)	(0.04)	(-1.74)	(-2.11)
			High income elasticity for food			
Base	563	547	339	458	440	3,001
REG	645	594	374	460	495	3,359
% diff	14.56	8.59	10.32	0.43	12.50	11.92
	(-1.21)	(1.04)	(0.45)	(0.03)	(0.00)	(0.36)
			High per capita GDP			
Base	571	552	342	458	445	3,036
REG	660	599	378	460	502	3,391
% diff	15.58	8.51	10.53	0.43	12.80	11.69
	(-0.19)	(0.96)	(0.66)	(0.03)	(0.30)	(0.13)
			High cost of land conversion			
Base	735	638	408	461	551	3,695
REG	827	687	444	463	609	4,062
% diff	12.52	7.68	8.82	0.43	10.52	9.93
	(-3.25)	(0.13)	(-1.05)	(0.03)	(-1.98)	(-1.63)
			High unit cost of oil			
Base	503	516	315	456	401	2,760
REG	581	557	346	458	452	3,077
% diff	15.51	7.95	9.84	0.43	12.72	11.48
	(-0.26)	(0.40)	(-0.03)	(0.03)	(0.22)	(-0.08)

Notes: % diff is the price shock expressed as a percentage between BASE and REG. The numbers in parentheses show the contribution of the parameter (e.g., food price elasticity in the second panel) to the price shock. It is the difference in the % diff values for that paramter and the initial values in the top panel.

Table B.9: Wage-price elasticity estimates: alternative method using predicted price changes

	Employment weights in all districts		Excluding own-district	
	Rural	Urban	Rural	Urban
Unskilled				
Wage-price elasticity	0.141***	0.263***	0.194*	0.203*
	(0.0368)	(0.0494)	(0.108)	(0.115)
R^2	0.440	0.521	0.439	0.512
N	13,735	1,242	13,697	1,236
Kleibergen-Paap p-value	0.000	0.000	0.0001	0.0002
First Stage F	3.60E+05	2.30E+05	65.72	42.51
Skilled				
Wage-price elasticity	0.157***	0.250***	0.269**	0.033
	(0.0305)	(0.0526)	(0.115)	(0.194)
R^2	0.413	0.485	0.408	0.461
N	15,102	1,797	15,006	1,766
Kleibergen-Paap p-value	0.000	0.000	0.0004	0.0007
First Stage F	4.40E+05	5.80E+05	27.85	23.54

Notes: An unskilled individual is one who is illiterate. Estimates based on wage income of individuals and unit prices from the 2004 – 2005 and 2009 – 2010 rounds of the NSS Consumer Expenditure Survey. Employment-weighted price levels are used. All regressions control for age, age-squared, gender, marital status, and interaction of state and year fixed effects. Standard errors are clustered at the district level. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table B.10: Matching between commodities, expenditure categories and industries

Products	NSS Codes	NSS Description	NIC Codes	NIC Description
(1)	(2)	(3)	(4)	(5)
Rice	101-102	Rice	1111	Growing of food grain crops
	103	Chira	1403	Activities establishing a crop, promoting its growth or protecting it from disease and insects.
	104	Khoi, lawa	1404	Harvesting and activities related to harvesting, such as preparation of crop cleaning, trimming, grading, drying.
	105-106	Muri and Other Rice Products		
Wheat	107-108	Wheat, atta	1111	Growing of food grain crops
	110	Maida	1403	Activities establishing a crop, promoting its growth or protecting it from disease and insects. Transplantation of rice in rice fields.
	111	Suji, rawa	1404	Harvesting and activities related to harvesting, such as preparation of crop cleaning, trimming, grading, drying.
	112-114	Bread, bakery, sewai, noodles, other wheat products		
Sugar	269	Sugar (sub-total)	1115	Growing of sugarcane or sugar beet
Meat/Dairy	160	Milk: liquid (litre)	1407	Activities to promote propagation, growth and output of animals and to obtain
	161	Baby food	1409	Other agricultural and animal service activities, n.e.c.
	162	Milk: condensed/ powder	1211	Farming of cattle , sheep, goats, horses, asses, mules and hinnies; dairy farming
	163	Curd	1212	Rearing of goats, production of milk
	164	Ghee	1213	Rearing of sheep; production of shorn wool
	165	Butter	1214	Rearing of horses, camels, mules and other.
	166	Ice-cream	1221	Raising of pigs and swine
	167	Other milk products	1222	Raising of poultry (including broiler) and other domesticated birds; production of eggs and operation of poultry hatcheries
	180	Eggs (no.)	1223	Raising of bees; production of honey
	181	Fish, prawn	1224	Raising of silk worms; production of silk worm cocoons
	182	Goat meat/mutton	1225	Farming of rabbits including angora rabbits
	183	Beef/ buffalo meat	1229	Other animal farming; production of animal products n.e.c.
	184	Pork	1500	Hunting, trapping and game propagation including related service activities
	185	Chicken	5011-5012	Fishing on commercial basis in ocean, sea and coastal areas
	186	Others: birds, crab, oyster, tortoise, etc.	5021-5023	Fishing, fish farming, gathering of marine materials, other fishing activities
Other food	115-122	Jowar, bajra, maize, barley, small millets other cereal	1112	Growing of oilseeds including peanuts or soya beans
	139	Cereal substitutes: tapioca, jackfruit, etc.	1119	Growing of other crops, n.e.c.
	159	Pulses & pulse products	1121	Growing of vegetables
	179	Edible oil (sub-total)	1122	Growing of horticultural specialties including: seeds for flowers, fruit or
	229	Vegetables (sub-total)	1131	Growing of coffee or cocoa beans
	249	Fruits (fresh, sub-total)	1132	Growing of tea or mate leaves including the activities of tea factories associated
	259	Fruits (dry, sub-total)	1133	Growing of edible nuts including coconuts
	289	Spices (sub-total)	1134	Growing of fruit: citrus, tropical pome or stone fruit; small fruit such as berries;
	290-293	Tea and coffee	1135	Growing of spice crops including: spice leaves